JOJ Horticulture & Arboriculture
ISSN: 2641-8215

Research Article
Volume 6 Issue 3 - August 2026
DOI: 10.19080/JOJHA.2026.06.555690

JOJ Hortic Arboric


# Geospatial Intelligence for Tree Biomass and Carbon Assessment: Integrating Remote Sensing, GIS and Artificial Intelligence in Horticultural and Arboricultural Systems

**Jaffar Waqas[1], Usama Ahmed[2], Adnan Anwar[3], Mahin Jamil[4] and Zeenat Khan[5]***

[1]*Institute of Geo-Information and Earth Observation, Pir Mehr Ali Shah Arid Agriculture University, Rawalpindi, Pakistan*

[2]*Institute of Geo-Information and Earth Observation, Pir Mehr Ali Shah Arid Agriculture University, Rawalpindi, Pakistan*

[3]*Civil Automation Engineer, Al Shahbaz Enterprises, Islamabad, Pakistan*

[4]*Department of Civil Engineering, University of Engineering and Technology (UET), Taxila, Pakistan*

[5]*Research Analyst, Al-Mussawir Engineers, Rawalpindi, Pakistan*

**Submission**: August 17, 2026; **Published:** August 28, 2026

***Corresponding author:** Zeenat Khan, Research Analyst, Al-Mussawir Engineers, Rawalpindi, Pakistan

**Abstract**

Above-ground biomass (AGB) is an important indicator of tree growth, vegetation productivity, ecosystem health, and carbon storage in horticultural and arboricultural systems. Accurate assessment of tree biomass and carbon stocks is essential for sustainable orchard management, urban tree planning, forest plantations, landscape management, and climate mitigation. Conventional field-based approaches, including destructive sampling and allometric measurements, are often constrained by high labour requirements, cost, limited spatial coverage, and difficulties in assessing heterogeneous tree populations. These limitations have increased the need for non-destructive, spatially explicit, and scalable approaches capable of monitoring biomass and carbon dynamics across horticultural and arboricultural landscapes. This review evaluates emerging applications of remote sensing, Geographic Information Systems (GIS), and artificial intelligence (AI) for tree biomass estimation, carbon-stock assessment, and spatial management of horticultural and arboricultural systems. The review synthesizes applications of multispectral and hyperspectral imagery, Synthetic Aperture Radar (SAR), LiDAR, unmanned aerial vehicle (UAV) observations, GIS-based spatial modelling, and machine learning approaches including Random Forest, Support Vector Regression, and Artificial Neural Networks. The reviewed approaches are examined in relation to spectral characteristics, canopy structure, environmental variables, spatial patterns, and biomass prediction. Integration of multi-source geospatial datasets improves biomass estimation by combining spectral, structural, environmental, and topographic information. LiDAR provides detailed three-dimensional canopy characterization, while AI-based models enhance the prediction of complex biomass–environment relationships. GIS further enables spatial visualization of tree biomass and carbon stocks and supports orchard planning, tree inventory, landscape management, and ecosystem conservation. Remaining challenges include limited field calibration data, sensor saturation, environmental variability, spatial heterogeneity, and model transferability. Future research should prioritize multi-sensor fusion, deep learning, UAV and LiDAR integration, cloud-based geospatial platforms, uncertainty quantification, and standardized frameworks for sustainable horticultural and arboricultural management.

**Keywords:** Above-ground biomass; Arboriculture; Horticultural systems; Remote sensing; Geographic Information Systems; Artificial intelligence; Carbon assessment

**Abbreviations:** AGB: Above Ground Biomass; GIS: Geographic Information Systems; AI: Artificial Intelligence; SAR: Synthetic Aperture Radar; UAV: Unmanned Aerial Vehicle; RF: Random Forest, SVAM: Support Vector Machines; ANN: Artificial Neural Networks; DEM: Digital Elevation Models; MI: Machine Learning; CEZ: Creative Engineering Zone

**Highlights**

- Remote sensing enables non-destructive tree biomass assessment.
- GIS and AI improve spatial tree biomass and carbon mapping.
- Geospatial intelligence supports sustainable arboricultural management.

## Introduction

Above-ground biomass (AGB) represents one of the most important components of terrestrial ecosystems, functioning as a major indicator of vegetation productivity, ecosystem health, and global carbon storage potential. It comprises the total dry mass of living vegetation components located above the soil surface, including stems, branches, bark, leaves, and woody structures, and serves as a critical carbon pool regulating atmospheric carbon dioxide ($CO_2$) dynamics [1,2]. Forest ecosystems, in particular, represent one of the largest terrestrial carbon reservoirs, where biomass accumulation through photosynthetic carbon fixation contributes significantly to climate regulation and ecosystem stability [3]. However, increasing anthropogenic pressures, including deforestation, land-use conversion, forest degradation, wildfires, and climate variability, have altered natural carbon cycling processes, resulting in substantial fluctuations in biomass distribution and carbon exchange between terrestrial ecosystems and the atmosphere [4,5]. Therefore, accurate assessment and continuous monitoring of AGB are essential for understanding ecosystem responses to environmental change, improving carbon inventories, supporting REDD+ initiatives, evaluating climate mitigation strategies, and promoting sustainable land management practices [6].

Traditionally, above-ground biomass estimation has relied on field-based inventories, destructive harvesting methods, and species-specific allometric equations. Although these approaches provide reliable local-scale measurements, their application at regional and global scales remains constrained due to high operational costs, extensive labour requirements, limited spatial coverage, and difficulties in representing heterogeneous ecosystem conditions [7]. Recent advances in remote sensing technologies have transformed biomass assessment by enabling non-destructive, spatially continuous, and repetitive observations of vegetation characteristics across large geographical areas [8]. Optical satellite platforms, including Landsat and Sentinel-2, provide spectral information associated with vegetation biochemical properties, chlorophyll activity, and canopy density, whereas Synthetic Aperture Radar (SAR) systems capture microwave interactions with vegetation structure, biomass distribution, and moisture conditions [9,10]. Additionally, LiDAR technology offers three-dimensional measurements of canopy height, vertical structure, and forest architecture, improving biomass estimation accuracy, particularly in complex forest environments [11]. The integration of multispectral, hyperspectral, SAR, LiDAR, and UAV-based observations has therefore established a comprehensive framework for monitoring vegetation biomass and assessing ecosystem carbon dynamics at regional and global scales [12].

The rapid development of Geographic Information Systems (GIS) and artificial intelligence (AI) has further enhanced biomass estimation by enabling the integration of multi-source spatial datasets, environmental variables, field observations, and advanced modelling approaches [13]. GIS-based biomass mapping enables spatial visualization of biomass distribution, identification of carbon-rich vegetation areas, and assessment of spatial variability in tree and plant biomass, thereby supporting conservation, restoration, and sustainable management of horticultural and arboricultural landscapes [14]. Furthermore, machine learning algorithms, including Random Forest (RF), Support Vector Machines (SVM), Extreme Gradient Boosting (XGBoost), and Artificial Neural Networks (ANN), have demonstrated strong potential for establishing complex relationships between remotely sensed predictors and field-measured biomass observations [15,16]. These approaches can improve biomass prediction by incorporating spectral indices, canopy structural parameters, topographic variables, climatic conditions, and ecological characteristics relevant to diverse vegetation systems [17]. Despite these advancements, significant challenges remain, including uncertainties in field calibration datasets, sensor limitations, spectral saturation effects, spatial heterogeneity, model transferability, and difficulties in achieving accurate biomass and carbon-stock estimation across diverse landscapes [18]. Addressing these limitations is essential for developing reliable geospatial biomass monitoring frameworks capable of supporting sustainable tree management, carbon assessment, and climate-mitigation objectives [19].

