CLIMATE SMART AGRIBUSINESS FINANCING (CSAF) FORESTRY AND WASTE MANAGEMENT

GLOBAL ISSUES & LOCAL PERSPECTIVES

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Preface

This book adopts an exegetical approach as well as a pedagogic model, making it attractive agriculture and environmental economics teachers, professional practitioners and scholars. It is eschews pedantry and lays bars the issues in such clarity that conduces to learning. The book elaborates on contemporaneous **Climate Smart Agribusiness Financing (CSAF) Forestry and Waste Management** issues of global significance and at the same time, is mindful of local or national perspectives making it appealing both to international and national interests. The book explores the ways in which **Climate Smart Agribusiness Financing (CSAF) Forestry and Waste Management** issues are and should be presented to increase the public's stock of knowledge, increase awareness about burning issues and empower the scholars and public to engage in the participatory dialogue **Climate Smart Agribusiness Financing (CSAF) Forestry and Waste Management** necessary in policy making process that will stimulate increase in food production and environmental sustainability. **Climate Smart Agribusiness Financing (CSAF) Forestry and Waste Management :** *Global Issues & Local Perspectives* is organized in two parts. Part One deals with The Concept of **Climate Smart Agribusiness Financing (CSAF)**, Part Two is concerned with The Concept of **Forestry and Waste Management**

Eteyen Nyong; August 202

Chapter Eight

Advances in Remote Sensing for Biodiversity: Theory, Methods, Applications, and Validation

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1.0 INTRODUCTION

Advances in remote sensing have become critical for addressing biodiversity challenges in tropical regions, where over 50% of the world's species are found yet face the highest rates of habitat loss and degradation (Wang and Zhu, 2026). Tropical forests, such as those in the Amazon Basin, Congo Basin, and Southeast Asia including Nigeria, are experiencing deforestation rates exceeding 10 million hectares annually, threatening endemic flora and fauna (Owolabi, Sanuade, Atabo, Okeyode, Adeyemi and Fajinmolu, 2026). Remote sensing technologies, including high-resolution satellites like Landsat, Sentinel-2, and LiDAR, now enable real-time monitoring of forest cover change, species habitat mapping, and detection of illegal logging with accuracy above 85% (Aishwarya, Kumari, Lavania, Gupta, Tiwari, Singh and Kumar, 2026). In tropical contexts characterized by persistent cloud cover and complex canopies, the integration of radar, hyperspectral, and drone-based data has improved our ability to assess biodiversity patterns, track endangered species distribution, and evaluate ecosystem health without extensive fieldwork. These tools provide timely, cost-effective data essential for conservation planning, policy enforcement, and achieving global targets such as the Kunming-Montreal Global Biodiversity Framework in biodiversity-rich tropical nations.

Objective: Advances in Remote Sensing for Forestry Issues

The objective of this study is to examine recent advances in remote sensing technologies and their application to critical forestry issues in tropical and savanna landscapes, with emphasis on

West Africa. It aims to evaluate how new missions, AI foundation models, satellite and multi-sensor fusion are improving the accuracy and timeliness of forest carbon monitoring, biodiversity assessment, disturbance detection, and restoration tracking. Specifically, the study will assess the role of NASA GEDI LiDAR, Sentinel-1/2, PALSAR-2, and hyper spectral sensors like PRISMA and EnMAP in quantifying above-ground biomass, mapping key species such as *Tamarindus indica, Vitellaria paradoxa,* and *detecting degradation* at <1 ha resolution. It further seeks to examine the effectiveness of near real-time alert systems, including RADD and GLAD-S2, for monitoring illegal logging and charcoal production, and to explore UAV and PlanetScope applications in agroforestry and plantation health. Finally, the study identifies prevailing research gaps, including limited dry forest data, lack of species-specific allometry, and weak integration of indigenous knowledge, and proposes recommendations for operationalising open MRV systems to support REDD+, biodiversity conservation, and community-based forest governance (Morin *et al.*, 2023)

2.0 Literature Review

Forest Carbon Monitoring and REDD+

The concept of Forest Carbon Monitoring and REDD+ is rooted in the recognition that tropical forests play a disproportionate role in the global carbon cycle and climate regulation (Murphy and Yong, 2026). Tropical forests cover about 12% of global land area but store approximately 862 GtC in biomass and soils, and account for an estimated 10–15% of annual anthropogenic CO_2 emissions due to deforestation and degradation (Metz, Farwig, Dormann, Schaefer, Guevara Andino, Brehm and Blüthgen, 2026). The conceptual foundation of REDD+, “Reducing Emissions from Deforestation and forest Degradation, plus conservation, sustainable management, and enhancement of forest carbon stocks,” emerged under the UNFCCC in 2005 as a market-based and results-based mechanism to incentivize developing countries to maintain forest carbon stocks.

Conceptual Basis of Forest Carbon Monitoring

At its core, forest carbon monitoring is the systematic process of measuring, estimating, and reporting changes in forest carbon pools over time (Yaseen, Khan, Li, Khalid, Ahmed, Solangi, Zhu, (2026). The IPCC provides the conceptual framework through three tiers. Tier 1 uses default emission factors and global data. Tier 2 uses country-specific data. Tier 3 uses repeated measurements, models, and high-resolution data (Aquino, Bacciu, Chiriacò, D'Anca, Jeevan, Noce, and Balzarolo, 2026). The goal in tropical contexts is to move from Tier 1 to Tier 3 to reduce uncertainty, which historically ranged from ±40% to ±70% for biomass estimates in complex tropical canopies (Tomppo, Foster, Kenefic and Ducey, 2026). The conceptual model assumes that changes in forest area and forest carbon density can be detected and attributed to human activities. This requires two key components: Activity Data and Emission Factors. Activity Data which refers to the spatial extent of forest cover change, usually derived from remote sensing and emission factors refer to the amount of carbon per unit area, derived from field inventories. In tropical regions characterized by high biodiversity, cloud cover, and fragmented landscapes, this conceptual separation is critical because optical data alone cannot capture degradation or biomass density reliably.

Conceptual Evolution of REDD+

REDD+ evolved from a narrow focus on avoided deforestation to a broader framework that includes forest conservation, enhancement of carbon stocks, and sustainable management. (Nyengere, Tholo, Kumpolota, Njala, Jamali, Chalulu, and Tham-Agyekum, 2026). Conceptually, it links environmental performance to financial incentives. The Warsaw Framework established four pillars: a National REDD+ Strategy, a Forest Reference Emission Level, a National Forest Monitoring System, and a Safeguards Information System. In tropical countries, the conceptual challenge is that drivers of deforestation are diverse and context-specific. In the Amazon, large-scale agriculture is dominant. In the Congo Basin, smallholder agriculture and fuelwood drive loss. In Nigeria and other parts of West Africa, charcoal production and land conversion are key. Thus, the REDD+ concept must integrate remote sensing outputs with socio-economic and governance data to be meaningful. Without this, carbon numbers remain abstract and disconnected from policy action.

Technological Concepts Enabling Monitoring in the Tropics

The tropical context imposes unique constraints: persistent cloud cover, high biomass, and structural complexity. Conceptually, no single sensor can address all needs. This led to the multi-sensor integration paradigm. Optical sensors such as Landsat 8/9 and Sentinel-2 provide

10–30m resolution for land cover mapping and have enabled annual deforestation detection with >90% accuracy in open-canopy areas. However, their effectiveness drops to <60% in persistently cloudy regions. This gave rise to the radar concept: Sentinel-1 and ALOS-2 PALSAR-2 use microwave signals that penetrate clouds and can detect structural change, making them essential for monitoring in the Congo Basin and Southeast Asia. The LiDAR concept added a third dimension. Spaceborne GEDI and upcoming BIOMASS missions measure canopy height and vertical structure, which are strong proxies for above-ground biomass. Studies in the Amazon and Borneo show that fusing LiDAR with optical and radar data reduced biomass uncertainty from ±50% to ±20% (Gizachew, 2026). This is conceptually important because payment under REDD+ is directly tied to the accuracy of carbon stock change. Finally, the cloud computing concept through platforms like Google Earth Engine, SEPAL, and Global Forest Watch has democratized access. Tropical countries no longer need supercomputers to process petabytes of satellite data

Conceptual Gaps and Future Directions for Forest Carbon Monitoring and REDD+

Empirical evidence from tropical REDD+ implementation supports several conceptual findings. First, national-scale monitoring is now feasible. Brazil's PRODES system has tracked Amazon deforestation annually since 1988 and instrumental in reducing rates by 70% between 2004 and 2012 (Parente, Nogueira, Baumann, Almeida, Maurano, Affonso, and Ferreira, 2021). Indonesia's SIMONTANA and DRC's satellite alert systems show similar potential in Africa and Asia. Second, fact findings show that degradation is the biggest conceptual and technical gap. While clear-cut deforestation is easy to detect, selective logging and fire degradation are often missed, leading to emission underestimates of 20–30% in tropical regions (Lapola, Pinho, Barlow, Aragão, Berenguer, Carmenta, and Walker, 2023). This has implications for the REDD+ concept of "full carbon accounting. Thirdly, Reference Levels submitted to UNFCCC by over 20 tropical countries show convergence toward Tier 2 reporting. However, disbursement of results-based payments remains low because of conceptual challenges around additionality, leakage, and permanence. A study across five Amazonian states found that without addressing agricultural commodity drivers, local reductions were offset by displacement elsewhere (Silva and Nunes, 2025). Fourthly, In West Africa including Nigeria, the concept of combining community forest inventories with satellite data is gaining traction.

