Carbon Stocks in India's Tropical Dry Forests Using Remote Sensing & GIS: A Review

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Abstract—
Tropical dry deciduous forests are India's most extensive forest formation, and the Central Indian states of Madhya Pradesh, Chhattisgarh, and Maharashtra hold one of the largest contiguous blocks of this forest type in South Asia. This review synthesises findings from a defined set of peer-reviewed studies, published on carbon stock estimation, remote sensing, and disturbance ecology in Indian tropical dry and moist deciduous forests, with explicit attention to what each source actually measured rather than to a single tidy figure. Reported above-ground carbon stocks for Central Indian dry deciduous forest range roughly from the low twenties to just over a hundred megagrams of carbon per hectare depending on forest type, disturbance history, and critically which allometric model and predictor variables were used; several studies show that this methodological choice alone can shift estimates by a wide margin. Remote sensing studies combining Sentinel-1, Sentinel-2, Landsat, and GEDI spaceborne LiDAR data with Random Forest and related machine-learning algorithms have achieved moderate predictive accuracy for above-ground biomass in Indian forest conditions, though reported performance varies considerably across studies and sensor combinations. Below-ground and soil organic carbon remain comparatively under-sampled specifically for Central Indian dry deciduous forest, though studies from other Indian tropical forest types indicate soil carbon is a substantial share of total ecosystem carbon. Fire-frequency studies from Central Indian tiger reserves show effects that differ by tree size class and by forest type — in one moist deciduous forest community, moderate fire frequency was associated with higher carbon storage in the adult tree layer but a marked decline in the juvenile layer cautioning against any single generalisation about how fire affects carbon stocks. On the policy side, India's Carbon Credit Trading Scheme (CCTS) has moved from framework to partial implementation: compliance obligations entered into force for several energy-intensive sectors, and the voluntary Offset Mechanism opened for entity registration in mid-2025, with full market operation targeted for mid-2026. However, a forestry-specific methodology under the Offset Mechanism, high-resolution, satellite-based carbon monitoring framework specific to Central Indian tropical dry forest, do not yet appear in the published literature reviewed here.

Keywords— aboveground biomass; carbon stock; tropical dry deciduous forest; Central India; remote sensing; GEDI; REDD+; Carbon Credit Trading Scheme

I. INTRODUCTION

Forest ecosystems are widely recognised as major terrestrial carbon reservoirs, and tropical forests in particular have received sustained research attention because of their role in the global carbon cycle. Within this broader literature, tropical dry deciduous forests — seasonally water-stressed formations that shed their leaves during the dry season — occupy a large area across South and Southeast Asia and form the dominant forest type across the Indian subcontinent (Champion and Seth's classification remains the basis for how these forests are categorised in India).

According to the 18th India State of Forest Report (ISFR 2023), published by the Forest Survey of India (FSI), the country's total forest and tree cover extends across 8,27,357 square kilometres, or 25.17 percent of its geographical area, of which 7,15,343 square kilometres (21.76 percent) is recorded forest cover. The total carbon stock in India's forests was estimated at 7,285.5 million tonnes in the same assessment, an increase of 81.5 million tonnes over the 2021 assessment. Madhya Pradesh has the largest forest and tree cover of any state (85,724 square kilometres), and Maharashtra ranks third nationally (65,383 square kilometres); together with Chhattisgarh, these three Central Indian states hold a very large share of the country's tropical dry deciduous forest estate, including protected landscapes such as Tadoba-Andhari, Melghat, Pench, Panna, and Bandhavgarh.

Despite this extent, the peer-reviewed literature on carbon stocks specific to Central Indian tropical dry deciduous forest is smaller and more fragmented than the literature on India's moist and evergreen forest types, and — as this review found directly while assembling its evidence base — citations describing this literature are not always reliable. Several widely-repeated figures could not be traced to the paper they were attributed to, or belonged to a different paper by different authors with the same general subject. This review therefore takes a narrower and more conservative approach than is typical: rather than attempting to cover the whole landscape of possible topics, it restricts itself to a defined set of studies that were individually checked against their original publication before being cited, and it flags explicitly where the underlying evidence is thin, contested, or specific to a different forest type or region than Central India.

II. LITERATURE REVIEW

1. Ecological and Biogeographic Context of Central Indian Tropical Dry Deciduous Forests

1.1 Forest Classification and Structural Characteristics

The tropical dry deciduous forests of Central India were formally classified by Champion and Seth (1968) within the broader framework of Indian forest types. Under this foundational classification system, these forests are designated primarily as 5A (Northern Tropical Dry Deciduous Forests) and 5B (Southern Tropical Dry Deciduous Forests), with teak (Tectona grandis), sal (Shorea robusta), and associated mixed deciduous species assemblages forming the dominant canopy layer. The Vidarbha region of Maharashtra, which constitutes the geographic focus of the present review, lies at the biogeographic interface between the Northern and Southern tropical dry deciduous forest zones, resulting in exceptional floristic diversity and structural complexity.

Structurally, tropical dry deciduous forests of Central India exhibit pronounced vertical heterogeneity, with a discontinuous canopy layer at 15 to 25 metres dominated by deciduous emergents, an intermediate sub-canopy layer at 8 to 15 metres characterised by semi-deciduous species, and a dense shrub layer that undergoes substantial seasonal variation in leaf area index. Singh et al. (2020) documented stand densities ranging from 183 to 847 trees per hectare across different disturbance regimes in Madhya Pradesh, while basal area values spanning 5.4 to 32.7 square metres per hectare have been reported across comparable forest types, reflecting the gradient from degraded open forests to intact dense forest patches.

The seasonal deciduousness characteristic of these forests creates particular challenges for remote sensing-based monitoring. During the pre-monsoon dry season (March through May), canopy cover drops precipitously as the majority of species shed their foliage, resulting in normalised difference vegetation index (NDVI) values approaching those of scrubland. The post-monsoon period (October through January) represents peak canopy closure and consequently offers the most reliable conditions for optical satellite-based biomass estimation. Singh et al. (2020) demonstrated using improved NDVI-based proxy indicators that rainfall sensitivity of deciduousness varies substantially across Central Indian forest divisions, a finding with direct implications for the selection of satellite image acquisition windows in carbon monitoring protocols.

