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WHAT INSIGHTS CAN SENTINEL-2A NDVI AND NUTRIENT VALIDATION PROVIDE FOR OIL PALM HEALTH ASSESSMENT? OBSERVATIONS FROM SOUTHEAST SULAWESI, INDONESIA

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Abstract: Monitoring oil palm health using spatial data is essential for optimizing plantation productivity and supporting sustainable management. This study assessed vegetation conditions at Sultra Prima Lestari Ltd. plantation in Southeast Sulawesi, Indonesia, using Sentinel-2A imagery acquired in June 2025 and field data collected from Leaf Sampling Units (LSUs) between April–July 2025. The Normalized Difference Vegetation Index (NDVI) was calculated from the imagery and classified into three health categories: *unhealthy* (from –1.00 to 0.15), *moderately healthy* (from 0.15 to 0.35), and *very healthy* (from 0.35 to 1.00). Field validation across 94 stratified random sampling plots confirmed that NDVI reflects differences in canopy density and leaf greenness. Correlation analyses showed positive associations with plant macronutrients: nitrogen ($R^2 = 0.603$), phosphorus ($R^2 = 0.575$), potassium ($R^2 = 0.645$), and magnesium ($R^2 = 0.520$). Spatial analysis revealed heterogeneity in vegetation health across the plantation, with very healthy areas concentrated in central and western divisions, and unhealthy patches primarily in the eastern division. These results indicate that NDVI, when interpreted alongside systematic field measurements, is a cost-effective and spatially explicit indicator of oil palm physiological condition, without implying absolute validation. The findings support targeted, site-specific agronomic interventions and demonstrate the value of integrating moderate-resolution satellite imagery with field-based data for scalable monitoring of large-scale tropical plantations.

Keywords: NDVI; oil palm health; macronutrients; remote sensing; spatial analysis

1. Introduction

As of 2019, Indonesia produced over 51.8 million tonnes of palm oil and is recognized as one of the world's leading producers of this commodity, with production continuing to expand in response to both global and domestic demand (Taufik et al., 2020). Oil palm cultivation has

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become a crucial component of national economic development, rural economies, and the global commodity supply chain. Despite these benefits, unstable productivity in large-scale oil palm plantations poses a significant risk, requiring continuous monitoring of vegetative health, as declining foliage condition can directly reduce yield and increase management costs.

The physiological condition and nutrient availability strongly influence oil palm growth, particularly macronutrients such as nitrogen (N), phosphorus (P), potassium (K), and magnesium (Mg). Deficiencies in these nutrients lead to reduced canopy density, leaf discoloration, and decreased photosynthetic activity (Yurianda et al., 2023). Conventional methods for assessing plantation condition, such as leaf sampling and visual inspection, remain widely used in the industry. While these methods provide accurate point-based information, they are inefficient for large-scale monitoring, as they are labor-intensive, time-consuming, and spatially limited.

Remote sensing has increasingly been applied for large-scale vegetation monitoring. Satellite imagery enables the assessment of vegetation conditions across extensive areas by capturing information related to canopy structure and chlorophyll content (Charloq et al., 2023). Geospatial technologies have also been widely applied in large-scale plantation management studies (Fragastia et al., 2024). Among available satellite platforms, Sentinel-2A is frequently used for plantation-scale analysis due to its high data availability, free access, and suitable multispectral capabilities. Its spatial resolution (10–60 m) is appropriate for capturing variability in crop conditions at the scale of plantation divisions or blocks (Saputro et al., 2024; Yuniasih & Adjie, 2022).

The Normalized Difference Vegetation Index (NDVI) is one of the most commonly applied indicators derived from multispectral satellite imagery. By exploiting differences in the reflectance of red and near-infrared wavelengths, NDVI represents vegetation greenness, canopy vigor, and photosynthetic activity. Previous studies have applied NDVI in oil palm plantations to evaluate plant health and detect spatial variability in vegetation performance (Masrol et al., 2023).

