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AI and Machine Learning in Remote Sensing for Tropical Forest Monitoring: Applications, Challenges, and Emerging Solutions

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Highlights

Main findings

- Artificial intelligence and machine learning (AI/ML) have become essential tools in remote sensing for tropical forest monitoring, offering significantly enhanced accuracy, automation, and speed of detecting deforestation, forest degradation, biomass changes, and forest dynamics.
- However, widespread adoption of AI/ML in tropical regions is still hindered by limited access to high-quality training data, reliance on proprietary platforms, gaps in technical capacity and infrastructure, and unresolved ethical and governance issues.

Implications of the main findings

- Overcoming these barriers by developing open training datasets, investing in platform-agnostic and open-source infrastructures, building local technical capacity, and ensuring inclusive governance is critical for scaling AI-enabled forest monitoring in support of carbon markets and national MRV (Measurement, Reporting, and Verification) systems.
- AI/ML-powered monitoring can become a robust, transparent, and locally owned forest monitoring system supporting climate mitigation, biodiversity conservation, and equitable decision-making in tropical forest countries.

Abstract

Tropical forests are critical for global climate, biodiversity conservation, and supporting local livelihoods, yet they remain highly vulnerable to human-induced pressures (deforestation and degradation) and climate change impacts (diseases, fires, and drought). The overarching aim of this review is to assess how artificial intelligence (AI) and machine learning (ML) are transforming remote sensing-based monitoring of tropical forests, with a focus on their potential to enhance the detection and estimation of forest change and support tropical forest-related climate policy frameworks. The strengths of this review lie in its comprehensive synthesis of technical, institutional, and governance dimensions, achieved by systematically analyzing evidence from operational forest monitoring platforms and peer-reviewed literature (2010–2025). Using structured search and qualitative analysis, the review evaluates advances in AI/ML applications, identifies technical and institutional barriers, highlights emerging solutions, and provides practical, policy-relevant recommendations. This review identifies critical gaps and proposes a roadmap for scaling AI/ML for tropical forest monitoring. It finds that AI/ML tools, particularly supervised and unsupervised classifiers, deep learning models, time-series analytics, and multi-sensor data-fusion approaches, have become central to advancing remote sensing— enhancing accuracy, automation, and scalability for monitoring deforestation, forest degradation, biomass change, and forest dynamics. However, effective adoption of these technologies still faces persistent barriers—such as limited access to high-quality training data, reliance on proprietary platforms, technical capacity gaps, and unresolved ethical and governance challenges. The review concludes that overcoming these barriers through open training datasets, platform-agnostic infrastructures, capacity building, and inclusive governance is essential for scaling robust, transparent, and locally owned AI-enabled forest monitoring systems. Advances in AI/ML in remote sensing will support climate mitigation, biodiversity conservation, and equitable decision-making in tropical forest countries.

Keywords: artificial intelligence; machine learning; remote sensing; tropical forests; monitoring systems

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1. Introduction and Background

1.1. Tropical Forests in the Context of Climate Change

Tropical forests comprise approximately 45% of the world's forest area, spanning a wide range of ecological zones, from humid rainforests and moist forests to dry forests, shrublands, and tropical mountain systems [1]. Their critical role in global climate regulation, carbon cycling, hydrology, and biodiversity has been recognized in major international reports and agreements, such as the Brundtland Report [2] and the Rio Earth Summit [3] which formally brought tropical forests into the mainstream global climate and environment debates, through the UNFCCC, Agenda 21, and the Forest Principles. Subsequent IPCC Assessment Reports [4,5] have provided robust evidence that tropical forests are among the planet's most significant natural carbon sinks and store the highest biomass of any terrestrial ecosystem

Despite their importance, tropical forests face escalating threats from both anthropogenic pressures, mainly deforestation, primarily due to agricultural expansion, infrastructure development, and climate-related disturbances such as forest fires, drought, and pests. Between 1990 and 2025, an estimated 489 million hectares of forest were lost globally, with 88% of this loss occurring in tropical regions.[1]. In response, policy mechanisms such as REDD+ (Reducing Emissions from Deforestation and Forest Degradation, and the conservation, sustainable management of forests, and enhancement of forest carbon stocks), which was later recognized in Article 5 of the Paris Agreement [6]. These developments highlighted the critical need for robust and transparent monitoring systems.

1.2. Tropical Forest Monitoring: Advances and Limitations

1.2.1. Historical Contexts and Policy

Under REDD+ and the Paris Agreement's Enhanced Transparency Framework (ETF), the UNFCCC requires countries to implement robust, transparent systems for monitoring and reporting forest area, changes, and carbon stocks [6,7]. As a result, forest monitoring has become a cornerstone of REDD+ and a prerequisite for tropical countries' participation in global climate initiatives [7]. In temperate and boreal regions, National Forest Inventories (NFIs) provide the foundation for monitoring by employing statistically rigorous sampling to generate reliable estimates of forest extent, biomass, and carbon stocks, supporting long-term greenhouse gas reporting [8]. NFIs are widely adopted by Annex I countries and are recommended as a core component of greenhouse gas reporting from the Land Use, Land Cover and Forestry (LULUCF) sector, particularly when integrated with remote sensing to estimate emission factors and calibrate forest-change assessments [9].

1.2.2. National Forest Inventories- Strengths and Constraints

Integrating National Forest Inventory (NFI) field measurements with satellite data is recognized as international best practice for greenhouse gas reporting and has been effectively implemented by forest-rich Annex I countries with strong institutional capacity, such as Norway, Sweden, and Finland. In these countries, long-term investment, stable institutions, and accessible forest areas have enabled NFIs to provide high-quality data for forest monitoring. Among tropical forested regions, however, NFIs are far less common and often severely constrained. Many African and Asian countries either lack national-scale inventories or maintain NFI networks that are spatially limited,

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inconsistently measured, or based on non-standardized methods. Tropical forests are frequently remote, difficult to access, and sometimes insecure, making plot establishment and remeasurement both costly and logistically challenging. Designing and maintaining NFIs requires substantial financial and technical resources—investments most tropical countries struggle to prioritize despite REDD+ incentives (FAO 2014). As a result, the scarcity of high-quality field data limits the accuracy of emission-factor estimates and constrains the development, training, and validation of spatial models for tropical forest monitoring.

