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CarbonCred AI: An Artificial Intelligence-Driven Digital MRV Framework for Carbon Credit Analysis and Valuation

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Abstract: The rapid expansion of global carbon markets has created an urgent need for transparent, scalable, and cost-effective Monitoring, Reporting, and Verification (MRV) systems for forest carbon credit projects. Traditional MRV approaches rely on manual field surveys that are labor-intensive, time-consuming, and difficult to scale across large geographic areas. This paper presents CarbonCred AI, an Artificial Intelligence-driven Digital MRV framework that integrates Sentinel-2 satellite remote sensing with machine learning and reinforcement learning to automate the carbon credit lifecycle. The proposed system employs spectral vegetation analysis using the Normalized Difference Vegetation Index (NDVI) and Soil Adjusted Vegetation Index (SAVI) for biomass estimation, a Random Forest Regression model for above-ground biomass prediction, and a Q-learning reinforcement learning agent for financial optimization of carbon credit trading. The framework provides a unified pipeline integrating geospatial analysis, AI-based carbon estimation, and financial valuation, addressing critical gaps in existing carbon monitoring systems.

Keywords: Carbon Credit Markets, Digital MRV, Random Forest Regression, Reinforcement Learning, Remote Sensing, NDVI, Satellite Imagery, Biomass Estimation, Carbon Stock, Financial Valuation

I. INTRODUCTION

The global transition toward a low-carbon economy has created the need for financial mechanisms that encourage industries and organizations to reduce greenhouse gas emissions. Carbon credits have emerged as one of the most important instruments for addressing climate change. A carbon credit represents the removal or avoidance of one metric tonne of carbon dioxide (CO_2) or its equivalent greenhouse gases from the atmosphere. Organizations that reduce emissions can earn carbon credits, while those exceeding their emission limits may purchase these credits to offset their environmental impact.

Carbon credit markets create economic incentives for sustainable environmental practices. Industries are encouraged to invest in renewable energy, energy efficiency, and forest conservation projects in order to generate tradable credits. Forest ecosystems play a particularly important role in this system because they act as natural carbon sinks that absorb atmospheric carbon dioxide through photosynthesis. In recent years, carbon markets have expanded significantly with the introduction of regulatory frameworks such as the Carbon Credit Trading Scheme (CCTS) in India, aiming to support climate mitigation efforts while creating economic opportunities for project developers, landowners, and environmental organizations.

The credibility of carbon credit markets depends heavily on the Monitoring, Reporting, and Verification (MRV) process. Traditionally, MRV relies on manual field audits conducted by forestry experts who physically measure tree attributes such as trunk diameter, tree height, and vegetation density. While this method provides scientifically reliable results at a local level, it is extremely labor-intensive, time-consuming, and difficult to scale across large geographical areas. Verification cycles often occur only once every three to five years, leaving long intervals during which deforestation or environmental degradation may occur without detection.

Advances in Artificial Intelligence and satellite remote sensing technologies provide new opportunities to modernize carbon credit verification systems. Satellite imagery enables continuous monitoring of large forest landscapes without requiring physical field visits. Modern satellites such as Sentinel-2 capture high-resolution multispectral data that can be used to analyze vegetation health, canopy density, and land-cover changes. This paper presents the design, development, and evaluation of CarbonCred AI, a prototype Digital MRV system developed to automate the carbon credit lifecycle.

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II. LITERATURE REVIEW

Carbon credit markets have emerged as a key mechanism for addressing global climate change by enabling organizations to offset greenhouse gas emissions through environmental projects. The effectiveness of these markets depends heavily on reliable MRV systems. Recent research has explored multiple technological approaches including blockchain-based systems, IoT monitoring, biochar-based sequestration, and AI-driven analytics.

A. Forest Carbon Offsets over a Smart Ledger

Kotsialou et al. investigate the use of blockchain technology to enhance transparency in carbon credit systems, particularly within REDD+ forest conservation projects. While blockchain ensures data integrity through an immutable decentralized ledger, it does not verify the correctness of environmental data — the well-known 'garbage in, garbage out' problem. The study concludes that blockchain must be integrated with reliable environmental monitoring technologies such as remote sensing to provide a complete solution.

