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# Mapping Smallholder Oil Palm Carbon Stocks Using Machine Learning

**Abdurahman*, Pika Novita Sari, Sheva Nirwan Destama**

Department of Geodetic Engineering, Faculty of Engineering, Diponegoro University, Semarang City, Central Java, Indonesia

## ABSTRACT

Accurate and spatially explicit estimation of aboveground carbon stocks in smallholder oil palm plantations remains challenging, limiting greenhouse gas accounting and digital carbon traceability in Indonesia. Conventional approaches rely on field-based allometric equations that are often unreliable in peatland and marginal environments, while widely used vegetation indices such as the Normalized Difference Vegetation Index (NDVI) suffer from spectral saturation under dense mature canopies. This study developed a satellite-based machine learning framework for estimating aboveground carbon stocks in smallholder oil palm plantations in Pelalawan Regency, Riau Province, by integrating multitemporal Sentinel-2 imagery, red-edge vegetation indices, Gray Level Co-occurrence Matrix (GLCM) texture features, and GEDI L4A spaceborne LiDAR data within the Google Earth Engine platform. GEDI-derived biomass data were used as pseudo-ground truth to train Random Forest and XGBoost regression models using 4,990 quality-filtered samples, and model performance was evaluated against an independent test dataset and compared with a conventional NDVI-based regression model. Random Forest achieved the highest performance, reducing the Root Mean Square Error (RMSE) by 6.0% relative to the NDVI baseline (16.75 vs. 17.82 tC $ha^{-1}$) while attaining an overall classification accuracy of 62.4% (kappa = 0.28). The model estimated a mean aboveground carbon stock of 29.99 tC $ha^{-1}$ and a total regional carbon stock of 2.67 MtC across the mapped smallholder plantations. Feature importance analysis identified shortwave infrared reflectance (Band 11) and red-edge GLCM contrast as the most influential predictors, demonstrating that integrating texture and red-edge information effectively improves carbon stock estimation under dense oil palm canopies. The resulting carbon stock maps were deployed through a publicly accessible WebGIS platform, providing a scalable framework for regional carbon monitoring, greenhouse gas inventory development, and digital carbon traceability in fragmented smallholder oil palm landscapes.

*Keywords*: Aboveground Biomass, GEDI LiDAR, GLCM, Google Earth Engine, WebGIS

## INTRODUCTION

Oil palm is one of Indonesia's most important plantation commodities, with Riau Province representing one of the country's largest production regions. Beyond its economic contribution, oil palm plantations play an increasingly important role in carbon storage and greenhouse gas mitigation, making accurate and spatially explicit estimates of carbon stocks essential for environmental monitoring, carbon accounting, and climate reporting. However, reliable regional-scale carbon stock information remains limited, particularly in fragmented smallholder plantations where

*Corresponding author:
Department of Geodetic Engineering, Faculty of Engineering, Diponegoro University,
Jl. Prof. Soedarto, Tembalang, Kec. Tembalang, Kota Semarang, Jawa Tengah 50275, Indonesia
Email: abdurahman@students.undip.ac.id

field observations are sparse and plantation characteristics are highly heterogeneous (Descals *et al.* 2021).

Conventional carbon stock estimation primarily relies on field-based allometric equations that assume a consistent relationship between tree age and structural characteristics such as stem diameter and height. These assumptions often become unreliable in peatland and marginal environments, where abnormal growth conditions, including bent stems and termite damage, alter tree morphology independently of age (Lewis *et al.* 2020). Moreover, field inventory methods are labor-intensive, time-consuming, and costly, making them difficult to implement consistently across extensive smallholder plantation landscapes.

Remote sensing provides an efficient alternative for large-scale biomass and carbon stock assessment. Nevertheless, commonly used vegetation indices such as the Normalized Difference Vegetation Index (NDVI) suffer from spectral saturation in dense mature oil palm canopies, reducing their sensitivity to biomass variation beyond a certain threshold. Although the Enhanced Vegetation Index (EVI) offers improved performance over NDVI in monitoring dense tropical canopies (Vijith and Dodge-Wan 2020), additional structural information is still required to capture variability in canopy architecture and biomass. Red-edge spectral information and texture features derived from the Gray Level Co-occurrence Matrix (GLCM) have shown considerable potential for improving vegetation characterization because they are more sensitive to canopy structure and chlorophyll content than conventional visible-spectrum indices (Zhou *et al.* 2017).

