

National-Scale Mapping of Oil Palm Plantation Ages in Indonesia Using Global Canopy Height Data on Google Earth Engine

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Abstract

The oil palm (Elaeis guineensis) is one of the most strategic plantation commodities in Indonesia. However, spatially explicit information on plantation age remains limited, which hampers evidence-based decision making for productivity assessment, replanting prioritization, and sustainable plantation management. This study is to investigate the spatial distribution of oil palm age across Indonesia based on 10 m Global Canopy Height (GCH) product within the Google Earth Engine (GEE) platform. The methodology included canopy-height extraction and masking, age estimation using a height–age regression model, multi-site validation, and national-scale mapping. Canopy height obtained from GCH was compared with field measurements at the Asahan calibration site were strongly correlated ($R^2 = 0.85$). The age model was validated using planting-year records from five plantations in Sumatra and Kalimantan. At the Asahan calibration site, the model reproduced recorded ages with the suitable is $R^2 = 0.88$ and RMSE = 2.8 years. However, model reliability may vary depending on topography, weather conditions, plantation management, and oil palm variety. The model was applied to 11.62 million hectares of mapped oil palm area. The mapped plantations were dominated by mature stands (5–25 years, 43.7%), followed by young stands (0–5 years, 30.3%) and old stands (>25 years, 26.1%). Regional mapping shows that Sumatra contains a high density of old stands targeted for replanting, particularly in Jambi, where old stands account for 30.4% of the mapped area. In contrast, Central Kalimantan is dominated by young stands, which account for 40.0%. At the national level, the resulting age map provides a spatially consistent baseline for identifying replanting priorities, supporting productivity monitoring, improving plantation inventory, and informing sustainable oil palm governance across Indonesia.

Keywords: Global Canopy Height, Oil Palm, Remote Sensing, Spatial Distribution

1. Introduction

Oil palm (*Elaeis guineensis*) is one of the most economically important plantations in the tropical world. Indonesia, the world's largest producer, cultivated approximately 15.9 million hectares of oil palm in 2023, contributing significantly to national export revenues, employment, and rural development [1]. However, the productivity and sustainability of this sector are increasingly constrained by the aging profile of plantations [2]. Oil palm productivity is

optimal between 8 and 18 years of age, after which yields decline and susceptibility to pests, diseases, and physical instability increases. Replanting old stands is necessary to maintain long-term production, however, effective replanting requires accurate and spatially explicit information on the age distribution of oil palm plantations at the national scale. The morphological characteristics and growth patterns of oil palm plants strongly support a measurable

approach to understanding the development phases of plantation [3]. Figure 1 is an illustration of planting geometry, the main structure of the plant, and visual changes in oil palms at various age groups. Oil palm planting patterns generally follow an equilateral triangle configuration with a spacing of approximately 9 meters, resulting in a spatially consistent tree arrangement [4]. As oil palms age, they show relatively linear vertical trunk growth, accompanied by changes in crown diameter and leaf density [5]. Among these structural parameters, tree height is the most representative indicator because it shows the accumulation of biomass growth over time and is strongly correlated with the age phase of the plant [6].

In monitoring the condition and growth of oil palm, several biophysical parameters have been explored to describe the physiological development stage, such as Leaf Area Index (LAI), spectral vegetation indices (such as NDVI, EVI), crown diameter, and crown height [7]. Among these parameters, canopy height is considered a robust, stable, and physically interpretable indicator for estimating oil palm age because it reflects cumulative vertical growth over time. However, the strength of the height–age relationship may vary depending on site conditions, planting material, soil fertility, topography, and plantation management practices. Therefore, canopy height should be interpreted as a key structural proxy for oil palm age estimation rather than as a universally superior parameter under all conditions [8] and [9]. This is due to the

predictable vertical growth pattern of oil palms, including species that grow at a relatively constant rate in the early and middle stages of the plant, typically adding 40–50 cm of stem height per year under optimal conditions [10]. In this case, canopy height shows cumulative growth over time that integrates biophysical growth and age [11]. In cultivation systems such as oil palm, canopy height shows a strong linear correlation with age, especially in the first growth [12]. Despite vegetation indices that can accommodate dense canopies and are influenced by short-term phenological changes, tree height provides more consistent measures and can be applied to both large and small plantations. Field studies support this finding where [7] and [13] showed that the canopy height model from UAV and satellite imagery was able to classify oil palm age into young (0–5 years), productive (6–15 years), and old (>20 years) groups with high accuracy.

Although several studies have estimated oil palm age through remote sensing, they are limited in scale and transferability. UAV photogrammetry and canopy projection metrics [14] operate at the block level over small areas; time-series optical analysis [15] and radar interferometry [16] infer relative maturity but struggle to determine absolute age in older stands and are sensitive to local conditions. None of these approaches produce spatially continuous and nationally consistent age estimates for Indonesia, and most rely on locally calibrated sensor-specific models that are difficult to reproduce at scale.

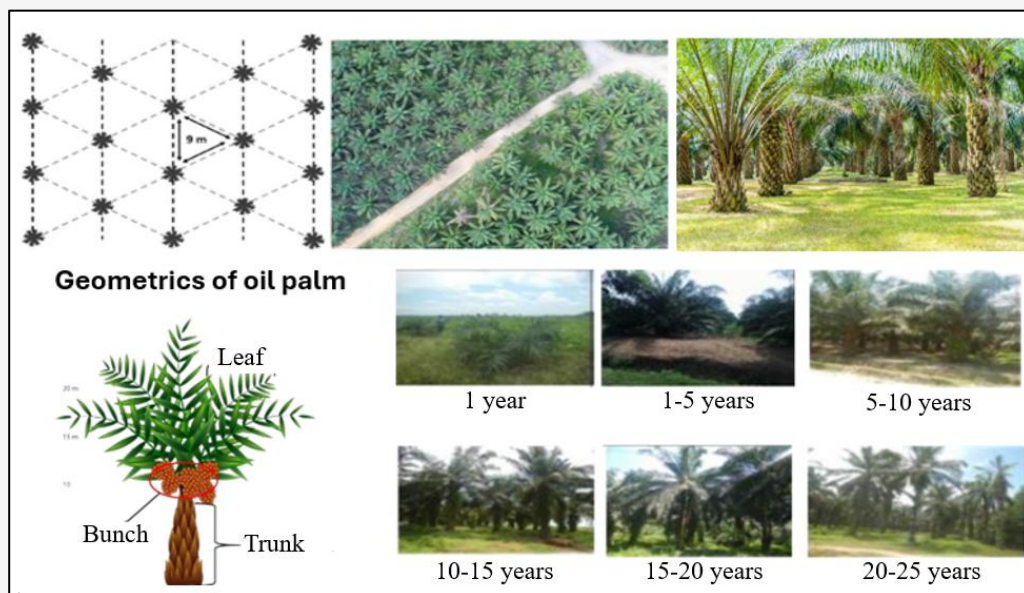


Figure 1: Geometry of oil palm tree [1][17] and [18]

The availability of comprehensive Global Canopy Height (GCH) products at 10 m resolution [19] and [20] generated by combining Global Ecosystem Dynamics Investigation (GEDI) LiDAR data with Sentinel-2 imagery, together with cloud-based processing in GEE, makes a reproducible, national-scale approach feasible. Therefore, this study addresses this gap rather than proposing a new estimation model; it adapts an established canopy height–age relationship to a 10 m GCH input and applies it consistently across Indonesian oil palm plantations in GEE, with performance assessed using one calibration site and four independent validation sites in Sumatra and Kalimantan. The use of GCH represents a significant advance in global-scale vegetation monitoring [11], but its application to oil palm plantations remains limited. Integrating GCH with scalable GEE processing enables not only national-scale age estimation but also interactive thematic visualisation of the resulting age distribution, providing a practical platform for policymakers, plantation managers, and researchers to evaluate plantation structure, identify ageing stands requiring replanting, and assess sustainability scenarios. Accordingly, this study investigates the

spatial distribution of oil palm age across Indonesia using GCH data within GEE, producing a high-resolution, nationally consistent age dataset to inform replanting strategies, policy formulation, and long-term sustainability planning for the sector.

