Global Research journal of Natural Science & Technology (GRJNST)

Volume: 04 - Issue 3 (2026), 2094
ISSN P: 2790-7643 ISSN E: 2790-7651
www.grjnst.net
https://doi.org/10.53762/grjnst.04.03.15

Remote Sensing–Based Assessment of Forest Carbon Sequestration and Land Use Change Dynamics under Climate Variability

Received: 30 March 2026. Accepted: 01 May 2026. Published: 30 May 2026

Muhammad Hassan Ali (Corresponding Author)
Department of Forestry and Range Management,
Shaheed Benazir Bhutto University of Veterinary and Animal Sciences,
Sarkrand, Sindh, Pakistan
soilscience1070@gmail.com
Fateh Ali Chohan
Department of Forestry and Range Management,
Shaheed Benazir Bhutto University of Veterinary and Animal Sciences,
Sarkrand, Sindh, Pakistan
fateh.ali0335@gmail.com
Asad ullah
Department of Forestry and Range Management, Shaheed Benazir Bhutto University of Veterinary and Animal Sciences, Sarkrand, Sindh, Pakistan
saad.janii.94@gmail.com
Kalsoom
Department of English literature University of Sindh Jamshoro, Sindh, Pakistan
mahachohan554@gmail.com
Muhammad Ismail Chohan
Department of Forestry and Range Management,
Shaheed Benazir Bhutto University of Veterinary and Animal Sciences,
Sarkrand, Sindh, Pakistan
imail40@gmail.com

Walliullah Lagahri
Department of Forestry and Range Management,
Shaheed Benazir Bhutto University of Veterinary and Animal Sciences,
Sarkrand, Sindh, Pakistan
raiswaliullah@gmail.com
Muhammad Afzal
Department of Forestry and Range Management,
Shaheed Benazir Bhutto University of Veterinary and Animal Sciences,
Sarkrand, Sindh, Pakistan
afzalshar66@gmail.com

Abstract:

Forest ecosystems are among the most significant terrestrial carbon reservoirs and play a crucial role in regulating the global carbon cycle through carbon sequestration. However, rapid land use and land cover change (LULC), combined with increasing climate variability, and has significantly altered the stability and efficiency of these ecosystems. This review paper examines the application of remote sensing technologies in assessing forest carbon sequestration and monitoring land use dynamics under changing climatic conditions. The study highlights how urbanization, agricultural expansion, deforestation, and wildfire activities contribute to carbon emissions and ecosystem degradation across tropical, coastal, semi-arid, and urban forest landscapes. Special emphasis is placed on the integration of optical, LiDAR, and Synthetic Aperture Radar (SAR) systems for estimating above-ground biomass (AGB), soil organic carbon (SOC), and vegetation structural characteristics. The review further explores the role of vegetation indices, multi-sensor fusion, and machine learning algorithms such as Random Forest (RF), Support Vector Machines (SVM), XGBoost, and Convolutional Neural

Networks (CNNs) in improving biomass estimation accuracy and carbon accounting. Additionally, the paper discusses the influence of climatic variables, including temperature rise, altered precipitation regimes, droughts, and wildfires, on forest carbon sequestration potential and ecosystem resilience. Emerging technologies such as ESA Biomass, NISAR missions, and Digital Twin Earth systems are also evaluated for their transformative potential in global forest monitoring and carbon management. The findings suggest that integrating advanced remote sensing with artificial intelligence and climate modeling provides an effective framework for sustainable forest management, climate mitigation strategies, and accurate carbon monitoring at regional and global scales.

Keywords: *Remote Sensing, Forest Carbon Sequestration, Land Use Change, Climate Variability, Above-Ground Biomass, LiDAR, SAR, Carbon Accounting, Machine Learning, Forest Monitoring*

Introduction

The terrestrial biosphere constitutes one of the most significant and dynamic components of the global carbon cycle, with forest ecosystems alone storing approximately 45% of all terrestrial carbon. These ecosystems function as critical natural sinks, sequestering an estimated 3.5 Pg C yr^{-1} from the atmosphere, thereby playing a pivotal role in mitigating the progression of anthropogenic climate change (Xu, 2025). However, the stability and efficacy of this sequestration capacity are currently under unprecedented pressure from the twin drivers of land use and land cover change (LULC) and intensifying climate variability. The transformation of natural landscapes driven by urbanization, agricultural expansion, and industrial resource exploitation accounts for nearly 25% of human-caused greenhouse gas (GHG) emissions (Merrikhpour et al., 2025). Concurrently, the increasing frequency of extreme climatic events, including droughts and wildfires, has begun to compromise the historical resilience of these carbon reservoirs, potentially shifting them from net sinks to net sources of atmospheric carbon (Xu et al., 2021).

In this context, remote sensing (RS) technologies have emerged as indispensable tools for the monitoring and assessment of forest carbon dynamics at multiple spatial and temporal scales. Since the launch of Landsat-1 in 1972, Earth observation has evolved from simple land cover classification to sophisticated, multi-sensor frameworks capable of quantifying three-dimensional forest structure, above-ground biomass (AGB), and soil organic carbon (SOC) (Wulder et al., 2019). Modern assessments now integrate high-resolution optical imagery, active microwave radar, and laser-scanning systems to provide a comprehensive, spatially explicit understanding of how LULC and climate variability interact to shape the future of terrestrial carbon sequestration (H. Nguyen et al., 2019).

