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GEOSPATIAL TECHNIQUES FOR ASSESSING CARBON SEQUESTRATION IN MANGO ORCHARDS

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ABSTRACT

Carbon sequestration in mango (*Mangifera indica* L.) orchards represents a promising nature-based strategy for climate change mitigation, yet accurate large-scale assessment remains challenging using conventional field methods. This review examines the application of geospatial technologies including Geographic Information Systems (GIS), remote sensing, Global Positioning Systems (GPS), Unmanned Aerial Vehicles (UAVs) and Light Detection and Ranging (LiDAR) for estimating carbon stocks in mango orchards. Satellite platforms such as Sentinel-2 and Landsat provide multispectral imagery enabling derivation of vegetation indices (NDVI, EVI, NDRE, GNDVI) strongly correlated with biomass and carbon storage. Integration of these spectral datasets with machine learning algorithms particularly Random Forest, Support Vector Machine, and Artificial Neural Networks, substantially improves prediction accuracy. Species-specific allometric models relating diameter, height and wood density to biomass further enhance carbon estimation. UAV and LiDAR technologies provide high-resolution three-dimensional canopy information for individual tree-level assessment. Despite advances, challenges persist regarding data availability, sensor integration, model transferability and standardized measurement protocols. Future research should prioritize multi-sensor data fusion, artificial intelligence applications, cloud-based platforms and robust measurement, reporting and verification frameworks. Integrating advanced geospatial techniques with sustainable orchard management offers a reliable pathway for enhancing carbon accounting, supporting precision agriculture, and contributing to global climate mitigation efforts.

KEYWORDS: Carbon sequestration, mango orchards, geospatial technologies, remote sensing, GIS, machine learning, UAV, LiDAR, biomass estimation, precision agriculture.

1. INTRODUCTION

Climate change, driven primarily by increasing atmospheric carbon dioxide (CO_2) concentrations, has become one of the most pressing global environmental challenges. Carbon sequestration, the process of capturing and storing atmospheric carbon in vegetation and soils, is recognized as an effective nature-based solution for mitigating climate change. Perennial agricultural systems, particularly fruit orchards, contribute significantly to carbon storage by accumulating biomass over long periods while enhancing soil organic carbon. Among these systems, mango (*Mangifera indica* L.) orchards have considerable potential for carbon sequestration due to their long lifespan, large canopy structure, extensive root systems, and ability to store carbon in both above-ground biomass and soil. Accurate estimation of carbon stocks in mango orchards is essential for sustainable orchard management, climate change mitigation, and participation in carbon credit programs. Conventional methods such as destructive sampling and field-based biomass measurements are accurate but require substantial time, labor, and financial resources, making them unsuitable for large-scale monitoring. Consequently, there is a growing need for efficient non-destructive approaches that can provide reliable estimates of carbon sequestration across extensive orchard landscapes.

Recent advancements in geospatial technologies have transformed carbon assessment by integrating Geographic Information Systems (GIS), remote sensing, Global Positioning Systems (GPS), Unmanned Aerial Vehicles (UAVs), Light Detection and Ranging (LiDAR), and machine learning techniques. Satellite platforms such as Sentinel-2 and Landsat enable the derivation of vegetation indices including NDVI, EVI, NDRE, and GNDVI, which are closely related to canopy characteristics, biomass accumulation, and carbon storage. When combined with species-specific allometric models and advanced machine learning algorithms such as Random Forest and Artificial Neural Networks, these technologies provide accurate, scalable, and cost-effective estimation of biomass and carbon stocks while enabling high-resolution spatial mapping and long-term monitoring. This review summarizes the recent developments in geospatial techniques for assessing carbon sequestration in mango orchards. It discusses the application of remote sensing, GIS, vegetation indices, allometric models, machine learning, UAVs, LiDAR, and soil organic carbon mapping, while highlighting their advantages, limitations, and future research opportunities. The integration of these advanced technologies offers a robust framework for precision orchard management, carbon accounting, and sustainable agricultural development, ultimately supporting global efforts to mitigate climate change.

2. Role of Geospatial Technologies in Carbon Assessment

Geographic Information Systems (GIS), Remote Sensing (RS), Global Positioning Systems (GPS), Unmanned Aerial Vehicles (UAVs) and Light Detection and Ranging (LiDAR) technologies enable continuous monitoring of vegetation characteristics, spatial variability, and temporal changes in biomass without damaging the ecosystem. These technologies facilitate carbon accounting by integrating field observations with spatial datasets, allowing researchers to generate high-resolution carbon stock maps and evaluate the effectiveness of climate-smart agricultural practices. In perennial agroecosystems such as mango orchards, geospatial technologies are particularly valuable because they allow repeated assessments of tree growth, canopy development, and carbon accumulation throughout the orchard's lifespan.