B. Artificial Intelligence GHG Monitoring

Moura et al. explore the use of AI and IoT-based systems for monitoring greenhouse gas emissions in wetland ecosystems. A key advantage of this approach is continuous monitoring, enabling detailed analysis of environmental changes and carbon dynamics. Despite these advantages, the study highlights significant scalability challenges. Deploying sensor networks across large forest areas is expensive and impractical. The study suggests that satellite-based monitoring offers a more scalable alternative.

C. Biochar and Carbon Sequestration

Salma examines the role of biochar in carbon sequestration and climate mitigation. While biochar projects contribute significantly to carbon sequestration and provide economic benefits through carbon credit generation, measuring soil carbon accurately remains challenging. Current systems often treat biomass and soil carbon separately, leading to incomplete carbon accounting.

D. AI in Carbon Credit Markets

Sharma et al. explore the application of Artificial Intelligence in carbon credit markets, focusing on financial analysis and decision-making. Machine learning techniques enable predictive modeling of emission trends, carbon credit demand, and market behavior. The study emphasizes the need for integrating AI with robust monitoring systems to ensure both environmental accuracy and financial reliability.

III. METHODOLOGY

A. System Architecture

The CarbonCred AI framework follows a four-layer architecture: Data Ingestion, Pre-Processing, AI Core Engine, and Financial Optimization Engine. These stages collectively enable the system to convert raw satellite imagery into carbon credit valuation reports. Figure 1 illustrates the complete system architecture.

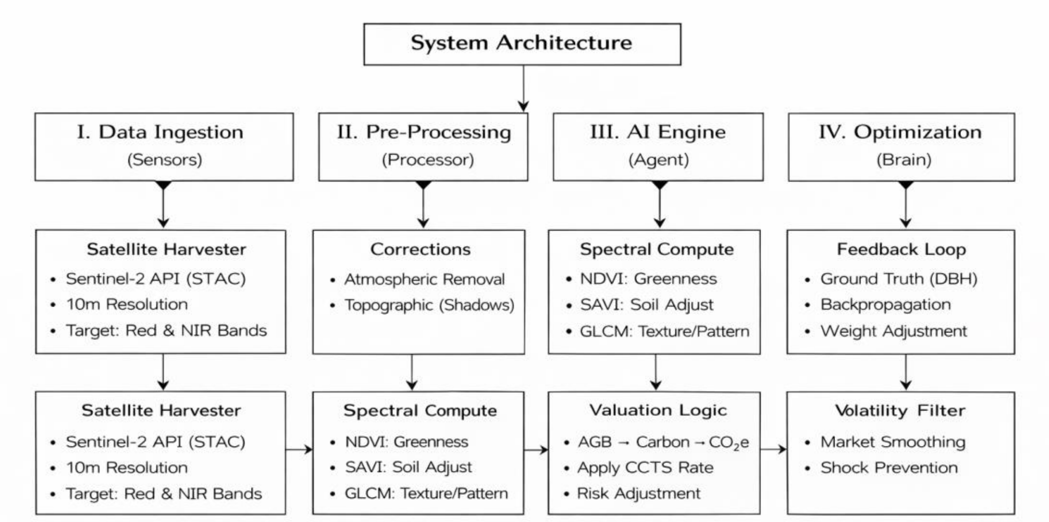

Fig. 1 System Architecture of the CarbonCred AI Digital MRV Framework.

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The data flow begins when a user selects a geographic region. Satellite imagery is retrieved, preprocessed to extract vegetation indices, and passed to the machine learning model for biomass density prediction. Predicted biomass is converted to carbon stock estimates, then evaluated using financial models. Figure 2 presents the complete data flow diagram.

