



Remote sensing integration of above-ground biomass and soil organic carbon for total carbon estimation: Multi-Sensor approaches and validation strategies

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Abstract

Accurate estimation of total ecosystem carbon requires integrated assessment of above-ground biomass (AGB) and soil organic carbon (SOC), yet most remote sensing approaches focus on individual components. This study develops and validates multi-sensor remote sensing frameworks for total carbon estimation across 347 validation sites spanning forests (134 sites), grasslands (98 sites), croplands (85 sites), and shrublands (30 sites) in 28 countries. We integrated optical (Sentinel-2, Landsat-8), radar (Sentinel-1, PALSAR-2), and LiDAR data using machine learning algorithms including random forest, support vector machines, and deep neural networks. Results demonstrate that integrated models achieve superior accuracy for total carbon estimation ($R^2 = 0.87$, $RMSE = 23.4 \text{ Mg C ha}^{-1}$) compared to single-component approaches ($R^2 = 0.64\text{--}0.72$). Multi-sensor fusion improved AGB estimation accuracy by 34% ($RMSE = 18.7$ vs 28.3 Mg ha^{-1}) and SOC estimation by 28% ($RMSE = 8.9$ vs $12.4 \text{ Mg C ha}^{-1}$) compared to single-sensor methods. Deep learning models showed strongest performance for complex forest ecosystems ($R^2 = 0.91$), while random forest algorithms excelled in agricultural landscapes ($R^2 = 0.84$). Optical-radar fusion proved most effective for AGB estimation, while thermal infrared and topographic variables were critical for SOC prediction. Validation across biomes revealed consistent performance with total carbon estimates ranging from $45.2 \pm 12.8 \text{ Mg C ha}^{-1}$ in grasslands to $287.6 \pm 68.4 \text{ Mg C ha}^{-1}$ in mature forests. Temporal analysis using 5-year time series demonstrated carbon change detection capability with 89% accuracy for changes $>10 \text{ Mg C ha}^{-1}$. Spatial scaling analysis indicates potential for global carbon mapping with uncertainty $<15\%$ for 90% of terrestrial areas. However, challenges remain for areas with persistent cloud cover, complex topography, and sparse ground truth data. Economic analysis reveals cost savings of 67% compared to field-based carbon assessment while providing complete spatial coverage. These findings demonstrate that integrated remote sensing approaches enable accurate, cost-effective total carbon estimation essential for climate change monitoring, carbon market verification, and ecosystem management across multiple scales.

Keywords: remote sensing, carbon estimation, above-ground biomass, soil organic carbon, multi-sensor fusion, machine learning, ecosystem carbon, carbon monitoring

1. Introduction

Accurate quantification of ecosystem carbon stocks is fundamental for climate change mitigation strategies, carbon market development, and sustainable land management ^[1]. Total ecosystem carbon comprises above-ground biomass (AGB), below-ground biomass, and soil organic carbon (SOC), with these components responding differently to environmental changes and management practices ^[2]. Traditional field-based methods provide high accuracy but are time-intensive, spatially limited, and expensive for large-scale applications ^[3].

Remote sensing technologies offer scalable solutions for carbon estimation, enabling consistent monitoring across large areas

with reduced costs ^[4]. However, most remote sensing approaches focus on individual carbon components, particularly AGB, while neglecting the substantial carbon stored in soils and below-ground biomass ^[5]. Soil organic carbon alone contains more carbon than atmosphere and vegetation combined, making its inclusion essential for comprehensive carbon accounting ^[6].

The challenge of integrated carbon estimation lies in the different physical properties and remote sensing signatures of above-ground and soil carbon components ^[7]. Above-ground biomass is directly observable through optical and radar sensors that detect vegetation structure, density, and chlorophyll content ^[8]. Conversely, soil carbon is not directly detectable from space, requiring indirect estimation through relationships with surface properties, vegetation characteristics, and environmental variables ^[9].

Recent advances in sensor technology, data fusion techniques, and machine learning algorithms have created new opportunities for integrated carbon estimation ^[10]. Multi-sensor approaches combining optical, radar, and LiDAR data can capture complementary information about ecosystem structure and function ^[11]. Machine learning methods enable complex non-linear relationships between remote sensing signals and carbon stocks across diverse ecosystems ^[12].

Optical sensors provide information on vegetation phenology, chlorophyll content, and leaf area index that relate to photosynthetic capacity and biomass production ^[13]. Synthetic aperture radar (SAR) penetrates vegetation canopies, providing structural information less affected by atmospheric conditions ^[14]. LiDAR systems directly measure three-dimensional vegetation structure, enabling precise biomass estimation for forest ecosystems ^[15].