Spatiotemporal Dynamics of Land Use Change and Carbon Flux

Land use and land cover change represents the second-largest source of global CO_2 emissions, trailing only the combustion of fossil fuels. Between 2001 and 2023, the global forest system was a net sink of -5.5 ± 8.1 Gt CO_2e yr^{-1}, a figure that obscures the volatile balance between -14.5 ± 7.7 Gt CO_2e yr^{-1} of carbon removals and 9.0 ± 2.7 Gt CO_2e yr^{-1} of gross emissions. The magnitude of these fluxes is heavily influenced by regional development trajectories and the specific nature of land transitions (Lu et al., 2014).

Urbanization and Peri-Urban Carbon Depletion

Rapid urban growth, particularly in developing metropolitan basins, catalyzes significant environmental transformations that often lead to a net increase in carbon emissions (Ashaolu et al., 2019). In the Kağıthane basin of Istanbul, for example, the expansion of residential and industrial areas has been driven by a 16.59% population increase over the past decade. Analysis using Sentinel-1 and Sentinel-2 data processed on the Google Earth Engine (GEE) platform reveals that while some vegetation growth is observed in managed urban green spaces, there is a systemic decline in natural forest cover and barren lands. This shift is projected to increase regional carbon emissions by up to 13% between 2035 and 2095 (Kocaman & Ağaçcıoğlu, 2025).

Beyond direct biomass loss, urbanization modifies local hydrological dynamics, including peak discharge patterns and surface runoff, which indirectly affects the health and carbon uptake of surrounding vegetation (Ashaolu et al., 2019). The conversion of natural land cover to built-up environments alters the surface energy balance, often leading to urban heat island (UHI) effects that can be accurately mapped using thermal infrared remote sensing. These thermal anomalies exacerbate physiological stress on remaining urban trees, potentially reducing their long-term carbon sequestration potential (Yang, 2025).

Agricultural Expansion and Coastal Ecosystem Vulnerability

Tropical coastal ecosystems represent some of the most carbon-dense environments on Earth, yet they are increasingly threatened by the expansion of industrial agriculture. In Phang Nga Bay, southern Thailand, extensive land use transitions between 2000 and

2020 were primarily driven by the replacement of evergreen and para rubber forests with oil palm plantations (Aratrakorn et al., 2006). This conversion led to a net carbon storage loss of approximately $821{,}000\ Mg\ C$, with the most intensive degradation occurring in upland forested areas between 100 and 400 meters in elevation (Alongi, 2014).

The role of "blue carbon" ecosystems, specifically mangroves, is particularly critical in these coastal landscapes. Despite covering only about one-fifth of the total area in Phang Nga Bay, mangroves consistently contributed over 50% of the regional carbon storage. This highlights a critical spatial disparity: while agricultural encroachment causes widespread low-intensity carbon loss across upland areas, the localized destruction of mangrove or swamp forests results in massive, immediate carbon releases (Murphy, Hall, & Jintana, 2020). Integrating the InVEST (Integrated Valuation of Ecosystem Services and Tradeoffs) model with high-resolution satellite data has allowed researchers to demonstrate that localized gains in mangrove sequestration can occasionally offset some conversion losses, provided that targeted conservation strategies are implemented (Sharp et al., 2018).

Table 1. Remote Sensing–Based Evaluation of Land Use Transitions and Associated Carbon Dynamics

Land Use Transition Category	Net Carbon Impact (Relative)	Primary RS Monitoring Strategy	Key Drivers
Forest to Urban	High Loss (Direct +	Optical (Sentinel-2) + Thermal	Pop. Growth, Infrastructure

	Indirect)		
Forest to Oil Palm	High Biomass Loss	SAR (Sentinel-1) + GEE	Commercial Agriculture
Coastal Forest to Aquaculture	Critical Carbon Release	LiDAR + Multi-spectral	Food Security, Economics
Reforestation/Afforestation	Gradual Accumulation	Time-series (NDVI/EVI)	Carbon Credits, Policy
Forest to Grassland/Pasture	Moderate-High Loss	Landsat GFC (Hansen et al.)	Livestock, Small-scale farming

Long-term Variations in Tropical and Semi-Arid Forests

In regions like Southeast Vietnam, the period between 1990 and 2020 saw significant fluctuations in carbon services due to ecological degradation and urban expansion. While ecological succession and forest restoration efforts partially compensated for some losses, the combined anthropogenic impact outweighed the natural recovery capacity, leading to a net decline in total carbon storage. This trend is echoed globally, with tropical deforestation particularly in Brazil and Indonesia accounting for nearly half of the global forest loss due to land conversion.

In contrast, India's semi-arid and dry forests, located in regions like Rajasthan and Gujarat, present a different challenge for carbon sequestration assessment. These ecosystems possess lower biomass accumulation and carbon storage capacity compared to humid tropical forests due to water scarcity and high temperatures. However, they often contain resilient below-ground carbon pools that contribute significantly to soil organic carbon (SOC) under extreme climatic conditions. Remote sensing of these drylands requires a shift in focus from canopy greenness to structural parameters and litter deposition rates, as fast-growing plantation species like Teak or Eucalyptus are increasingly used for reforestation on wastelands.

Remote Sensing Technologies for Carbon Accounting

The evolution of remote sensing has provided a multi-layered framework for assessing forest carbon, moving from broad land cover mapping to the precise quantification of individual tree components (Pendleton et al., 2012)

Optical Remote Sensing and Spectral Limitations

Optical sensors, including Landsat 8/9 and Sentinel-2, remain the foundation of global monitoring due to their consistent spectral libraries and high revisit frequencies. These platforms allow for the calculation of vegetation indices such as the normalized difference vegetation index (NDVI), the enhanced vegetation index (EVI), and the photochemical reflectance index (PRI). These indices serve as proxies for canopy greenness, leaf area index (LAI), and photosynthetic vigor, which are empirically linked to above-ground biomass (AGB) (Li et al., 2021).

