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CARBON INSIGHT: A COMPREHENSIVE SURVEY OF AI-BASED CARBON ESTIMATION AND VERIFICATION SYSTEMS FOR BLUE CARBON ECOSYSTEMS

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ABSTRACT

Blue carbon ecosystems, particularly mangroves, salt marshes, and seagrass meadows, are among the most efficient natural carbon sinks, capable of capturing and storing significant amounts of atmospheric carbon over long periods. Accurate estimation of carbon sequestration within these ecosystems is essential for environmental monitoring, restoration planning, and carbon credit generation. However, conventional carbon assessment techniques rely heavily on field-based measurements, multispectral remote sensing data, and complex geospatial pro- cessing methods that require specialized expertise and substantial resources. Recent advancements in artificial intelligence and computer vision have introduced new possibilities for vegetation analysis using standard RGB satellite imagery, reducing depen- dence on specialized spectral indices and extensive field surveys. Deep learning techniques such as semantic segmentation models enable automated extraction of vegetation regions by learning visual characteristics including color patterns, textures, and spatial structures directly from image data. This paper presents a comprehensive survey of AI-based carbon estimation systems using RGB satellite imagery and computer vision techniques, examining existing methodologies, technological architectures, practical applications, and research challenges. Furthermore, the paper highlights future directions including advanced deep learn- ing models, multisource data integration, and scalable automated systems for environmental monitoring and carbon assessment.

INDEX TERMS: Arbon Estimation, RGB Satellite Imagery, Com- puter Vision, Vegetation Detection, Biomass Estimation, Deep Learning, Carbon Credits, Environmental Monitoring.

1. INTRODUCTION

Blue carbon ecosystems such as mangroves, salt marshes, and seagrass meadows are among the most efficient natural carbon sinks due to their exceptional ability to capture and store atmospheric carbon over long periods. These ecosystems sequester carbon within both vegetation biomass and under- lying sediments, making them highly important for climate change mitigation and environmental sustainability. Compared to terrestrial forests, blue carbon ecosystems have the capabil-ity to preserve carbon for significantly longer durations and contribute substantially to reducing atmospheric greenhouse gas concentrations [1]. However, increasing urbanization, in- dustrial expansion, coastal development, and land-use changes have created considerable threats to the preservation and restoration of these ecosystems [2]. Accurate estimation of carbon sequestration in blue carbon ecosystems is essential for environmental monitoring, restora- tion planning, and carbon credit generation. Traditional carbon assessment approaches primarily rely on field-based biomass measurements, ecological surveys, and allometric equations for estimating carbon content. Although these methods provide reliable results, they are often expensive, labor-intensive, and time-consuming. Field-based measurements become particu- larly difficult in mangrove ecosystems because of muddy terrain, tidal variations, and limited accessibility [3]. Further-more, the dependence on specialized expertise and significant resources creates challenges for local communities and small- scale restoration projects attempting to participate in carbon monitoring initiatives and carbon credit systems [4]. Recent developments in satellite imagery and artificial in- telligence have transformed environmental monitoring systems by enabling automated analysis of large geographical regions. High-resolution satellite datasets have made large-scale vege- tation assessment feasible and have significantly reduced the dependency on manual observations. Earlier studies focused on multispectral imagery and vegetation indices for analyzing vegetation characteristics and biomass distribution [5]. Cloud- based geospatial platforms such as Google Earth Engine pro- vide efficient access to large satellite datasets and distributed computing resources, enabling scalable environmental analysis and reducing computational complexity [6]. Recent advancements in computer vision and deep learning have introduced new possibilities for vegetation detection using standard RGB satellite imagery. Unlike conventional approaches that rely heavily on specialized spectral indices and complex geospatial processing workflows, computer vi- sion methods can learn visual characteristics directly from image data. Deep learning architectures such as U-Net and semantic segmentation models have demonstrated promising performance in extracting vegetation regions from remotely sensed imagery [7]. Machine learning approaches for biomass estimation have further improved prediction capabilities by establishing relationships between vegetation characteristics and carbon content [8], [9]. This survey paper presents a systematic review of AI-based carbon estimation systems using RGB satellite imagery and computer vision techniques. Section II presents a comprehen- sive literature survey discussing previous studies related to vegetation detection, biomass estimation, and environmental monitoring systems. Section III examines technologies and computational frameworks supporting AI-based carbon esti- mation platforms. Section IV discusses practical applications of automated carbon monitoring systems. Section V identifies key technical and methodological challenges associated with these systems. Finally, Section VI concludes with future re- search directions for improving the scalability, accessibility, and accuracy of AI-based carbon estimation systems.