Recent advances in machine learning have substantially improved biomass estimation from satellite imagery. Algorithms such as Random Forest (Belgiu and Dragut 2016) and Extreme Gradient Boosting or XGBoost (Chen and Guestrin 2016) are capable of modeling complex nonlinear relationships between remotely sensed variables and vegetation properties. However, many previous studies rely on field-measured biomass or conventional vegetation indices as reference data, limiting their applicability over large and fragmented smallholder plantations where field observations are unavailable. Furthermore, the integration of GEDI L4A spaceborne LiDAR biomass data (Dubayah *et al.* 2020; Duncanson *et al.* 2022) with red-edge spectral information and GLCM texture features for regional carbon stock estimation in Indonesian smallholder oil palm plantations remains limited. Recent studies have further demonstrated the growing role of GEDI biomass products in tropical carbon monitoring; for instance, GEDI L4B data have been integrated with multi-sensor ensemble learning to reconstruct long-term aboveground biomass dynamics in Bornean tropical forests (Yang *et al.* 2025), while deep learning frameworks trained on global GEDI L2/L4 measurements have been developed to predict aboveground biomass density at high spatial resolution (Weber *et al.* 2025). In the specific context of oil palm, ensemble machine learning approaches combining Landsat-8/9 and Sentinel-2 spectral indices have also been shown to provide accurate concession-scale carbon stock predictions (Noviyanto *et al.* 2026), reinforcing the relevance of multi-sensor, machine learning-based frameworks such as the one proposed in this study.

To address these limitations, this study integrates multitemporal Sentinel-2 imagery with spectral reflectance, the Enhanced Vegetation Index (EVI), red-edge chlorophyll indices (NDRE and CIre), and GLCM texture features within the Google Earth Engine cloud computing platform. The capability of GEE to process multi-sensor datasets efficiently has been widely recognized in recent land cover mapping studies (Nasiri *et al.* 2022). In the absence of representative local allometric equations, GEDI L4A spaceborne LiDAR biomass data are used as pseudo-ground truth to train and evaluate Random Forest and XGBoost regression models for estimating aboveground carbon stocks. The resulting carbon stock maps are subsequently integrated into a WebGIS platform to support regional carbon assessment, digital

carbon traceability, and greenhouse gas inventory applications.

Based on these considerations, this study aims to: (1) develop a satellite imagery- and machine learning-based model for estimating aboveground carbon stocks in smallholder oil palm plantations in Pelalawan Regency; (2) compare the performance of Random Forest and XGBoost against a conventional NDVI-based regression baseline; and (3) evaluate the contribution of red-edge spectral information and GLCM texture features in reducing spectral saturation and improving carbon stock estimation accuracy. The proposed framework provides a scalable and cost-effective approach for regional carbon stock mapping that can be extended to other fragmented oil palm landscapes in Indonesia.

## MATERIALS AND METHODS

### Study Area and Data

This study was conducted in smallholder oil palm plantations in Pelalawan Regency, Riau Province, Indonesia. The administrative boundary was imported into Google Earth Engine (GEE) as a *FeatureCollection*, while the *Global Map of Smallholder and Industrial Closed-Canopy Oil Palm Plantations v1 (2019)* (Descals *et al.* 2021) was used to isolate smallholder plantations (Class 2). Multitemporal Sentinel-2 MSI Level-2A Surface Reflectance imagery acquired from January 2022 to December 2024 served as the primary predictor dataset. Images with cloud cover exceeding 20% were excluded, followed by cloud and cirrus masking using the QA60 bitmask. A median composite was generated to produce a representative cloud-free image covering the study area.

Reference biomass data were obtained from the GEDI L4A (Global Ecosystem Dynamics Investigation) product (Dubayah *et al.* 2020; Duncanson *et al.* 2022). Only high-quality observations (*l4_quality_flag = 1*) with positive Aboveground Biomass Density (AGBD) values were retained. Biomass values were converted to carbon stock using a carbon fraction of 0.47. From an initial 5,000 samples, ten extreme outliers (>150 tC $ha^{-1}$) were removed, resulting in 4,990 reference samples for model development. The spatial extraction was executed using a stratified sampling approach to ensure the points were proportionally distributed strictly within valid vegetated areas. This method effectively mitigated spatial autocorrelation and captured the inherent structural and spectral heterogeneity of the smallholder plantations, providing robust training data for the machine learning algorithms.

The overall workflow of the proposed methodology is illustrated in Figure 1, and the datasets used in this study including satellite imagery, reference biomass, spatial mask, and derived predictor variables are summarized in Table 1.