2. Method

This study adopted approaches developed by [19] [20][21][22] and [23] which integrate canopy height data from the GEDI LiDAR mission with optical and radar imagery to produce high-resolution canopy height maps. However, unlike these studies which are generally applied to natural forests or mixed vegetation cover, in this study the approach is specifically adapted to estimate the age of oil palm trees throughout Indonesia. The utilization of canopy height as the main parameter is based on the linear and consistent correlation between the increase in oil palm stem height and its age. The entire process is carried out computationally using the Google Earth Engine (GEE) platform such as canopy height extraction including masking and validation, age estimation, validation, and national-scale spatial distribution of oil palm age (Figure 2).

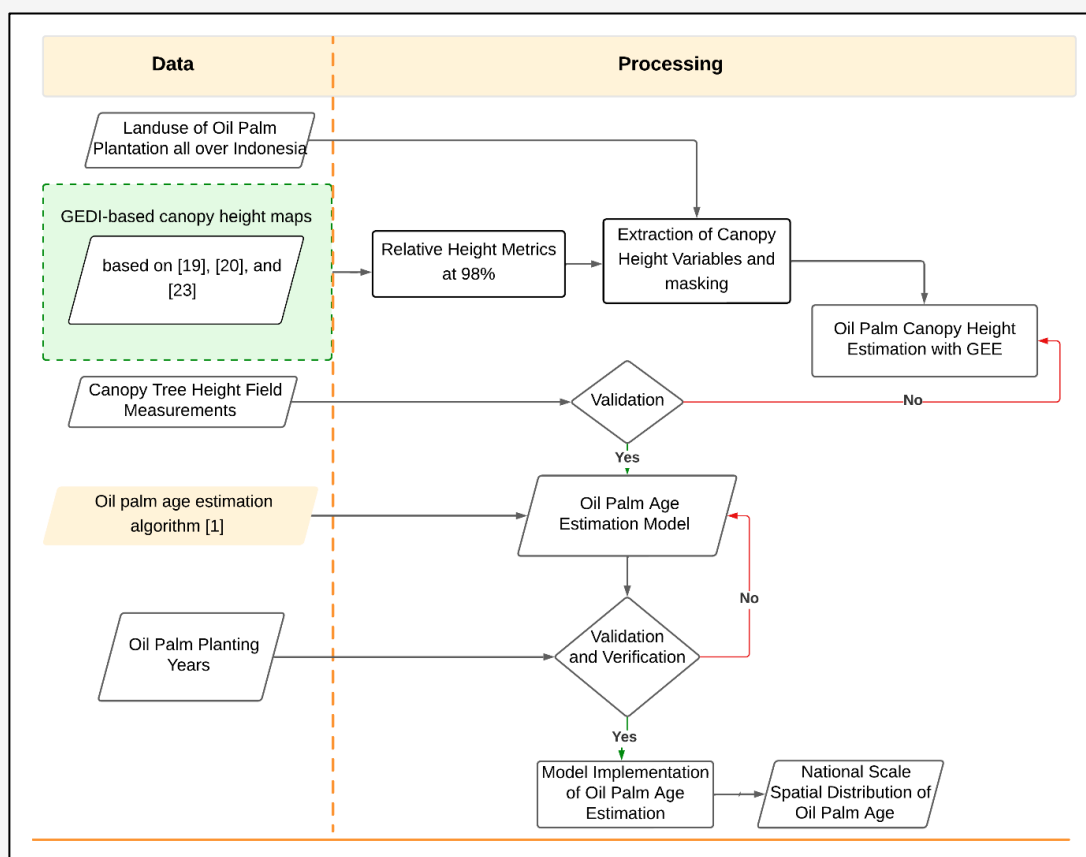


Figure 2: Oil palm plantation age estimation workflow

2.1 Study Area

This study covers the Indonesian archipelago (Figure 3), which spans approximately 1.9 million km² and is the world's largest oil palm-producing country. According to national statistics, Indonesia cultivated approximately 15.9 million hectares of oil palm plantations in 2023. This official figure is used consistently throughout the manuscript as the national reference area. However, the GCH-based age estimation was applied only to the mapped oil palm area retained after spatial masking, canopy-height data screening, and the 0.5 ha minimum mapping unit filter, resulting in an analyzed area of 11.62 million hectares. Therefore, the difference between the official national plantation area and the analyzed area reflects the operational spatial coverage of the remote-sensing workflow rather than an inconsistency in plantation statistics [24]. Oil palm plantations are located in many agroecological zones, mostly in lowland alluvial plains at elevations below 200 meters, characterized by fertile, well-drained soils [25]. They are primarily located in Sumatra and Kalimantan, which contribute 85% of national production [26]. Soil fertility is influenced by various variables, including parent material, climate, terrain, and anthropogenic activities such as cultivating and drainage [25]. The main oil palm production regions include:

1. Sumatra (Riau, North Sumatra, South Sumatra, Jambi) which is characterized by mature plantations established since the 1980s [27].
2. Kalimantan (Central, West, East, and South Kalimantan) are also known for large-scale plantation development that began in the 2000s [28].
3. Sulawesi and Papua are developing regions experiencing recent expansion, with plantations dominated by young trees [29].

The equatorial tropical climate, with average temperatures ranging between 26-28°C and rainfall more than 2,000 mm per year, supports continuous vegetative growth [30]. However, variations in topography, soil fertility, management practices, and land-use history result in complex plantation structures, which affect the accuracy of canopy height and age estimates [31].

2.2 Data

This study used multiple geospatial datasets and reference data to estimate and map the spatial distribution of oil palm plantation age across Indonesia. The datasets included Global Canopy Height (GCH), GEDI LiDAR RH98 observations, the BIOPAMA Global Oil Palm v1 dataset, plantation planting-year records, and field tree-height measurements. The spatial resolution, temporal coverage, source, and purpose of each dataset are summarized in Table 1.

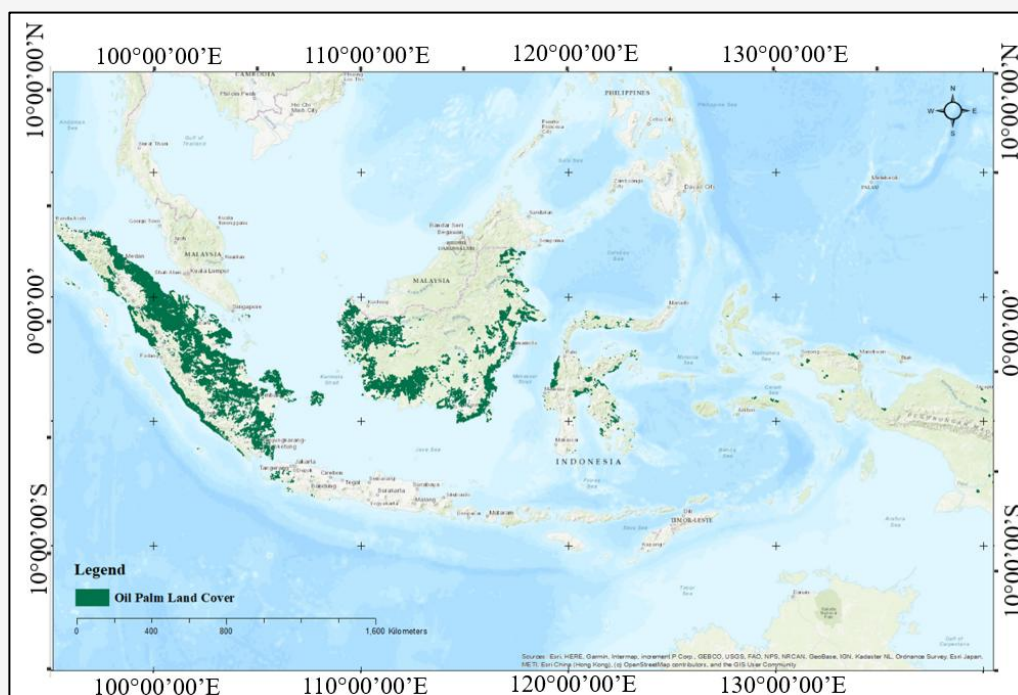


Figure 3: Oil palm in Indonesia

Table 1: Overview of datasets and specifications for national scale oil palm age

Data	Spatial Resolution	Temporal Coverage	Source / Platform	Reference
Global Canopy Height (GCH)	10 m	2020–2021	Google Earth Engine	[19] and [32]
GEDI LiDAR RH98	~25 m footprint	2019–2023	NASA / GEDI mission	[11]
Oil Palm Land Cover Map	10 m	2019	BIOPAMA Global Oil Palm v1 / Google Earth Engine	[33]
Planting Year Data (5 sites)	–	2000–2020	Plantation survey	Indonesian Oil Palm Research Institute (IOPRI)
Field Tree Height Measurements	–	2022	Field survey	Primary data