Recent studies indicate that NDVI and other vegetation indices have become key tools in oil palm research, covering aspects such as productivity estimation and plantation health monitoring. Rahmasari et al. (2022) utilized NDVI and the Atmospherically Resistant Vegetation Index (ARVI) derived from Sentinel-2A imagery to estimate oil palm productivity, demonstrating that combining vegetation indices with plant age can improve yield variability models at the plantation block scale. Furthermore, NDVI-derived features have been used to identify tree abnormalities, count individual oil palm trees, and classify plantation conditions through the integration of machine learning and deep learning approaches, including neural networks and object-based detection methods, achieving accuracies exceeding 90% (Minarto et al., 2024; Wibowo et al., 2022). In addition, combining NDVI with other vegetation indices using multi-index approaches, supported by Unmanned Aerial Vehicle (UAV) imagery and field observations, has enabled reliable differentiation between healthy and stressed oil palm trees in heterogeneous plantation environments (Judith et al., 2025; Nuthammachot & Stratoulas, 2023), with spatial verification using drone-based data (Ningrum Amrul et al., 2025).

Despite these advancements, several important limitations remain. Many studies focus primarily on productivity estimation or classification accuracy (Akmal et al., 2022; Taufik et al., 2020; Yuniasih & Adjie, 2022), while relatively few validate NDVI-derived vegetation conditions using field-based physiological indicators, particularly leaf nutrient status (Masrol et al., 2023). Moreover, although UAVs, deep learning, and multi-sensor integration offer significant potential, they are often costly and operationally complex, making them less suitable for routine plantation monitoring (Charloq et al., 2023; Puttinaovarat et al., 2025).

Another limitation is the lack of empirical studies on oil palm health in Eastern Indonesia (particularly Sulawesi), compared to more extensively studied regions such as Sumatra (e.g., Taufik et al., 2020; Yurianda et al., 2023) and Java (Akmal et al., 2022). Therefore, there is a clear need for spatially explicit and operationally feasible methodologies that can accurately and consistently represent oil palm health under real plantation management conditions.

Langgikima Subdistrict, North Konawe Regency, Southeast Sulawesi, is an important oil palm production area characterized by favorable natural conditions, including fertile soils, adequate rainfall, and a tropical climate. Sultra Prima Lestari Ltd., which operates a large plantation in this area, is a major contributor to the local economy. However, the region still lacks comprehensive and spatially detailed studies of oil palm health using satellite remote sensing integrated with field-based nutrient validation. Understanding the spatial variability of plantation health is essential for supporting sustainable land management through targeted interventions.

To address this gap, this study integrates NDVI derived from Sentinel-2A imagery with field-based measurements of macronutrients (N, P, K, Mg) collected at Leaf Sampling Units (LSUs). This approach enables a spatially explicit assessment of oil palm health and examines how environmental factors (e.g., topography and soil conditions) and management practices influence vegetation responses across the plantation. By linking systematic field sampling with moderate-resolution satellite data, the study provides empirical support for the use of NDVI as an operational tool for plantation health assessment. The findings contribute to GIS-based approaches in human–environment geography and plantation monitoring, offering a rapid, cost-effective, and scalable method to support sustainable oil palm production in Indonesia and other tropical regions.

2. Materials and methods

2.1. Study area

The research was conducted at Sultra Prima Lestari Ltd. oil palm plantation in Langgikima Subdistrict, North Konawe Regency, Southeast Sulawesi Province, Indonesia (03°16'00"–03°24'00" S; 122°10'00"–122°18'00" E). The study area boundaries were delineated using the official Indonesian administrative geodatabase published by the Badan Informasi Geospasial (BIG, 2023), September 2023 edition, representing the most recent nationally standardized spatial reference. This dataset integrates topographic maps (Rupabumi Indonesia; 1:25,000–1:50,000), field-based boundary surveys, legally established administrative limits, and updated coastline and national boundary data to ensure spatial accuracy and consistency.

The plantation is divided into several management units, with Divisions II (Molore), III (Langgikima), and IV (Tobimeita) included in this study, while Division I was excluded due to persistent cloud interference and incomplete satellite coverage. These divisions represent heterogeneous planting conditions, including variations in palm age, canopy density, and management intensity, providing a representative framework for spatial vegetation analysis. Land use within the plantation is dynamic, requiring continuous monitoring to support sustainable management.