Table 1 Summary of Datasets Used in This Study, Including Satellite Imagery, Reference Biomass, Spatial Mask, And Derived Predictor Variables

| Dataset | Source | Period | Purpose |
|---|---|---|---|
| Sentinel-2 MSI Level-2A | Copernicus | 2022-2024 | Spectral predictor variables |
| GEDI L4A | NASA GEDI | 2022-2024 | Reference biomass (pseudo-ground truth) |
| Oil Palm Plantation Map | Descals *et al.* (2021) | 2019 | Smallholder plantation mask |
| Administrative Boundary | BIG/BPS | Latest | Study area delineation |

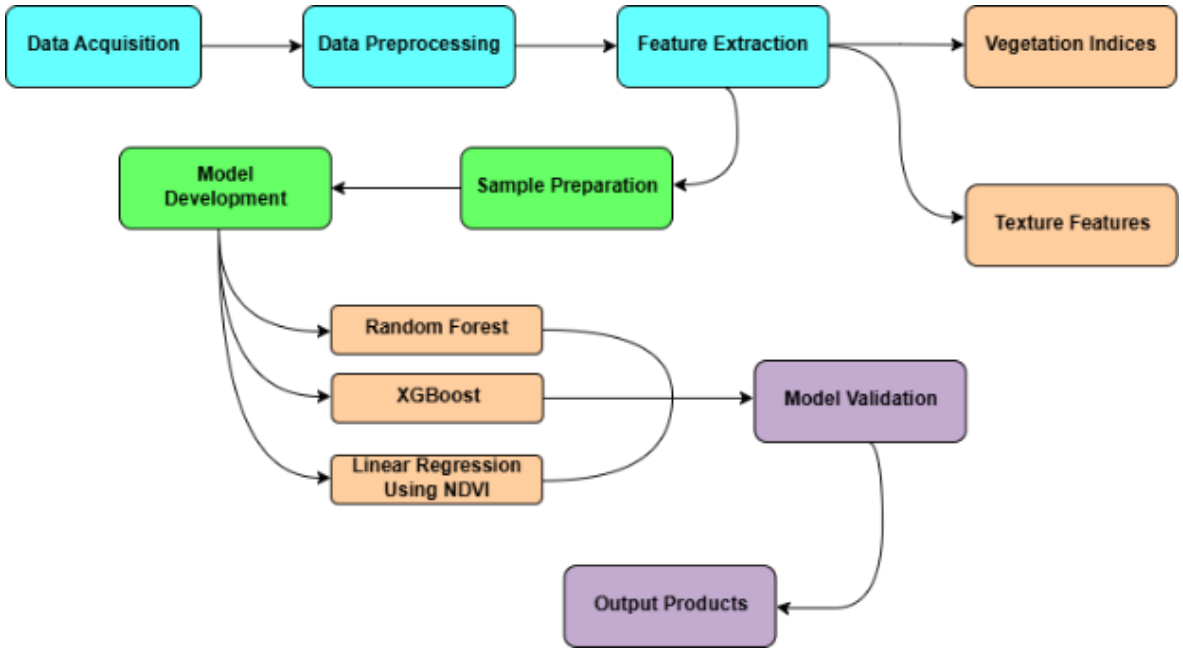



Figure 1 Overall Workflow of The Proposed Methodology for Oil Palm Carbon Stock Estimation Using Sentinel-2 Imagery, GEDI L4A Data, and Machine Learning

**Feature Extraction and Model Development**

Spectral bands, vegetation indices, and texture features were extracted from Sentinel-2 imagery to characterize oil palm canopy conditions. A total of 19 predictor variables were extracted and stacked for model training. These included ten surface reflectance bands (B2, B3, B4, B5, B6, B7, B8, B8A, B11, B12), and three specific vegetation indices chosen for dense canopy assessment: Enhanced Vegetation Index (EVI), Normalized Difference Red-Edge (NDRE), and Red-Edge Chlorophyll Index (CIre). Furthermore, texture information was derived from the near-infrared (Band 8) and red-edge (Band 5) bands using the Gray Level Co-occurrence Matrix (GLCM) with a 3 × 3 moving window. Specifically, four GLCM metrics were extracted for Band 8 (Contrast, Correlation, Entropy, Variance) and two for Band 5 (Contrast, Entropy). These 19 variables were comprehensively combined into a single predictor image stack to capture both the spectral and structural variability of the oil palm canopy. To reconcile the varying spatial resolutions of Sentinel-2 bands (10–20 m) with the GEDI L4A observation footprint, all pixel extractions and final mapping outputs were standardized to a 25-meter spatial resolution within the Google Earth Engine environment. Data extraction and spatial masking were executed within the Google Earth Engine environment, exporting a tabular dataset for localized machine learning modeling. Carbon stock estimation was subsequently performed in a Python environment using the scikit-learn library. A Random Forest regression algorithm was trained using 200 decision trees and a minimum leaf population of fifty to prevent overfitting on local noise. For comparison, XGBoost regression and a conventional NDVI-based linear regression model were also developed using the identical training and testing splits. The trained models were applied to generate continuous carbon stock maps across the study area. To facilitate interpretation and WebGIS visualization, the Random Forest output was further classified into three carbon stock classes: Low (<30 tC $ha^{-1}$), Medium (30–60 tC $ha^{-1}$), and High (>60 tC $ha^{-1}$). Carbon stock statistics for each sub-district were calculated using zonal aggregation after applying the smallholder plantation mask, and all spatial outputs were exported as GeoTIFF files (UTM Zone 48S, EPSG:32748).