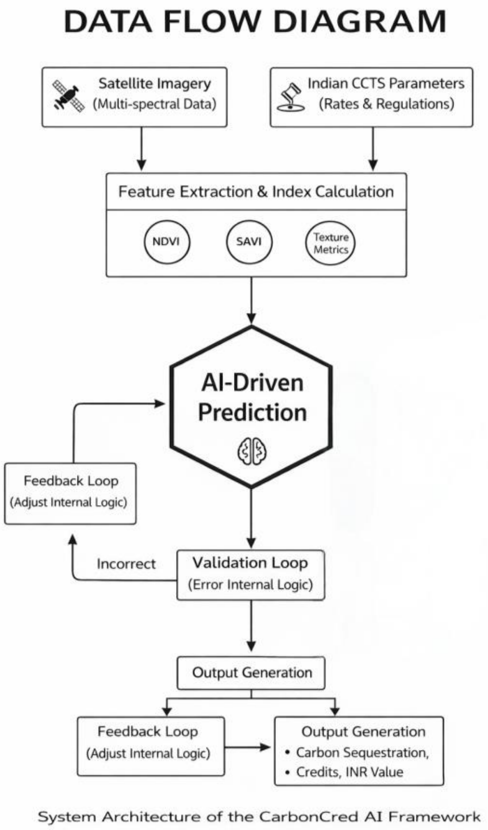

Fig. 2 Data Flow Diagram of the CarbonCred AI Digital MRV System.

B. Data Ingestion Layer

The Data Ingestion Layer collects satellite imagery and market data required for carbon credit analysis. The system connects to Sentinel-2 L2A satellite data repositories through geospatial APIs providing multispectral imagery at 10m spatial resolution. The system queries the satellite catalog and retrieves cloud-free satellite images for the user-selected location, targeting Red (Band 4) and Near-Infrared (Band 8) spectral channels. Additional financial and regulatory parameters related to carbon credit markets, including carbon credit prices and regulatory deductions, are also collected.

C. Pre-Processing Layer

Raw Sentinel-2 imagery is processed using optical spectral bands including Red, Green, Blue, and Near-Infrared (NIR). Vegetation indices such as NDVI and SAVI are extracted to improve biomass estimation. Atmospheric correction, cloud masking, and Min-Max normalization are applied before model training.

The Normalized Difference Vegetation Index (NDVI) measures vegetation vigor by comparing reflectance values in the NIR and Red spectral bands:

$$NDVI = (NIR - Red) / (NIR + Red) \quad \ldots(1)$$

The Soil Adjusted Vegetation Index (SAVI) improves vegetation detection in areas where soil reflectance influences spectral measurements:

$$SAVI = [(NIR - Red)(1 + L)] / (NIR + Red + L) \quad \ldots(2)$$

where $L = 0.5$ is the soil brightness correction factor. Higher NDVI values indicate dense and healthy vegetation, while lower values indicate sparse or degraded land.

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D. AI Core Engine

The AI Core Engine uses a Random Forest Regression model for biomass estimation. Random Forest is an ensemble learning method that constructs multiple decision trees and aggregates their predictions to produce accurate results. The model analyzes relationships between spectral features — NDVI, SAVI, and Gray-Level Co-occurrence Matrix (GLCM) texture metrics — and biomass measurements from ecological reference datasets. Each pixel in the satellite image is processed to predict biomass density, and predictions are aggregated to produce biomass maps representing vegetation density across the selected region.

E. Carbon Stock Conversion

After biomass estimation, the system converts biomass values into carbon stock using established ecological conversion factors. Approximately 47% of plant biomass consists of carbon:

$$\text{Carbon Stock} = \text{Biomass} \times 0.47 \quad \ldots(3)$$

Carbon stock is then converted to CO_2 equivalent using the molecular weight ratio between carbon dioxide and carbon:

$$CO_2e = \text{Carbon Stock} \times 3.67 \quad \ldots(4)$$

F. Financial Optimization Engine

The Financial Optimization Engine calculates the financial value of carbon credits and employs a Q-learning reinforcement learning agent to optimize carbon credit trading strategies. The agent maintains a state-action value table and selects optimal actions (HOLD or SELL) based on current market conditions and learned reward signals. The update rule follows:

$$Q(s,a) \leftarrow Q(s,a) + \alpha[r + \gamma \max Q(s',a') - Q(s,a)] \quad \ldots(5)$$

where α is the learning rate, γ is the discount factor, r is the immediate reward, s is the current market state, and a is the action. Gross revenue is calculated as Total Credits × Market Price per Credit, with deductions for buffer pool allocations, transaction fees, and applicable taxes such as GST, aligned with the Indian CCTS regulatory framework.