2.1. Remote Sensing and GIS Applications

Geospatial techniques has become one of the most powerful tools for estimating biomass and carbon sequestration of Perennial agricultural systems because vegetative growth of the tree exhibits unique spectral signatures in different portions of the electromagnetic spectrum. Modern satellite techniques such as Sentinel-2, Landsat-8/9, MODIS, and Planet Scope provide multispectral imagery that captures reflectance in visible, near-infrared region (NIR), and red edge wavelengths. Healthier vegetative growth strongly reflects NIR radiation while absorbing red light due to chlorophyll activity which enables the calculation of vegetation indices such as NDVI, EVI, NDRE, and SAVI, which are highly correlated with biomass and carbon stocks. Also, GIS applications gives organised, integrated, and analysed datasets for environmental variables such as soil type, elevation, slope, rainfall, and land-use patterns. Also GIS and remote sensing together allow delineating orchard boundaries, map carbon distribution, identifying carbon-rich and carbon-deficient areas, etc,.

2.2. Advanced Geospatial Technologies

Recent advancements in machine learning techniques have significantly improved the accuracy of remote sensing-based carbon estimation. Algorithms such as Random Forest (RF), Support Vector Machine (SVM), Artificial Neural Networks (ANN), Gradient Boosting, and Convolutional Neural Networks (CNN) can analyse complex relationships between spectral information, vegetation indices, canopy structure, and field-measured biomass. These algorithms effectively handle nonlinear relationships and heterogeneous orchard conditions, producing more reliable biomass predictions than conventional statistical methods. In addition, UAVs equipped with RGB, multispectral, hyperspectral, and thermal sensors provide ultra-high-resolution imagery that enables individual tree detection, crown segmentation, canopy height estimation, and three-dimensional structural analysis. LiDAR technology further enhances biomass estimation by accurately measuring tree height, crown volume, and canopy architecture, even in dense vegetation. The integration of UAV imagery, LiDAR data, and machine learning has emerged as a promising approach for precision carbon monitoring in orchard ecosystems, including mango plantations.

3. Remote Sensing Data Sources for Mango Orchard Mapping

Remote sensing has become one of the most effective geospatial technologies for mapping mango orchards and assessing their carbon sequestration potential over large geographical areas. Conventional field surveys for estimating orchard extent, biomass, and carbon stocks are labor-intensive, expensive, and often impractical for repeated monitoring. Satellite remote sensing overcomes these limitations by providing consistent, repetitive, and spatially extensive observations of vegetation characteristics. Sensors mounted on satellites record reflected electromagnetic radiation from the Earth's surface, enabling the identification of vegetation health, canopy density, biomass, and land-cover changes. Because mango orchards are perennial tree systems with distinct canopy structures, they can be effectively identified and monitored using multispectral satellite imagery. Continuous remote sensing observations support carbon accounting by enabling temporal monitoring of orchard growth, biomass accumulation, and changes in vegetation conditions, making them valuable tools for sustainable orchard management and climate change mitigation.

3.1. Sentinel-2 as the Primary Data Source

Among the available Earth observation satellites, Sentinel-2 has emerged as one of the most suitable platforms for mango orchard mapping because of its high spatial resolution, frequent revisit interval, and rich spectral information. The Sentinel-2 Multi Spectral Instrument (MSI) acquires imagery in 13 spectral bands covering the visible, near-infrared (NIR), red-edge, and shortwave infrared (SWIR) regions with spatial resolutions of 10 m, 20 m, and 60 m. The red-edge bands (705, 740, and 783 nm) are particularly valuable for estimating canopy chlorophyll content, vegetation vigor, and biomass, which are directly related to carbon sequestration. ***Panumonwatee et al. (2025)*** used Sentinel-2 imagery to evaluate carbon sequestration in mango orchards across Thailand by integrating twelve vegetation indices, including NDVI, NDRE, EVI, GNDVI, TVI, TVI-2, and Chlorophyll Index Red Edge (CIRE). Their Random Forest model achieved a very high prediction accuracy ($R^2 = 0.97$) demonstrating that Sentinel-2 imagery provides a reliable, scalable, and cost-effective approach for estimating carbon stocks.

Although Sentinel-2 is widely used, other remote sensing platforms also contribute valuable information for orchard mapping and biomass estimation. Landsat-8 and Landsat-9 provide long-term historical datasets useful for monitoring changes in orchard extent and vegetation over several decades, while MODIS offers high temporal resolution for regional-scale vegetation monitoring despite its coarser spatial resolution. At finer scales, unmanned aerial vehicles (UAVs) equipped with RGB, multispectral, or hyperspectral sensors provide centimetre-level imagery for individual tree detection, crown delineation, canopy height estimation, and biomass assessment. Studies have shown that combining UAV imagery with satellite data significantly improves biomass prediction accuracy because UAVs capture detailed canopy structure that satellites cannot resolve. In addition, hyperspectral sensors record hundreds of narrow spectral bands, allowing precise estimation of leaf chlorophyll, nitrogen concentration, and plant physiological status, which are closely linked to carbon assimilation and productivity.