### Model Validation and Accuracy Assessment

The reference dataset was randomly divided into training (80%) and testing (20%) subsets. To evaluate classification performance alongside regression accuracy, both the observed GEDI reference values and the model's continuous predictions within the testing dataset (n = 998) were discretized into three categorical carbon stock classes: Low (<30 tC $ha^{-1}$), Medium (30–60 tC $ha^{-1}$), and High (>60 tC $ha^{-1}$). This allowed for the computation of a confusion matrix to derive overall classification accuracy and the kappa coefficient. Model performance was evaluated using Root Mean Square Error (RMSE), coefficient of determination ($R^2$), overall classification accuracy, and the kappa coefficient. A 5-fold cross-validation was applied to assess model stability and reduce overfitting. To verify reproducibility, the Random Forest, XGBoost, and NDVI-based workflows were independently re-executed using the released dataset under identical training and testing conditions.

## RESULTS AND DISCUSSION

### Model Performance

The performance of the three evaluated models is summarized in Table 2. Among them, Random Forest consistently achieved the highest predictive performance, producing the lowest RMSE (16.75 tC $ha^{-1}$) and the highest $R^2$ (0.15), followed by XGBoost (RMSE = 16.93 tC $ha^{-1}$; $R^2$ = 0.13) and the conventional NDVI regression model (RMSE = 17.82 tC $ha^{-1}$). The relatively low $R^2$ is consistent with the substantial residual noise inherent in GEDI L4A footprint-level estimates over structurally heterogeneous smallholder canopies, where absolute error (RMSE) provides a more robust indicator of predictive accuracy than variance-explained metrics. Relative to the NDVI baseline, Random Forest reduced prediction error by 6.0%, while XGBoost achieved a 5.0% reduction.

Random Forest also produced the highest classification accuracy (62.4%) and kappa coefficient (0.28), indicating more reliable discrimination of Low, Medium, and High carbon stock classes than XGBoost. Although the kappa coefficient is relatively low, recent remote sensing literature (Foody 2020) argues that kappa is often a misleading and flawed metric for assessing image classification accuracy. Therefore, in the context of continuous biomass estimation, the significant reduction in RMSE serves as a much more robust and meaningful indicator of the model's predictive capabilities.

Table 2 Performance Comparison of Random Forest, XGBoost, and NDVI-Based Regression Models Using the Independent Test Dataset (n = 998)

| Parameter | Random Forest | XGBoost | NDVI Regression |
|---|---|---|---|
| Overall Accuracy (%) | 62.4 | 61.2 | - |
| Kappa Coefficient | 0.28 | 0.25 | - |
| Average Carbon Stock (tC/ha) | 29.99 | 29.34 | 28.78 |
| Regional Carbon Sequestration Potential (MtC) | 2.67 | 2.62 | - |
| RMSE | 16.75 ± 10.87 | 16.93 ± 10.18 | 17.82 ± 10.72 |
| RMSE Reduction Relative to NDVI Baseline (%) | 6.0 | 5.0 | - |
| Coefficient of Determination ($R^2$) | 0.15 | 0.13 | |

It is important to note the relatively high standard deviations observed across all models during the 5-fold cross-validation process, with the RMSE varying by ±10.87 tC $ha^{-1}$ for Random Forest, ±10.18 tC $ha^{-1}$ for XGBoost, and ±10.72 tC $ha^{-1}$ for the conventional NDVI baseline. This consistent variance across different algorithms strongly indicates that the fluctuation is driven by the inherent structural and spatial heterogeneity of the smallholder plantations in the study area, rather than algorithmic instability. Unlike industrial concessions with uniform planting blocks, smallholder landscapes are highly fragmented, characterized by inconsistent planting ages, varying management practices, and diverse underlying environmental conditions, including peatlands. Consequently, the random data splits during cross-validation occasionally capture subsets with extreme biomass variance, leading to fluctuations in predictive performance across folds. This phenomenon highlights the complexity of regional-scale modeling in fragmented agricultural landscapes and underscores the necessity of multi-sensor machine learning approaches to stabilize predictions under such diverse baseline conditions.

