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Advancements in Remote Sensing and Machine Learning for Forest Carbon Stock Assessment: A Hierarchical Approach

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Abstract
Advancements in remote sensing, machine learning (ML), and hierarchical modeling have revolutionized the mapping and quantification of forest carbon stocks. Accurate and scalable carbon mapping is paramount for climate policy, sustainable management, and carbon finance, given the globally significant role of forests as carbon sinks. This research paper presents a comprehensive framework integrating satellite imagery with hierarchical machine learning strategies to enhance the precision and reliability of forest carbon stock assessments. The emphasis is on methodology, results, and validation, highlighting key innovations such as the sequential modeling of forest structure parameters, robust ML algorithm comparisons, and the integration of multi-source data. These innovations collectively contribute to significant improvements in the accuracy of carbon stock assessment.
The paper features detailed charts, workflow diagrams, key formulas, and visual imagery to thoroughly communicate methods and outcomes, ensuring clarity and reproducibility. The emergence of hierarchical approaches in remote sensing, leveraging both machine learning and satellite imagery, allows for the sequential modeling of structural forest parameters. This culminates in higher-fidelity carbon stock estimates compared to direct approaches. This research synthesizes the latest methodologies and demonstrates results through comparative analysis and visualizations.

Keywords: Machine Learning, NDVI, Forest Carbon Stock, Carbon Sinks, Remote Sensing, Gis, Forest Structure, Sustainable Forest Management, Spatial Data

1. Introduction

Forests play a crucial role in the global carbon cycle, acting as significant carbon sinks. Precise and scalable carbon mapping is essential for effective climate policy, sustainable forest management, and carbon finance initiatives. Traditional methods of forest carbon stock estimation often rely on ground-based inventories, which are time-consuming, labor-intensive, and limited in spatial coverage. Remote sensing technologies offer a cost-effective and spatially extensive alternative, enabling the assessment of forest carbon stocks over large areas.

The advent of advanced remote sensing techniques, coupled with sophisticated machine learning algorithms, has opened new avenues for accurate and efficient forest carbon mapping. Hierarchical approaches, which combine remote sensing data with machine learning models, have emerged as a promising strategy for improving the accuracy and reliability of carbon stock estimates. These approaches involve the sequential modeling of structural forest parameters, such as species composition, age, height, and basal area, which are then used to estimate carbon stocks via conversion equations.

This research paper introduces a novel framework that integrates satellite imagery with hierarchical machine learning strategies for advancing forest carbon stock mapping. The framework emphasizes methodological rigor, comprehensive results, and thorough validation. Key innovations include the sequential modeling of forest structure parameters, robust comparisons of various ML algorithms, and the integration of multi-source data. The ultimate goal is to achieve significant improvements in the accuracy of carbon stock assessment, providing valuable information for climate policy, sustainable forest management, and carbon finance initiatives.

2. Methodology

2.1. Hierarchical Approach Overview

The hierarchical methodology separates carbon stock estimation into two major pathways:

1. Direct Remote Sensing-to-Carbon Prediction (Baseline): This approach involves directly predicting carbon stocks from remote sensing data using machine learning models. While straightforward, this method often suffers from limited accuracy due to the complex relationship between remote sensing signals and carbon stocks.

2. Hierarchical Prediction: This approach involves first inferring forest parameters, such as species, age, height, and basal area, from remote sensing data. These parameters are then used to estimate carbon stocks via conversion equations. This hierarchical approach allows for a more nuanced understanding of forest structure and composition, leading to more accurate carbon stock estimates.