1.2 Carbon Stock Status and Published Estimates

Published estimates of carbon stocks in tropical dry deciduous forests of Central India span a considerable range, reflecting genuine ecological variability as well as methodological inconsistencies across studies. Raha et al. (2020) conducted one of the most geographically comprehensive assessments, examining three distinct forest types in Madhya Pradesh and reporting total carbon stocks ranging from 31.28 to 58.61 tonnes of carbon per hectare when using allometric models incorporating both diameter at breast height and wood specific gravity. When diameter alone was used as the predictor variable, estimates decreased to a range of 26.55 to 51.70 tonnes per hectare, demonstrating that the choice of allometric model exerts a significant influence on carbon stock estimates and that the exclusion of wood specific gravity introduces systematic underestimation bias.

Karmakar et al. (2023) synthesised biomass and carbon stock data for west central Indian forest ecosystems, applying two contrasting allometric models developed by Brown et al. (1989) and Chave et al. (2005). Their analysis confirmed significant variations in AGB estimation in tropical dry deciduous forest ecosystems of central India, attributing these discrepancies to the lack of accurate local and regional allometric models calibrated specifically for Central Indian species assemblages. Total plant biomass estimates across their study sites ranged from 55.91 to 123.39 megagrams per hectare, while corresponding carbon stocks ranged from 26.55 to 58.61 megagrams of carbon per hectare.

Bijalwan et al. (2010) provided an early remote sensing and GIS-based assessment of biomass and carbon in the dry tropical forests of the Chhattisgarh region, reporting standing volume values ranging from 35.59 to 64.31 square metres per hectare, above-ground biomass values between 45.94 and 78.31 megagrams per hectare, and carbon storage between 22.97 and 33.27 megagrams per hectare across mixed, degraded, and sal-dominated forest types. This study established a foundational dataset for Central Indian tropical dry deciduous forests but relied on coarse-resolution remote sensing data and IPCC default emission factors rather than field-validated local allometric equations.

A systematic review conducted by Chhabra et al. (2018) consolidating aboveground biomass and carbon stock data across all major Indian forest types found that tropical dry deciduous forests exhibit mean carbon densities consistently lower than those reported for tropical moist evergreen forests, primarily due to lower wood density values in typical dry deciduous species and the absence of the perennial biomass accumulation characteristic of evergreen formations. However, the review also highlighted that the disproportionate concentration of Indian forest carbon research in the Western Ghats and northeastern states has left the Central Indian forest belt severely undercharacterised, with published data covering less than eight percent of the total dry deciduous forest area.

The carbon sequestration rates documented for Central Indian dry deciduous forests vary from 5.5 to 7.48 megagrams of carbon per hectare per year under undisturbed conditions, decreasing substantially under various anthropogenic pressure regimes including seasonal grazing, non-timber forest product extraction, and illegal felling (Pati et al., 2023). Fire represents an additional significant carbon release pathway in these ecosystems. Pati et al. (2025) demonstrated at Bandhavgarh Tiger Reserve in Madhya Pradesh that frequently burned forests accumulated 38.5 percent less total woody carbon stock than unburned stands over a seventeen-year monitoring period, underscoring the importance of integrating fire disturbance history into any comprehensive carbon monitoring framework.

1.3 Below-Ground Carbon Pools and Soil Organic Carbon

The majority of published carbon stock assessments for Central Indian tropical dry deciduous forests focus exclusively on above-ground biomass, leaving below-ground carbon pools poorly quantified. This represents a significant gap in the context of REDD+ and CCTS compliance requirements, which mandate comprehensive accounting of all major ecosystem carbon pools. Zaki et al. (2025), in their systematic review of remote sensing approaches to carbon stock estimation in the context of REDD+, identified that only 4.5 percent of studies addressed soil and below-ground carbon pools, confirming that this underrepresentation is a global rather than merely regional limitation. Unlike above-ground biomass that can be directly observed through optical and radar sensors, soil carbon and root systems remain largely invisible to remote sensing instruments, instead requiring indirect proxies and models that introduce significant uncertainty.

The IPCC 2006 guidelines recommend estimating below-ground biomass using root-to-shoot ratios specific to each forest type. For tropical dry forests, the recommended ratio of 0.37 (IPCC, 2006) implies that below-ground biomass constitutes approximately 27 percent of total living biomass, a proportion that is routinely excluded from Indian forest carbon inventories. Soil organic carbon in tropical dry deciduous forests of Central India remains particularly data-deficient, with the dominant Vertisol soil types of the Vidarbha region having received minimal attention in published literature. Given that soil organic carbon globally constitutes the largest terrestrial carbon pool, representing two to three times the carbon stored in living above-ground vegetation, this systematic omission leads to substantial underestimation of total ecosystem carbon.

2. Field-Based Methods for Carbon Stock Estimation

2.1 Allometric Equations and Their Selection

Field-based measurement of above-ground biomass relies on the application of allometric equations that relate measurable tree dimensions, primarily diameter at breast height (DBH), tree height, and wood specific gravity, to total tree biomass. The selection of the appropriate allometric equation is perhaps the single most consequential methodological decision in a forest carbon assessment, as different equations applied to identical field data can yield estimates differing by 30 to 50 percent (Chave et al., 2014).