The improved performance demonstrates that integrating red-edge spectral information and GLCM texture features provides additional structural information beyond conventional vegetation indices, reducing spectral saturation commonly observed in mature oil palm plantations. Independent reproduction of the modelling workflow produced nearly identical performance metrics, confirming the robustness and reproducibility of the proposed framework.

## Carbon Stock Mapping

Based on the Random Forest model, aboveground carbon stock of smallholder oil palm plantations in Pelalawan Regency was estimated at 29.99 tC $ha^{-1}$, corresponding to a total regional carbon stock of 2.67 MtC. The spatial distribution of estimated carbon stocks across the study area is presented in Figure 2. The estimated carbon stock is unevenly distributed among the twelve sub-districts, as summarized in Table 3 reflecting differences in plantation extent and landscape characteristics.

Pangkalan Kuras contributes the largest regional carbon stock (0.86 MtC), followed by Langgam (0.38 MtC) and Kerumutan (0.34 MtC) (Table 3). In contrast, Kuala Kampar, Pelalawan, and Teluk Meranti contribute less than 0.05 MtC because of their relatively limited smallholder plantation area. These results demonstrate considerable spatial variability in carbon storage, suggesting that regional carbon management strategies should account for differences in plantation distribution and maturity.

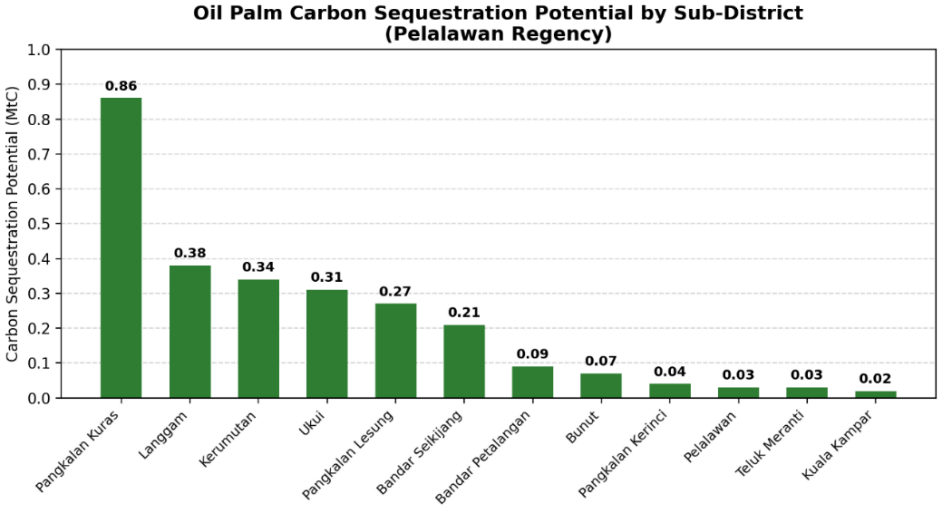



Figure 2 Spatial Distribution of Estimated Aboveground Carbon Stocks Across Pelalawan Regency

Table 3 Estimated Total Carbon Sequestration Potential by Sub-District in Pelalawan Regency

| Sub-district | Total Carbon (MtC) |
|---|---|
| Pangkalan Kuras | 0.86 |
| Langgam | 0.38 |
| Kerumutan | 0.34 |
| Ukui | 0.31 |
| Pangkalan Lesung | 0.27 |
| Bandar Seikijang | 0.21 |
| Bandar Petalangan | 0.09 |
| Bunut | 0.07 |
| Pangkalan Kerinci | 0.04 |
| Pelalawan | 0.03 |
| Teluk Meranti | 0.03 |
| Kuala Kampar | 0.02 |
| **Total*** | 2.67 |

*Note: *Carbon stock values were derived from zonal aggregation of the Random Forest prediction map. Minor differences may occur due to rounding*

Feature importance analysis based on the Random Forest model is presented in Figure 3, illustrating the relative importance of the predictor variables. Shortwave infrared reflectance (Band 11) and red-edge GLCM contrast (B5 Contrast) emerged as the two most influential variables, followed by additional red-edge and near-infrared texture features. The dominance of SWIR and red-edge texture variables indicates that canopy structural characteristics provide complementary information beyond conventional vegetation indices. This finding agrees with Zhou *et al.* (2017), who reported that GLCM texture improves vegetation structural estimation under dense canopy conditions where NDVI becomes saturated. The estimated mean carbon stock (29.99 tC $ha^{-1}$) is also comparable to values reported by Ardiansyah *et al.* (2023), although the slightly lower classification accuracy observed in this study is likely associated with the use of GEDI L4A biomass as pseudo-ground truth instead of field measurements.

