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Mapping Smallholder Oil Palm Carbon Stocks Using Machine Learning

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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

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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

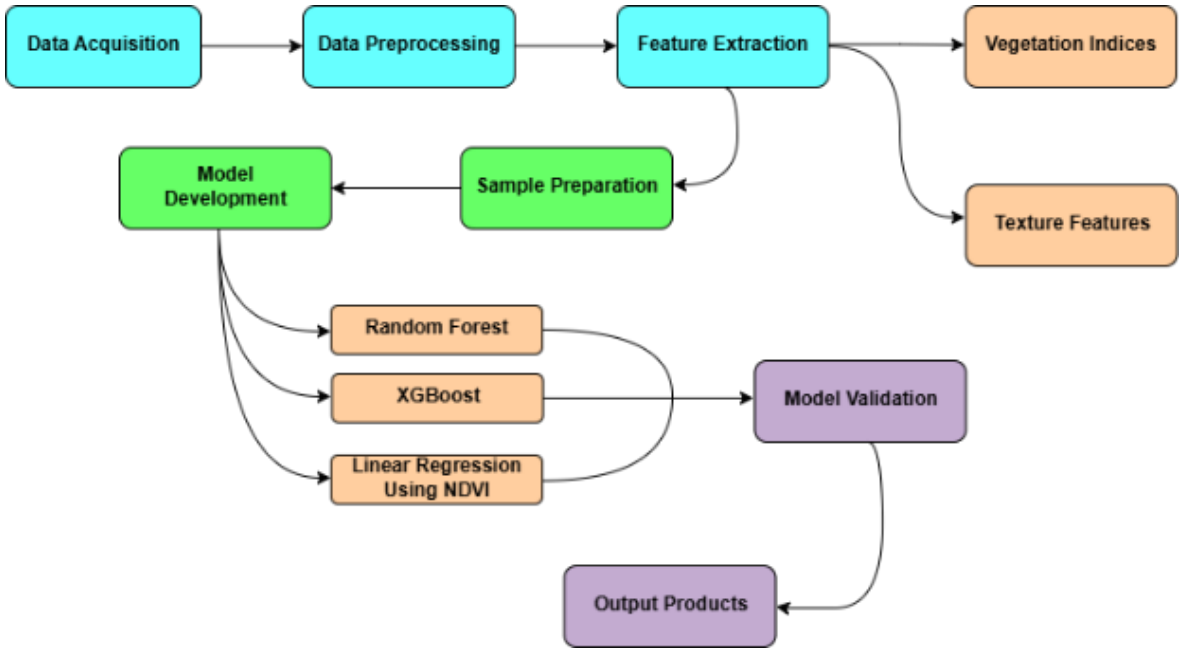


Figure 1 Overall Workflow of The Proposed Methodology for Oil Palm Carbon Stock Estimation Using Sentinel-2 Imagery, GEDI L4A Data, and Machine Learning

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.

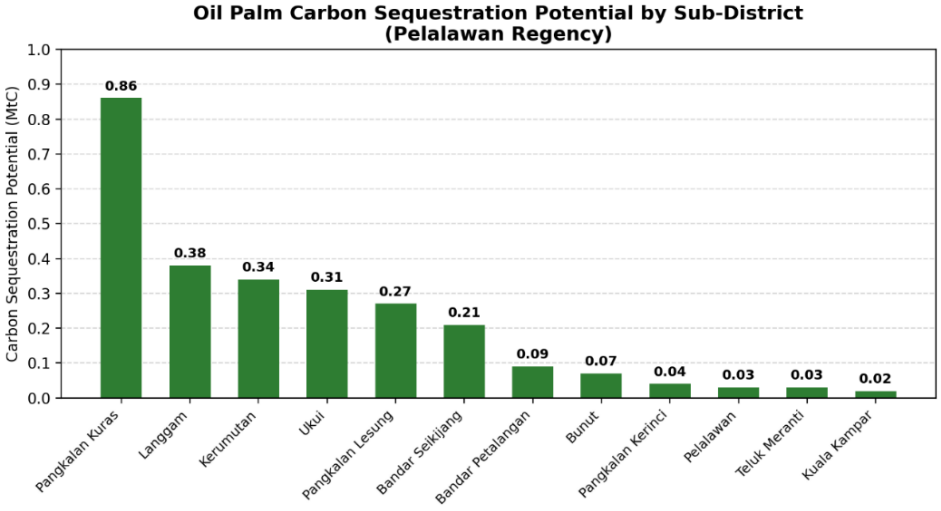


Figure 2 Spatial Distribution of Estimated Aboveground Carbon Stocks Across Pelalawan Regency

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.

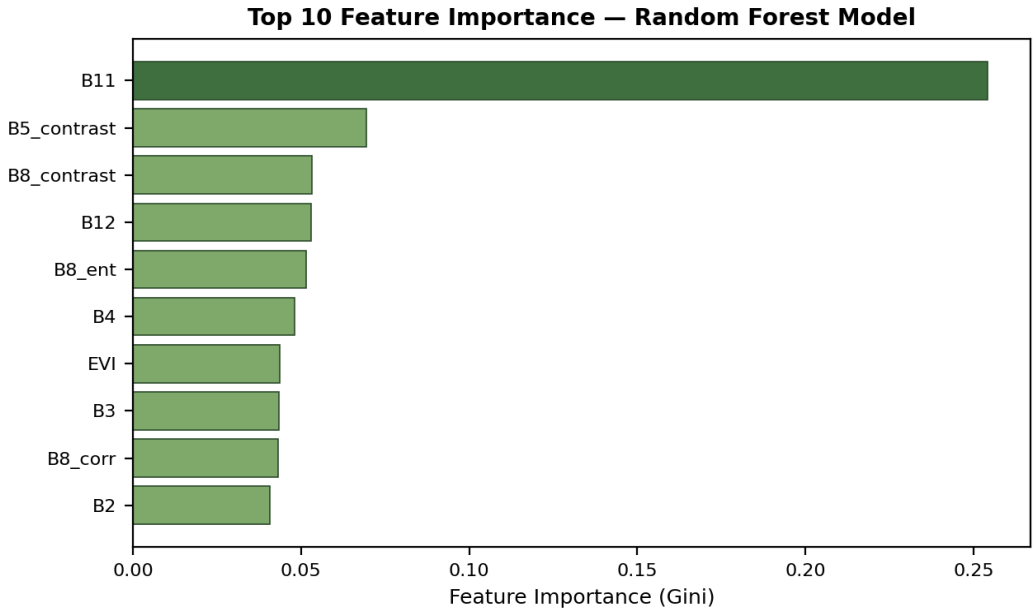


Figure 3 Illustrates the Relative Importance of Predictor Variables Used by The Random Forest Model. Shortwave Infrared Reflectance (Band 11) And Red-Edge GLCM Contrast (B5 Contrast) Emerged as The Two Most Influential Variables, Followed by Additional Red-Edge and Near-Infrared Texture Features

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.

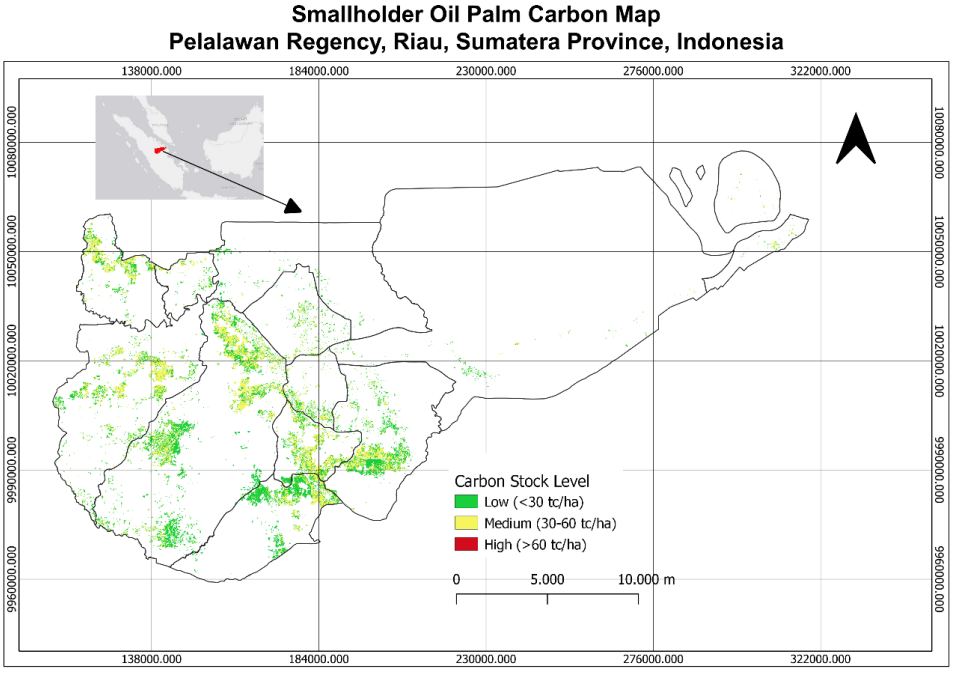


Figure 4 Smallholder Oil Palm Carbon Map Pelalawan Regency

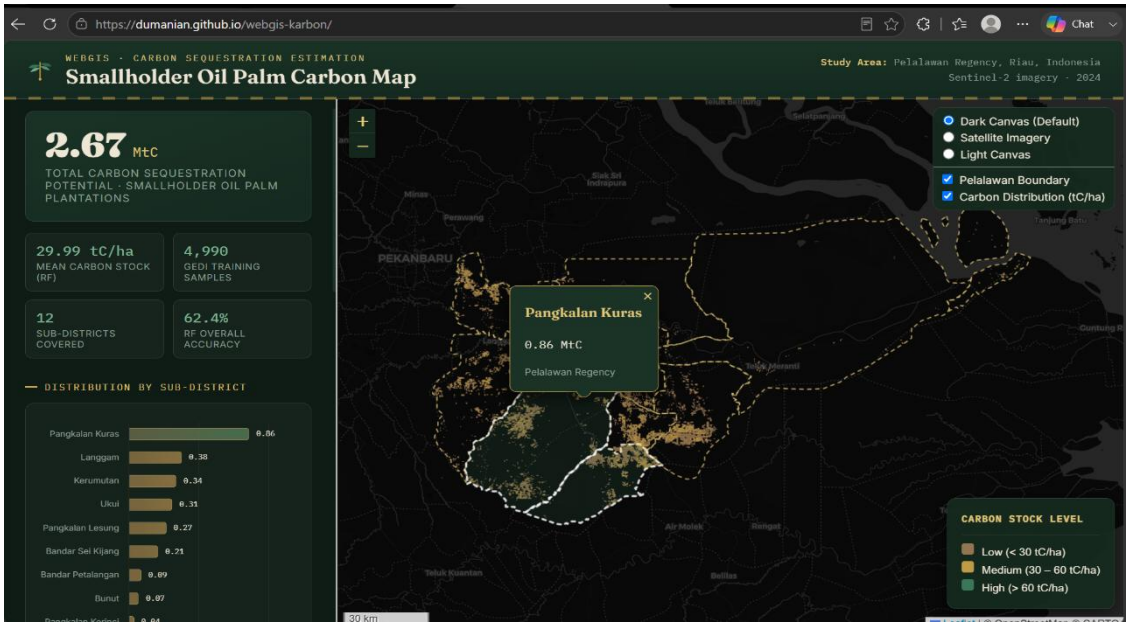


Figure 5 WebGIS Interface for Interactive Visualization Of Estimated Aboveground Carbon Stocks In Smallholder Oil Palm Plantations, Available At https://dumanian.github.io/webgis-karbon/

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.