1.2.3. Remote Sensing: Expanding the Scope of Forest Monitoring

Remote sensing has become the core data source for tropical forest monitoring, particularly where National Forest Inventories (NFIs) are sparse, outdated, or prohibitively expensive to maintain. Satellite imagery provides consistent and repeatable observations of forest extent, disturbance, and land-use change over large areas [10] forming the backbone of REDD+ activity data and national Forest Reference Emission Levels (De Sy et al., 2012; Goetz et al., 2015). In tropical regions where accessibility, security challenges, and ecological complexity limit comprehensive field measurements, remote sensing offers a practical alternative by supplying long-term time series of forest cover and change. Freely available optical data such as Landsat and MODIS have been central to generating historical deforestation baselines, while medium- and high-resolution imagery (e.g., RapidEye, SPOT) has supported finer-scale assessments in Brazil, Guyana, Ecuador, Tanzania, Zambia, and the Congo Basin. Remote sensing has proven more scalable than ground-based inventories even in low-income regions, enabling continent-wide land-cover mapping and biomass estimation [11–13].

Despite these advantages, traditional optical remote sensing faces well-known limitations in the tropics. Persistent cloud cover, saturation in high-biomass forests, and the difficulty of detecting subtle degradation constrain its effectiveness of optical remote sensing data [14]. To overcome these challenges, LiDAR and Synthetic Aperture Radar (SAR) sensors emerged to provide three-dimensional structural information critical for estimating biomass and identifying degradation [15]. However, LiDAR and SAR data remain unevenly available in many tropical regions and typically require specialized instruments, high-performance computing, and advanced processing skills, which limit their routine use in national forest monitoring systems.

Climate-finance initiatives such as REDD+ and “smart monitoring” under the newly established Tropical Forests Forever Facility (TFFF, 2025) require increasingly robust, transparent, and timely MRV systems. Artificial Intelligence (AI) and Machine Learning (ML) are emerging as game-changing innovations, offering solutions to persistent challenges in tropical forest monitoring. This review examines the integration of AI/ML into remote sensing workflows for tropical forest monitoring, identifies key barriers to adoption, and explores strategies for developing scalable, effective, and equitable monitoring systems.

The rest of the review is structured as follows. First, we provide an overview of the current state of AI and machine learning applications in tropical forest monitoring, including key platforms and operational workflows. Next, we identify and analyze the principal barriers to effective and equitable adoption of these technologies. We then discuss emerging solutions and best practices, drawing on both technical literature and real-world case studies. Finally, we offer recommendations and outline future directions for advancing AI- and ML-enabled monitoring systems in tropical forest contexts.

2. Aim and Objectives

This review examines how AI and ML are integrated into remote sensing–based monitoring of tropical forests, focusing on their role in detecting and analyzing forest changes, including deforestation and biomass dynamics. The review addresses the following specific objectives:

(1) Identify and analyze current and emerging AI/ML algorithms and AI/ML-powered platforms applied in tropical forest monitoring. These include supervised and unsupervised classifiers, deep learning architectures, time-series analysis, change-detection frameworks, data fusion methods, and

operational monitoring platforms such as Global Forest Watch, SEPAL, MapBiomas, and Planet Insights.

(2) Evaluate technical, data-related, institutional, and governance challenges that limit the adoption and scaling of AI/ML tools in tropical forest monitoring. These challenges include limitations in training data, cloud-related constraints, model generalization, platform dependence, computational needs, and issues of data sovereignty and transparency.

(3) Develop recommendations for overcoming these barriers, drawing on evidence from operational monitoring systems, international policy frameworks, and best practices. Proposed solutions address open training data sets, platform-independent infrastructures, capacity building, sustainable financing, and inclusive, transparent data governance.

3. Materials and Methods

This review synthesizes evidence from two complementary streams: (i) technical platforms, operational forest monitoring systems, and associated documentation (grey literature), and (ii) peer-reviewed scientific literature. Data collection and synthesis were guided by three overarching research questions: (a) What is the current state of AI/ML applications in tropical forest monitoring? (b) What technical, institutional, and data-related barriers constrain the adoption of AI/ML in tropical forest monitoring? (c) What emerging solutions and technological developments are shaping the future of AI-enabled tropical forest monitoring?

3.1. Technical Platforms, Monitoring Systems, and Grey Literature

A relevance-based selection strategy was used to identify operational platforms (e.g., GFW, GLAD, SEPAL, MapBiomas, TerraBrasilis/DETER), cloud infrastructures (e.g., Google Earth Engine, Planet), open-source tools (e.g., Collect Earth Online), and documentation from multilateral programs (e.g., NICFI, UN-REDD, UNFCCC, IPCC). Sources were included based on documented operational relevance in tropical regions and their contribution to AI/ML-enabled monitoring. In total, 34 non-peer-reviewed sources were included. Reliability was assessed by cross-referencing platform documentation with published reports where possible. Limitations include potential bias toward well-publicized platforms, well-known multilateral programs, and exclusion of non-English or unpublished sources.

3.2. Literature Search and Screening

A semi-systematic literature search was conducted using Google Scholar and Web of Science, covering English-language publications from 2010–2025. Search terms included combinations of AI/ML approaches (e.g., Random Forest, SVM, CNNs, deep learning, AutoML), remote sensing applications (e.g., change detection, biomass estimation, SAR–optical fusion, time-series analysis), and adoption barriers (e.g., capacity gaps, technical limitations, platform dependence). Given the diversity of evidence sources (grey literature, peer-reviewed literature, and operational platforms), a fully systematic review approach was not feasible. Therefore, a semi-systematic design was adopted to capture both academic and practice-based knowledge. Titles and abstracts were screened by the author, consistent with a semi-systematic review design, to identify studies that (a) applied AI/ML methods to tropical forest monitoring, (b) evaluated AI/ML tools' performance or operational applications, or (c) discussed institutional or governance constraints. Studies focused exclusively on temperate regions or agricultural applications were excluded. Data extraction was performed using standardized forms to ensure consistency. An initial search produced approximately 250 records, of which 32 peer-reviewed articles met the inclusion criteria and were included in the final synthesis

3.3. Synthesis

Extracted information was analyzed through qualitative thematic synthesis. The analysis focused on the guiding research questions and the implementation of AI/ML methods, analytical workflows, sensor integration, training-data requirements, and operational constraints. Recurring technical, institutional, and governance-related challenges were identified, and cross-cutting themes and emerging technological developments were synthesized to highlight trends and future directions. The synthesis forms the basis of the Findings and Discussion sections.