This review aims to provide a comprehensive assessment of recent advancements in above-ground biomass estimation, with particular emphasis on the integration of remote sensing, GIS, and artificial intelligence-based approaches for tree biomass and carbon assessment in horticultural and arboricultural systems. The primary objective is to synthesize current methodologies, identify technological developments, evaluate the mechanisms through which multi-sensor remote sensing and machine-learning models estimate biomass, and examine their applications in tree monitoring, canopy assessment, carbon accounting, landscape management, and sustainable vegetation planning. The existing challenge addressed in this review is the persistent uncertainty in biomass estimation resulting from limitations in conventional field measurements, sensor constraints, heterogeneous environmental conditions, and insufficient integration of multi-dimensional datasets [20]. The novelty of this review lies in presenting an integrated perspective that combines ecological principles, remote sensing technologies, GIS-based spatial modelling, and AI-driven analytical frameworks to improve the accuracy, scalability, and applicability of biomass and carbon-stock assessment across horticultural and arboricultural environments. The review systematically evaluates optical, SAR, LiDAR, hyperspectral, and UAV-based approaches; discusses GIS-enabled biomass mapping and carbon assessment strategies; analyzes current methodological limitations; and proposes future directions involving deep learning, multi-source data fusion, cloud-based geospatial platforms, uncertainty quantification, and standardized monitoring frameworks for reliable tree biomass assessment and sustainable horticultural and arboricultural management.

## Above-Ground Biomass (AGB)

Above-ground biomass (AGB) represents the total dry mass of living vegetation components present above the soil surface,


How to cite this article: Jaffar W, Usama A, Adnan A, Mahin J, Zeenat K. Geospatial Intelligence for Tree Biomass and Carbon Assessment: Integrating Remote Sensing, GIS and Artificial Intelligence in Horticultural and Arboricultural Systems. JOJ Horticulture & Arboriculture, 6(3). 555690.
DOI: 10.19080/JOJHA.2026.06.555690

including stems, branches, bark, leaves, and other woody structures, and serves as one of the most important indicators of terrestrial ecosystem productivity and carbon storage capacity. Forest ecosystems represent major global carbon reservoirs, with above-ground biomass accounting for a substantial proportion of terrestrial carbon stocks and playing a critical role in regulating atmospheric carbon dioxide concentrations. Accurate estimation of AGB is therefore essential for understanding carbon sequestration processes, evaluating ecosystem responses to climate change, monitoring forest degradation, supporting REDD+ initiatives, and developing reliable carbon inventory systems. Unlike below-ground carbon pools, AGB is highly dynamic and continuously affected by deforestation, land-use conversion, wildfire, climatic variability, and anthropogenic disturbances, resulting in significant variations in carbon exchange between vegetation and the atmosphere. Consequently, continuous and spatially explicit monitoring of AGB has become a fundamental requirement for assessing ecosystem stability and predicting future carbon cycle dynamics.

The assessment of above-ground biomass has evolved from traditional field-based measurements toward advanced remote sensing and artificial intelligence-based approaches capable of providing large-scale, repetitive, and non-destructive biomass estimates. Conventional destructive harvesting methods and allometric equations provide accurate local measurements but are limited by high costs, labor requirements, and restricted spatial applicability, particularly in heterogeneous forest environments. Remote sensing technologies overcome these limitations by capturing vegetation characteristics through optical reflectance, microwave backscatter, and three-dimensional structural information derived from multiple sensor platforms. The integration of multispectral, hyperspectral, Synthetic Aperture Radar (SAR), LiDAR, UAV observations, and machine learning algorithms has significantly improved biomass estimation accuracy by combining spectral, structural, and environmental information . These developments have established remote sensing as a powerful framework for monitoring biomass distribution, quantifying carbon stocks, and supporting sustainable ecosystem management at regional and global scales.

## Ecological Significance and Carbon Dynamics of Above-Ground Biomass

Above-ground biomass (AGB) constitutes the total dry mass of living vegetation above the soil surface, including stems, branches, bark, foliage, and other woody components, and represents one of the most dynamic terrestrial carbon pools. According to reviewed studies, AGB accounts for a significant proportion of terrestrial ecosystem carbon reservoirs, while forests contribute the majority of global vegetation biomass, emphasizing their dominant role in regulating global carbon cycling and climate processes. Through photosynthetic carbon assimilation, vegetation removes atmospheric $CO_2$ and stores carbon within structural components such as stems, branches, leaves, and woody tissues, thereby functioning as an important natural carbon sink. The dynamic nature of AGB makes it highly sensitive to environmental disturbances including deforestation, forest degradation, wildfire, drought stress, and land-use transformation. These disturbances alter vegetation structure, biomass distribution, and carbon exchange processes, resulting in fluctuations between carbon sequestration and greenhouse gas emissions. Consequently, accurate quantification of AGB forms the scientific foundation for carbon stock inventories, climate mitigation strategies, REDD+ implementation, sustainable forest management, wildfire assessment, and ecosystem conservation planning. Unlike relatively stable soil carbon pools, above-ground biomass responds rapidly to ecological changes, making continuous monitoring essential for understanding ecosystem resilience and predicting future carbon cycle trajectories.

## Mechanism of Above-Ground Biomass Estimation through Remote Sensing

Remote sensing-based AGB estimation operates through the interaction between electromagnetic radiation and vegetation components, where canopy structure, leaf biochemical properties, biomass density, and vegetation architecture influence the reflected and backscattered signals recorded by sensors (Figure 1). Optical sensors such as Landsat and Sentinel-2 capture spectral responses associated with vegetation pigments, canopy density, and photosynthetic activity, while Synthetic Aperture Radar (SAR) systems such as Sentinel-1 and PALSAR provide microwave information related to vegetation moisture, woody components, and structural characteristics. LiDAR technology further improves biomass estimation by measuring three-dimensional canopy height, vertical vegetation distribution, and forest structural complexity, providing direct indicators of biomass variation.

The acquired remote sensing datasets are processed to derive vegetation indices, canopy parameters, texture characteristics, and environmental variables, which are subsequently integrated into statistical and artificial intelligence-based models for biomass prediction. Machine learning algorithms including Random Forest, Support Vector Machine, Artificial Neural Networks, and gradient boosting models establish complex relationships between remotely sensed predictors and field-derived biomass observations, enabling estimation of AGB in Mg $ha^{-1}$. The estimated biomass values are converted into carbon stocks by applying biomass-to-carbon conversion factors, generally considering approximately 50% of dry biomass as carbon, thereby supporting carbon accounting, REDD+ monitoring, climate assessment, and ecosystem management applications.

## Environmental and Structural Drivers Governing Above-Ground Biomass Distribution

The spatial distribution and magnitude of above-ground biomass are regulated by the integrated influence of climatic


How to cite this article: Jaffar W, Usama A, Adnan A, Mahin J, Zeenat K. Geospatial Intelligence for Tree Biomass and Carbon Assessment: Integrating Remote Sensing, GIS and Artificial Intelligence in Horticultural and Arboricultural Systems. JOJ Horticulture & Arboriculture, 6(3). 555690.
DOI: 10.19080/JOJHA.2026.06.555690

conditions, vegetation structure, soil characteristics, forest maturity, and functional ecosystem attributes. The reviewed studies consistently demonstrate that temperature variability and precipitation exert strong controls on biomass accumulation, whereas favorable soil texture and stable environmental conditions promote greater carbon storage. Structural attributes, particularly the proportion of large-diameter and mature trees, emerge as the strongest determinants of biomass, with large trees contributing nearly two-thirds of the total biomass stored within subtropical forests. Furthermore, community-weighted functional traits—including maximum tree height, specific leaf area, leaf nitrogen concentration, and wood density—significantly influence ecosystem productivity by regulating photosynthetic efficiency, growth dynamics, and biomass allocation. Across tropical, subtropical, temperate, and savannah ecosystems, biomass stocks vary according to forest composition, climatic gradients, and disturbance history, highlighting the complex interactions among ecological processes that govern carbon sequestration. Collectively, these findings demonstrate that structurally mature forests with favorable environmental conditions exhibit the highest biomass accumulation and therefore constitute the most effective long-term terrestrial carbon reservoirs.