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Expansion-Share Threshold for Indonesia's B50 Palm Biodiesel

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ABSTRACT

Indonesia raised its mandatory biodiesel blend to B40 in January 2025 and has outlined a pathway toward B50, primarily to strengthen energy security, reduce diesel- import dependence, and absorb domestic crude palm oil. Higher blending, however, increases demand for palm-based fatty acid methyl ester (FAME), making the climate value of B50 dependent on how the marginal feedstock is sourced. This study evaluates the B40-to-B50 switch using a scenario-based operational fuel-cycle screen based on published lifecycle emission factors. The two blends are compared on an equal-energy basis, with land-use change (LUC) treated as a forward-looking sensitivity on incremental feedstock. Coal-mine overburden is used purely as an arbitrary arithmetic placeholder to express volume displacement per bank cubic metre (bcm); the break-even is scale-invariant and independent of this proxy. B50 displaces 0.0335 L of fossil diesel per bcm, independent of LUC assumptions, allocation rules, and emission-factor choices. Under low-LUC sourcing, B50 reduces fuel-cycle greenhouse-gas intensity by 2.8% to 5.6%, depending on engine efficiency penalties; the central estimate is 5.6% under idealised conditions. This benefit is bounded by marginal-feedstock LUC intensity: the break-even is about 44 g CO_2e MJ^{-1} under marginal allocation and 9 g CO_2e MJ^{-1} under precautionary full attribution. Measured mineral-soil forest conversion at 156 g CO_2e MJ^{-1} exceeds both thresholds. Expressed as a sourcing condition, the caps are 28% (marginal) and 6% (full attribution). Crucially, when the European Commission's provisional indirect LUC value for oil crops (55 g CO_2e MJ^{-1}) is included, the marginal threshold (44 g) is exceeded before any direct conversion is counted, implying that under comprehensive accounting the climate case for B50 is likely negative unless indirect effects are explicitly excluded. Because the national B40-to-B50 step requires about 4.06 Mt yr^{-1} of additional CPO, low-LUC supply cannot be assumed by default. Fossil-diesel displacement is therefore robust, whereas the greenhouse-gas benefit is constrained by the expansion share of marginal feedstock, not by any claim that mining itself becomes low-carbon. The study's contribution is the expansion-share limit: a theoretical benchmark against which future empirical estimates of Indonesian expansion share can be compared. It does not provide a measurement protocol or claim that current supply meets this threshold.

Keywords: Carbon intensity, Deforestation, Fossil-diesel displacement, Greenhouse-gas intensity, Indirect land-use change

INTRODUCTION

Indonesia raised its mandatory biodiesel blend from B35 to B40 in January 2025 and announced a pathway toward B50, later deferred in 2026 pending further fuel trials in heavy equipment, rail, and industrial machinery (ESDM 2025; Petromindo 2026; Reuters 2026). The mandate is framed primarily around energy security, diesel-import substitution, foreign-exchange savings, and domestic crude palm oil (CPO) absorption. It is financed through the palm-oil export levy. Domestic instruments such as the Nationally

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Determined Contribution (NDC) and the mandatory Indonesian Sustainable Palm Oil (ISPO) certification do address production-side and land-use emissions, largely in response to broader stakeholder concerns over deforestation, but the mandate itself is not governed by a fuel-carbon-intensity standard comparable to the European Union Renewable Energy Directive (EU 2018). The relevant climate question is therefore not whether B50 satisfies a domestic carbon score, but how much land-conversion emission the switch can tolerate before its fuel-cycle climate rationale is lost.

Each increase in the blend ratio raises demand for palm-based fatty acid methyl ester (FAME), and therefore for palm feedstock. The climate value of this incremental volume is not automatic. It depends on whether the marginal supply is drawn from existing planted areas, replanting, and yield gains, or from new conversion of forest or peatland. These pathways vary by producer: smallholder expansion often differs from that of large plantations, with informal, fire-based clearing near forest margins concentrated among smallholders. This heterogeneity is itself a central challenge for monitoring the expansion share. Measured and modelled studies show that land-use-change (LUC) emissions can dominate the GHG balance of palm biodiesel and can reverse its apparent advantage over fossil diesel once forest or peat conversion is included (Searchinger *et al.* 2008; Harsono *et al.* 2012; Meijide *et al.* 2020). Identifying the point at which this reversal occurs is the central analytical concern of this paper.

The feedstock question is also a food–energy allocation question. The CPO stream that supplies biodiesel is the same stream used for domestic cooking oil. During the 2022 cooking-oil crisis, rising CPO prices, constrained domestic supply, and competing uses were among the leading causes of sharp retail-price increases and state intervention through domestic-market obligations, domestic-price obligations, and a temporary export ban (Fulcrum 2022; Chain Reaction Research 2022). This episode matters because it shows the CPO stream is already supply-constrained and contested between food and fuel, so incremental biodiesel demand cannot be assumed land-neutral. Additional FAME demand must be met through some combination of yield improvement, reallocation from food or export markets, and new planted area. Of these, yield improvement is the clearest low-LUC route, though it is not emission-free due to fertiliser-related N_2O and mechanisation; reallocation from food or export markets is not automatically low-LUC, since displaced supply may be met elsewhere, and new planted area carries the highest LUC risk.

Policy discussion of B50 has largely centred on blend volume, energy security, subsidy cost, and feedstock adequacy. Existing palm-biodiesel LCA studies already imply a simple carbon-intensity break-even between fossil diesel and palm biodiesel. What is rarely developed is the next step: translating that break-even into a theoretical sourcing condition namely the maximum share of incremental feedstock that can come from new high-carbon conversion before the climate benefit disappears. This threshold matters because it connects a fuel-cycle calculation with the practical sourcing problem created by food–energy competition.

This paper quantifies the B40-to-B50 switch through four linked results: (i) LUC-independent fossil-diesel displacement; (ii) fuel-cycle GHG reduction under low-LUC sourcing; (iii) the LUC break-even under marginal and full-attribution allocation rules (the average rule is algebraically equivalent to the marginal rule); and (iv) the expansion-share limit that converts the break-even into a policy-relevant sourcing condition, supported by a national feedstock balance. Coal mining is one of the largest off-road consumers of blended diesel in Indonesia, which makes it a natural setting for testing the fuel-switching claim. The results are expressed per bcm as a scale-independent proxy for diesel-intensive equipment; the break-even threshold itself does not depend on this proxy. Coal-mine overburden is used only as a diesel-

intensive operational stress test to express the physical fuel-switching effect per bank cubic metre (bcm) against externally auditable activity data.

MATERIALS AND METHODS

Study design and system boundary

The study uses a scenario-based fuel-cycle screen to compare the greenhouse-gas (GHG) intensity of the B40 baseline and a B50 scenario. The assessment follows the main scoping elements of ISO 14040/14044, including goal and scope definition, an energy-based functional unit of 1 MJ of fuel delivered, system boundary, and interpretation, but it is not presented as a full third-party-reviewed life-cycle assessment. Primary inventories for cultivation, milling, transesterification, and logistics were not collected. Instead, the model applies published life-cycle emission factors to a clearly defined fuel-switching question. The contribution is therefore conceptual, introducing the expansion-share limit as a policy framework, rather than a claim to the absolute numerical accuracy of the underlying emission factors. The modelling approach is primarily attributional, using average emission factors for the fuels supplied, with one consequential element: a marginal land-use-change (LUC) term applied to the additional feedstock induced by the B40-to-B50 switch. This treatment is made explicit because attributional and consequential choices can materially affect biofuel LCA outcomes (Nematian and Scown 2025).

The functional unit is one bank cubic metre (bcm) of overburden moved. Results are calculated internally as fuel-cycle carbon intensity in g CO_2e MJ^{-1} and then expressed per bcm using an energy-per-bcm conversion. The system boundary covers the liquid-fuel cycle: feedstock production, FAME conversion, and combustion in mobile equipment. Downstream coal combustion, coal-mine methane blasting, grid electricity, and equipment manufacturing are outside the boundary (Figure 1). Coal-mine overburden is used as a diesel-intensive stress-test denominator. Indonesian mining companies and contractors report overburden volumes in audited annual and sustainability disclosures, allowing the physical fuel-displacement effect to be expressed against an externally auditable activity measure rather than assumed in isolation (Adiansyah *et al.* 2017). The bcm denominator therefore affects the reporting scale, but not the LUC threshold.

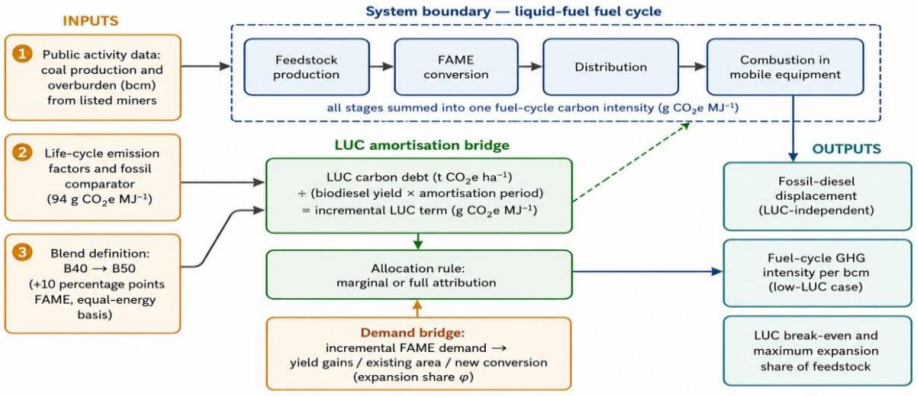


Figure 1 B40-to-B50 fuel-cycle screening framework and LUC sourcing bridges

Equal-energy comparison of B40 and B50

Palm biodiesel has a lower volumetric energy density than fossil diesel; comparing equal litres would therefore overstate the higher blend's fuel displacement. The model instead holds delivered energy per bcm constant using lower heating values LHV_d = 36 and LHV_f = 33 MJ L^{-1}. For a volumetric FAME fraction b, the blend energy density

and the FAME energy share are

$$H(b) = (1 - b)\cdot LHV_d + b\cdot LHV_f \quad (1)$$

$$x(b) = b\cdot LHV_f / H(b) (2)$$

With a B40 fuel-use intensity FI_{40} = 0.35 L bcm^{-1}, delivered energy per bcm is E = FI_{40}·H(0.40) = 12.180 MJ bcm^{-1} and the equal-energy B50 volume is V_{50} = E/H(0.50) = 0.3530 L bcm^{-1}, so fossil-diesel displacement follows deterministically:

$$\Delta_{diesel} = 0.60\cdot FI_{40} - 0.50\cdot V_{50} = 0.0335 \; L bcm^{-1} (3)$$

This is a first-order stoichiometric correction; it does not capture second-order changes in brake-specific fuel consumption (BSFC) when a high-FAME blend alters cetane number, oxygen content, and viscosity. Heavy-equipment testing of blends up to B35 indicates such effects are small (Uhanto *et al.* 2025), so the equal-energy result is treated as an idealised bound and a 0 to +3% BSFC penalty is carried as a sensitivity rather than modelled.

