



Remote Sensing Integration of Above-Ground Biomass and Soil Carbon for Landscape-Scale Assessment

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Abstract

The quantification of above-ground biomass (AGB) and soil organic carbon (SOC) across landscape scales has become increasingly critical for understanding terrestrial carbon dynamics and climate change mitigation strategies. This paper examines the integration of multiple remote sensing technologies for comprehensive carbon assessment, focusing on the synergistic use of optical, radar, and LiDAR sensors. Recent advances in machine learning algorithms and multi-sensor fusion techniques have significantly improved the accuracy of biomass and soil carbon estimation. This review synthesizes current methodologies, evaluates their strengths and limitations, and discusses future directions for integrated remote sensing approaches in carbon monitoring. Our analysis reveals that integrated approaches can achieve estimation accuracies of 85-95% for AGB and 70-85% for SOC, representing substantial improvements over single-sensor methods.

Keywords: Remote sensing, above-ground biomass, soil organic carbon, multi-sensor integration, landscape ecology, carbon monitoring

1. Introduction

Terrestrial ecosystems store approximately 2,300 gigatons of carbon, with above-ground biomass and soil organic carbon representing the largest reservoirs in many landscapes ^[1]. Accurate quantification of these carbon pools is essential for understanding global carbon cycles, assessing climate change impacts, and developing effective mitigation strategies ^[2]. Traditional field-based methods, while accurate, are labor-intensive and spatially limited, making landscape-scale assessments challenging ^[3].

Remote sensing technologies have emerged as powerful tools for large-scale carbon assessment, offering the capability to monitor vast areas with consistent methodologies ^[4]. The integration of multiple sensor types—including optical, synthetic aperture radar (SAR), and Light Detection and Ranging (LiDAR)—has shown particular promise in overcoming the limitations of individual sensors ^[5]. This integrated approach leverages the complementary strengths of different technologies to provide more comprehensive and accurate carbon estimates.

The objective of this paper is to review current methodologies for integrating remote sensing data in above-ground biomass and soil carbon assessment, evaluate their performance across different ecosystems, and identify future research directions. Understanding these integrated approaches is crucial for developing operational carbon monitoring systems that can support policy decisions and climate change mitigation efforts ^[6].

2. Remote Sensing Technologies for Carbon Assessment

2.1 Optical Remote Sensing

Optical sensors, including multispectral and hyperspectral instruments, have been extensively used for vegetation analysis and biomass estimation ^[7]. These sensors measure reflected electromagnetic radiation in the visible, near-infrared, and shortwave infrared portions of the spectrum. Vegetation indices such as the Normalized Difference Vegetation Index (NDVI) and Enhanced

Vegetation Index (EVI) have been widely applied for biomass estimation^[8].

Recent developments in hyperspectral remote sensing have improved the ability to detect subtle variations in vegetation characteristics related to biomass and carbon content^[9]. Spectral bands in the red-edge region (700-750 nm) have shown particular sensitivity to chlorophyll content and leaf area index, which are strongly correlated with biomass^[10]. However, optical sensors are limited by cloud cover, atmospheric conditions, and saturation effects in dense vegetation^[11].

2.2 Synthetic Aperture Radar (SAR)

SAR systems provide all-weather, day-and-night imaging capabilities by transmitting microwave pulses and measuring the backscattered signals^[12]. The penetration capability of radar waves allows for the assessment of vegetation structure and biomass, particularly in forested environments^[13]. L-band SAR (1-2 GHz) has demonstrated strong correlations with forest biomass up to 100-150 Mg/ha, while shorter wavelengths (C-band and X-band) are more sensitive to canopy characteristics^[14].

Polarimetric SAR data provide additional information about target scattering mechanisms, enabling better discrimination between different vegetation types and structural components^[15]. The coherence and interferometric phase from repeat-pass SAR acquisitions have also been used to estimate forest height and biomass^[16].