However, a fundamental challenge with optical remote sensing is the "saturation" effect. In high-biomass tropical forests, the spectral response of vegetation indices often reaches a plateau once the canopy is fully closed, typically at biomass levels between 150 and 200 Mg ha^{-1}. This makes it difficult to distinguish between moderately dense and very old-growth forests using optical data alone (Sinha et al., 2019). To mitigate this, newer missions such as Sentinel-2 utilize red-edge spectral bands, which have shown higher sensitivity to chlorophyll content and nitrogen status, thereby improving AGB and soil organic carbon (SOC) estimations even in dense canopies (Jagadish et al., 2024).

Active Systems: LiDAR and SAR

Active remote sensing technologies light detection and ranging (LiDAR) and synthetic aperture radar (SAR) have revolutionized biomass estimation by providing information on the vertical and three-dimensional structure of forests (Choi, 2024). LiDAR systems use laser pulses to measure the distance between the sensor and the Earth's surface, generating high-resolution "point clouds" that represent the forest's vertical profile. Airborne laser scanning (ALS) is currently considered the most accurate technology for extracting major forest attributes such as tree height, canopy density, and volume for above-ground biomass (AGB) estimation. On a finer scale, terrestrial laser scanning (TLS) and close-range sensing from unmanned aerial vehicles (UAVs) allow for the measurement of diameter at breast height (DBH) and trunk shape with centimeter-level precision (Xu et al., 2023). A meta-analysis of close-range sensing accuracy indicates that ground-based LiDAR remains the "gold standard" for single-tree and plot-level assessments, though UAV-based systems are more efficient for stand-scale analysis (Fayad et al., 2016).

SAR systems, on the other hand, use microwave energy to penetrate cloud cover and, depending on the wavelength, the forest canopy itself. The sensitivity of SAR to biomass is primarily a function of its wavelength:

- **X-band and C-band (e.g., Sentinel-1):** These shorter wavelengths interact primarily with leaves and small branches in the upper canopy. They are effective for forest cover change detection but saturate at relatively low biomass levels.
- **L-band (e.g., ALOS PALSAR-2, NISAR):** This longer wavelength penetrates deeper into the canopy, interacting with larger branches and trunks. It provides a more robust proxy for AGB and is less prone to saturation than optical or C-band SAR (Le Toan et al., 2024).
- **P-band (e.g., ESA Biomass mission):** With a wavelength of approximately 70 cm, P-band SAR can penetrate the entire canopy to interact with the main trunks and the ground surface, making it the most effective tool for measuring high-biomass forests up to 500 Mg ha^{-1} (Ho Tong Minh et al., 2016).

Multi-Sensor Fusion and Advanced Modeling

The most accurate forest carbon assessments are increasingly based on the "fusion" of multi-source data. By integrating optical spectral data with 3D structural information from LiDAR or SAR, researchers can overcome the limitations of individual sensors. For example, combining Sentinel-2 spectral bands with Digital Elevation Models (DEMs) and LiDAR-derived canopy heights has been shown to significantly improve the accuracy of machine learning models for AGB prediction (Ali, 2025).

This fusion approach is particularly relevant for meeting the Measurement, Reporting, and Verification (MRV) standards required by international climate frameworks such as the UNFCCC and REDD+. Integrated models can leverage the broad spatial coverage of satellite imagery and the high-precision "truth" provided by field plots and airborne LiDAR to generate wall-to-wall maps of carbon stocks and fluxes (Santos, 2025).

Table 2. Comparison of Remote Sensing Sensor Types for Forest Structural and Biomass Assessment

Sensor Type	Specific Platform/Band	Structural Variable Measured	Accuracy Range (R2)	Primary Limitation
Optical	Sentinel-2 (Red-edge)	Canopy Greenness/LAI	0.55 – 0.82	Spectral Saturation
LiDAR	ALS (Airborne)	Tree Height/Canopy Profile	0.85 – 0.95	High Acquisition Cost
SAR	L-band (ALOS/NISAR)	Large Branches/Trunks	0.60 – 0.80	Signal De-correlation
SAR	P-band (Biomass)	Main Stem/Trunk Volume	0.75 – 0.90	Ionospheric Interference
Passive Microwave	SMOS/SMAP (VOD)	Vegetation Optical Depth	0.50 – 0.70	Coarse Spatial Res (>9 km)

Climate Variability and its Impact on Sequestration Potential

Climate variability exerts a profound influence on the physiological processes and spatial distribution of forest vegetation, thereby altering its carbon sequestration potential (CSP). CSP is defined as the difference between an ecosystem's maximum carbon carrying capacity (CCC) and its actual carbon stock, representing the potential for future carbon uptake (Xu, 2025).

Temperature and Precipitation Thresholds

Ongoing climate changes, characterized by shifting temperature regimes and altered precipitation patterns, can severely impact forest structure and function. In the mountain ecosystems of Yunnan Province, China, simulation models have shown that the suitability of forest habitats is primarily limited by the minimum temperature of the coldest month (TMW) and total seasonal precipitation (PRS). For example, a 1 °C increase in temperature combined with a 20\% decrease in precipitation could reduce the potential distribution area of major forest types by 12.41\% (Iheaturu, 2026).

Interestingly, the combined effect of increased temperature and decreased precipitation can, in some specific cases, increase the CSP of certain forest types by accelerating biomass turnover, though this is often a transient response. Generally, however, frequent and severe drought events such as the "flash droughts" observed in southeastern Australia or the record-low water levels in the Amazon River in 2023 pose a significant threat to forest health. These events cause unusually rapid drying of soil and vegetation, leading to widespread tree mortality and reduced carbon uptake (Tian et al., 2023).