LUC break-even and allocation rules

LUC is treated as a forward-looking sensitivity on incremental supply. A converted hectare releases a carbon debt C_{debt} (t CO_2e ha^{-1}), equal to the loss of biomass, litter, and soil carbon relative to the prior ecosystem plus forgone sequestration, amortised over the plantation rotation:

$$L = C_{debt} / (Y_{bio} \times T) \quad (4)$$

with Y_{bio} the biodiesel energy yield (MJ ha^{-1} yr^{-1}) and T = 25 y, the period over which the land-use carbon debt is spread, matching the rotation over which the reference flux measurements were integrated (Meijide *et al.* 2020). For the 156 g CO_2e MJ^{-1} value, the underlying yield assumption is approximately 3.8 t CPO ha^{-1} yr^{-1}, corresponding to a FAME yield of Ybio ≈ 43 GJ ha^{-1} yr^{-1}; this is consistent with the Sumatran plantation studied by Meijide *et al.* (2020). The threshold is also recomputed at T = 20 and 30 y to show how it responds to this period. The measured high-LUC value for mineral-soil forest conversion is 156 g CO_2e MJ^{-1}, with peat conversion substantially higher because drained peat continues to oxidise and release stored carbon (ICCT 2011; Meijide *et al.* 2020). Peat conversion is not separately parameterised in the central scenario, as the focus is on mineral-soil forest conversion—the most extensively measured pathway for Indonesian palm expansion—and peat constitutes a distinct carbon pool with different management and drainage dynamics. Its exclusion means the high-LUC scenario is conservative; including peat would tighten the expansion-share limits further. Fuel-cycle emissions per bcm are the energy-weighted sum of the two intensities, with the LUC term applied only to the feedstock energy the switch newly induces:

$$G_{40} = E\cdot[(1 - x_{40})\cdot CI_d + x_{40}\cdot (5)$$

$$G_{50}(L) = E\cdot[(1 - x_{50})\cdot CI_d + x_{50}\cdot CI_f] + e_{inc}\cdot L \quad (6)$$

where G denotes fuel-cycle emissions per bcm, E the fuel energy used per bcm, CId and CIf the diesel and FAME intensities, and x the FAME energy share of the blend, with x_{40} = 0.3793 under B40 and x_{50} = 0.4783 under B50, and the bridging indicator

$$e_{inc} = E\cdot(x_{50} - x_{40}) = 1.205 \; MJ_{FAME} \; bcm^{-1} (7)$$

converts a per-MJ land term into a per-bcm quantity commensurable with the combustion ledger. The two ledgers are never differenced directly but summed into one intensity per blend. Setting G_{50}(L) = G_{40} gives the incremental-LUC break-even:

L = CId − CIf = 94 − 50 = 44 g CO_2eMJ^{-1} (8)*

Here CIf = 50 assumes methane capture at the mill; open-pond milling would raise the core intensity toward 76 g CO_2e MJ^{-1} and lower the break-even accordingly. The low-LUC case therefore depends on policies that promote POME methane capture *(8).*

Equation (8) has three implications for the analysis. First, the break-even LUC intensity is independent of the delivered energy per bcm, and therefore of fuel-use intensity, overburden volume, and the end-use selected for the stress test. The threshold intensity is also unaffected by the blend step and the lower heating values, though the absolute equivalent land area in Equations (10) and (11) still scales with it. No characteristic of the mining case can therefore shift the threshold; uncertainty in

L* comes only from the fossil-diesel comparator and the non-LUC palm-biodiesel core intensity. Across CI_f = 46–52 g CO_2e MJ^{-1} and CI_d = 89–99 g CO_2e MJ^{-1}, the resulting range is 37–53 g CO_2e MJ^{-1}. Second, applying the conversion debt symmetrically across all palm energy in both blends does not alter the break-even. Under this average rule, the difference between B40 and B50 reduces to $(x_{50} - x_{40})\cdot(CI_d - CI_f - L) = 0$, so the same threshold is obtained. This is because the same added palm intensity is applied to both blends, leaving their relative difference unchanged. Third, the threshold tightens only under an asymmetric full-attribution rule, in which the LUC term is charged to the entire B50 palm volume while the B40 palm volume is exempted. This rule answers a precautionary attribution question rather than the incremental B40-to-B50 question, but it provides a useful lower bound: $L^*_full = (1 - x_{40}/x_{50})\cdot(CI_d - CI_f)$ 9g CO_2e MJ^{-1}. Both the incremental and full-attribution bounds are therefore reported.

Feedstock balance and expansion share

The break-even identifies the LUC intensity that can be tolerated, but not the land pressure implied by the B40-to-B50 step. To close this gap, the incremental biodiesel demand is converted into a national feedstock balance. A full B50 mandate is estimated to require about 20.1 million kL yr^{-1} of biodiesel, compared with about 15.6 million kL yr^{-1} under B40, giving an increment of approximately 4.5 billion L yr^{-1} (Petromindo 2026). These volumes assume total diesel demand is held constant across the two blends; demand growth of a few percent per year would raise the increment and the additional CPO proportionally. Using a FAME density of 0.875 t kL^{-1} and a CPO-to-FAME mass ratio of 1.03, this increment requires about 4.06 Mt yr^{-1} of additional CPO.

$$\Delta M_{CPO} = \Delta V \cdot \rho \cdot r \approx 4.06\ \text{Mt CPO yr}^{-1} \quad (9)$$

$$A_{eq} = \Delta M_{CPO} / Y_{CPO} \quad (10)$$

$$\Delta MCPO = \Delta Myield + \Delta Mreallocated + YCPO \cdot Anew \quad (11)$$

Equation (10) converts the increment into the land-equivalent area at CPO yield Y_{CPO}; Equation (11) partitions it among yield-gap closure on existing area, reallocation from food and export, and new planted area A_{new}. Letting φ denote the share of incremental feedstock energy from newly converted high-carbon land, the effective incremental LUC intensity is $L_{eff} = \varphi \cdot L_{conv}$, and the switch stays beneficial while $L_{eff} < L^*$; setting $L_{eff} = L^*$ gives the maximum tolerable expansion share

$$\varphi^* = L^* / L_{conv} \quad (12)$$

This reframes the vague marginal LUC rate as a calculable theoretical quantity, following the European Commission's logic for high-ILUC-risk feedstocks in which a share-of-expansion threshold is obtained by dividing an emission saving by a conversion intensity (European Commission 2019a). φ is the scenario variable, not a known input: scenarios are φ = 0 (second-rotation replanting, degraded land, or intensification), φ = 0.14 (the Commission reference expansion share, European Commission 2019a; L_{eff} 22 g CO_2e MJ^{-1}), and φ = 1 (all incremental feedstock from mineral-soil forest conversion).

Data sources and sensitivity

Emission factors and the fossil comparator were taken from recognised lifecycle references, while activity denominators were drawn from audited public disclosures. The non-LUC palm-biodiesel core intensity is represented as 46–52 g CO_2e MJ^{-1} under a methane-capture milling pathway, with an open-pond pathway near 76 g CO_2e MJ^{-1} shown for comparison. The difference is driven mainly by palm-oil-mill-effluent (POME) methane management, and the stage decomposition is reported in Table 1 (Kalam and Masjuki 2002; Harsono *et al.* 2012; Singh *et al.* 2021). The fossil comparator is the RED II Annex V value of 94 g CO_2e MJ^{-1}, used only as a transparent reference point rather than as an Indonesian eligibility criterion (EU 2018). The bcm denominators are bracketed using a panel of listed miners and

contractors (Table 2). They are used to define a realistic stress-test range and are not aggregated into a sector-wide mining estimate. Fuel-use intensity is set at 0.35 L bcm^{-1} as a standardised literature-based assumption, not a fleet-measured value; because it drives the absolute per-bcm results, it is carried with a ±30% sensitivity band. Sensitivity tests vary one input at a time and cover the palm core intensity, fossil comparator, FAME heating value, brake-specific fuel-consumption penalty, fuel-use intensity, overburden volume, LUC time horizon T, allocation rule, and expansion share φ. All model inputs and ranges are summarised in Table 3.

Table 1 Indicative stage-level decomposition of the non-LUC palm-biodiesel core intensity.

Fuel-cycle stage	Indicative intensity	Main driver / interpretation
Cultivation, including fertiliser N_2O	14–20 g CO_2e MJ^{-1}	Field emissions from fertiliser use and plantation management; excludes historical direct LUC.
FFB transport to mill	1–3 g CO_2e MJ^{-1}	Short-haul-road transport from plantation to mill; relatively minor contribution.
Milling and CPO extraction	6–18 g CO_2e MJ^{-1}	Strongly influenced by POME management; methane capture gives the lower range, while open ponds raise emissions.
Transesterification	8–12 g CO_2e MJ^{-1}	Methanol input and process energy; glycerol co-product handled by energy allocation.
Distribution and blending	1–2 g CO_2e MJ^{-1}	Depot logistics and blending operations; relatively minor contribution.
Combustion	≈0 g CO_2e MJ^{-1}	Tailpipe biogenic CO_2 treated as carbon-neutral; non-CO_2 tailpipe emissions are small.
Core total, methane-capture pathway	46–52 g CO_2e MJ^{-1}	Non-LUC core intensity used in the low-LUC case; open-pond pathway shown separately at about 76 g CO_2e MJ^{-1}.

Notes: FFB = fresh fruit bunches; POME = palm-oil-mill effluent. Stage ranges are literature-consistent and sum to the 46–52 g CO_2e MJ^{-1} core (Kalam and Masjuki 2002; Harsono *et al.* 2012; Singh *et al.* 2021).

Table 2 Operational stress-test panel used to bracket the per-bcm denominators

Company	Coal (Mt)	Overburden (Mbcm)	Stripping ratio	Scope 1 (Mt CO_2e)
United Tractors / Pamapersada	148	1,217	8.2	-
Adaro Andalan	65.8	286	4.35	-
Indo Tambangraya	20.2	n.d.	10–11	1.82
Delta Dunia / BUMA	90	545	6.05	0.72
Bukit Asam	43.3	n.d.	5.98	-

n.d. = not disclosed. Sources: company annual and sustainability reports, financial year 2024. The panel is not used to infer whole-sector mining emissions.

Table 3 Key model inputs and scenario parameters used in the B40-to-B50 fuel-cycle screen.

Model input	Value / range	Unit	Role in the calculation
Fossil-diesel comparator	94	g CO_2e MJ^{-1}	Reference carbon intensity used for blend comparison and LUC break-even calculation.
Palm-biodiesel core intensity, methane-capture pathway	46–52	g CO_2e MJ^{-1}	Non-LUC palm-biodiesel intensity under methane capture; used as the low-LUC core assumption.
Palm-biodiesel core intensity, open-pond pathway	76	g CO_2e MJ^{-1}	Higher-intensity processing pathway shown for comparison.
Blend definition	B40 = 40%; B50 = 50%	vol. FAME	Defines the additional ten percentage points of FAME in the B40-to-B50 switch.
Lower heating value	Diesel = 36; FAME = 33	MJ L^{-1}	Converts the blend comparison to an equal-energy basis.
Fuel-use intensity	0.35 ± 30%	L bcm^{-1}	Standardised operating assumption used to express results per bcm; not site-measured.
LUC amortisation period, T	25; sensitivity 20–30	years	Converts one-time land-conversion debt into a per-MJ LUC intensity.
Incremental LUC scenarios	0; 22; 156	g CO_2e MJ^{-1}	Represents low-LUC, moderate expansion-share, and forest-conversion-equivalent sourcing cases.
Allocation rule	Marginal; symmetric average; full attribution	—	Determines how LUC is assigned to palm energy; marginal and symmetric average give $L^* \approx 44$, while full attribution gives ≈9 g CO_2e MJ^{-1}.
Incremental FAME-energy bridge, e_inc	1.205	MJ_FAME bcm^{-1}	Converts a per-MJ incremental LUC term into a per-bcm land-use penalty.
Incremental CPO requirement	4.06	Mt yr^{-1}	Converts the B40-to-B50 volume step into additional feedstock demand.
Expansion share, φ	0–100	%	Share of incremental feedstock supplied from new high-carbon conversion.

