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Modeling Terrestrial Carbon Sequestration: A Review-Based Mathematical Framework Integrating Remote Sensing and GIS

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Research Article

Keywords: Carbon Sequestration, Aboveground Biomass, Carbon Monitoring Framework

Posted Date: August 13th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-10456472/v1

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Additional Declarations: No competing interests reported.

Abstract

Terrestrial ecosystems play a vital role in mitigating climate change by sequestering atmospheric CO_2 in vegetation and soils. Accurate, large-scale, and spatially explicit quantification of carbon stocks is essential for informing climate policy, improving carbon accounting, and supporting credible carbon credit systems. However, traditional field-based methods are labor-intensive, spatially limited, and time-consuming, resulting in substantial uncertainties in national and global carbon budgets. Addressing this challenge requires scalable, efficient, and precise monitoring approaches. This review-based study presents an integrated mathematical framework that harnesses the spatial and spectral capabilities of Remote Sensing (RS) and Geographic Information Systems (GIS) to estimate carbon stocks across diverse terrestrial ecosystems. By combining satellite-derived vegetation indices such as the Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI), with established allometric equations and biomass-to-carbon conversion factors, the framework accurately estimates Aboveground Biomass (AGB) and associated carbon storage. It effectively captures spatial heterogeneity across forests, croplands, grasslands, and arid lands at high spatial resolution. This scalable and reproducible approach provides a powerful tool for high-resolution carbon monitoring, thereby enhancing capabilities for climate mitigation, sustainable land management, and transparent, verifiable carbon credit mechanisms, such as the Reducing Emissions from Deforestation and Forest Degradation (REDD+) mechanism.

Highlights

- Traditional field methods for carbon stock estimation are labor-intensive and limited.
- Developed an integrated framework using remote sensing, GIS, and mathematical modeling.
- Satellite vegetation indices combined with allometric equations create carbon maps.
- Forests store dense but vulnerable aboveground carbon; grasslands store resilient belowground.
- Framework enables scalable monitoring, land management, and climate policy support.

1. Introduction

The Earth's carbon cycle is a foundational biogeochemical system that has maintained planetary climate stability for millennia. This cycle regulates the exchange of carbon between the atmosphere, oceans, terrestrial ecosystems, and the geosphere, creating a dynamic equilibrium that sustains life and climate patterns. However, since the onset of the Industrial Revolution, this delicate balance has been disrupted by an unprecedented and accelerating perturbation in both magnitude and speed, predominantly driven by human activities (Regnier et al., 2013). The rapid release of greenhouse gases, particularly carbon dioxide (CO_2), from fossil fuel combustion, industrial processes, and land-use changes has fundamentally altered the atmospheric composition, triggering a persistent warming trend. This anthropogenic warming threatens the resilience and stability of natural ecosystems and human societies globally, making the understanding of these disruptions vital for devising effective mitigation and

adaptation strategies (Keenan & Williams, 2018). At the core of addressing this challenge lies the precise quantification of terrestrial carbon stocks and fluxes, which are critical components of the global carbon budget and climate regulation.

Continuous and direct monitoring of atmospheric CO_2 concentrations provides the most compelling evidence of human influence on the climate system. Since 1958, when pioneering measurements began at the Mauna Loa Observatory, atmospheric CO2 has exhibited a relentless upward trajectory, documented with increasing precision (Canadell et al., 2007). By 2024, the global average CO_2 concentration reached an unprecedented 422.7 parts per million (ppm), approximately 50% above pre-industrial levels (~280 ppm circa 1750). This sharp rise is primarily attributable to fossil fuel combustion, whose emissions have surged from roughly 11 billion metric tons of CO_2 annually in the 1960s to an estimated 37.4 billion metric tons in 2024. Additionally, industrial activities such as cement production and land-use changes, including deforestation, have substantially contributed to this increase (Intergovernmental Panel on Climate Change (IPCC), 2023).

More alarming than the absolute concentration is the accelerating, non-linear rate of CO_2 accumulation. The atmosphere absorbed an additional 3.75 ppm from 2023 to 2024 alone, the largest single-year increase ever recorded (https://www.noaa.gov/climate). Over the last six decades, the average annual accumulation rate has more than tripled, climbing from approximately 0.8 ppm/year during the 1960s to about 2.6 ppm/year in the past decade (https://wmo.int/). This rapid acceleration strongly suggests that Earth's natural carbon sinks, primarily the oceans and terrestrial ecosystems, are becoming progressively overwhelmed and less capable of buffering anthropogenic emissions. Climatic extremes, such as prolonged droughts and extensive biomass burning, exemplified by the recent massive wildfires in Canada and the Amazon rainforest, further exacerbate this trend, underscoring the presence of intensifying positive feedback loops within the climate system (Friedlingstein, 2015).

To fully appreciate the anomalous nature of modern atmospheric CO_2 levels, it is instructive to examine the long-term paleo-climatic record. Antarctic ice core data provide high-resolution snapshots of ancient atmospheric composition spanning 800,000 years. These records demonstrate that, throughout numerous glacial-interglacial cycles, CO_2 concentrations naturally oscillated between approximately 180 ppm during glacial periods and around 300 ppm during warmer interglacial phases (Canadell et al., 2007; Raupach et al., 2007). The current concentration, exceeding 422 ppm, vastly surpasses these historical bounds, representing the highest level in at least 800 millennia and very likely exceeding any point in the entirety of human evolution (https://wmo.int/). Equally striking is the velocity of this modern increase; CO_2 accumulation today is occurring 100 to 200 times faster than natural rises observed during the last deglaciation period, roughly 11,000 to 17,000 years ago (Lüthi et al., 2008). The Intergovernmental Panel on Climate Change (IPCC) unequivocally attributes this unprecedented surge to anthropogenic activities, chiefly fossil fuel combustion, industrial processes, and land-use changes (IPCC, 2023). This robust scientific consensus firmly links the current climate crisis to the industrial-scale disruption of the global carbon cycle.