Biogeophysical and Biogeochemical Feedback Loops

The interaction between forests and the climate system occurs through two primary feedback pathways: biogeochemical (BGC) and biogeophysical (BGP). The biogeochemical pathway involves the exchange of greenhouse gases, primarily CO_2, between the forest and the atmosphere. Deforestation and forest degradation release stored carbon, increasing atmospheric CO_2 concentrations and contributing to global warming (Boysen et al., 2020). Earth system models (ESMs) estimate that historical land use and land cover change (LULC)-induced carbon emissions have resulted in a global warming of approximately 0.21 ± 0.14 °C. The biogeophysical pathway involves changes in the physical characteristics of the land surface, such as albedo, surface roughness, and evapotranspiration (ET) (Amali et al., 2024).

Albedo: Converting dark, absorbent forests to reflective pastures or snow-covered grasslands increases surface albedo, reflecting more solar radiation back into space. This has a cooling effect, particularly in high-latitude boreal regions (Jiao et al., 2023).

Evapotranspiration: Forests are highly efficient at transferring water from the soil to the atmosphere through ET, a process that cools the local environment. In tropical regions, the loss of ET due to deforestation generally leads to significant local warming that can overcompensate for any albedo-related cooling (Boysen et al., 2020).

Surface Roughness: Forests have high surface roughness, which promotes atmospheric turbulence and efficient heat transfer (Prestele et al., 2016). Reducing this roughness through land clearing can lead to higher temperature gradients at the surface.

The net effect of forest land use change is often a delicate balance between these two pathways. On a global scale, the BGC temperature effects historically dominate the BGP effects, meaning that the overall impact of historical land use change has been to warm the climate. However, at regional scales, particularly in the tropics and high latitudes, the

BGP effects can be equal in magnitude to the BGC effects, highlighting the need for spatially explicit climate mitigation strategies (Amali et al., 2024).

Table 3. Biogeochemical and Biogeophysical Feedback Pathways Associated with Land Use Change

Feedback Pathway	Mechanism	Climate Impact (Global)	Climate Impact (Regional)
Biogeochemical (BGC)	CO_{2} Release/Storage	Consistent Warming from Loss	Varies with biomass density
Biogeophysical (BGP)	Albedo Shift	Negligible to Slight Cooling	Cooling in Boreal (High Albedo)
Biogeophysical (BGP)	Evapotranspiration	Slight Warming from Loss	Intense Warming in Tropics
Biogeophysical (BGP)	Surface Roughness	Slight Warming from Loss	Localized Heat Flux change

The Wildfire-Climate Feedback Loop

Climate change is increasingly driving a dangerous "two-way street" relationship with land use through the intensification of wildfires. Warming temperatures and longer periods of drought create hotter, drier conditions that escalate fire risk. Emissions from forest fires have increased by 60% globally since 2001, with fire now accounting for one-third of all land cover change in some regions (Jiao et al., 2023). This creates a self-reinforcing feedback loop: climate change fuels fires, which release vast quantities of CO_2, which in turn accelerates further warming. Boreal and humid tropical regions, which contain the world's last great tracts of natural forest, have seen the most dramatic increases in fire-driven forest loss, with a strong correlation $r^2 = 0.85$ in tropical regions) between global temperature anomalies and fire-induced forest loss (Papucci, 2026).

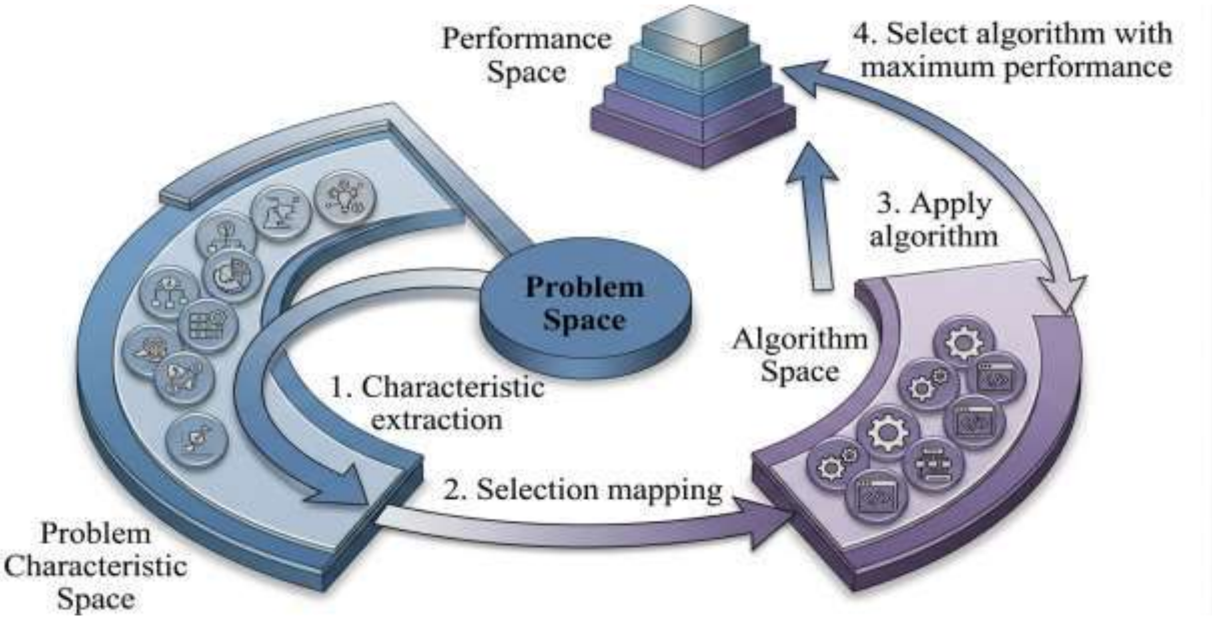
Machine Learning Frameworks for Biomass Estimation

The transition from traditional forest inventories to remote sensing-based assessment has been accelerated by the application of advanced machine learning (ML) and deep learning (DL) algorithms. These methods are particularly effective at capturing the non-linear and high-dimensional relationships between remote sensing features and forest carbon stocks (Fayad et al., 2016).