RESULTS AND DISCUSSION

Fossil-diesel displacement is robust and LUC-independent

Holding delivered energy per bcm constant, B50 requires slightly more total liquid fuel than B40 because FAME has a lower energy density, but the fossil-diesel share falls as the blend increases (Figure 2). Relative to B40, B50 displaces 0.0335 L of fossil diesel per bcm, with a range of 0.023–0.044 L bcm^{-1} across the ±30% fuel-intensity band. This displacement follows only from the blend ratio and the equal-energy correction. It therefore supports the mandate's import-substitution rationale at the operation level.

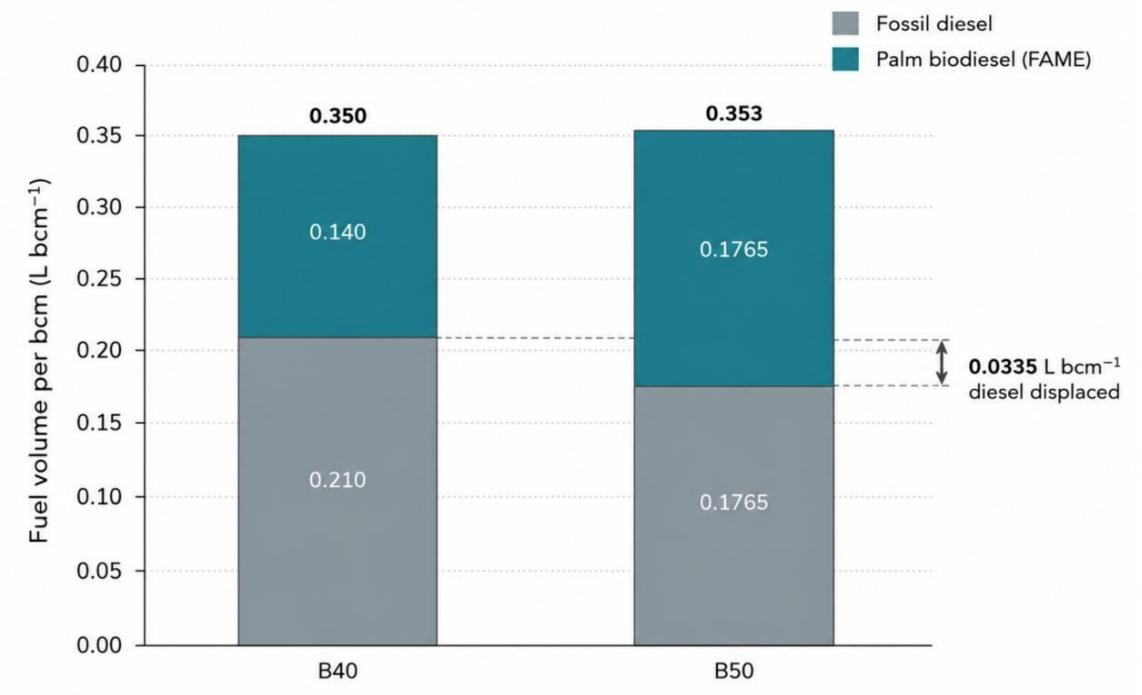


Figure 2 Equal-energy fuel composition of B40 and B50 per bank cubic metre of overburden moved

The LUC break-even defines the climate boundary

The climate benefit is bounded by an incremental-LUC break-even of 44 g CO_2e MJ^{-1}, with a range of 42–48 across the palm core-intensity assumption and 37–53 when the fossil comparator is also varied (Figure 3). As Equation (8) shows, the threshold depends only on the fossil comparator and the non-LUC palm core intensity; fuel-use

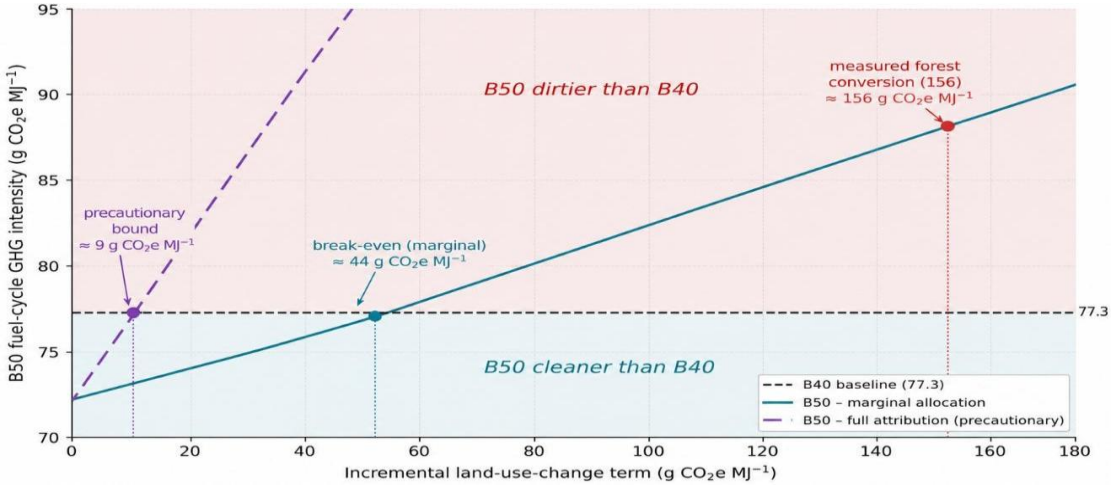


Figure 3 Land-use-change (LUC) break-even for the B40-to-B50 switch.

intensity, overburden volume, and heating values do not change it. Under the precautionary full-attribution rule, the tolerance tightens to about 9 g CO_2e MJ^{-1}. At the measured mineral-soil forest-conversion intensity of 156 g CO_2e MJ^{-1}, the land penalty is 188 g CO_2e bcm^{-1}, exceeding the 53 g CO_2e bcm^{-1} combustion-side saving and producing a net increase of 135 g CO_2e bcm^{-1}. This corresponds to the gap between 1.077 and 0.942 kg CO_2e bcm^{-1} in Figure 4. Forest-conversion sourcing therefore exceeds both thresholds and reverses the low-LUC climate benefit, consistent with palm-biodiesel studies showing that LUC can be a sign-reversing rather than marginal term (de Souza *et al.* 2010; Searchinger *et al.* 2008; Harsono *et al.* 2012; Meijide *et al.* 2020).

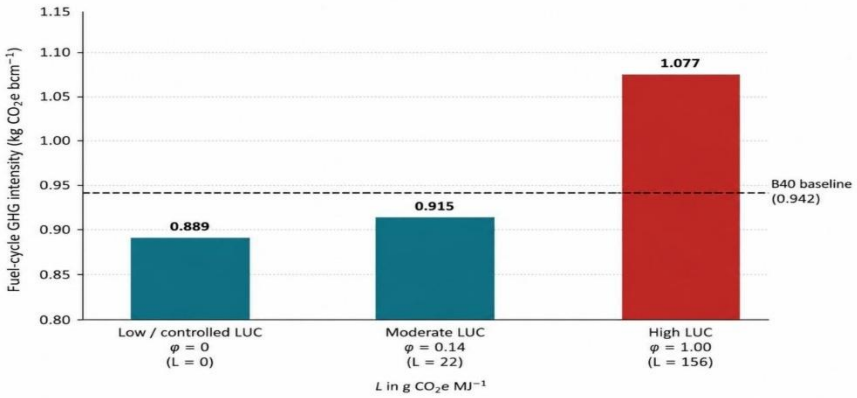


Figure 4 B50 fuel-cycle GHG intensity under incremental LUC scenarios

The expansion-share limit makes the boundary policy-relevant

Translating the break-even through Equation (12) gives the main policy-relevant quantity of the study. If a share φ of incremental feedstock is supplied from land converted at 156 g CO_2e MJ^{-1}, the switch remains beneficial only while $\varphi < \varphi^* = L^*/156$. This gives a maximum tolerable expansion share of 28% under the marginal rule and 6% under full attribution (Figure 5). Put differently, the fuel-cycle benefit is lost once more than 28% of the additional CPO for B50, or 6% under precautionary accounting, comes from forest-conversion-equivalent land. The break-even is therefore converted from a carbon-intensity threshold into a monitorable sourcing condition. This is the more useful policy question: not only whether 156 exceeds 44, but how much high-carbon expansion the B40-to-B50 step can absorb before its climate benefit is lost. The threshold sets the boundary but does not by itself show that the actual expansion share lies below it.

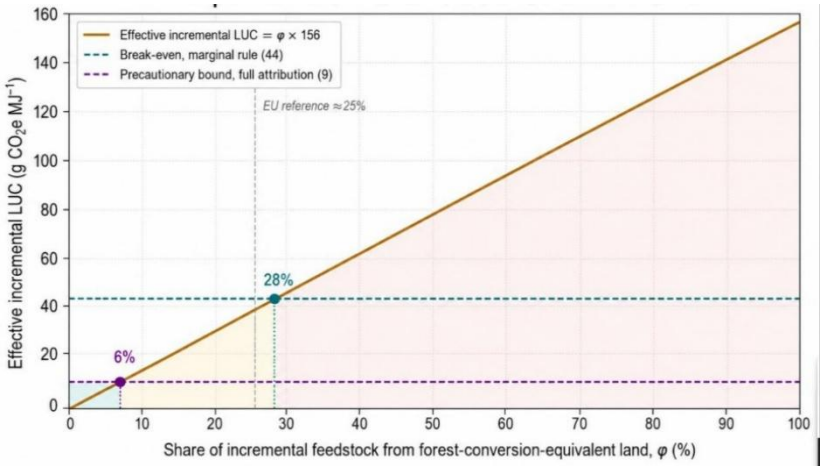


Figure 5 Expansion-share limit for incremental B50 feedstock

The feedstock balance shows low-LUC supply cannot be assumed

The expansion share must be read against the physical supply requirement of the B40-to-B50 step (Table 4). The incremental mandate implies ΔM_CPO ≈ 4.06 Mt yr^{-1} of additional CPO (Equation 9), consistent with market estimates of 3.5–4.0 Mt yr^{-1} (S&P Global 2025). Depending on yield assumptions, this is equivalent to 1.26, 1.07, or 0.92 Mha of land-equivalent output at the all-planted-area yield, the mature-stand average, or a 22% improved yield, respectively (Equation 10). they show the scale of supply that must be met through yield improvement, reallocation from food or export markets, or new planted area. the incremental requirement is too large to be treated as automatically low-LUC. Expansion alone cannot supply the step on the mandate timeline, while the required supply gain exceeds what replanting is currently delivering (Woittiez *et al.* 2017). The remaining adjustment would have to come from existing uses, principally food and export markets; ΔM_CPO is equivalent to about 41% of the 9.83 Mt of CPO used domestically for food in 2025 (GAPKI 2026; USDA FAS 2026). This reallocation channel is why a direct-LUC break-even