In response to rising anthropogenic emissions, Earth's natural carbon sinks, the oceans and terrestrial ecosystems, play an indispensable role by partially offsetting atmospheric CO_2 accumulation and moderating the pace of global warming (Prentice et al., 2000). The Global Carbon Budget provides a comprehensive, quantitative framework that annually tracks sources, sinks, and atmospheric CO_2 concentrations. Analysis of emissions data from 2010 to 2019 indicates that approximately 46% of human-induced carbon emissions (~5.1 petagrams of carbon per year) remained in the atmosphere. The remainder was absorbed by natural sinks, with the oceans sequestering about 23% and terrestrial ecosystems capturing a significant 31% (~3.4 petagrams of carbon per year) (Liang et al., 2025). Collectively, these sinks remove roughly half of all anthropogenic CO_2 emissions annually, providing an essential yet often underappreciated ecosystem service that slows global warming and supports the global economy (Ussiri & Lal, 2017c). Despite the apparent stability of the "airborne fraction," the proportion of emissions remaining in the atmosphere, which has hovered around 44% for six decades, this conceals a system under mounting stress. Over this period, total anthropogenic emissions have more than tripled, necessitating that natural sinks also triple their carbon uptake to maintain this balance. This increasing burden pushes natural systems further from their historical equilibrium, threatening their long-term resilience and effectiveness.

The terrestrial carbon sink operates primarily through two mechanisms: photosynthetic uptake of CO_2, known as GPP, and subsequent carbon storage in vegetation biomass and soils. Terrestrial ecosystems exhibit substantial heterogeneity, with forests, croplands, grasslands, and arid lands each contributing distinctly to the global carbon cycle. Tropical, temperate, and boreal forests store the majority of their carbon in AGB, including trunks, branches, and leaves, and represent the largest active land carbon sink. Consequently, forest AGB is a critical metric for climate mitigation efforts, especially under international programs such as REDD+. Croplands and grasslands, while generally holding less AGB, contribute significantly to belowground biomass (BGB) and soil organic carbon (SOC), the latter being more stable and resilient to short-term climatic fluctuations. These ecosystems constitute globally important, though spatially diffuse, carbon reservoirs (Ussiri & Lal, 2017c). Arid and semi-arid lands, which cover extensive areas, also play a pivotal role in SOC storage, with carbon dynamics strongly influenced by interannual rainfall variability and pulse-driven uptake. The total terrestrial carbon stock is estimated at approximately 2,500 petagrams of carbon (PgC), with soils alone storing about 1,500 PgC, underscoring the critical need for accurate quantification of both biomass and soil carbon pools to effectively manage this global reservoir (Liang et al., 2025).

A major scientific concern is that the capacity and efficiency of these natural carbon sinks may decline under future climate change scenarios. Coupled climate-carbon cycle models consistently project diminished CO_2 absorption by terrestrial and oceanic systems as global temperatures rise (N. Krishnan et al., 2024). This reduction constitutes a potent positive feedback loop: warming decreases sink efficiency, leaving more emissions airborne, which in turn accelerates warming and further weakens the sinks. Consequently, achieving atmospheric CO_2 stabilization will require substantially deeper emissions cuts than currently projected. Terrestrial sinks are especially vulnerable, facing degradation from direct

human impacts, such as deforestation and land-use change, as well as climate-induced stressors, including more frequent droughts, heatwaves, and wildfires (Ussiri & Lal, 2017a). Under medium- to high-emission trajectories, there is a credible risk that terrestrial ecosystems could transition from net carbon sinks to net sources within decades, triggering rapid increases in atmospheric CO_2 and exacerbating the severity of climate change. This looming vulnerability highlights the urgent need for enhanced monitoring and robust quantification of terrestrial carbon stocks to inform timely land management and mitigation policies.

Despite their critical importance, quantifying terrestrial carbon stocks explicitly at the spatial scale remains methodologically challenging. Traditional field-based methods, including forest inventories, plot sampling, and destructive harvesting, yield highly accurate local data but are labor-intensive and temporally infrequent. Scaling these measurements to heterogeneous, landscape-wide extents introduces significant sampling error and non-representativeness, leading to considerable uncertainty in national and global carbon budgets. These uncertainties hinder accurate reporting under international climate agreements and impede verification for carbon credit markets.

The primary objective of this review-based study is to develop and validate an integrated, scalable mathematical framework for modeling terrestrial carbon sequestration by leveraging the complementary strengths of remote sensing and Geographic Information Systems (GIS). Specifically, the framework will utilize satellite-derived vegetation indices and widely accepted allometric relationships to estimate AGB across diverse ecosystems, including forests, croplands, grasslands, and arid lands, demonstrating transferability and capacity to capture spatial heterogeneity. By producing high-resolution carbon stock maps and rigorously validating them against independent field data, the study aims to quantify the accuracy and robustness of this approach. Ultimately, the framework aims to serve as a policy-relevant tool to support climate mitigation programs (such as REDD+), sustainable land management, and carbon credit mechanisms. The following sections detail the methodology and broader implications of this integrative Modeling approach.

2. Pre-Existing Overview on Quantifying Terrestrial Carbon Stocks

2.1. Forest Ecosystems as Carbon Sinks

Forests constitute the largest terrestrial carbon sinks due to their high biomass density and structural complexity. Globally, forest ecosystems store approximately 45% of all land-based organic carbon, distributed between living biomass and soils (Augusto & Boča, 2022). Carbon sequestration capacity varies notably across forest biomes, with tropical forests generally exhibiting the highest carbon density per unit area. Carbon within these ecosystems is partitioned into several key pools: AGB (including stems, branches, and foliage); BGB (primarily root systems); forest floor litter; and soil organic carbon (SOC). Precise quantification of these carbon pools is critical for effective climate change mitigation, accurate carbon accounting, and sustainable forest management practices (Araújo Filho et al., 2018). Traditional forest inventory methods involve direct field measurements of tree parameters such as

diameter at breast height (DBH), tree height, and wood density (Hese et al., 2005). These measurements are applied to allometric equations to estimate biomass. While this approach yields high accuracy at localized plot scales, it is inherently labor-intensive, time-consuming, and spatially limited (Blakemore, 2024). Moreover, scaling these measurements to broader regional or national levels introduces potential errors arising from sampling design biases, species diversity, and variability in measurement protocols. These challenges underscore the need for complementary approaches, particularly remote sensing technologies, to provide comprehensive, high-resolution, wall-to-wall coverage of forest carbon stocks.