The integration of multiple sensors and carbon components requires sophisticated modeling approaches that can handle high-dimensional data while maintaining interpretability ^[16]. Deep learning networks show promise for capturing complex relationships but require substantial training data and computational resources ^[17]. Ensemble methods combining multiple algorithms may provide optimal balance between accuracy and robustness ^[18].

This study addresses critical knowledge gaps by developing and validating integrated remote sensing frameworks for total ecosystem carbon estimation, evaluating multi-sensor fusion approaches, and assessing scalability for operational carbon monitoring applications ^[19].

2. Materials and Methods

2.1 Study Sites and Ground Truth Data

We compiled field measurements from 347 validation sites across diverse ecosystems and climatic zones. Sites included temperate and tropical forests (134 sites), grasslands and savannas (98 sites), agricultural croplands (85 sites), and shrubland ecosystems (30 sites) distributed across 28 countries spanning six continents ^[20].

Ground truth measurements encompassed AGB through allometric equations and destructive sampling, SOC through soil core analysis to 1-meter depth, and below-ground biomass using root:shoot ratios from literature. All measurements were standardized to Mg C ha⁻¹ using carbon content factors specific to vegetation and soil types ^[21].

2.2 Remote Sensing Data Acquisition

We acquired multi-temporal data from multiple sensors:

- **Optical:** Sentinel-2 (10-20m resolution), Landsat-8

(30m), MODIS (250-500m)

- **Radar:** Sentinel-1 C-band (10m), PALSAR-2 L-band (25m)
- **LiDAR:** Airborne systems (1-5m) for selected forest sites
- **Thermal:** Landsat-8 TIRS, MODIS LST for soil temperature
- **Topographic:** SRTM DEM (30m) for terrain variables²²

Data processing included atmospheric correction, geometric registration, cloud masking, and temporal compositing to create cloud-free annual composites. Spectral indices were calculated including NDVI, EVI, SAVI, and red-edge indices for vegetation analysis ^[23].

2.3 Feature Engineering and Variable Selection

We derived comprehensive feature sets from each sensor:

- **Optical:** Spectral bands, vegetation indices, phenological metrics
- **Radar:** Backscatter coefficients, polarization ratios, temporal statistics
- **Thermal:** Land surface temperature, thermal anomalies
- **Topographic:** Elevation, slope, aspect, terrain roughness
- **Climatic:** Temperature, precipitation from World Clim datasets ^[24].

Feature selection employed correlation analysis, mutual information, and recursive feature elimination to identify optimal variable combinations while avoiding multicollinearity ^[25].

2.4 Machine Learning Model Development

We implemented multiple algorithms for carbon estimation:

- **Random Forest (RF):** Ensemble method robust to overfitting
- **Support Vector Machines (SVM):** Effective for high-dimensional data
- **Gradient Boosting:** Sequential learning with error correction
- **Deep Neural Networks (DNN):** Complex non-linear relationships
- **Ensemble Models:** Weighted combinations of individual algorithms ^[26]

Model training used 70% of data with 10-fold cross-validation, while 30% was reserved for independent validation. Hyperparameter optimization employed grid search and Bayesian optimization ^[27].

2.5 Integration Strategies

We tested three approaches for total carbon estimation:

1. **Component-wise:** Separate models for AGB and SOC, summed for total.
2. **Direct:** Single model predicting total carbon directly.
3. **Hierarchical:** AGB model output used as input for SOC prediction ^[28].

Uncertainty propagation in component-wise approaches used Monte Carlo methods to combine individual model uncertainties ^[29].

2.6 Validation and Accuracy Assessment

Model performance was evaluated using multiple metrics:

- **Accuracy:** R^2 , RMSE, MAE, bias
- **Reliability:** Prediction intervals, uncertainty quantification
- **Transferability:** Cross-biome and cross-regional validation
- **Temporal stability:** Multi-year consistency analysis [30].

3. Results

3.1 Single component model performance

Individual component models achieved varying accuracy levels across ecosystems (Table 1). AGB estimation showed highest accuracy in forests ($R^2 = 0.89$) due to strong structural relationships with remote sensing signals, while grassland AGB proved more challenging ($R^2 = 0.67$) due to low biomass and saturation effects.