3.2. Selection of Spectral Bands and Future Applications

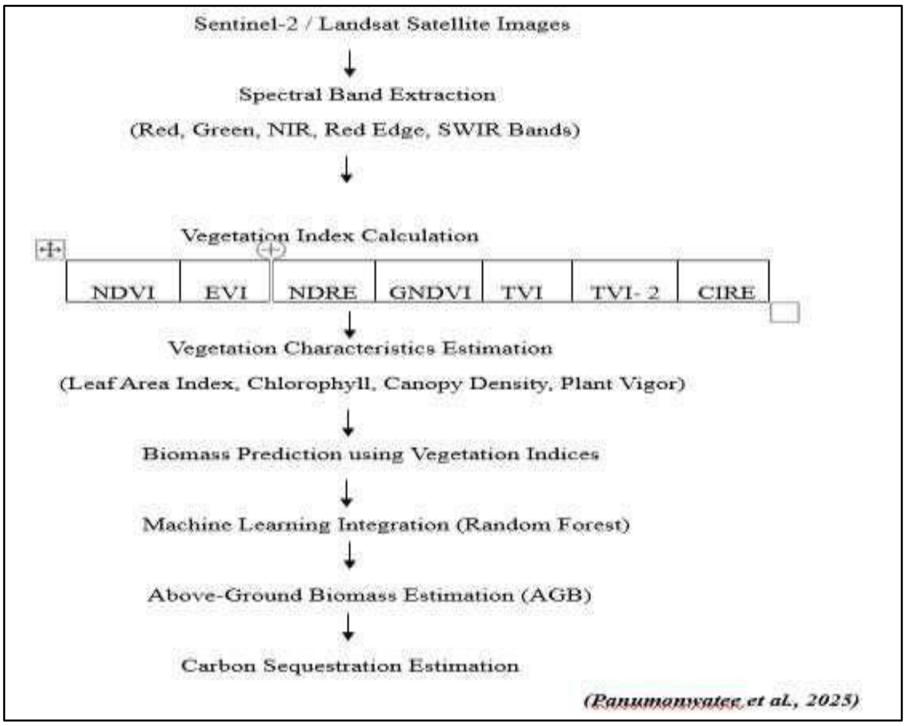
The effectiveness of remote sensing for carbon assessment depends largely on the selection of appropriate spectral bands and vegetation indices. The visible red band is sensitive to chlorophyll absorption, while the near-infrared band responds to leaf cellular structure and canopy density. Sentinel-2's unique red-edge bands provide additional sensitivity to chlorophyll concentration and nitrogen status, reducing saturation problems commonly encountered with traditional vegetation indices such as NDVI in dense canopies. ***Clevers and Gitelson (2013)*** demonstrated that red-edge-based indices, including the Red-edge Chlorophyll Index (CIred-edge), Green Chlorophyll Index (CIgreen), and the MERIS Terrestrial Chlorophyll Index (MTCI), are highly effective for estimating canopy chlorophyll and nitrogen content, making Sentinel-2 especially suitable for agricultural applications. Future developments combining Sentinel-2 imagery with LiDAR, hyperspectral sensors, UAV observations, and machine learning algorithms are expected to further improve the accuracy of mango orchard mapping and carbon stock estimation, supporting precision agriculture, carbon credit verification, and sustainable orchard management.

4. Vegetation Indices for Biomass and Carbon Estimation

4.1. Importance of Vegetation Indices in Biomass and Carbon Estimation

Vegetation indices (VIs) are mathematical transformations of spectral reflectance values obtained from remote sensing data and are widely used to estimate vegetation characteristics such as chlorophyll content, leaf area index (LAI), canopy density, biomass, and carbon storage. Healthy vegetation absorbs most of the incoming red light for photosynthesis while strongly reflecting near-infrared (NIR) radiation due to the internal structure of leaves. By combining reflectance values from these spectral bands, vegetation indices provide quantitative information about plant vigour and productivity that can be directly related to biomass accumulation and carbon sequestration.

Flowchart of Vegetation Indices for Biomass and Carbon Estimation



4.2. Common Vegetation Indices Used for Mango Orchard Biomass Estimation

Vegetation indices have become indispensable tools for monitoring biomass and carbon sequestration because they provide continuous, spatially explicit information over large areas with relatively low operational costs.