To overcome these inherent spatial limitations, Remote Sensing has emerged as a transformative technology for upscaling forest carbon estimations to landscape and regional scales (Xu et al., 2025). Optical satellite data, such as that from the Landsat series, provide various Vegetation Indices, like the NDVI and EVI, that exhibit strong spectral correlations with AGB. Crucially, active remote sensing modalities, including Light Detection and Ranging (LiDAR) and Synthetic Aperture Radar (SAR) (Elaksher, 2008), offer complementary capabilities by providing detailed three-dimensional information on canopy structure (e.g., height, density, and vertical foliage distribution). This structural data is particularly valuable for improving biomass estimates in dense or structurally complex forests where optical signals often saturate, limiting accuracy (Ahmad et al., 2021).

The integration of RS data within a Geographic Information System (GIS) framework is paramount. GIS enables spatial processing and integration of ancillary datasets, including soil type, climate variables, and topography, thereby generating spatially explicit and accurate carbon stock maps. Allometric models remain a critical component in converting RS-derived structural variables (such as canopy height) into biomass and, subsequently, carbon estimates (Canadell et al., 2007). These integrated RS-GIS approaches have been successfully deployed across diverse forest ecosystems globally, providing critical, scalable data to support international sustainable management practices and climate policies. The necessity of this integrated approach extends beyond forests to other, less structurally complex, yet globally vital, terrestrial biomes.

2.2. Agricultural Lands

Agricultural ecosystems contribute significantly to the global carbon cycle through sequestration in both crop biomass and Soil Organic Carbon. While the carbon stored in the aboveground biomass of annual crops is generally transient and quickly cycled, the soils within croplands and agroforestry systems represent significant long-term carbon reservoirs. The magnitude of this sequestration is highly contingent upon local variables such as crop type, soil characteristics, and, most critically, management practices. The adoption of climate-smart agriculture, including conservation tillage (e.g., no-till systems), planting cover crops, and integrating trees into agroforestry, has been consistently shown to substantially enhance SOC accumulation and improve overall ecosystem sustainability. The potential impact is substantial; some analyses suggest that increasing soil carbon sequestration by just 0.4% annually could offset 20 – 35% of global greenhouse gas emissions (Lessmann et al., 2022).

Remote Sensing offers a scalable, cost-effective means to monitor crop productivity, transient biomass, and SOC dynamics at regional to national scales. Vegetation indices derived from optical imagery are widely employed to estimate crop biomass, while multispectral and hyperspectral sensors provide detailed insights into crop type, phenological stage, and physiological health (Savaliya & Raj, 2024). Geographic Information Systems (GIS) platforms are instrumental for integrating RS-derived variables with essential soil, land-use, and climate datasets, thereby supporting robust spatial modeling of both SOC and biomass stocks (Wang et al., 2025). Integrated methodologies combining RS, GIS, and advanced modeling have proven highly effective at capturing the spatial variability of carbon stocks in heterogeneous agricultural landscapes. Furthermore, the use of multi-temporal satellite data enables the critical assessment of carbon dynamics across single crop cycles and over multi-year trends, offering invaluable insights for refining climate-smart agricultural policies and for accurate carbon accounting initiatives (Ouattara et al., 2025).

2.3. Grasslands and Belowground Carbon Storage

Covering approximately 40% of the Earth's terrestrial surface, grasslands constitute a globally significant carbon reservoir, with their importance primarily in the vast quantities of carbon stored in belowground biomass and SOC. While the aboveground biomass is considerably lower than in forests, the extensive, dense root systems of grasses, coupled with the biome's vast spatial extent, result in a cumulative carbon stock of global importance, storing an estimated 20 – 30% of the world's soil carbon. The long-term sequestration potential of these ecosystems is fundamentally underpinned by the persistence of this large belowground organic matter pool, with approximately 90% of a grassland's total carbon stored safely underground (Terasaki Hart et al., 2023).

The use of multi-temporal datasets is crucial here for capturing rapid seasonal fluctuations in growth, enabling the monitoring of carbon fluxes over time (Lu et al., 2024). GIS facilitates mapping of grassland carbon stocks across diverse landscapes and provides critical support for decision-making on grazing management, conservation strategies, and land-use planning. Recent methodological advancements involve integrating RS data with machine learning algorithms, such as Random Forests and neural networks. These techniques significantly improve estimation accuracy by effectively modeling the non-linear relationships and inherent heterogeneity within grassland ecosystems. Such integrated approaches are particularly valuable for assessing carbon stocks in remote or inaccessible regions where the collection of extensive field data is logistically challenging and expensive (Lessmann et al., 2022).

2.4. Deserts and Arid Lands

Desert ecosystems, though characteristically defined by sparse vegetation and low annual productivity, make a notable contribution to terrestrial carbon storage, primarily through their vast extent and stable soil pools. Covering approximately 35% of the Earth's land surface, these biomes represent a substantial, though often overlooked, global carbon reservoir. Organic matter accumulates slowly in desert soils over millennial timescales, forming a highly stable, long-term Soil Organic Carbon (SOC) reservoir (Xiaohong

et al., 2023). Short-term carbon storage occurs through the growth of shrubs, ephemeral grasses, and lichens during brief periods of favorable climatic conditions, linking the carbon sink to precipitation pulses.

Remote Sensing (RS) techniques are essential for overcoming the remoteness and heterogeneity of arid environments. Indices like the Normalized Difference Vegetation Index (NDVI) and the Soil Adjusted Vegetation Index (SAVI), derived from high-resolution imagery, are crucial for detecting sparse vegetation patches and assessing highly dynamic biomass patterns (Almalki et al., 2022). Geographic Information Systems (GIS) platforms are vital for integrating these spectral observations with essential soil, topographic, and climatic data to produce spatially explicit assessments of carbon stocks. Given the episodic nature of productivity in these systems, the use of multi-temporal RS datasets is particularly effective for capturing intermittent vegetation growth and for evaluating the impacts of desertification and land degradation on carbon storage potential over time (Tian et al., 2023).

3. Integrated Modeling Approaches for Terrestrial Carbon Quantification

Mathematical and computational models serve as the necessary bridge for converting raw RS-derived variables into quantifiable carbon estimates. The classical approach relies on allometric equations, which are widely applied to estimate AGB from structural parameters (e.g., height, canopy cover) inferred from satellite data. Similarly, BGB is typically estimated using empirically derived root-to-shoot ratios specific to the ecosystem type, and the total biomass is subsequently converted to carbon mass using standardized conversion factors.