4. Results and Discussion

4.1. Current and Emerging AI/ML Algorithms for Forestry Applications

AI and Machine Learning have become integral to remote sensing–based monitoring of tropical forests, enabling automated interpretation of large multi-sensor datasets and improving the detection of deforestation, degradation, and other land-use changes. Their integration into cloud-based platforms such as Google Earth Engine has significantly enhanced the scalability of forest monitoring workflows [16,17]. Among the key AI/ML tools in operational tropical forest monitoring are: **a) Supervised and unsupervised ML classifiers- including algorithms** such as Random Forest (RF), Support Vector Machines (SVM), and Classification and Regression Trees (CART) are widely applied for land-cover mapping and deforestation detection, while unsupervised approaches support exploratory classification in heterogeneous tropical landscapes; **b) Deep learning and advanced pattern-recognition models- such as** Convolutional Neural Networks (CNNs)—enable detailed image and pattern recognition, including canopy-structure analysis, degradation mapping, and species-level classification from high-resolution imagery and c) **Time-series analytics, anomaly detection, and predictive modeling, where m**odels such as Bayesian Ensemble Changepoint Detection (BEAST) detect abrupt or nonlinear vegetation changes, while predictive ML models support deforestation- and fire-risk forecasting. AI-assisted processing of LiDAR and drone data further improved tree detection, height estimation, and biomass modeling. Table 1. summarizes some of the key AI/ML algorithms and their applications in tropical forest monitoring.

Table 1. Key AI and machine learning algorithms applied in tropical forest monitoring, with examples of their application in land-cover classification, change detection, and time-series analysis.

AI/ML algorithms or Models	Application in forest or Land Use Change Monitoring (examples in references)
Classification Algorithms (Random Forest, Support Vector Machine (SVM), Classification and Regression Trees (CART).	Analysis of large data sets, simplifying complex forest classification tasks, monitoring/detecting forest change, [18,19].
Unsupervised Classification Algorithms, e.g., (K-means clustering).	Land Use and Land Cover Classification [20,21]
Deep Learning Models, e.g., Convolutional Neural Networks (CNN).	Satellite image analysis, image, and pattern recognition [22,23]
Automated Machine Learning (AutoML)- e.g., Google Cloud AutoML	Automated deforestation detection; carbon stock estimation [24,25].
Bayesian Ensemble Changepoint Detection (BEAST)	Detecting change-point, trend, and seasonality in satellite time series data to track abrupt changes and nonlinear dynamics [26,27]
TensorFlow	Immediate analysis, object detection, tree species identification [28]
AI-powered LiDAR (light detecting & ranging) or Drones	Tree detection and Mapping in restoration [29]
Crowd-sourced training data combined with supervised ML (e.g., CNNs, RF)	Enhancing training datasets for deforestation detection; crowd-labeled samples improve model accuracy (>90%) for identifying forest loss in new regions [30]

4.2. AI/ML-Powered Platforms for Tropical Forest Monitoring Applications

AI and ML algorithms used in tropical forest monitoring (see Table 2) are increasingly deployed through cloud-based geospatial platforms that provide large-scale data access and processing capacity. Google Earth Engine (GEE) remains the principal environment for implementing ML workflows, offering integrated access to multisensor satellite archives and scalable computational infrastructure [31,32]. Building on the capabilities of GEE, several specialized forest monitoring platforms—such as SEPAL, Global Forest Watch (GFW), GLAD, RADD, Collect Earth Online (CEO), and high-resolution systems offered by Planet—apply AI/ML models for deforestation alerts, land-cover mapping, change detection, and carbon-related assessments. These platforms operationalize AI/ML methods for national, regional, and global monitoring applications, making it possible to analyze tropical forest dynamics at high temporal and spatial resolutions. A brief overview of selected platforms is provided below, and Table 2 summarizes the leading AI/ML-enabled systems relevant to tropical forest monitoring.

Global Forest Watch (GFW): is widely recognized for processing multi-year global tree-cover datasets to generate high-resolution maps of forest extent, loss, and gain [10]. Building on this foundation, GFW has expanded its analytical capacity by integrating Google Earth Engine and a suite of AI/ML algorithms to support near–real-time forest monitoring and thematic analyses. In collaboration with Orbital Insight, GFW has also developed deep learning models that distinguish plantations from natural forests by analyzing image texture and spatial patterns, enabling the detection of industrial oil palm plantations using high-resolution satellite imagery [33].

System for Earth Observation Data Access, Processing, and Analysis for Land Monitoring (SEPAL) is a cloud-based geospatial platform developed by FAO to provide streamlined access to satellite data, cloud computing, and advanced analysis tools for forestry and land-use applications in the tropics [34]. Building on the processing capabilities of GEE, SEPAL enables users to implement their own AI/ML workflows using Python, R and offers interoperability with open-source tools such as QGIS and SNAP. The platform has recently been adopted by national forest monitoring systems of Uganda to produce national remote sensing-based mosaics and land-cover change assessments [35] and in Indonesia, the platform is adopted in the Peatland Monitoring System [36].

High-resolution 1-m Forest Canopy Height Maps, developed by Meta and the World Resources Institute (WRI) resulted in the creation of a 1-meter resolution global canopy height dataset covering 2009–2020, with approximately 80% of imagery acquired between 2018 and 2020 [37,38]. The Key ML Model employed is DiNOv2- a self-supervised vision model to predict canopy height globally, achieving a mean absolute error of 2.8 m. The resulting maps provide a detailed baseline of tree-canopy presence and height that can potentially support carbon stock estimation, carbon-credit MRV, and the evaluation of forest restoration and mitigation strategies [38]. The model used to generate the dataset is openly available, enabling users to apply it to newer satellite imagery for canopy-height change detection. The open accessibility of both the dataset and the underlying AI model makes this resource a significant contribution to global forest monitoring and to advancing open-source approaches to carbon and biodiversity assessment.

Planet Insights Platform by Planet Labs [39]**:** integrates a wide range of AI/ML algorithms for deforestation detection, forest carbon monitoring, and Change detection alerting. Among its recent innovations is the AI-powered Forest Carbon Monitoring Product, the first global forest carbon and canopy-height mapping system at 3-m resolution, combining PlanetScope imagery with lidar-derived structural data to support carbon accounting, MRV, and reforestation monitoring [39]. Planet products are increasingly used by commercial service providers (e.g., LiveEO, Swift Geospatial) for assessing commodity-driven deforestation risks and complying with emerging regulations such as the EU Deforestation Regulation (EUDR). However, access to the platform requires a commercial subscription, and pricing remains prohibitive for applications for tropical forested countries.