Topographically, the area is characterized by mountainous, hilly, and undulating terrain surrounding lowland agricultural zones, with elevations ranging from approximately 10 to 91 m a.s.l. (BPS-Statistics Indonesia, 2025). This variability influences drainage patterns, surface runoff, and soil moisture distribution, which are critical for oil palm productivity. The

plantation is intersected by small rivers and runoff channels that contribute to local hydrology and may support irrigation and drainage management.

Climatically, the region experiences a tropical monsoonal climate, with a wet season from December to May and a dry season from June to November. A transitional period (Pancaroba) occurs around September, characterized by irregular rainfall. Annual rainfall averages approximately 3,006 mm, with 18–19 rainy days per month, peaking in December (BPS-Statistics Indonesia, 2025). Air temperatures in the study area generally range from 22 to 29 °C throughout the year, indicating persistently warm tropical conditions that support optimal oil palm growth (Badan Meteorologi, Klimatologi, dan Geofisika, 2025). The geographic location and administrative extent of the study area are presented in Figure 1.

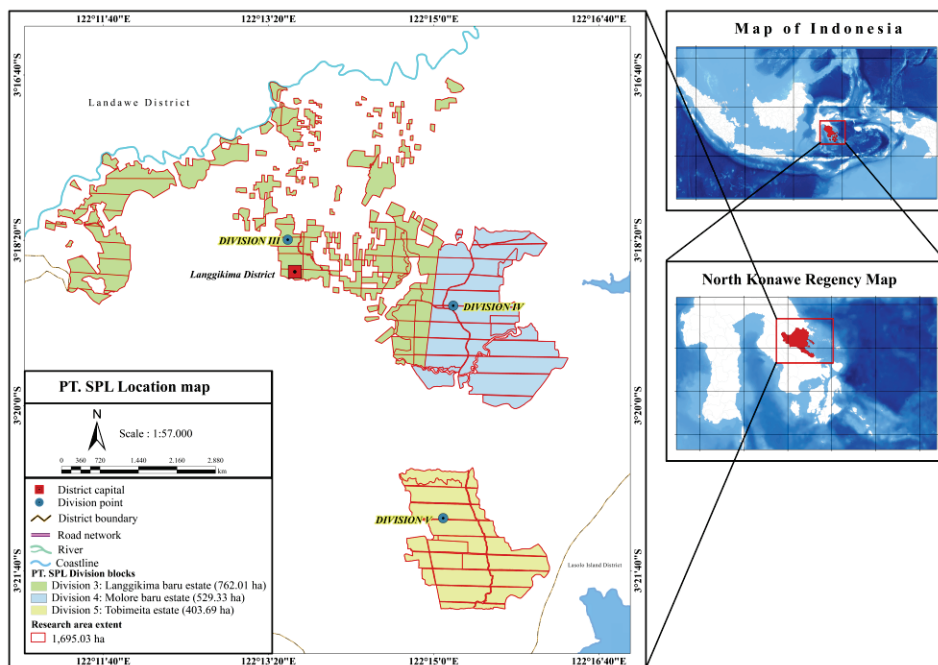


Figure 1. Location of the study area.

Note. Contains data adapted from *Geodatabase of Indonesian administrative boundaries (regency/city level)*, September 2023 edition [Data set], by Badan Informasi Geospasial, 2023 (<https://geoportal.big.go.id>).
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Soil characteristics within the plantation are typical of tropical lowlands, with relatively fertile alluvial soils in valley areas and less fertile soils on hills and slopes. In combination with topography and rainfall, these factors influence drainage, erosion potential, and spatial variability in productivity (BPS-Statistics Indonesia, 2025). Accessibility and internal road infrastructure vary, with some areas difficult to reach, potentially affecting the availability of cloud-free satellite imagery for monitoring. Sultra Prima Lestari Ltd. is a major palm oil producer in North Konawe Regency, covering approximately 7,777.62 ha across Divisions II–IV. Its spatial heterogeneity and dynamic land use provide an ideal setting for NDVI-based assessment of oil palm health and variability.