The primary input was canopy height derived from the 10 m Global Canopy Height (GCH) product, which was accessed and processed through the Google Earth Engine (GEE) platform. The GCH product integrates sparse Global Ecosystem Dynamics Investigation (GEDI) LiDAR observations with dense satellite imagery to generate a wall-to-wall canopy-height dataset at high spatial resolution [19][22] and [32]. GEDI RH98 represents the relative height at which 98% of the returned LiDAR energy has been accumulated and is commonly used as a robust proxy for canopy-top height [34]. The GCH product provides an estimated global RMSE of approximately 2.7 m with low bias, representing an important improvement over the spatially discrete GEDI footprints [35]. Previous validation studies have also demonstrated that GEDI-derived canopy-height metrics can provide reliable height estimates across multiple vegetation types [36]. The official national oil palm plantation area and the spatially analyzed area in this study refer to different quantities. The official figure of approximately 15.9 million hectares represents the national oil palm estate reported in Indonesian statistical records for 2023 [24]. In contrast, the GCH-based age estimation was applied to 11.62 million hectares of mapped oil palm area retained after applying the oil palm land-cover mask, screening for GCH data availability, and removing fragmented patches smaller than 0.5 ha. Therefore, the difference between the official national plantation area and the analyzed area reflects the operational spatial coverage of the remote-sensing workflow rather than an inconsistency in the reported national plantation statistics. To delineate oil palm plantations, this study used the BIOPAMA Global Oil Palm v1 dataset available in GEE as an external spatial mask [37]. The dataset provides a 10 m global

map of industrial and smallholder closed-canopy oil palm plantations for 2019. It was generated using a convolutional neural network based on Sentinel-1 radar and Sentinel-2 optical half-year composite imagery. The BIOPAMA oil palm layer was not produced, modified, or reclassified in the present study. Instead, it was used solely to restrict GCH-based canopy-height extraction and subsequent age estimation to areas mapped as oil palm plantations.

The published validation of the BIOPAMA dataset reported class-specific accuracy measures for both industrial and smallholder oil palm plantations [33]. Specifically, the source study reported a producer's accuracy of $91.9 \pm 3.4\%$ and a user's accuracy of $91.8 \pm 1.0\%$ for industrial closed-canopy plantations, and $72.7 \pm 1.3\%$ and $75.7 \pm 2.5\%$ respectively for smallholder plantations. These results support its use as a national-scale spatial mask. However, residual omission and commission errors may still influence the extraction of canopy-height values, particularly near plantation boundaries and in fragmented smallholder landscapes. Because smallholder plantations are mapped less reliably than industrial estates, the retained analysis area is biased towards industrial holdings, and this bias should be considered when interpreting the national age proportions. This limitation was considered when interpreting the resulting oil palm age estimates. Planting-year data were obtained from five plantation sites located in Asahan, Betung Krawo, Ngabang, Tabara, and Tanah Laut. These records were used to derive reference plantation ages at the time of observation. Complementary field tree-height measurements were collected in 2022 using Hagameter and were used to assess the agreement between GCH-derived canopy height and field observations.

2.3 Processing

The processing methodology includes the following steps: canopy height extraction including masking and validation, age estimation, accuracy validation, and national-scale spatial distribution of oil palm age. Data processing and analysis were conducted on the Google Earth Engine (GEE) cloud computing platform, which allows the efficient management of large geospatial datasets and integrates multi-source remote sensing data with ground reference measurements. Field measurements comprised 160 trees distributed across 16 planting-year blocks at the Asahan calibration site (10 trees per block), with block means used as the unit of analysis ($n = 16$ blocks). The age model was subsequently tested against planting-year records at four plantation sites, each comprising 9 planting-year blocks of 10 trees, and model performance was evaluated using R^2 and RMSE.

2.3.1 Canopy height extraction

Canopy heights are derived from the 10 m Global Canopy Height (GCH) dataset, applying the GEDI LiDAR RH98 metric, which is defined as the height at which 98% of the returned LiDAR energy is collected known as a precise and noise-resistant indicator of canopy top height [38]. The GCH product integrates sparse GEDI data (about 25 m in diameter) with dense optical imagery via machine learning, producing a continuous wall-to-wall canopy height map [34]. In this study, GCH values were screened to remove physically implausible and extreme outlier values before spatial analysis. Values below 0 m were excluded because negative canopy heights are not physically meaningful. Values above 35 m were also removed because mature oil palm

stands generally remain below approximately 25–30 m in height, while values substantially above this range are more likely to represent residual errors in the GCH product, mixed pixels, non-oil-palm vegetation, or local masking errors. The 35 m upper threshold was therefore applied as a conservative quality-control buffer rather than as an assumed maximum oil palm height (Figure 4). The retained GCH values were then resampled to a standard 10 m grid before masking and age estimation [39] and [40].

2.3.2 Oil palm masking

The BIOPAMA Global Oil Palm v1 layer was used as a categorical spatial mask to restrict the analysis to areas mapped as oil palm plantations. A 3×3 majority filter was applied only to the binary oil palm mask, not to the GCH values, in order to reduce isolated salt-and-pepper pixels and small discontinuities caused by classification noise [41]. At the 10 m spatial resolution of the mask, the 3×3 window represents an area of approximately 30×30 m. This scale is larger than the typical oil palm planting distance of approximately 9 m and was therefore used to improve the spatial continuity of plantation blocks rather than to represent individual trees or smooth canopy-height variation [41]. After majority filtering, isolated fragments smaller than 0.5 ha were removed as a minimum mapping unit to reduce likely classification artefacts and non-representative edge patches. The 0.5 ha threshold was applied as a quality-control criterion for fragmented map objects and not as a definition of the minimum size of oil palm plantations.

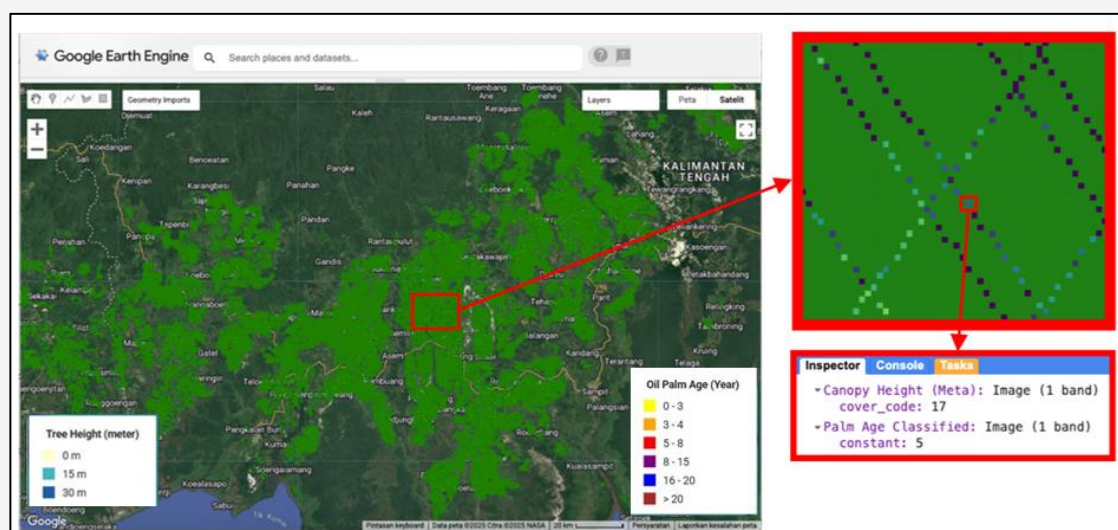


Figure 4: Visualization of oil palm canopy height and age classification on Google Earth Engine (GEE)

We acknowledge that this procedure may exclude some smallholder plantations smaller than 0.5 ha or highly fragmented plantation patches.