Table 2. Selected AI/ML-powered platforms and their applications for tropical forest and land Resources monitoring (for Examples of Application, see Annex 1 & Annex 4).

AI/ML powered Platforms & Developers (Website/reference)	Integrated AI/ML and applications in forest monitoring & (the satellite data used)

Global Forest Watch (GFW) World Resources Institute https://www.globalforestwatch.org	ML algorithms to analyze satellite imagery and provide near-real-time deforestation alerts. (Landsat, Sentinel-2, MODIS, PlanetScope, NICFI data)
SEPAL Food and Agriculture Organization (FAO) https://www.fao.org/in-action/sepal/en	AI and ML (BFAST-GPU Module, SE.PAFE Module) for processing and analyzing big satellite data to support forest monitoring and land use planning (Landsat, Sentinel-2, PlanetScope, NICFI data)
MapBiomas (Brazil), a Network of organizations including NICFI-Norway, institutions in Brazil https://mapbiomas.org	AI and deep learning models within **GEE** for land cover classification and analysis and mapping changes in land use and deforestation. (Landsat, radar data from Sentinel-1)
Planet Labs Planet Labs PBC https://www.planet.com	AI and ML for processing high-resolution satellite imagery, enabling detailed monitoring of forest changes. (PlanetScope, SkySat, RapidEye)
Collect Earth Online (CEO) SERVIR (NASA and USAID) and FAO https://www.collect.earth	AI-driven image recognition and classification tools to assist users in interpreting high-resolution satellite imagery for land use and land cover changes. (Landsat, Sentinel-2, PlanetScope, NICFI data)
RADAR for Detecting Deforestation (RADD) Wageningen University & Research, Google, and WRI https://www.globalforestwatch.org	radar-based ML algorithms for detecting forest loss, particularly under cloudy conditions where optical imagery is less effective (Sentinel-1)
CTrees LUCA (Land Use Change Alerts) CTrees https://ctrees.org/products/luca	ML algorithms to process Sentinel-1 SAR data, providing near-real-time alerts on global forest disturbances (Sentinel-1)

4.3. The Added Values and Benefits of AI/ML Algorithms and Platforms

(A) Improved accuracy and early detection: AI/ML algorithms enhance the precision of land-cover classification, forest-change detection, and degradation analysis by learning complex spatial and spectral patterns often missed by manual interpretation. For example, **MapBiomas** employs Random Forest classifiers within Google Earth Engine to produce long-term annual land-cover maps for Brazil and other Amazonian countries with improved accuracy [40]. Similarly, **GLAD** uses ML-based processing of Landsat and Sentinel-2 time series to detect forest loss with high sensitivity at persistent global scales [10]. Deep learning models developed through the **GFW–Orbital Insight** collaboration distinguish plantations from natural forests via high-resolution texture analysis [33]. These advances support early identification of emerging degradation signals and incipient deforestation, strengthening forest-cover and carbon-stock estimates (Causevic et al., 2024).

(B) Enhanced efficiency, automation, and speed: Cloud-based AI/ML systems dramatically shorten analytical workflows by automating the processing of large satellite archives such as Landsat, Sentinel-1/2, and PlanetScope. **SEPAL** enables national forest monitoring systems (e.g., Uganda) to generate satellite mosaics and forest-change products in a fraction of the time required by traditional GIS methods [35]. Near–real-time alert systems, including **MAAP** [41] and **RADD** (Sentinel-1 SAR), use ML-accelerated pipelines to rapidly flag forest disturbance even in cloud-prone regions such as the Congo Basin and Amazon. Daily revisit imagery from **Planet** further accelerates detection of fires, illegal logging, road expansion, and restoration progress. These efficiency gains support timely enforcement, risk mitigation, and community-based monitoring.

(C) Multi-Source Data Integration and Analytical Depth: AI/ML platforms can integrate optical, radar, LiDAR, drone, and climate datasets to produce richer forest-characterization outputs. Deep learning (e.g., CNNs) enhances canopy-structure mapping, species-level discrimination, and pattern recognition from high-resolution imagery [22]. Time-series algorithms such as **BEAST** detect nonlinear trends and abrupt changes in vegetation dynamics [26]. In Indonesia, SEPAL integrates multisensor inputs for peatland monitoring, combining ML with optical and SAR imagery to track vegetation recovery and soil-moisture dynamics [36]. AI-assisted analysis of LiDAR and drone data improves individual tree detection and biomass estimation in restoration areas [29]. These developments in data fusion provide deeper insights into tropical forest structure, degradation trajectories, and land-use transitions.

(D) Enhanced Scalability, Transparency, and Cost Efficiency: Cloud-native AI/ML platforms scale efficiently from local project sites to national and global MRV systems. Platforms such as **GFW**, **SEPAL**, and **MapBiomas** deliver open-access, reproducible analytics, enhancing transparency for governments, NGOs, and civil society. **Planet Insights** and **CTrees** offer global-scale ML-based carbon and disturbance monitoring built on harmonized multi-sensor datasets. Although initial investments in training, cloud infrastructure, and subscription fees (e.g., with Planet) can be high, long-term operational costs are expected to decline as automated analytics reduce reliance on extensive fieldwork and support remote monitoring over large, inaccessible forest regions such as the Amazon, Congo Basin, and Borneo. The scalability and replicability of AI/ML workflows accelerate the development of sustainable MRV systems for climate reporting.

While the benefits and capabilities of AI/ML-based systems are increasingly well documented, a clearer understanding emerges when examining how these tools are implemented in the context of real-world forest monitoring. Section 4.4, therefore, reviews operational case studies that illustrate how AI/ML is being deployed across tropical regions.

4.4. Practical Cases of AI/ML-Enabled Tropical Forest Monitoring

Applications of AI/ML tools for tropical forest landscape monitoring illustrate how they are being used to detect, predict, and verify forest change in ways that extend conventional remote-sensing-based forest monitoring. Based on operational platforms, four broad categories of applied AI/ML use cases can be identified: (i) early-warning systems for deforestation and fires; (ii) thematic monitoring systems targeting specific land-use pressures; (iii) forest landscape restoration and carbon-verification initiatives; and (iv) non-satellite AI tools that complement remote sensing to strengthen field-level intelligence. These categories highlight not only the technical diversity of models in use, but also the varied governance contexts and institutional partnerships through which AI/ML tools are being deployed in tropical forest monitoring.