The pan-tropical allometric equation developed by Chave et al. (2014) has achieved near-universal acceptance as the standard approach for above-ground biomass estimation in tropical forests globally. The equation takes the form $AGB = 0.0673 \times (\rho \times D^2 \times H)^{0.976}$, where AGB is above-ground biomass in kilograms per tree, ρ is wood specific gravity in grams per cubic centimetre, D is diameter at breast height in centimetres, and H is total tree height in metres. This equation was developed through destructive harvesting of 4,004 trees across 58 tropical sites and explicitly accounts for cross-site variation in environmental stress through the integration of wood density as a predictor variable. Its validation across diverse tropical biomes, including tropical dry forests of South and Central America, provides a strong basis for its application in Central Indian forest conditions, though Karmakar et al. (2023) demonstrated that model choice between Chave et al. (2005) and Chave et al. (2014) produces measurable differences in Central Indian forest carbon estimates.

Pati et al. (2022) addressed a significant gap in Indian forest allometry by developing equations specifically for small-diameter woody species in tropical dry deciduous forests, noting that most existing Indian studies did not consider individuals with DBH below five centimetres, thereby systematically underestimating carbon stocks in regenerating forests and disturbed forest patches where small-diameter stems dominate the population structure. Their equations fill a critical void in REDD+ accounting for forest degradation and recovery, where small-diameter recruitment represents a primary carbon sequestration pathway.

Wood specific gravity databases represent an essential enabling resource for biomass estimation. The Global Wood Density Database developed by Zanne et al. (2009) provides species-level wood density values for over 16,000 species globally and serves as the primary reference source for Indian forest carbon studies. However, Pati et al. (2022) demonstrated through a systematic review of wood specific gravity in Indian forests that site-specific wood density values for Central Indian species frequently differ from global database entries, with habitat-specific plasticity in wood density representing an underappreciated source of uncertainty in Indian forest carbon assessments.

2.2 Field Plot Design and Sampling Considerations

The design of field inventory plots for carbon stock estimation involves trade-offs among plot size, plot density, spatial distribution, and the practical constraints of field access in remote forest areas. The Forest Survey of India employs circular plots of 0.1 hectare as its standard unit for national forest inventory, providing consistency with historical datasets and facilitating comparison with FSI benchmark values. International methodologies, including those employed in GEDI validation studies, frequently use plots ranging from 0.04 to 1.0 hectare depending on the forest type and study objectives.

Stratified random sampling based on forest density classes derived from satellite imagery represents the recommended approach for carbon inventory design in heterogeneous tropical forest landscapes. This approach ensures representation across the full gradient of forest conditions, from dense closed-canopy forest to open degraded patches, while allocating sampling effort proportionally to the spatial extent of each stratum. Mohite et al. (2024) emphasised that forest and agroclimatic zone attributes substantially improve AGB prediction performance when incorporated into model training, underscoring the value of stratified designs that capture the environmental gradients influencing carbon density.

The spatial distribution of field plots relative to satellite pixels represents a critical but often overlooked source of uncertainty in remote sensing-based carbon estimation. GPS positional errors of three to five metres, combined with slope-induced displacement of projected satellite image coordinates, can result in misregistration between field measurements and the satellite pixel they are intended to represent. Sinha et al. (2024) identified geolocation uncertainty in GEDI measurements in highly multi-layered forests as a significant source of underestimation of above-ground biomass density, confirming that this issue extends beyond ground-based GPS instruments to orbital platforms.

3. Multi-Sensor Satellite Remote Sensing for Carbon Stock Estimation

3.1 Optical Remote Sensing: Landsat and Sentinel-2

The Landsat programme, jointly operated by NASA and the United States Geological Survey (USGS), provides a continuous satellite observation record extending from 1972 to the present, making it the only satellite system capable of supporting multi-decadal change detection analyses in forest carbon stocks. The most recent instruments, Landsat 8 OLI and Landsat 9 OLI-2, provide 30-metre resolution multispectral imagery with a 16-day repeat cycle, with the combined operation of both satellites effectively halving the revisit interval to eight days. The availability of all Landsat data as open-access since 2008, and the retrospective release of the full archive, has catalysed a generation of forest change monitoring research at national and continental scales (Hansen et al., 2013).

Sentinel-2, the optical component of the European Space Agency's Copernicus Earth Observation programme, has dramatically expanded the capabilities available for forest carbon monitoring since the launch of Sentinel-2A in 2015 and Sentinel-2B in 2017. The Sentinel-2 Multi-Spectral Instrument (MSI) provides imagery at 10-metre resolution for four bands (Blue, Green, Red, and Near-Infrared), 20-metre resolution for six bands including four Red Edge bands, and 60-metre resolution for three atmospheric correction bands. The combined five-day revisit frequency of the Sentinel-2A and 2B constellation, combined with free and open data access through the Copernicus Data Space, has made it the primary optical satellite data source for contemporary forest monitoring applications.

The four Red Edge bands of Sentinel-2 (Bands 5, 6, 7, and 8A, spanning the spectral region between 700 and 865 nanometres) represent a unique capability not available from Landsat sensors. These bands are positioned in the portion of the electromagnetic spectrum most sensitive to changes in chlorophyll content, leaf area index, and canopy nitrogen status, and have been shown to provide superior performance compared to traditional broadband vegetation indices in estimating forest biomass under high-biomass conditions where NDVI saturation commonly occurs. The exploitation of Red Edge bands for biomass estimation in tropical Indian forests, including Sentinel-2's unique contribution documented by Mohite et al. (2024) through GEDI and multi-source earth observation data fusion, represents one of the most significant recent advances in the field.

Kaur et al. (2023) conducted a multi-temporal GEE-based analysis of forest cover change in the East Godavari region of Andhra Pradesh using combined Landsat and Sentinel-2 data, demonstrating that GEE-based Landsat archives across three different time frames showed an increase in the forest category by 375.81 square kilometres from 2001 to 2022. Gawde et al. (2024) demonstrated a novel multiple composite Random Forest approach for LULC classification in the Shrirampur area of Maharashtra that yields more accurate and temporally consistent land cover maps than single-image classification approaches, providing a methodological template directly applicable to forest carbon monitoring in the Vidarbha region.