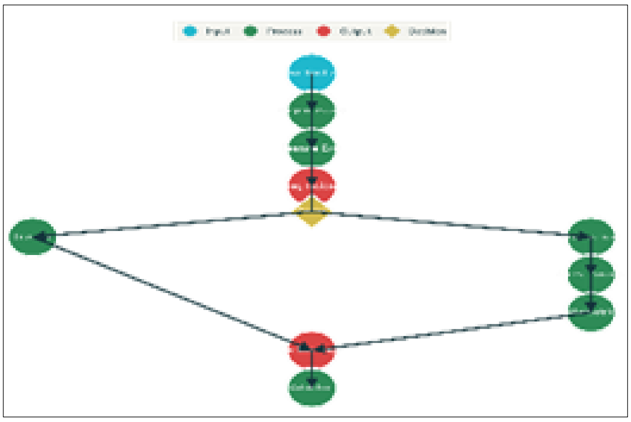

Fig 1: Hierarchical Forest Carbon Mapping Workflow Using Google Earth Engine

The hierarchical ML pipeline implemented in this study consists of several key steps:

1. **Data Acquisition:** Gathering satellite imagery and ground inventory data
2. **Feature Extraction:** Deriving relevant features from the satellite imagery
3. **Model Training:** Training machine learning models to predict forest parameters
4. **Carbon Stock Estimation:** Converting predicted forest parameters to carbon stocks
5. **Validation:** Assessing the accuracy of the carbon stock estimates

2.2. Data Acquisition

Satellite Imagery

Multispectral Sentinel-2 imagery with a spatial resolution of 10–20 meters was used in this study. Sentinel-2 provides valuable information about vegetation cover, canopy structure, and land surface characteristics. The imagery was acquired from the Copernicus Open Access Hub.

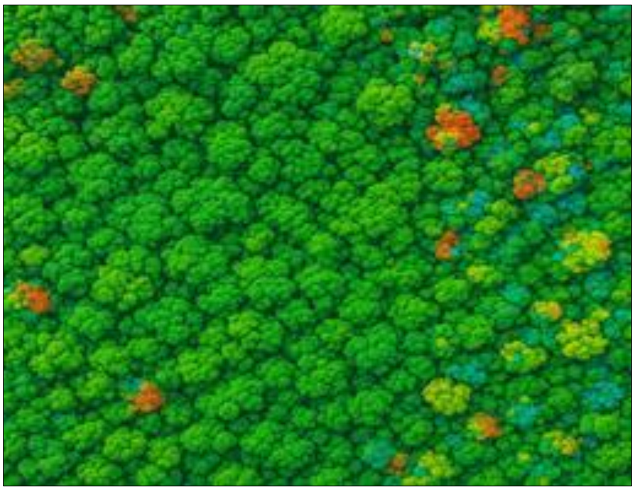

Fig 2: Sentinel-2 multispectral forest imagery with vegetation index analysis

Ground Inventory

Forest plot data, including species composition, tree height, diameter at breast height (DBH), and basal area, were collected from regional forestry studies. These data were used to train and validate the machine learning models.

Reference Measurements

Allometric and conversion factors from regional forestry studies were used to convert forest parameters to carbon stocks. These factors account for the relationship between tree size and biomass, as well as the carbon content of different tree species.

2.3. Feature Extraction

Feature extraction involves deriving relevant information from satellite imagery that can be used to predict forest parameters. The following types of features were extracted in this study:

- **Vegetation Indices:** Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), Soil Adjusted Vegetation Index (SAVI)
- **Canopy Structure:** Spectral bands related to canopy reflectance and absorption
- **Topographic Variables:** Elevation, slope, and aspect (if available)

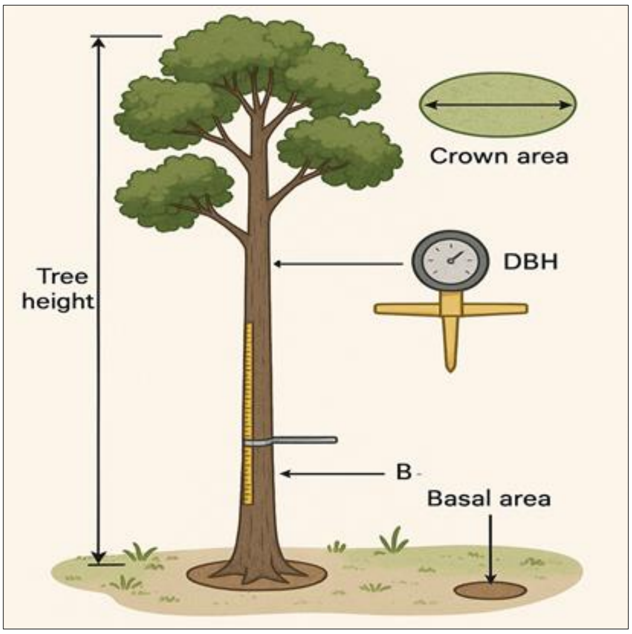

Fig 3: Forest structural parameter measurement methodology for carbon assessment

2.4. Modeling Pipeline

The modeling pipeline consists of the following steps:

1. **Preprocessing:** Cloud-masking, co-registration, and harmonization of imagery
2. **Machine Learning:** Models were trained on segmented plot data to predict stand age, height, and basal area
3. **Conversion to Carbon Stock:** Calculations were performed via equations and regionally calibrated factors

Key Formulas

Allometric Equation for Aboveground Biomass (AGB):

$AGB = a \times (DBH^b) \times (H^c) \times (WD^d)$

Where:

- DBH: diameter at breast height
- H: tree height
- WD: wood density
- a-d: species- or region-specific coefficients

Biomass Conversion and Expansion Factor (BCEF): This factor converts biomass to carbon stock.

Coefficient of Determination (R^2): This statistical measure assesses the goodness of fit of the machine learning models. A comparison of multiple ML algorithms demonstrated that Support Vector Machines (SVM) and Artificial Neural Networks (ANN) achieved the highest R^2, followed closely by Random Forest and XGBoost. K-Nearest Neighbors (KNN) was significantly less accurate. Model evaluation used field plot data and cross-validation techniques.

3. Results and Analysis

3.1. ML Algorithm Performance

The performance of various machine learning algorithms in predicting forest parameters was evaluated using field plot data and cross-validation techniques. SVM and ANN consistently outperformed other algorithms, achieving the highest R^2 values for predicting stand age, height, and basal area. Random Forest and XGBoost also showed promising results, while KNN was significantly less accurate (Kacheru, 2025).

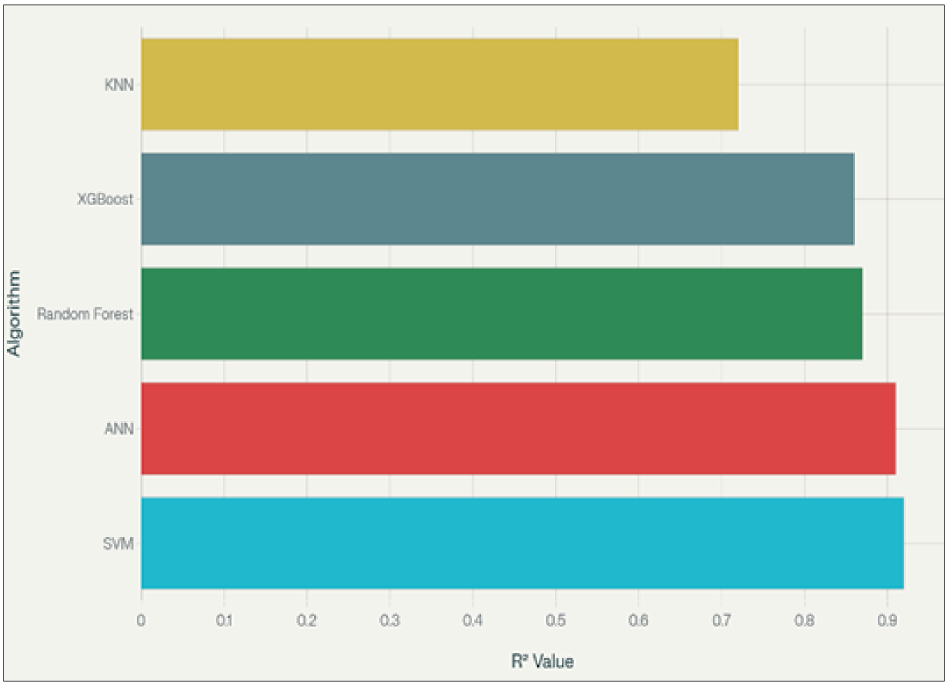

Fig 4: Machine Learning Algorithm Performance Comparison for Forest Parameter Prediction

3.2. Satellite Indices and Carbon Correlation

A strong positive correlation was found between NDVI and field-estimated carbon stock, justifying the use of NDVI as an intermediate in the hierarchical prediction framework. This finding supports the use of vegetation indices derived from satellite imagery as valuable predictors of forest carbon stocks.