This foundational approach is now being significantly advanced by the emergence of machine learning (ML) and artificial intelligence (AI) techniques, which have substantially enhanced the accuracy and generalizability of terrestrial carbon modeling (Vassilis & Vassilia, 2025). Algorithms such as Random Forests, Support Vector Machines, and Neural Networks can effectively capture the complex, non-linear relationships between spectral and structural RS data and highly heterogeneous field-measured biomass. This capability is critical because traditional linear models often fail in areas of high biomass (due to saturation of optical signals) or in mixed-species ecosystems. The superior predictive performance of ML models enables improved accuracy and, crucially, better transferability across diverse ecosystems. Coupling these advanced computational models with GIS enables the seamless creation of detailed, high-resolution, and validated carbon stock maps. These integrated RS-GIS-ML frameworks are now recognized as essential tools for national and regional ecosystem monitoring, transparent carbon accounting, and the science-based development of effective climate policy.

3.1. Methods for Estimating Terrestrial Carbon Sequestration (Field-Based Approach)

Terrestrial ecosystems store carbon in five major pools: above-ground biomass (AGB), below-ground biomass (BGB), dead litter, woody debris, and soil organic matter (SOM). Among these, above-ground tree biomass is the largest and most readily observable carbon pool, making forests the most significant terrestrial carbon sinks. Carbon exchange among these pools occurs primarily via photosynthesis, respiration, litterfall, and decomposition (Dahy et al., 2019).

3.1.1. Field Sampling Design

The choice of non-destructive sampling methods is justified because it allows for biomass estimation without damaging the carbon reservoir (i.e., the trees), which is standard practice in ecological and conservation-focused studies (Piao et al., 2022). The field sampling design, employing a systematic grid with random selection, is a robust technique for ensuring both spatial coverage and statistical randomness across a large, heterogeneous study area (Jr et al., 2016).

Specifically, Systematic Grid (1×1 km) is the division of the study area into 1×1 km grids, establishing a systematic sampling frame that ensures the entire landscape, regardless of access or cover type, is available for potential sampling. This grid size is a common unit for linking localized field data to coarse-resolution satellite imagery pixels or GIS layers, thereby facilitating the crucial upscaling process (Gibbs et al., 2007). However, Random Selection (10%) involves selecting 10% of these grids at random, ensuring that the sampled plots are statistically representative of the overall variability in the study area and reducing the risk of subjective bias in site selection. A 10% intensity is generally considered sufficient to achieve a reasonable balance between the necessary statistical power and the logistical constraints of fieldwork. Moreover, the Use of Quadrats involves laying fixed-area quadrats (plots) within the selected grids, which provides standardized boundaries for data collection. This ensures that all measurements. This standardization is critical for calculating biomass density (e.g., tons per hectare) and for providing the necessary calibration points for RS models (Longhini et al., 2022).

Basically, the Tree height was measured using a clinometer and mentioned in Fig. 1. The height of each tree was calculated using the formula:

$$Tree\ Height = H + D \times\ tan\,(A)$$

Where,

- H = height of the clinometer from the ground (m)
- D = horizontal distance from the observer to the tree (m)
- A = angle of elevation measured with the clinometer (°)

GBH was measured with a tape measure at 1.3 m above ground level.

3.1.2. Estimation of Above-Ground Biomass

The AGB represents all biomass aboveground, including stems, branches, and leaves (Thenkabail, 2015), and is the most significant carbon pool in woody ecosystems. For a review-based study, the AGB estimation methodology was based on established forest inventory protocols designed to maximize accuracy and minimize sampling effort. Trees with a diameter greater than 50 cm were sampled using a random sampling approach (Zimudzi & Chapano, 2016). This focus on large-diameter individuals is justified because, in most forest structures, a small number of large trees contribute disproportionately (often over 50%) to the total stand biomass, making them critical for accurate AGB estimates (Ma et al., 2024). Random sampling was employed to ensure that the sampled plots were statistically representative of the entire study area, reducing potential spatial bias in the overall biomass calculation (Husch et al., 2003). Within the defined sample plots, quadrats were used to record Girth at Breast Height (GBH) and tree height for each dominant species (Zimudzi & Chapano, 2016). These direct measurements are essential because they serve as the independent variables for subsequently calculating AGB using widely accepted allometric equations (Longhini et al., 2022). Allometric equations, which convert these easily measurable dimensions into biomass, are the industry standard for non-destructive AGB estimation. Generally, ABG is estimated using species-specific allometric equations:

$$\mathrm{AGB}(\mathrm{g/tree}) \;=\; \mathrm{Tree\ Volume}\ \left(\mathrm{cm}^3\right) \times\ \ \mathrm{Wood\ Density}\ \left(\mathrm{g/cm}^3\right)$$

Tree volume was approximated as a cylindrical shape:

$$Tree\ Volume = \pi\, r^2 H$$

Where:

$$r = \frac{GBH}{2\pi}\ (cm)$$

•

- H =tree heights (cm)
- Wood density (ρ) = 0.6 g/cm^3 (average value used if species-specific data unavailable)

Thus, the final AGB formula becomes:

$$AGB = \frac{(GBH)^2}{4\pi} \times\ H \times\ \ \rho$$

Units: Kilograms (kg) per tree.

3.1.3. Estimation of Below-Ground Biomass

The methodology for estimating BGB is standard practice in ecosystem carbon accounting due to the difficulty of direct measurement. The definition of BGB as including live roots with a diameter greater than 2 mm is a common convention used to focus the measurement on the major structural root

biomass, while fine roots (which have very high turnover rates and are difficult to completely sample) are often treated separately or omitted for large-scale carbon stock assessments (Suárez-Fernández et al., 2025).