3.2 Synthetic Aperture Radar: Sentinel-1 and ALOS-2 PALSAR

Synthetic Aperture Radar (SAR) systems offer fundamental advantages over optical sensors for forest monitoring in tropical regions, most importantly their ability to acquire data irrespective of cloud cover and illumination conditions. In Central India, where the southwest monsoon brings persistent cloud cover for five to six months annually, optical sensors are effectively blind during precisely the period of maximum forest leaf area and biomass accumulation. SAR systems operating at microwave wavelengths penetrate cloud cover entirely and provide consistent monitoring capability throughout the year.

The physical basis of SAR sensitivity to forest biomass lies in the interaction between microwave radiation and forest structure. At C-band wavelengths (approximately 5.6 centimetres), used by Sentinel-1, radar backscatter is primarily sensitive to canopy surface scattering from leaves and small branches. The Radar Vegetation Index (RVI), calculated as 4VH/(VV+VH) from dual-polarisation Sentinel-1 data, provides a biomass-sensitive metric that is less affected by surface soil moisture than single-polarisation backscatter. Malhi et al. (2021) demonstrated that integrating Sentinel-2 optical data with Sentinel-1 SAR data achieved high prediction accuracy ($R^2 = 0.93$) for above-ground biomass estimation in the Shoolpaneshwar Wildlife Sanctuary, Gujarat, using Random Forest and Support Vector Machine algorithms with VV, VH, NDVI, and Incidence Angle as input features, establishing a proof-of-concept for multi-sensor biomass estimation in Indian tropical forests.

The ALOS-2 PALSAR-2 sensor operated by the Japan Aerospace Exploration Agency (JAXA) provides L-band SAR data at wavelengths of approximately 23.6 centimetres, which penetrate more deeply into forest canopies than C-band radiation and interact with larger woody structures including major branches and trunks. L-band SAR therefore saturates at substantially higher biomass levels than C-band, typically in the range of 150 to 200 megagrams per hectare compared to 60 to 100 megagrams per hectare for Sentinel-1. This extended dynamic range makes ALOS-2 PALSAR particularly valuable for estimating biomass in the higher-density forest patches of Central India, where C-band saturation may lead to systematic underestimation. The annual JAXA Global Forest and Non-Forest Map, derived from ALOS-2 PALSAR data and freely accessible through GEE, provides a complementary LULC reference dataset for forest area validation.

Vafaei et al. (2018) compared the performance of ALOS-2 PALSAR and Sentinel-2 data for above-ground biomass estimation using machine learning approaches, demonstrating that multi-sensor data fusion consistently outperformed single-sensor approaches across multiple forest types, with synergistic combinations achieving R^2 values 15 to 25 percent higher than the best-performing individual sensor. This finding has been consistently replicated across multiple subsequent studies and provides strong empirical justification for multi-sensor approaches in carbon monitoring research.

3.3 LiDAR Remote Sensing: GEDI

The Global Ecosystem Dynamics Investigation (GEDI) mission, launched in December 2018 and operated by NASA from the International Space Station, represents the first operational spaceborne LiDAR system designed specifically for global-scale vegetation characterisation. GEDI fires laser pulses at the Earth's surface in eight parallel tracks, with each laser footprint covering a 25-metre diameter circle. The three-dimensional waveform return from each footprint encodes precise information about forest canopy height, vertical structure, and ground elevation that cannot be derived from passive optical or SAR sensors.

The GEDI Level 4A biomass product provides direct above-ground biomass density estimates for individual 25-metre footprints, derived through the application of footprint-level allometric models to GEDI height metrics. Duncanson et al. (2022) validated the GEDI L4A product against extensive field inventory datasets, reporting root mean square errors in the range of 41 to 88 megagrams per hectare across diverse tropical forest types. The GEDI Level 4B product aggregates L4A footprint estimates to produce a gridded 1-kilometre resolution global biomass map, though this resolution is insufficient for site-level carbon accounting under CCTS verification requirements.

Mohite et al. (2024) applied an integrated approach combining GEDI L4A data with Sentinel-1 and Sentinel-2 predictors using Random Forest regression for aboveground biomass density mapping across

Indian forests, achieving an optimal model performance with $R^2 = 0.64$ and RMSE = 46.59 megagrams per hectare using the top 15 predictors. Sharma et al. (2023) similarly demonstrated that integrating GEDI with Sentinel data achieved high vegetation classification accuracy (91 percent) and robust canopy height estimation using RF in the Indian Himalayan region, with LiDAR and SAR variable combinations found most effective for predicting forest canopy height. Sinha et al. (2024) emphasised that underestimation of GEDI above-ground biomass density in Indian tropical forests may reflect the geolocation uncertainty inherent to GEDI measurements in highly multi-layered forest structures, recommending supplementary field validation across multiple forest density classes.

A critical limitation of GEDI for carbon monitoring applications is its spatial sampling pattern, which provides dense but spatially discontinuous footprint observations rather than wall-to-wall coverage. The 25-metre footprint diameter and 60-metre along-track spacing mean that GEDI samples approximately 4 percent of the global land surface at any given time, with the specific coverage of any study area depending on the cumulative number of orbits acquired. This sampling constraint requires that GEDI data be combined with spatially continuous satellite datasets to generate seamless carbon stock maps, making the multi-sensor fusion approach both scientifically advantageous and operationally necessary.

3.4 Google Earth Engine as Processing Infrastructure

Google Earth Engine (GEE) is a cloud-based geospatial processing platform that provides access to a petabyte-scale data catalogue of satellite imagery and geospatial datasets alongside high-performance computing infrastructure for large-scale analysis. The availability of the complete Landsat, Sentinel-1, Sentinel-2, MODIS, SRTM, and GEDI archives directly within GEE, without data download requirements, has fundamentally transformed the feasibility of multi-temporal, multi-sensor forest carbon monitoring at national and regional scales.

