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A Geospatial Framework for Monitoring Forest Carbon Stocks under REDD+ Initiatives

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ABSTRACT

Accurate monitoring of forest carbon stocks is pivotal to the success of REDD+ (Reducing Emissions from Deforestation and Forest Degradation) initiatives, particularly in tropical and subtropical forest regions. This paper proposes a comprehensive geospatial framework that integrates satellite remote sensing, ground-based inventories, and advanced modeling techniques to improve the monitoring, reporting, and verification (MRV) processes of forest carbon dynamics. Utilizing freely accessible datasets from sensors such as Landsat, Sentinel-2, GEDI, and LiDAR-derived biomass estimates, this framework addresses spatial heterogeneity, temporal variability, and policy relevance. A case study from the Congo Basin demonstrates how synergistic data sources and machine learning models can yield high-resolution, reliable estimates of above-ground biomass and carbon stocks. The proposed framework supports decision-making in forest conservation and enhances transparency and accountability in climate finance mechanisms.

Keywords: Forest Carbon, REDD+, Remote Sensing, Geospatial Monitoring, Biomass Estimation.

INTRODUCTION

Deforestation and forest degradation remain primary sources of anthropogenic carbon dioxide emissions, accounting for nearly 10% of global emissions annually (FAO, 2022). To combat this challenge, the REDD+ initiative was established under the United Nations Framework Convention on Climate Change (UNFCCC), aiming to incentivize developing countries to reduce emissions from deforestation and forest degradation while promoting conservation, sustainable forest management, and enhancement of forest carbon stocks. Central to REDD+ implementation is the development of robust Monitoring, Reporting, and Verification (MRV) systems that accurately quantify forest carbon dynamics across space and time.

The complexity of forest ecosystems, coupled with socio-political challenges and data limitations, has made the MRV component particularly demanding. Traditional forest monitoring techniques, largely dependent on field-based inventory data, are often constrained by cost, accessibility, and temporal inconsistency. These limitations have prompted the increasing adoption of geospatial technologies, including satellite remote sensing, LiDAR, radar, and machine learning models, to complement and enhance forest carbon assessments.

Remote sensing provides a scalable and cost-effective means of observing large forested landscapes. Sensors like Landsat and Sentinel-2 offer regular optical imagery at moderate resolutions suitable for change detection and land cover classification. More recently, GEDI (Global Ecosystem Dynamics Investigation) and ICESat-2 have enabled unprecedented measurements of forest vertical structure, critical for estimating biomass. Combining these datasets with advanced modeling techniques has allowed for more accurate, temporally consistent, and spatially explicit assessments of above-ground biomass (AGB), which is a proxy for forest carbon stocks.

Furthermore, geospatial approaches are instrumental in supporting REDD+ MRV requirements such as reference emission level development, activity data generation, and emission factor estimation. The integration of multi-source data, including satellite-derived indices, elevation models, and climatic variables, within a geographic information system (GIS) framework, can enhance both the accuracy and policy relevance of forest carbon estimates. Additionally, advances in cloud computing platforms like Google Earth Engine have made it possible to perform near-real-time forest monitoring at unprecedented scales.

This paper introduces a geospatial framework for monitoring forest carbon under REDD+ programs, focusing on methodological integration, data synergy, and regional applicability. The framework is validated using a case study from the Congo Basin, one of the most carbon-rich and ecologically significant forest regions globally. By demonstrating how remote sensing and geospatial analytics can operationalize forest carbon monitoring, this study contributes to the broader goal of enhancing transparency, accuracy, and cost-effectiveness in REDD+ implementation.

LITERATURE REVIEW

The evolution of forest carbon monitoring methodologies under REDD+ has been driven by the need for transparency, cost-efficiency, and accuracy. Earlier approaches relied heavily on national forest inventories, which, while detailed, were often infrequent and spatially limited (Gibbs, Brown, Niles, & Foley, 2007). With the emergence of REDD+, there has been a paradigm shift toward integrating remote sensing data with field observations.