Several vegetation indices have been developed to estimate biomass and carbon stocks by exploiting differences in spectral reflectance between vegetation and atmospheric surfaces. Due to the effective representation of vegetation greenness and photosynthetic activity, the Normalized Difference Vegetation Index (NDVI) is the most widely used one. Other indices, such as the Enhanced Vegetation Index (EVI), improve sensitivity in dense vegetation by reducing atmospheric and soil background effects, while the Normalized Difference Red Edge Index (NDRE) utilizes Sentinel-2 red-edge bands to estimate chlorophyll concentration in mature canopies. Additional indices including the Green Normalized Difference Vegetation Index (GNDVI), Green Chlorophyll Index (Clgreen), Triangular Vegetation Index (TVI), Modified Triangular Vegetation Index (TVI-2), Ratio Vegetation Index (RVI), Modified Simple Ratio Index (MSRI), and Chlorophyll Index Red Edge (CIRE) provide complementary information related to leaf chlorophyll, nitrogen content, and canopy structure. *Panumonwatee et al. (2025)* evaluated twelve vegetation indices using Sentinel-2 imagery and demonstrated that these indices showed significant relationships with field-measured biomass, highlighting their usefulness for estimating carbon sequestration in mango orchards.

4.3. Integration of Vegetation Indices with Machine Learning Techniques

Although individual vegetation indices provide valuable information about vegetation condition, combining multiple indices with machine learning techniques substantially improves biomass and carbon prediction accuracy. *Panumonwatee et al. (2025)* integrated twelve Sentinel-2-derived vegetation indices into a Random Forest (RF) model to estimate aboveground carbon storage in mango orchards. The model achieved an excellent coefficient of determination ($R^2 = 0.97$) with a Root Mean Square Error (RMSE) of 1.57 t C ha^{-1}, demonstrating the effectiveness of integrating spectral information with advanced statistical approaches.

5. GIS-Based Spatial Carbon Mapping

5.1. Importance of GIS in Spatial Carbon Mapping

Geographic Information Systems (GIS) have become an essential component of geospatial technologies for assessing and mapping carbon sequestration potential. GIS provides a platform for collecting, storing, integrating, analyzing, and visualizing spatial data from multiple sources such as satellite imagery, field surveys, soil databases, climate records, and topographic information. GIS enables researchers to produce spatially explicit carbon distribution maps across entire orchard landscapes. These maps reveal the spatial variability of biomass carbon and soil organic carbon (SOC), allowing researchers to identify carbon-rich and carbon-deficient zones. The integration of GIS with remote sensing also facilitates continuous monitoring of orchard growth and land-use changes, supporting precision orchard management and climate-smart agricultural planning. In perennial systems such as mango orchards, GIS-based spatial analysis is particularly valuable because it enables repeated assessment of carbon dynamics over time while reducing the cost and effort associated with extensive field sampling.

5.2. Integration of Remote Sensing and GIS for Carbon Mapping

The effectiveness of GIS-based carbon mapping depends on its ability to integrate remotely sensed data with field observations. ***Panumonwatee et al. (2025)*** utilized QGIS software to calculate twelve vegetation indices from Sentinel-2 multispectral imagery and combined these indices with field-measured carbon sequestration data to investigate spatial variability in mango orchards. The vegetation indices provided information on leaf area index, chlorophyll content, canopy vigor, and plant growth, all of which are closely related to biomass accumulation and carbon storage. By linking these remotely sensed variables with geographic coordinates collected during field surveys, GIS enabled the creation of spatial datasets representing carbon stocks across the study area. Such integration improves the visualization of carbon distribution and provides a reliable framework for identifying areas with high carbon sequestration potential, thereby supporting targeted management interventions and improving the accuracy of regional carbon inventories.

5.3. GIS Applications in Carbon Stock Estimation and Spatial Analysis

GIS is widely applied in carbon stock estimation because it allows the combination of multiple environmental datasets, including vegetation indices, soil properties, climatic variables, elevation, slope, and land-use information, into a single analytical framework. According to *Zomer et al. (2016)*, integrating remote sensing-derived tree cover with IPCC Tier-1 biomass carbon estimates enabled the development of global and regional biomass carbon maps for agricultural lands. Their study estimated that agricultural lands worldwide stored 45.3 Pg of biomass carbon in 2000, increasing to 47.37 Pg in 2010, with more than 75% of this carbon contributed by trees. GIS-based spatial analysis also revealed considerable regional variation in biomass carbon, with Southeast Asia and South America exhibiting the highest carbon densities because of greater tree cover. These findings demonstrate that GIS is not only useful for local orchard-scale assessments but also for national and global carbon accounting, policy development, and climate change mitigation planning.

Recent advances in GIS have greatly enhanced the precision and applicability of spatial carbon mapping through the integration of machine learning, cloud-based geospatial platforms, UAV imagery, and LiDAR data. Machine learning algorithms such as Random Forest can be incorporated into GIS workflows to improve carbon stock prediction by analyzing complex relationships between spectral indices and field-measured biomass. Modern GIS platforms also support temporal monitoring, enabling researchers to assess changes in orchard biomass over multiple years and evaluate the impacts of management practices on carbon storage. As high-resolution satellite imagery and cloud computing technologies continue to evolve, GIS-based carbon mapping is expected to play an increasingly important role in carbon credit verification, precision horticulture, sustainable orchard management, and national greenhouse gas inventories.