Algorithm Selection and Performance Metrics

A wide range of machine learning (ML) algorithms is currently utilized in the literature, with random forest (RF), support vector machines (SVM), and extreme gradient boosting (XGBoost) being the most prominent (Donato et al., 2011).

figure:2 Characteristic extraction" leads to the first concentric arc segment, "Problem Characteristic Space".



- **Random Forest (RF):** RF is the most frequently used algorithm, appearing in approximately 88% of recent studies. It is an ensemble method that constructs multiple decision trees and averages their predictions, making it robust against outliers and noisy predictors. In Xinjiang, China, the RF model combined with topographic and meteorological data significantly improved above-ground biomass (AGB) estimation accuracy across diverse forest types, achieving R^2 values greater than 0.65 (Cohen & Goward, 2004).

- **XGBoost:** While RF is common, XGBoost has recently shown superior performance in approximately 75% of the studies where it was directly compared with other methods. In a study of *Larix principis-rupprechtii* plantations in northern China, XGBoost achieved an R^2 of 0.82 and a root mean square error (RMSE) of 0.73 Mg ha^{-1} using Sentinel-2 data, outperforming both SVM ($R^2 = 0.79$) and RF ($R^2 = 0.74$). XGBoost's success is attributed to its efficient handling of non-linearities and its regularization parameters that prevent overfitting (Lü et al., 2023).
- **Deep Learning (DL):** Convolutional neural networks (CNNs) are increasingly applied to extract textural and structural features from high-resolution imagery (e.g., UAV-RGB or PlanetScope). DL models can reduce biomass estimation errors by 5% to 20% compared to traditional regression methods, particularly in complex, heterogeneous stands (Xu, 2025).

Feature Selection and Variable Importance

The performance of ML models is highly dependent on the selection of characteristic variables. Feature selection algorithms, such as the Boruta algorithm or the Least Absolute Shrinkage and Selection Operator (LASSO), are used to identify the most relevant predictors from a pool of spectral bands, vegetation indices, and texture features (Yazar et al., 2023).

In large-scale provincial models, climate (e.g., mean annual temperature, precipitation), topography (e.g., slope, elevation), and texture factors often emerge as more significant than individual spectral bands. For instance, adding Digital Elevation Model (DEM) data to optical imagery frequently makes the DEM the most important predictor variable, as it accounts for the environmental gradients that govern tree growth and biomass accumulation (Amali et al., 2024).

Table 4. Performance Comparison of Machine Learning and Process-Based Models in Carbon and Biomass Assessment

Model Type	**Best Performance (R2)**	**Primary Data Source**	**Key Feature for Accuracy**
XGBoost	0.82	Sentinel-2	Red-edge + Vegetation Indices
RF	0.75	UAV-RGB/LiDAR	Texture + Height metrics
SVM	0.79	Landsat-9	NIR and SWIR bands
CNN	0.85 – 0.98	High-res Drone Imagery	Spatial pattern/Segmentation
InVEST	N/A (Process-based)	LULC + Biomass maps	Carbon pool coefficients

The 2025 Technological Frontier: Digital Twins and Next-Gen Missions

The field of forest carbon monitoring is currently entering a transformative phase characterized by the launch of dedicated biomass satellites and the operationalization of "Digital Twin" Earth systems.

The ESA Biomass and NISAR Missions

The year 2025 marks the launch of two critical radar missions designed to quantify global forest structure with unprecedented precision (Orlov et al., 2024).

ESA BIOMASS Mission (scheduled launch: April 29, 2025): This mission will utilize a P-band synthetic aperture radar (SAR) to deliver global maps of forest biomass and tree height every seven months. Its unique wavelength will allow it to "see" through dense tropical canopies to measure the primary woody biomass, achieving a projected canopy height root mean square error (RMSE) of 1–2 m and an above-ground biomass (AGB) RMSE of 15–25 Mg ha^{-1} (Prestele et al., 2016).

NASA-ISRO NISAR Mission (scheduled launch: July 30, 2025): NISAR is a dual-frequency (L-band and S-band) SAR mission. The L-band is highly sensitive to large branches and trunks, while the S-band is responsive to upper canopy foliage. The integration of these two frequencies will extend the dynamic range of biomass retrieval and improve coherence stability for long-term monitoring (Prestele et al., 2016).

Destination Earth (DestinE) and Forest Digital Twins

The European Commission's Destination Earth (DestinE) initiative is building a highly accurate digital replica of the Earth system, powered by high-performance computing (HPC) and AI. A flagship component of this system is the **Forest Digital Twin (Forest DTC)**, led by organizations like VTT and ECMWF.