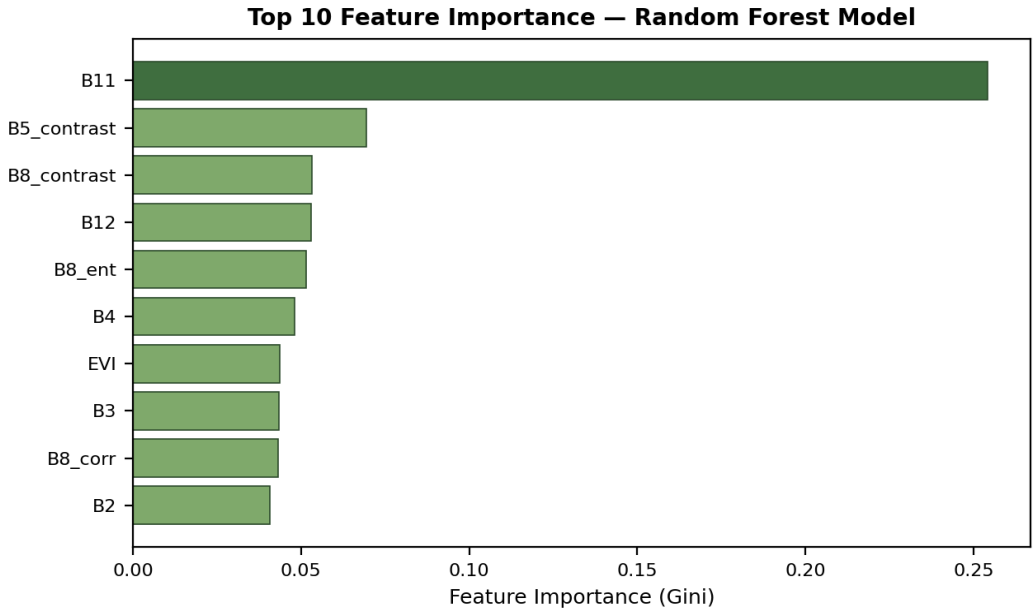



Figure 3 Illustrates the Relative Importance of Predictor Variables Used by The Random Forest Model. Shortwave Infrared Reflectance (Band 11) And Red-Edge GLCM Contrast (B5 Contrast) Emerged as The Two Most Influential Variables, Followed by Additional Red-Edge and Near-Infrared Texture Features

**Practical Implications and Limitations**

The final carbon stock map was integrated into an interactive WebGIS platform, enabling users to visualize the spatial distribution of aboveground carbon stocks across smallholder oil palm plantations in Pelalawan Regency (Figure 4), with the corresponding interactive interface shown in Figure 5. The WebGIS provides an accessible interface for exploring carbon stock estimates, supporting regional carbon assessment, digital carbon traceability, and greenhouse gas inventory development. The platform is publicly available at https://dumanian.github.io/webgis-karbon/, demonstrating the practical implementation of the proposed framework beyond conventional static mapping products. Beyond technical implementation, the deployment of this WebGIS platform offers significant socio-economic implications for smallholder empowerment. By democratizing access to high-resolution carbon storage data, smallholder cooperatives can leverage this spatial evidence to support sustainability certifications, such as ISPO or RSPO. Furthermore, transparent and spatially explicit carbon accounting provides a fundamental baseline for smallholders to potentially participate in voluntary carbon markets. By providing an open-access, spatially explicit baseline for voluntary carbon market participation, this platform effectively supports the digitalization of the smallholder supply chain for global compliance, thereby transforming sustainable management into a tangible economic incentive for local farmers.

Although the proposed framework demonstrates promising performance for regional carbon stock mapping, several limitations should be acknowledged. The reference data were derived from GEDI L4A footprint observations rather than field measurements, introducing uncertainty associated with footprint coverage and geolocation accuracy. Consequently, the proposed approach should be regarded as an efficient regional screening tool that complements, rather than replaces, field-based biomass inventories. Future studies should incorporate field validation and locally calibrated allometric equations to further improve model accuracy and strengthen its application for carbon accounting and environmental certification.