The calculation of BGB using the root-to-shoot ratio (RSR) method is widely justified as the most pragmatic, non-destructive, and scalable approach for forest and grassland inventories (N. Krishnan et al., 2024). Direct measurement of BGB is highly labor-intensive, costly, and destructive (involving soil excavation), making it infeasible for large-area studies. Therefore, RSR is used to indirectly estimate BGB as a fixed fraction of the more easily measurable AGB (BGB = AGB×RSR). The RSR values used are derived from comprehensive meta-analyses that provide reliable, ecosystem-specific factors (Cairns et al., 1997; Mokany et al., 2006). This reliance on RSR ensures that BGB estimation is consistent, cost-effective, and scalable, which is crucial for integration with RS/GIS frameworks.

For example, the BGB includes live roots with a diameter > 2 mm. It is calculated as a fraction of AGB using the root-to-shoot ratio method. (N. Krishnan et al., 2024):

$$\mathrm{BGB} = \mathrm{AGB} \times\ 0.26$$

Where 0.26 is the standard root-to-shoot ratio for the studied forest ecosystem.

3.1.4 Estimation of Total Biomass

The estimation of Total Biomass as the sum of Above-Ground Biomass and Below-Ground Biomass is the fundamental definition used in terrestrial ecology and carbon accounting for quantifying the complete living carbon reservoir of an organism. The calculation is mathematically straightforward:

TB = AGB+BGB

Where:

- &TB = Total biomass (ton/tree)
- AGB = Above-ground biomass (ton/tree)
- BGB = Below-ground biomass (ton/tree)

This approach is justified for various reasons, like Summing AGB (calculated via allometry) and BGB (calculated via the root-to-shoot ratio) provides the most comprehensive, non-destructive estimate of the total carbon sequestration capacity contained within the tree's living structure. This is a critical metric for accurate ecosystem-level carbon budgets (IPCC, 2006). Additionally, the Standard Protocol is the universally accepted standard established by international bodies, including the Intergovernmental Panel on Climate Change (IPCC), for calculating biomass in national greenhouse gas inventories and global carbon models. Adhering to this protocol ensures that the results of a review-based study are comparable and compatible with other regional and global assessments (Brown, 1997).

3.1.5. Estimation of Carbon Storage

The estimation of carbon storage by assuming that 50% of total biomass is carbon (expressed as C = TB×0.5) is the universally accepted convention for large-scale carbon accounting in ecological studies and national inventory reporting. The use of a fixed factor, typically 0.5 (or 50%), is the default and most widely recognized standard recommended by the Intergovernmental Panel on Climate Change (IPCC) for national greenhouse gas inventories (IPCC, 2006). This factor reflects the average carbon concentration across various plant species, wood densities, and tissue types (Brown, 1997). Whereas, Scalability and Comparability: Employing a standardized factor ensures that the carbon estimates are comparable with other regional, national, and global carbon stock assessments, which is crucial for meeting international reporting requirements and evaluating climate mitigation efforts. Moreover, Practicality for RS/GIS: This simplified conversion is highly practical for large-scale RS/GIS modelling, as it allows for the seamless scaling of plot-level biomass data to entire forest stands and, subsequently, to the regional level by aggregating carbon stocks across all sampled and mapped units.

3.2. Methods for Estimating Terrestrial Carbon Sequestration (Remote Sensing + GIS Approach)

3.2.1. Remote Sensing Data Acquisition

The selection of Landsat-8 OLI, Sentinel-2 MSI, and MODIS datasets is justified by the need to capture a complementary range of spatial, spectral, and temporal resolutions essential for robust, scalable, and dynamic carbon sequestration modelling (Gibbs et al., 2007). No single sensor can effectively meet all these requirements, necessitating a multi-sensor approach. Furthermore, this sensor provides the long-term historical context and a widely accepted moderate spatial resolution (30 m), making it ideal for calculating Vegetation Indices (VIs) and serving as the foundational layer for regional AGB estimation where high spatial detail is needed but LiDAR is unavailable (Wawrzyniak et al., 2017). Additionally, Sentinel-2 MSI (10–20 m): This sensor provides high spatial detail (10 m to 20 m resolution) and superior spectral bands (e.g., three red-edge bands), which are critical for high-detail vegetation monitoring and reducing the effects of canopy signal saturation in dense forests. Its frequent revisit time improves the probability of obtaining cloud-free imagery for accurate VI calculation and calibration of AGB models (Drusch et al., 2012). Also, MODIS (Moderate Resolution Time-Series): This sensor, despite its coarser spatial resolution (~250 m to 1 km), offers high temporal resolution (daily to weekly). This makes it indispensable for monitoring seasonal and interannual vegetation dynamics and carbon flux trends, particularly in grasslands and agricultural lands where phenology and productivity change rapidly (Alcantara et al., 2012).

Vegetation indices derived from these datasets serve as proxies for aboveground biomass:

$$NDVI = \frac{NIR - Red}{NIR + Red}$$

$$EVI = 2.5 \times \frac{NIR - Red}{NIR + 6 \times\ Red - 7.5 \times\ Blue + 1}$$

$$SAVI = \frac{(1 + L) \times (NIR - Red)}{NIR + Red + L}$$

Where NIR, Red, and Blue represent spectral reflectance; L is the soil adjustment factor (0.5)

3.2.2. GIS Data Integration

The use of Geographic Information Systems (GIS) to integrate various ancillary spatial layers is fundamentally justified because carbon sequestration is a complex process controlled by biophysical factors that extend beyond what satellite imagery alone can measure (Dahy et al., 2020; Hese et al., 2005). GIS acts as the crucial spatial platform for fusing these disparate data sources to build a comprehensive prediction model.

Specifically, the Land-use / Land-cover (LULC) Map is essential for stratifying the study area, allowing the application of ecosystem-specific models (e.g., forest allometric, grassland root-to-shoot ratios). This stratification is key to minimizing prediction errors that arise from applying a single model across diverse biomes (Araújo Filho et al., 2018). Also, Soil Type and Texture: These factors are primary determinants of Soil Organic Carbon (SOC) stability and storage capacity. They are vital for the spatial interpolation of SOC stocks, as they influence decomposition rates, nutrient availability, and plant productivity (Ussiri & Lal, 2017b). Most probably, Topography influences microclimate, soil depth, and moisture regimes, which in turn impact vegetation distribution and biomass accumulation. Digital Elevation Models allow for the correction of topographic effects on spectral data and serve as an important independent variable in spatial modelling of AGB (Ahmad et al., 2021). However, Climate Variables (Precipitation, Temperature), and these variables directly control plant growth, Net Primary Productivity (NPP), and decomposition rates. Integrating climate data allows the models to account for regional productivity gradients and temporal variations, which is essential for accurate spatial interpolation of both biomass and soil carbon, and the eventual generation of reliable carbon stock maps (Dahy et al., 2020).