The Forest DTC operates at a 10 -meter resolution, primarily utilizing Sentinel-2 data to provide a comprehensive description of the forest subsystem. It integrates several specialized models:

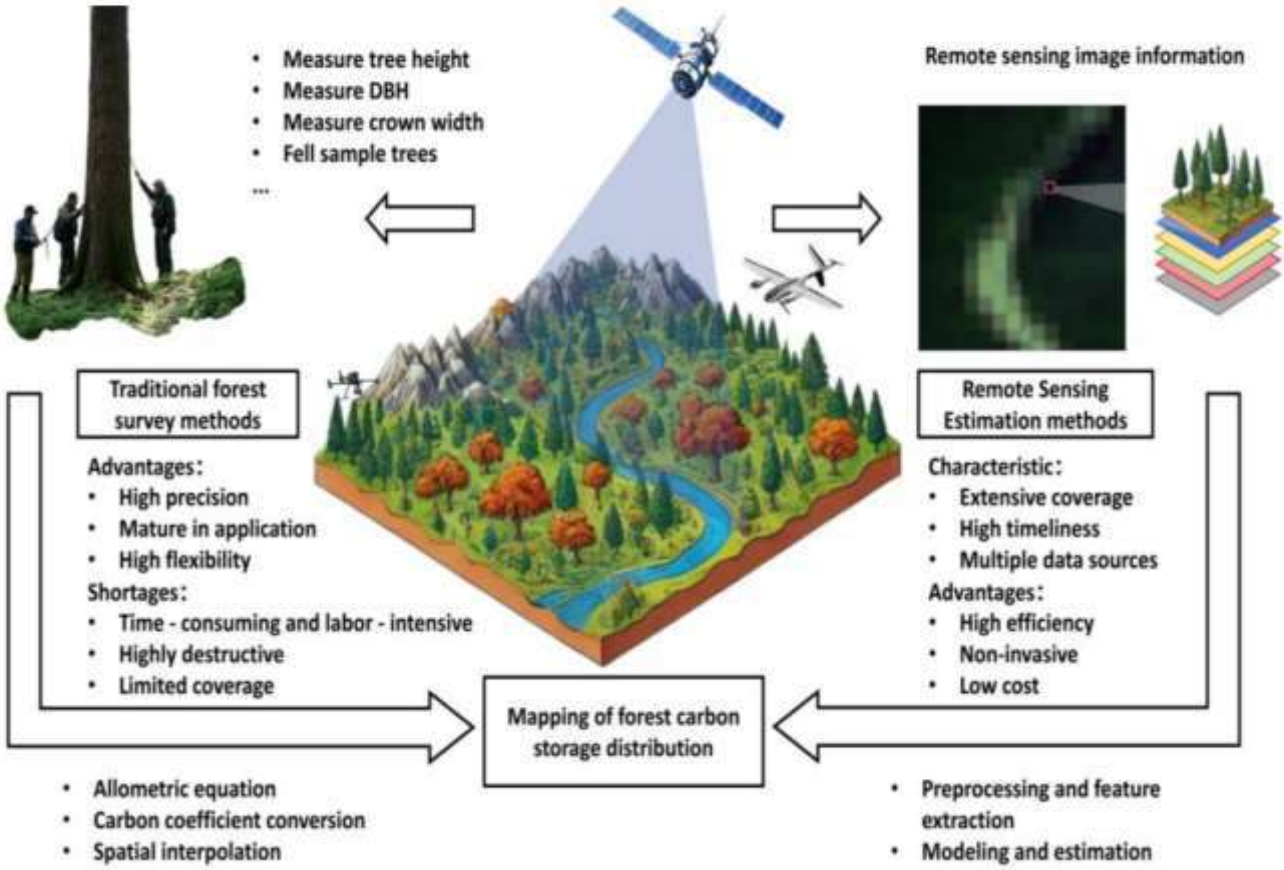
- **PRELES:** A light use efficiency model that outputs Gross Primary Production (GPP), ET, and Net Ecosystem Exchange (NEE) using daily weather data.
- **CROBAS:** A tree growth model that uses stand variables (species, density, DBH) to simulate biomass and litterfall.
- **YASSO15:** A soil carbon model that estimates soil respiration and carbon accumulation based on litterfall and climate (Jiao et al., 2021).

This "living digital twin" allows users to run "what-if" scenarios, testing the impact of different climate pathways and forest management strategies (e.g., selective logging vs. afforestation) on future carbon sequestration. Such systems are revolutionary for carbon markets, as they provide a transparent, investible, and auditable ledger of forest health that surpasses traditional multi-year verification cycles (Boysen et al., 2020)

Methodological Challenges and Strategic Implications

Despite these technological leaps, several persistent challenges continue to limit the absolute accuracy of remote sensing-based carbon assessments (Amali et al., 2024).

Figure 1. Comparison of ground-based traditional inventories and remote sensing estimation methods within the forest carbon accounting framework.



Scale Inversion and Ground-Truthing

A significant trade-off exists between spatial scale and estimation accuracy. While ground-based LiDAR offers sub-centimeter precision at the single-tree level, its accuracy tends to diminish when scaled up to plot-level or stand-level analyses due to cumulative errors in single-tree segmentation and the interconversion of variables like DBH and height. Furthermore, there is an "R&D gap" in ground-truthing for diverse ecological zones; most high-precision allometric models are developed for temperate or plantation forests, leaving significant uncertainties when applied to natural tropical or semi-arid ecosystems (Amali et al., 2024).

Non-Permanence Risks and Policy Alignment

For forest carbon projects to remain viable in global markets, the risk of "non-permanence" the potential for sequestered carbon to be re-released due to wildfire, drought, or illegal logging must be addressed. Remote sensing allows for the detailed analysis of multi-year datasets to spot patterns in precipitation and temperature, helping developers identify whether a location is experiencing increasing drought stress or shifting toward conditions unsuitable for long-term forest growth (Orlov et al., 2024).