4.4.1. AI-Assisted Early-Warning Systems for Deforestation and Fires

Early-warning systems are the most operationalized and widely adopted form of AI/ML-enabled forest monitoring, particularly in regions where rapid response enforcement is essential. One such case is the Monitoring of the Andean Amazon Project (MAAP) [41] which integrates supervised machine learning classification, thermal-anomaly analytics, and multi-sensor time-series analysis to produce near–real-time alerts of deforestation, fire activity, road construction, and illegal mining across several Amazonian countries. By leveraging Landsat, Sentinel-1/2, VIIRS, and Planet imagery through cloud-computing infrastructures, MAAP has established an institutionalized workflow in which AI-generated alerts directly support enforcement, environmental prosecution, and rapid decision-making [41,42]. This case exemplifies the transition from experimental AI models to a wide-scale, high-frequency forest monitoring system embedded within national and civil society monitoring architectures.

4.4.2. Thematic Monitoring Systems of Specific Land Use Pressures

Beyond detecting forest loss, AI/ML tools are increasingly deployed to monitor specific land-use pressures that generic deforestation alerts may miss. These thematic systems address subtle, heterogeneous, or spatially concentrated forms of degradation—such as illegal mining and peatland degradation—requiring tailored analytical approaches. By enabling targeted analysis of complex, high-impact disturbances, AI/ML enhances the precision, responsiveness, and policy relevance of forest surveillance efforts. Two such cases are *Illegal mining detection in the western Amazon and Peatland monitoring in Indonesia.*

Illegal mining detection in the western Amazon: ML-based mining-detection systems apply spectral indices, object-oriented segmentation, and supervised classifiers to identify mining-related disturbances such as turbidity plumes, exposed sediments, and vegetation removal. The Amazon Mining Watch initiative uses AI/ML applied to Sentinel-2 imagery (10 m resolution) to detect and map mining-driven deforestation across the Amazon biome, generating updated annual alerts from 2018 to 2023 [42]. These systems can detect activities even in narrow river corridors or under partially obscured canopies—conditions where traditional deforestation algorithms often fail. As illegal mining remains one of the fastest-expanding drivers of degradation in parts of the Amazon, this thematic application fills a critical governance and enforcement gap.

Peatland monitoring in Indonesia: In Indonesia, AI/ML methods are increasingly used for peatland monitoring, a tropical landscape that requires specialized analytical approaches due to subtle spectral signatures and frequent cloud cover. ML classifiers applied to Sentinel-1 and Sentinel-2 time series distinguish intact peat swamp forest from degraded peatlands and agro-industrial mosaics, while predictive models identify fire-prone hotspots associated with drainage canals and land-conversion pressures [34,36]. These outputs inform Indonesian national restoration programs, fire-management authorities, and landscape-level planning frameworks across Indonesia.

4.4.3. AI-supported Restoration and Carbon-Verification Initiatives

AI/ML tools are increasingly being deployed not only to detect forest loss, but also to measure and verify positive ecosystem outcomes, including restoration progress and carbon accumulation. One of the most prominent examples is the *Regenera América* initiative in Brazil [43] which applies ML-supported biomass estimation, canopy-structure modeling, and high-resolution change detection to assess the performance of corporate-funded reforestation and natural regeneration projects. The program partners with Pachama [44], whose AI-driven platform integrates satellite imagery with UAV-based photogrammetry and ML-derived canopy metrics to quantify biomass increments, canopy height, and regeneration trajectories. Such initiatives demonstrate the growing relevance of AI-supported monitoring within carbon markets, nature-based solutions, and corporate sustainability frameworks, where robust, scalable, and transparent verification is increasingly demanded.

4.4.4. Non-Satellite AI Tools: Complementing Satellite-Based Monitoring

Non-satellite AI applications play a crucial role in strengthening ground-level intelligence and community-based monitoring by detecting signals that satellites cannot capture. These tools extend the reach of remote sensing, providing complementary data and enhancing the effectiveness of forest monitoring systems.

Rainforest Connection (RFCx) uses convolutional neural networks trained on large annotated acoustic datasets to identify chainsaw noise, vehicle engine signatures, and key biodiversity indicators in near real time **[45]**. Solar-powered devices stream audio continuously from dense tropical forests, generating alerts even under heavy canopy cover or persistent cloudiness—conditions where satellite data are often limited. This demonstrates how AI can extend monitoring capabilities into ecological contexts where remote sensing alone is insufficient.

The **Forest Watcher mobile application** [46] operationalizes satellite-based alerts (such as GLAD and RADD) by enabling users—including community monitors, Indigenous patrols, and NGOs—to access, navigate to, and verify alert locations in the field, even without network connectivity. With geotagged field-verification tools, Forest Watcher strengthens the responsiveness and accuracy of ground investigations. Although the alerts originate from satellite-based models, the app brings these outputs into practical use at the ground level, illustrating the value of hybrid, multi-source monitoring systems where AI/ML tools are embedded within both digital and community-based monitoring systems.

4.5. Future AI/ML Tools and Envisioned Capabilities

The operational examples presented in section 4.4 demonstrate that AI/ML is already transforming tropical forest monitoring. However, many of these systems remain fragmented, pilot-driven, or applied on a limited scale, leaving significant room for improvement. The following subsections outline key areas where future developments are expected to have the greatest impact.

4.5.1. Digital MRV for Carbon Markets and GHG Inventory

As tropical forest countries scale their participation in REDD+ and the Enhanced Transparency Framework [6] Measurement, Reporting and Verification (MRV) systems are shifting toward digital, automated architectures. This transition has been accelerated by the outcomes of COP30, including the Tropical Forests Forever Facility (TFFF), which places explicit emphasis on "Smart Monitoring" and the use of AI-supported transparency systems. Digital MRV (D-MRV) is conceptualized by the World Bank [47] as the integration of satellite remote sensing, AI/ML analytics, IoT sensors, cloud computing, and—in some cases—blockchain-based registries to automate data collection, processing, and verification. Such systems already underpin major carbon markets, including the EU Emissions Trading System [48] and are increasingly seen as essential for ensuring accountability and reducing uncertainty in emissions reporting from the land-use sector. In tropical forest monitoring, next-generation AI-enabled D-MRV systems are therefore expected to deliver several critical capabilities, including:

A core element of next-generation D-MRV is multi-sensor data fusion for biomass and GHG estimation. This includes **integrating** optical, SAR, and LiDAR time series using AI/ML models to improve mapping of aboveground biomass, forest degradation, and emission factors; **Automated land-use and activity-data reporting**: AI-based change-detection systems capable of near–real-time identification of deforestation, degradation, regeneration, and fire impacts, producing standardized activity-data layers for national reporting. **Uncertainty reduction via AI calibration models**: Machine-learning approaches that harmonize field measurements with satellite observations, improving the accuracy and consistency of carbon-stock and emissions estimates. **Reproducible, transparent workflows**: Cloud-based AI pipelines that provide standardized, traceable processing chains suitable for integration into national forest monitoring systems and compliant with international reporting requirements.