2. LITERATURE SURVEY

Research in carbon estimation and vegetation monitoring has evolved considerably with the rapid advancement of satel- lite imaging technologies, machine learning techniques, and artificial intelligence-based environmental monitoring systems. Earlier approaches relied primarily on field-based biomass measurements and multispectral remote sensing methods for estimating vegetation characteristics and carbon stocks. How- ever, recent developments have shifted towards computer vision and deep learning approaches capable of analyzing RGB satellite imagery for automated vegetation detection and carbon assessment.

A. RGB Satellite Imagery and Vegetation Analysis

Remote sensing technologies have played a vital role in large-scale carbon estimation because of their capability to collect information over extensive geographical regions. Bindu et al. [1] conducted a study on mangrove carbon stock as- sessment using remote sensing and Geographic Information Systems. Their work integrated field measurements with satel- lite observations for estimating biomass and carbon content in mangrove ecosystems. The study demonstrated that remotely sensed data can effectively reduce dependence on extensive field surveys while supporting large-scale carbon monitoring. Similarly, Neto et al. [4] proposed an approach for carbon stock estimation in Brazilian mangroves using optical satellite imagery. Their findings indicated that satellite-derived vege- tation information could explain biomass distribution and im- prove carbon estimation efficiency. These studies established the importance of remotely sensed imagery for environmental analysis and carbon assessment applications.

Systematic Reviews and Recent Developments in Carbon Monitoring

Traditional vegetation analysis approaches commonly relied on multispectral imagery containing near-infrared spectral information. However, recent developments have shown that vegetation characteristics can also be extracted from standard RGB satellite imagery using computer vision techniques.

RGB satellite images contain visual information through red, green, and blue channels that enable machine learning systems to analyze vegetation patterns based on color distri- butions, texture information, and spatial structures. Compared to multispectral approaches, RGB imagery provides higher accessibility and requires relatively simpler preprocessing pro- cedures.

Dutta Roy et al. [5] conducted a systematic review of mangrove blue carbon assessment techniques and reported increasing utilization of satellite imagery for environmental monitoring. The study highlighted the importance of integrat- ing advanced computational methods with remotely sensed imagery for improving monitoring capabilities.

B. Deep Learning for Vegetation Detection and Segmentation

Deep learning techniques have significantly improved veg- etation detection performance by enabling automatic feature extraction from image data. Unlike traditional methods that rely on manually designed descriptors, convolutional neural networks learn hierarchical image representations directly from training data.

Maung et al. [8] implemented a U-Net-based deep learn- ing architecture for mangrove land-use classification using multisource remote sensing datasets. Their study achieved classification accuracies of 94.05% using PlanetScope imagery and 86.94% using Sentinel-2 imagery. These findings demon- strate the effectiveness of semantic segmentation models in identifying vegetation regions within satellite imagery.

Deep learning architectures such as U-Net and Fully Con- volutional Networks have become widely adopted because of their capability to classify image pixels with high precision, enabling accurate vegetation extraction and environmental monitoring.

C. *Machine Learning for Biomass Estimation*

Machine learning approaches have demonstrated substantial potential for improving biomass estimation and carbon predic- tion accuracy. Regression algorithms including Random Forest (RF) and Extreme Gradient Boosting (XGBoost) have shown improved performance in modeling nonlinear relationships between vegetation characteristics and carbon content.