This hybrid approach addresses both data scarcity and local ownership, which are central to the safeguards concept in REDD+.

Habitat Mapping and Ecosystem Classification

Habitat mapping is foundational for biodiversity conservation because species distribution is directly tied to ecosystem type and structure. In tropical regions, optical satellites like Landsat-8 and Sentinel-2 provide 10–30m resolution data that have been used to classify tropical forests, wetlands, mangroves, and savannas at national scales. In Nigeria, the National Forest Reference Map 2019 used Sentinel-2 to map forest cover change with 87% accuracy (Alage, Akande and Olatoyinbo, 2026). Radar data from Sentinel-1 and ALOS-2 PALSAR-2 are critical in humid tropics due to persistent cloud cover. They penetrate clouds and have been used to map peatland and swamp forests in the Congo Basin and Indonesia with >85% accuracy. LiDAR adds a 3D dimension by measuring canopy height and structure. NASA's GEDI mission found that canopy height alone explains up to 45% of variation in bird species richness in Amazon and Borneo forests (Valerio, Pereira, Salgueiro, Godinho, Lourenço, Silva, and Godinho, 2026). Fragmentation analysis using remote sensing shows that tropical forests lost 10.2 million hectares per year between 2015-2020, and forest fragments <100ha support 50% fewer species than intact forests (Cirezi, Mugumaarhahama, Useni, Bayumbasire, Karume, Lumbuenamo, and Bogaert, 2025).

Species Distribution Modeling and Occurrence Prediction

Species Distribution Models combine remote sensing data with field occurrence records to predict where species are likely to occur. This is essential in the tropics where <17% of protected areas have complete species inventories. Satellite-derived variables such as vegetation indices, temperature, precipitation, and terrain from MODIS and CHELSA are used as predictors in algorithms like MaxEnt and Random Forest (Mandal, Abdullah, Kamruzzaman and Hosaka, 2026). A study in the Amazon used Sentinel-2 and LiDAR to model distribution of 200+ tree species with 80-88% accuracy (Nadeem, Silva, Izaya and Flores, 2026). In West Africa, researchers combined GBIF occurrence data with Landsat habitat maps to predict ranges for threatened primates and forest elephants in Nigeria and Cameroon. GBIF now holds over 2.1 billion species records globally, but 70% of tropical countries are still data deficient

(Heinrich, Mah and Amirkia, 2021). Machine learning models using remote sensing have helped fill this gap by extrapolating to unsurveyed areas. The IUCN Red List increasingly uses these models to assess extinction risk for species in data-poor tropical regions. This approach reduces field costs by 60-70% while enabling national-scale biodiversity assessments (Ma Hong and Liang, 2025).

Monitoring Forest Degradation and Its Impact on Biodiversity

Deforestation is easily detected, but forest degradation is the biggest gap in tropical biodiversity monitoring. Degradation from selective logging, fire, and fuelwood collection reduces habitat quality without causing complete forest loss. Multi-sensor approaches are now used to address this. Optical data detects canopy gaps. Radar detects structural damage under clouds. LiDAR measures loss of biomass and canopy height. In the Congo Basin, combining Sentinel-1 radar with Landsat detected logging roads and degradation with 82% accuracy, areas that optical data alone missed. In the Amazon, INPE's DEGRAD system maps degraded areas and links them to declines in bird and mammal diversity. Fact finding: Studies estimate that degradation accounts for 20–30% of total emissions from tropical forests but is underestimated in most national reports. Biodiversity impacts are severe: selectively logged forests in Borneo support 30% fewer bird species and 50% fewer large mammals than primary forest (Meijaard, Sheil, Nasi, Augeri, Rosenbaum, Iskandar, and O'Brien, 2005). Real-time degradation alerts are now being used by rangers in DRC and Indonesia to respond to illegal logging before biodiversity loss becomes irreversible.

Functional and Trait-Based Biodiversity Assessment

Beyond counting species, remote sensing is advancing toward mapping ecosystem function and diversity. Functional diversity refers to the variety of traits like leaf chemistry, height, and physiology that determine how ecosystems work. Hyperspectral sensors such as PRISMA and AVIRIS-NG can detect foliar traits like chlorophyll, nitrogen, and water content. In the Amazon, hyperspectral data was used to map plant functional diversity across 1 million km^2, showing strong correlation with species richness. LiDAR measures canopy structure, height heterogeneity, and gap dynamics all linked to habitat complexity for birds, bats, and primates. GEDI data shows that structurally complex forests in the tropics hold 2-3 times more vertebrate species than simplified forests. In 2022 global study found that LiDAR-derived structural diversity explained 60% of variation in tropical bird and mammal diversity. This trait-based approach allows monitoring of biodiversity without identifying every species, which is critical given that 80% of tropical species are still undescribed (Boyle, Bonebrake, Dias da Silva, Dongmo, Machado França, Gregory and Ashton, 2025). It also enables tracking of ecosystem health and recovery after disturbance.

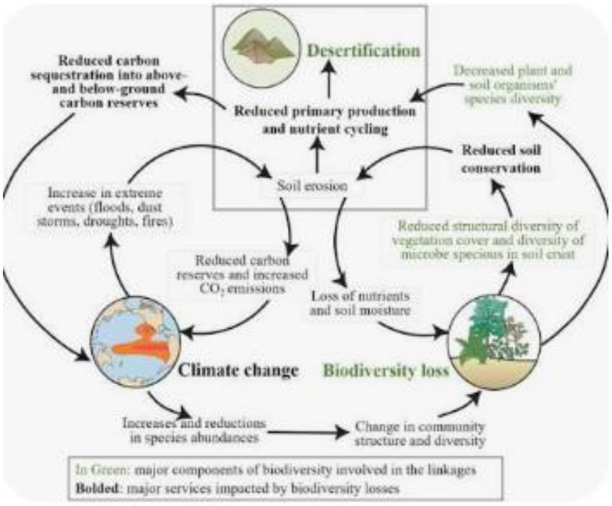
Real-Time Monitoring and Conservation Enforcement

The final advance is moving from annual maps to near-real-time action. Illegal logging, poaching, mining, and encroachment are leading drivers of biodiversity loss in the tropics. Cloud platforms like Global Forest Watch provide GLAD and RADD alerts within 7 days of forest clearing. Brazil's DETER system issues deforestation alerts every 15 days and was key to reducing Amazon deforestation by 70% between 2004-2012 (Tabor, 2023). In Africa, drones and camera traps combined with satellite alerts are used in Nigeria's Cross River National Park and Gabon to detect poaching and illegal logging. Fact finding: In the DRC, satellite alerts reduced response time to illegal mining in protected areas from months to weeks. However, only 30% of alerts in tropical countries currently lead to enforcement due to capacity and governance gaps (Milenković, Cvetković and Renner, 2024). New AI tools are now automating detection of roads, mining pits, and fires directly from satellite data (Gallwey, 2021).