6. Above-Ground Biomass Estimation Using Allometric Models

Above-ground biomass (AGB) refers to the total dry weight of all living plant components present above the soil surface, including the stem, branches, bark, twigs, and leaves. It is one of the most important indicators used to quantify carbon storage because nearly half of the dry biomass consists of carbon. Therefore, accurate estimation of AGB is essential for evaluating carbon sequestration potential, monitoring forest productivity, assessing ecosystem health, and developing climate change mitigation strategies.

Allometric models are mathematical equations that estimate tree biomass using easily measurable tree characteristics such as Diameter at Breast Height (DBH), total tree height (H), and wood specific gravity or wood density (ρ). These variables have a strong relationship with tree biomass and can be measured during routine forest inventories. Among these parameters, DBH is considered the most important predictor because it is simple to measure and has a strong correlation with biomass accumulation. Including tree height and wood density further improves the accuracy of biomass estimation. One of the most widely accepted pantropical allometric models was developed by ***Chave et al. (2014)*** using data from **4,004 destructively harvested trees collected from 58 tropical forest sites** across Africa, Asia, Australia, and South America. Their study demonstrated that biomass estimation is most accurate when diameter, tree height, and wood density are all included in the model, **AGB = 0.0673 × (ρD²H)^0.976**, where AGB is above-ground biomass, ρ is wood density, D is diameter at breast height, and H is total tree height. This model performs well across different tropical forest types and has become one of the standard equations used in biomass and carbon stock estimation worldwide.

Allometric models offer several advantages over destructive sampling methods. They provide a rapid, economical, and non-destructive approach for estimating biomass without cutting trees. These models are suitable for large-scale forest inventories, long-term monitoring programs, and carbon accounting projects. They also serve as the foundation for greenhouse gas inventories and climate change mitigation initiatives. Although, allometric equations can be integrated with remote sensing technologies such as satellite imagery and LiDAR to estimate biomass over extensive geographical areas with improved efficiency and accuracy.

7. Machine Learning Models in Carbon Prediction

Machine learning (ML) has emerged as a powerful tool for predicting carbon stocks and carbon sequestration in forests, agroforestry systems, and agricultural landscapes. Unlike traditional statistical methods, machine learning algorithms can analyze large and complex datasets, identify non-linear relationships, and generate highly accurate predictions. These models integrate field measurements with remote sensing data, such as satellite imagery, vegetation indices, and environmental variables, enabling efficient estimation of above-ground biomass and carbon storage over large geographical areas. As a result, machine learning has become an essential approach for carbon accounting, climate change mitigation, and sustainable land management.

Machine learning models use field-based carbon measurements as training data and establish relationships with remotely sensed variables to predict carbon stocks. Commonly used algorithms include **Random Forest (RF), Support Vector Machine (SVM), Artificial Neural Networks (ANN), Gradient Boosting, and Decision Trees**. These algorithms are capable of handling high-dimensional datasets, reducing prediction errors, and modeling complex interactions among vegetation, climate, and soil variables. Among these methods, the **Random Forest algorithm** is one of the most widely applied because it combines the predictions of multiple decision trees, resulting in improved accuracy, robustness, and resistance to overfitting. The Random Forest algorithm, introduced by **Leo Breiman (2001)**, is an ensemble learning technique that constructs a large number of decision trees using randomly selected subsets of data and predictor variables. Each tree independently predicts the output, and the final prediction is obtained by averaging the results of all trees in the forest. The algorithm is particularly suitable for carbon prediction because it efficiently handles non-linear relationships and interactions among vegetation indices, biomass measurements, and environmental factors.

Recent studies have demonstrated the effectiveness of integrating machine learning with **Sentinel-2 satellite imagery** for carbon prediction. In a study conducted by **Panumonwatee et al. (2025)**, field measurements from 49 mango orchard plots were combined with twelve vegetation indices derived from Sentinel-2 imagery, including NDVI, NDRE, EVI, GNDVI, TVI-2, and CIRE. These vegetation indices showed strong correlations with above-ground biomass and carbon storage. The Random Forest model integrated all vegetation indices to predict carbon sequestration and achieved an excellent coefficient of determination (**R^2 = 0.97**), with a low Root Mean Square Error (RMSE) of **1.57 t C ha^{-1}** and Mean Absolute Error (MAE) of **1.05 t C ha^{-1}**. Feature importance analysis revealed that **TVI-2, NDVI, GNDVI, and NDRE** contributed the most to prediction accuracy.