Zhang [**?**] developed machine learning-based methodologies for mangrove biomass estimation using multisource satellite datasets. The proposed framework integrated high-resolution optical imagery and environmental variables, achieving a val- idation performance of:

$$R^2 = 0.72 \quad (1)$$

with:

$$RMSE = 37.24\ Mg/ha \quad (2)$$

Land Imager (OLI) captures multispectral imagery at a spatial resolution of 30 m with a revisit period of approximately 16 days [4]. Landsat datasets have been widely used in biomass estimation and land-cover studies because of their The study further identified approximately 5.10 million Mg of above-ground biomass (AGB) gains in naturally regenerat- ing mangrove ecosystems.

Similarly, Pang *et al.* [**?**] proposed a fine-scale carbon stock estimation framework using remotely sensed datasets and geospatial processing techniques. Their approach integrated Global Ecosystem Dynamics Investigation (GEDI) LiDAR observations and Sentinel-2 imagery within the Google Earth Engine (GEE) platform. The study quantified annual carbon stocks totaling approximately 302,558.77 tonnes within se- lected mangrove regions.

Machine learning models provide considerable advantages over conventional statistical approaches because of their ca- pability to handle complex nonlinear environmental relation- ships, process high-dimensional datasets, and improve pre- diction performance. These methods also support scalable biomass estimation over large geographic areas while reducing dependence on labor-intensive field measurements.

D. *Cloud-Based Geospatial Platforms for Carbon Monitoring*

Cloud-based geospatial platforms have transformed large- scale environmental analysis by providing distributed compu- tational resources and access to extensive satellite datasets.

Gorelick et al. [3] introduced Google Earth Engine as a cloud-based platform for planetary-scale geospatial analysis. The platform enables retrieval, preprocessing, and analysis of satellite imagery while reducing computational complexity for environmental applications. Modern carbon monitoring systems increasingly combine satellite imagery, cloud processing, and artificial intelligence techniques within unified frameworks. The general workflow

commonly follows:

RGB Satellite Image → Vegetation Detection → Biomass Estimation → Carbon Calculation → Carbon Credits This integration significantly reduces manual effort and enables scalable environmental monitoring systems.

3. TECHNOLOGIES USED

A. Satellite Remote Sensing Platforms

Sentinel-2: The European Space Agency's Sentinel-2 mis- sion provides high-resolution optical imagery with spatial resolutions ranging from 10–60 m and a revisit frequency of approximately 5 days. Sentinel-2 imagery contains visible spectral bands including Blue (Band 2), Green (Band 3), and Red (Band 4), which can be utilized for RGB image gener- ation and vegetation analysis [5]. The high spatial resolution and frequent image acquisition make Sentinel-2 suitable for environmental monitoring applications and carbon assessment studies [7].Landsat 8 and Landsat 9: The Landsat program has pro- vided continuous Earth observation datasets for environmental analysis and vegetation monitoring. Landsat-8 Operational long historical record and large spatial coverage [4], [5]. Unlike conventional carbon estimation systems relying on infrared spectral information and vegetation indices, the pro- posed framework utilizes RGB imagery for computer vision- based vegetation detection and biomass estimation.

B. Cloud-Based Geospatial Platforms

Google Earth Engine (GEE): Gorelick et al. [3] introduced Google Earth Engine as a cloud-based geospatial platform that combines a large catalog of satellite imagery with distributed computational infrastructure. The platform provides access to satellite datasets and supports image retrieval, cloud filtering, preprocessing, and large-scale geospatial analysis [3]. Google Earth Engine simplifies environmental analysis by eliminating the requirement for local storage and computa- tional resources while enabling access to extensive historical satellite imagery collections [3].