Additionally, there is a need to align satellite-based flux estimates with National Greenhouse Gas Inventories (NGHGIs) used under the Paris Agreement. Current bottom-up models and atmospheric top-down observations often show a gap in estimated anthropogenic land use fluxes, primarily due to differing definitions of "natural" versus "anthropogenic" forest land. Reconciling these differences using Earth observation-based frameworks like Global Forest Watch is essential for building global confidence in forest carbon accounting (Lu et al., 2014).

Conclusions

Remote sensing–based assessment of forest carbon sequestration and land use change dynamics has become an essential approach for understanding the interaction between terrestrial ecosystems and climate change. The review demonstrates that forests function as major carbon sinks, yet their sequestration capacity is increasingly threatened by urbanization, agricultural expansion, deforestation, droughts, and wildfire disturbances. Land use and land cover changes significantly alter ecosystem structure and contribute to greenhouse gas emissions, thereby intensifying global warming and ecological instability. Advanced remote sensing technologies, including optical sensors, LiDAR, and SAR systems, have greatly enhanced the ability to monitor forest structure, biomass distribution, and carbon dynamics across multiple spatial and temporal scales. The integration of multi-sensor data with machine learning and deep learning algorithms has further improved the accuracy of above-ground biomass estimation and carbon stock mapping. Moreover, climate variability strongly influences forest productivity, evapotranspiration, and carbon sequestration potential, creating complex biogeophysical and biogeochemical feedback mechanisms within the Earth system. Emerging technologies such as ESA Biomass, NISAR, and Forest Digital Twin systems represent a major advancement in global carbon monitoring and sustainable forest management. Despite these developments, challenges related to scale, sensor limitations, ground validation, and non-permanence risks remain significant. The study concludes that combining remote sensing, artificial intelligence, ecological modeling, and policy-driven conservation strategies is essential for effective carbon accounting, climate mitigation, and long-term ecosystem sustainability under changing environmental conditions.

References

Cohen, W. B., & Goward, S. N. (2004). Landsat's role in ecological applications of remote sensing. *BioScience, 54*(6), 535. https://doi.org/10.1641/0006-3568(2004)054[0535:lrieao]2.0.co;2

H. Nguyen, T., Jones, S., Soto-Berelov, M., & Haywood, A. (2019). Landsat time-series for estimating forest aboveground biomass and its dynamics across space and time: A review. *Remote Sensing, 12*(1), 98. https://doi.org/10.3390/rs12010098

Lu, D., Chen, Q., Wang, G., Liu, L., Li, G., & Moran, E. (2014). A survey of remote sensing-based aboveground biomass estimation methods in forest ecosystems. *International Journal of Digital Earth, 9*(1), 63-105. https://doi.org/10.1080/17538947.2014.990526

Lü, F., Song, Y., & Yan, X. (2023). Evaluating carbon sink potential of forest ecosystems under different climate change scenarios in Yunnan, Southwest China. *Remote Sensing, 15*(5), 1442. https://doi.org/10.3390/rs15051442

Merrikhpour, H., Badamfirooz, J., Zarandian, A., & Mousazadeh, R. (2025). Assessing carbon storage and economic valuation of stocked carbon function based on land use/land cover using the InVEST model. *Environmental Health Engineering and Management Journal, 12*(4).

Wulder, M. A., Loveland, T. R., Roy, D. P., Crawford, C. J., Masek, J. G., Woodcock, C. E., ... & Lymburner, L. (2019). Current status of Landsat program, science, and applications. *Remote Sensing of Environment, 225*, 127-147. https://doi.org/10.1016/j.rse.2019.02.015

Xu, L., Saatchi, S. S., Yang, Y., Yu, Y., Pongratz, J., Bloom, A. A., ... & Schimel, D. (2021). Changes in global terrestrial live biomass over the 21st century. *Science Advances, 7*(27), eabe9829. https://doi.org/10.1126/sciadv.abe9829

Xu, X. (2025). Biochar application for soil carbon sequestration and greenhouse gas mitigation in forest ecosystems: A bibliometric analysis using CiteSpace. *MDPI.*

Ashaolu, E. D., Olorunfemi, J. F., & Ifabiyi, I. P. (2019). Assessing the spatio-temporal pattern of land use and land cover changes in Osun drainage basin, Nigeria. *Journal of Environmental Geography, 12*(1-2), 41–50. https://doi.org/10.2478/jengeo-2019-0005

Kocaman, B., & Ağaçcıoğlu, H. (2025). Assessment of the impact of land use/land cover changes on carbon emissions using remote sensing and deep learning: A case study of the Kağıthane basin. *Sustainability, 17*(23), 10690. https://doi.org/10.3390/su172310690

Yang, H. R. (2025). Exploring the complex relationships between influential factors of urban land development patterns and urban thermal environment: A study on downtown Shanghai. *Sustainability, 17*(19), 8547. https://doi.org/10.3390/su17198547

Yazar, M., Daloglu Cetinkaya, I., Iban, M. C., & Bilgilioglu, S. S. (2023). The green divide and heat exposure: Urban transformation projects in Istanbul. *Frontiers in Environmental Science, 11,* Article 1265332. https://doi.org/10.3389/fenvs.2023.1265332

Alongi, D. M. (2014). Carbon cycling and storage in mangrove forests. *Annual Review of Marine Science*, 6, 195-219.

Aratrakorn, S., Thunhikorn, S., & Donald, P. F. (2006). Changes in bird communities following conversion of lowland forest to oil palm and rubber plantations in southern Thailand. *Bird Conservation International,* 16(1), 71-82.