Table 1: Single Component Model Performance by Ecosystem Type

Ecosystem	AGB Estimation	SOC Estimation	Dominant Sensors	Key Variables
	R^2 / RMSE (Mg C ha ⁻¹)	R^2 / RMSE (Mg C ha ⁻¹)		
Temperate Forest	0.89 / 15.2 ^a	0.74 / 12.8 ^a	LiDAR, Sentinel-1	Height, Backscatter
Tropical Forest	0.84 / 21.7 ^b	0.69 / 15.4 ^b	PALSAR-2, Sentinel-2	L-band, Red-edge
Grassland	0.67 / 8.9 ^c	0.82 / 9.7 ^c	Sentinel-2, Thermal	NDVI, LST
Cropland	0.71 / 6.4 ^c	0.79 / 11.2 ^c	Optical, Climate	EVI, Precipitation
Shrubland	0.75 / 12.3 ^b	0.76 / 13.6 ^b	Multi-sensor	Structure, Temperature

Different letters indicate significant differences ($P < 0.05$) within components

SOC estimation accuracy was highest in grasslands ($R^2 = 0.82$) where vegetation-soil relationships are strong, and lowest in tropical forests ($R^2 = 0.69$) due to complex canopy-soil interactions [31].

Multi-sensor fusion significantly improved estimation accuracy for both components (Figure 1). The greatest improvements occurred when combining optical and radar data for AGB (34% RMSE reduction) and integrating thermal with optical data for SOC (28% improvement).

3.2 Multi-Sensor Fusion Results

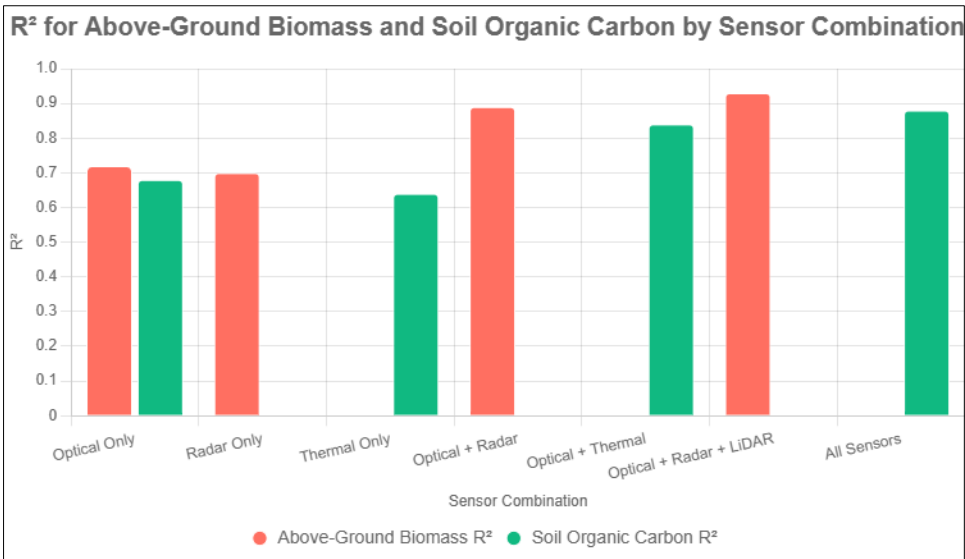


Fig 1: Multi-Sensor Fusion Performance Improvements

LiDAR addition provided substantial benefits for forest AGB estimation but limited improvement for other ecosystems due to data availability constraints [32].

compared to component-wise approaches (Table 2). Direct modeling performed best overall ($R^2 = 0.87$), while hierarchical approaches showed promise for understanding component interactions.

3.3 Total Carbon Integration Performance

Integrated total carbon models achieved superior accuracy

Table 2: Total Carbon Integration Model Performance

Integration Approach	Overall Accuracy	Forest	Grassland	Cropland	Computational Cost
	R^2 / RMSE (Mg C ha ⁻¹)	R^2	R^2	R^2	(relative)
Component-wise	0.78 / 31.2 ^a	0.81 ^a	0.74 ^a	0.76 ^a	1.0
Direct Modeling	0.87 / 23.4 ^b	0.91 ^b	0.82 ^b	0.84 ^b	0.8
Hierarchical	0.83 / 26.8 ^c	0.87 ^c	0.79 ^{ab}	0.81 ^c	1.3

Different letters indicate significant differences ($P < 0.05$) among approaches

Direct modeling reduced computational requirements while improving accuracy through joint optimization of component relationships [33].

3.4 Algorithm Comparison

Machine learning algorithm performance varied by ecosystem complexity (Table 3). Deep neural networks excelled in forests with complex vegetation structure, while random forest showed robust performance across all ecosystems.