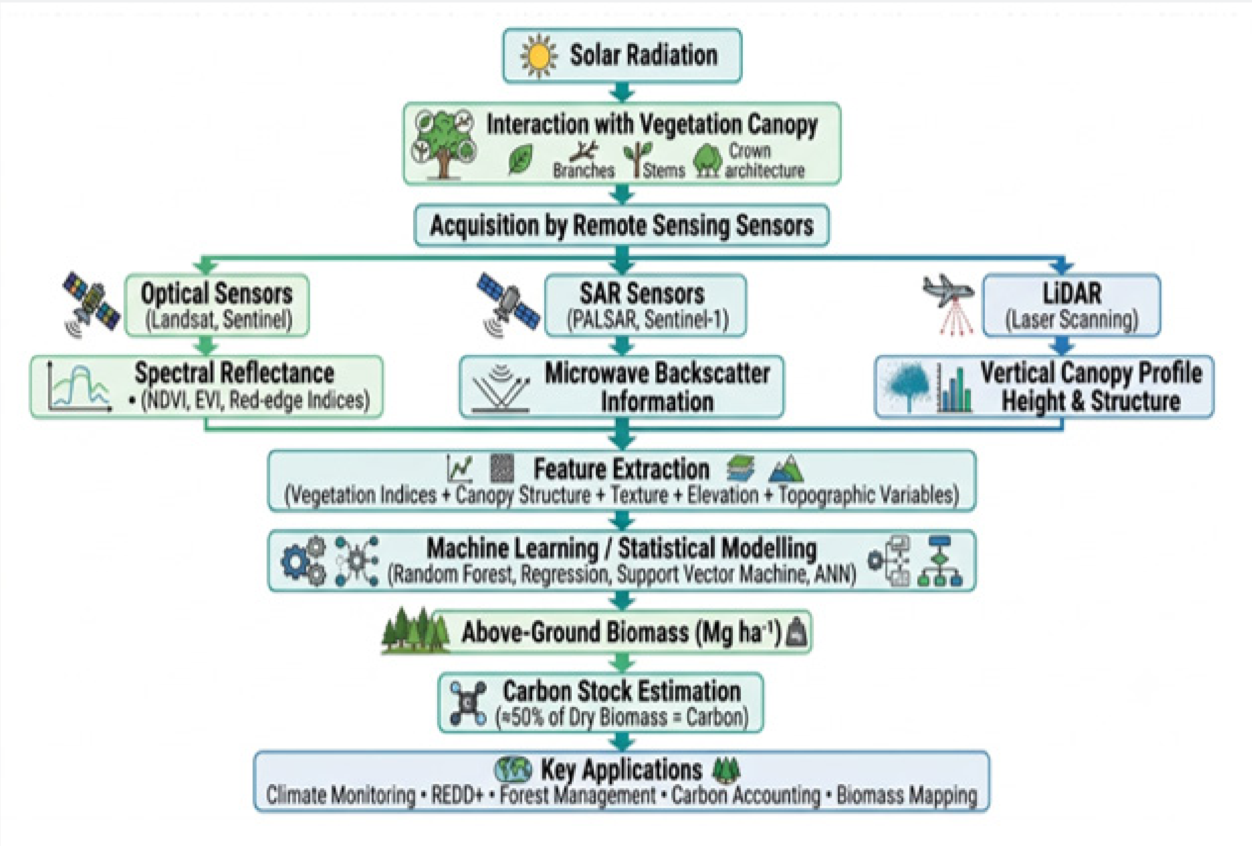


**Figure 1:** Integrated Methodology for Forest Above-Ground Biomass and Carbon Stock Estimation Using Remote Sensing.

## Remote Sensing Technologies for Large-Scale Above-Ground Biomass Assessment

Remote sensing has transformed above-ground biomass assessment by providing a non-destructive, spatially continuous, and cost-effective alternative to conventional field-based measurements. Although destructive harvesting and allometric equations remain the benchmark for local biomass estimation, their application is constrained by extensive labor requirements, financial costs, and limited spatial scalability. In contrast, optical satellite platforms such as Landsat, Sentinel, MODIS, SPOT, and World View enable repeated observations through vegetation spectral indices, whereas Synthetic Aperture Radar (SAR) systems provide cloud-independent measurements of canopy structural properties using microwave backscatter. LiDAR technology further enhances biomass estimation by directly capturing canopy height, crown architecture, and vertical forest complexity, resulting in superior estimation accuracy. Recent developments increasingly integrate optical imagery, SAR, LiDAR, UAV observations, and advanced machine learning algorithms to reduce uncertainty, overcome spectral saturation in dense forests, and improve


How to cite this article: Jaffar W, Usama A, Adnan A, Mahin J, Zeenat K. Geospatial Intelligence for Tree Biomass and Carbon Assessment: Integrating Remote Sensing, GIS and Artificial Intelligence in Horticultural and Arboricultural Systems. JOJ Horticulture & Arboriculture, 6(3). 555690.
DOI: 10.19080/JOJHA.2026.06.555690

biomass prediction across multiple spatial and temporal scales. Therefore, the integration of complementary remote sensing technologies with artificial intelligence has established a robust framework for accurate large-scale biomass mapping, carbon stock estimation, and evidence-based ecosystem management.

## Remote Sensing Technologies for Biomass Estimation

Remote sensing technologies have emerged as essential tools for large-scale and accurate estimation of above-ground biomass (AGB) by providing continuous spatial and temporal observations of forest and agricultural ecosystems. Conventional field-based biomass inventories are often limited by high cost, time requirements, and restricted spatial coverage; therefore, satellite and airborne remote sensing approaches provide efficient alternatives for regional and global biomass assessment. Passive optical sensors, including Landsat-9 and Sentinel-2, estimate biomass through vegetation spectral responses associated with chlorophyll activity, canopy density, and leaf structure. Vegetation indices such as NDVI, EVI, TNDVI, ARVI, GNDVI, and red-edge indices enhance the relationship between spectral characteristics and biomass distribution. However, optical-based approaches may experience spectral saturation in dense vegetation, limiting their accuracy in high-biomass forests. Active remote sensing systems, particularly Synthetic Aperture Radar (SAR) and LiDAR, overcome several limitations by capturing structural information related to vegetation height, canopy volume, stem density, and vertical biomass distribution . SAR sensors provide microwave backscatter information influenced by vegetation moisture and woody components, whereas LiDAR generates three-dimensional canopy measurements, making it highly effective for structural biomass estimation. Recent studies demonstrate that the integration of multi-source datasets, including optical imagery, SAR, LiDAR, hyperspectral data, and topographic variables derived from Digital Elevation Models (DEM), significantly improves AGB prediction accuracy by representing both spectral and biophysical characteristics of vegetation (Table 1).

**Table 1:** Case Studies of Remote Sensing Applications for Above-Ground Biomass Estimation [21-35].

| Study Region/ Ecosystem | Remote Sensing Data Used | Modelling Approach | Key Predictors | Major Findings | Application |
|---|---|---|---|---|---|
| Forest ecosystems (Global review studies) | Optical sensors, SAR, LiDAR | Empirical, physical, mechanistic, and machine learning models | Spectral bands, vegetation indices, canopy height, structural parameters | Remote sensing parameters act as proxies for biomass estimation; LiDAR provides improved structural information | Global carbon cycle assessment and forest monitoring |
| Forest landscape using Landsat-9 and SRTM DEM | Landsat-9 OLI + DEM | Random Forest, XGBoost, SVR, Multiple Linear Regression | B4, B5 bands, NDVI, TNDVI, GNDVI, elevation, slope, TWI | RF achieved highest accuracy with $R^2$ = 0.81, RMAE = 14.33%, and RRMSE = 22.23% | Regional AGB mapping and forest management |
| Moist temperate forests, Abbottabad, Pakistan | Sentinel-2 multispectral imagery | Regression models and kriging interpolation | ARVI, NDVI, coastal aerosol band, precipitation, distance variables | ARVI showed strong biomass prediction capability ($R^2$ = 0.67); remote sensing models outperformed geostatistical approaches | REDD+ potential assessment and carbon stock estimation |
| Agricultural biomass estimation (Potato crop) | UAV RGB imagery | Multiple Stepwise Regression and Extreme Learning Machine | RGB vegetation indices, GLCM texture, crop height models | Integration of spectral, texture, and height features improved estimation accuracy and reduced optical saturation effects | Precision agriculture and yield prediction |
| Northern Europe agricultural systems | Airborne hyperspectral data | AutoML regression models | Narrow-band vegetation indices and hyperspectral features | AI-based modelling achieved high biomass prediction accuracy ($R^2$ up to 0.96 for wheat biomass estimation) | Sustainable agriculture and crop monitoring |
| Forest plantations (China) | Airborne LiDAR + hyperspectral imagery | Random Forest feature selection and regression modelling | Canopy height, point cloud density, spectral and texture features | Fusion of LiDAR and hyperspectral data significantly improved species-specific AGB estimation | Forest inventory and carbon storage assessment |
| Coastal wetlands | AVIRIS-NG hyperspectral, Sentinel-1, Sentinel-2 | Random Forest modelling | Spectral bands, vegetation indices, multi-temporal features | Multi-scale modelling improved wetland biomass mapping with $R^2$ up to 0.65 | Blue carbon assessment and wetland conservation |
| Large-area forest biomass assessments (1992–2022 review) | LiDAR, RADAR, aerial photogrammetry, satellite data | Statistical and machine learning approaches | Forest structure metrics, field inventory parameters | Increased use of structural remote sensing improved biomass reliability, but uncertainties remain due to field data scarcity and model limitations | National carbon reporting and |