Table 4 Incremental feedstock requirement and land-equivalent supply implied by the B40-to-B50 step

Quantity	Value	Unit	Source / derivation
Biodiesel volume under B40	15.6	million kL yr^{-1}	ESDM estimate reported in Petromindo (2026).
Biodiesel volume under B50	20.1	million kL yr^{-1}	ESDM estimate reported in Petromindo (2026).
Incremental biodiesel volume, ΔV	4.5	billion L yr^{-1}	Difference between B50 and B40 biodiesel requirements.
FAME density, ρ	0.875	t kL^{-1}	Standard FAME density assumption.
CPO-to-FAME mass ratio, r	1.03	t CPO t^{-1} FAME	Based on an approximate 97% transesterification mass yield.
Incremental CPO requirement, ΔM_CPO	4.06	Mt yr^{-1}	Calculated from Eq. (9); comparable with the 3.5–4.0 Mt yr^{-1} estimate reported by S&P Global (2025).
CPO yield, Y_CPO	3.23 / 3.80 / 4.40	t ha^{-1} yr^{-1}	National planted-area yield; mature-stand average; and 22% yield-uplift case.
Land-equivalent output, A_eq	1.26 / 1.07 / 0.92	Mha	Calculated from Eq. (10) using the three yield assumptions above.
Observed net planted-area expansion	<0.15	Mha yr^{-1}	USDA FAS (2026).
National replanting programme delivered	<0.05	Mha yr^{-1}	USDA FAS (2026).
Domestic CPO use for food, 2025	9.83	Mt yr^{-1}	GAPKI (2026); ΔM_CPO is approximately 41% of this volume.
Domestic CPO use for biodiesel, 2025	12.70	Mt yr^{-1}	GAPKI (2026); reported as increasing by 11.0% year-on-year under B40.

alone is incomplete. Diverting CPO from food or export markets does not place direct land conversion on the biodiesel ledger, but it can transfer supply pressure elsewhere. Regulatory practice also indicates that the omitted indirect term can be material. That value already exceeds the 44 g CO_2e MJ^{-1} break-even before direct conversion is added. Low-LUC sourcing therefore needs to be verified through supply-chain traceability and certification, not assumed.

Sourcing safeguards and the upstream role of smallholders and SMEs

The break-even and expansion-share limit together define the sourcing condition for B50: incremental feedstock must remain below the LUC, either through existing planted area, yield gains, or verified low-deforestation-risk supply.The model establishes the displacement rate and carbon threshold; the link to sourcing is an interpretation based on secondary evidence on Indonesian oil-palm governance. Because Indonesia manages land conversion through legality, spatial planning, ISPO, RSPO, and traceability instruments rather than a fuel-carbon score, the relevant safeguards are administrative and supply-chain based (Table 5).

Table 5 Supply-chain safeguards for maintaining low-LUC incremental feedstock for B50 palm biodiesel

Safeguard	**Relevance to low-LUC B50 sourcing**	**Smallholder / SME role**	**Indonesian mechanism**
Legal land status	Reduces the risk that incremental feedstock is sourced from unlawful or high-conversion-risk areas.	Provide plot documentation and participate in registration or aggregator-based verification.	STDB; APL / forest-estate distinction; ISPO legality requirements.
No forest or peat expansion	Prevents sourcing from high-carbon conversion that would exceed the LUC break-even.	Avoid new planting in forest or peat areas and supply through screened value chains.	Primary-forest and peatland moratorium; RSPO / NDPE commitments.
Documented sourcing to mill or plot	Helps distinguish feedstock from existing or productivity-based supply from expansion-driven supply.	Share plot and supply-chain data through cooperatives, mills, or SME service providers.	STDB / e-STDB; traceability-to-mill and, where feasible, traceability-to-plot systems.
Replanting and yield improvement	Increases feedstock availability without proportional spatial expansion, thereby lowering φ.	Adopt replanting, improved seedlings, and good agricultural practices where support is available.	Smallholder replanting programmes; extension services; cooperative aggregation.
Certification access	Provides documentation of legality and management practices, while not by itself proving low-LUC supply.	Participate through group certification, cooperatives, or SME-supported compliance services.	ISPO and RSPO smallholder certification approaches.

APL = Areal Penggunaan Lain or non-forest land; NDPE = No Deforestation, No Peat, No Exploitation; STDB = Surat Tanda Daftar Budidaya or cultivation registration. These safeguards can reduce LUC risk by improving legality, documentation, and traceability, but they should not be interpreted as automatic proof of low-LUC sourcing or as evidence of welfare improvement (Carlson et al. 2018; Santika et al. 2021).

Smallholders and SMEs matter within this upstream layer. They can support plot documentation, group certification, aggregation, replanting, and yield improvement, all of which can help reduce the expansion share of marginal supply. This role should be interpreted cautiously. Independent smallholders vary widely in land status, market access, productivity, and certification readiness (Jelsma *et al.* 2017), and yield-gap closure can increase supply without proportional land expansion only where replanting, inputs, and technical support are effective (Woittiez *et al.* 2017). Certification and documentation can reduce LUC risk, but they do not automatically prove low-LUC sourcing or generate welfare gains (Carlson *et al.* 2018; Santika *et al.* 2021).

Limitations

Several limitations frame the interpretation of the results. First, the model is a scenario-based operational fuel-cycle screen using published emission factors, not a full reviewed life-cycle assessment, and no field measurements were collected. The fuel-use intensity of 0.35 L bcm^{-1} is a standardised assumption carried at ±30%; it scales the per-bcm results but, by Equation (8), does not affect the LUC break-even. Second, the equal-energy comparison is a first-order correction. Potential changes in brake-specific fuel consumption are bounded through a 0 to +3% sensitivity range rather than modelled from equipment-specific data. Third, the LUC scenarios are sensitivity tests of incremental expansion risk, not predictions of actual sourcing. The 156 g CO_2e MJ^{-1} value represents one measured mineral-soil conversion case in Sumatra, and peat conversion is not separately parameterised. Fourth, the link to sourcing and the smallholder role are interpretive: no primary data were collected for this link, and the study does not model income, welfare, or supply-chain outcomes.

The analysis also does not model indirect land-use change endogenously. The RED II Annex VIII value is used only as a bounding reference; a consequential CPO-market model would be needed to estimate how food, export, and biodiesel demand interact. Coal mining is used only as a diesel-intensive activity denominator and should not be interpreted as representative of all B50 end uses. Future work should therefore prioritise spatially explicit concession and moratorium mapping to estimate φ directly, fleet telemetry to replace the fuel-intensity assumption, engine-dynamometer testing of B50 under mining duty cycles, and consequential modelling of the CPO market.

CONCLUSION

In the mining stress test, the B40-to-B50 switch reduces fossil-diesel use by about 0.0335 L bcm^{-1}, with the absolute value scaling by ±30% under the fuel-intensity assumption. This displacement is independent of land-use assumptions and therefore supports the mandate's import-substitution rationale rather than its climate rationale. The fuel-cycle GHG benefit is conditional. Under low-LUC sourcing, B50 reduces GHG intensity by about 5.6%, falling to roughly 2.8% if a 3% engine-efficiency penalty is realised. The benefit disappears once the incremental LUC term exceeds about 44 g CO_2e MJ^{-1}, or about 9 g CO_2e MJ^{-1} under precautionary full attribution. Expressed as a sourcing condition, the switch can tolerate at most about 28% of incremental feedstock from forest-conversion-equivalent land under the marginal rule, or about 6% under full attribution. Measured mineral-soil forest conversion at 156 g CO_2e MJ^{-1} exceeds both bounds, while the RED II provisional oil-crop iLUC value of 55 g CO_2e MJ^{-1} exceeds the marginal break-even before any direct conversion is counted.

The policy implication is that the climate value of higher blends depends less on the blend ratio itself than on the expansion share of marginal feedstock. This matters because Indonesia governs land conversion mainly through legality, certification, and traceability rather than a fuel-carbon score, and because the B40-to-B50 step implies about 4.06 Mt yr^{-1} of additional CPO, equivalent to roughly 41% of domestic food consumption. Keeping the

expansion share low would require traceable low-LUC sourcing through yield improvement, replanting, verified supply from existing planted areas, and safeguards against forest or peat conversion, with smallholders and SME aggregators playing an upstream role. A practical implication is that reporting the new-conversion share of incremental mandate feedstock against a declared ceiling near φ* could complement blend-volume targets and provide a clearer decision boundary. Future work should estimate φ directly from concession, moratorium, and land-cover data, validate fuel-use intensity using fleet telemetry, and model CPO food–fuel allocation consequentially so that iLUC enters endogenously. The mining case provides an auditable operational stress test and should not be read as evidence that coal mining becomes low carbon.

REFERENCES

Adiansyah JS, Haque N, Rosano M, Biswas W. 2017. Application of a life cycle assessment to compare environmental performance in coal mine tailings management. J Environ Manage. 199:181–191. DOI:10.1016/j.jenvman.2017.05.050.

Aguirre-Villegas HA, Benson CH. 2017. Case history of environmental impacts of an Indonesian coal supply chain. J Clean Prod. 157:47–56. DOI:10.1016/j.jclepro.2017.03.232.

[BPS] Badan Pusat Statistik. 2025. Indonesian permanent estate crops statistics. 2024. Jakarta (ID): Statistics Indonesia.

Carlson KM, Heilmayr R, Gibbs HK, Noojipady P, Burns DN, Morton DC, Walker NF, Paoli GD, Kremen C. 2018. Effect of oil palm sustainability certification on deforestation and fire in Indonesia. Proc Natl Acad Sci USA. 115(1):121–126. DOI:10.1073/pnas.1704728114.

Chain Reaction Research. 2022. The chain: how limited supply, alleged corruption, and the biodiesel market led to Indonesia's cooking oil crisis. Washington (DC): Chain Reaction Research; [accessed 2026 Jul 10].https://chainreactionresearch.com.

de Souza SP, Pacca S, de Avila MT, Borges JLB. 2010. Greenhouse gas emissions and energy balance of palm oil biofuel. Renew Energy. 35(11):2552–2561. DOI:10.1016/j.renene.2010.03.028.

[ESDM] Ministry of Energy and Mineral Resources. 2025. Mandatory B40 effective 1 January 2025 and Regulation No. 4/2025 on commercial biofuel blending. Jakarta (ID): ESDM.

European Commission. 2019a. Report on the status of production expansion of relevant food and feed crops worldwide. COM(2019) 142 final. Brussels (BE): European Commission.

European Commission. 2019b. Commission Delegated Regulation (EU) 2019/807 supplementing Directive (EU) 2018/2001 as regards high indirect-land-use-change-risk feedstock and the certification of low indirect-land-use-change-risk biofuels. Off J Eur Union. CELEX:32019R0807.

European Union. 2018. Directive (EU) 2018/2001 on the promotion of the use of energy from renewable sources. Off J Eur Union. Annex V. CELEX:32018L2001.

Fulcrum. 2022. Indonesia's cooking oil crisis: causes and consequences. Singapore (SG): ISEAS–Yusof Ishak Institute; [accessed 2026 Jul 10]. https://fulcrum.sg.

[GAPKI] Gabungan Pengusaha Kelapa Sawit Indonesia. 2026. Performance of the Indonesian palm oil industry 2025 and outlook for 2026. Jakarta (ID): GAPKI.