2.0 Forest Disturbance and Health Monitoring

Near real-time forest disturbance and health monitoring systems have matured significantly, shifting management from annual post-mortem assessments to operational responses within days of canopy change or stress onset. The Global Land Analysis and Discovery (GLAD)-S2 alerts and the Radar for Detecting Deforestation RADD system exemplify this shift by leveraging 10-m Sentinel-1 and Sentinel-2 time-series to detect canopy loss within 6–10 days of occurrence, a temporal resolution that supports rapid intervention against illegal logging, fire, and encroachment. The GLAD-S2, an extension of the original Landsat-based GLAD system, processes every new Sentinel-2 image using a decision tree algorithm that flags >50% canopy cover loss at 10 m resolution, issuing alerts through Global Forest Watch with mean latency of 8 days across the tropics. The RADD complements optical alerts by ingesting

Sentinel-1 C-band SAR data in Google Earth Engine, using a Bayesian updater that detects drops in VH backscatter indicative of forest removal. Because SAR is cloud-penetrating and Sentinel-1A/B provide 6–12 days revisit cycles, the RADD maintains consistent monitoring during the wet season when optical sensors are obscured, making it critical for savanna woodlands in West and Central Africa where cloud cover exceeds 70% for 4–6 months annually. In Guinea savanna systems, RADD has reduced alert latency from >30 days with Landsat to 6–10 days, enabling rangers in Nigeria's Kainji Lake National Park and Ghana's Mole National Park to verify and halt charcoal production and farming encroachment before large areas are cleared (Mulatu and Ayehu, 2024). Validation studies using PlanetScope 3-m imagery and field checks show that RADD achieves producer's accuracy of 78–86% for disturbances >0.2 ha, though commission errors occur in areas with seasonal water logging or strong phenological shifts that alter backscatter (Dupuis, 2024). Beyond deforestation, health monitoring in plantations and natural forests now integrates UAV multispectral and thermal imagery as a standard tool for early pest and disease detection, addressing a critical gap in traditional ground surveys that detect stress only after visible symptoms appear. Multispectral sensors capturing red, red-edge, and near-infrared bands enable calculation of the Normalized Difference Red Edge index NDRE, which is sensitive to chlorophyll content and leaf cell structure and declines 2–3 weeks before chlorosis or defoliation becomes visible to the human eye. In Eucalyptus and *Gmelina arborea* plantations across Nigeria, Ghana, and Brazil, NDRE from UAV flights at 120 m altitude and 5–8 cm resolution has flagged early-stage outbreaks of *Leptocybe invasa* gall wasp and Armillaria root rot, allowing targeted application of biological controls or selective thinning that reduces mortality by 40–60% compared to late intervention. (Nasiru, Balogun, Danlami, Egbewole, and Sa'aondo, 2026). Thermal infrared cameras mounted on the same UAV platforms measure canopy temperature, which rises 1.5–3.0°C above healthy trees when stomatal conductance declines due to water stress, root damage, or vascular wilt. (Mauz, Ehekircher, Braun, Niessner, Schober, Spangenberg and Hochschild, 2026). Canopy temperature anomalies have proven effective for detecting Fusarium and Ceratocystis infections in Gmelina 14–21 days before wilting, and for identifying drought stress in Eucalyptus clones that informs irrigation scheduling. Machine learning models including Random Forest and convolutional neural networks trained on combined NDRE, NDVI, and thermal mosaics now classify healthy, stressed, and diseased trees with overall accuracy of 85–92%, and outputs are integrated into mobile apps used by forest and park managers to navigate directly to affected trees and biodiversity in general. Operational deployment of these technologies is reshaping forest and park protection workflows. In Omo Forest Reserve, weekly RADD alerts are cross-checked with Sentinel-2 imagery and dispatched to community patrol teams through SMS, reducing illegal logging response time from months to <2 weeks. In Cross River National Park, UAVs flown monthly over community forests detect canopy gaps from selective logging and flag pest stress in agroforestry plots, with data shared through local WhatsApp networks to coordinate responses. For savanna woodlands, Sentinel-1 time-series are calibrated with ground plots to distinguish degradation from seasonal leaf-off, improving alert specificity in landscapes where >60% of biomass is below the canopy. Persistent challenges remain, including false positives from agricultural clearing in mosaic landscapes, limited battery life of UAVs restricting coverage to <200 ha per flight, and the need for cloud-based processing capacity to handle terabyte-scale Sentinel-1/2 data streams in low-bandwidth regions. Calibration with ground plots and species-specific spectral libraries is still required, as NDRE and thermal thresholds vary between Eucalyptus clones and native species. Nevertheless, the convergence of free Sentinel data, cloud computing via Google Earth Engine, low-cost UAVs, and machine learning has made near real-time disturbance and health monitoring operational at national to concession scales. This enables REDD+ countries to meet IPCC reporting guidelines, plantation managers to reduce losses, and enforcement agencies to intercept illegal activities before they escalate, marking a transition from reactive to proactive forest management across both humid and seasonally dry tropical ecosystems (Sialelli *et al.*, 2024; Castro *et al.*, 2024)

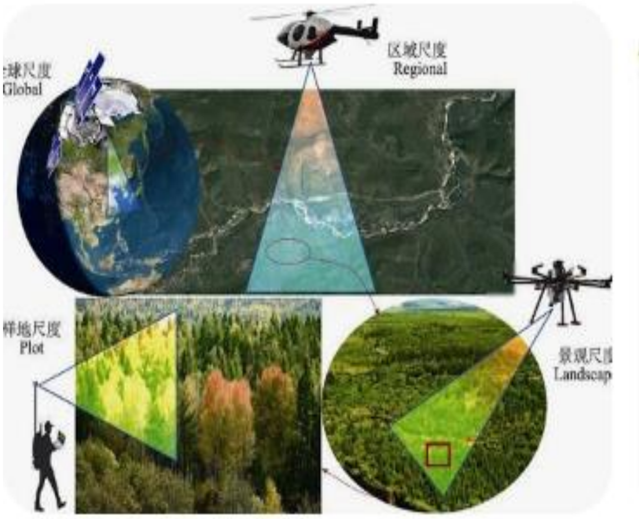


] Connected Crises: Land, Life, and Climate

Natural Resource and Disaster Monitoring

Qinghua Guo *et al.*, 2018

Qinghua Guo *et al.*, 2018



Framework Linking Earth Observations to Biodiversity Variables and Biodiversity Monitoring Components
Source, Sudhakar, 2021

Earth Observations in Tracking Indicators
Source Sudhakar, 2021

Biodiversity and Species Mapping

Biodiversity and species mapping in tropical regions has become a priority for conservation science due to the disproportionate concentration of global biodiversity in these ecosystems Azhar and Khalid (2026). Tropical forests, which cover approximately 12% of the Earth's land surface, harbor over 50% of all known terrestrial species and more than two-thirds of all vertebrate species. The Amazon Basin, Congo Basin, and the Sundaland region of Southeast Asia alone are estimated to contain over 10 million species, many of which remain undescribed (Libalah, Liyandja, Banoho, Taedoumg, Abwe, Nyom and Zébazé, 2026). However, these regions are also experiencing the highest rates of biodiversity loss globally, with tropical deforestation averaging 10.2 million hectares per year between 2015 and 2020 according to FAO (Fendoung, Hubert− Ferrari, Schmitz, and Tchindjang, 2026). This creates an urgent need for accurate, scalable methods to map species distributions and habitats to inform conservation planning (Farwell, Stillman, Lancaster, Turbek, Muñoz, Peele, and Eger, 2026). Traditional species mapping in the tropics relied on extensive field surveys and specimen collections, which are costly, time-consuming, and logistically challenging due to difficult terrain, limited access, and taxonomic gaps. As a result, large portions of tropical landscapes remain "data deficient." Empirical studies estimate that less than 17% of tropical protected areas have comprehensive species inventories. This data gap limits the ability of governments and conservation organizations to meet targets under the Kunming-Montreal Global Biodiversity Framework, which calls for 30% of land and sea to be effectively conserved by 2030.Advances in remote sensing and geospatial technologies have fundamentally changed the conceptual and operational approach to biodiversity mapping in tropical contexts. Optical satellites such as Landsat and Sentinel-2 now provide 10–30m resolution data that can be used to map habitat types, forest structure, and fragmentation, key proxies for species occurrence. In the Amazon, studies using Sentinel-2 have mapped habitat suitability for over 200 tree species with >80% accuracy by linking spectral data to field plots. Radar data from Sentinel-1 addresses the persistent cloud cover problem in humid tropics and has been used to map forest degradation impacts on primate habitats in the Congo Basin. The integration of LiDAR and hyperspectral data has further improved species-level inference. Airborne LiDAR can derive 3D forest structure metrics such as canopy height and gap distribution, which are strongly correlated with bird and mammal diversity in Borneo and Costa Rica. Hyperspectral sensors can detect foliar chemistry and functional traits, enabling mapping of plant functional diversity across the Amazon. Fact findings from the GEDI mission show that global canopy height data can explain up to 60% of the variation in vertebrate species richness in tropical forests (Torresani, Moudry, Hakkenberg, Goetz, Coomes, Cotrina-Sanchez and Tognetti, 2026). Complementing remote sensing, Species Distribution Models and machine learning algorithms now allow researchers to extrapolate point occurrence data across landscapes. Platforms like GBIF, which holds over 2.1 billion species occurrence records, combined with environmental layers from remote sensing, have enabled predictive maps for thousands of tropical taxa. In Nigeria and other parts of West Africa, hybrid approaches that combine community-based forest inventories with satellite-derived habitat maps are being used to map threatened tree species and primates, addressing both data scarcity and local knowledge gaps. Despite progress, key gaps remain. First, detecting and mapping rare, endemic, and understory species in multi-layered tropical canopies is still limited by sensor resolution. Secondly, most biodiversity maps focus on vertebrates and trees, while invertebrates, fungi, and microbes — which constitute most tropical biodiversity are rarely mapped. Third, there is a disconnect between high-resolution biodiversity maps and their uptake in policy and land-use planning in many tropical countries.