2.3.3 Local canopy-height calibration and validation

The GCH-derived canopy-height values were evaluated against field measurements collected in Asahan, North Sumatra, where a field survey measured 160 individual oil palm trees using Hagameter. The trees were distributed across 16 planting-year blocks with 10 trees per block. Block-level means were used as the unit of analysis ($n = 16$ blocks), since trees within a block share planting year, soil, and management conditions and are therefore not independent observations. This dataset was used as a local calibration and validation dataset to assess the agreement between GCH-derived canopy height and field-observed tree height under the plantation conditions represented in Asahan. The validation was not intended to demonstrate national-scale canopy-height accuracy because the field measurements were collected in a single geographic region.

The national-scale application of the workflow was supported by an additional age-validation procedure using plantation planting-year records from five sites distributed across Sumatra and Kalimantan. Therefore, the Asahan validation provides evidence of local agreement between GCH and field height measurements, whereas the multi-site validation evaluates the transferability of the GCH-based age estimation approach across several

plantation environments. The national results should nevertheless be interpreted with caution because canopy-height accuracy may vary with topography, plantation structure, planting material, management practices, and local environmental conditions [1] and [41].

2.3.4 Age estimation

The oil palm age-estimation model used in this study was derived from a single-parameter regression model developed using Sentinel-1A InSAR-derived canopy height model (CHM) data. In the selected model, oil palm age was treated as the dependent variable, while CHM was used as the predictor variable. The original model calibration was conducted at PTPN III Sei Dadap Plantation, Asahan, North Sumatra, Indonesia. The calibration dataset consisted of 160 field observations distributed across 16 planting-year blocks. Each block represented a different planting year and included approximately 10 sampled oil palm trees, with some blocks containing more than 10 trees. The sampled blocks covered planting years from 2000 to 2022, representing an oil palm age range of approximately 0.5 to 22 years at the time of observation. The calibration dataset was spatially distributed across the plantation area rather than being concentrated in a single plot. The sampled trees were measured within multiple planting-year blocks to capture canopy-height variation associated with different oil palm growth stages. The spatial distribution of the sampled trees and planting-year blocks is shown in Figure 5.

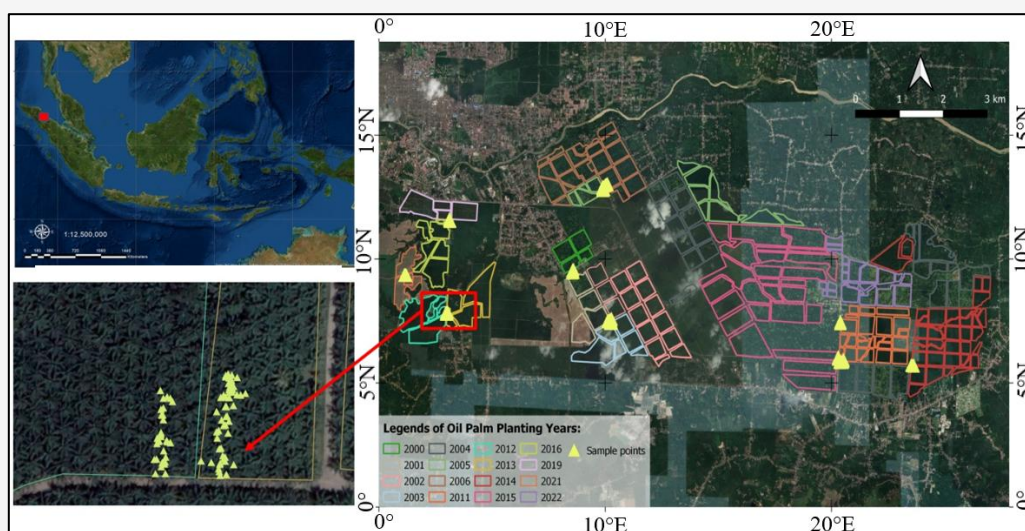


Figure 5: Spatial distribution of field sample trees and planting-year blocks at PTPN III Sei Dadap Plantation, Asahan, North Sumatra, used to calibrate the CHM-based oil palm age estimation model. The calibration dataset consisted of 160 field observations distributed across 16 planting-year blocks, with approximately 10 sampled trees or more per block

Several regression models were evaluated using different combinations of Sentinel-1A-derived biophysical parameters. For the present study, the CHM-only model was selected because the Global Canopy Height (GCH) product provides canopy-height information but does not provide the additional Sentinel-1A-derived parameters used in the multi-parameter regression models, such as radar vegetation index, backscatter, biomass, and texture variables. The selected CHM-only model was expressed as (Equation 1) [1]:

$$\text{Age (year)} = -2.25 + 1.11 \times \text{CHM} \quad \text{Equation 1}$$

Where *CHM* is canopy height in metres derived from Sentinel-1A InSAR. The CHM-only model achieved an R^2 of 0.936 and an *RMSE* of 1.79 years (Table 2). Although models incorporating additional biophysical parameters produced higher accuracy in the original Sentinel-1A analysis, the CHM-only model was selected because it provides a physically

interpretable and operationally compatible relationship for application to the GCH dataset.

To assess the consistency between the Sentinel-1A InSAR-derived CHM and the Global Canopy Height product, a block-level comparison was conducted using the same planting-year blocks in Asahan (Figure 6). The two products are positively and linearly related ($R^2 = 0.79$), indicating that they capture comparable structural variation across oil palm planting-year blocks. However, the two products are not identical, they differ in sensor characteristics, spatial sampling properties, and uncertainty structures, and comparisons show that GCH systematically records lower canopy heights than InSAR-derived CHM for the same blocks. In this study, we directly apply the CHM-only model in Equation 1 to GCH values assuming that both datasets represent the same underlying structural attributes and vary consistently with each other. The uncertainty introduced by this cross-sensor application is not analyzed analytically but assessed empirically using multi-site age validation.

Table 2: Summary of the CHM-only oil palm age estimation model used for GCH-based mapping

Model	Dependent variable	Predictor	Calibration data	Age range	R^2	<i>RMSE</i>
CHM-only age model	Oil palm age (years)	Sentinel-1A InSAR-derived CHM (m)	160 field observations from 16 planting-year blocks at PTPN III Sei Dadap Plantation, Asahan, North Sumatra	0.5–22 years	0.94	1.79 years

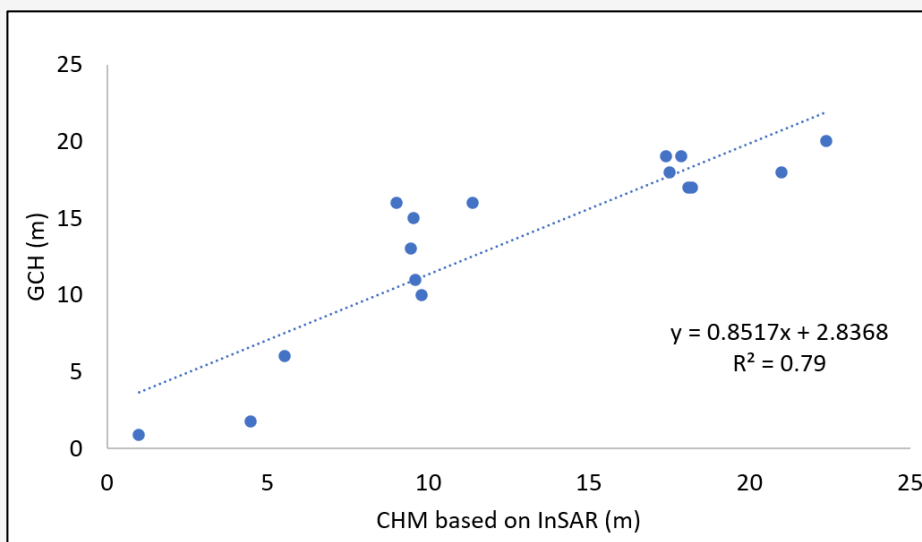


Figure 6: Block-level comparison between Sentinel-1A InSAR-derived canopy height model (CHM) and Global Canopy Height (GCH) values at the Asahan calibration site, showing consistent structural variation between the two products

2.3.5 Age validation

To evaluate the accuracy of the oil palm age estimation workflow, validation was conducted using two main approaches including (1) comparison of GCH-derived canopy height with field-measured tree height at the Asahan calibration site, and (2) comparison of estimated plantation age with planting-year records from five plantation sites in Sumatra and Kalimantan. The validation process was conducted by extracting GCH-derived canopy height and model-estimated age at locations with reference planting-year data. Plantation records were converted into reference ages corresponding to the GCH acquisition epoch. Model performance was evaluated using the coefficient of determination (R^2) and Root Mean Square Error ($RMSE$), which quantify the agreement between estimated and reference ages (Equation 2) [42].