How to cite this article: Jaffar W, Usama A, Adnan A, Mahin J, Zeenat K. Geospatial Intelligence for Tree Biomass and Carbon Assessment: Integrating Remote Sensing, GIS and Artificial Intelligence in Horticultural and Arboricultural Systems. JOJ Horticulture & Arboriculture, 6(3). 555690.
DOI: 10.19080/JOJHA.2026.06.555690

The advancement of artificial intelligence (AI) and machine learning (ML) algorithms has further enhanced remote sensing-based biomass estimation by establishing complex relationships between remotely sensed predictors and field-measured biomass observations. Algorithms such as Random Forest (RF), Extreme Gradient Boosting (XGBoost), Support Vector Regression (SVR), Artificial Neural Networks (ANN), and automated machine learning frameworks have demonstrated superior performance compared with traditional regression approaches. For instance, Landsat-9 integrated with SRTM DEM predictors achieved high AGB estimation accuracy using RF modelling, while Sentinel-2-based studies in moist temperate forests of Pakistan showed that vegetation indices such as ARVI and NDVI provided strong correlations with field-measured biomass. Similarly, fusion of airborne LiDAR and hyperspectral data improved biomass estimation by combining spectral information with three-dimensional canopy characteristics. Despite these advancements, uncertainties remain due to limitations in field calibration data, sensor resolution, environmental variability, canopy complexity, and signal saturation effects. Future developments involving multi-sensor data fusion, deep learning architectures, cloud-based processing platforms, and high-resolution satellite missions are expected to enhance the reliability of biomass mapping and support forest carbon monitoring, REDD+ implementation, climate change assessment, and sustainable ecosystem management.

### GIS Applications in Biomass Mapping

Geographic Information Systems (GIS) have become a fundamental geospatial framework for biomass mapping by integrating remote sensing data, field observations, statistical inventories, and environmental variables to generate spatially explicit biomass distribution models [36]. GIS-based approaches enable the identification, quantification, and visualization of biomass resources across diverse landscapes, including forests, agricultural regions, wastelands, and wetland ecosystems [37]. By combining satellite-derived land use/land cover classifications, vegetation indices, crop productivity data, and biomass conversion factors, GIS facilitates accurate estimation of above-ground biomass (AGB), crop residue potential, and carbon storage capacity at regional and national scales [38]. Several studies have demonstrated the effectiveness of GIS-based thematic mapping for identifying biomass availability zones and supporting renewable energy planning [39]. For instance, integration of satellite imagery with agricultural statistics has enabled the spatial assessment of crop residue biomass potential, while GIS-based biomass atlases have provided detailed information on the distribution of forest residues, agricultural waste, and other biomass resources [40]. Furthermore, coupling GIS with remote sensing and digital elevation models enhances biomass modelling by incorporating topographic, climatic, and ecological variables that influence vegetation productivity and spatial variability [41].

Beyond biomass quantification, GIS serves as a decision-support tool for sustainable resource management, bioenergy development, carbon accounting, and optimal facility planning [42]. Spatial analysis techniques, including suitability modelling, multi-criteria evaluation, network analysis, and location-allocation optimization, allow researchers and policymakers to identify suitable sites for biomass-based power plants, biorefineries, and bioenergy supply chains while minimizing transportation costs and environmental impacts [43]. GIS-integrated machine learning approaches, including Artificial Neural Networks and regression models, have further improved biomass prediction accuracy by establishing relationships between environmental factors and biomass distribution patterns [44]. Applications in forest ecosystems have demonstrated the capability of GIS to integrate Sentinel-2 imagery, forest inventory data, and regression models for generating reliable biomass and carbon stock maps [45]. Despite significant progress, challenges remain regarding spatial data availability, uncertainty in biomass conversion parameters, temporal variability, and integration of heterogeneous datasets [46]. Future advancements involving cloud-based GIS platforms, artificial intelligence, high-resolution remote sensing data, and real-time geospatial monitoring are expected to enhance biomass mapping accuracy and support climate mitigation strategies, renewable energy development, and sustainable ecosystem management [47].

### Carbon Stock Assessment and Climate Change Mitigation

Carbon stock assessment provides a scientific framework for quantifying the amount of carbon stored within terrestrial, coastal, and aquatic ecosystems and evaluating their potential contribution to climate change mitigation [48]. Carbon storage occurs through the process of atmospheric $CO_2$ capture via photosynthesis, followed by carbon allocation into vegetation biomass, woody components, litter, and soil organic matter (Figure 2) [49]. In forest ecosystems, absorbed carbon is incorporated into above-ground biomass (leaves, stems, branches, and crowns) and below-ground pools through root growth and soil carbon stabilization [50]. Similarly, blue carbon ecosystems, including mangroves, tidal marshes, and seagrass meadows, enhance long-term carbon sequestration by trapping organic matter within anaerobic sediments, where decomposition rates are reduced and carbon remains stored for centuries to millennia [51]. Remote sensing, GIS, LiDAR, and machine learning-based approaches have significantly improved carbon stock estimation by enabling spatial mapping of biomass distribution, ecosystem carbon density, and carbon change dynamics over large geographical regions [52]. Recent global assessments indicate substantial unrealized carbon storage potential through forest conservation, ecosystem restoration, improved land management, and soil carbon enhancement [53]. However, accurate carbon quantification requires integration of field inventories, remote sensing observations, ecological parameters, and advanced modelling frameworks to minimize uncertainties associated with ecosystem variability, climate impacts, and measurement limitations [54].


How to cite this article: Jaffar W, Usama A, Adnan A, Mahin J, Zeenat K. Geospatial Intelligence for Tree Biomass and Carbon Assessment: Integrating Remote Sensing, GIS and Artificial Intelligence in Horticultural and Arboricultural Systems. JOJ Horticulture & Arboriculture, 6(3). 555690.
DOI: 10.19080/JOJHA.2026.06.555690