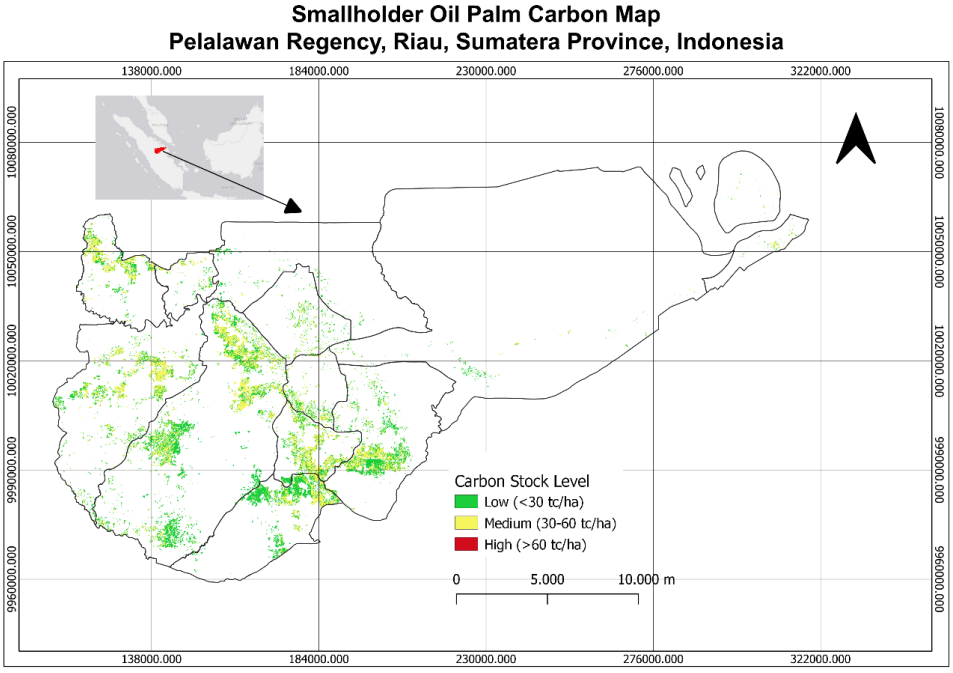



Figure 4 Smallholder Oil Palm Carbon Map Pelalawan Regency

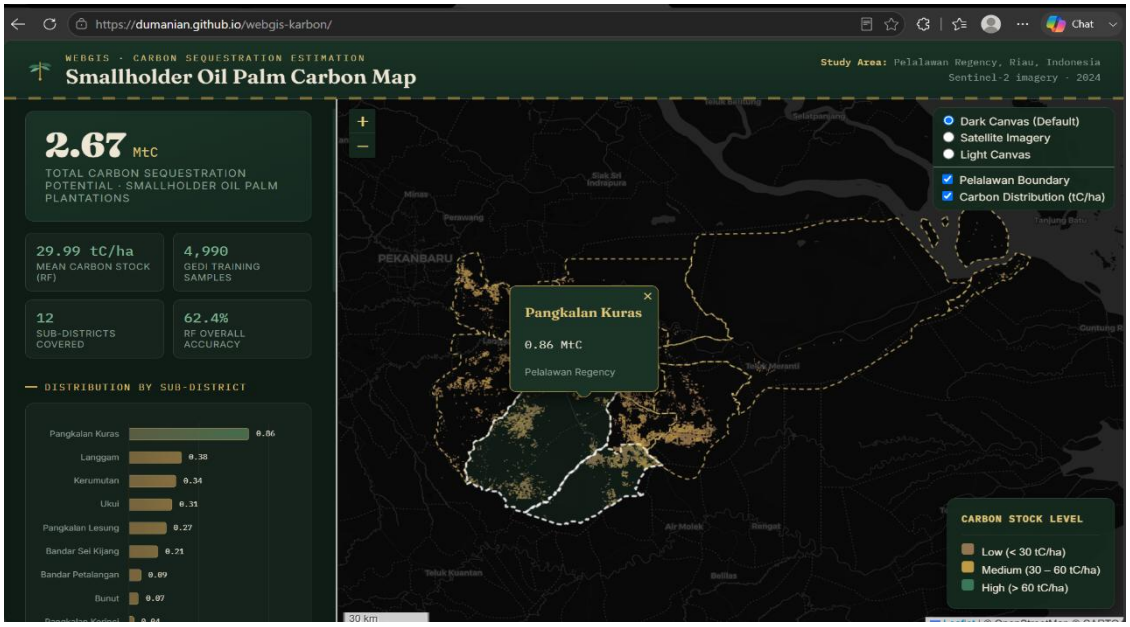


Figure 5 WebGIS Interface for Interactive Visualization Of Estimated Aboveground Carbon Stocks In Smallholder Oil Palm Plantations, Available At https://dumanian.github.io/webgis-karbon/

## CONCLUSION

This study demonstrates that integrating multitemporal Sentinel-2 imagery, red-edge vegetation indices, GLCM texture features, and GEDI L4A spaceborne LiDAR within a Google Earth Engine workflow provides an effective approach for estimating aboveground carbon stocks in fragmented smallholder oil palm plantations. Among the evaluated models, Random Forest achieved the best performance, reducing RMSE by 6.0% relative to the conventional NDVI-based regression approach while attaining an overall classification accuracy of 62.4%. The resulting model estimated a mean aboveground carbon stock of 29.99 tC $ha^{-1}$ and a total regional carbon stock of 2.67 MtC across smallholder plantations in Pelalawan Regency.