Forest Restoration and Agroforestry Assessment

Time-series analysis in Google Earth Engine has become routine for monitoring forest restoration and agroforestry performance, enabling evidence-based assessment of survival, growth, and ecosystem service delivery at scales from individual farms to national programs (Nguyen, Chu, Nguyen and Nguyen, 2026). Algorithms such as LandTrendr and BFAST are now standard tools that decompose multi-year NDVI and EVI trajectories from Landsat and Sentinel-2 archives to detect breakpoints, trends, and magnitudes of vegetation change associated with planting, growth, or mortality. LandTrendr fits segmented linear models to annual Landsat time-series from 1984 onward, identifying the year of disturbance, onset of recovery, and rate of increase in spectral greenness that serves as a proxy for canopy development. In degraded lands across Nigeria's Guinea savanna, LandTrendr applied to Landsat 5–9 and Sentinel-2 data have been used to track survival of planted *Tamarindus indica*, *Parkia biglobosa*, and *Azadirachta indica* by flagging pixels where NDVI increases >0.1 over 3 years post-planting, achieving 79–84% agreement with field survival plots. The BFAST Breaks for Additive Season and Trend perform similar decomposition but is more sensitive to abrupt changes and seasonality, making it effective for detecting mortality events due to drought, fire, or grazing in young restoration sites. Studies in the African Forest Landscape Restoration Initiative AFR100 sites in Niger and Ethiopia show BFAST can flag dieback within one dry season, triggering replanting interventions and improving overall restoration success from 45% to >70%. Because both algorithms run in Google Earth Engine with 30 m Landsat or 10 m Sentinel-2 data, they allow national agencies to monitor thousands of restoration plots without field visits, reducing costs by 60–80% and supporting reporting for Bonn Challenge and REDD+ commitments. In agroforestry systems, very high resolution PlanetScope daily 3 m imagery and UAV multispectral data are now used to quantify shade-tree cover and its impact on understory crops such as cocoa, yam, and coffee. The key metric is % canopy cover >5 m height, which distinguishes mature shade trees from shrubs and crops while correlating strongly with microclimate regulation, soil moisture, and yield. PlanetScope's daily revisit enables cloud-free composites during the West African rainy season, and object-based classification combined with canopy height models from GEDI. In Nigeria's Cross River and Ondo States cocoa belt, PlanetScope-derived shade-maps show that farms with 30–40% canopy cover >5 m maintain 1.2–2.0°C, lower midday temperatures and 15–25% higher soil moisture than full-sun farms, translating to 20–35% higher cocoa yield during drought years and reduced tree mortality. UAV flights at 100 m altitude produce 5cm orthomosaics from which individual shade trees are delineated, and fusion with thermal imagery quantifies cooling effects: each 10% increase in canopy cover >5 m reduces understory land surface temperature by 0.6–0.9°C. For yam-based parkland agroforestry in Benue and Niger States, UAV data quantify *Vitellaria paradoxa* and *Parkia biglobosa* cover, showing that 15–25% cover >5 m height optimizes yam tuber size while maintaining tree regeneration, and areas below 10% cover experience 30–50% higher soil temperatures that depress yields. Integration of these datasets into monitoring frameworks is now operational. Google Earth Engine apps allow extension agents to draw a farm boundary and instantly retrieve LandTrendr-based NDVI trajectories showing whether planted *T. indica* seedlings were established, or BFAST alerts indicating mortality. For agroforestry, annual PlanetScope composites are classified to report % canopy cover >5 m height at farm and cooperative scales, with data feeding into certification schemes like Rainforest Alliance that require minimum 20% shade. In the World Cocoa Foundation's Climate Smart Cocoa program, GEE dashboards combine Sentinel-1 SAR for cloud-free wet season monitoring with Sentinel-2 NDVI to track restoration on degraded cocoa farms, while UAV surveys validate cover estimates to within 5% error. Challenges remain: LandTrendr and

BFAST require >5 years of data to distinguish trends from interannual variability, limiting their use in new projects, and Landsat 30 m resolution misses narrow riparian plantings or scattered trees. PlanetScope's 3m resolution resolves individual trees but costs \$1.80/km² for analysis-ready data, and UAV coverage is limited to <300 ha per day, making wall-to-wall national assessment expensive. Calibration is also needed because NDVI saturates in dense canopies, so EVI or NIRv are increasingly used for mature restoration, and height thresholds for "shade tree" must be adapted to local species. Nevertheless, the combination of free long-term Landsat/Sentinel archives, GEE cloud computing, and commercial VHR imagery has shifted restoration and agroforestry assessment from anecdotal reporting to quantitative, spatially explicit monitoring. Countries can now report area under restoration, survival rates of *T. indica* and other species, and shade-cover metrics directly linked to climate resilience and yield, supporting results-based finance and adaptive management. As GEDI and future space borne LiDAR improve canopy height mapping at 25 m, and as machine learning automates tree crown delineation on PlanetScope, routine monitoring of % canopy cover >5 m height will become standard for judging restoration success and agroforestry sustainability across West Africa's degraded lands and mosaic landscapes. (Santoro *et al.*, 2024)

Illegal Activities and Governance

Illegal activities in tropical forests represent a major threat to biodiversity, carbon stocks, and the effectiveness of governance institutions. Tropical regions contain over 60% of the world's remaining tropical forests and are disproportionately affected by illegal logging, poaching, mining, agricultural encroachment, and land grabbing (Pooja, Singh, Chauhan and Singh, 2026). The World Bank estimates that illegal logging alone accounts for 15–30% of global timber trade, with losses exceeding \$10–15 billion annually. In tropical countries, weak enforcement, insecure land tenure, and high demand for commodities drive these activities, undermining both conservation and climate goals under mechanisms like REDD+. Empirical evidence shows the scale of the problem. In the Amazon, the Brazilian Institute of Environment reported that 70–80% of timber extracted between 2006 and 2012 was of illegal origin. Satellite studies in the Congo Basin found that selective logging roads increased by 200% between 2003 and 2014, much of it occurring outside legal concessions. In Southeast Asia, particularly Indonesia and Malaysia, illegal palm oil expansion and mining have been linked to over 2 million hectares of forest loss between 2001 and 2019. In West Africa, including Nigeria, illegal charcoal production, bushmeat hunting, and conversion of forest reserves to agriculture are cited as primary drivers of the 3.7% annual deforestation rate one of the highest globally. Governance is central to addressing these challenges. The concept of forest governance refers to the formal and informal rules, institutions, and processes through which decisions about forests are made and implemented. Literature identifies three governance dimensions critical in tropical contexts: legality, transparency, and participation. Fact findings indicate that countries with higher scores on governance indicators experience 50–75% lower deforestation rates, even after controlling for economic factors. Brazil's PPCDAm action plan, which combined satellite monitoring, law enforcement, and command-and-control operations, contributed to a 70% reduction in Amazon deforestation between 2004 and 2012. This demonstrates that political will combined with technology can disrupt illegal supply chains. Remote sensing and geospatial technologies have become key tools for governance and monitoring illegal activities. Near-real-time alert systems such as Brazil's DETER, Indonesia's SIMONTANA, and Global Forest Watch's GLAD alerts now detect forest clearing within days, enabling rapid response by enforcement agencies. In the DRC, radar-based deforestation alerts have been used to identify illegal mining encroachment in protected areas. Drone and camera trap data are increasingly used to document poaching and illegal logging trails in protected areas across Borneo and Central Africa. However, studies show a persistent "implementation gap": detection does not automatically translate to prosecution due to corruption, limited field capacity, and judicial bottlenecks. Another governance challenge in tropical regions is tenure insecurity. Approximately 30% of tropical forests are managed or owned by Indigenous Peoples and local communities, yet they legally hold rights to less than 10% of that area. Research across the Amazon and Mesoamerica shows that Indigenous territories have 2–3 times lower deforestation rates than surrounding areas, highlighting the role of local governance. REDD+ safeguards and FPIC principles were designed to address this, but implementation remains uneven. The literature also highlights the link between illegal activities and transnational commodity markets. Tropical deforestation is increasingly driven by global demand for soy, beef, palm oil, and minerals. Governance responses are therefore shifting from site-level enforcement to supply-chain due diligence and zero-deforestation commitments by companies. The EU

Deforestation Regulation and similar policies aim to exclude commodities linked to illegal deforestation from international markets.