C. Computer Vision and Deep Learning Frameworks

U-Net Architecture: U-Net is a fully convolutional neural network architecture developed for semantic image segmenta- tion and has demonstrated superior performance for vegetation detection and land-cover classification tasks [8]. Maung et al. [8] applied U-Net models for mangrove classification and achieved overall classification accuracies of 94.05 DeepLabV3: DeepLabV3 employs atrous convolution op- erations to capture image features at multiple spatial scales and has demonstrated improved segmentation performance in environmental monitoring applications [8]. Random Forest (RF): Random Forest is an ensemble ma- chine learning technique widely used for biomass estimation and environmental prediction tasks because of its capability to handle nonlinear relationships and high-dimensional variables [5]. XGBoost: XGBoost is a gradient-boosting algorithm fre- quently utilized for vegetation classification and carbon pre- diction due to its ability to optimize prediction performance and reduce estimation errors [5]. OpenCV: OpenCV supports image preprocessing, feature extraction, and vegetation region identification from RGB satellite imagery, enabling automated image analysis work- flows.

D. Web Technologies and Databases

Frontend: React.js provides a component-based framework for creating responsive interfaces including map visualizations, area selection modules, and result dashboards.

Backend: Python frameworks such as Flask and FastAPI enable communication between user interfaces, geospatial processing components, and machine learning models.

Task Queues: Celery supports asynchronous processing of computationally intensive operations such as satellite image retrieval and image analysis.

Databases: MySQL, PostgreSQL, and MongoDB can be used for storing structured datasets, geospatial information, and analytical results generated by environmental monitoring systems.

4. REAL-TIME APPLICATIONS

A. Carbon Estimation

AI-based systems can automatically estimate carbon se- questration by analyzing vegetation coverage extracted from RGB satellite imagery. Satellite observations combined with machine learning methods have demonstrated considerable potential for biomass and carbon estimation across large geographical regions [1], [6].

B. Environmental Monitoring

Satellite imagery integrated with AI models enables con- tinuous monitoring of vegetation changes and ecosystem con- ditions. Such systems support the identification of land-cover changes, vegetation degradation, and restoration progress [5], [8].

C. Carbon Credit Assessment

Estimated carbon values can be converted into potential carbon credits for environmental and economic evaluation. Carbon stock estimation studies have demonstrated the impor- tance of accurate biomass estimation for supporting carbon market initiatives [4], [9].

D. Restoration Planning and Decision Support

AI-based monitoring systems assist environmental agencies and restoration organizations in identifying regions with high restoration potential and prioritizing conservation activities [1], [5].

E. Automated Carbon Monitoring Systems

Modern environmental monitoring systems integrate cloud computing, satellite imagery, and artificial intelligence tech- niques within a unified workflow [3]:

Location + Area Selection → RGB Satellite Image Retrieval→ Vegetation Detection → Biomass Estimation → Carbon Calculation → Carbon Credit Estimation Such integrated systems significantly reduce manual effort and improve scalability in environmental monitoring applica- tions [3], [6].

5. CHALLENGES

Despite significant advancements in artificial intelligence, computer vision, and satellite-based environmental monitor- ing systems, several technical and methodological limitations continue to affect the performance and scalability of AI-based carbon estimation systems. Existing research identifies multi- ple challenges related to data availability, model performance, computational constraints, and carbon estimation reliability.

A. Technical and Computational Challenges

Cloud-Based Processing Latency: Cloud-based geospatial platforms such as Google Earth Engine provide efficient access to large satellite datasets; however, processing large geograph- ical regions often introduces computational delays. Image retrieval, preprocessing, and environmental analysis operations may require considerable processing time depending on image resolution and computational complexity [3]. Efficient asyn- chronous processing and task scheduling mechanisms become essential for maintaining acceptable system performance.

API Usage Constraints and Computational Resources: Large-scale environmental monitoring systems depend heavily on cloud resources and external APIs for image retrieval and processing. Geospatial platforms impose computational limitations and usage quotas that may affect system scalability and increase response latency during high-volume processing [3].