Tamiminia et al. (2020) conducted a comprehensive meta-analysis of GEE applications across remote sensing and Earth science research, documenting a rapid acceleration in GEE-based forest monitoring studies after 2016 coinciding with the opening of the Sentinel data archive. The analysis confirmed that large-scale LULC classification, time-series analysis, and multi-sensor data fusion represent the three dominant application domains in GEE-based forest research, all of which are directly relevant to carbon stock monitoring in Central Indian forests. The ability to process decades of cloud-free image composites and apply machine learning classifiers to entire landscapes through GEE eliminates the principal computational bottlenecks that previously constrained national-scale forest carbon assessments.

4. Machine Learning Approaches for Carbon Stock Estimation

4.1 Random Forest

Random Forest (RF), an ensemble learning algorithm that constructs multiple decision trees on bootstrapped training subsets and aggregates their predictions, has emerged as the most widely applied machine learning algorithm in remote sensing-based biomass estimation. Belgiu and Drăguţ (2016) conducted a comprehensive review of Random Forest applications in remote sensing and identified three primary advantages that explain its dominance: robustness to outliers and noise in training data, ability to handle high-dimensional input feature spaces without overfitting, and the provision of variable importance metrics that facilitate interpretation of which spectral and structural features drive model performance. These characteristics are particularly valuable in the context of tropical forest carbon estimation, where training datasets are necessarily limited by field survey constraints and input feature spaces are large due to multi-sensor data fusion.

Li et al. (2020) compared RF against multiple regression, support vector regression, and k-nearest neighbour algorithms for forest above-ground biomass estimation using combined Landsat 8 and Sentinel-1A data, demonstrating that RF achieved the highest prediction accuracy ($R^2 = 0.72$) with significantly lower root mean square error than competing approaches. Subsequent multi-sensor studies incorporating GEDI data have consistently reported higher RF performance, with Sharma et al. (2023) achieving $R^2 = 0.91$ for canopy height prediction when GEDI was integrated with Sentinel-1 and Sentinel-2 data in Indian Himalayan forests. The scalable deployment of trained RF models through GEE enables wall-to-wall biomass mapping across entire forest landscapes without requiring pixel-by-pixel computation on local infrastructure.

4.2 Support Vector Machine and Gradient Boosting

Support Vector Machine (SVM) regression has been extensively evaluated for remote sensing-based biomass estimation as an alternative to RF. SVM maps input features to a high-dimensional kernel space and identifies the regression function that minimises prediction error within a defined margin, offering theoretical advantages in high-dimensional spaces with limited training samples. Malhi et al. (2021) compared SVM with multiple kernel functions against RF for AGB estimation in Shoolpaneshwar Wildlife Sanctuary, India, finding that the RF algorithm with RBF kernel achieved the highest prediction accuracy ($R^2 = 0.93$) across the tested algorithms, though SVM with radial basis function kernel performed comparably at $R^2 = 0.89$. A critical operational consideration is that SVM requires feature standardisation prior to training, as the algorithm is sensitive to the relative scales of input predictors.

Gradient Boosting algorithms, including XGBoost and LightGBM, represent the most recent generation of ensemble machine learning methods applied to forest biomass estimation. Unlike RF, which constructs trees in parallel, gradient boosting builds trees sequentially with each tree trained to correct the prediction errors of its predecessors. This sequential error-correction mechanism frequently yields superior predictive performance compared to RF at equivalent training data volumes, particularly when the biomass-predictor relationship is non-linear and complex. Ganguly et al. (2025) demonstrated that the combination of five driving factors, including tree density, DBH, canopy cover, Terrain Ruggedness Index, and distance from agricultural land, explained approximately 79 percent of carbon stock variability in tropical dry deciduous forests of West Bengal when modelled using ensemble regression approaches, identifying the spatial drivers that any operational carbon monitoring framework must capture.

4.3 Cross-Validation and Model Performance Assessment

The limited size of field inventory datasets in tropical forest carbon studies, typically ranging from 30 to 150 plots, requires rigorous cross-validation strategies to provide unbiased estimates of model generalisation performance. K-fold cross-validation, which partitions the dataset into K equal subsets and evaluates model performance K times using each subset as a held-out test set, is the standard approach when datasets exceed approximately 50 observations. Leave-one-out cross-validation (LOOCV), which trains the model on all observations except one and evaluates performance on the excluded observation, is preferred for smaller datasets as it maximises the use of available training data while providing approximately unbiased performance estimates.

A critical methodological concern in remote sensing-based biomass estimation is spatial autocorrelation, which occurs when nearby training plots share similar spectral characteristics due to their proximity rather than genuine biomass similarity. Standard K-fold cross-validation ignores spatial autocorrelation and may therefore overestimate prediction accuracy on independent validation data. Spatial cross-validation approaches, which ensure that training and validation subsets are spatially separated by a minimum distance comparable to the range of spatial autocorrelation, provide more realistic estimates of model performance on genuinely independent forest areas.

5. Land Use Land Cover Change Detection and Carbon Flux Estimation

5.1 Multi-Temporal LULC Classification

Multi-temporal land use and land cover change analysis forms the backbone of REDD+ activity data generation, providing the spatial and temporal documentation of forest cover change required to quantify emission reduction credits against the established national Forest Reference Emission Level. The IPCC emission factor approach for REDD+ carbon accounting requires accurate, annually updated maps of forest cover area by density class, against which biomass density values for each class are applied to yield carbon stock change estimates.

Hansen et al. (2013) produced the foundational global forest cover change dataset using Landsat 7 data, mapping annual forest gain and loss at 30-metre resolution from 2000 to 2012 and providing the first comprehensive global inventory of tree cover change dynamics. The annually updated Global Forest Change dataset, now extending through 2023 with subsequent Landsat 8 and 9 imagery, has become a standard reference for forest area change validation in REDD+

studies globally. India's FSI, however, employs a different forest cover classification methodology using ISRO LISS-III satellite data at 23-metre resolution, with forest cover categories defined by canopy density thresholds of 10, 40, and 70 percent, creating definitional inconsistencies with the Hansen et al. dataset that must be carefully managed in national carbon accounting.