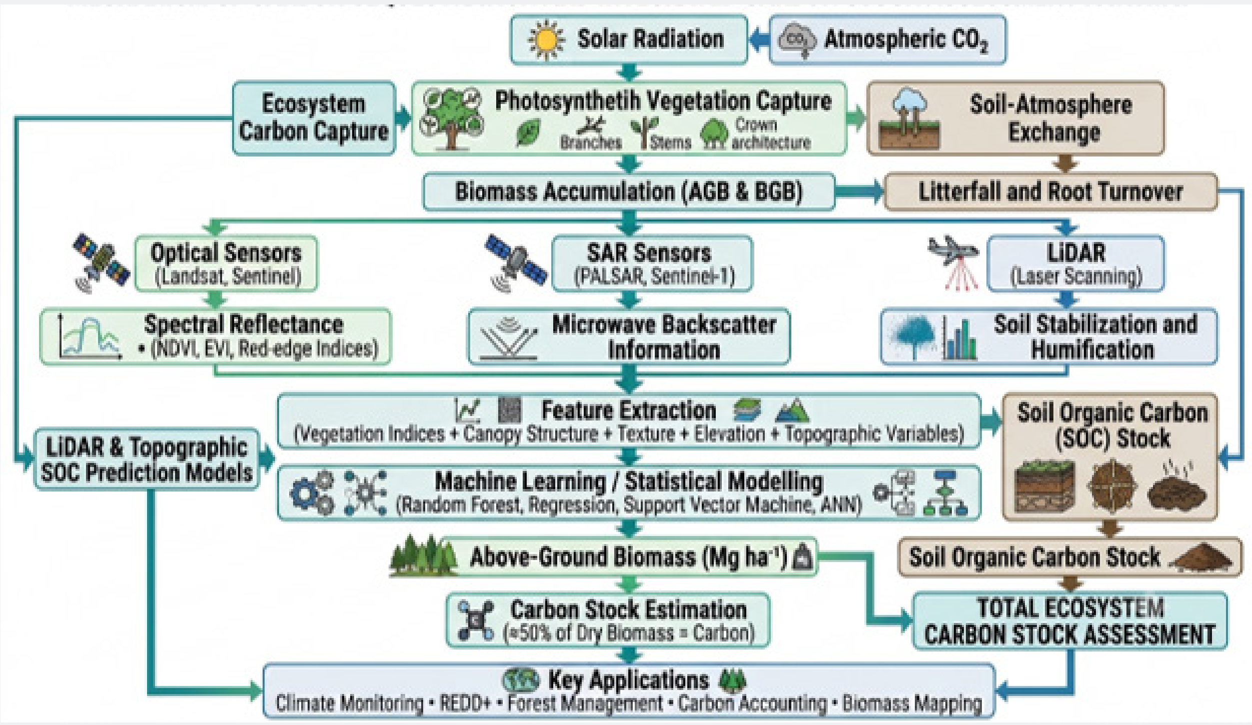


**Figure 2:** Mechanism of Carbon Sequestration and Integrated Carbon Stock Assessment Pathway.

Carbon stock conservation and enhancement represent critical nature-based solutions for achieving climate mitigation targets by reducing greenhouse gas emissions and increasing carbon dioxide removal from the atmosphere [55]. Forest protection, restoration of degraded landscapes, sustainable agricultural practices, and conservation of blue carbon ecosystems can significantly strengthen global carbon sinks while providing additional ecological benefits such as biodiversity conservation, soil fertility improvement, water regulation, and ecosystem resilience [56]. Protected forests contribute to climate regulation by preventing biomass loss and avoiding emissions from deforestation and degradation, whereas mangrove conservation offers disproportionate mitigation benefits due to its high carbon density and sediment-based carbon storage capacity [57]. Soil carbon management practices, including biochar application, reduced tillage, agroforestry, and organic amendments, further enhance carbon retention; however, their effectiveness depends on long-term monitoring, permanence, and consideration of potential greenhouse gas trade-offs [58]. Emerging approaches integrating satellite-based biomass mapping, artificial intelligence, carbon modelling, and carbon credit frameworks provide new opportunities for transparent carbon accounting and climate policy implementation. Therefore, a comprehensive carbon assessment strategy combining ecosystem monitoring, technological innovation, and sustainable management practices is essential for maximizing carbon sequestration potential and supporting global efforts toward net-zero emission pathways.

## Applications of Geospatial Technologies in Horticultural and Arboricultural Systems

The integration of remote sensing, Geographic Information Systems (GIS), and artificial intelligence (AI) provides new opportunities for monitoring vegetation characteristics and supporting sustainable management of horticultural and arboricultural systems [59]. Above-ground biomass (AGB) estimation can provide information on tree growth, canopy development, vegetation productivity, and carbon storage, making biomass assessment relevant not only to forest ecosystems but also to orchards, plantations, urban trees, parks, gardens, and other managed perennial vegetation systems [22]. Conventional field measurements remain important for calibrating biomass models; however, their high labour requirements and restricted spatial coverage can limit their application across extensive horticultural and arboricultural landscapes [60]. Remote sensing provides a non-destructive alternative capable of repeatedly characterizing vegetation structure and condition over large areas [24]. Optical imagery can capture variations in canopy reflectance and vegetation condition, while vegetation indices provide spatial indicators associated with canopy density and plant productivity [25]. Such information can support the assessment of tree vigour, canopy development, and spatial variability within managed vegetation systems.

High-resolution remote sensing is particularly valuable for individual-tree and orchard-scale assessment because tree crowns,


**How to cite this article:** Jaffar W, Usama A, Adnan A, Mahin J, Zeenat K. Geospatial Intelligence for Tree Biomass and Carbon Assessment: Integrating Remote Sensing, GIS and Artificial Intelligence in Horticultural and Arboricultural Systems. JOJ Horticulture & Arboriculture, 6(3). 555690.
DOI: 10.19080/JOJHA.2026.06.555690

canopy gaps, planting patterns, and structural differences can be characterized at fine spatial scales [26]. UAV platforms provide flexible and high-resolution observations that can be used to assess individual trees and heterogeneous horticultural landscapes, while LiDAR provides three-dimensional information on tree height, crown structure, canopy volume, and vertical vegetation distribution [61]. The combination of optical imagery with LiDAR or UAV observations can therefore improve characterization of tree architecture and biomass by integrating spectral and structural information [28]. Hyperspectral observations provide additional information on vegetation biochemical properties and can contribute to the detection of variations in plant condition and canopy characteristics [29]. Similarly, SAR observations can provide complementary structural information where optical observations are affected by cloud cover or where vegetation structure and moisture influence biomass estimation [62]. Multi-sensor integration consequently provides a more comprehensive framework for assessing tree biomass and vegetation condition across complex horticultural and arboricultural environments.

GIS provides an important spatial framework for integrating remotely sensed observations with field measurements, environmental variables, topographic information, and management data [63]. GIS-based approaches can facilitate spatial tree inventories, canopy mapping, biomass distribution assessment, carbon-stock visualization, and identification of areas requiring targeted management [32]. In horticultural systems, spatial biomass and canopy information can contribute to orchard characterization, plantation planning, vegetation monitoring, and assessment of spatial differences in tree development [33]. In arboricultural systems, geospatial databases can support the identification and mapping of individual trees, canopy characteristics, tree populations, and urban green infrastructure [34]. The integration of biomass and carbon information with spatial datasets can further assist landscape planning, conservation, restoration, and sustainable management of managed vegetation [35]. GIS therefore transforms biomass observations from isolated measurements into spatial decision-support information that can be interpreted at individual-tree, orchard, landscape, and regional scales. Artificial intelligence and machine learning further enhance the potential of geospatial technologies for horticultural and arboricultural applications by enabling complex relationships between remotely sensed variables and field observations to be modelled. Random Forest, Support Vector Machines, Support Vector Regression, XGBoost, and Artificial Neural Networks can integrate spectral indices, canopy parameters, environmental variables, topographic characteristics, and field measurements to predict biomass and related vegetation attributes [64]. These models are particularly useful where relationships between remotely sensed characteristics and tree biomass are non-linear and influenced by multiple environmental and structural factors. The integration of machine learning with high-resolution imagery can also support automated tree detection, crown delineation, vegetation classification, and spatial characterization of individual trees. Such capabilities create opportunities for developing digital tree inventories and precision management frameworks in orchards, plantations, urban forests, parks, and other managed landscapes.

Geospatial technologies also have potential applications beyond direct biomass estimation by linking vegetation structure with tree health, environmental stress, productivity, and management requirements. Repeated satellite, UAV, or airborne observations can provide temporal information for detecting changes in canopy condition and vegetation development. Integration of spectral, structural, climatic, and soil-related information can improve interpretation of spatial variability within horticultural systems and support more targeted management interventions [65]. Biomass and carbon maps can additionally contribute to the evaluation of carbon sequestration potential and the environmental benefits of trees within managed landscapes. In urban and peri-urban environments, geospatial assessment can support green-space planning and characterization of tree resources, while in orchards and plantations it can contribute to improved understanding of canopy distribution and vegetation variability. These applications demonstrate that remote sensing, GIS, and AI can extend biomass assessment from a conventional measurement exercise toward an integrated framework for tree monitoring and sustainable vegetation management.

Despite these opportunities, the transfer of geospatial biomass assessment approaches between different horticultural and arboricultural systems remains challenging because tree species, age, canopy architecture, planting density, environmental conditions, and management practices can vary substantially. Differences in sensor resolution and data acquisition conditions can further influence the consistency of biomass and canopy estimates. Field calibration remains essential for developing reliable predictive models, while insufficient representation of tree species and environmental conditions can reduce model generalizability. AI-based approaches may also require large and representative datasets and careful validation before being applied across different geographical regions or vegetation systems. These limitations highlight the importance of combining field observations with multi-source geospatial datasets and developing standardized approaches for biomass and carbon assessment.