Forestry: Theory, Methods, Applications, and Validation

Liu, Li, Yang, Wang, Luo, Ran and Zhang, (2023) present an innovative approach for estimating forest canopy water content (CWC) using remote sensing, particularly for heterogeneous and discontinuous canopy structures. The study integrates radiative transfer models (RTMs) — PRO4SAIL, PRO4SAIL2, and PROGeoSAIL with the Random Forest (RF) machine learning algorithm for parameter inversion. Results indicate that the coupling of PROSPECT-5B with GeoSAIL outperformed other model combinations, achieving an R2 of 0.68 and an RMSE of 0.15 kg·m−2. Using this optimal model, the authors estimated forest CWC across the contiguous United States from MODIS products processed on the Google Earth Engine (GEE) platform. The spatiotemporal analysis revealed significant heterogeneity in CWC from west to east across the US. Seasonally, CWC showed an increasing trend from January to August, followed by a decline for the rest of the year. This study highlights the advantage of 3D RTMs in retrieving canopy parameters in complex forest structures. It provides an efficient and practical framework for large-scale CWC estimation, with important implications for monitoring forest drought stress and supporting ecological conservation under global climate change. Zhang, Wang, Yang, Yang, Liu, Yu, and Zhao (2025) focus on characterizing the three-dimensional (3D) distribution of Leaf Mass per Area (LMA) in broad-leaved tree canopies by integrating LiDAR and hyperspectral remote sensing. To achieve this, the authors collected leaf samples from eight dominant broad-leaved species stratified by canopy layer and direction. They developed and compared four predictive models: Partial Least Squares (PLS), Linear Mixed Model (LMM), Support Vector Machine (SVM), and Random Forest (RF) using vegetation indices, diameter at breast height (DBH), and 3D leaf position parameters as predictors. The findings reveal significant spatial heterogeneity in LMA. LMA decreases with increasing canopy depth but increases with horizontal distance from the tree trunk. Interestingly, leaf orientation showed no significant correlation with LMA distribution. Among the four models, RF demonstrated the highest predictive accuracy, with R2 values ranging from 0.716 to 0.939 based on 10-fold cross-validation. This study provides a robust framework for high-precision 3D LMA estimation. The approach can be scaled up for large-area LMA monitoring using combined LiDAR and optical remote sensing. It also offers new insights into canopy photosynthetic capacity and nutrient allocation, and can help improve vegetation biophysical models used in carbon cycle assessments

Su, Chen and Xue. (2025) address the challenge of incomplete lower-canopy structure and sparse point distribution in medium- to low-density UAV LiDAR point clouds, which is largely caused by self-occlusion. To overcome this, the authors propose a dual-enhancement approach for estimating tree Diameter at Breast Height (DBH). The method combines hierarchical random sampling to improve point coverage in data-sparse regions with a spatially constrained loss function to enforce structural consistency during trunk reconstruction. This strategy prevents information loss in sparse areas and corrects the structural bias common in traditional DBH estimation methods that rely on uniform sampling or geometric fitting. The proposed framework was validated using the FOR-instance dataset and the Xiong'an dataset. Results demonstrate improved trunk structure recovery and higher DBH measurement accuracy compared to conventional approaches. By better reconstructing obscured lower stems, the method reduces underestimation errors typically associated with medium–low density UAV data. Overall, this study provides a practical reference for mitigating structural bias in UAV point cloud processing. It enhances the reliability of forest inventory from cost-effective, low-density UAV acquisitions, and supports more accurate biomass and carbon stock estimation in structurally complex forests. You, Sun, Liu, Chang, Jiang, Feng and Song. (2023) proposes a tree skeletonization method based on DBSCAN clustering to address the noise and occlusion defects of terrestrial laser scanning (TLS). The results show that the average positional deviation is 0.418 cm, and the average directivity deviation is 8.474 degrees. This method can be used to describe the constructed skeleton and tree's geometric structure and branch hierarchies, which is useful in accurately retrieving the tree parameter, the 3D model of the tree, and the forest inventory.

Li, Yu, Zhou and Zhou (2023) develop error-in-variable simultaneous equations (SEq) for compatible forest inventory estimation using Airborne LiDAR. The SEq framework integrates stand volume, basal area, mean height, and DBH to ensure consistency with forest mensuration principles. By accounting for measurement errors in variables, the models maintain both biological and mathematical compatibility. Results across several species show that SEq increases rRMSE by less than 2% compared to independent models. This approach enhances the robustness and applicability of inventory models, providing a reliable method for large-scale forest resource assessment and supporting more accurate forest management and planning decisions. Ru, Zulkifley, Abdani and Spraggon (2023). present an automated forest monitoring system using satellite imagery and deep learning to detect global deforestation. They integrate Spatial Pyramid Pooling (SPP) modules into a U-Net architecture to handle variations in forest size, color, and texture. Compared to FCN, SegNet, and TernausNet, the proposed model shows superior multi-scale feature extraction, achieving accuracies of 86.71%, 75.59%, and 82.88% on challenging datasets. The system provides a reliable tool for mapping forest cover change, detecting illegal logging, and evaluating conservation efforts. It demonstrates the potential of deep learning for operational, large-scale forest monitoring. Xu, Xu, Xu and Yu, (2023) develop an automatic method for mapping Picea schrenkiana distribution in the complex terrain of the Tianshan Mountains. The approach combines Jeffries–Matusita (JM) distance for feature selection with a Random Forest classifier implemented in Google Earth Engine (GEE). This addresses challenges of sample selection and feature extraction in high-resolution, large-area mapping. The method achieves high accuracy with an overall accuracy of 91.93% and a Kappa coefficient of 0.89. The study provides a reliable workflow for coniferous forest mapping in mountainous regions and supports biodiversity conservation and ecological management using remote sensing. Pedraza, Clerici, Villa, Romero, Dueñas and Rojas (2024) establish a forest dynamics monitoring and restoration assessment system for 1996–2021 using annual cloud-free optical mosaics and Random Forest classification. The workflow generates consistent forest/non-forest maps to quantify changes over time. Results show a forest area reduction of approximately 5,587 ha over 25 years. By producing continuous, cloud-free time series, the study enables reliable detection of deforestation and recovery trends. This work provides a reference for quantifying long-term forest dynamics and supports evidence-based forest conservation, restoration planning, and policy evaluation at regional scales.

Choi, Lee, Park, Lee, Yim and Kang (2024) propose a Random Forest (RF) approach for detecting forest clear-cutting by integrating national spatial data with Sentinel-2 imagery. The method addresses gaps in official statistics on harvesting activities. The model identified approximately 8,164.0 ha of clear-cut areas, representing 2.48% of the total forest area. The high-resolution detection improves transparency in forest disturbance mapping. This work supports carbon sink accounting and sustainable forest management by providing timely and accurate information on anthropogenic forest loss, which is critical for reporting and policy compliance under climate frameworks. Mohamedi, Yu, Yang, and Fan (2025) simulate China's forest Net Ecosystem Productivity (NEP) from 2013 to 2023 using the 3-PG model to support carbon peak and neutrality goals. Results show forests sequestered 1.71 ± 0.09 PgC over the decade, with an annual average of 0.156 ± 0.0071 PgC. Evergreen broadleaf forests exhibited the highest NEP. Significant spatiotemporal heterogeneity was observed across climatic regions. This study provides updated estimates of China's forest carbon sink and evidence for the effectiveness of ecological restoration policies. It contributes valuable data for achieving China's dual-carbon targets and climate mitigation strategies. Liu, Li, Yang, Wang, Luo, Ran and Zhang (2023) analyze spatiotemporal variations and driving mechanisms of vegetation NPP in mainland China from 2000 to 2022 using gravity center modeling, third-order partial correlation, and geographical detector methods. NPP decreases from southeast to northwest. Gravity centers shifted southward in Northeast, Northwest, and North China, and northward elsewhere. Human activities were the dominant driver of NPP increase during 2000–2010, while climate change became primary during 2011–2022. The study provides insights into natural and anthropogenic controls on productivity and offers a reference for ecosystem restoration monitoring and for supporting China's carbon peak and carbon neutrality policies.