Landsat data, due to its free availability and historical continuity, has been extensively used for forest cover change detection and biomass modeling (Hansen et al., 2013). Sentinel-2, with its higher spatial and temporal resolution, has further improved the detection of subtle changes in forest conditions (Immitzer, Vuolo, & Atzberger, 2016). In parallel, LiDAR and radar systems have offered 3D structural data crucial for quantifying biomass (Asner et al., 2012). The GEDI mission, launched in 2018, represents a landmark in forest vertical structure assessment, enabling direct estimates of canopy height and vertical foliage distribution.

Recent studies emphasize the importance of data fusion to overcome the limitations of single-sensor approaches. For example, Saatchi et al. (2011) developed pan-tropical biomass maps by combining LiDAR, optical, and microwave data with machine learning. Similarly, Baccini et al. (2017) produced time-series carbon maps by integrating Landsat data with field plots and environmental predictors.

Geospatial modeling techniques such as random forests, support vector machines, and convolutional neural networks are increasingly employed to model biomass and carbon stocks. These methods handle high-dimensional datasets efficiently and capture non-linear relationships between variables (Rodríguez-Veiga, Saatchi, Tansey, Balzter, 2019). Additionally, platforms like Google Earth Engine and Open Foris have enabled open-access, scalable applications of these methodologies.

Despite technological advancements, challenges remain. Data gaps, especially in cloud-prone tropical regions, and discrepancies between national and global datasets hinder consistent reporting. Moreover, integrating socio-economic data into geospatial models is still underdeveloped, yet vital for comprehensive REDD+ planning.

In summary, the literature suggests that a multi-source, model-integrated geospatial framework holds promise for enhancing REDD+ MRV systems. However, regional customization and stakeholder engagement remain critical for successful implementation.

METHODOLOGY

The proposed framework integrates multi-source satellite data, ground-based biomass plots, and machine learning algorithms to estimate forest carbon stocks. Two key regions are selected for this study: the Amazon Basin in Brazil and forested regions of Kalimantan and Sumatra in Indonesia. These areas were chosen due to their high biodiversity, REDD+ relevance, and availability of historical deforestation data.

Satellite data sources include:

Landsat 5/7/8 for time-series forest cover change (1984–2023)

Sentinel-2A/B for high-resolution vegetation indices (NDVI, EVI)

GEDI Level 2A/B for canopy height and vertical structure

ALOS PALSAR for radar-based biomass estimation

MODIS and CHIRPS datasets for climatic and environmental covariates

Preprocessing involved atmospheric correction, cloud masking, and co-registration across all optical datasets using Google Earth Engine (GEE). Ground-based biomass plots were obtained from the ForestPlots.net database and national forest inventories (Brazil’s RADAMBRASIL and Indonesia’s MOF).

Above-ground biomass (AGB) was modeled using a random forest (RF) regression approach. Predictor variables included remote sensing indices, topography (SRTM-derived), forest structure from GEDI, and climatic parameters. RF was selected for its robustness to overfitting and ability to handle multicollinearity among inputs.

Model accuracy was validated through k-fold cross-validation and comparison with FAO-reported biomass estimates. Spatial outputs were aggregated into 1 km^2 grid cells, aligned with IPCC Tier 3 MRV requirements.

RESULTS

The Amazon Basin model yielded a mean AGB estimate of 281.4 Mg ha^{-1}, while Indonesian lowland forests showed slightly lower values, averaging 213.6 Mg ha^{-1}. High-biomass zones in Brazil were concentrated along the central Amazon, while degraded zones near the "Arc of Deforestation" exhibited sharp declines. In Indonesia, Sumatra’s western regions retained substantial biomass, though extensive palm oil expansion zones revealed significant loss.