3.2.3. Aboveground Biomass

AGB is estimated using RS-derived VIs calibrated with field-measured biomass. This relationship is mathematically modeled using various regression techniques (linear, non-linear, or machine learning), but fundamentally relies on the principle that the VI is a proxy for photosynthetic capacity and green biomass density (Yang et al., 2023). The core challenge in using Remote Sensing (RS) data for carbon assessment is the transition from spectral information (reflectance values) to physical, biophysical properties (biomass). The use of Vegetation Indices (VIs) and their calibration with field data is justified as the standard mathematical approach for estimating AGB across large areas (D. Jensen et al., 2024).

AGB is estimated using RS-derived vegetation indices calibrated with field-measured biomass:

$$AGB_{RS} = a \times VI^{b}$$

Where:

- V I = NDVI, EVI, or SAVI
- a, b = regression coefficients determined from field data

Machine learning models (Random Forest, Support Vector Regression) can be used to capture nonlinear relationships

$$AGB_{RS} = f\left(NDVI,\ EVI,\ SAVI,\ SoilType,\ Elevation,\ Climate\right)$$

3.2.4 Belowground Biomass

The estimation of Belowground Biomass (BGB) using the root-to-shoot ratio (RSR) method is justified as a necessary and scalable indirect approach for RS/GIS modeling, particularly given the large spatial extent of the study area. Direct measurement of BGB (i.e., root excavation) is environmentally destructive, extremely labor-intensive, and logistically infeasible for regional-scale remote sensing studies (Mokany et al., 2006).

Following the above statement, BGB is calculated using the root-to-shoot ratio:

$$BGB_{RS} = AGB_{RS} \times\ R/S$$

Where R/S depends on ecosystem type:

Forests: 0.24–0.30

Grasslands: 0.25–0.40

Agricultural lands: 0.10–0.20

By integrating BGB to the continuous AGB map, the RSR method allows for wall-to-wall mapping of belowground carbon stocks without harmful sampling, ensuring the technology stays cost-effective and scalable for GIS integration (A. R. Krishnan et al., 2024). Although simplified, using biomes-specific RSR values (for example, higher for grasslands than forests) is a generally acknowledged norm supported by international carbon accounting rules, guaranteeing that the results are comparable to other global and country carbon budget estimates (IPCC, 2006).

3.2.5. Soil Organic Carbon

The estimation of Soil Organic Carbon (SOC) by integrating field measurements and GIS-based spatial interpolation is justified as the most accurate and practical method for mapping this heterogeneous and highly complex carbon pool over large areas. Unlike biomass, SOC cannot be directly measured by current Remote Sensing (RS) technology; therefore, a hybrid approach is essential (Dahy et al., 2020).

In general, SOC is estimated by integrating field measurements and GIS-based spatial interpolation:

$$SOC_{RS} = f(SpectralIndices,\ SoilType,\ Elevation,\ Precipitation,\ Temperature)$$

Methods such as Kriging or Inverse Distance Weighting (IDW) are applied to create spatial SOC maps.

Initial field sampling provides the necessary ground-truth points (actual measured SOC concentrations) against which all spatial models must be calibrated and validated. Since SOC storage is highly sensitive to local factors and varies significantly even over small distances, these physical measurements are irreplaceable (Ussiri & Lal, 2017c). GIS Integration and Digital Soil Mapping (DSM platform is used to integrate environmental covariates (Soil Type, Texture, Climate, DEM, and LULC) that are known to drive the spatial distribution of SOC (Dahy et al., 2020). These static layers provide continuous spatial data that explain the variance in SOC (Jenny, 1941). Additionally, the spatial interpolation method (g) uses the relationship between the SOC ground-truth points and the environmental covariates to predict SOC values across the entire study area (Hese et al., 2005). This Digital Soil Mapping (DSM) technique is the state-of-the-art for generating continuous, high-resolution SOC maps at regional scales, which is critical for complete ecosystem carbon accounting.

3.2.6. Total Carbon Stock Calculation

The calculation of Total Terrestrial Carbon (TC) at a pixel or stand level is performed by summing the carbon stored in all major terrestrial pools: Aboveground Biomass (AGB), Belowground Biomass (BGB), and Soil Organic Carbon (SOC). This additive approach is the universally accepted methodology for comprehensive carbon stock accounting, as established by global reporting standards (IPCC, 2006).

Therefore, the total terrestrial carbon at a pixel or stand level is calculated as

$$C_{total}\left(x,y\right)=4.7\times\ \left(ABG_{RS}\left(x,y\right)+BGB_{RS}\left(x,y\right)\right)+SOC_{RS}(x,y)$$

Where 0.47 is the biomass-to-carbon conversion factor. This generates spatially explicit carbon stock maps for forests, agricultural lands, grasslands, and deserts.

This comprehensive summation is justified by the Completeness of the Carbon Budget: It captures all three major, quantifiable pools, providing a holistic and accurate representation of the total carbon sequestered by the ecosystem, which is critical for national-level inventories and ecological modelling (Brown, 1997). Compatibility with the Policy formula directly aligns with the reporting requirements of international climate frameworks, ensuring the results are directly applicable to policies like REDD + and voluntary carbon market validation.

3.2.7. Model Validation

Model validation is the essential final step in the integrated RS/GIS methodology and is justified by the need to quantify and report the predictive reliability and uncertainty of the regional carbon maps (Drusch et al., 2012). Since RS models rely on empirical relationships established through calibration, their outputs must be independently verified against data not used during the model training phase. Validation is conducted by comparing the RS/GIS-based carbon estimates (predicted values) with the field-measured biomass and SOC (observed ground-truth values). Measures the proportion of variance in the field data that is explained by the RS/GIS model. A high R^2 (e.g., above 0.80) indicates a strong linear

relationship and high explanatory power. Further, Root Mean Square Error (RMSE) quantifies the average magnitude of the error between the predicted and observed values. RMSE is reported in the same units as the carbon estimate (e.g., tons per hectare) and provides a crucial measure of the model's accuracy (S. S. Jensen et al., 2017). Also, Bias (Mean Error): Indicates whether the model systematically overestimates or underestimates the carbon stocks, which is critical for accurate national-level inventories.