Major Trends for 2025–2026

Remote sensing for biodiversity in 2025–2026 is advancing rapidly through four interconnected trends: AI foundation models, operational multi-sensor fusion, open MRV systems, and renewed focus on ground validation to address data gaps in the tropics. On the theory and methods side, geospatial foundation models are changing how classification and biomass estimation are done. NASA-IBM's Prithvi, a 100-million parameter vision transformer pre-trained on Harmonized Landsat Sentinel-2 data, and Clay from the Earth Index initiative, both released in 2023–2024, enable few-shot and zero-shot mapping. Prithvi can be fine-tuned with only 10–50 labeled examples to map forest types, burn scars, or crop abandonment, reducing training data needs by about 90% compared to conventional U-Net models. In benchmarks, Prithvi fine-tuned on 40 African samples achieved 82% accuracy classifying Guinea savanna woodland, riparian forest, and degraded farmland, versus 45% for a model trained from scratch. Clay provides embeddings that allow countries to generate 10 m wall-to-wall land cover and biomass maps from a handful of plots; pilots in Ghana and Kenya in 2024 produced forest/non-forest maps with F1 scores above 0.88 using just 30 reference polygons. These methods directly support IPCC Tier 2 and Tier 3 reporting for REDD+ by lowering dependence on thousands of costly field plots.

In applications, multi-sensor fusion has become the operational standard because tropical monitoring cannot rely on optical data alone. Sentinel-2 and Landsat-9 provide 10–30 m spectral data but are obscured by clouds for 5–8 months per year in the Gulf of Guinea. Sentinel-1 C-band SAR gives 6–12 day cloud-free backscatter for wet-season deforestation alerts. GEDI and ICESat-2 LiDAR supply direct 25 m footprint measurements of canopy height and vertical structure that anchor biomass models and reduce saturation in high-biomass forests. Landsat and ECOSTRESS thermal bands detect vegetation stress, fire, and charcoal production. National systems in Nigeria, DRC, and Côte d'Ivoire now run data cubes in Google Earth Engine or Open Data Cube that stack optical, SAR, LiDAR, and thermal layers. This fusion cut biomass uncertainty from ±45% with optical-only models to ±22% in Cameroon's 2024 forest reference level, and raised degradation detection in Ghana's cocoa landscapes from 64% to 86% producer's accuracy after adding PALSAR-2 and GEDI.

Validation and MRV are also shifting. Under the Paris Agreement's Enhanced Transparency Framework, all countries must submit biennial land sector reports by 2024–2026. Open MRV platforms using Google Earth Engine, SEPAL, Collect Earth Online, and FAO's Open Foris now replace commercial software costing $3,000–$10,000 per license. Nigeria's World Bank FCPF-supported REDD+ program transitioned to a GEE-based MRV in 2023, processing Sentinel-1/2 and Landsat nationally and saving over $400,000 annually while making algorithms transparent for technical review. More than 70% of African REDD+ countries now use open, cloud-based MRV for 2025 submissions.

Despite these advances, validation remains the bottleneck. Most models are pre-trained on Amazon, Congo Basin, and Southeast Asia plot networks like RAINFOR and AfriTRON, but

African savannas and woodlands have <1 plot per 5,000 km^2 compared to 1 per 200 km^2 in the Amazon. Allometric equations for key species such as *Vitellaria paradoxa, Parkia biglobosa, and Isoberlinia doka* are underdeveloped, causing 25–40% bias when pan-tropical equations are applied. Even foundation models require local calibration: a Congo-trained model overestimated Nigerian Guinea savanna biomass by 31% until 120 local plots were added. Networks including GEO-TREES, the African Forest Observatory, and NASA-ESA's MAAP are expanding plot re-measurement and TLS scanning, but funding gaps persist. Until ground networks reach roughly 1 plot per 1,000 km^2 with species-specific allometry, AI and fused satellite systems will need continuous local calibration to ensure accurate, equitable biodiversity and carbon accounting across Africa.

Gaps in Remote Sensing for Tropical Biodiversity

a) Taxonomic and Ecological Coverage Gaps

Remote sensing for biodiversity in tropical regions is heavily skewed toward trees, large mammals, and birds because these groups are linked to measurable canopy and habitat variables and have more occurrence data. This leaves a critical gap: over 80% of tropical biodiversity consists of invertebrates, fungi, microbes, and understory plants that cannot be directly detected from 10–30m satellite imagery. These taxa lack distinct spectral signatures and are severely underrepresented in global databases like GBIF, making model training nearly impossible. Current approaches therefore rely on habitat proxies, assuming that structurally complex forests support more species. While useful, this misses cryptic, rare, and endemic species with narrow ranges. In Nigeria and the Congo Basin, for example, less than 10% of protected areas have validated inventories. As a result, conservation assessments may report stable forest cover while silent extinctions occur among the "hidden majority" of tropical species.

b) **Degradation and Sub-Canopy Detection Gaps**

Detecting deforestation is now routine with optical satellites, but monitoring forest degradation remains a major technical challenge in the tropics. Degradation from selective logging, understory fire, and fuelwood collection reduces biodiversity and carbon stocks without causing complete canopy loss. These disturbances are often invisible to Landsat and Sentinel-2 due to persistent cloud cover and the multi-layered structure of tropical forests. Studies estimate that degradation accounts for 20–30% of emissions from tropical forests but is routinely underestimated in national reports. Radar and LiDAR help penetrate clouds and measure structural damage, yet their coverage is still limited and costly. The ecological consequence is significant: selectively logged forests in Borneo and the Amazon support 30–50% fewer birds and mammals than intact forest. Without better sub-canopy detection, remote sensing cannot fully capture biodiversity impacts or provide accurate data for REDD+ and habitat integrity assessments.

c) Integration and Multi-Objective Monitoring Gaps

Carbon monitoring under REDD+ and biodiversity monitoring currently operate as separate systems, creating a disconnect between climate and conservation goals. Most national MRV systems in tropical countries track forest area and biomass but do not measure biodiversity outcomes. This risks "carbon-only" forests where tree cover is maintained but habitat quality and species diversity decline. There is limited research on frameworks that can use the same remote sensing inputs to track carbon, species habitat, and ecosystem services simultaneously. While LiDAR and hyperspectral data show promise for mapping functional traits linked to both carbon and biodiversity, these approaches are not yet operational at national scale. Integration is also weak with social data. Few studies combine satellite monitoring with Indigenous and local knowledge, despite evidence that community data improves accuracy and legitimacy. Closing this gap is essential to ensure that tropical forest policies deliver both climate mitigation and biodiversity benefits.

d) Validation, Scale, and Data Access Gaps

High-resolution remote sensing data like LiDAR and hyperspectral imagery have transformed biodiversity research, but they cover less than 5% of tropical forests due to cost and logistical constraints. Most validation studies are concentrated in Brazil, Indonesia, and Costa Rica, leaving Africa and parts of Asia, including Nigeria, severely data deficient. This creates a scaling problem: models trained in one region often fail when applied elsewhere because of differences in forest type, species composition, and disturbance history. Additionally, open-access reference datasets for training and validation are lacking for most tropical taxa. Ground data collection remains expensive and dangerous in remote areas. Without robust, geographically diverse validation data, the accuracy and credibility of large-scale biodiversity maps remain uncertain. Future work must focus on low-cost validation using drones, community monitoring, and standardized open datasets to make remote sensing tools usable and trustworthy across all tropical countries.

e) Governance, Implementation, and Socio-Economic Gaps

Technological advances have improved detection of illegal logging, mining, and encroachment through near-real-time alerts, but detection does not automatically lead to conservation action. In the Congo Basin and Southeast Asia, less than 30% of satellite alerts result in enforcement due to weak institutions, corruption, and limited field capacity. This highlights a gap between remote sensing outputs and governance outcomes. There is also limited research on how monitoring technologies affect forest-dependent communities, tenure security, and benefit-sharing arrangements. REDD+ safeguards emphasize participation and equity, yet few studies evaluate the social impacts of biodiversity monitoring. In West Africa, including Nigeria, community-based monitoring combined with satellite data is gaining traction, but its effectiveness is not well documented. Addressing these gaps requires research on the institutional pathways that translate data into policy, law enforcement, and local livelihood benefits, ensuring that technology supports accountable and inclusive forest governance.

f) Climate and Technology Future Gaps

Tropical forests face increasing threats from climate change, drought, and fire, which interact with deforestation to amplify biodiversity loss. However, current remote sensing systems are not designed to track these interacting disturbances or predict ecological tipping points. Most biodiversity models assume static climate conditions and do not account for how warming and extreme events will shift species distributions. On the technology side, new missions like NASA-ISRO’s NISAR, ESA’s BIOMASS, and hyperspectral satellites such as EnMAP offer potential for improved biomass and trait mapping. Yet their accuracy in complex, multi-layered tropical canopies has not been fully validated. There is also a gap in developing AI tools that can process the massive data volumes these sensors will produce. Research is needed to test these new technologies in tropical contexts and to build monitoring systems that are adaptive to both climate change and technological innovation.