Machine learning models are increasingly integrated with remote sensing technologies because satellite data provide continuous, large-scale observations of vegetation characteristics. Sensors such as Sentinel-2, Landsat, and LiDAR capture spectral information related to plant health, canopy structure, chlorophyll content, and biomass. Machine learning algorithms analyze these datasets to estimate above-ground biomass and carbon stocks without relying solely on labor-intensive field surveys. This integration significantly reduces the cost and time required for carbon assessment while improving the spatial coverage and frequency of monitoring. Despite their high predictive performance, machine learning models have certain limitations. Their accuracy depends on the quality and quantity of field data used for training and validation. Poor-quality input data, limited sample sizes, or inappropriate model selection may reduce prediction accuracy. Additionally, machine learning models often function as "black-box" systems, making it difficult to interpret the contribution of individual variables. Therefore, careful model calibration, cross-validation, and independent validation datasets are necessary to ensure reliable carbon prediction.

8. Soil Organic Carbon Spatial Analysis

Soil Organic Carbon (SOC) spatial analysis is a geospatial approach used to evaluate and map the distribution of soil organic carbon across different landscapes. It combines field observations with geostatistical methods, Geographic Information Systems (GIS), remote sensing, and machine learning techniques to identify spatial variations in SOC. Several factors, including parent material, topography, climate, vegetation, land use, and soil management practices influence the distribution of SOC. Understanding these spatial patterns is essential for assessing soil fertility, estimating carbon sequestration potential, supporting precision agriculture, and developing sustainable land management strategies (Dhiman et al., 2025).

Flowchart of Soil Organic Carbon (SOC) Spatial Analysis

Soil Sample Collection

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Laboratory SOC Determination

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Collection of Spatial Information

(Remote Sensing, GIS, DEM, Climate, Land Use)

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GIS Database Development

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Geostatistical Analysis (Semi-variogram & Ordinary Kriging)

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Machine Learning & Spatial Prediction

(Random Forest, SVM, Artificial Neural Network)

↓

Soil Organic Carbon Distribution Map

↓

Identification of Carbon-Rich & Carbon-Poor Zones

↓

Precision Nutrient Management - Carbon Accounting Sustainable Land Management - Climate Change Mitigation

(*Dhiman et al., 2025*)

Conventional methods of assessing soil organic carbon involve extensive soil sampling and laboratory analysis, which are accurate but costly, labor-intensive, and difficult to implement over large areas. Recent advances in geospatial technologies have enabled researchers to integrate field-based SOC measurements with GIS and remote sensing data to generate high-resolution spatial maps of soil carbon. These approaches improve the efficiency of SOC assessment by reducing sampling intensity while maintaining prediction accuracy. Global initiatives such as the **Global Soil Organic Carbon Sequestration Potential Map (GSOCseq v1.1)** developed by the Food and Agriculture Organization (FAO) further demonstrate the importance of spatial mapping in estimating regional and global soil carbon sequestration potential (Peralta et al., 2022).

Geostatistics plays a central role in SOC spatial analysis because it accounts for the spatial dependence of soil properties. Techniques such as semi-variogram analysis and ordinary kriging are widely used to model the spatial variability of SOC and interpolate carbon values at unsampled locations. Semi-variograms quantify the degree of spatial correlation among sampling points, whereas kriging provides unbiased estimates with minimum prediction variance, producing continuous SOC distribution maps. These methods have become standard tools in soil science for evaluating spatial variability and improving the reliability of soil property prediction (Webster & Oliver, 2007).

Recent studies have demonstrated the effectiveness of combining geostatistics with multivariate statistical approaches for soil nutrient and carbon assessment. For example, ***Dhiman et al. (2025)*** investigated the spatial variability of soil fertility parameters in mango orchards using semivariogram modelling, kriging interpolation, and Principal Component Analysis (PCA). Their study revealed significant spatial heterogeneity in soil properties and emphasized that understanding spatial variability is essential for delineating site-specific management zones and optimizing fertilizer application. Although the study primarily focused on soil nutrients, the same geostatistical framework can be effectively applied to Soil Organic Carbon mapping because SOC exhibits similar spatial dependence influenced by environmental and management factors.

In recent years, machine learning algorithms have been increasingly integrated with remote sensing and geostatistical techniques to improve SOC spatial prediction. Algorithms such as **Random Forest**, **Support Vector Machine (SVM)**, and Artificial Neural Networks can model complex, non-linear relationships between SOC and environmental variables, often outperforming conventional interpolation methods. The integration of satellite-derived vegetation indices, terrain attributes, climate variables, and field observations enables more accurate and continuous mapping of SOC over large areas while reducing field sampling requirements. These advanced approaches support precision agriculture, carbon accounting, and climate change mitigation by providing reliable estimates of soil carbon stocks (Dhiman et al., 2025).