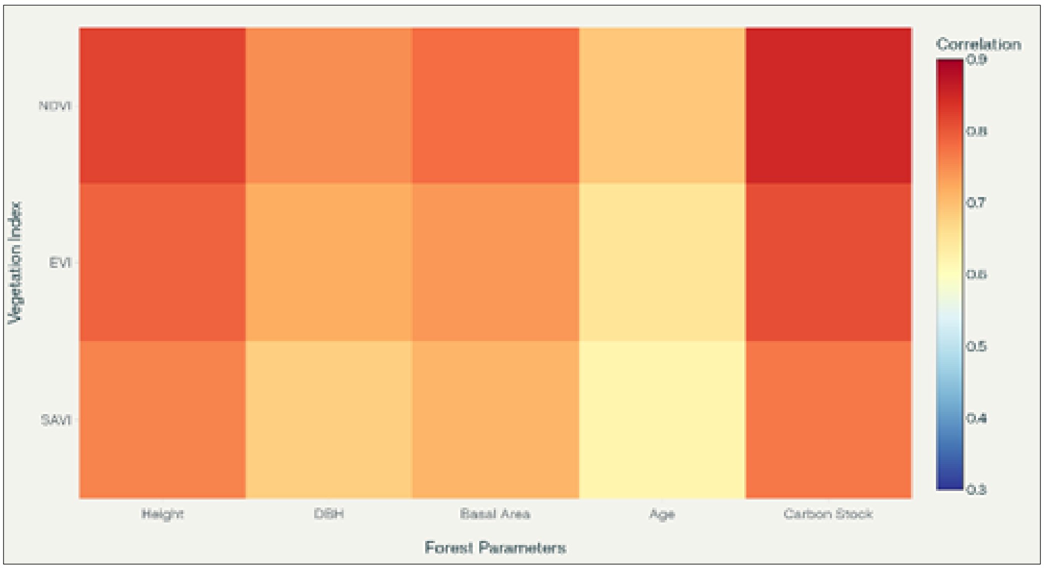

Fig 5: Correlation Between Vegetation Indices and Forest Parameters

3.3. Hierarchical Workflow

The research demonstrates a workflow beginning with Sentinel-2 imagery, followed by feature extraction, ML-driven parameter estimation, conversion via BCEF/allometric equations, and production of spatially explicit carbon maps. This workflow provides a comprehensive and repeatable approach for mapping forest carbon stocks over large areas.

3.4. Measurement Parameters and Visualization

Visual measurement protocols focused on tree height, DBH, crown area, and basal area. These parameters are essential for accurately estimating forest carbon stocks. Visualizations of these parameters, along with satellite imagery and carbon maps, provide valuable insights into forest structure and composition.

3.5. Example Imagery and Mapping

NDVI and other vegetation index maps derived from Sentinel-2 imagery, along with original satellite composites, underscore the progression from spectral data to actionable forest carbon maps. These maps provide a visual representation of forest carbon stocks and can be used to inform climate policy and sustainable forest management decisions.