Cross-Sensor Data Variability: Satellite sensors differ in terms of spatial resolution, radiometric properties, and image acquisition methods. Such variations create inconsistencies across datasets obtained from different satellite platforms and complicate environmental analysis and model generalization [4], [5].

B. Methodological Limitations

Biomass-to-Carbon Estimation Uncertainty: Carbon esti- mation systems generally depend on empirical relationships between vegetation characteristics and biomass values. Sys- tematic reviews indicate that variability in ecosystem proper- ties can significantly influence estimation accuracy [5]. Fixed biomass-to-carbon conversion factors may not adequately represent ecological differences across various geographical regions.

Carbon estimation commonly follows: Carbon=Biomass×0.5

However, such generalized relationships may introduce un- certainties in carbon prediction [6]. Transferability of Prediction Models: Machine learning models trained for specific environmental conditions may not perform effectively across different ecosystems and geograph- ical regions. Bindu et al. [1] developed biomass estimation relationships using South Indian mangrove datasets; however, such region-specific models may not generalize well to ecosys- tems with different vegetation compositions.

Limited Generalization of Deep Learning Models: Deep learning architectures such as U-Net demonstrate high perfor- mance for vegetation segmentation; however, prediction qual- ity can decrease significantly when applied to datasets with different image characteristics or environmental conditions [8].

1. ***Carbon Estimation and Credit Assessment Challenges:*** Variability in Carbon Stock Estimation: Carbon stock estima- tion accuracy directly influences carbon credit calculations. Small variations in biomass prediction may lead to significant differences in estimated carbon credits, affecting financial and environmental evaluations [9].

Standardization Issues in Carbon Assessment: Carbon esti- mation methodologies differ across studies and environmental projects. The absence of universally accepted computational standards creates inconsistencies in carbon quantification pro- cedures and complicates comparison across systems [9].

2. ***Data Quality and Validation Challenges:*** Limited Ground-Truth Datasets: Deep learning models require large quantities of labeled satellite imagery for training and valida- tion. Existing studies consistently identify insufficient ground- truth datasets as a major limitation affecting vegetation detec- tion accuracy [5], [8]. Variations in Satellite Image Quality: Environmental condi- tions such as cloud cover, shadows, atmospheric interference, and illumination changes can influence image quality and affect model predictions [4]. Image Resolution Limitations: Satellite imagery with lower spatial resolution may fail to capture fine vegetation struc- tures, reducing segmentation accuracy and impacting biomass estimation performance [7].

6. CONCLUSION AND FUTURE SCOPE

A. Conclusion

This survey paper presented a comprehensive review of AI- based carbon estimation systems using RGB satellite imagery and computer vision techniques for environmental monitoring and carbon assessment. The integration of satellite imagery, cloud-based geospatial platforms, and machine learning algo- rithms has significantly transformed traditional carbon moni- toring approaches by reducing dependence on extensive field surveys and manual analysis [3]. Recent advancements in remote sensing and artificial intelligence have enabled auto- mated vegetation detection and biomass estimation at larger geographical scales [5].

Foundational studies by Bindu et al. [1] demonstrated the potential of remotely sensed data for carbon stock estimation in mangrove ecosystems, while subsequent studies expanded these approaches through machine learning and advanced computational techniques [4]. Zhang [6] showed that ma- chine learning models integrating environmental variables and satellite datasets could improve biomass prediction accuracy, achieving a validation performance of R 2 =0.72. Furthermore, Maung et al. [8] demonstrated the effectiveness of deep learn- ing architectures such as U-Net for vegetation classification, achieving overall classification accuracies exceeding 90 The integration of RGB satellite imagery and computer vision techniques presents an alternative approach for environ- mental monitoring by enabling vegetation extraction directly from image data without relying extensively on specialized spectral indices. However, several challenges continue to af- fect system performance, including limited labeled datasets, variations in image quality, uncertainty in biomass-to-carbon conversion, and reduced model transferability across different ecosystems [5], [8]. Addressing these limitations is essential for improving the reliability and scalability of AI-based carbon estimation systems.