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y})^2}{\sum_{i=1}^n (y_i - \bar{y})^2}$$

Equation 2

Where y_i is actual age, $\hat{y}_i$ is estimated oil palm age, $\bar{y}$ is actual average age, n is number of samples. $RMSE$ is used to measure the mean squared deviation between estimated and observed values (Equation 3) [43]:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}$$

Equation 3

$RMSE$ highlights significant errors, and a lower $RMSE$ value indicates more model accuracy.

Independent validation was conducted using planting year records from five plantation sites managed by large and medium-scale companies, including Asahan (North Sumatra), Betung Krawo (South Sumatra), Ngabang (West Kalimantan), Tabara (East Kalimantan), and Tanah Laut (South Kalimantan) (Figure 7). Complementary field measurements of tree height were collected between 15–19 November 2022 using a Hagameter. The same block-based design was used at every site: 10 trees were measured per planting-year block and averaged to a block mean, which served as the unit of analysis. This yielded 16 blocks at Asahan and 9 blocks at each of the other four sites. Block-mean canopy height was compared with block age, so the reported n refers to the number of age blocks per site rather than the number of trees. Because block averaging suppresses within-block variance, the site-level R^2 characterises block-mean agreement and is expected to exceed the accuracy attainable at the level of individual 10 m pixels, which is the resolution at which the national map is delivered. Besides that, the number of block-level samples at each independent validation site was limited, the validation statistics should be interpreted as site-level indicators of model transferability rather than definitive estimates of national-scale predictive accuracy.

2.3.6 Temporal consistency and uncertainty assessment

Because the GCH product represents canopy conditions from 2020–2021 whereas the field measurements and plantation reference data were collected in 2022, a temporal mismatch may affect the validation results.

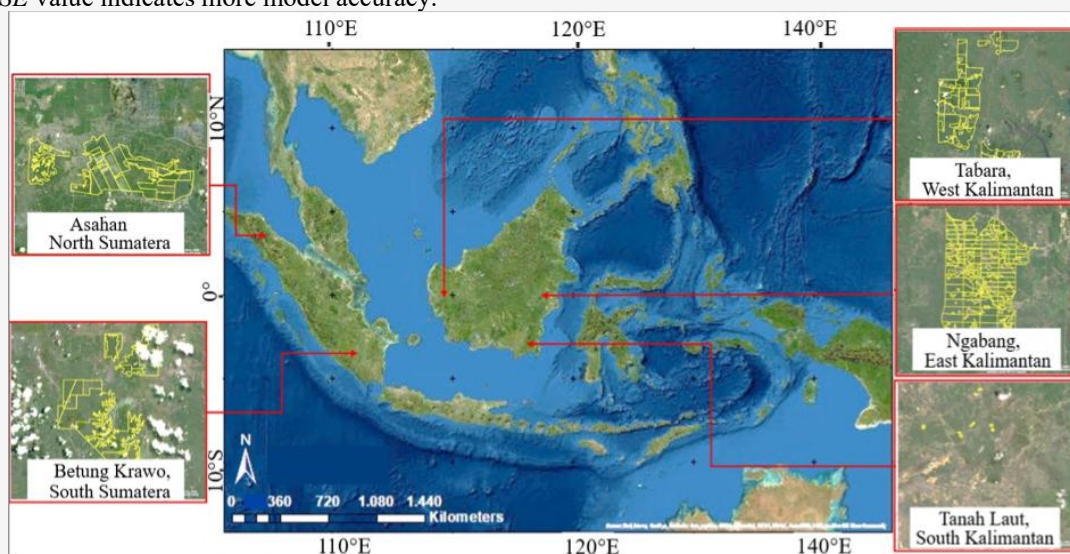


Figure 7: Oil palm plantation areas used for age validation and verification

Oil palm stem height may increase by approximately 0.4–0.5 m per year during active growth stages; therefore, a one- to two-year interval may introduce a potential height difference of approximately 0.4–1.0 m. To assess the potential influence of this mismatch, we interpreted the validation results with consideration of this expected growth range and evaluated the corresponding age uncertainty using the height–age regression model. Reference ages were computed relative to the GCH acquisition epoch rather than the field survey year, so that estimated and reference ages refer to the same point in time. The estimated temporal effect should be interpreted as an approximate sensitivity range because growth rates vary with stand age, site conditions, planting material, soil fertility, and management practices.

2.3.7 Spatial distribution of oil palm age

The age estimation model was applied to all pixels within the masked oil palm cover in Indonesia, producing a national age distribution map at 10 m spatial resolution using the Google Earth Engine platform. Plantation age was classified into three groups: 0–5 years (young), 5–25 years (mature), and >25 years (old). These boundaries follow the recognised production phases of oil palm: the immature and early-yielding phase before approximately five years, the peak productive phase between 8 and 18 years extending to about 25 years, and the post-productive phase beyond 25 years at which replanting is normally considered [10]. The boundaries are also operationally relevant because they correspond to the decision points used by plantation managers for replanting scheduling. Each age class is displayed in a different colour to facilitate interpretation, and the final map is presented interactively in GEE, allowing spatial exploration from national to local level.

3. Results

The estimation of oil palm age relies on the relationship between canopy height and age based on the empirical relationship. Canopy height data were obtained from the Global Canopy Height (GCH) product, which combines GEDI LiDAR measurements with optical and radar satellite imagery to create this relationship. The GCH provides wall-to-wall canopy height estimates at 10-meter resolution, overcoming the spatial limitations of separate GEDI footprints. This section presents the comprehensive results of the oil palm age estimation framework, organized into spatial distribution of canopy height and validation (Section 3.1), oil palm age model performance (Section 3.2),

and spatial distribution of oil palm age across Indonesia (Section 3.3).

3.1 Spatial Distribution of Canopy Height and Validation

Canopy height extraction process using the RH98 metric from GEDI data, which covers 98% of the total LiDAR return energy. This metric has been widely validated as a robust proxy for canopy top height across various vegetation types. For oil palm plantations, the extraction was confined to areas identified as oil palm land cover through national classification maps, ensuring that height values corresponded exclusively to oil palm stands. The relationship between GCH-derived canopy height and actual oil palm age was investigated through regression analysis using field measurements and planting year records. Figure 8(a) shows sample application of the model validation site in Asahan, North Sumatra, Indonesia.

Linear regression analysis produced a coefficient of determination of $R^2 = 0.85$ between GCH-derived and field-measured tree height, indicating that the two datasets vary consistently with one another. However, correlation alone does not establish agreement (Figure 8(b)). GCH systematically underestimated field-measured height at every block above 2 m, with a mean bias of -5.9 m and a root mean square error of 6.8 m relative to the 1:1 line. Regressing field height on GCH height gave a slope of 1.667, which excludes unity and therefore indicates a difference in height scaling rather than a constant offset; the discrepancy widens with stand height. The frequently cited value of 2.54 m corresponds to the residual scatter around the fitted regression line, not to the deviation from the 1:1 line, and therefore should not be compared with the global GCH accuracy benchmark of approximately 2.7 m [44]. The distribution of data points in the scatterplot shows that most samples align with the regression trendline, although there are minor deviations. This variation is likely influenced by several factors such as topography and measurement technique [44]. The mixed pixel effect in remote sensing imagery causes a single pixel to encompass several land cover types with different spectral characteristics, resulting in varying fractional contributions from tree canopy, illuminated ground, and shaded ground depending on the sensor's viewing angle [45] and [46]. Topography also significantly affects canopy height extraction, while clumped canopy structure and vertical leaf orientation can affect the quality of canopy height estimates from satellite data [34] and [47].