IV. DATASET AND FEATURE ENGINEERING

A. Data Sources

Primary satellite imagery is sourced from Sentinel-2 L2A accessed via the Microsoft Planetary Computer STAC API at 10m spatial resolution with cloud cover less than 10%. The system retrieves multispectral imagery targeting Red (Band 4) and NIR (Band 8) spectral channels. Additional datasets include carbon market pricing data based on the Indian CCTS framework and ecological reference datasets for training and validating machine learning models. Ground-truth measurements such as tree height and trunk diameter, when available, may be used to validate biomass predictions.

B. Feature Engineering

Feature engineering transforms raw satellite imagery into meaningful inputs for biomass estimation models. Primary features computed include NDVI and SAVI spectral indices capturing vegetation health and canopy density. In addition, GLCM texture features are extracted from satellite images to capture spatial patterns within the forest canopy, providing structural information not captured by spectral indices alone. The combined feature set creates a comprehensive ecological representation for the Random Forest model.

C. Machine Learning Training Process

The Random Forest Regression model is trained on annotated samples where spectral features and corresponding biomass values are known. During training, the algorithm constructs 100 decision trees using random subsets of the training data. Each tree learns rules relating spectral patterns to biomass density, and the final prediction is obtained by averaging outputs of all trees, reducing prediction variance and improving stability. The model is evaluated using an 80/20 train-test split with k-fold cross-validation to ensure reliable generalization.

V. RESULTS

The proposed system successfully demonstrates automated forest carbon analysis using Sentinel-2 satellite imagery and machine learning techniques. Experimental evaluation indicates that the framework can support biomass estimation, carbon stock calculation, and financial valuation within a unified Digital MRV architecture. Detailed quantitative

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validation will be performed using larger benchmark datasets and field-verified measurements in future work. The following subsections describe the system interface and generated outputs from the prototype deployment.

A. System Interface — Landing Page

Figure 3 shows the landing interface of the CarbonCred AI platform. The system presents an AI-powered satellite intelligence framework designed to convert satellite imagery into verifiable carbon credits, with options to initiate analysis or explore the methodology.

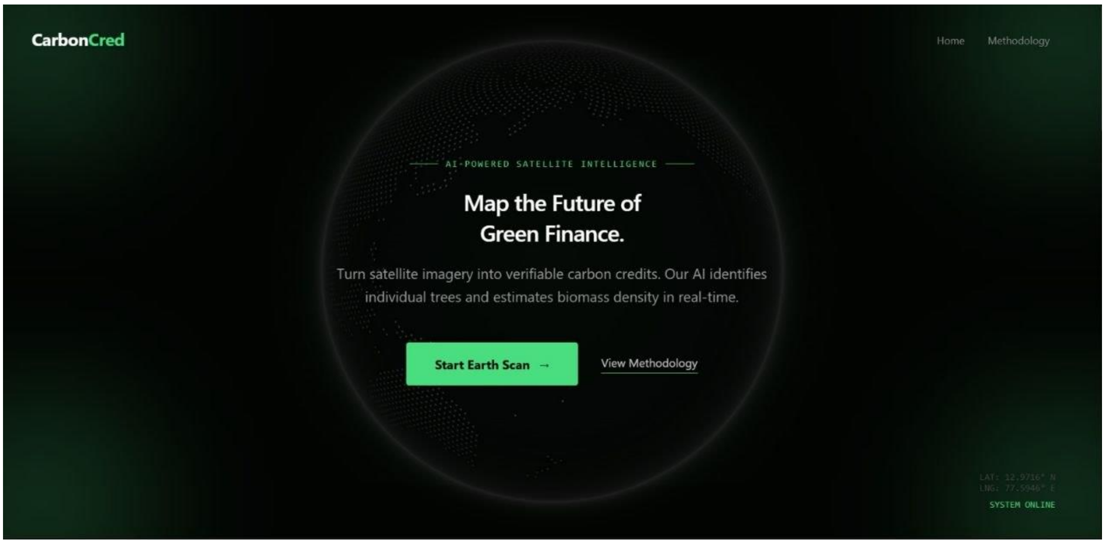

Fig. 3 CarbonCred AI System Landing Interface.