Donato, D. C., Kauffman, J. B., Murdiyarso, D., Kurnianto, S., Stidham, M., & Kanninen, M. (2011). Mangroves among the most carbon-rich forests in the tropics. *Nature Geoscience,* 4(5), 293-297.

Murphy, D. J., Hall, J., & Jintana, V. (2020). Land use change and carbon losses in Southeast Asian tropical peatlands. *Wetlands Ecology and Management,* 28(3), 457-472.

Pendleton, L., Donato, D. C., Murray, B. C., Crooks, S., Jenkins, W. A., Sifleet, S., ... & Baldera, A. (2012). Estimating global "blue carbon" emissions from conversion and degradation of vegetated coastal ecosystems. *PLoS ONE,* 7(9), e43542.

Sharp, R., Tallis, H. T., Ricketts, T., Guerry, A. D., Wood, S. A., Chaplin-Kramer, R., ... & Vogl, A. L. (2018). *InVEST 3.7.0 user's guide.* The Natural Capital Project, Stanford University.

Fayad, I., Baghdadi, N., Guitet, S., Bailly, J.-S., Hérault, B., Gond, V., El Hajj, M., & Tong Minh, D. H. (2016). Aboveground biomass mapping in French Guiana by combining remote sensing, forest inventories and environmental data. *International Journal of Applied Earth Observation and Geoinformation, 52*, 502–514. https://doi.org/10.1016/j.jag.2016.07.015

Jagadish, B., Behera, M. D., Prakash, A. J., Paramanik, S., Ghosh, S. M., Patnaik, C., & Das, A. (2024). Indicating saturation limits of multi-sensor satellite data in estimating aboveground biomass of a mangrove forest. *Journal of the Indian Society of Remote Sensing, 52*, 2483–2500. https://doi.org/10.1007/s12524-024-01968-1

Li, C., Zhou, L., & Xu, W. (2021). Estimating aboveground biomass using Sentinel-2 MSI data and ensemble algorithms for grassland in the Shengjin Lake Wetland, China. *Remote Sensing, 13*(8), 1595. https://doi.org/10.3390/rs13081595

Sinha, S., Mohan, Brun, S., Das, A. K., Sharma, L. K., Jeganathan, C., Santra, A., Santra Mitra, S., & Nathawat, M. S. (2019). Multi-sensor approach integrating optical and multi-frequency synthetic aperture radar for carbon stock estimation over a tropical deciduous forest in India. *Carbon Management, 11*(1), 39–55. https://doi.org/10.1080/17583004.2019.1686931

Choi, C. (2024). Combining TanDEM-X Interferometric SAR and GEDI Lidar Measurements for Improving Forest Height, Structure and Biomass Estimates. *Deutsches Zentrum für Luft- und Raumfahrt (DLR).*

Ho Tong Minh, D., Le Toan, T., Rocca, F., Tebaldini, S., Villard, L., Réjou-Méchain, M., Phillips, O. L., Feldpausch, T. R., Dubois-Fernandez, P., Scipal, K., & Chave, J. (2016). SAR tomography for the retrieval of forest biomass and height: Cross-validation at two tropical forest sites in French Guiana. *Remote Sensing of Environment, 175*, 138-147. https://doi.org/10.1016/j.rse.2015.12.037

Le Toan, T., Villard, L., Ho Tong Minh, D., Doblas, J., Mermoz, S., Ferro-Famil, L., Koleck, T., Bouvet, A., Planells, M., & Polidori, L. (2024). Tackling high biomass in tropical forests through the BIOMASS mission. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, XLVIII-3-2024*, 287-293. https://doi.org/10.5194/isprs-archives-xlviii-3-2024-287-2024

Xu, Y., Lu, Z., Bürgmann, R., Hensley, S., Fielding, E., & Kim, J. (2023). P-band SAR for ground deformation surveying: Advantages and challenges. *Remote Sensing of Environment, 287*, 113474. https://doi.org/10.1016/j.rse.2023.113474

Ali, J. (2025). Remote sensing and integration of machine learning algorithms for above-ground biomass estimation in Larix principis-rupprechtii Mayr plantations: a case study using Sentinel-2 and Landsat-9 data in northern China. *Frontiers in Environmental Science*.

Iheaturu, C. J. (2026). Remote sensing of tropical forest recovery. *Remote Sensing of Environment, 335*, 115257.

Jiao, Y., Wang, B., Yao, X., Wang, S., Chi, T., & Meng, Y. (2023). Forest emissions reduction assessment using optical satellite imagery and space LiDAR fusion for carbon stock estimation. *Remote Sensing, 15*(5), 1410. https://doi.org/10.3390/rs15051410

Papucci, E. (2026). Review of forest biomass assessments based on remote sensing reveals progress in methodological quality but major challenges remain. *Forestry*.

Santos, D. T. D. (2025). Multi-sensor data fusion for operational monitoring of deforestation and forest carbon stocks in tropical ecosystems. *International Journal of Science, Architecture, Technology, and Environment, 2*(12).

Tian, L., Wu, X., Tao, Y., Li, M., Qian, C., Liao, L., & Fu, W. (2023). Review of remote sensing-based methods for forest aboveground biomass estimation: Progress, challenges, and prospects. *Forests, 14*(6), 1086. https://doi.org/10.3390/f14061086

Xu, X. (2025). Estimation of forest aboveground biomass using Sentinel-1/2 synergized with extrapolated parameters from LiDAR data and analysis of its ecological driving factors. *Remote Sensing*.