2.2. Research design and analytical approach

To evaluate oil palm health at Sultra Prima Lestari Ltd., this study integrates NDVI derived from Sentinel-2A imagery with field-based macronutrient measurements (N, P, K, Mg) collected at LSU. This approach enables spatially explicit assessment of vegetation health and the influence of environmental and management factors across the plantation. A quantitative spatial research design with a case study approach was applied, combining satellite remote sensing and ground-based observations. Vegetation condition was assessed using NDVI, while field validation was conducted through LSU measurements and visual canopy observations, providing a detailed evaluation of vegetation health and supporting the reliability of NDVI under operational plantation conditions (Nikolić, 2025).

This study is explicitly designed as a single-period spatial analysis conducted within a harmonized temporal window (April–July 2025). Sentinel-2A imagery, field measurements, canopy observations, and photographic documentation were all collected within the same phenological period to ensure full temporal consistency. No multi-year or multi-temporal comparison was performed, and all analyses are interpreted as a single-season vegetation condition snapshot.

2.3. Data sources

The researchers collected two types of data: primary and secondary. Primary data collection used field observations and LSU measurements to validate how well satellite-derived vegetation indices could capture oil palm health in other studies integrating remote sensing (Nuthammachot & Stratoulis, 2023). The satellite-derived NDVI values were supported by systematic leaf sampling at LSU plots to measure key macronutrients, ensuring that field observations provide a biophysical reference for interpreting remotely sensed vegetation conditions.

Primary data consisted of field observations conducted during April–July 2025, including LSU measurements, canopy density assessments, and photographic documentation. These measurements captured macronutrient concentrations (N, P, K, Mg) and canopy structural attributes used as independent field-based indicators of vegetation condition. Secondary data included Sentinel-2A Level-2A multispectral imagery acquired in June 2025, plantation boundary datasets, oil palm planting year (age structure), maps from Sultra Prima Lestari Ltd., and administrative boundary data from Badan Informasi Geospasial (2023).

The integration of remotely sensed and field-based datasets follows a remote sensing-based crop monitoring framework, where multi-source data fusion is recommended to improve the robustness of vegetation health assessment in plantation systems (Judith et al., 2025; Tamburadzhiev, 2024). Accordingly, the alignment between satellite imagery and field observations was ensured through synchronized data acquisition within the same observation period, enabling direct spatial comparison between remotely sensed vegetation signals and ground-based biophysical measurements.

2.4. Sentinel-2 data and pre-processing

Sentinel-2A multispectral imagery (Tile IDs: T51SFC, T51SFD) was used as the primary remote sensing dataset for this study. The imagery was selected to align with the field campaign framework defined in Section 2.1, ensuring consistency with the study's temporal design. Cloud cover was below 10%, and image selection was based on optimal vegetation observation conditions within the study period, ensuring sufficient spatial heterogeneity for NDVI analysis. All image processing was conducted using ArcGIS Pro 3.1 (Esri Inc., 2023).

All images were geometrically and atmospherically corrected to Bottom of Atmosphere (BOA) reflectance as Level-2A products, ensuring standardized spectral inputs for vegetation analysis (Nuthammachot & Stratoulas, 2023). Cloud and shadow contamination were removed using the QA60 band and Fmask algorithm (Zhu & Woodcock, 2014; Zhu et al., 2020), with masked pixels treated as NoData to preserve only valid vegetation signals. Images were clipped to plantation boundaries and internal management divisions provided by Sultra Prima Lestari Ltd., restricting analysis to the study area. All datasets were projected to UTM WGS84 Zone 51S, and bilinear resampling was applied to maintain spatial consistency. This preprocessing workflow supports robust NDVI derivation and ensures spatial comparability across the study area. It follows established Sentinel-2 processing standards for vegetation monitoring in plantation systems (Nadzirah et al., 2024; Potić et al., 2024; Zhu et al., 2020).