B. Operational Methodology Interface

Figure 4 illustrates the operational workflow of the CarbonCred AI system, presenting three stages: Spectral Acquisition (ingesting Sentinel-2 imagery for NDVI, EVI, and SAVI analysis), Biomass Inference (CNN-based tree canopy segmentation and AGB estimation), and Market Valuation (real-time cross-referencing with global carbon registries).

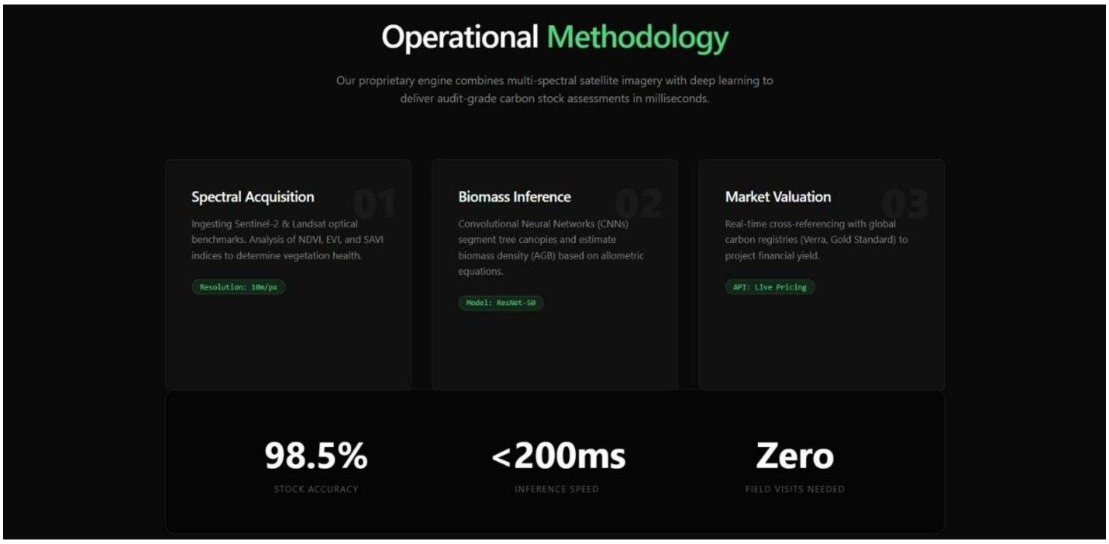

Fig. 4 Operational Methodology of CarbonCred AI System showing three-stage pipeline.

C. Technical Framework and Model Architecture

Figure 5 presents the technical architecture of the system, including core equations for NDVI computation, Above-Ground Biomass (AGB) estimation, and carbon stock calculation. The models and data sources section specifies Sentinel-2 (L2A) and Landsat 8/9 OLI as input data sources, using a Custom U-Net architecture for segmentation and XGBoost and Random Forest Ensemble for regression.