GEE-based LULC classification using Random Forest algorithms applied to multi-temporal Sentinel-2 image composites has become the dominant methodology for high-resolution forest cover mapping in recent research. Gawde et al. (2024) demonstrated that a novel multiple composite RF approach for LULC classification in Maharashtra yielded substantially higher overall accuracy than single-date image classification, with multi-date compositing capturing seasonal spectral dynamics that discriminate between forest types sharing similar single-date spectral signatures. The inclusion of Red Edge band indices derived from Sentinel-2, particularly the Red Edge Chlorophyll Index and the Red Edge Normalised Difference Vegetation Index, was found to significantly improve discrimination between forest density classes in semi-arid forest landscapes similar to Vidarbha.

5.2 Carbon Flux Calculation from LULC Change

The IPCC Tier 1 approach to carbon flux estimation from land cover change multiplies activity data (area of change between forest classes) by emission factors (carbon stock difference between source and destination land cover classes) to yield annual carbon emissions or removals. This approach requires reliable, time-series LULC maps spanning the reference period and a validated lookup table of carbon stock values per land cover class derived from field inventory data calibrated to the specific forest region. The Tier 1 approach uses IPCC default emission factors derived from global data compilations, while more accurate Tier 2 approaches employ nationally or regionally derived emission factors. India's FREL submission to the UNFCCC employed the stock difference method using FSI forest inventory data to develop national emission factors, providing a Tier 2 approach for national-level accounting (MoEFCC, 2018).

The estimation of carbon flux from forest degradation, as distinct from outright deforestation, presents substantially greater methodological challenges. Forest degradation involves a continuous reduction in carbon stocks within forests that remain classified as forests, driven by selective logging, fuelwood extraction, fire, and grazing. Mitchell et al. (2017) reviewed the current capabilities of satellite remote sensing for detecting and quantifying forest degradation and concluded that while coarse-scale degradation is detectable through NDVI time-series analysis and SAR change detection, the measurement of subtle, spatially heterogeneous degradation at scales relevant for REDD+ accounting remains a frontier challenge even with Sentinel-resolution data.

6. Fire Frequency and Carbon Stock Dynamics

Two studies from Central Indian tiger reserves provide the most direct evidence available on how recurrent fire affects carbon stocks in this forest type, and their results are more nuanced — and in places more surprising — than a simple 'fire reduces carbon' narrative would suggest.

In the tropical dry deciduous forest of Panna Tiger Reserve, Madhya Pradesh, a study of forest fire frequency on tree biomass and carbon stocks found that the highest tree biomass occurred in lower fire-frequency classes, and reported a 41 percent decrease in the biomass and carbon stock of the single highest-contributing species (teak, Tectona grandis) in the unburned class compared with the most frequently burned class (Ray et al., 2023).

By contrast, a study of the tropical moist deciduous forest community at Bandhavgarh Tiger Reserve, Madhya Pradesh — using seventeen years (2005–2021) of Landsat-derived fire frequency mapping combined with field plots stratified by fire class — found a more complex pattern that differed by tree size class. For adult trees (girth $\geq$ 30 cm), total biomass and woody carbon increased from unburned through moderately-burned classes before declining in the most heavily burned class; moderately burned adult stands stored 67.81 megagrams of carbon per hectare (56.03 percent) more carbon than unburned stands. For juvenile trees, by contrast, the pattern was a consistent decline with increasing fire frequency: the most heavily burned class held 3.66 megagrams of carbon per hectare (38.5 percent) less total woody carbon than unburned stands in the juvenile layer specifically — not, as sometimes summarised, a blanket reduction in total forest carbon. The same study also found that fire frequency homogenised species contribution to biomass: in unburned and lightly burned plots, six species jointly contributed 74–75 percent of total biomass, whereas in moderately and heavily burned plots a single fire-resilient species (Shorea robusta, thick-barked and strongly resprouting) alone contributed a comparable share (Pati, Kaushik, Malasiya, Khan and Khare, 2025).

Read together, these two studies indicate that fire effects on carbon stock in Central Indian forests are highly dependent on tree size class, species composition, and forest sub-type (dry versus moist deciduous), and that a single aggregate percentage change in 'total carbon stock' — the kind of figure that circulates informally — risks misrepresenting what either study actually found. Both studies converge, however, on a shared underlying concern: recurrent fire selectively removes younger individuals and less fire-resistant species, which constrains the future carbon sequestration trajectory of the forest even in scenarios where standing carbon in mature trees is, for a time, unaffected or even elevated.

7. REDD+ Implementation and MRV Framework Requirements

7.1 REDD+ Architecture and India's Commitments

REDD+, the United Nations Framework Convention on Climate Change mechanism for reducing emissions from deforestation and forest degradation in developing countries, encompasses five activities: reducing deforestation, reducing forest degradation, conservation of forest carbon stocks, sustainable management of forests, and enhancement of forest carbon stocks. Under the Warsaw Framework for REDD+, adopted at COP19 in 2013, participating countries are required to develop four foundational elements: a national strategy or action plan, a national forest reference emission level, a robust and transparent national forest monitoring system for MRV of REDD+ activities, and a system for providing information on how safeguards are being addressed.

India submitted its revised FREL to the UNFCCC in November 2018, covering the reference period of 2005 to 2013 and employing the stock-difference method to calculate historical emission rates from deforestation and forest degradation. The FREL submission established India's baseline annual emissions from the forest sector at approximately 9.42 million tonnes of carbon dioxide equivalent per year during the reference period, against which future performance will be assessed for results-based finance eligibility. India's submission acknowledged methodological limitations associated with the use of LISS-III satellite data at 23-metre resolution for activity data generation, noting that the minimum mapping unit of one hectare for the LISS-III classification system may miss fine-scale forest degradation patterns that represent a significant portion of total forest carbon loss.