Spatial analysis of Soil Organic Carbon is increasingly recognized as an essential tool for sustainable soil management and carbon sequestration studies. Accurate SOC maps help identify carbon-rich and carbon-deficient areas, evaluate the impacts of land-use change, prioritize soil restoration efforts, and support national greenhouse gas inventories. Since soil represents one of the largest terrestrial carbon reservoirs, understanding its spatial variability is fundamental for enhancing carbon sequestration, improving soil quality, and mitigating climate change. As emphasized by Rattan Lal, increasing soil organic carbon through sustainable land management not only contributes to climate change mitigation but also improves soil productivity, water-holding capacity, and long-term agricultural sustainability (Lal, 2004).

9. UAV and LiDAR-Based High-Resolution Carbon Mapping

The integration of Unmanned Aerial Vehicles (UAVs) and Light Detection and Ranging (LiDAR) has significantly improved the accuracy and spatial resolution of forest carbon mapping. LiDAR provides detailed three-dimensional information about forest canopy structure by directly measuring tree height, canopy density, and vertical vegetation profiles, which are strongly correlated with aboveground biomass (AGB) and carbon storage. Unlike conventional optical remote sensing, LiDAR performs well even in dense forests where canopy saturation limits biomass estimation. Studies have demonstrated that LiDAR-derived structural metrics explain a high proportion of the variation in aboveground biomass, making it one of the most reliable technologies for carbon stock assessment across diverse forest ecosystems (Lefsky et al., 2002; Lefsky et al., 2005).

Recent advances combine LiDAR with high-resolution UAV imagery to generate detailed carbon maps at the individual-tree level. UAV platforms equipped with RGB, multispectral cameras, or photogrammetric sensors provide ultra-high spatial resolution imagery that enables accurate delineation of tree crowns, species identification, canopy dimensions, and structural characteristics. When integrated with LiDAR-derived height information, these datasets improve biomass estimation by incorporating species-specific allometric relationships and crown geometry. Machine learning and deep learning approaches further enhance this integration by automatically detecting tree crowns, classifying species, and estimating biomass, thereby producing high-resolution carbon maps with improved spatial accuracy while reducing dependence on extensive field measurements.

Drone-based photogrammetry has also emerged as a cost-effective alternative or complement to LiDAR for modelling individual trees. High-resolution UAV imagery can reconstruct accurate three-dimensional tree models, allowing estimation of branch architecture, canopy volume, and structural complexity. Although LiDAR remains superior for capturing under-canopy vegetation and fine structural details, UAV photogrammetry offers an affordable approach for monitoring individual trees and open-grown forests with high accuracy. Combining UAV-derived structural models with LiDAR measurements enables comprehensive assessment of forest biomass and carbon distribution at fine spatial scales, making these technologies particularly valuable for precision forestry, carbon accounting, and climate change mitigation strategies.

Furthermore, recent research has demonstrated that integrating aerial imagery, LiDAR data, and artificial intelligence enables scalable carbon estimation across large landscapes. LiDAR data can be used to calibrate biomass estimation models, while machine learning algorithms infer tree height, crown dimensions, and species information from UAV or aerial imagery alone. This approach reduces the need for repeated LiDAR acquisition while maintaining high mapping accuracy, enabling the production of near real-time, high-resolution carbon maps suitable for monitoring forest carbon dynamics and supporting carbon trading, forest management, and ecosystem conservation initiatives.

10. Temporal Monitoring of Carbon Sequestration

Temporal monitoring of carbon sequestration is essential for understanding how carbon stocks change over time in response to land-use practices, vegetation growth, climate variability, and management interventions. Long-term monitoring enables researchers to quantify trends in carbon accumulation, evaluate the permanence of carbon storage, and assess the effectiveness of climate change mitigation strategies. Repeated measurements of aboveground biomass, soil organic carbon (SOC), and vegetation characteristics provide valuable information on carbon dynamics, while integrating field observations with remote sensing technologies allows for continuous monitoring across multiple spatial and temporal scales. Such long-term assessments are critical for supporting sustainable land management, ecosystem restoration, and carbon credit verification.

Monitoring soil carbon over time remains challenging because SOC changes occur slowly and are influenced by climate, land use, soil properties, and management practices. Reliable temporal assessments require well-designed measurement, reporting, and verification (MRV) systems that combine repeated soil sampling, long-term experiments, process-based models, and Earth observation data. Smith et al. (2020) emphasized that the integration of field measurements with modelling approaches and remote sensing provides a robust framework for detecting gradual changes in soil carbon while reducing monitoring costs. The use of permanent monitoring plots, standardized sampling protocols, and benchmark sites further improves the accuracy and consistency of long-term carbon assessments.

Advances in satellite remote sensing and machine learning have significantly enhanced temporal carbon monitoring by enabling frequent and cost-effective assessments of vegetation growth and biomass. Time-series imagery from platforms such as Sentinel-2 provides repeated observations that capture seasonal and annual variations in vegetation indices closely related to carbon sequestration. When combined with machine learning algorithms such as Random Forest, these datasets can accurately estimate carbon stocks over successive time periods, allowing continuous monitoring of changes in agricultural landscapes and orchards. This approach reduces reliance on repeated field inventories while providing scalable and timely information for carbon accounting, sustainable land management, and carbon trading programs.