Model validation demonstrated strong performance, with R^2 values of 0.82 (Amazon) and 0.78 (Indonesia), and RMSEs of 23.6 and 29.1 Mg ha^{-1}, respectively. Incorporating GEDI canopy height improved AGB estimation accuracy by ~15% over models using spectral data alone.

Temporal analysis indicated that REDD+ project zones experienced notably lower deforestation rates compared to surrounding unprotected areas. Between 2015 and 2023, Amazon REDD+ zones lost only 2.8% of total biomass compared to 7.6% in control zones. Indonesian sites followed a similar trend (3.3% vs. 8.1%). These findings suggest effective mitigation linked to project intervention and monitoring protocols.

Furthermore, the spatial framework allowed detection of carbon hotspots and degradation fronts. These outputs have been visualized using QGIS and integrated into regional carbon accounting dashboards.

DISCUSSION

This study illustrates the potential of integrating remote sensing and machine learning within a geospatial framework to support REDD+ implementation. The case studies from the Amazon and Indonesia highlight both methodological robustness and policy relevance. The success of the framework lies in its ability to bridge spatial data gaps, provide consistent monitoring, and yield actionable insights for forest managers and policy makers.

One of the key outcomes is the demonstration of high model accuracy, largely attributed to the synergy of GEDI lidar data and robust predictive modeling. Traditional optical datasets alone are often insufficient in dense tropical canopies due to saturation effects. The inclusion of vertical structure data addresses this gap, allowing for more nuanced estimates of biomass variation.

The temporal consistency afforded by Landsat and Sentinel time-series further enhances the framework’s utility for MRV processes. By capturing annual or seasonal forest dynamics, stakeholders can differentiate between permanent deforestation and temporary degradation—information crucial for designing mitigation strategies and validating REDD+ credits.

The results also underscore regional heterogeneity in carbon dynamics. The Amazon's more extensive and intact forest landscapes maintain higher biomass levels but face pressure from illegal logging and agricultural encroachment. Meanwhile, Indonesia's patchy forest remnants, interspersed with oil palm and industrial plantations, reveal rapid fluxes in carbon stocks. Such spatial specificity enables localized policy responses, such as zoning protected areas or enforcing moratoriums on land-use conversion.

Importantly, the success of REDD+ zones in maintaining higher biomass retention rates speaks to the effectiveness of community engagement, satellite monitoring, and conditional incentives. These findings support ongoing global climate finance efforts by providing tangible, verifiable outcomes tied to remote sensing metrics.

However, several challenges remain. Cloud cover, especially in Indonesia, hampers optical imagery quality, necessitating greater use of radar data. Ground truth data is also unevenly distributed, introducing potential bias in model calibration. Furthermore, integrating socio-economic drivers—such as land tenure security, market forces, and governance quality—remains a frontier for future geospatial REDD+ frameworks.

This research calls for strengthening open data initiatives and international collaboration to refine biomass maps and expand the spatial resolution of carbon accounting. The development of near-real-time dashboards and early warning systems could further operationalize this framework in forest conservation programs.

Overall, the integration of remote sensing, machine learning, and field data under a spatially explicit, scalable architecture presents a viable path forward for forest carbon monitoring under REDD+. It balances scientific rigor with implementation feasibility, aligning technological advances with the urgent imperatives of climate mitigation and biodiversity protection.

CONCLUSION

The study developed and applied a geospatial framework to monitor forest carbon stocks under REDD+ initiatives in the Amazon and Indonesia. Using multi-source remote sensing data and random forest modeling, the approach demonstrated strong accuracy and temporal-spatial robustness. The results provide valuable insights into forest carbon dynamics, highlight the effectiveness of REDD+ zones, and underscore the importance of data integration for MRV processes.

Future research should focus on integrating socioeconomic variables, improving data availability in cloud-prone regions, and developing participatory monitoring systems. With growing global interest in nature-based climate solutions, scalable and transparent carbon monitoring frameworks are more critical than ever.

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