Future applications should increasingly focus on integrating high-resolution satellite imagery, UAV observations, LiDAR, hyperspectral data, SAR, GIS, and advanced AI models to develop comprehensive tree monitoring systems. Multi-temporal observations could enable continuous assessment of tree growth, canopy development, biomass accumulation, and carbon dynamics, while cloud-based geospatial platforms could facilitate the processing of large datasets across extensive horticultural and arboricultural landscapes. Deep learning and automated machine learning may further improve individual-tree detection, biomass prediction, canopy characterization, and spatial classification


How to cite this article: Jaffar W, Usama A, Adnan A, Mahin J, Zeenat K. Geospatial Intelligence for Tree Biomass and Carbon Assessment: Integrating Remote Sensing, GIS and Artificial Intelligence in Horticultural and Arboricultural Systems. JOJ Horticulture & Arboriculture, 6(3). 555690.
DOI: 10.19080/JOJHA.2026.06.555690

when supported by adequate training and validation datasets. Integration of geospatial outputs with digital tree inventories and management databases could provide decision-support systems for orchard planning, urban tree management, landscape design, and carbon accounting. Standardized protocols, uncertainty quantification, improved field calibration networks, and transferable models will nevertheless remain necessary to ensure reliable application across diverse tree-based systems. Ultimately, the convergence of remote sensing, GIS, and AI can provide a scalable framework for linking tree structure, biomass, carbon storage, vegetation condition, and spatial management, thereby strengthening the role of geospatial intelligence in sustainable horticulture and arboriculture.

## Challenges and Limitations

Despite significant advancements in remote sensing, GIS, and artificial intelligence-based approaches for above-ground biomass (AGB) estimation and carbon stock assessment, several methodological and operational challenges continue to limit their accuracy and large-scale applicability. One of the major limitations is the uncertainty associated with field-based biomass measurements, as destructive sampling and allometric equations are often restricted to specific forest types, species compositions, and environmental conditions, resulting in limited transferability across diverse ecosystems. Remote sensing-based approaches also face sensor-specific constraints, including spectral saturation in high-biomass forests, limited penetration capability of optical sensors, signal interference due to atmospheric conditions, and uncertainties in radar backscatter responses caused by vegetation moisture and structural variability. Although LiDAR provides highly accurate three-dimensional canopy information, its application is constrained by high acquisition costs, limited spatial coverage, and data processing complexity [39]. Furthermore, biomass estimation models based on machine learning and artificial intelligence require large, representative, and high-quality training datasets; however, scarcity of field observations remains a significant source of model uncertainty. Variations in forest structure, climate conditions, soil properties, disturbance history, and ecosystem dynamics further complicate the development of universal biomass estimation models. In GIS-based biomass mapping, challenges include spatial and temporal inconsistencies among datasets, uncertainties in biomass conversion factors, limited availability of high-resolution geospatial information, and difficulties in integrating heterogeneous data sources. Additionally, carbon stock assessment faces uncertainties related to carbon permanence, ecosystem responses to climate change, greenhouse gas trade-offs, and the long-term stability of nature-based carbon sequestration pathways.

## Future Perspectives

Future developments in above-ground biomass estimation and carbon-stock monitoring are expected to increasingly focus on the integration of multi-source remote sensing data, advanced artificial intelligence techniques, and improved geospatial modelling frameworks for horticultural and arboricultural systems. The combination of optical imagery, Synthetic Aperture Radar (SAR), LiDAR, hyperspectral observations, UAV-based measurements, and environmental variables can provide more comprehensive representations of tree structure, canopy characteristics, biomass distribution, and carbon dynamics. Emerging satellite missions with enhanced spatial, spectral, and temporal resolution, together with increasingly available LiDAR datasets, are expected to improve the assessment of tree biomass and carbon stocks across orchards, plantations, urban green spaces, parks, and other managed vegetation systems. Furthermore, deep learning architectures, automated machine learning (AutoML), and cloud-based geospatial platforms such as Google Earth Engine can facilitate efficient processing of large-volume Earth observation datasets and support repeated monitoring of tree growth, canopy development, vegetation condition, biomass accumulation, and carbon dynamics.

Future research should emphasize the development of standardized biomass estimation protocols, improved field calibration networks, uncertainty quantification frameworks, and transferable AI models capable of operating across diverse tree species, horticultural landscapes, and arboricultural environments. Greater integration of individual-tree observations with GIS-based decision-support systems could strengthen tree inventories, orchard planning, canopy management, urban tree assessment, landscape planning, and spatial carbon accounting. Multi-temporal remote sensing can further enable the monitoring of changes in tree structure, biomass, and vegetation condition, providing opportunities for early identification of environmental stress and improved management interventions. The integration of remote sensing-derived biomass products with GIS and AI-based management frameworks can therefore extend biomass assessment beyond conventional carbon monitoring toward precision horticulture, sustainable arboriculture, tree-resource management, and climate-resilient landscape planning. Ultimately, the convergence of remote sensing, GIS, artificial intelligence, and ecological modelling is expected to provide a robust pathway for accurate tree biomass and carbon assessment while supporting science-based strategies for sustainable horticultural and arboricultural management.

## Conclusion

Above-ground biomass (AGB) assessment provides an important basis for understanding tree productivity, vegetation structure, carbon storage, and climate-mitigation potential in horticultural and arboricultural systems. This review demonstrates that accurate biomass quantification can support assessment of carbon sequestration, tree development, vegetation condition, and sustainable management across orchards, plantations, urban green spaces, parks, gardens, and other managed tree-based landscapes. Although conventional field inventories and allometric equations remain valuable for local-scale biomass estimation, their labour-intensive nature, high operational requirements,


How to cite this article: Jaffar W, Usama A, Adnan A, Mahin J, Zeenat K. Geospatial Intelligence for Tree Biomass and Carbon Assessment: Integrating Remote Sensing, GIS and Artificial Intelligence in Horticultural and Arboricultural Systems. JOJ Horticulture & Arboriculture, 6(3). 555690.
DOI: 10.19080/JOJHA.2026.06.555690

and limited spatial coverage restrict their application across extensive and heterogeneous vegetation systems. The integration of optical remote sensing, Synthetic Aperture Radar (SAR), LiDAR, hyperspectral imagery, and UAV platforms provides increasingly effective approaches for generating spatially explicit biomass estimates by combining spectral, structural, and environmental information. The advancement of Geographic Information Systems (GIS) and artificial intelligence (AI) has further strengthened biomass assessment by enabling the integration of multi-source geospatial datasets, environmental variables, field observations, and advanced predictive models. Machine learning and deep learning approaches, including Random Forest, Support Vector Machine, XGBoost, and Artificial Neural Networks, can improve the modelling of complex relationships between remotely sensed characteristics and field-measured biomass. GIS-based biomass and carbon mapping further extends the application of AGB assessment toward tree inventories, canopy assessment, orchard planning, landscape management, urban tree monitoring, and spatial carbon accounting. The convergence of remote sensing, GIS, and AI therefore provides a powerful framework for improving tree biomass prediction and supporting evidence-based horticultural and arboricultural management.

Despite considerable technological progress, uncertainties associated with field calibration datasets, tree species and canopy variability, environmental conditions, sensor limitations, spectral saturation, biomass conversion factors, and model transferability continue to affect the reliability of AGB estimation. Future research should prioritize standardized biomass estimation protocols, expanded field observation networks, improved uncertainty quantification, multi-sensor data fusion, and transferable AI models capable of operating across diverse horticultural and arboricultural environments. Emerging satellite missions, global LiDAR datasets, UAV-based observations, cloud-based geospatial platforms, and explainable artificial intelligence are expected to improve the spatial and temporal monitoring of tree biomass, canopy development, vegetation condition, and carbon stocks. Ultimately, the integration of ecological knowledge, remote sensing, GIS-based spatial analysis, and artificial intelligence represents a transformative pathway for advancing tree biomass and carbon assessment. Future monitoring frameworks should focus on scalable, transparent, and interoperable systems capable of supporting precision horticulture, sustainable arboriculture, tree inventories, orchard and landscape planning, carbon accounting, and climate-resilient vegetation management. By improving the accuracy, spatial coverage, and accessibility of biomass information, integrated geospatial approaches can strengthen science-based management of horticultural and arboricultural resources while enhancing the contribution of trees and managed vegetation to long-term carbon sequestration and environmental sustainability.