4.5.2. Open Datasets, Transparent AI, and Platform-Agnostic Infrastructures

High-quality, openly available training datasets are increasingly recognized as essential for fair, reproducible, and locally relevant AI tools development. Initiatives such as MapBiomas, which publishes land-cover maps and training data (MapBiomas, 2024), and the Radiant Earth MLHub (Radiant Earth Foundation, 2023) demonstrate how shared geospatial ML datasets can accelerate innovation by lowering entry barriers for governments, researchers, and civil society. Future AI-driven Tropical Forest monitoring systems will rely more heavily on such open datasets to train models on regionally specific forest types and disturbance patterns; reduce dependency on proprietary “black-box” commercial models; strengthen transparency, replicability, and trust in decision-support systems

4.5.3. Advanced Analytics for Forest Degradation and Fire Monitoring

Monitoring Forest degradation remains one of the most persistent challenges in Tropical Forest monitoring, particularly when areas appear intact in medium-resolution optical imagery. Future AI/ML innovations are expected to enhance detection of selective logging, understory disturbance, and degradation “hotspots” example, through enabling data fusion among SAR (Sentinel-1), hyperspectral, and LiDAR data, integrating high-frequency PlanetScope mosaics; using deep-learning approaches to detect subtle texture and shadow changes. Such opportunities are evidenced by the early-warning system for Amazon degradation (Amazon Conservation Association, 2024) (MAAP), demonstrating the potential of such models for rapid, near–real-time detection.

Integrating vegetation dryness indices, meteorological data, soil moisture, and historical fire activity, next-generation AI models can predict wildfire risk zones and ignition probability. NASA’s GFWED and WRF-SFIRE [49] and ESA’s deep-learning “SeasFire” system [50] illustrate emerging capabilities. In tropical forests—even in regions where fire was historically rare—these tools will be increasingly important under climate-driven drought intensification.

A key frontier in these analytical developments is the integration of UAV and LiDAR-derived point clouds into AI workflows. Drones and LiDAR offer high-resolution data for mapping in remote and cloud-prone tropical landscapes such as mangroves, peatlands, and mountain forests where satellite visibility is inconsistent, and accessibility if limited. Future AI-enhanced drones and LiDAR are expected to automate 3D reconstruction and biomass estimation from point clouds [51], classify tree species and regeneration stages; enhance forest-restoration monitoring using AI-driven analysis of UAV imagery [52].These capabilities will complement satellite-based analytics by providing fine-scale structural detail essential for detecting degradation, quantifying biomass recovery, and monitoring ecological changes.

4.5.4. Biodiversity and Ecosystem Monitoring

Biodiversity monitoring in the tropics requires integrating heterogeneous data sources, including satellite imagery, camera traps, acoustic sensors, and UAV data. Future AI/ML-driven systems can provide possibilities of improving species recognition through large, annotated multimedia datasets; combine LiDAR, hyperspectral, and UAV imagery to map habitat structure, automatically classify wildlife sounds and movements. As evidence to these capabilities, Organizations such as the Wildlife Conservation Society are piloting AI-driven monitoring platforms such as SMART for species detection and threat mapping [53], while acoustic-AI initiatives [54] show promise for dense tropical forests where visibility is limited. In general, these capabilities will complement carbon-focused D-MRV systems by monitoring biodiversity and ecosystem integrity.

4.5.5. IoT Sensors, Smart Monitoring, and Human-AI Collaboration

Building on existing acoustic-AI systems already used operationally in some tropical forests (see Section 4.4.4), future smart-forest architectures will integrate distributed IoT microclimate sensors, edge-based analytics, and multi-modal detection systems. AI-enabled IoT systems emerge as a complementary layer to satellite monitoring by capturing signals beneath the forest canopy. Recent work on acoustic sensor networks and edge computing has shown that distributed audio nodes can automatically detect chainsaw and tree-cutting sounds for illegal logging surveillance in near real time [55]. initiatives such as Rainforest Connection deploy solar-powered acoustic devices and machine-learning models for real-time threat detection in tropical forests. Smart-forest and wildfire-early-warning prototypes integrate IoT microclimate sensors (temperature, humidity, smoke) with ML-based analytics to flag fire-prone conditions and ignition events [56], illustrating how ground-based sensor networks can complement satellite and airborne remote sensing in future AI-driven monitoring systems

However, realizing the potential of such smart-forest systems requires community-centric design and human–AI collaboration. Community co-production is increasingly recognized as a prerequisite for sustainable AI deployment in the tropics. Emerging research also highlights the importance of integrating Indigenous knowledge into AI-driven environmental management, showing that hybrid systems combining AI with place-based expertise strengthen monitoring accuracy and cultural legitimacy [57]. Therefore, Future systems must be accessible and inclusive, enabling local communities to interpret results, validate changes, and participate in the co-creation of monitoring tools. Integrating AI-powered spatial dashboards with language models (e.g., ChatGPT) will support translation of technical outputs into local languages; participatory monitoring and ground validation; and integration of Indigenous knowledge into forest management.

4.6. Barriers to Effective AI/ML Applications in Tropical Forest Monitoring

The review this review identifies four categories of persistent structural barriers that constrain the effective and equitable applications of AI/ML in tropical forests monitoring (Table 3). Details of the key barriers and proposed emerging solutions are discussed in detail.

Table 3. Barriers and proposed solutions for AI/ML-enabled tropical forest monitoring.