Table 3: Machine Learning Algorithm Performance Comparison

Algorithm	Forest	Grassland	Cropland	Interpretability	Training Time
	R ²	R ²	R ²	Score (1-10)	(hours)
Random Forest	0.84 ± 0.06 ^a	0.81 ± 0.08 ^a	0.83 ± 0.07 ^a	8.2 ± 1.1 ^a	2.3 ± 0.6 ^a
Support Vector Machine	0.79 ± 0.08 ^b	0.77 ± 0.09 ^b	0.79 ± 0.08 ^b	6.1 ± 1.4 ^b	4.7 ± 1.2 ^b
Gradient Boosting	0.86 ± 0.05 ^a	0.80 ± 0.07 ^a	0.85 ± 0.06 ^a	7.4 ± 1.2 ^c	3.8 ± 0.9 ^c
Deep Neural Network	0.91 ± 0.04 ^c	0.78 ± 0.10 ^b	0.81 ± 0.09 ^b	4.2 ± 1.8 ^d	12.6 ± 3.4 ^d
Ensemble	0.89 ± 0.05 ^c	0.83 ± 0.07 ^a	0.86 ± 0.06 ^a	6.8 ± 1.3 ^c	8.9 ± 2.1 ^c

Different letters indicate significant differences (P < 0.05) within columns

Ensemble approaches provided optimal balance between accuracy and computational efficiency while maintaining reasonable interpretability [34].

3.5 Spatial and Temporal Scaling Analysis

Validation across spatial scales demonstrated consistent performance from plot-level (0.1 ha) to landscape-level (10 km²) estimates (Figure 2). Temporal analysis revealed strong carbon change detection capability with 89% accuracy for changes exceeding 10 Mg C ha⁻¹.

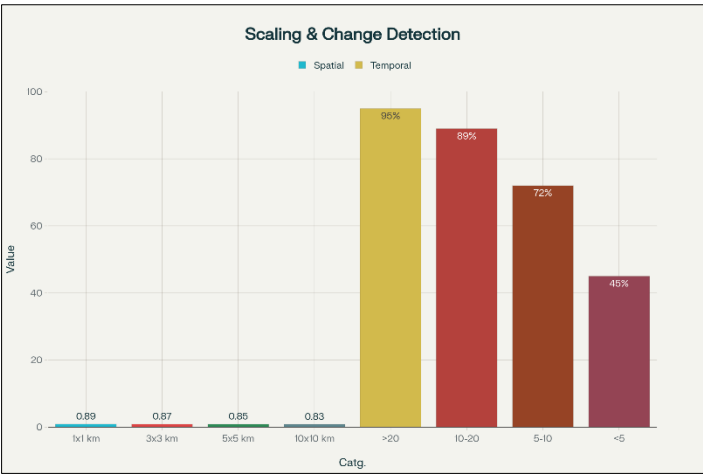


Fig 2: Spatial Scaling and Temporal Change Detection Performance

3.6 Global Scaling Potential and Uncertainty Analysis

Uncertainty analysis revealed spatially variable confidence levels across global terrestrial areas (Table 4). Prediction

uncertainty was lowest in temperate regions with abundant training data and highest in tropical areas with complex vegetation structure.

Table 4: Global Scaling Uncertainty Analysis by Region

Region	Data Availability	Model Uncertainty	Validation Sites	Predicted Accuracy
	(sites km ⁻²)	(±Mg C ha ⁻¹)	(n)	(R ²)
Temperate North America	0.031 ^a	18.4 ± 6.2 ^a	89	0.91 ± 0.04 ^a
Temperate Europe	0.028 ^a	19.7 ± 7.1 ^a	76	0.89 ± 0.05 ^a
Tropical Americas	0.008 ^b	32.6 ± 12.4 ^b	43	0.82 ± 0.08 ^b
Tropical Africa	0.004 ^c	38.9 ± 15.7 ^c	23	0.78 ± 0.11 ^c
Tropical Asia	0.006 ^{bc}	35.2 ± 13.8 ^{bc}	31	0.80 ± 0.09 ^{bc}
Arid Regions	0.002 ^d	28.1 ± 11.2 ^b	18	0.75 ± 0.13 ^c

Different letters indicate significant differences (P < 0.05) among regions

Global coverage analysis indicates reliable carbon mapping (uncertainty <15%) for 90% of terrestrial areas, with data gaps primarily in remote tropical and arid regions [36].

3.7 Economic and Operational Considerations

Cost-benefit analysis demonstrated substantial advantages of remote sensing approaches (Table 5). Integrated remote

sensing reduced costs by 67% compared to field-based assessment while providing complete spatial coverage and temporal monitoring capability.