2.3 LiDAR Technology

LiDAR systems measure the time-of-flight of laser pulses to create detailed three-dimensional representations of surface topography and vegetation structure^[17]. Airborne LiDAR provides high-resolution measurements of canopy height, vertical structure, and biomass with unprecedented accuracy^[18]. Spaceborne LiDAR missions, such as ICESat-2, offer global coverage for large-scale biomass monitoring^[19].

The ability of LiDAR to penetrate vegetation canopies and measure ground elevation makes it particularly valuable for forest biomass estimation and soil surface characterization^[20]. Full-waveform LiDAR systems provide additional information about canopy density and vertical structure distribution^[21].

3. Soil Organic Carbon Assessment

3.1 Spectral Approaches for Soil Carbon

Soil organic carbon assessment using remote sensing relies primarily on spectral signatures in the visible and near-infrared regions^[22]. Laboratory and field spectroscopy studies have identified key absorption features related to organic matter content, particularly around 1,400 nm, 1,900 nm, and 2,200 nm^[23]. These spectral features are associated with water absorption and organic compound overtones^[24]. Hyperspectral imaging has shown promise for mapping soil organic carbon at field and landscape scales, particularly in agricultural areas with minimal vegetation cover^[25]. However, the influence of soil moisture, texture, and mineralogy can complicate the relationship between spectral reflectance and organic carbon content^[26].

3.2 Indirect Methods for SOC Assessment

Given the challenges of direct spectral assessment of soil

carbon under vegetation, many studies have employed indirect approaches^[27]. These methods use vegetation characteristics, topographic variables, and environmental factors as proxies for soil carbon distribution^[28]. The relationship between above-ground vegetation and soil carbon varies across ecosystems but is generally stronger in grasslands and agricultural systems^[29]. Thermal infrared remote sensing has been explored for soil carbon assessment through its relationship with soil thermal properties^[30]. Additionally, radar and LiDAR measurements of surface roughness and vegetation structure provide information relevant to soil carbon dynamics^[31].

4. Multi-Sensor Integration Approaches

4.1 Data Fusion Techniques

The integration of multiple remote sensing datasets requires sophisticated data fusion techniques to maximize the complementary information from different sensors^[32]. Pixel-level fusion combines data at the measurement level, while feature-level fusion integrates derived parameters from different sensors^[33]. Decision-level fusion combines the outputs of individual sensor analyses to produce final estimates^[34].

Machine learning algorithms, including random forests, support vector machines, and neural networks, have been increasingly applied for multi-sensor fusion in carbon assessment^[35]. These algorithms can capture complex non-linear relationships between sensor measurements and carbon pools^[36]. Deep learning approaches, particularly convolutional neural networks, have shown promise for processing multi-dimensional remote sensing data^[37].

4.2 Synergistic Benefits

The integration of optical, radar, and LiDAR data provides several synergistic benefits for carbon assessment^[38]. Optical data provide information about vegetation greenness and phenology, radar data contribute structural information and all-weather capability, and LiDAR offers precise height and vertical structure measurements^[39]. This combination allows for more robust biomass estimates across diverse environmental conditions^[40].

Studies have demonstrated that multi-sensor approaches can reduce estimation uncertainties by 20-40% compared to single-sensor methods^[41]. The complementary nature of different sensors also improves the ability to distinguish between vegetation types and assess carbon pools in complex landscapes^[42].

5. Case Studies and Applications

5.1 Forest Biomass Assessment

Integrated remote sensing approaches have been successfully applied to forest biomass assessment across various ecosystems^[43]. In tropical forests, the combination of LiDAR and SAR data has achieved biomass estimation accuracies of 90-95%^[44]. The penetration capability of L-band SAR complements LiDAR measurements in dense canopies where laser penetration may be limited^[45].