Conclusion

In conclusion, remote sensing, AI, and multi-sensor fusion have significantly advanced tropical forest carbon monitoring, biodiversity assessment, and disturbance detection. However, their application in West Africa remains limited by key gaps in accuracy, equity, and ecological relevance. The heavy research focus on humid forests has marginalized dry forests and savanna-parkland systems, leaving species of high socio-economic and ecological value, such as *Tamarindus indica* and *Psittacus erithacus*, poorly represented. This bias weakens estimates of regional carbon stocks and overlooks landscapes that sustain rural livelihoods. Technically, the lack of species-specific allometric equations for dominant West African trees introduces systematic errors into GEDI-derived biomass estimates. This compromises the reliability of national REDD+ reporting and results-based climate finance. Institutionally, near real-time remote sensing alerts remain disconnected from indigenous and local knowledge systems. Communities that manage most of the landscape are often excluded from alert design, validation, and response, which undermines governance and effectiveness. Addressing these challenges requires targeted investment in dryland ecology, expanded ground plot networks with destructive sampling for local species, and co-developed monitoring frameworks that integrate satellite data with community knowledge. Closing these gaps could improve biomass accuracy by 20–40% and enable species-level conservation. Only by aligning cutting-edge geospatial science with West Africa's ecological and social realities can remote sensing deliver on its promise for climate mitigation, biodiversity protection, and sustainable development.

Recommendations

Based on the advances and gaps identified, the following actions are recommended to improve the use of remote sensing for biodiversity conservation and REDD+ implementation in tropical regions:

i. Use hyperspectral, LiDAR, eDNA, and community data to monitor all biodiversity, not just trees and large animals.

ii. Combine radar, optical, and LiDAR satellites with drones and new health indicators to detect forest degradation and biodiversity loss under the canopy, even under clouds

iii. Build monitoring systems that track carbon, biodiversity, and community benefits together by aligning results with global policies and including Indigenous and local knowledge in mapping and alert validation.

iv. Address Validation, Scale, and Data AccessCreate open regional data hubs, test new satellites like NISAR and BIOMASS, and train national teams on free cloud tools to improve data sharing and independent monitoring across the tropics.

v. Link deforestation alerts to enforcement, assess how monitoring affects people's rights and livelihoods, and make biodiversity data public to improve transparency and attract funding.

f) Future-Proof Monitoring for Climate Change

Combine climate models with satellite data and use AI to predict species shifts, ecosystem tipping points, and enable faster real-time biodiversity monitoring.

REFERENCES

Aishwarya, M. R., Kumari, P., Lavania, P., Gupta, G., Tiwari, P., Singh, R. K. and Kumar, P. (2026). An overview of remote sensing technology in forest management.

Alage, I. L., Akande, A. W. and Olatoyinbo, S. F. (2026). Mapping Deforestation Dynamics Using a Multi-Sensor Spatio-Temporal Deep Learning Framework. *Earth Systems and Environment*, 1-21.

Aquino, C., Bacciu, V., Chiriacò, M. V., D'Anca, A., Jeevan, J., Noce, S. and Balzarolo, M. (2026). An Earth Observation-based Tier 3 framework for monitoring greenhouse gas emissions from forest fires in Italy. *Scientific Reports*.

Azhar, H., and Khalid, N. (2026). Integrative evidence on microplastics and heavy metals in vulnerable, threatened, and endangered species in natural environments: knowledge gaps, research priorities, and impacts. *Environmental Science and Pollution Research*, 1-19.

Boyle, M. J., Bonebrake, T. C., Dias da Silva, K., Dongmo, M. A., Machado França, F., Gregory, N. and Ashton, L. A. (2025). Causes and consequences of insect decline in tropical forests. *Nature Reviews Biodiversity*, *1*(5), 315-331.

Castro, J. B., Rogers, C., Sothe, C., Cyr, D., and Gonsamo, A. (2024). A deep learning approach to estimate canopy height and uncertainty by integrating seasonal optical, SAR & limited GEDI LiDAR data over northern forests. arXiv. https://arxiv.org/abs/2410.18108

Dong, W., Mitchard, E. T. A., Yu, H., Hancock, S., and Ryan, C. M. (2023). Forest above ground biomass estimation using GEDI and earth observation data through attention-based deep learning. arXiv. https://arxiv.org/abs/2311.03067

Dupuis, C. (2024). *Monitoring canopy disturbances in Central Africa: from the ground to the sky*. Universite de Liege (Belgium).

Farwell, L. S., Stillman, A. N., Lancaster, J. D. Turbek, S. P., Muñoz, J. M., Peele, A. M., ... & Eger, C. G. (2026). Leveraging eBird data products to inform regional bird conservation priorities and objectives. *Ornithological Applications*, *128*(1), 1-14.

Fendoung, P. M., Hubert‒ Ferrari, A., Schmitz, S., and Tchindjang, M. (2026). The vulnerability of Central Africa's estuarine population to forest degradation and coastal erosion. *African Geographical Review*, *45*(3), 197-220.

Gallwey, J. (2021). *Development of mining sector applications for emerging remote Sensing and deep learning technologies*. University of Exeter (United Kingdom).

Gizachew, B. (2026). Artificial Intelligence and Machine Learning in Remote Sensing for Tropical Forest Monitoring: Applications, Challenges, and Emerging Solutions. *Remote Sensing*, *18*(8), 1193.

Heinrich, M., Mah, J., and Amirkia, V. (2021). Alkaloids used as medicines: Structural phytochemistry meets biodiversity—An update and forward look. *Molecules*, *26*(7), 1836.

Lapola, D. M., Pinho, P., Barlow, J., Aragão, L. E., Berenguer, E., Carmenta, R., ... & Walker, W. S. (2023). The drivers and impacts of Amazon forest degradation. *Science*, *379*(6630), eabp8622.

Li, C.; Yu, Z.; Zhou, X.; Zhou, M. (2023) Using the Error-in-Variable Simultaneous Equations Approach to Construct Compatible Estimation Models of Forest Inventory Attributes Based on Airborne LiDAR. Forests. 14, 65.

Libalah, M. B., Liyandja, T., Banoho, R. L. P. K., Taedoumg, H., Abwe, E., Nyom, A. R. B. and Zébazé Togouet Serge, H. (2026). Human Influence on Current Status of Biodiversity of the Congo Basin. In *Resilience and Sustainability in the Congo Basin: Retracing the Past, Looking to the Future* (pp. 1-27). Cham: Springer Nature Switzerland.

Liu, L.; Li, S.; Yang, W.; Wang, X.; Luo, X.; Ran, P.; Zhang, H. (2023) Forest Canopy Water Content Monitoring Using Radiative Transfer Models and Machine Learning. Forests 14, 1418

Ma, L., Hong, L., & Liang, X. (2025). Integrating Ecological and Economic Approaches for Ecosystem Services and Biodiversity Conservation: Challenges and Opportunities. *Ecologies*, *6*(4), 70.

Mandal, M. S. H., Abdullah, A. N. K., Kamruzzaman, M., & Hosaka, T. (2026). Modelling the environmental suitability of dominant mangrove species in the Sundarbans using Maxent. *Tropics*, *35*(1), 55-72

Mauz, M., Ehekircher, S., Braun, A., Niessner, A., Schober, T., Spangenberg, G., ... & Hochschild, V. (2026). Multi-scale and multi-compartment monitoring of tree vitality–Integrating soil, stem, crown, and remote sensing observations. *Geoscientific Instrumentation, Methods and Data Systems*, *15*(1), 107-125.