2.5. NDVI classification and interpretation

The NDVI is a remote sensing indicator of vegetation, its greenness (vegetation index) and its ability to photosynthesize (vegetative photosynthetic activity). NDVI was calculated from Sentinel-2A images using two bands: the red band (Band 4) and the near infrared band (Band 8) as indicated in Equation (1):

$$NDVI = \frac{NIR - Red}{NIR + Red} \quad (1)$$

where NIR or near-infrared reflectance, is recorded in Band 8 and Red reflectance is recorded in Band 4 (Nițu et al., 2025; Zhao & Qu, 2024).

Prior to classification, all non-vegetation areas including water bodies, roads, bare soil, and shadows were masked using the QA60 band, Fmask algorithm (Zhu & Woodcock, 2014; Zhu et al., 2020), and plantation boundaries, with masked pixels treated as NoData to ensure negative or near-zero NDVI reflects sparse or stressed vegetation. NDVI (from -1 to $+1$) was classified into *unhealthy* (from -1.00 to 0.15), *moderately healthy* (from 0.15 to 0.35), and *very healthy* (from 0.35 to 1.00) plants, adopting thresholds from Taufik et al. (2020) and calibrated with field observations. This approach follows standard oil palm remote sensing practices (Nadzirah et al., 2024; Potić et al., 2024). Field validation using the 94 plots in Divisions II–IV confirmed that high NDVI corresponded to dense, healthy canopies, and low NDVI to sparse/stressed vegetation, supporting the reliability of this classification.

2.6. Field sampling design (LSU, number of points)

Field sampling covered the entire oil palm plantation owned by Sultra Prima Lestari Ltd. as the spatial unit of analysis. Field measurements were conducted within a pre-defined study timeframe to support the validation of vegetation conditions derived from NDVI. Sample plot size (A) was determined based on the Sentinel-2A spatial resolution and RMSE considerations (Justice & Townshend, 1981, cited by McCoy, 2005) using:

$$A = P(1 + 2L) \quad (2)$$

where P is the spatial resolution of the imagery (10 m) and L is the RMSE (0.5). This resulted in 20×20 m plots, suitable for moderate-resolution satellite imagery.

A stratified random sampling approach was applied, dividing the plantation into strata according to NDVI-derived vegetation health classes. Sampling points were randomly selected within each stratum, and plots were distributed across Divisions II–IV to mitigate

potential circularity from NDVI-based stratification, ensuring representative coverage of heterogeneous canopy conditions (Nadzirah et al., 2024).

The total number of sampling points ($n = 94$) was calculated using Slovin's formula ($e = 0.1$; $N = 1,567$), resulting in 94 plots. This presentation provides transparency of sample size derivation while remaining concise for readers familiar with Slovin's formula (Lv et al., 2021).

Field measurements included LSU sampling, canopy observations, and photographic documentation, all conducted under consistent field conditions within the study period framework. This field design ensures that field data represent spatial variability of plantation conditions rather than a single-date snapshot, providing robust validation for NDVI-derived vegetation health classes.

2.6.1. Leaf sampling and sample preparation

Leaf samples were collected from the 17th frond, consisting of four leaflets taken from the middle portion on both sides. Samples were oven-dried at 70–80 °C for approximately 20 hours to constant weight and subsequently ground into fine powder prior to laboratory analysis.

2.6.2. Laboratory nutrient analysis and quality assurance/quality control (QA/QC)

All macronutrient analyses were conducted at a certified soil and plant tissue laboratory using standard procedures. Total N was determined by the Kjeldahl digestion method, P by the molybdenum blue spectrophotometric method after acid digestion, and K and Mg by atomic absorption spectrophotometry (AAS) following dry ashing and acid extraction. Nutrient concentrations were expressed on a dry weight basis, with N and P reported as percentage (%) and K and Mg as mg/kg, as presented in Table 2.

Quality assurance and quality control (QA/QC) procedures were implemented to ensure analytical reliability, including reagent blanks, calibration with certified standard solutions, and duplicate analysis of 10% of samples to assess precision. Calibration curves achieved a minimum coefficient of determination ($R^2 \geq 0.99$) prior to measurement, while instrument detection and quantification limits followed certified laboratory standard operating procedures and remained within acceptable ranges for plant tissue analysis.