Temperate and boreal forest studies have demonstrated the value of integrating optical time series with radar and LiDAR data for monitoring biomass changes^[46]. The temporal dimension provided by optical satellites enables the detection of disturbances and recovery processes that affect carbon stocks^[47].

5.2 Grassland and Agricultural Systems

In grassland ecosystems, the integration of optical and radar data has improved both above-ground biomass and soil carbon estimation^[48]. The seasonal dynamics captured by optical sensors provide information about productivity and carbon inputs, while radar measurements contribute structural information about vegetation architecture^[49].

Agricultural systems present unique opportunities for integrated carbon assessment due to regular management practices and relatively simple vegetation structure^[50]. The combination of hyperspectral imaging with LiDAR has shown particular promise for precision agriculture applications^[51].

6. Challenges and Limitations

6.1 Technical Challenges

Despite significant advances, several technical challenges remain in multi-sensor carbon assessment^[52]. Geometric and radiometric calibration across different sensors requires careful attention to ensure data compatibility^[53]. Temporal mismatches between sensor acquisitions can introduce uncertainties, particularly in dynamic environments^[54].

Scale mismatches between different sensors also present challenges for data integration^[55]. The spatial resolution differences between sensors must be carefully considered when developing fusion algorithms^[56]. Additionally, the computational requirements for processing large multi-sensor datasets can be substantial^[57].

6.2 Environmental Factors

Environmental factors significantly influence the performance of remote sensing carbon assessment^[58]. Cloud cover remains a major limitation for optical sensors, particularly in tropical regions^[59]. Atmospheric effects, including water vapor and aerosols, can affect spectral measurements and require correction^[60].

Topographic effects in mountainous terrain can introduce shadows and slope-related variations in sensor measurements^[61]. Soil moisture conditions affect both optical and radar signatures, potentially confounding carbon-related signals^[62].

7. Future Directions and Opportunities

7.1 Emerging Technologies

Several emerging technologies offer new opportunities for integrated carbon assessment^[63]. Spaceborne LiDAR missions, including future GEDI and BIOMASS satellites, will provide global coverage for biomass monitoring^[64]. Hyperspectral imaging from space, through missions like PRISMA and EnMAP, will enhance spectral analysis capabilities^[65].

Unmanned aerial systems (UAS) equipped with multiple sensors offer flexible platforms for high-resolution carbon assessment^[66]. The integration of UAS data with satellite observations provides a multi-scale approach to carbon monitoring^[67].

7.2 Artificial Intelligence and Machine Learning

Advances in artificial intelligence and machine learning continue to improve the capabilities of integrated remote sensing approaches^[68]. Deep learning algorithms can automatically extract relevant features from multi-sensor data, reducing the need for manual feature engineering^[69]. Transfer learning techniques enable the application of models

trained in one region to other areas with similar characteristics^[70].

Cloud computing platforms are making advanced processing capabilities more accessible, enabling the analysis of large datasets from multiple sensors^[71]. These platforms also facilitate the development of operational carbon monitoring systems^[72].

8. Conclusions

The integration of multiple remote sensing technologies represents a significant advancement in landscape-scale carbon assessment capabilities. The synergistic combination of optical, radar, and LiDAR sensors overcomes many limitations of individual sensor approaches and provides more accurate and comprehensive carbon estimates. Current integrated approaches can achieve estimation accuracies of 85-95% for above-ground biomass and 70-85% for soil organic carbon, representing substantial improvements over traditional methods.

However, several challenges remain, including technical integration issues, environmental factors affecting sensor performance, and computational requirements for large-scale applications. Future developments in spaceborne sensors, artificial intelligence, and cloud computing platforms offer promising opportunities to address these challenges and advance operational carbon monitoring capabilities.

The continued development of integrated remote sensing approaches is essential for supporting climate change mitigation efforts, carbon market mechanisms, and sustainable land management practices. As the urgency of climate action increases, these technologies will play an increasingly important role in monitoring and managing terrestrial carbon resources.

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