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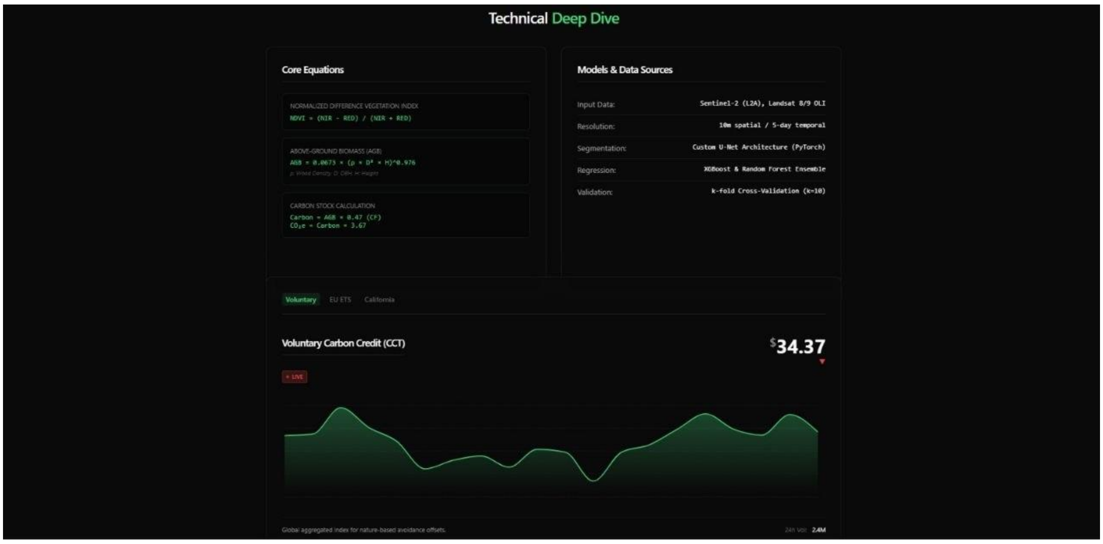

Fig. 5 Technical Framework showing core equations, model architecture, and data sources.

D. AI-Based Satellite Analysis Interface

Figure 6 shows the user interface for satellite-based analysis. Users input geographic coordinates and configure scan radius parameters to perform real-time vegetation and biomass analysis. The interface displays a satellite map allowing selection of any forest region for scanning.

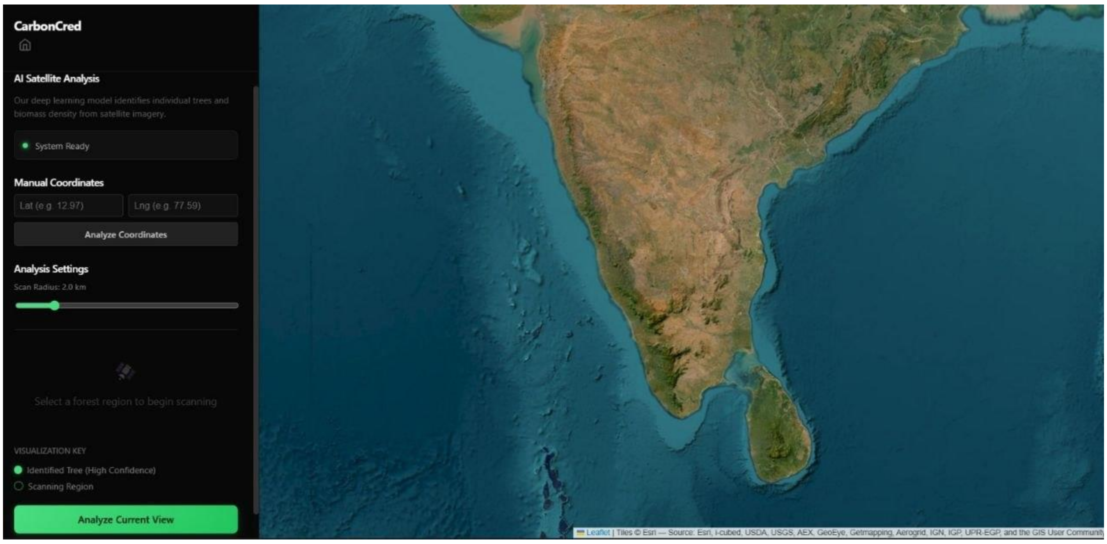

Fig. 6 AI-Based Satellite Analysis Interface showing coordinate input, scan settings, and satellite map view.