Long-term monitoring also supports the evaluation of ecosystem management practices that enhance carbon sequestration. Studies of agroforestry systems have shown that temporal changes in belowground processes, root development, soil organic carbon accumulation, water cycling, and nutrient dynamics influence the long-term stability of carbon storage. Monitoring these ecological processes over time helps identify management practices that maximize carbon sequestration while improving ecosystem resilience, soil quality, and agricultural productivity. Consequently, continuous temporal monitoring forms the foundation for adaptive management strategies and informed policy decisions aimed at achieving long-term climate change mitigation goals.

11. Challenges and Limitations

Despite significant advances in remote sensing and machine learning for carbon sequestration estimation, several challenges and limitations continue to affect the accuracy, scalability, and operational implementation of these approaches. One of the primary challenges is the dependence on high-quality and multisource datasets. While combining optical imagery, Synthetic Aperture Radar (SAR), and LiDAR improves biomass estimation, acquiring and processing these heterogeneous datasets requires considerable computational resources, technical expertise, and data harmonization. Furthermore, LiDAR datasets, although highly accurate for estimating forest structure, are often expensive and have limited spatial and temporal coverage, making them inaccessible for continuous large-scale monitoring. In the absence of LiDAR, optical and radar data alone may suffer from signal saturation in dense forests, reducing the accuracy of aboveground biomass and carbon stock estimation.

Another significant limitation is the variability in machine learning model performance across different ecosystems and forest conditions. Although algorithms such as Random Forest, XGBoost, Support Vector Machine, and deep learning models have demonstrated high predictive accuracy, no single model consistently performs best under all environmental conditions. Model performance depends heavily on feature selection, training data quality, forest type, sensor characteristics, and geographic variability. Poorly selected predictor variables or insufficient field reference data can introduce substantial uncertainty, limiting the transferability of models to new regions. Moreover, complex machine learning models often require extensive computational resources and large training datasets, which may not be readily available in developing countries.

Accurate carbon accounting is also constrained by measurement, reporting, and verification (MRV) challenges, particularly in agroforestry and heterogeneous landscapes. Many countries lack standardized definitions, consistent inventory methods, high-resolution satellite imagery, and institutional capacity to effectively incorporate agroforestry into national carbon accounting systems. Technical barriers include the difficulty of detecting small and scattered trees, limited availability of agroforestry-specific allometric equations, and inconsistencies in land-use classification. In addition, overlapping institutional responsibilities, inadequate technical expertise, and limited financial resources hinder the development of reliable MRV frameworks required for national greenhouse gas inventories and carbon credit programs.

Temporal monitoring presents additional challenges because carbon sequestration is a dynamic process influenced by climate variability, disturbances, land-use change, and vegetation growth. Frequent field measurements remain expensive and labor-intensive, while remote sensing observations may be affected by cloud cover, sensor resolution, and differences between acquisition dates. Ensuring long-term consistency across multiple sensors and observation periods requires standardized preprocessing methods and robust calibration techniques. Consequently, future research should focus on improving multisensor data fusion, developing transferable machine learning models, increasing the availability of open-access high-resolution datasets, and strengthening national MRV systems to support accurate, scalable, and cost-effective carbon sequestration monitoring.

12. Future Research Directions

Future research on geospatial techniques for assessing carbon sequestration in mango orchards should focus on improving the accuracy, scalability, and efficiency of carbon estimation methods through the integration of advanced technologies. Developing **species-specific allometric models** for mango under different climatic conditions and management practices will reduce uncertainties in biomass estimation. In addition, integrating multi-source datasets from **Sentinel-2, Landsat, UAVs, LiDAR, hyperspectral sensors, and Synthetic Aperture Radar (SAR)** can provide more comprehensive information on orchard structure and carbon dynamics. The application of **artificial intelligence (AI)** and advanced machine learning algorithms is expected to further enhance carbon prediction by improving tree detection, biomass estimation, and spatial carbon mapping. Cloud-based geospatial platforms such as **Google Earth Engine** and real-time data processing systems can facilitate large-scale monitoring of orchard carbon stocks, while long-term satellite time-series analysis will enable continuous assessment of seasonal and annual changes in carbon sequestration under different management and climatic conditions.

Future studies should also strengthen **soil organic carbon (SOC)** assessment by integrating digital soil mapping, geostatistics, remote sensing, and IoT-based field monitoring systems. Establishing standardized **Measurement, Reporting and Verification (MRV)** frameworks will improve the reliability of carbon accounting and support carbon credit certification, greenhouse gas inventories, and sustainable orchard management. Collaborative research combining geospatial technologies, precision agriculture, and climate-smart management practices will play a crucial role in maximizing the carbon sequestration potential of mango orchards and contributing to global climate change mitigation efforts.

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