Feature importance analysis demonstrated that shortwave infrared reflectance and red-edge GLCM texture contributed substantially to improving model performance, indicating that structural and red-edge information effectively mitigates the spectral saturation commonly encountered in dense oil palm canopies. The resulting carbon stock map was successfully implemented in a publicly accessible WebGIS platform, providing an operational tool for regional carbon assessment, digital carbon traceability, and greenhouse gas inventory support.

Although the proposed framework provides an efficient and scalable alternative for regional carbon stock mapping, its accuracy remains dependent on the quality of the reference data derived from GEDI L4A. Future studies should incorporate field-based biomass measurements and locally calibrated allometric equations to further improve model reliability and support broader applications in carbon accounting, environmental monitoring, and sustainable oil palm management.

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## REFERENCES

Ardiansyah M, Barus B, Puspita G, Jaya A. 2023. Estimation of palm oil biomass carbon from Sentinel-2 image using the random forest classification method. Int J Multidiscip Approach Res Sci. 1(2):207-220. DOI: 10.59653/ijmars.v1i02.95.

Belgiu M, Draguţ L. 2016. Random forest in remote sensing: a review of applications and future directions. ISPRS J Photogramm Remote Sens. 114:24-31. DOI: 10.1016/j.isprsjprs.2016.01.011.

Chen T, Guestrin C. 2016. XGBoost: a scalable tree boosting system. Proc 22nd ACM SIGKDD Int Conf Knowl Discov Data Min. p. 785-794. DOI: 10.1145/2939672.2939785.

Descals A, Wich S, Meijaard E, Gaveau DLA, Peedell S, Szantoi Z. 2021. High-resolution global map of smallholder and industrial closed-canopy oil palm plantations. Earth Syst Sci Data. 13(3):1211-1231

Dubayah R, Blair JB, Goetz S, Fatoyinbo L, Hansen M, Healey S, Hofton M, Hurtt G, Kellner J, Luthcke S, *et al.* 2020. The Global Ecosystem Dynamics Investigation: high-resolution laser ranging of the Earth's forests and topography. Sci Remote Sens. 1:100002. DOI: 10.1016/j.srs.2020.100002.

Duncanson L, Kellner JR, Armston J, Dubayah R, Minor DM, Hancock S, Healey SP, Patterson PL, Saarela S, Marselis S, *et al.* 2022. Aboveground biomass density models for NASA's Global Ecosystem Dynamics Investigation (GEDI) lidar mission. Remote Sens Environ. 270:112845.

Foody GM. 2020. Explaining the unsuitability of the kappa coefficient in the assessment and comparison of the accuracy of thematic maps obtained by image classification. Remote Sens Environ. 239:111630. DOI: 10.1016/j.rse.2019.111630.

Lewis K, Rumpang E, Kho LK, McCalmont J, Teh YA, Gallego-Sala A, Hill TC. 2020. An assessment of oil palm plantation aboveground biomass stocks on tropical peat using destructive and non-destructive methods. Sci Rep. 10:2230. DOI: 10.1038/s41598-020-58982-9.

Nasiri V, Deljouei A, Moradi F, Sadeghi SMM, Borz SA. 2022. Land use and land cover mapping using Sentinel-2, Landsat-8 satellite images, and Google Earth Engine: a comparison of two composition methods. Remote Sens. 14(9):1977. DOI: 10.3390/rs14091977.

Noviyanto A, Ramadhani F, Kautsar V, Avianto Y, Gunawan S, Astuti YTM, Maimunah S. 2026. Advancing concession-scale carbon stock prediction in oil palm using machine learning and multi-sensor satellite indices. Resources. 15(1):12.

Vijith H, Dodge-Wan D. 2020. Applicability of MODIS land cover and Enhanced Vegetation Index (EVI) for the assessment of spatial and temporal changes in strength of vegetation in tropical rainforest region of Borneo. Remote Sens Appl Soc Environ. 18:100311.

Weber M, Beneke C, Wheeler C. 2025. Unified deep learning model for global prediction of aboveground biomass, canopy height, and cover from high-resolution, multi-sensor satellite imagery. arXiv:2408.11234.

Yang C, Liu A, Chen Y. 2025. Seventeen-year reconstruction of tropical forest aboveground biomass dynamics in Borneo using GEDI L4B and multi-sensor data fusion. Remote Sens. 17(18):3231. DOI: 10.3390/rs17183231.

Zhou J, Guo RY, Sun M, Di TT, Wang S, Zhai J, Zhao Z. 2017. The effects of GLCM parameters on LAI estimation using texture values from Quickbird satellite imagery. Sci Rep. 7:7366.