2.7. Statistical analysis and validation

Each sampling site included field data on geographical coordinates, planting block, planting year (oil palm age), canopy density, and LSU measurements. Coordinates were obtained using GPS, while canopy density was visually assessed as a proxy for leaf abundance and photosynthetic potential, which is closely associated with NDVI-derived vegetation greenness (Nuthammachot & Stratoulis, 2023). The location of the sampling plots is shown in Figure 2, providing a spatial context for linking field observations with NDVI data.

Leaf sampling followed standardized protocols and was conducted between 08:00 and 11:00 under dry weather conditions. Samples were collected from the 17th frond, consisting of four leaflets taken from the middle portion on both sides, followed by oven drying at 70–80 °C for approximately 20 hours and subsequent grinding for laboratory analysis.

Vegetation health classes derived from NDVI were validated using field observations and LSU measurements. NDVI thresholds were adopted from previous oil palm studies and adjusted based on field data to ensure representativeness under local plantation conditions (Congalton & Green, 2019). Field validation of oil palm health conditions is illustrated in

Figure 4, showing three classes of plants: *very healthy* (A), *moderately healthy* (B), and *unhealthy* (C; see Results). These data allowed for a spatially explicit analysis, linking biophysical conditions (e.g., topography, soil composition) and land management practices to vegetation responses across the plantation.

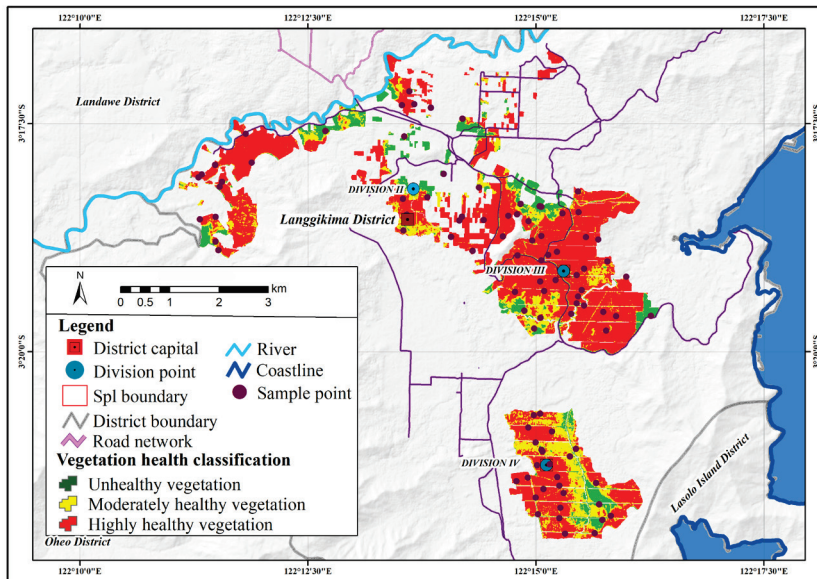


Figure 2. Spatial distribution of sampling plots at Sultra Prima Lestari Ltd. plantation, Southeast Sulawesi, Indonesia.

Note. Contains adapted data from *Sentinel-2 MSI Level 2-A* (Collection 1) [Data set] (images acquired in June, 2025), by European Union, European Space Agency, and Copernicus, 2021 (<https://dataspace.copernicus.eu/>), CC BY-SA 4.0; *Plantation boundary* [Data set], by Sultra Prima Lestari Ltd., 2025. Copyright 2025 by Sultra Prima Lestari Ltd., adapted with permission; *Geodatabase of Indonesian administrative boundaries (regency/city level)*, *September 2023 edition* [Data set], by Badan Informasi Geospasial, 2023 (<https://tanahair.indonesia.go.id/portal-web>), in the public domain.

Map produced from the authors' analysis (2025), based on Sentinel-2A imagery and plantation boundary data provided by Sultra Prima Lestari Ltd, and administrative boundary data from the Badan Informasi Geospasial (2023). Plantation boundary data and internal management divisions were provided by Sultra Prima Lestari Ltd. under restricted access for research purposes and are not publicly available. Sampling plots were generated using a stratified random sampling design based on NDVI-derived vegetation health classes.