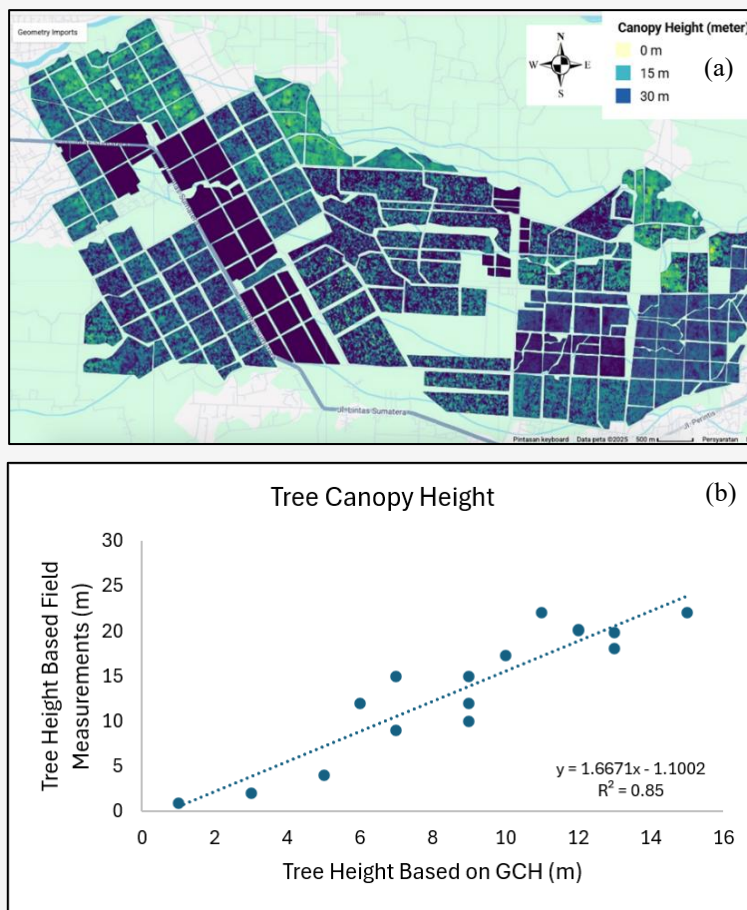


Figure 8: (a) Sample oil palm canopy height distribution based on GCH in Asahan, North Sumatra; (b) relationship between oil palm tree height estimated from GCH data and field-measured tree height

It should be noted that the canopy-height validation was conducted only in Asahan, North Sumatra. Therefore, the R^2 and $RMSE$ values reported in this section represent local validation performance rather than national-scale canopy-height accuracy. Although the subsequent age validation across five plantation sites provides evidence of model transferability across several regions in Sumatra and Kalimantan, additional field height measurements from diverse oil palm environments are required to establish a more comprehensive national validation of the GCH product.

3.2 Oil Palm Age Estimation and Validation Performance

The oil palm age estimation was implemented across Indonesia. Figure 9 shows the spatial distribution of estimated oil palm age across a sample plantation landscape, with individual management blocks classified into three age categories: red blocks (0–5 years) representing young plantations, green blocks (5–25 years) indicating mature productive stands,

and blue blocks (>25 years) indicating older plantations that may require replanting interventions. This spatial pattern demonstrates the mixed-age landscape characteristic of large-scale plantation management [40].

Validation was conducted at five plantation sites: Asahan (North Sumatra), Betung Krawo (South Sumatra), Ngabang (West Kalimantan), Tabara (East Kalimantan), and Tanah Laut (South Kalimantan). Statistical parameters were computed for each validation site (Table 3). The model's performance varied across the validation sites. At Asahan, where the model was calibrated, the estimated and recorded ages showed an in-block agreement with $R^2 = 0.88$ and $RMSE = 2.8$ years. This result is included for completeness but should not be interpreted as independent predictive skill. Across the four independent validation sites, R^2 values ranged from 0.61 to 0.90, while $RMSE$ values ranged from 1.0 to 2.1 years. This independent validation range better represents the reliability of the national mapping workflow than the calibration-site result.



Figure 9: Sample oil palm age distribution based on GCH

Table 3: Validation results of the GCH-based oil palm age estimation model across five plantation sites in Indonesia

Plantation Site	Province	R^2	$RMSE$ (years)	n block	Role
Asahan	North Sumatra	0.88	2.8	16	Calibration (in block)
Tanah Laut	South Kalimantan	0.90	2.1	9	Independent
Ngabang	West Kalimantan	0.76	1.0	9	Independent
Tabara	East Kalimantan	0.75	1.0	9	Independent
Betung Krawo	South Sumatra	0.61	2.0	9	Independent

The functional form of the height–age relationship for oil palm trees indicates that height growth tends to slow in older stands. To test the assumption of linearity, several models were applied to data from the calibration blocks. The same dataset was fitted with a linear model, a logarithmic model, and a saturating exponential model, and compared using the Akaike Information Criterion (AIC). The linear model had the lowest AIC value (37.7; $R^2 = 0.84$, $RMSE = 2.86$ years), followed by the saturating model (39.7; $R^2 = 0.84$, $RMSE = 2.86$ years) and the logarithmic model (48.9; $R^2 = 0.67$, $RMSE = 4.07$ years). Within the range of 0.5 to 22 years a linear model is therefore statistically preferred, and there is no evidence of curvature. This conclusion does not extend beyond the calibrated range: the data do not allow us to determine whether the relationship plateaus during the post-productive phase, and for stands older than 22 years linearity remains an assumption.

Evidence of systematic compression of estimates at the extremes was also observed. A plot of estimated against recorded age at the calibration site gave a slope of 0.70 and an intercept of 3.06, crossing the 1:1 line at about 10.3 years. Estimates are therefore higher than recorded ages in young stands and lower than recorded ages in older stands, with a difference of about 2.9 years at age 20 and 4.4 years at age 25. Part of this compression is an inevitable consequence of least-squares fitting, which reduces the slope of predicted against observed values by

approximately the coefficient of determination; for an R^2 of 0.84 the expected slope is about 0.84. The observed slope of 0.70 is lower than this expectation, indicating compression beyond statistical attenuation alone and consistent with the scale difference between GCH and the canopy-height source on which the model was calibrated. Age estimates are therefore expected to be conservative for the oldest stands, and the distinction between mature and old stands is the least reliable aspect of the model.

The Tanah Laut site in South Kalimantan demonstrated the highest independent accuracy ($R^2 = 0.90$; $RMSE = 2.1$ years), indicating that the model captures age variation effectively in homogeneous plantation structures. Moderate to reliable performance was observed at Ngabang and Tabara, each showing R^2 above 0.75 with $RMSE$ of around 1 year. These results suggest that the model performs best in regions with relatively consistent canopy structures and limited topographic variability. The lowest independent-site performance was observed in Betung Krawo ($R^2 = 0.61$, $RMSE = 2.0$ years). This result suggests that the height–age relationship was less stable at this site than at the other validation locations. Several factors may explain this reduced performance, including local variation in planting material, management intensity, soil fertility, drainage condition, and within-block canopy heterogeneity. In addition, differences between the BIOPAMA oil palm mask and actual plantation boundaries may affect GCH extraction near block

edges. Therefore, the Betung Krawo result is interpreted as an indication that the GCH-based age estimation workflow is more reliable in structurally homogeneous plantation blocks and less reliable in sites with heterogeneous canopy structure or management conditions [11].

Taken together, the validation results indicate that the GCH-based model is most reliable for homogeneous lowland plantations with a wide range of stand ages, and least reliable in highland, structurally heterogeneous, or narrow-age-range settings. The model should therefore be regarded as an operational screening tool for national and regional planning rather than as a substitute for block-level ground inventory.