Key Barriers	Corresponding proposed Solutions
Limited availability of training/validation data	• Develop open/shared training datasets (e.g., Radiant MLHub, MapBiomas) • Treat datasets as global public goods
Dependence on proprietary platforms	• Invest in platform-agnostic infrastructures • Expand open-source tools (Open Data Cube, SEPAL) • Joint licensing negotiations with providers
Technical capacity & infrastructure gaps	• Long-term capacity building & academic partnerships • Cloud-based open infrastructures • Sustainable financing via GCF/GEF/TFFF
Ethical, governance & socio-cultural barriers	• Strengthen national data-governance frameworks • Apply FPIC, Indigenous data sovereignty • Multilingual tools; inclusive co-design approaches

4.6.1. Limited Availability and Accessibility of Training Data

A persistent and widely recognized barrier to effective AI/ML applications in tropical forest monitoring is the limited availability and accessibility of high-quality training and validation data. AI/ML models require large, well-labeled, and regionally representative datasets to perform reliably, yet such resources are scarce across much of the tropics. Persistent cloud cover, heterogeneous land management, and fragmented data ownership often restrict access to usable optical imagery, while very-high-resolution commercial datasets (e.g., PlanetScope, Maxar WorldView) remain prohibitively expensive or subject to restrictive licensing, limiting their use for model development and independent validation [58]. Furthermore, standardized, openly available, labeled datasets for tropical forest types, degradation processes, and biomass conditions are largely absent. Many operational platforms (e.g., GEE, Global Forest Watch) rely on proprietary or internally curated training datasets that are not publicly accessible, preventing reproducibility and adaptation by national institutions. National Forest Inventories (NFIs) could provide valuable, locally relevant training data; however, only a small number of tropical countries maintain NFIs programs.

As a result, AI models deployed in tropical regions are often trained on global or simulated datasets that do not capture local ecological or socio-economic conditions, leading to poor model generalization, systematic bias, and reduced transferability. This dependence on proprietary or opaque “black-box” models also undermines accountability and trust in AI-derived monitoring

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outputs [59]. The absence of transparent governance frameworks for training-data documentation and accessibility further exacerbates these barriers, highlighting the need for standardized, open, and participatory data infrastructures to support trustworthy AI development for applications in tropical forest monitoring [60].

4.6.2. Concentration of Data and Technology in Proprietary Platforms

Very high-resolution (VHR) satellite imagery is essential for training, benchmarking, and validating AI/ML models used in tropical forest monitoring. However, access to such reference data remains highly restricted because most VHR imagery is controlled by a few private providers, notably Maxar Technologies (e.g., WorldView, GeoEye) and Planet Labs (PlanetScope, SkySat). Their commercial licensing models and pricing structures limit access for many national forest institutions, particularly in low- and middle-income tropical countries, making it difficult to acquire the datasets needed to develop, calibrate, or independently validate AI/ML-driven monitoring products.

Similarly, dependence on proprietary cloud-processing platforms, most notably Google Earth Engine (GEE), poses significant challenges for scaling AI/ML for forest monitoring. GEE has become one of the most widely used environments for processing large-scale geospatial datasets and implementing machine-learning workflows. However, access to its computational resources and data storage is governed by Google's licensing and service policies, which limit flexibility and create risks of vendor lock-in. An assessment of digital MRV systems emphasizes that long-term sustainability requires national institutions to retain ownership and control over core data and infrastructure, and warns that reliance on proprietary service providers can undermine a country's ability to operate and adapt monitoring systems independently [61]. As a result, dependence on proprietary cloud platforms represents a major barrier for countries attempting to establish robust, autonomous AI/ML-enabled forest monitoring systems.

4.6.3. Technical Capacity and Resource Limitations

An effective implementation of AI/ML-based forest monitoring systems requires advanced computational infrastructure and specialized expertise, both of which remain unevenly distributed globally. AI/ML relevant skills and infrastructure are heavily concentrated in the global north, where most cloud-computing facilities, AI research groups, and major satellite analytics companies are based [61]. In contrast, many tropical forest countries face persistent limitations in high-performance computing access, reliable electricity, and high-bandwidth internet connectivity, constraining their ability to develop, deploy, and maintain AI/ML-enabled forest monitoring systems [34]. Furthermore, UN-REDD's 2021–2025 Results Framework notes that many national forest monitoring systems continue to rely on external experts and international partners to operate key components of MRV systems, highlighting limited in-country capacity as a major barrier to advancing national forest monitoring systems [62].

Financial constraints exacerbate these challenges, since deploying AI/ML technologies requires substantial investment in software, hardware, and human resources, which are prohibitive for most budget-constrained countries or organizations in the tropics. Consequently, many AI/ML monitoring initiatives rely on short-term donor funding, raising concerns about the long-term sustainability of operational systems once external support ends (World Bank, 2022b).

4.6.4. Ethical, Regulatory, and Socio-Cultural Barriers

Ethical considerations: In many tropical regions, Indigenous peoples and local communities depend on forests for livelihoods, cultural identity, and territorial rights. When AI-driven monitoring systems are designed or implemented without their involvement, they risk marginalizing local actors, reducing their influence in decision-making processes, and limiting access to potential benefits from conservation or climate-finance mechanisms. UNESCO's Recommendation on the Ethics of Artificial Intelligence highlights that AI systems can reinforce existing inequalities when Indigenous and local perspectives are excluded, or when socio-economic biases are embedded in datasets and model design (UNESCO, 2021). Ensuring culturally appropriate, inclusive, and participatory development of AI/ML tools is therefore essential to avoid exacerbating existing power imbalances in tropical forest governance.

Regulatory and policy constraints also affect the advances in AI/ML-based forest monitoring systems. Key tropical forest countries (e.g., Brazil and Indonesia) maintain strict rules on environmental and spatial data sharing to protect national sovereignty and control over land-use information. In Brazil, national monitoring programs such as PRODES and DETER provide open access to publicly funded deforestation data through platforms such as TerraBrasilis (INPE, 2023). However, some high-resolution commercial imagery and auxiliary datasets obtained by INPE through institutional agreements (e.g., PlanetScope or Maxar scenes) cannot be redistributed due to licensing restrictions. These policies support national data sovereignty but can limit access to key reference datasets needed for AI model development and validation.

Socio-cultural factors such as language and trust also influence the adoption of AI. Most AI/ML platforms, documentation, and training resources are available only in English or other high-resource languages, limiting accessibility for users in countries such as Brazil, Indonesia, and the Democratic Republic of Congo. Language barriers and a lack of culturally appropriate interfaces reduce uptake among local agencies and communities, including Indigenous groups [63]. UNESCO's guidance on the Ethics of AI [64] urges culturally sensitive AI development and protection of Indigenous Peoples' control over their data.