The relationship between NDVI and nutrient concentrations (N, P, K, Mg) was analyzed using both correlation and regression approaches. Correlation analysis was used to investigate the relationship between NDVI and field-based indicators, with its magnitude expressed by the coefficient of determination (R^2), a standard approach in remote sensing validation studies where higher R values indicate stronger relationships (Lee et al., 2024; Rudorff et al., 2018; Qin et al., 2021). Simple linear regression was applied to quantify these relationships, reporting slope (β), standard error, p -value, and 95% confidence interval for each nutrient (see Table 2).

Model diagnostics were performed to verify the assumptions of linearity, homoscedasticity, and normality of residuals. The analysis focuses on continuous relationships between NDVI and nutrient status rather than classification accuracy; therefore, validation is based on regression-based metrics rather than confusion matrix-based measures.

3. Results

3.1. Spatial distribution of vegetation density based on NDVI

NDVI values ranged from -0.05 to 0.78 across the plantation, with higher values concentrated in the central and southern blocks of Division III, indicating denser and healthier canopies. Lower NDVI values were observed mainly on the northern slopes of Division II, corresponding to areas with thinner canopy and visible stress symptoms. This spatial heterogeneity confirms that NDVI effectively captures intra-plantation differences in canopy density and vegetation health, as calculated and validated following the procedures described in Section 2.4 and 2.6 (Figure 2, Table 1).

Table 1. NDVI-based vegetation health area distribution (Sultra Prima Lestari Ltd. plantation, 2025)

Class	NDVI range	Area coverage (%)	Vegetation health	Map color
1	from -1.00 to 0.15	8	<i>Unhealthy</i>	Red
2	from 0.15 to 0.35	57	<i>Moderately healthy</i>	Yellow
3	from 0.35 to 1.00	35	<i>Very healthy</i>	Green

Note. Area coverage calculated from NDVI raster analysis of Sentinel-2A imagery (2025). Colors correspond to the classification scheme used in Figure 6.

NDVI values theoretically range from -1 to $+1$, with higher values representing healthier vegetation. Sentinel-2 imagery has been widely used globally to assess oil palm health, showing strong correlations with canopy density and nutrient status, although classification thresholds depend on study objectives and vegetation conditions (Akmal et al., 2022; Minarto et al., 2024). In this study, NDVI was divided into three categories, initially based on literature and fine-tuned through field validation (Table 1): *unhealthy* (from -1.00 to 0.15), *moderately healthy* (from 0.15 to 0.35), and *very healthy* (from 0.35 to 1.00) plants. This classification allows practical and geographically explicit differentiation of oil palm health across the plantation, consistent with Sentinel-2 NDVI-based monitoring practices (Banyuriatiga et al., 2025; Taufik, 2020).

Using the NDVI classification shown in Table 1, raster analysis revealed that most of the plantation is dominated by moderately dense vegetation (NDVI ~ 0.15 – 0.35), while areas above 0.35 represent high-density, very healthy vegetation. Figure 3 illustrates the spatial distribution of moderate and high-density vegetation across Divisions II, III, and IV.

To ensure robust NDVI-based results, the analysis included Divisions II, III, and IV, where high-quality Sentinel-2A imagery and complete field sampling data were available. A total of 94 plots were sampled across the three divisions: 33 plots in Division II, 35 plots in Division III, and 26 plots in Division IV (Figure 2). This approach ensures transparency in sampling while minimizing bias from low-quality or missing data, and aligns with recommended practices for NDVI-based vegetation monitoring (Congalton & Green, 2019; Rudorff et al., 2018). NDVI classification and spatial mapping were then applied across all three divisions, with Figures 3 and 6 illustrating the spatial distribution of vegetation density and oil palm health, respectively.