3.3.1 National-scale age distribution

The implementation of the oil palm age estimation model using Global Canopy Height (GCH) data resulted in a comprehensive national-scale age distribution map at 10-meter spatial resolution (Figure 10). This 10-meter spatial resolution was achieved through the fusion of GEDI observations with Sentinel-2 imagery, which increased the spatial and temporal resolution of the canopy height model. The use of GCH data for age estimation has been validated in previous studies as a reliable predictor for oil palm structural parameters [48]. The spatial distribution shows clear regional heterogeneity. Mature plantations (5–25 years) dominate large areas in Sumatra and Kalimantan, which represent as the national production [49]. Meanwhile, newly developed areas such as Sulawesi and Papua show a higher proportion of young stands, indicating the presence of an active expansion front, consistent with patterns documented in recent land-use change studies. This spatial pattern is consistent with the characteristics of young plantations which show low canopy heights (5–10 m for 3–10 years of age)

compared to mature stands which have higher canopy heights (15–18 m for 15–30 years of age) [40].

The mapped oil palm area analyzed in this study covered 11.62 million hectares after applying the oil palm land-cover mask, GCH data availability screening, and the 0.5 ha minimum mapping unit filter. Within this analyzed area, mature plantations (5–25 years) accounted for 43.68%, followed by young plantations (0–5 years) at 30.28% and old plantations (>25 years) at 26.05% (Figure 11). These proportions should be interpreted with an appropriate margin of uncertainty. Given the independent-site RMSE of 1.0–2.1 years, pixels within approximately two years of a class boundary may be assigned to an adjacent class. More importantly, the calibration data span only 0.5–22 years, so no calibration observation falls within the >25-year class. The proportion reported for old plantations therefore rests on extrapolation beyond the calibrated range and carries substantially greater uncertainty than the young and mature figures. The reported percentages should be read as indicative rather than exact.

3.3.2 Regional patterns and analysis

Younger age classes represent replanted areas, particularly in Central Kalimantan and South Sumatra, which demonstrate sustained sectoral growth. In contrast, older plantations are predominantly located in North Sumatra, Riau, and Jambi, known as established production areas with aging plantations that increasingly require replanting. This pattern shows the dynamics of production saturation in older areas and expansion-driven regeneration in newer areas. Age distribution varies significantly across Indonesian for example in Sumatera Island (Figure 12) and Spatial distribution of oil palm plantation area by age group across Indonesia (Figure 13).

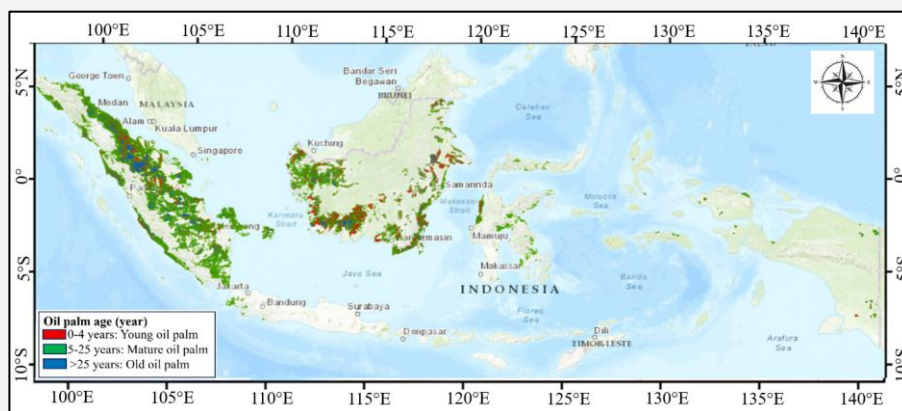


Figure 10: the spatial distribution of oil palm plantation based age in Indonesia

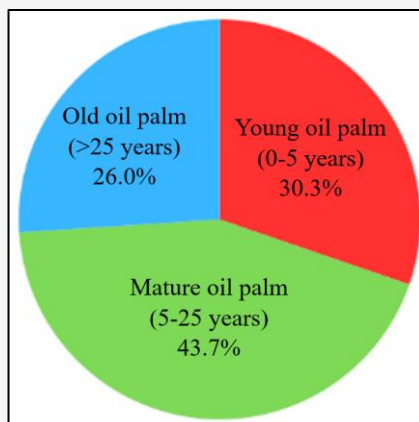


Figure 11: Proportional distribution of oil palm plantation area in Indonesia by age class

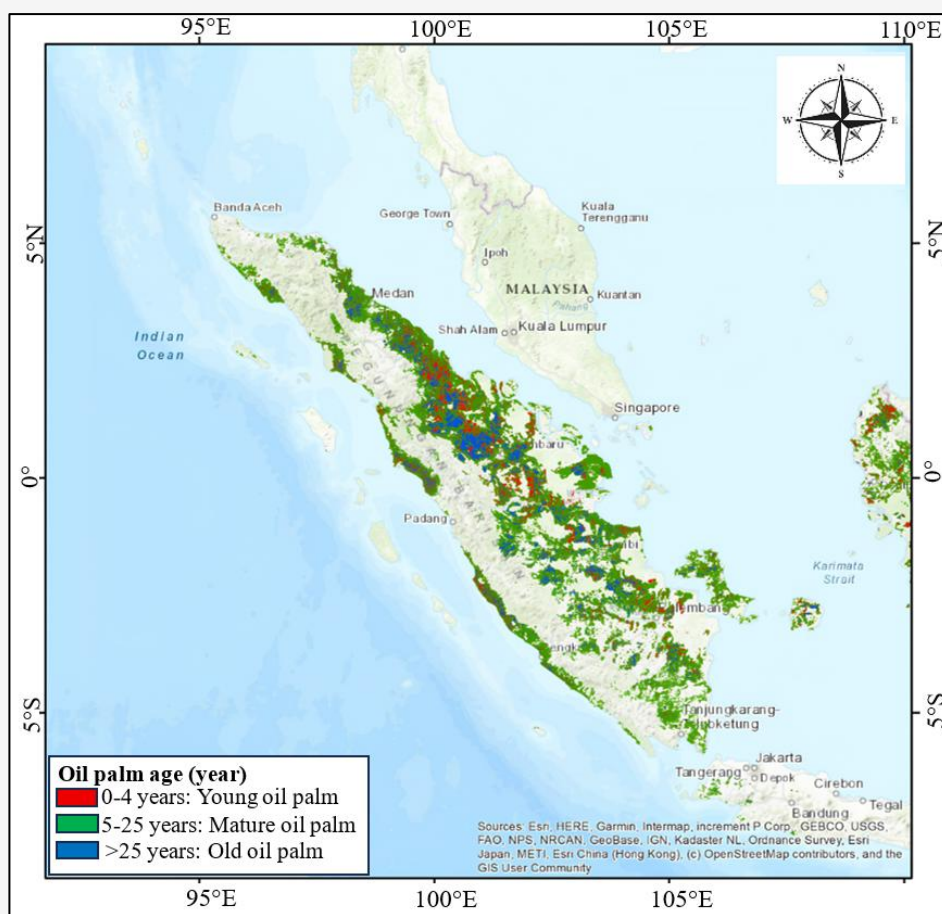


Figure 12: Estimated age distribution of oil palms on the Island of Sumatra

In general, South Sumatra, Jambi, and North Sumatra are the provinces with the largest areas of oil palm plantations. The age distribution in this region is relatively balanced between young, mature, and old plantations, although mature plantation blocks still dominate. This indicates that Sumatra is a major

production center but also faces significant replanting pressure due to the high proportion of aging plantations. A more detailed analysis of Indonesia's top five oil palm producing provinces is summarized in Table 4.