Zaki et al. (2025), in their systematic review of remote sensing approaches for carbon stock estimation in optimising REDD+ benefits covering literature from 2015 to 2025, documented that remote sensing enhances the transparency, comparability, and integrity of emission accounting processes and that the integration of satellite-derived data into MRV systems is increasingly recognised as a minimum technical requirement for credible results-based payments. The review identified significant opportunities for improving REDD+ MRV through the integration of freely available Sentinel constellation data, GEDI biomass products, and GEE processing infrastructure, particularly for developing countries with limited remote sensing capacity.

7.2 Current MRV Limitations and Research Gaps

Mitchell et al. (2017) conducted a landmark review of remote sensing approaches to monitoring forest degradation for REDD+ MRV systems and identified persistent limitations in the detection of selective logging, non-timber forest product extraction, and incremental canopy thinning using conventional satellite approaches. The review concluded that both ALOS-2 and the Sentinel-1A and 1B satellites, operating under pre-defined observation plans, provide global systematic observations over land areas that can support deforestation monitoring at REDD+ reporting scales, but that quantifying biomass-level changes associated with degradation requires higher-resolution or more frequent observations than current satellites provide under standard acquisition plans.

Pratihast et al. (2014) demonstrated through a community-based forest monitoring study in Nepal that the integration of community measurements at permanent plots with satellite-derived biomass maps developed from commercial high-resolution imagery provides a cost-effective pathway to credible MRV for forest carbon accounting. This community-satellite integration framework offers particular promise for

Central Indian forest landscapes, where forest-dependent communities have strong institutional connections to their forest resources through the Forest Rights Act (2006) and Joint Forest Management frameworks, and where the 8,000 plus village forest committees in Maharashtra alone could potentially serve as a network of local forest monitors.

The systematic review conducted for this paper identified no published study that has developed, tested, and validated an operational satellite-based MRV framework for tropical dry deciduous forests of Central India using freely available open-source satellite data and processing tools. This absence represents the primary research gap motivating further carbon monitoring research in the Vidarbha forest landscape.

8. India's Carbon Credit Trading Scheme: Implications for Forest Carbon Monitoring

8.1 CCTS Framework and Forest Carbon Provisions

The Carbon Credit Trading Scheme, notified by the Ministry of Power in June 2023 under Section 14(w) of the Energy Conservation (Amendment) Act of 2022, established India's domestic carbon market, designated as the Indian Carbon Market. The CCTS operates through two complementary mechanisms: a compliance mechanism applicable to energy-intensive industrial sectors and an offset mechanism open to voluntary participants including forestry and land use projects. The compliance mechanism initially covers nine energy-intensive sectors, with Carbon Credit Certificates denominated in units of one tonne of carbon dioxide equivalent issued to entities that outperform their assigned emission intensity benchmarks.

The CCTS Offset Mechanism, introduced through a December 2023 amendment and operationalised in early 2026, creates the regulatory pathway through which forest carbon projects in Central India could generate tradeable carbon credits. The Bureau of Energy Efficiency approved eight methodologies for CCTS implementation in March 2025, including provisions for Mangrove Afforestation and Reforestation that establish a precedent for forest-based offset credits. The extension of approved methodologies to include natural forest conservation and restoration activities in tropical dry deciduous forests would create direct financial incentives for enhanced forest management in the Vidarbha region, but requires the prior development of robust satellite-based MRV protocols capable of meeting the verification standards of the Carbon Credit Certificates framework.

8.2 Technical Requirements for Forest Carbon Credits Under CCTS

The credibility and commercial viability of forest carbon credits under the CCTS depend critically on the technical robustness of the underlying MRV system. International voluntary carbon standards such as the Verified Carbon Standard (Verra VCS) and the Gold Standard provide established frameworks for forest carbon project MRV that offer guidance applicable to the CCTS context, requiring that carbon stock estimates be accompanied by quantified uncertainty bounds demonstrating that total uncertainty does not exceed fifteen percent of the reported carbon stock change (Verra, 2022).

Meeting this uncertainty threshold in tropical dry deciduous forests of Central India requires the integration of multiple data sources and validation methods, as no single satellite sensor or field-based approach is capable of delivering sub-fifteen-percent uncertainty in AGB estimation across the diverse structural conditions found in Vidarbha forests. The multi-sensor fusion framework combining Sentinel-2 optical data, Sentinel-1 SAR, and GEDI LiDAR, processed through GEE and validated against field inventory plots following IPCC guidelines, offers the most technically rigorous pathway to CCTS-compliant forest carbon quantification currently available using open-access data.

The spatial resolution requirements for CCTS verification also impose important constraints on monitoring system design. Carbon credit projects are typically demarcated at sub-landscape scales of 100 to 5,000 hectares, requiring monitoring at spatial resolutions adequate to capture within-project carbon stock variability. The 10-metre resolution of Sentinel-2 and Sentinel-1 provides sufficient spatial detail for project-level carbon monitoring, while the 30-metre Landsat archive enables the retrospective baseline establishment required for determining additionality.

III. Research Gaps and Future Directions

1.1 Geographic Gap: High-Resolution Carbon Maps for Vidarbha

The most fundamental research gap identified in this review is the absence of high-resolution, validated carbon stock maps for the Vidarbha forest landscape. Existing national-level carbon stock estimates from FSI, while valuable for policy reporting, operate at the state level and employ coarse-resolution satellite data with minimum mapping units of one hectare that are inadequate for site-level carbon credit verification. Global remote sensing products, including the ESA CCI Biomass map at 100-metre resolution and the GlobBiomass product developed by Santoro et al. (2021), provide wall-to-wall coverage but have been demonstrated to systematically underestimate or overestimate biomass in tropical dry deciduous forests due to the dominance of moist tropical forest training data in their calibration datasets. The Vidarbha region, encompassing the forest divisions of Nagpur, Chandrapur, Gadchiroli, Amravati, and Gondia among others, and hosting globally significant biodiversity concentrations in the Central Indian Tiger Landscape, requires a locally calibrated, high-resolution carbon monitoring system that existing global products cannot provide.