## Funding Statement

Not Applicable.

## Conflict of Interest

Authors declare that they have no conflict of interest with this publication.

## Acknowledgement

The authors would like to express their sincere gratitude to all individuals and departments who contributed to the successful completion of this research. Special thanks are extended to Al-Mussawir Engineers and Creative Engineering Zone (CEZ) for their technical support and assistance throughout the study. The authors are also highly grateful to S.E. PHED Rawalpindi Syed Hussnain, Public Health Engineering Department Rawalpindi, for his valuable guidance and support.

## References

1. Kumar L, O Mutanga (2017) Remote sensing of above-ground biomass. Remote Sensing 9(9): 935.
2. Santoro M, O Cartus, N Carvalhais, D M A Rozendaal, V Avitabile, A Araza, S De Bruin, et al. (2021) The global forest above-ground biomass pool for 2010 estimated from high-resolution satellite observations. Earth System Science Data 13(8): 3927-3950.
3. Lewis, L B Sonké, T Sunderland, S K Begne, G Lopez Gonzalez, et al. (2013) Above-ground biomass and structure of 260 African tropical forests. Philosophical Transactions of the Royal Society B Biological Sciences 368(5):1625.
4. Finegan, B M Peña Claros, A de Oliveira, N Ascarrunz, M S Bret-Harte, et al. (2015) Does functional trait diversity predict above-ground biomass and productivity of tropical forests Testing three alternative hypotheses. Journal of Ecology 103(1):191–201.
5. Bordin, A Esquivel Muelbert, R S Bergamin, J Klipel, R C Picolotto, et al. (2023) Climate and large-sized trees, but not diversity, drive above-ground biomass in subtropical forests. Forest Ecology and Management 21(2): 93-196.
6. Cuni Sanchez, A M Pfeifer, R Marchant, K Calders, C L Sørensen, et al. (2020) New insights on above ground biomass and forest attributes in tropical montane forests. Forest Ecology and Management 58(3): 503-513.
7. Chen, X M Luo, M Larjavaara (2024) Effects of climate and plant functional types on forest above-ground biomass accumulation. Carbon Balance and Management 18(1): 5.
8. Chen, M Luo, M Larjavaara (2024) Effects of climate and plant functional types on forest above-ground biomass accumulation. 4(7) Carbon Balance and Management.
9. Araza A, M Herold, S De Bruin, P Ciais, D A Gibbs, et al. (2023) Past decade above-ground biomass change comparisons from four multi-temporal global maps. International Journal of Applied Earth Observation and Geoinformation 118 (4): 103274.
10. Bouvet A, S Mermoz, T Le Toan, L Villard, R Mathieu, et al. (2018) An above-ground biomass map of African savannahs and woodlands at 25 m resolution derived from ALOS PALSAR 156-173.
11. Quegan S, T Le Toan, J Chave, J Dall, J F Exbrayat, et al. The European Space Agency BIOMASS mission: Measuring Forest above-ground biomass from space. Remote Sensing of Environment 227 (2019): 44-60.
12. Anees, S A K Mehmood, W R Khan, M Sajjad, T A Alahmadi, et al. (2024) Integration of machine learning and remote sensing for above ground biomass estimation through Landsat-9 and field data in temperate forests of the Himalayan region. Ecological Informatics 82:102732.


How to cite this article: Jaffar W, Usama A, Adnan A, Mahin J, Zeenat K. Geospatial Intelligence for Tree Biomass and Carbon Assessment: Integrating Remote Sensing, GIS and Artificial Intelligence in Horticultural and Arboricultural Systems. JOJ Horticulture & Arboriculture, 6(3). 555690.
DOI: 10.19080/JOJHA.2026.06.555690

13. Tian, L X Wu, Y Tao, M Li, C Qian, et al. (2023) Review of remote sensing-based methods for forest aboveground biomass estimation Progress challenges and prospects. Forests 14(6): 1086.

14. Ahmad, N S Ullah, N Zhao, F Mumtaz, A Ali, et al. (2023) Comparative analysis of remote sensing and geo-statistical techniques to quantify forest biomass. Forests 14(2): 379.

15. Xu W, Y Cheng, M Luo, X Mai,W Zhang, et al. (2025) Progress and limitations in forest carbon stock estimation using remote sensing technologies A comprehensive review. Forests 16 (3):449.

16. Liu Y, H Feng, J Yue, Z Li, G Yang, et al. (2022) Remote-sensing estimation of potato above-ground biomass based on spectral and spatial features extracted from high-definition digital camera images. Computers and Electronics in Agriculture 27:107089.

17. Li K Y, de Lima, N G Burnside, E Vahtmäe, T Kutser, K Sepp, V H C Pinheiro et al. (2022) Toward automated machine learning-based hyperspectral image analysis in crop yield and biomass estimation. Remote Sensing 14(5): 1114.

18. Gao L, G Chai, X Zhang (2022) Above-ground biomass estimation of plantation with different tree species using airborne lidar and hyperspectral data. Remote Sensing 14 (11): 2568.

19. Borsah A M Nazeer, M S Wong (2023 LIDAR-based forest biomass remote sensing: A review of metrics, methods, and assessment criteria for the selection of allometric equations. Forests 14(10): 2095.

20. Hemati M, M Mahdianpari, H Shiri, F Mohammadimanesh (2024) Integrating SAR and optical data for aboveground biomass estimation of coastal wetlands using machine learning: Multi-scale approach. Remote Sensing 16 (5): 831.

21. Bahrami H, H McNairn, M Mahdianpari, S Homayouni (2022) A meta-analysis of remote sensing technologies and methodologies for crop characterization. Remote Sensing14 (22): 5633.

22. Deodoro S, C R Fealy, T McCarthy (2026) The use of remote sensing data for above-ground biomass estimation. In Wildlife Monitoring Integrating Conservation and Innovation in Human-Altered Landscapes, Cham Springer Nature Switzerland 105–138.

23. Rani M, P Kumari, P Lavania, G Gupta, R K Singh, et al. (2025) An overview of remote sensing technology in forest management. In Advanced Geospatial and Ground Based Techniques in Forest Monitoring, 37–59.

24. Papucci, E R Valbuena, C Roberge, A Mensah, G Ståhl (2026) A review of forest biomass assessments based on remote sensing reveals progress in methodological quality but major challenges remain. Forestry An International Journal of Forest Research 99 (2): cpag007.

25. Pande C B, S K Singh, A M Varade, A Elbeltagi, P Choudhari (2021) Estimation of crop and forest biomass resources in a semi-arid region using satellite data and GIS. Journal of the Saudi Society of Agricultural Sciences 20(5): 302–311.

26. Bharti, A K Paritosh, V R Mandla, A Chawade (2021) and V Vivekanand. GIS application for the estimation of bioenergy potential from agriculture residues: An overview. Energies 14(4): 898.

27. Chakraborty A, A Biswal, V Pandey, S Shadab, K Kalyandeep, et al. (2022) Developing a spatial information system of biomass potential from crop residues over India: A decision support for planning and establishment of biofuel/biomass power plant." Renewable and Sustainable Energy Reviews 165: 112575.

28. Mesthrige T G, P Kaparaju (2025) Decarbonisation of Natural Gas Grid A review of GIS-based approaches on spatial biomass assessment, plant siting and biomethane grid injection. Energies 18(3): 734.

29. Lehtonen E, P Anttila, K Hakala, S Luostarinen, Lehtinen et al. (2024) An open web-based GIS service for biomass data in Finland. Environmental Modelling & Software 176: 105972.

30. Guido R E, C R Rodríguez, V M Javi, O A Oviedo (2024) A multicriteria GIS-based approach for mapping biomass agricultural residues availability for biopower plants. Clean Technologies and Environmental Policy 26:1989–2006.

31. Heck R, A Rudi, D Lauth, F Schultmann (2024) An estimation of biomass potential and location optimization for integrated biorefineries in Germany A combined approach of GIS and mathematical modeling. Sustainability 16(16): 6781.

32. Naeimi E F, G A K Gürdil, B Demirel (2025) Integrating GIS mapping and Artificial Neural Networks for assessing biomass energy potential from agricultural residues in Iran. Food and Energy Security 14(1): e70045.