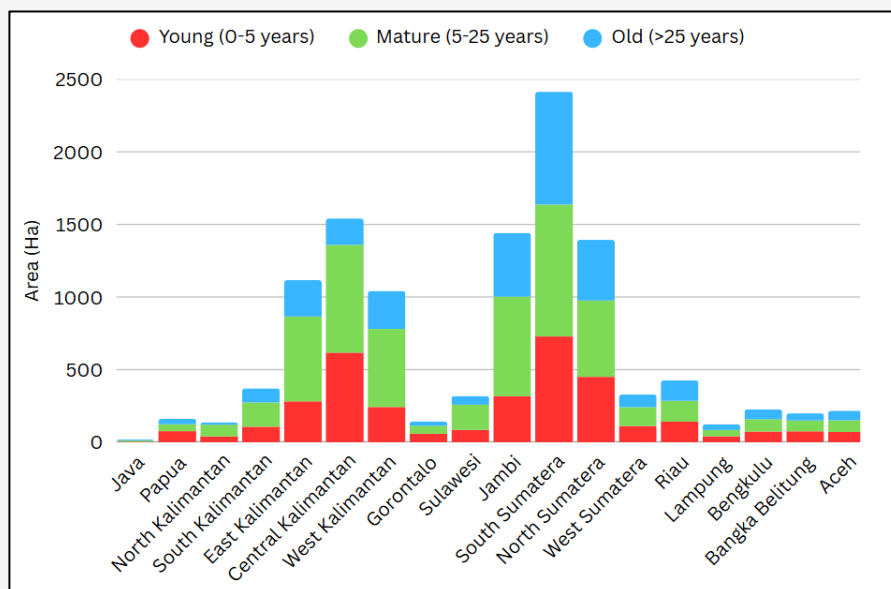


Figure 13: Spatial distribution of oil palm plantation area by age group across Indonesia

Table 4: Regional distribution of oil palm age classes by province. Area values are expressed in thousands of hectares

Region	Total Area (thousand ha)	Young area (thousand ha)	Mature area (thousand ha)	Old area (thousand ha)	Dominant Age Phase
South Sumatra	2,413.2	728.26	908.72	776.26	Balanced
Central Kalimantan	1,540.1	616.51	742.74	180.84	Young–Mature
Jambi	1,441.7	316.63	685.98	439.03	Mature–Old
North Sumatra	1,393.8	450.15	525.71	417.89	Transitional
East Kalimantan	1,116.3	281.34	584.48	250.48	Mature

South Sumatra emerges as the region with the largest total plantation area (2.41 million ha), characterized by a relatively balanced distribution across young (30.2%), mature (37.7%), and old (32.2%) classes. Central Kalimantan (1.54 million ha) is dominated by young plantations (40.0%) and mature plantations (48.2%), reflecting ongoing expansion supported by large-scale estates. With only 11.7% of plantations classified as old, the province faces minimal replanting pressure in the short term, allowing management to focus on optimizing young plantation development and soil fertility management to maximize future productivity [27] and [40]. Jambi (1.44 million ha) shows a contrasting and concerning trend, with older plantations (approximately 439,000 ha or 30.4%) accounting for a large share of the total area. The high proportion of older stands may indicate that many plantations are approaching the end of their productive life cycle [10]. The relatively low proportion of young plantations (22.0%) indicates that replanting activities are unable to replace the aged plantation availability [27]. Without a well-planned replanting strategy and proper

management zoning, the province risks experiencing a significant decline in productivity in the coming decades, as oil palm productivity typically peaks between 8 and 18 years and declines sharply after 25 years [10] and [41]. These results are indications for screening purposes rather than operational instructions. The older age classes lie outside the model's calibrated age range and are therefore its least reliable output; field verification of stand age is recommended before replanting decisions are made on this basis. North Sumatra (1.39 million ha) shows a relatively equal distribution across all age classes: young (32.3%), mature (37.7%), and old (30.0%). This reflects one of Indonesia's oldest oil palm areas, characterized by continuous processes of planting, maturation, and replanting, resulting in a landscape with varied ages and variable canopy structures [32] and [38]. East Kalimantan (1.12 million ha) mostly consists of mature plantations (584,000 ha or 52.4%). With a moderate proportion of young (25.2%) and old (22.4%) plantations, the province demonstrates relatively balanced plantation management with controlled replanting needs [47].

4. Conclusion

This study developed and evaluated an operational workflow for estimating the spatial distribution of oil palm age across Indonesia using Global Canopy Height (GCH) data within the Google Earth Engine platform. The principal contribution of this study is methodological and informational rather than the development of a new age-estimation model. An established canopy height–age relationship was adapted to a 10 m GCH input and applied consistently at the national scale, producing a nationally uniform oil palm age dataset for Indonesia.

At the Asahan calibration site, GCH-derived canopy height correlated strongly with field measurements ($R^2 = 0.855$) but systematically underestimated absolute height by a mean of 5.9 m. This indicates that GCH and field-measured height capture consistent canopy-height variation, although their absolute values differ because of sensor characteristics, spatial sampling, canopy structure, and field measurement geometry. The CHM-only age model used in this study was derived from Sentinel-1A InSAR-based canopy height and achieved $R^2 = 0.94$ with $RMSE = 1.79$ years in the original calibration. When applied to GCH data, the model reproduced recorded plantation ages at the Asahan calibration site with $R^2 = 0.88$ and $RMSE = 2.8$ years. This result represents in-block agreement and should not be interpreted as independent predictive capability.

Across four independent validation sites in Sumatra and Kalimantan, the age model achieved R^2 values between 0.61 and 0.90 with $RMSE$ values ranging from 1.0 to 2.1 years. These results indicate moderate to strong transferability across the evaluated lowland plantation environments, although performance varied among sites. Applied to 11.62 million hectares of mapped oil palm area, the model estimated that mature plantations (5–25 years) account for 43.68% of the analyzed area, young plantations (0–5 years) for 30.28%, and old plantations (>25 years) for 26.05%. Regional analysis identified Jambi as having the highest proportion of old stands (30.4%) and Central Kalimantan as having the highest proportion of young stands (40.0%). At the national level, the resulting oil palm age map provides a spatially consistent baseline for supporting evidence-based plantation planning, replanting prioritization, productivity monitoring, and sustainable oil palm governance in Indonesia. The dataset can help government agencies, plantation companies, and related stakeholders identify regions where aging stands may require field verification and replanting intervention, while also distinguishing areas

dominated by young and mature plantations for long-term productivity planning. By providing nationally comparable information on plantation age structure, the workflow can support more targeted allocation of replanting programs, improve plantation inventory systems, strengthen monitoring of strategic plantation commodities, and contribute to sustainability-oriented land management policies. The approach also demonstrates the potential of cloud-based geospatial analytics to support national-scale decision making in the plantation sector, particularly in contexts where spatially explicit field inventories remain limited.

Several limitations qualify these results and should guide their interpretation. First, the age model was calibrated using Sentinel-1A InSAR-derived canopy height and applied to GCH values.

Although GCH and InSAR-derived CHM showed consistent block-level variation, GCH systematically recorded lower canopy-height values, and the cross-sensor uncertainty was not analytically corrected in this workflow. Second, the age model was calibrated at a single site using 16 planting-year blocks spanning 0.5–22 years. No calibration observation falls within the >25-year class, so estimates for old plantations rely on extrapolation and should be treated as the least reliable output. Because replanting priorities depend strongly on the identification of old stands, areas mapped as >25 years should be interpreted as screening indications requiring field verification. Third, model performance varied across validation sites, indicating that transferability is influenced by local plantation structure, management practices, topography, soil conditions, and environmental variability. The workflow is therefore more suitable for relatively homogeneous lowland plantations than for topographically complex or structurally heterogeneous landscapes. Fourth, the GCH product represents 2020–2021 conditions while reference data were collected in 2022. This introduces a modest temporal offset, which was addressed by referencing plantation ages to the GCH acquisition epoch. Fifth, the 0.5 ha minimum mapping unit and the accuracy characteristics of the BIOPAMA oil palm mask may bias the analyzed area toward larger and more spatially continuous plantation blocks. As a result, fragmented smallholder plantations may be under-represented in the national proportions.

Future research should refine the workflow by incorporating multi-region calibration data, additional field measurements from both industrial and smallholder plantations, improved oil palm masks, and locally adjusted canopy height–age models. These improvements would strengthen the

reliability of national oil palm age monitoring and enhance its operational use for replanting policy, productivity assessment, and sustainable plantation management in Indonesia.

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