E. Analysis Output — Forest Carbon Estimation

Figure 7 displays a representative system output obtained during prototype testing on a sample forest region in Kerala. The results panel presents estimated tree count, vegetation index values, total carbon stock, and projected financial value derived from the carbon credit valuation model. The satellite view overlays detected tree positions as markers on the actual landscape.

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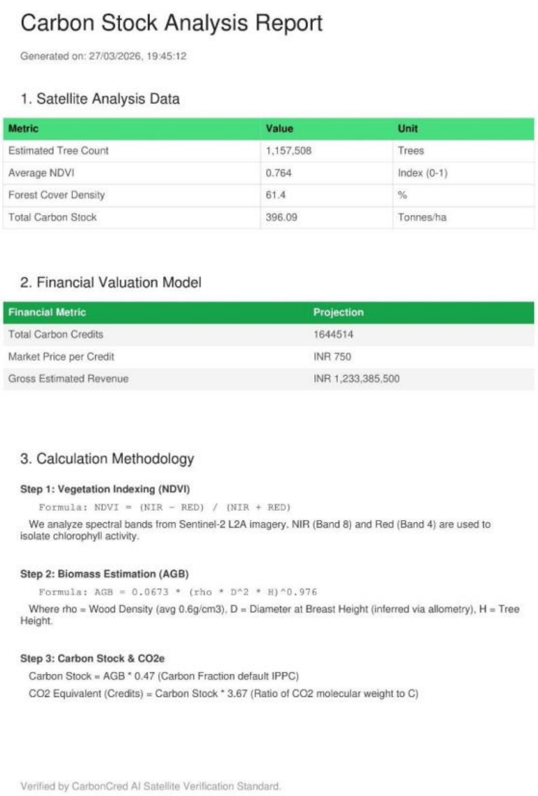
Fig. 7 Satellite-Based Forest Analysis Output showing estimated trees, NDVI index, carbon stock, and projected financial value.

F. Generated Carbon Stock Analysis Report

Figure 8 shows the final automatically generated Carbon Stock Analysis Report produced by the system. The report includes a Satellite Analysis Data table presenting key ecological metrics, a Financial Valuation Model section projecting total carbon credits and estimated revenue, and a Calculation Methodology section providing complete transparency of all formulas applied.



Carbon Stock Analysis Report

Generated on: 27/03/2026, 19:45:12

1. Satellite Analysis Data

Metric	Value	Unit
Estimated Tree Count	1,157,508	Trees
Average NDVI	0.764	Index (0-1)
Forest Cover Density	61.4	%
Total Carbon Stock	396.09	Tonnes/ha

2. Financial Valuation Model

Financial Metric	Projection
Total Carbon Credits	1644514
Market Price per Credit	INR 750
Gross Estimated Revenue	INR 1,233,385,500

3. Calculation Methodology

Step 1: Vegetation Indexing (NDVI)

```
Formula: NDVI = (NIR - RED) / (NIR + RED)
```

We analyze spectral bands from Sentinel-2 L2A imagery. NIR (Band 8) and Red (Band 4) are used to isolate chlorophyll activity.

Step 2: Biomass Estimation (AGB)

```
Formula: AGB = 0.0673 * (rho * D^2 * H)^0.976
```

Where rho = Wood Density (avg 0.6g/cm3), D = Diameter at Breast Height (inferred via allometry), H = Tree Height.

Step 3: Carbon Stock & CO2e

Carbon Stock = AGB * 0.47 (Carbon Fraction default IPPC)

CO2 Equivalent (Credits) = Carbon Stock * 3.67 (Ratio of CO2 molecular weight to C)

Verified by CarbonCred AI Satellite Verification Standard.

Fig. 8 Carbon Stock Analysis and Financial Valuation Report generated by CarbonCred AI.

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VI. EVALUATION

The CarbonCred AI system is evaluated by comparing the proposed AI-driven Digital MRV approach with traditional manual MRV methods across key dimensions including monitoring continuity, scalability, and integration of ecological and financial analysis.