Validation is conducted by comparing RS/GIS-based carbon estimates with field-measured biomass and SOC:

$$R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \hat{y}_i)^2}$$

$$RMSE = \sqrt{\frac{\sum (y_i - \hat{y}_i)^2}{n}}$$

Where:

$$y_i = \text{field} - \text{measured carbon}$$

$$\hat{y}_i = \text{RS/GIS } - \text{prefiсated carbon}$$

n = number of validation points

High R^2 (> 0.85) and low RMSE (< 15%) indicate robust model performance

This rigorous statistical validation ensures that the final carbon maps are not only spatially comprehensive but also scientifically credible and policy-relevant, directly addressing the primary barrier of persistent uncertainty identified in the introduction (Hese et al., 2005).

The differences outlined in Table 1 are consistently validated across the academic literature, reflecting the inherent trade-off between detail and spatial extent in carbon accounting methodologies. Field-based methods are the *sine qua non* for high-accuracy, localized data (Hese et al., 2005), providing the necessary species-specific detail and microenvironmental sensitivity that serve as the ground truth (Blakemore, 2024), essential for developing and validating allometric equations. Conversely, the RS/GIS approach overcomes the inherent scalability and logistical constraints of fieldwork by providing continuous, wall-to-wall coverage across vast, heterogeneous regions at a significantly lower cost and faster temporal resolution (Ouattara et al., 2025; Xu et al., 2025). While RS data may suffer from limitations like signal saturation in dense forests (Ahmad et al., 2021), its integration with GIS and mathematical modeling remains the only viable strategy for generating the scalable, policy-relevant carbon maps required for national reporting and climate mitigation mechanisms like REDD+ (Andoh & Lee, 2018; Gibbs et al., 2007).

Table 1
Qualitative Comparison of Terrestrial Carbon Quantification Approaches

Feature	Field-Based Approach (Ground-Truth)	RS/GIS Approach (Modeling)
Accuracy	High for localized plots; captures species-specific and microenvironmental heterogeneity (ground truth).	Moderate to High at regional scales; calibrated by field data; may suffer saturation or underestimation in dense/sparse areas.
Spatial Coverage	Limited to sampled quadrats and grids; spatially discontinuous; resource-intensive.	Continuous spatial coverage (wall-to-wall mapping) over vast regions (regional to global).
Temporal Resolution	Static (single-time measurements); requires repeated, costly surveys for time-series analysis.	Dynamic (multi-temporal monitoring) is possible using satellite time-series data (e.g., MODIS); it is cost-effective for trend analysis.
Ecosystem Sensitivity	Captures fine-scale variations in species composition and vertical structure.	Sensitive to Vegetation Indices (VIs); limited by signal saturation in high-biomass forests and atmospheric interference.
Scalability	Challenging and impractical to scale beyond sampled plots due to logistical demands.	Highly scalable to regional, national, and global levels for policy and reporting.
Labor and Cost	High in labor, time, and monetary cost due to intensive fieldwork logistics.	Lower fieldwork labor; cost primarily allocated to data processing and high-performance computing resources.
Integration with Models	Provides essential validation and calibration datasets; direct input for allometric calculations.	Core platform for spatial modeling and carbon mapping; relies on field data for rigorous calibration and uncertainty assessment.

4.3. Significant Observations and Synthesis

The synthesis of findings reveals a clear methodological dichotomy and distinct ecosystem-specific carbon allocation strategies. Field-based inventory methods provide unparalleled local precision, capturing fine-scale variations in biomass and soil carbon influenced by species composition, soil properties, and microclimatic conditions (Drusch et al., 2012). In sharp contrast, Remote Sensing (RS) and Geographic Information System (GIS) technologies offer extensive spatial coverage, which is indispensable for regional-scale assessment and for monitoring temporal changes in carbon stocks (Bustamante et al., 2016; Grinand et al., 2017). The integration of these two approaches is thus critical for reliable estimation; calibrating RS-derived models with high-fidelity field data significantly enhances predictive reliability (Łągiewska & Panek-Chwastyk, 2025), creating a complementary methodology that leverages both local accuracy and broad-scale applicability.

The analysis also underscores marked differences in carbon storage strategies across biomes. Forests exhibit the highest carbon density, predominantly concentrated in vulnerable Aboveground Biomass (AGB) (Augusto & Boča, 2022). Grasslands, conversely, store the vast majority of their carbon—often as

much as 90%—belowground in extensive root systems and stable Soil Organic Carbon (SOC), a strategy that confers greater resilience to surface disturbances like fire (Terasaki Hart et al., 2023). Carbon stocks in agricultural lands are highly dynamic and fundamentally dependent on strategic management practices such as conservation tillage and the use of cover crops, highlighting the potential for offset schemes (Lessmann et al., 2022). Finally, deserts, despite their sparse vegetation, represent globally significant and highly stable carbon reservoirs, with SOC accounting for nearly 90% of the total ecosystem stock in some arid regions (Xiaohong et al., 2023).

4.4. Implications for Carbon Management and Policy

The methodological synergy established between field-based measurements and RS/GIS technologies provides a robust framework for terrestrial carbon assessment, effectively capitalizing on the respective strengths of local accuracy and broad spatial coverage (Xu et al., 2025). The spatially explicit carbon maps generated by this integrated approach are invaluable for guiding strategic land-use planning and enabling targeted efforts in reforestation, sustainable forest management, and conservation in carbon-rich landscapes. Furthermore, RS's capacity to monitor carbon dynamics over time is critical for tracking sequestration trends and quantitatively evaluating the efficacy of climate mitigation policies (Ouattara et al., 2025). This enhanced, ecosystem-specific understanding of carbon dynamics provides the essential scientific foundation necessary for credible carbon accounting in voluntary carbon markets and international frameworks such as REDD+ (Reducing Emissions from Deforestation and Forest Degradation), ultimately bridging the gap between scientific measurement and actionable climate policy (Araújo Filho et al., 2018).