Halimatussadiah A, Nainggolan D, Yui S, Moeis FR, Siregar AA. 2021. Progressive biodiesel policy in Indonesia: does the government's economic proposition hold? Renew Sustain Energy Rev. 150:111431. DOI: 10.1016/j.rser.2021.111431.

Harahap F, Silveira S, Khatiwada D. 2019. Evaluating the palm oil demand in

Indonesia: production trends, yields, and emerging issues. Biofuels. 10(1):23–38.

Harsono SS, Prochnow A, Grundmann P, Hansen A, Hallmann C. 2012. Energy balances and greenhouse gas emissions of palm oil biodiesel in Indonesia. GCB Bioenergy. 4(2):213–228. DOI: 10.1111/j.1757-1707.2011.01118.x.

[ICCT] International Council on Clean Transportation. 2011. Review of peat surface greenhouse gas emissions from oil palm plantations in Southeast Asia.Washington (DC): ICCT. Jelsma I, Schoneveld GC, Zoomers A, van Westen ACM. 2017. Unpacking Indonesia's independent oil palm smallholders: an actor-disaggregated approach to identifying environmental and social performance challenges. Land Use Policy. 69:281–297. DOI: 10.1016/j.landusepol.2017.08.012.

Kalam MA, Masjuki HH. 2002. Biodiesel from palm oil – an analysis of its properties and potential. Biomass Bioenergy. 23(6):471–479. DOI: 10.1016/S0961-9534(02)00085-5.

Meijide A, de la Rua C, Guillaume T, Roll A, Hassler E, Stiegler C, Tjoa A, June T, Corre MD, Veldkamp E, Knohl A. 2020. Measured greenhouse gas budgets challenge emission savings from palm-oil biodiesel. Nat Commun. 11:1089. DOI: 10.1038/s41467-020-14852-6.

Nematian M, Scown CD. 2025. Advances and emerging issues in life-cycle assessment for biofuel policy. GCB Bioenergy. 17(8):e70061. DOI: 10.1111/gcbb.70061.

Petromindo. 2026. Indonesia delays B50 biodiesel mandate, maintains B40, and raises palm oil export levy. Jakarta (ID): Petromindo.

Reuters. 2026. Indonesia scraps plan to introduce B50 biodiesel this year, will raise palm oil export levy. London (UK).

Palm Oil. 2018. RSPO principles and criteria for the production of sustainable palm oil. Kuala Lumpur (MY): RSPO.

Sahara, Dermawan A, Amaliah S, Irawan T, Dilla S. 2022. Economic impacts of biodiesel policy in Indonesia: a computable general equilibrium approach. J Econ Struct. 11(1):22. DOI: 10.1186/s40008-022-00281-9.

Santika T, Wilson KA, Law EA, St John FAV, Carlson KM, Gibbs H, Morgans CL, Ancrenaz M, Meijaard E, Struebig MJ. 2021. Impact of palm oil sustainability certification on village well-being and poverty in Indonesia. Nat Sustain. 4:109–119. DOI: 10.1038/s41893-020-00630-1.

Searchinger T, Heimlich R, Houghton RA, Dong F, Elobeid A, Fabiosa J, Tokgoz S, Hayes D, Yu TH. 2008. Use of U.S. croplands for biofuels increases greenhouse gases through emissions from land-use change. Science. 319(5867):1238–1240. DOI: 10.1126/science.1151861.

Singh D, Sharma D, Soni SL, Inda CS, Sharma S, Sharma PK, Jhalani A. 2021. A comprehensive review on 1st-generation biodiesel feedstock palm oil: production, engine performance, and exhaust emissions. BioEnergy Res. 14:1–22. DOI: 10.1007/s12155-020-10171-2.

S&P Global. 2025. Indonesia keeps 2026 biodiesel quota flat, raising doubts over B50 target. Platts Agric News.

Uhanto U, Yandri E, Hilmi E, Saiful R, Ariati R. 2025. Evaluating engine durability and operational effects of biodiesel blends in heavy equipment applications. Next Energy. 9:100392. DOI: 10.1016/j.nxener.2025.100392.

[USDA FAS] United States Department of Agriculture, Foreign Agricultural Service. 2026. Oilseeds and products annual: Indonesia. Report ID2026 0013. Jakarta (ID): USDA FAS.

Woittiez LS, van Wijk MT, Slingerland M, van Noordwijk M, Giller KE. 2017. Yield gaps in oil palm: a quantitative review of contributing factors. Eur J Agron. 83:57–77. DOI: 10.1016/j.eja.2016.11.002.

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Barriers to MSPO 2.0 Certification Transition: Empirical Evidence from Independent Oil Palm Smallholders in Malaysia

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ABSTRACT

The revision of the Malaysian Sustainable Palm Oil standard requires already-certified independent smallholders to adjust established practices rather than make an initial certification decision. This study examined certification transition capacity among MSPO 1.0 certified independent oil palm smallholders preparing for MSPO 2.0. A quantitative cross-sectional survey was conducted across 11 Malaysian states from 1 November to 31 December 2024, and 400 eligible and complete questionnaires were retained. Seven observed composite indices represented certification cost,extension services, agricultural inputs, plot and boundary conditions, plantation conditions, pesticide and herbicide management, and standard operating procedure and policy implementation. Focused transition readiness was calculated from willingness, commitment and confidence in the benefits of continued certification. Descriptive results showed very high ratings for all transition barriers, with mean scores ranging from 4.49 to 4.61, alongside very high readiness at a mean of 4.70. This pattern indicates that commitment to certification can coexist with substantial operational constraints. All bivariate correlations with readiness were positive and statistically significant. The simultaneous-entry regression model was statistically significant, $F(7,392)=77.589$, $p<0.001$, and accounted for 58.1% of the observed variance in readiness ($R^2=0.581$; adjusted $R^2=0.573$). Certification cost, pesticide and herbicide management, and SOP and policy implementation showed negative conditional associations with readiness, whereas extension services, agricultural inputs, plot and boundary conditions, and plantation conditions showed positive conditional associations. These positive coefficients do not indicate that barriers improve readiness; rather, they reflect substantial overlap among implementation conditions and suggest that committed smallholders may recognise constraints more clearly. The findings support an implementation capacity approach combining targeted finance, continuing extension support, suitable inputs, agrochemical guidance, plot documentation and simplified compliance tools. The implications are most directly relevant to SDG 12, with supporting links to SDGs 8 and 15, although ESG performance and SDG progress were not directly measured.

Keywords: Agricultural Extension, Compliance Capacity, Mandatory Sustainability Standards, Sustainable Palm Oil, Sustainability Governance

INTRODUCTION

Sustainability certification converts environmental, social, and governance standards into agricultural practices, which must be proven by documentation, inspections, and periodic evaluation. Malaysia introduced the Malaysian Sustainable Palm Oil (MSPO) scheme as a national certification system and moved

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towards mandatory implementation across the industry from 2020 (Kumaran 2019; Kannan *et al.* 2021). The revised MS 2530:2022 standard, commonly described as MSPO 2.0, supersedes MS 2530:2013 and introduces more comprehensive requirements across the palm oil value chain. This standard applies to a more comprehensive set of requirements across the palm oil value chain. MS 2530-2–1:2022 outlines requirements for independent smallholders managing less than 40.46 Ha, including legal compliance, record keeping, environmental responsibility, safe working conditions, good agricultural practices and audit readiness (MSPO 2026). The transition from MSPO 1.0 to MSPO 2.0 is analytically different from the adoption of the initial certification. Adoption studies ask whether an uncertified producer enters a scheme while transition studies concern producers who already possess certification experience but must realign routines, documents and farm practices with a revised standard. Familiarity with audits may reduce uncertainty but it does not guarantee adequate finance, suitable inputs, technical guidance, documented plot boundaries or the administrative time needed for stronger compliance. Research on smallholder certification repeatedly shows that continued participation depends on resources and facilitation as well as formal willingness (Hutabarat *et al.* 2018; Ogahara *et al.* 2022; de Vos *et al.* 2023).

Existing MSPO research has documented national certification arrangements, smallholder transfor-mation and constraints affecting certification participation (Senawi *et al.* 2019; Kannan *et al.* 2021; Zainal Abidin *et al.* 2024). Comparable evidence from Indonesian smallholders also identifies land legality, external facilitation and implementation gaps as persistent concerns (Soebirin *et al.* 2021; de Vos *et al.* 2023). However, less empirical attention has been given to the transition between successive versions of a mandatory national standard among producers who are already certified. This distinction matters because an upgraded standard can create new demands even where initial certification has been achieved. This study uses an implementation capacity framework. Transition capacity is treated as the practical ability to maintain certification through five connected components which are financial resources, institutional support, access to suitable agricultural inputs, manageable farm and environmental conditions, and workable compliance mechanisms. The seven observed barriers examined in the study map onto these components. Certification cost represents financial pressure, extension services represent institutional support, agricultural inputs, plantation conditions and agrochemical management represent farm and environmental capacity and plot boundaries together with SOP and policy implementation represent documentation traceability and governance capacity. Accordingly, the study examines the pattern of perceived MSPO 2.0 transition barriers and their associations with focused certification transition readiness among MSPO 1.0 certified independent smallholders in Malaysia. It shows how financial, institutional, farm, environmental and governance constraints are related to willingness, commitment and confidence in continued certification. The analysis is intended to identify an interconnected implementation pattern and practical support needs while it does not estimate causal effects or rank the barriers by statistical coefficient size.

MATERIALS AND METHODS

Study Design, Population and Data Collection

Aquantitative cross sectional survey was used to examine MSPO 2.0 certification transition capacity at a defined stage of implementation (Hendrawan *et al.* 2024). Eligibility was restricted to Malaysian independent oil palm smallholders certified under MSPO 1.0

because the research concerned adjustment to a revised standard rather than first-time certification. The target population was approximately 176,658 certified independent smallholders. Krejcie and Morgan (1970) indicate a minimum sample of 384 for a large population at a 95% confidence level and 5% margin of error. Eligibility and completeness screening retained 400 records for analysis after accommodating screening and incomplete responses. Respondents were drawn from 11 states which are Johor, Kedah, Kelantan, Melaka, Negeri Sembilan, Pahang, Perak, Sabah, Sarawak, Selangor and Terengganu. Data was collected through a structured online questionnaire from 1 November to 31 December 2024.

Measurement and Statistical Analysis

The present analysis included seven observed composite indices representing the main conditions that may constrain the transition from MSPO 1.0 to MSPO 2.0. These conditions comprised certification cost, extension services, access to suitable agricultural inputs, plot and boundary management, plantation conditions, pesticide and herbicide management, and SOP and policy implementation. Each transition barrier index was calculated as the mean of three questionnaire statements relating to the respective implementation conditions. All statements were measured using a five-point response scale ranging from 1 (strongly disagree) to 5 (strongly agree). Higher index values indicated stronger perceived transition barriers. The indices were treated as observed composite measures rather than validated psychometric scales. Certification transition readiness was measured using three statements representing the respondents' willingness to participate in MSPO 2.0 implementation, commitment to completing the transition process, and confidence in the benefits of continued certification. The mean of these three statements formed the readiness index, with higher scores indicating greater certification transition readiness. Figure 1 summarises the analytical structure of the study, including the observed transition barrier indices, the certification transition readiness measure, and the statistical procedures used to examine their associations.