33. Dang H N, D Ba, D N Trung, H N H Viet (2022) A novel method for estimating biomass and carbon sequestration in tropical rainforest areas based on remote sensing imagery A case study in the Kon Ha Nung Plateau Vietnam. Sustainability 14 (24): 16857.

34. Leanza P M, F Valenti, P R D Urso, C Arcidiacono (2022) A combined MaxEnt and GIS-based methodology to estimate cactus pear biomass distribution: Application to an area of southern Italy. Biofuels Bioproducts and Biorefining 13(2): 549.

35. Mishra H, F Kayusi, R Mishra, I Adamopoulos, D Bohra (2026) Remote sensing and GIS for monitoring delta agro-ecosystems. In Sustainable Management of Delta Ecosystems Resilience Case Studies on Delta Adaptation Pathways ChamSpringer Nature Switzerland 175-233.

36. Zhou J, M Zan, L Zhai, S Yang, C Xue, et al. (2025) Remote sensing estimation of aboveground biomass of different forest types in Xinjiang based on machine learning. Scientific Reports 15: 6187.

37. Rana P, S Popescu, A Tolvanen, B Gautam, Tokola, et al. (2023) Estimation of tropical forest aboveground biomass in Nepal using multiple remotely sensed data and deep learning. International Journal of Remote Sensing 44(17): 5147–5171.

38. Wongchai W, T Onsree, N Sukkam, A Promwungkwa, N Tippayawong (2022) Machine learning models for estimating above ground biomass of fast growing trees. Expert Systems with Applications 199: 117186.

39. Jiang F, H Sun, K Ma, L Fu, J Tang (2022) Improving aboveground biomass estimation of natural forests on the Tibetan Plateau using spaceborne LiDAR and machine learning algorithms. Ecological Indicators 143: 109365.

40. Tang Z, X Xia, Y Huang, Y Lu, Z Guo (2022) Estimation of national forest aboveground biomass from multi-source remotely sensed dataset with machine learning algorithms in China. Remote Sensing 14 (21): 5487.

41. Saim A, M H Aly (2026) Machine learning and multisensor data fusion for forest above ground biomass estimation in Arkansas. Earth Systems and Environment (10): 1783–1800.

42. Bui Q T, Q T Pham, D HNguyen, Q H Nguyen, et al. (2024) Ecological Informatics 79: 102421.

43. Zadbagher E, A M Marangoz, K Becek (2024) Estimation of above-ground biomass using machine learning approaches with InSAR and LiDAR data in tropical peat swamp forest of Brunei Darussalam. iForest—Biogeosciences and Forestry 17(3): 172-179

44. Khan K, S N Khan, A Ali, M F Khokhar, J A Khan (2025) Estimating aboveground biomass and carbon sequestration in afforestation areas using optical/SAR data fusion and machine learning. Remote Sensing 17(5) 934.

45. Nguyen T P, P K Nguyen, H N Nguyen, T H Nguyen, V B Nguyen (2024) Evaluation of statistical and machine learning models using satellite data to estimate aboveground biomass A study in Vietnam tropical forests. Forest Science and Technology 20(4):370-382

46. Hilmi N, R Chami, M D Sutherland, L Lebleu, M B Benitez (2021) The role of blue carbon in climate change mitigation and carbon stock conservation. Frontiers in Climate (3): 710546.



**How to cite this article:** Jaffar W, Usama A, Adnan A, Mahin J, Zeenat K. Geospatial Intelligence for Tree Biomass and Carbon Assessment: Integrating Remote Sensing, GIS and Artificial Intelligence in Horticultural and Arboricultural Systems. JOJ Horticulture & Arboriculture, 6(3). 555690.
DOI: 10.19080/JOJHA.2026.06.555690

47. Walker W S, Cook Patton, A Baccini, M K Farina, P W Ellis, et al. (2022) The global potential for increased storage of carbon on land. Proceedings of the National Academy of Sciences 119(23): e2111312119.

48. Khan N, M K Jhariya, A Raj, A Banerjee (2021) and R S Meena. Soil carbon stock and sequestration Implications for climate change adaptation and mitigation. In Ecological Intensification of Natural Resources for Sustainable Agriculture Singapore Springer Singapore.461–489

49. Duncanson L, M Liang, V Leitold, J Armston, S Costedoat, et al. (2023) The effectiveness of global protected areas for climate change mitigation. Nature Communications 14: 2908.

50. Arifanti V B, J B Kauffman, Subarno, M Ilman, N Novita (2022) Contributions of mangrove conservation and restoration to climate change mitigation in Indonesia. Global Change Biology 28(15): 4523-4538.

51. Rodrigues C I D, L M Brito, L J R Nunes (2023) Soil carbon sequestration in the context of climate change mitigation A review. Soil Systems 7 (3): 64.

52. Guenet B, B Gabrielle, C Chenu, D Arrouays, E Bruni, et al. (2021) Can $N_2O$ emissions offset the benefits from soil organic carbon storage Global Change Biology 27 (2):237-256.

53. Zeng Y, D A Friess, T V Sarira, K Siman, L P Koh (2021) Global potential and limits of mangrove blue carbon for climate change mitigation. Current Biology 31 (8): 1737–1743.

54. Don A, F Seidel, J Leifeld, T Kätterer, M Martin, et al. (2023) Carbon sequestration in soils and climate change mitigation Definitions and pitfalls. Global Change Biology 3(1): e16983.

55. Paul C, B Bartkowski, C Dönmez, M Steffens, S Weigl et al. (2023) Carbon farming: Are soil carbon certificates a suitable tool for climate change mitigation Journal of Environmental Management 330:117142.

56. Streck C, S Minoli, S Roe, C Barry, M Brander, G Cullity, et al. (2026) Considering durability in carbon dioxide removal strategies for climate change mitigation. Climate Policy 26(3):493–501.

57. Tomar J M S, A Barh, R Kumar, D Singh, K Singh et al. (2026) Long-term ecological recovery of a minespoil watershed Hydrological vegetation, and carbon stock assessment. Ecological Engineering 224: 107883.

58. Sarun H, H Hun (2026) Mangroves and Blue Carbon Importance for Climate Change Mitigation and Adaptation. Journal of Agriculture and Environment 3(2): 281–284.

59. Contreras F, M L Cayuela, M A Sánchez, Monedero, P Pérez Cutillas (2025) Multi-source Remote Sensing for Large-scale Biomass Estimation in Mediterranean Olive Orchards Using GEDI LiDAR and Machine Learning. Biogeosciences 22(23): 7625–7646.

60. Liu Y, Y Fan, J Yue, Y Ma, H Feng, et al. (2025) UAV-based Remote Sensing Estimation of Above-ground Biomass in Different Crops: A Review. International Journal of Applied Earth Observation and Geoinformation 144:104938.

61. Asli OZDARICIOK, Ali Ozgun OK (2023) Using Remote Sensing to Identify Individual Tree Species in Orchards: A Review. Scientia Horticulturae 321(1): 112333

62. Luo P, Y Zhang, J Ruan, G Zhang, JK Shang (2025) Estimation of Individual Tree Biomass for Three Tree Species Using LiDAR and Multispectral Data in Megacity Shanghai. Frontiers in Remote Sensing 6:1697927.

63. Dan Munteanu, Gabriel Murariu, et al. (2026) rSustainable Estimation of Tree Biomass and Volume Using UAV Imagery A Comprehensive Review. Sustainability 18(2): 1095.

64. Sana Ullah, Majid Nazeer, Man Sing Wong, Gomal Amin (2025) Remote Sensing for Aboveground Biomass Monitoring in Terrestrial Ecosystems A Systematic Review. Remote Sensing Applications: Society and Environment 39: 101635.

65. Sandamali J, LL Narine (2026) Spaceborne LiDAR for Forest Aboveground Biomass Estimation A Systematic Review of Methodological Trends. Advances in Space Research 78: 1768–1785.





**How to cite this article:** Jaffar W, Usama A, Adnan A, Mahin J, Zeenat K. Geospatial Intelligence for Tree Biomass and Carbon Assessment: Integrating Remote Sensing, GIS and Artificial Intelligence in Horticultural and Arboricultural Systems. JOJ Horticulture & Arboriculture, 6(3). 555690.
DOI: 10.19080/JOJHA.2026.06.555690