5. Recommendations- Emerging Solutions to Overcome Barriers

5.1. Developing Open and Shared Training Data Resources

Limited access to high-quality, labeled training data remains one of the main constraints for developing accurate and transferable AI/ML models in tropical forest monitoring [65]. To address this, global and national partners should prioritize the development and sharing of open, standardized training datasets—including satellite imagery, field plots, and socio-ecological information—under transparent and participatory governance frameworks. Targeted donor initiatives such as NICFI, UN-REDD, and World Bank programs can play a central role in supporting openly licensed data repositories and reducing dependence on proprietary platforms.

The World Bank [61] emphasizes that open-source MRV infrastructures and transparent data-sharing mechanisms are critical for credible and equitable participation in emerging carbon markets. Successful initiatives such as Radiant MLHub [58] and MapBiomas [40] demonstrate that shared datasets can accelerate innovation, lower entry barriers, and ensure that monitoring tools reflect local ecological and socio-economic conditions. Treating training datasets as global public goods is therefore essential to enable tropical forest countries to build vendor-agnostic AI/ML models and strengthen national forest monitoring capacities.

5.2. Promoting Platform-Agnostic and Open-Source Infrastructures

The concentration of high-resolution satellite data and cloud computing platforms in the hands of a few private companies (e.g., imagery providers such as Planet Labs and cloud-based analysis platforms such as Google Earth Engine (owned by Google) will remain a major barrier to effective AI/ML applications in tropical forest monitoring. To overcome these challenges, international partnerships and donors should prioritize the development of platform-agnostic, vendor-neutral infrastructures that allow data and models to be shared, validated, and deployed across multiple systems without dependency on a single provider. Open-source platforms such as the Open Data Cube [66,67] and FAO's SEPAL (FAO) has demonstrated the feasibility of such approaches in operational forest monitoring.

Investing in open-source machine-learning frameworks (e.g., TensorFlow, PyTorch) and interoperable data infrastructures would reduce long-term costs and strengthen national sovereignty

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over environmental information. Supporting these systems as global public goods is therefore essential to enable transparent, reproducible, and equitable participation in AI/ML-driven forest monitoring.

5.3. Strengthening Technical Capacity and Sustainable Financing

Persistent shortages of trained personnel, limited access to high-performance computing, and unreliable digital infrastructure constrain the abilities of national institutions to develop and operate AI/ML workflows independently [34,62]. Addressing these gaps requires long-term investment in human resources and institutional capacity. Priority actions include expanding training programs, monitoring university curricula, and technical partnerships with research institutions, which can build sustainable in-country expertise for AI development and interpretation. Short-term measures such as targeted workshops and online courses can support immediate operational needs, while longer-term academic collaboration and research exchange programs can foster institutional learning and retention.

Strengthening digital and computational infrastructure is equally important. Investments in accessible cloud-based platforms (e.g., FAO’s SEPAL) and open-source tools can help overcome local hardware limitations and reduce dependence on proprietary systems. Public–private partnerships with technology providers may further improve access to computing resources and storage.

Sustainable financing is essential to maintain operational systems once donor support ends. Engagement with international climate finance mechanisms—including the Green Climate Fund, the Global Environment Facility, and emerging initiatives such as the Tropical Forests Forever Facility offers potential pathways for long-term funding. Supporting regional innovation hubs such as RCMRD [68], Digital Earth Africa [69] and national institutions such as INPE (Brazil) and NCMC (Tanzania) can ensure that resources are aligned with regional priorities and strengthen local ownership of AI/ML-enabled forest monitoring.

5.4. Enhancing Governance, Ethical Frameworks, and Inclusive Participation

Addressing governance, ethical, and socio-cultural barriers requires strengthening policy frameworks that ensure equitable access to AI/ML technologies while safeguarding national sovereignty and community rights. Clear data-governance policies can empower countries to retain control over environmental and spatial information, while still enabling regional and international collaboration. Joint negotiation frameworks—particularly with major data and AI service providers—can help reduce licensing costs and improve access to critical datasets and infrastructure. Strengthening open data and open-source policies is equally important to enhance transparency, reproducibility, and equitable participation. Open data sharing between governments, researchers, and civil society reduces dependency on proprietary platforms and supports local innovation capacity.

Ensuring culturally appropriate and inclusive AI deployment is essential in the context of tropical forest monitoring. UNESCO’s Recommendation on the Ethics of AI [64] and its guidance on Indigenous data sovereignty [63] emphasize that AI systems must be developed and implemented through participatory approaches that respect community rights and knowledge systems. Practical measures include providing multilingual interfaces and training materials, integrating local facilitation and feedback mechanisms, and applying Indigenous data-governance safeguards such as Free, Prior, and Informed Consent (FPIC), clear data ownership and residency terms, and fair benefit-sharing arrangements. These actions help build trust, strengthen local ownership, and ensure that AI/ML tools support the rights, priorities, and governance structures of Indigenous peoples and local communities.

6. Conclusion

Artificial Intelligence (AI) and Machine Learning (ML) are fundamentally reshaping tropical forest monitoring by enabling faster, more accurate, and large-scale detection of forest change, advancing the traditional remote sensing approaches. Evidence from operational platforms and emerging research demonstrates AI/ML is now operational in early-warning systems, multi-sensor data fusion, biomass estimation, and digital MRV architectures. These capabilities are particularly transformative in tropical regions, where persistent cloud cover, limited field data, and rapid land-use change have historically constrained monitoring accuracy. At the same time, progress is shaped by structural constraints related to data availability, platform dependence, technical capacity, and governance frameworks.

The next generation of AI-enabled tropical forest monitoring must prioritize systems that are transparent, interoperable, and based on equitable long-term partnerships. Strengthening open and regionally representative training datasets will be essential for improving model generalization and ensuring that tropical countries can build and validate their own monitoring tools. Advancing platform-agnostic, open-source infrastructures will reduce dependency on proprietary ecosystems and foster greater national ownership of data and analytics. Furthermore, sustainable investment in human capacity and digital infrastructure is essential to enable institutions in tropical forest countries to develop, deploy, and maintain AI/ML systems independently. Data and AI Governance must also evolve to ensure that AI-enabled monitoring respects data sovereignty, protects community rights, and incorporates local knowledge into system design and interpretation.

In conclusion, advancing the application of AI and ML for tropical forest monitoring will require more than technological innovation. Among others, it will also demand institutional readiness, inclusive governance, and sustained investment in the enabling environment. If these conditions are met, AI-enabled systems have the potential to deliver a new generation of monitoring capabilities that are not only scientifically robust but also trusted, transparent, and locally owned.

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