B. Future Scope

Several promising research directions can further improve the performance and applicability of AI-based carbon esti- mation systems. One important direction involves integrating multisource datasets such as optical imagery, LiDAR obser- vations, and environmental variables within unified machine learning frameworks to improve vegetation detection and biomass estimation accuracy [6], [7]. Combining multiple data sources may provide richer environmental information and reduce prediction uncertainty.

Advanced deep learning architectures and self-supervised learning techniques represent another important area of fu- ture research. Current vegetation detection models require large quantities of labeled datasets for training, whereas self- supervised approaches can reduce dependency on manually annotated data and improve model generalization [8].

Future systems may also incorporate high-resolution drone imagery and real-time environmental monitoring frameworks to improve spatial accuracy and support dynamic ecosystem analysis [5]. Additionally, AI-driven automated carbon assess- ment platforms capable of estimating vegetation coverage, biomass, carbon sequestration, and carbon credits through a unified workflow can significantly improve accessibility for restoration agencies and local communities.

The integration of cloud-based geospatial platforms with computer vision and machine learning techniques can further enable scalable environmental monitoring systems for global climate initiatives [3]. Addressing these research challenges will require collaboration among computer scientists, envi- ronmental researchers, remote sensing specialists, and policy makers to develop robust and reliable carbon estimation frame- works for future sustainability applications.

REFERENCES

1. G. Bindu, P. Rajan, E. S. Jishnu, and K. A. Joseph, "Carbon stock as- sessment of mangroves using remote sensing and geographic information system," *Egyptian Journal of Remote Sensing and Space Science*, vol. 23, no. 1, pp. 1–9, 2020.
2. J. W. Rouse, R. W. Haas, J. A. Schell, D. W. Deering, and J. C. Harlan, "Monitoring the vernal advancement and retrogradation (greenwave effect) of natural vegetation," NASA/GSFC, Greenbelt, MD, USA, Type III Final Rep., 1974.
3. N. Gorelick, M. Hancher, M. Dixon, S. Ilyushchenko, D. Thau, and R. Moore, "Google Earth Engine: Planetary-scale geospatial analysis for everyone," *Remote Sensing of Environment*, vol. 202, pp. 18–27, 2017.
4. M. Neto, J. B. da Silva, and H. C. de Brito, "Carbon stock estimation in a Brazilian mangrove using optical satellite data," *Environmental Monitoring and Assessment*, vol. 196, no. 1, p. 9, Jan. 2024.
5. A. Dutta Roy, P. S. Pitumpe Arachchige, M. S. Watt, A. Mishra, and S. D. Ray, "Remote sensing-based mangrove blue carbon assessment in the Asia-Pacific: A systematic review," *Science of the Total Environment*, vol. 938, p. 173270, Aug. 2024.
6. K. Zhang, "Mangrove biomass estimation through remote sensing and machine learning based approaches," Ph.D. dissertation, School of Geographical and Earth Sciences, University of Glasgow, Glasgow, U.K., 2025.
7. T. Pang *et al.*, "Classification and carbon-stock estimation of mangroves in Dongzhaigang based on multi-source remote sensing data using Google Earth Engine," *Remote Sensing*, vol. 17, no. 6, p. 964, Mar. 2025.
8. W. S. Maung, S. Tsuyuki, and Z. Guo, "Improving land use and land cover information of Wunbaik Mangrove Area in Myanmar using U-Net model with multisource remote sensing datasets," *Remote Sensing*, vol. 16, no. 1, p. 76, Jan. 2024.
9. C. Qi *et al.*, "The path to robust evaluation of carbon credits generated by forest restoration and REDD+ projects," *Remote Sensing of Environment*, vol. 325, 2025.
10. L. S. Romadoni and H. Husamah, "Accuracy comparison of remote sensing methods (UAV, LiDAR, Radar) and field allometry in mangrove blue carbon quantification: A systematic literature review," *GTLabs*, vol. 2, no. 2, Dec. 2025.