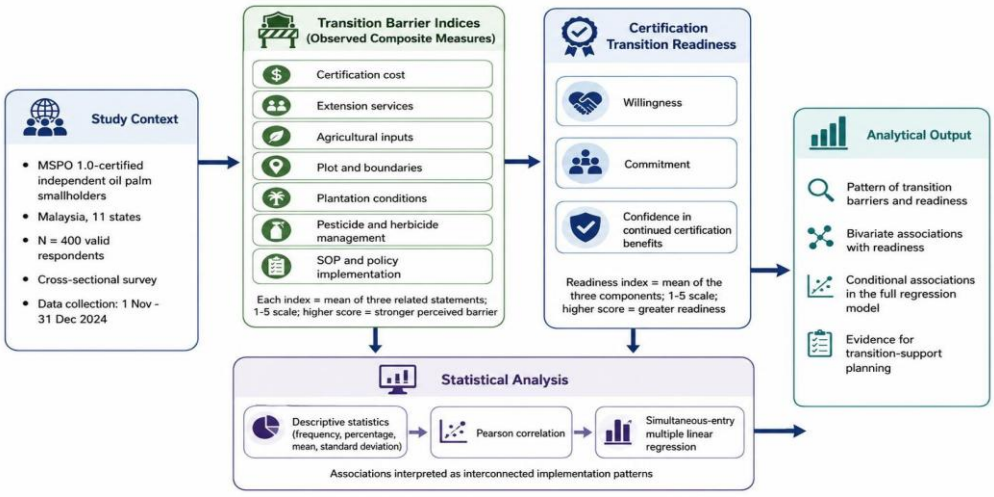


Figure 1 Analytical Framework for MSPO 2.0 Certification Transition Readiness

As shown in Figure 1, the study assessed seven transition barrier indices and one certification transition readiness index before examining their patterns using descriptive statistics, Pearson correlation and simultaneous-entry multiple linear regression. Frequencies and percentages summarised selected respondent characteristics. Means and standard deviations were recalculated directly from the primary dataset. Mean scores were interpreted as very low (1.00-

1.80), low (1.81-2.60), moderate (2.61-3.40), high (3.41-4.20) or very high (4.21-5.00). Pearson correlations described bivariate associations between each barrier and focused readiness. Simultaneous-entry multiple linear regression assessed their conditional associations when considered together. Model reporting used R, R^2, adjusted R^2, the standard error of the estimate and the F-statistic, while the conditional results used unstandardised coefficient standard errors, t-statistics, p-values and 95% confidence intervals. Statistical significance was set at $p<0.05$. The barrier indices displayed severe overlap, consistent with the practical interdependence of implementation conditions. Regression coefficients were therefore interpreted as conditional associations within an interconnected system, not as isolated effects or a ranking of importance. Heteros-cedasticity-consistent HC3 robust standard errors were examined as a sensitivity check, and the significance pattern remained unchanged. Because the design was cross-sectional and based on self-reported responses, all findings are reported as associations rather than causal relationships.

RESULTS AND DISCUSSION

Respondent Context for Certification Transition

Table 1 presents characteristics relevant to the capacity of certified smallholders to manage revised requirements. Secondary education was the largest educational category, accounting for 45.0%, while 28.5% held a bachelor's degree or higher. The mixed educational profile suggests that transition communication should combine written guidance with demonstrations, visual checklists and field-based explanation rather than rely on complex documentation alone. Extension arrangements under MSPO play an important role in translating certification requirements into practical farm actions (Kannan *et al.* 2021; Senawi *et al.* 2019).

Table 1 Selected Characteristics of the Respondents (N=400)

Characteristic	Category	n	%
Education	Primary or no formal education	36	9.0
	Secondary	180	45.0
	Diploma	70	17.5
	Bachelor's degree or higher	114	28.5
Employment	Government	77	19.3
	Private sector	14	3.5
	Retired	57	14.2
	Self-employed	252	63.0
Smallholder category	Full-time	160	40.0
	Part-time	240	60.0
Land tenure	Leased	233	58.3
	Owned	167	41.8
Farm size	1-10 acres	253	63.2
	11-20 acres	105	26.3
	More than 20 acres	42	10.5

Employment status and smallholder category described different aspects of respondents' livelihoods. Although 63.0% were self-employed, only 40.0% were full-time smallholders and 60.0% were part-time smallholders. Self-employment may involve non-farm businesses or several income activities. It should not be treated as equivalent to full-time oil palm work. The predominance of part-time smallholders makes the time required for training, record keeping, audit preparation and corrective action particularly relevant. Land and farm structure also shape practical transition capacity. Leased holdings accounted for 58.3% of respondents, creating possible documentation and boundary verification demands where tenure evidence or plot records must be assembled. Tenure arrangements can affect both compliance evidence and willingness to invest in long-term farm improvements (Murken and Gornott 2022; de Vos *et al.* 2023). In addition, 63.2% managed 1-10 acres. Smaller holdings may have less scope to distribute fixed compliance expenditure across production, increasing the value of targeted finance, shared services and simplified records (Hutabarat *et al.* 2018; Herdiansyah *et al.* 2020).

Patterns of Transition Barriers and Readiness

The descriptive results reveal a concentrated pattern of implementation pressure as shown in Table 2. Every barrier mean fell within the very high range and the spread between the lowest and highest barrier means was only 0.126 points. Agricultural inputs, pesticide and herbicide management, and extension services formed the upper part of this tightly grouped pattern, but the small differences do not support a substantive ranking. Instead, the results indicate that financial, institutional, farm and administrative constraints were experienced simultaneously.

Table 2. Descriptive Statistics for MSPO 2.0 Transition Barriers and Readiness

Observed composite index	Mean	SD	Interpretation
Certification cost	4.532	0.369	Very high
Extension services	4.581	0.360	Very high
Agricultural inputs	4.614	0.352	Very high
Plot and boundaries	4.562	0.370	Very high
Plantation conditions	4.488	0.362	Very high
Pesticide and herbicide management	4.603	0.377	Very high
SOP and policy implementation	4.550	0.372	Very high
Certification transition readiness	4.704	0.266	Very high

Focused transition readiness was also very high (M=4.704, SD=0.266). Thus, strong willingness, commitment and confidence in continued certification coexisted with very high perceived barriers. This is not contradictory. Smallholders can value continued certification and remain committed to MSPO 2.0 while recognising that implementation requires finance, guidance, inputs, documentation and changes to farm routines. Readiness in the present study represents transition orientation and it does not mean that all operational requirements have already been secured.

Associations Between Barriers and Transition Readiness

The bivariate results were uniformly positive as shown in Table 3. Extension services had a correlation of r=0.581 with focused readiness, while the other associations ranged from r=0.270 to

r=0.471. All were statistically significant at p<0.001. These correlations show that respondents reporting stronger readiness also tended to report stronger recognition of implementation barriers. It should not be read as evidence that constraints increase readiness. Rather, willingness and commitment may make the practical demands of transition more visible.

Table 3 Pearson Correlations Between Transition Barriers and Certification Transition Readiness

Transition barrier	r	p
Certification cost	0.438	<0.001
Extension services	0.581	<0.001
Agricultural inputs	0.464	<0.001
Plot and boundaries	0.306	<0.001
Plantation conditions	0.471	<0.001
Pesticide and herbicide management	0.438	<0.001
SOP and policy implementation	0.270	<0.001

Note: Two-tailed Pearson correlations with focused certification transition readiness; N=400.

When the seven barriers were entered simultaneously, the model was statistically significant and accounted for 58.1% of variation in focused readiness as shown in Table 4. The coefficient directions changed from all positive bivariate patterns to a mixture of positive and negative conditional associations. Certification cost, pesticide and herbicide management, and SOP and policy implementation had statistically significant negative conditional coefficients. Extension services, agricultural inputs, and plot and boundary conditions had statistically significant positive conditional coefficients. Plantation conditions had a positive coefficient but did not retain a statistically significant conditional association. Because several barrier indices overlapped severely, each coefficient represents the association of the remaining portion of that index after the other conditions are held constant.

Table 4. Multiple Linear Regression Results for Certification Transition Readiness

Transition barrier	**B**	**SE**	**t**	**p**	**95% CI for B**
Certification cost	−0.431	0.083	−5.202	<0.001	−0.594 to −0.268
Extension services	0.512	0.045	11.299	<0.001	0.423 to 0.601
Agricultural inputs	2.348	0.224	10.472	<0.001	1.907 to 2.789
Plot and boundaries	1.508	0.134	11.276	<0.001	1.245 to 1.771
Plantation conditions	0.093	0.054	1.719	0.086	−0.013 to 0.200
Pesticide and herbicide management	−1.722	0.188	−9.142	<0.001	−2.092 to −1.351
SOP and policy implementation	−1.686	0.123	−13.689	<0.001	−1.929 to −1.444

Note: Dependent variable: focused certification transition readiness. R=0.762; R^2=0.581; adjusted R^2=0.573; standard error of the estimate= 0.17370;F(7,392)=77.589; p<0.001. Coefficients are unstandardisedconditional associations from the simultaneous-entry model and are not ranked by magnitude. HC3 robust standard errors produced the same significance pattern.

The negative cost coefficient indicates that, conditional on the other implementation conditions, greater financial pressure was associated with lower readiness. The negative conditional associations for agrochemical management and SOP implementation similarly suggest that difficulties in

converting requirements into safe field practice and verifiable records can constrain transition orientation. The positive conditional coefficients for extension services, agricultural inputs, and plot and boundary conditions must not be interpreted as evidence that stronger barriers improve readiness. They are consistent with committed smallholders recognising these implementation gaps more clearly once shared variance with the other barriers is controlled. Plantation conditions did not retain a statistically significant conditional association in the full model. The mixed signs are therefore evidence of an interconnected implementation pattern rather than separate, measurable effects.

Integrated Interpretation of Transition Capacity

Financial and institutional capacity must be considered together. Certification transition can involve recurring expenditure for records, corrective action, protective equipment, storage, training and farm improvement even when initial certification costs were previously supported. Evidence from smallholder certification shows that compliance costs can offset gains and create dependence on external assistance (Hutabarat *et al.* 2018; de Vos *et al.* 2023). Continuous extension is therefore not simply an awareness activity. It is the mechanism through which revised requirements are interpreted, farm-specific gaps are identified and financial support is directed to necessary actions. The conditional negative association for cost and positive pattern for extension are compatible with a system in which willingness remains present, but implementation depends on accessible finance and sustained guidance. Farm and environmental capacity centres on suitable inputs,plantation conditions and pesticide and herbicide management. Compliant production requires timely access to appropriate fertilisers, protective equipment and pest-management options as well as drainage, access and maintenance conditions that support good agricultural practice. Input constraints among palm oil producers have been linked to limited capital and technology access (Aminu and Umoh 2020). Agricultural inputs retained a positive conditional association, whereas pesticide and herbicide management retained a negative conditional association. Plantation conditions were positively related to readiness at the bivariate level but did not retain a statistically significant conditional association in the full model. This pattern further supports interpreting the indices as overlapping implementation conditions rather than independent effects. Support should therefore combine access to suitable products with field coaching on selection, storage, application, personal protection, record keeping and integrated pest management. Documentation and governance capacity connects plot boundaries, traceability and SOP implementation. Accurate plot identification and tenure documentation underpin audit evidence and supply-chain traceability, especially where land is leased. Clear boundaries alone are insufficient if smallholders cannot translate policies into routine records for fertilisation, harvesting, chemical use, safety and environmental management. The negative SOP coefficient shows how difficult it is to operationalise written requirements once shared implementation constraints are taken into consideration, while the positive conditional association for plot and boundary conditions may reflect increased recognition among respondents getting ready for transition. Digital mapping assistance, standardised plot files, bilingual templates, visual checklists and short farm logs should be designed as one compliance system rather than separate interventions. Across these themes, the central result is not that one barrier is more important than another. The indices capture a linked implementation environment: finance affects input purchases and corrective action; extension affects agrochemical practice and documentation; tenure affects traceability

and investment; and SOP tools determine whether field activity becomes auditable evidence. This interpretation is consistent with reviews showing that certification outcomes remain limited when programmes focus on formal compliance without addressing smallholder livelihoods, tenure and implementation support (Ogahara *et al.* 2022).