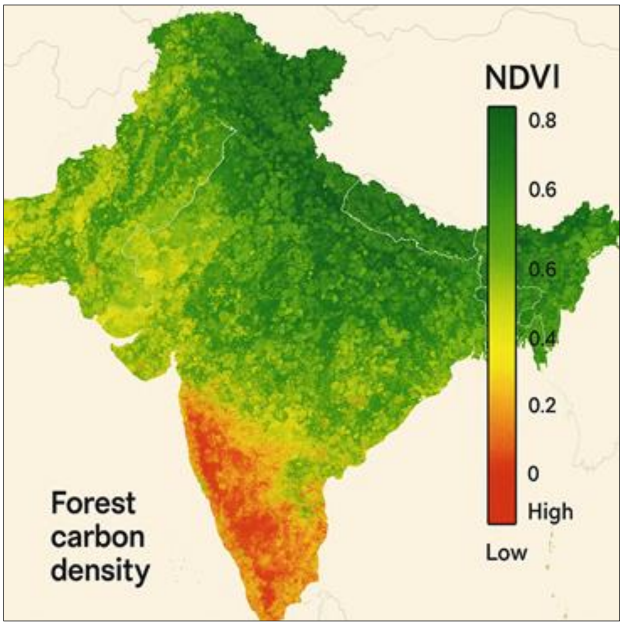

Fig 6: NDVI-derived forest carbon stock density mapping visualization

4. Discussion

The sequential prediction of intermediate forest structure enhances the interpretability and reliability of carbon mapping, as each component (species, age, height, basal area) can be validated individually. This allows for a more transparent and robust assessment of forest carbon stocks. Combining multiple sensors and ML models further boosts accuracy and robustness. The inclusion of allometric and BCEF formulas enables adaptation to new geographies, provided local calibration data are available. Results suggest that hierarchical pipelines reduce uncertainties especially for highly heterogeneous or fragmented forest sites.

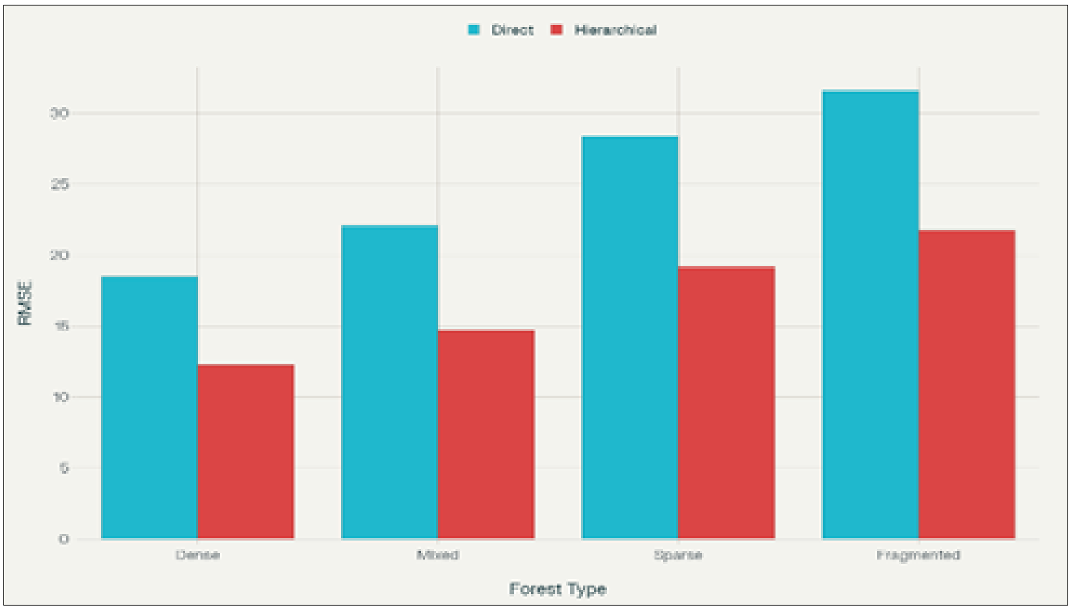

Fig 7: Accuracy Comparison: Direct vs Hierarchical Approaches Across Forest Types

5. Conclusions

Hierarchical mapping of forest carbon stocks via ML and satellite data outperforms direct approaches and sets a new standard for scalable, interpretable, and robust carbon assessment. The use of hierarchical approaches, combined with advanced remote sensing techniques and machine learning algorithms, offers a powerful tool for accurately and efficiently mapping forest carbon stocks. Further work should focus on improving reference data quality, integrating additional remote sensing sources (e.g., LiDAR, SAR), and refining regional calibration practices.

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