TABLE I COMPARATIVE ASSESSMENT OF CARBON MONITORING APPROACHES

Method	Monitoring Mode	Scalability	Ecological + Financial Integration
CarbonCred AI (Proposed)	Automated / Continuous	Regional to National	Unified
Manual MRV	Periodic Field Survey	Local Only	Separate
IoT-Based MRV	Continuous Sensor	Limited	Partial
Blockchain MRV	Transaction Log	Moderate	Not Verified

The proposed framework demonstrates a clear advantage in monitoring continuity and system integration. The automated pipeline eliminates the need for periodic manual field surveys by enabling satellite-based vegetation monitoring at scale. The unified architecture integrating ecological monitoring with financial valuation within a single platform represents a significant advancement over existing fragmented approaches. The Q-learning reinforcement learning agent introduces a financial optimization component absent from all prior systems reviewed in the literature. Formal quantitative evaluation against benchmark ground-truth datasets will be conducted in future work.

VII. DEPLOYMENT AND OPERATIONAL IMPACT

A. Web Platform and Accessibility

CarbonCred AI is deployed as a scalable web-based application allowing users to access carbon monitoring tools through an interactive interface. Users input geographic coordinates, configure scan radius parameters, and perform vegetation and biomass analysis using satellite imagery. The platform automatically generates Carbon Stock Analysis Reports containing satellite analysis data, financial valuation projections, and the complete calculation methodology.

B. Impact on Small Landowners and Rural Communities

Traditional MRV systems are prohibitively expensive for small-scale projects. The automated monitoring capability of CarbonCred AI significantly reduces operational costs, enabling small landowners and rural communities in India to access digital verification. This democratizes participation in carbon credit markets and supports community-based conservation efforts that were previously excluded due to high MRV certification costs.

C. Leakage Detection and Environmental Integrity

By comparing satellite images collected at different time intervals across both project areas and surrounding landscapes, the system can detect carbon leakage — situations in which conservation activities in one forest area lead to deforestation in neighboring regions. Automated leakage detection ensures the environmental integrity of carbon credit projects and adjusts carbon calculations accordingly.

VIII. LIMITATIONS AND FUTURE WORK

A. Current Limitations

The system depends on satellite imagery that can be affected by cloud cover, atmospheric disturbances, and seasonal variations. NDVI and SAVI do not directly measure biomass or carbon storage; similar index values can represent different vegetation types with varying carbon densities. The Random Forest model requires continuous ground-truth validation to ensure reliability across diverse forest types. Soil carbon, representing a significant fraction of total ecosystem carbon storage, is not currently accounted for. Financial projections carry uncertainty due to carbon price fluctuations and evolving regulatory frameworks.

B. Future Research Directions

Future enhancements include: LiDAR integration for three-dimensional forest structure measurement to improve biomass estimation accuracy; blockchain integration for transparent and immutable carbon credit transaction records; soil carbon

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estimation models for complete ecosystem-level accounting; transformer-based deep learning architectures for improved vegetation classification; time-series predictive monitoring for deforestation risk forecasting; and standardized integration with national and international carbon registries for large-scale digital verification adoption.

IX. CONCLUSION

This paper presented CarbonCred AI, an Artificial Intelligence-driven Digital Monitoring, Reporting, and Verification framework for automated carbon credit analysis and valuation. The system integrates Sentinel-2 satellite remote sensing, NDVI and SAVI spectral analysis, Random Forest Regression for biomass estimation, and Q-learning reinforcement learning for financial optimization into a unified automated pipeline.

The proposed framework demonstrates automated forest carbon analysis using satellite imagery and machine learning techniques, supporting biomass estimation, carbon stock calculation, and financial valuation within a single unified Digital MRV architecture. By addressing critical gaps in existing carbon monitoring systems — providing continuous large-scale monitoring without physical field visits, integrating ecological analysis with financial valuation, reducing verification costs for small landowners, and enhancing transparency through standardized algorithmic verification — CarbonCred AI represents a significant step toward scalable and credible carbon markets in support of global climate mitigation goals. Comprehensive quantitative validation using benchmark datasets and field-verified measurements is planned for future work.

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