ESG, SDG and Implementation Implications

Environmental, social and governance (ESG) categories provide a useful interpretive framework for organising the transition issues, but the study did not directly measure ESG performance. Environmentally, access to appropriate agricultural inputs, manageable plantation conditions and responsible pesticide and herbicide management affect the capacity to meet good agricultural and environ-mental requirements. Socially, certification cost and uneven extension access raise inclusion concerns because resource constrained smallholders may be committed to continued certification yet lack the means or time to implement it. From a governance perspective, plot documentation, traceability, SOP use and verifiable records determine whether compliance can be demonstrated consistently under the revised standard (MSPO 2026). The findings are most closely aligned with Sustainable Development Goal (SDG)12, particularly the emphasis on sustainable production and responsible resource management. Supporting contributions can be interpreted for SDG 8 through inclusive livelihoods, access to finance, training and safe work practices, and for SDG 15 through improved land management and reduced environmental risk (United Nations 2015). These are conceptual connections only. The survey did not measure SDG indicators or demonstrate achievement of any SDG target. A practical transition support package should integrate six elements: targeted finance for documented corrective needs; continuing extension support beyond one-off training; access to inputs and safety equipment; farm-specific agrochemical guidance; plot and tenure documentation linked to traceability; and simplified, bilingual or visual compliance tools. Delivery through coordinated local clusters could reduce duplication and allow finance, field advice and documentation support to be sequenced around the same farm assessment. Such support would align regulatory expectations with the capacity of already-certified smallholders to remain consistently engaged in the certified supply chain.

CONCLUSION

This study shows that being certified under MSPO 1.0 does not automatically mean that independent smallholders are fully prepared for the transition to MSPO 2.0. Many respondents were willing and committed to remain certified, yet they continued to face practical constraints involving cost, technical support, farm management, agrochemical practices, documentation and compliance procedures.

Therefore, transition readiness must be understood as more than willingness. It also depends on whether smallholders have the resources and support needed to implement the revised requirements in practice. The findings suggest that these barriers are closely connected and should not be addressed separately. A more effective transition strategy should combine targeted financial assistance, continuous extension support, access to suitable inputs, practical agrochemical guidance, plot documentation, traceability assistance and simplified compliance tools.

Since the study was cross-sectional, the results represent associations rather than causal effects. Overall, a successful MSPO 2.0 transition is likely to require closer alignment between the revised standard and the actual implementation capacity of independent smallholders.

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REFERENCES

Aminu FO, Umoh J. 2020. Factors influencing economic performance of palm oil producers in Akwa Ibom State, Nigeria. Int J Oil Palm. 3(3):69–77.

de Vos RE, Suwarno A, Slingerland M, van der Meer PJ, Lucey JM. 2023. Pre-certification conditions of independent oil palm smallholders in Indonesia: assessing prospects for RSPO certification. Land Use Policy. 130:106660. DOI:10.1016/j.landusepol.2023.106660.

Hendrawan D, Chrisendo D, Musshoff O. 2024. Strengthening oil palm smallholder farmers' resilience to future industrial challenges. Sci Rep. 14:12105. DOI:10.1038/s41598-024-62426-z.

Herdiansyah H, Negoro HA, Rusdayanti N, Shara S. 2020. Palm oil plantation and cultivation: prosperity and productivity of smallholders. Open Agric. 5(1):617–630. DOI:10.1515/opag-2020-0063.

Hutabarat S, Slingerland M, Rietberg PI, Dries L. 2018. Costs and benefits of certification of independent oil palm smallholders in Indonesia. Int Food Agribus Manag Rev. 21(6):681–700. DOI:10.22434/IFAMR2016.0162.

Kannan P, Mansor NH, Rahman NK, Tan SP, Mazlan SM. 2021. A review on the Malaysian sustainable palm oil certification process among independent oil palm smallholders. J Oil Palm Res. 33(1):171–180. DOI:10.21894/jopr.2020.0056.

Krejcie RV, Morgan DW. 1970. Determining sample size for research activities. Educ Psychol Meas. 30(3):607–610. DOI:10.1177/001316447003000308.

Kumaran S. 2019. The dynamics for mandatory MSPO certification scheme to be successfully implemented. J Oil Palm Environ Health. 10:1–7.

Malaysian Sustainable Palm Oil (MSPO). 2026. Standards: MSPO 2.0, MS 2530:2022.

Murken L, Gornott C. 2022. The importance of different land tenure systems for farmers' response to climate change: a systematic review. Clim Risk Manag. 35:100419. DOI:10.1016/j.crm.2022.100419.

Ogahara Z, Jespersen K, Theilade I, Nielsen MR. 2022. Review of smallholder palm oil sustainability reveals limited positive impacts and identifies key implementation and knowledge gaps. Land Use Policy. 120:106258. DOI:10.1016/j.landusepol.2022.106258.

Senawi R, Rahman NK, Mansor N, Kuntom A. 2019. Transformation of oil palm independent smallholders through Malaysian sustainable palm oil. J Oil Palm Res. 31(3):496–507. DOI:10.21894/jopr.2019.0038.

Soebirin EJ, Maswadi, Suharyani A. 2021. The readiness of self-manage oil palm farmers at Sekadau District in ISPO implementation. Int J Oil Palm. 4(2):46–57.

United Nations. 2015. Transforming our world: the 2030 Agenda for Sustainable Development.

Zainal Abidin MN, Abdul Fatah F, Noor WNWM, Aris NFM. 2024. A review on adoption of the Malaysian Sustainable Palm Oil (MSPO)certification scheme. IOP Conf Ser Earth Environ Sci. 1397(1):012035. DOI:10.1088/1755-1315/1397/1/012035.

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Pahan I, Gumbira-Sa'id E,Tambunan M. 2011. The future of palm oil industrial cluster of Riau region Indonesia. Eur J Soc Sci. 24(3):421-431.

Purnamasari MI, Prihatna C, Gunawan AW, Suwanto A. 2012. Isolasi dan identifikasi secara molekuler *Ganoderma* spp. yang berasosiasi dengan penyakit busuk pangkal batang di kelapa sawit. J Fitopatol Indones. 8(1):9-15. DOI: 10.14692/jfi.8.1.9.

Van Duijn G. 2013. Traceability of the palm oil supply chain. Lipid Technol. 25(1):15- 18. DOI: 10.1002/lite.201300251.

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References for books follow the order Author(s). Year.Title. Edition. Place of publication (Country Code): publisher.

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Allen C. 2007. Bacteria, bioterrorism, and the geranium ladies of Guatemala. In: Cabezas AL, Reese E, Waller M, editors. Wages of empire: neoliberal policies, repress-sion, and women's poverty. Boulder (US): Paradigm Press. p. 169- 177.

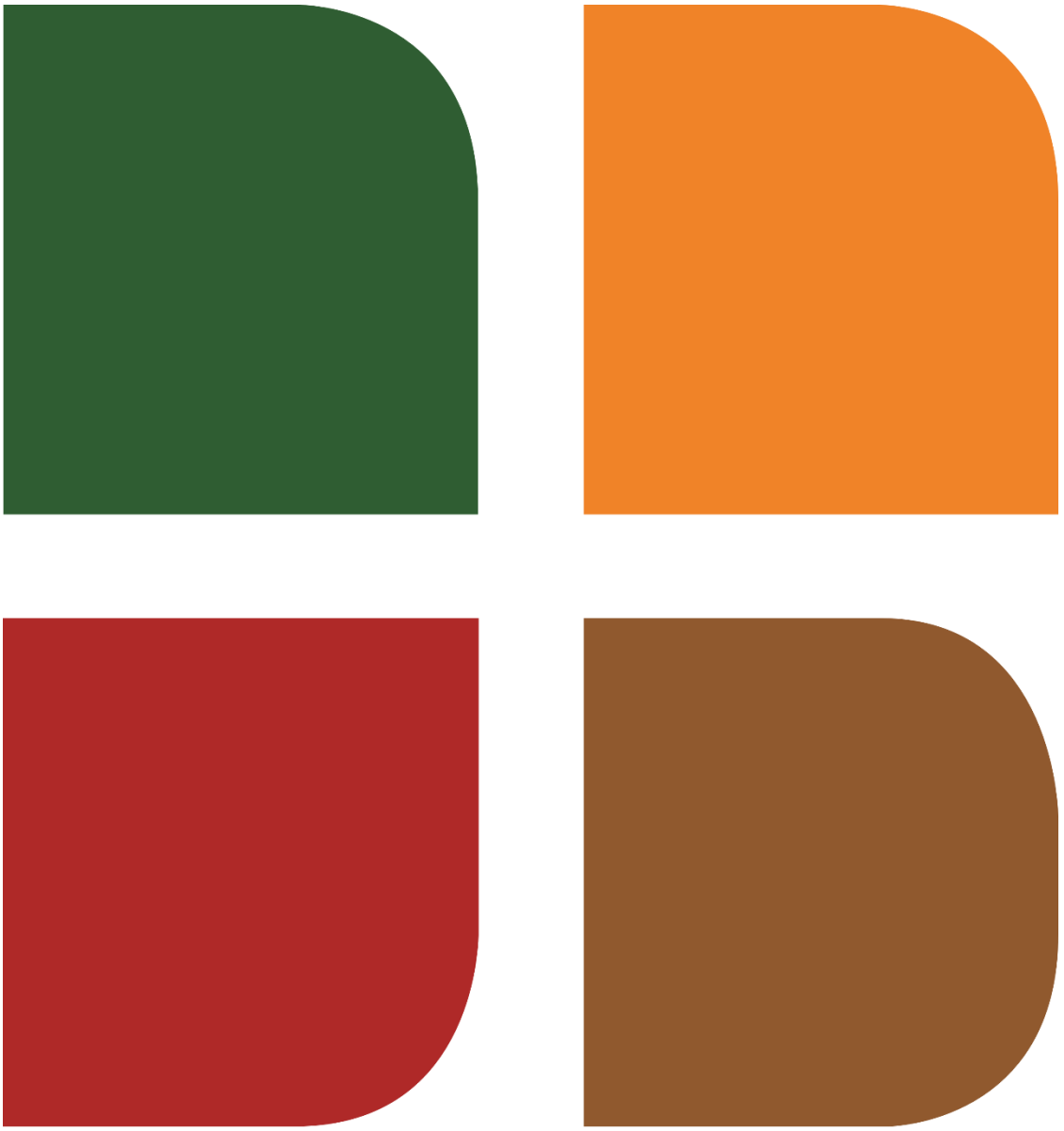
Otegui MS. 2007.Endosperm: development and molecular biology. In: Olson OA, editor. Endosperm cell walls: formation, composition, and functions. Heidelberg (DE): Springer. p. 159178.

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