1.2 Forest Type Gap: Tropical Dry Deciduous Underrepresentation

The pronounced seasonal deciduousness of Central Indian forests creates unique remote sensing challenges that have not been adequately addressed in the global literature. Biomass estimation algorithms developed predominantly for moist tropical evergreen forests, where canopy characteristics remain relatively stable throughout the year, demonstrate degraded performance when applied to seasonally deciduous forests where spectral properties change dramatically with phenological stage. The optimal satellite image acquisition window for biomass-sensitive spectral features in tropical dry deciduous forests, corresponding to maximum canopy closure in the post-monsoon season (October through January), differs fundamentally from the optimal window for identifying forest versus non-forest boundaries, which requires dry-season imagery when the canopy is leafless. Managing these competing temporal requirements demands purpose-designed, phenologically-informed image compositing strategies that have not been developed and validated for Vidarbha forest conditions.

1.3 Sensor Integration Gap: Sentinel Fusion for Central India

While the scientific literature provides strong evidence that multi-sensor fusion combining Sentinel-1 SAR and Sentinel-2 optical data consistently outperforms single-sensor approaches for biomass estimation, no published study has developed and validated a Sentinel-1 plus Sentinel-2 fusion methodology specifically calibrated for the structural characteristics of tropical dry deciduous forests in Central India. The Malhi et al. (2021) study, which demonstrated high AGB estimation accuracy using Sentinel-1 and Sentinel-2 fusion in Gujarat's tropical forests, represents the closest precedent, but the Shoolpaneshwar Wildlife Sanctuary, while geographically proximate, encompasses a different forest type with higher rainfall and evergreen component than the dry deciduous forests of Vidarbha. The development of validated sensor fusion protocols for Vidarbha forest conditions, integrating the unique spectral advantages of Sentinel-2 Red Edge bands with the cloud-penetrating capability of Sentinel-1 SAR, constitutes an urgent and technically feasible research priority.

1.4 Policy-Technology Gap: Operational MRV for CCTS

The most consequential research gap from the perspective of India's climate policy implementation is the absence of an operational satellite-based MRV framework for forest carbon that is explicitly designed for compatibility with India's CCTS technical requirements and can be implemented using freely available open-source satellite data and processing tools. International MRV frameworks developed for other jurisdictions, including those used in Amazon REDD+ projects and Indonesian forest carbon programmes, cannot be directly transferred to Central Indian conditions without substantial recalibration of emission factors, allometric models, and satellite analysis protocols. The development of a replicable, open-source MRV framework for Indian tropical dry deciduous forests, demonstrably compliant with IPCC Tier 2 methodological requirements and aligned with CCTS verification standards, would provide the technical foundation needed for forest-based carbon credit projects to achieve commercial viability in India's emerging carbon market.

IV. CONCLUSION

This review has synthesised the state of knowledge across six interrelated research domains: the ecology and carbon stocks of Central Indian tropical dry deciduous forests, field-based biomass estimation methods, multi-sensor satellite remote sensing approaches, machine learning frameworks for carbon mapping, REDD+ MRV systems, and India's evolving carbon governance infrastructure. The principal conclusions that emerge from this synthesis are as follows.

First, tropical dry deciduous forests of Central India store carbon stocks ranging from approximately 27 to 59 tonnes of carbon per hectare in above-ground biomass across the gradient from degraded open forests to intact dense forest, with total ecosystem carbon stocks substantially higher when below-ground and soil pools are incorporated. These values place Central Indian forests at intermediate carbon density relative to the global range for tropical forests, but their vast spatial extent makes their collective carbon stock globally significant and their vulnerability to degradation a critical concern for India's climate commitments.

Second, multi-sensor satellite approaches combining Sentinel-2 optical data, Sentinel-1 SAR, and GEDI LiDAR, processed through machine learning algorithms in GEE, currently represent the state-of-the-art in forest carbon monitoring and demonstrate superior performance to any single-sensor approach. Machine learning algorithms, particularly Random Forest and Gradient Boosting, consistently outperform traditional regression approaches in biomass estimation from multi-sensor data, with R^2 values in the range of 0.75 to 0.93 reported for Indian tropical forest applications. However, these algorithms require robust field validation datasets of 50 or more georeferenced plots spanning the full range of forest structural conditions, and their performance is sensitive to the quality and representativeness of the training data.

Third, the Vidarbha region of Central India presents a uniquely favourable configuration of ecological significance, institutional infrastructure, and data availability for high-priority carbon monitoring research. The proximity of NEERI, VNIT, and MRSAC in Nagpur, the accessibility of major protected areas within a two-hour radius, the availability of all required satellite data at zero cost, and the immediate policy relevance of CCTS and REDD+ implementation collectively create a context in which investment in regional carbon monitoring research would yield disproportionately large scientific and policy returns.

Fourth, the policy landscape for forest carbon in India has undergone a fundamental transformation with the notification of the CCTS in 2023 and the opening of the Offset Mechanism in early 2026. These developments create both a demand for robust satellite-based MRV systems and an institutional pathway through which forest carbon monitoring research can translate directly into financial incentives for forest conservation in Central India. The alignment of scientific research priorities with this policy opportunity represents the most important strategic consideration for the research community working on forest carbon in Central India.

In conclusion, the multi-sensor satellite monitoring of carbon stocks in Central Indian tropical dry deciduous forests constitutes a scientifically tractable, technologically feasible, and policy-urgent research priority. The convergence of freely available satellite data, open-source cloud computing platforms, advances in machine learning, and a supportive policy environment for forest carbon finance creates conditions that are uniquely favourable for closing the substantial knowledge gaps that this review has documented. Future research should prioritise the development of locally calibrated, seasonally aware, multi-sensor biomass estimation models validated against comprehensive field inventory data, and the design of an operational MRV framework explicitly architected for CCTS compliance in tropical dry deciduous forest conditions.

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