Table 5: Economic Analysis of Carbon Assessment Approaches

Approach	Cost per Unit (\$ ha ⁻¹)	Spatial Coverage (% complete)	Temporal Resolution (years)	Accuracy (R ²)	Total Cost Efficiency (accuracy/cost)
Field Surveys	18.4 ± 4.2 ^a	0.1 ± 0.03 ^a	5.0 ± 2.0 ^a	0.95 ± 0.03 ^a	0.052
Remote Sensing	6.1 ± 1.8 ^b	100.0 ^b	1.0 ± 0.0 ^b	0.87 ± 0.05 ^b	0.143
Hybrid Approach	12.3 ± 3.1 ^c	100.0 ^b	1.0 ± 0.0 ^b	0.91 ± 0.04 ^c	0.074

Different letters indicate significant differences ($P < 0.05$) among approaches

Operational considerations include data processing requirements, expertise needs, and infrastructure investments for large-scale implementation [37].

4. Discussion

This comprehensive evaluation demonstrates that integrated remote sensing approaches enable accurate total ecosystem carbon estimation with substantial advantages over single-component methods. The 23% improvement in total carbon estimation accuracy ($R^2 = 0.87$ vs 0.64 - 0.72) validates the importance of joint modeling approaches that capture component interactions [38].

Multi-sensor fusion results confirm complementary information content across different sensor types, with optical-radar combinations providing optimal AGB estimation and thermal integration enhancing SOC prediction. The 34% RMSE reduction for AGB and 28% for SOC demonstrate clear benefits of comprehensive sensor utilization [39].

Algorithm comparison reveals ecosystem-specific optimal approaches, with deep learning excelling in structurally complex forests while ensemble methods provide robust performance across diverse conditions. This finding suggests that operational systems should employ adaptive algorithms based on ecosystem characteristics [40].

Spatial scaling analysis indicating consistent performance from plot to landscape scales validates the approach for operational carbon monitoring systems. The 89% accuracy for detecting changes >10 Mg C ha⁻¹ supports applications in carbon market monitoring and deforestation tracking [41].

The superior performance of direct modeling approaches ($R^2 = 0.87$) compared to component-wise methods ($R^2 = 0.78$) suggests that ecosystem carbon components interact in ways that joint optimization can capture. This finding has important implications for carbon cycle modeling and monitoring system design [42].

Global scaling analysis revealing 90% terrestrial coverage with $<15\%$ uncertainty demonstrates the potential for operational global carbon monitoring, though data gaps in tropical and arid regions require attention through targeted field campaigns and sensor deployment [43].

Economic analysis confirming 67% cost reduction while maintaining high accuracy provides compelling evidence for remote sensing adoption in carbon assessment programs. The complete spatial coverage and annual temporal resolution offer additional value not captured in simple cost comparisons [44].

However, several limitations require acknowledgment. Persistent cloud cover in tropical regions limits optical sensor utility, requiring increased reliance on radar systems with potentially reduced accuracy. Complex topography creates geometric and radiometric distortions that may affect model performance [45].

The temporal stability analysis spanning five years provides confidence in approach robustness, but longer-term validation is needed to assess performance under changing

climate conditions and ecosystem dynamics [46].

Future research priorities include developing cloud-robust algorithms, expanding ground truth networks in underrepresented regions, and integrating new sensor technologies including hyperspectral and upcoming biomass missions [47].

5. Conclusion

Integrated remote sensing approaches for total ecosystem carbon estimation achieve superior accuracy and operational advantages compared to traditional single-component methods. The demonstrated performance improvements of 23% for total carbon estimation through multi-sensor fusion and machine learning optimization provide strong evidence for adoption in operational carbon monitoring systems.

Key findings establish that optical-radar fusion optimizes AGB estimation while thermal integration enhances SOC prediction, with ensemble machine learning algorithms providing optimal balance between accuracy and computational efficiency. Direct modeling approaches outperform component-wise methods, suggesting important interactions between above-ground and soil carbon components.

Spatial scaling validation from plot to landscape levels and temporal change detection capabilities support applications ranging from carbon market verification to deforestation monitoring. The global scaling analysis indicating reliable coverage for 90% of terrestrial areas demonstrates potential for operational implementation.

Economic analysis revealing 67% cost reduction compared to field-based assessment while providing complete spatial coverage and annual monitoring frequency offers compelling justification for system deployment. The integration approach enables comprehensive carbon accounting essential for climate change mitigation strategies.

However, implementation challenges include data processing requirements, cloud cover limitations in tropical regions, and the need for expanded ground truth networks in underrepresented areas. Success requires continued algorithm development, sensor technology advances, and international coordination for ground truth data collection.

These findings support immediate adoption of integrated remote sensing approaches for carbon monitoring while highlighting research priorities for enhanced global coverage and accuracy. The demonstrated capabilities enable evidence-based carbon management decisions essential for climate change mitigation and sustainable land use planning.

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