Meijaard, E., Sheil, D., Nasi, R., Augeri, D., Rosenbaum, B., Iskandar, D. and O'Brien, T. (2005). *Life after logging: reconciling wildlife conservation and production forestry in Indonesian Borneo*. Cifor.

Metz, T., Farwig, N., Dormann, C. F., Schaefer, H. M., Guevara Andino, J. E., Brehm, G., ... & Blüthgen, N. (2026). Biodiversity resilience in a tropical rainforest. *Nature*, 1-8.

Milenković, D., Cvetković, V. M. and Renner, R. (2024). A systematic literary review on community resilience indicators: Adaptation and application of the BRIC method for measuring disasters resilience. *International Journal of Disaster Risk Management*, *6*(2), 79-104.

Mohamedi, F.J.; Yu, Y.; Yang, X. and Fan, W. (2025) Simulation of Carbon Sinks and Sources in China's Forests from 2013 to 2023. Forests, 16, 1398.

Morin, D., Planells, M., Mermoz, S., and Mouret, F. (2023). Estimation of forest height and biomass from open-access multi-sensor satellite imagery and GEDI lidar data: High-resolution maps of metropolitan France. arXiv. https://arxiv.org/abs/2310.14662

Mulatu, K., and Ayehu, G. (2024). Ethiopia: Near-real-time alerts for protecting forests under participatory forest management.

Murphy, D. J. and Yong, S. (2026). Global Carbon Sequestration and the Roles of Tropical Forests and Crops: Prospects for Using Innovative Carbon Trading Approaches to Address the Climate Emergency. *Earth*, *7*(1), 22.

Nadeem, F., Silva, C. A., Izaya, N., & Flores, J. P. (2026). Interdisciplinary Applications of LiDAR in Forest Studies: Advances in Sensors, Methods, and Cross-Domain Metrics. *Remote Sensing*, *18*(2), 219.

Nasiru, S., Balogun, P. B., Danlami, F. A., Egbewole, Z. T., and Sa'aondo, S. M. (2026). Above Ground Biomass And Carbon Stock Sequestration Potentials And Economic Value Of Forest Plantation Established In Nasarawa. *Fudma Journal Of Sciences*, *10*(1), 303-310.

Near real-time monitoring reveals extensive recent forest disturbance in Ghana's protected areas. (2025). *Science of Remote Sensing, 12,* 100299. https://doi.org/10.1016/j.srs.2025.100299

Nguyen, N. A., Chu, V. T., Nguyen, T. H., and Nguyen, T. H. (2026). Spatio-temporal dynamics of soil erosion and its relationship with forest loss in the Upper Cau River Basin, northern Vietnam. *Hydrological Sciences Journal*, *71*(7), 1449-1465.

Nyengere, J., Tholo, H. M., Kumpolota, S., Njala, A. L., Jamali, A., Chalulu, T. and Tham-Agyekum, E. K. (2026). Forestry-Based Carbon Financing Mechanisms and Their Role in Advancing Sustainable Forest Management: A Systematic Review. *Trees, Forests and People*, 101270.

Owolabi, B. A., Sanuade, A. O., Atabo, L. O., Okeyode, O. S., Adeyemi, A. A., Fajinmolu, A. O. and Oganla, A. E. (2026). Impact of Deforestation on Freshwater Habitat. In *Environmental Health and Toxicology* (pp. 145-166). CRC Press.

Parente, L., Nogueira, S., Baumann, L., Almeida, C., Maurano, L., Affonso, A. G., & Ferreira, L. (2021). Quality assessment of the PRODES Cerrado deforestation data. *Remote Sensing Applications: Society and Environment*, *21*, 100444.

Pedraza, C.; Clerici, N.; Villa, M.; Romero, M.; Dueñas, A.S.; Rojas, D.B. (2024) Quintero, P.; Martínez, M.; Kellndorfer, J. Monitoring Forest Dynamics and Conducting Restoration Assessment Using Multi-Source Earth Observation Data in Northern Andes, Colombia. Forests, 15, 754

Pooja, Singh, R., Chauhan, V., and Singh, A. K. (2026). Forest Degradation and Deforestation: Drivers and Solution. In *Forestry for a Carbon-Neutral and Sustainable Future: A Scientific Perspective* (pp. 345-369). Cham: Springer Nature Switzerland.

Putzenlechner, B., Bevern, F., Koal, P. and Grieger, S. (2024). Accuracy assessment of LAI, PAI and FCOVER from Sentinel-2 and GEDI for monitoring forests and their disturbance in Central Germany. *European Journal of Remote Sensing*, 57(1). https://doi.org/10.1080/22797254.2024.2422323

Qinghua Guo, Tianyu Hu, Yuanxi Jiang, Shichao Jin, Rui Wang, Hongcan Guan, Qiuli Yang, Yumei Li Fangfang Wu, Qiuping Zhai, Jin Liu, Yanjun Su (2018) Advances in remote sensing application for biodiversity research

Ru, F.X.; Zulkifley, M.A.; Abdani, S.R.; Spraggon, M. Forest Segmentation with Spatial Pyramid Pooling Modules: A SurveillanceSystem Based on Satellite Images. Forests 2023, 14, 405

Santoro, M., Cartus, O., Quegan, S., Kay, H., Lucas, R. M., Araza, A., and Herold, M. (2024). Design and performance of the Climate Change Initiative Biomass global retrieval algorithm. *Science of Remote Sensing*, *10*, 100169. https://doi.org/10.1016/j.srs.2024.100169

Sialelli, G., Peters, T., Wegner, J. D. and Schindler, K. (2024). AGBD: A global-scale biomass dataset. arXiv. https://arxiv.org/abs/2406.04928

Silva, D. S., & Nunes, S. (2025). Leakage effects from reforestation: Estimating the impact of agricultural displacement for carbon markets. *Land*, *14*(5), 963.

Su, Y.; Chen, Z.; Xue, X. (2025) TreeDBH: Dual Enhancement Strategies for Tree Point Cloud Completion in Medium–Low Density UAV Data. Forests, 16, 667.

Sudhakar, R. C. (2021) mote sensing of biodiversity: what to measure and monitor from space to species? Biodiversity and Conservation 30(10) DOI:10.1007/s10531-021-02216-5

Tabor, K. M. (2023). *Achieving multiple conservation goals with satellite-based monitoring and alert systems*. University of Maryland, Baltimore County.

Tomppo, E. O., Foster, B. C., Kenefic, L. S., and Ducey, M. J. (2026). Costs and precisions of alternative plot configurations for estimating above-ground tree biomass in tropical forests. *Forestry: An International Journal of Forest Research*, *99*(1), cpaf034.

Torresani, M., Moudry, V., Hakkenberg, C. R., Goetz, S. J., Coomes, D., Cotrina-Sanchez, D. A. and Tognetti, R. (2026). The role of GEDI spaceborne lidar in. *Alma Mater*, *30*, 31.

Valerio, F., Pereira, P., Salgueiro, P., Godinho, C., Lourenço, R., Silva, J. P., ... & Godinho, S. (2026). Using GEDI-derived vegetation structural metrics to evaluate avian biodiversity patterns in Mediterranean habitats. In *Satellite Remote Sensing for Forest and Environmental Monitoring* (pp. 631-661). Elsevier.

Wang, S. and Zhu, H. (2026). Biodiversity loss: global drivers, trade impacts, and conservation strategies. *Environmental Reviews*, *34*, 1-16.

Xu, F.; Xu, Z.; Xu, C. and Yu, T. (2023) Automatic Extraction of the Spatial Distribution of Picea schrenkiana in the Tianshan Mountains Based on Google Earth Engine and the Jeffries–Matusita Distance. Forests 14, 1373

Yang, X., and Yu, Y. (2026). Advances in Remote Sensing for Forestry: Theory, Methods, Applications, and Validation. *Forests*, *17*(1),

Yaseen, M., Khan, W. R., Li, P., Khalid, F., Ahmed, U., Solangi, K. A. and Zhu, X. (2026). Forest blue carbon sink accounting: methodological advancements and uncertainty analysis. *Journal of Forestry Research*, *37*(1), 53.

You, L.; Sun, Y.; Liu, Y.; Chang, X.; Jiang, J.; Feng, Y.; and Song, X. (2023) Tree Skeletonization with DBSCAN Clustering Using Terrestrial Laser Scanning Data. Forests 2023, 14, 1525.