5. Conclusion and Future Direction

The pivotal role of terrestrial ecosystems in the global carbon cycle underscores the need for an integrated methodological approach to assess them accurately. This framework successfully combines the precise, plot-level data from field measurements (serving as ground-truth) with the broad, spatially continuous coverage provided by Remote Sensing (RS) and Geographic Information Systems (GIS). This dual approach effectively balances local accuracy with landscape-scale evaluation, enabling quantification of both microenvironmental heterogeneity and regional carbon dynamics. Our analysis revealed fundamentally distinct carbon storage strategies across biomes: Forests are high-density reservoirs concentrated in vulnerable Aboveground Biomass (AGB), whereas grasslands, croplands, and deserts rely heavily on vast, resilient Belowground and Soil Organic Carbon (SOC) pools. The crucial step of calibrating RS models with high-fidelity field data mitigates the inherent limitations of each method, such as saturation in dense canopies, significantly enhancing the predictive accuracy and reliability of the resulting carbon maps.

Looking forward, the methodological synergy between field-based and RS/GIS technologies must shift from static stock assessment to dynamic monitoring of carbon fluxes. Future research should prioritize expanding field datasets to improve model calibration across diverse ecosystems, integrating high-resolution environmental variables such as soil texture and microclimate into GIS models, and exploring

advanced machine learning algorithms (e.g., deep learning) to overcome technical challenges in highly heterogeneous landscapes. From a policy standpoint, the continued application of this robust, scalable framework is vital to evidence-based climate action. The spatially explicit carbon maps generated are indispensable for developing accurate national greenhouse gas inventories, supporting credible carbon credit schemes, and optimizing international frameworks like REDD+. Ultimately, this methodology not only advances the scientific understanding of global carbon dynamics but also provides an essential, practical tool for guiding strategic land-use planning and ensuring effective, evidence-based climate mitigation.

Declarations

Funding

Not applicable.

Author Contribution

Raj Singh: Conceptualization, Literature Review, Methodology, Data Curation, Formal Analysis, Visualization, Writing – Review & Editing.Dusmant Maharana: Methodology, Validation, Writing – Review & Editing.Prashantkumar Sathvara: Conceptualization, Methodology, Supervision, Project Administration, Validation, Writing – Original Draft, Resources, Corresponding Author.All authors have read and approved the final version of the manuscript and agree to be accountable for all aspects of the work.

Acknowledgement

The authors sincerely thank the Department of Environmental Science, School of Sciences, P P Savani University, Surat, Gujarat, India, and the Department of Environmental Science, Parul University, Vadodara, Gujarat, India, for their academic support and encouragement during the preparation of this manuscript.The authors are grateful to the anonymous reviewers and the Editor for their valuable comments and suggestions, which helped improve the quality of the manuscript.

Data availability

Data will be made available on reasonable request.

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Figures

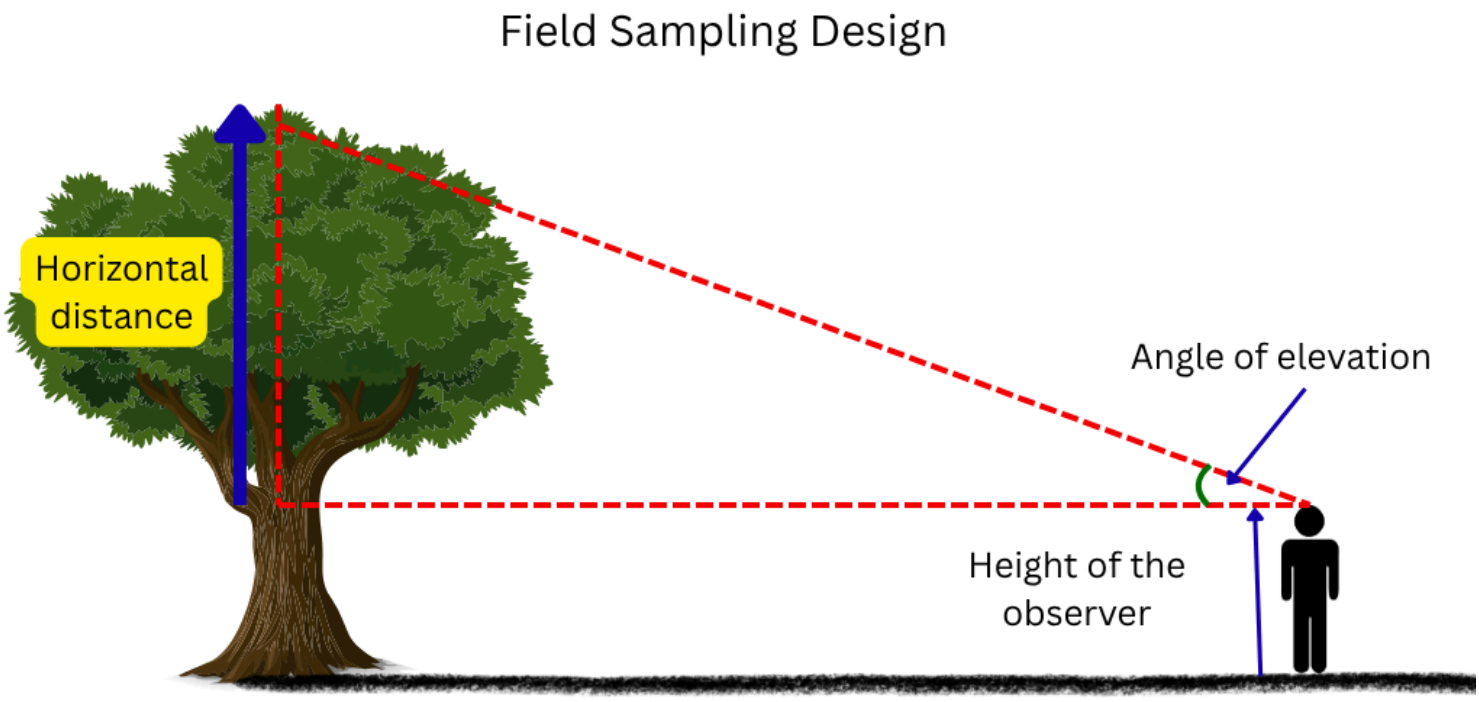


Figure 1

Field Sampling Design