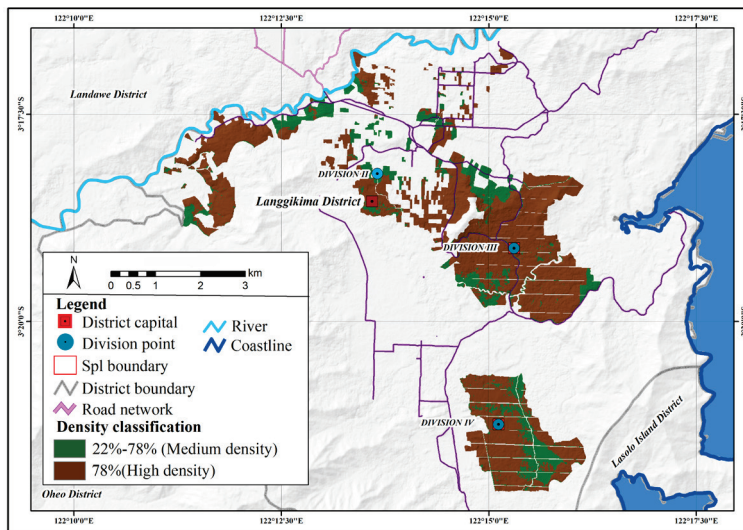


Figure 3. Vegetation density classification of Sultra Prima Lestari Ltd. plantation based on NDVI.

Note. Contains adapted data from *Sentinel-2 MSI Level 2-A* (Collection 1) [Data set] (images acquired in June, 2025), by European Union, European Space Agency, and Copernicus, 2021 (<https://dataspace.copernicus.eu/>), CC BY-SA 4.0; *Plantation boundary* [Data set], by Sultra Prima Lestari Ltd., 2025. Copyright 2025 by Sultra Prima Lestari Ltd., adapted with permission; *Geodatabase of Indonesian administrative boundaries (regency/city level)*, September 2023 edition [Data set], by Badan Informasi Geospasial, 2023 (<https://tanahair.indonesia.go.id/portal-web/>), in the public domain.

3.2. Field validation of NDVI-based oil palm health

Field validation of NDVI classifications showed that plots with high NDVI values generally corresponded to higher nutrient content and denser canopies, while plots with low NDVI values were associated with visible stress symptoms such as leaf chlorosis and sparse canopy structure. Rather than reporting categorical agreement metrics, validation is presented descriptively and supported by continuous statistical analysis to ensure methodological consistency with the study design. Figure 4 illustrates these three health classes, providing a spatially explicit confirmation of NDVI's reliability as a proxy for oil palm health.

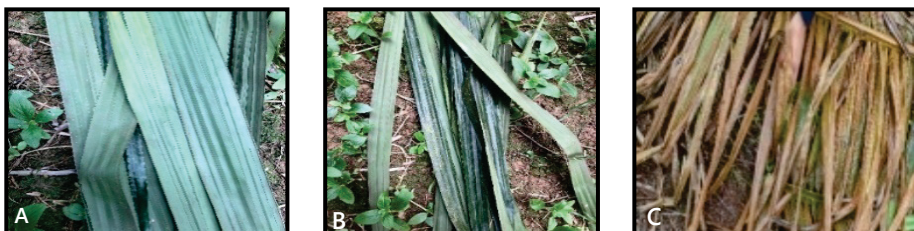


Figure 4. Field validation of oil palm health conditions at Sultra Prima Lestari Ltd. plantation.

Note. Photographs were taken by the author during field sampling in 2025 under dry weather conditions, following standard oil palm leaf sampling protocols. Panel A: *Very healthy* plants showing dense crowns and bright leaf color. Panel B: *Moderately healthy* plants with moderate crown density. Panel C: *Unhealthy* plants showing low crown density and discolored leaves. Sampling was conducted in Divisions II–IV, which correspond to areas with high Sentinel-2A quality (refer to Figures 1–3).

Field inspections by plantation representatives were consistent with NDVI-based patterns of vegetation condition. High NDVI values were associated with dense tree canopies and bright green leaves, whereas low NDVI values were observed in areas with reduced canopy cover and visible stress symptoms. Leaf samples were collected following standardized protocols (08:00–11:00 WITA), oven-dried (70–80 °C) for approximately 20 hours, and subsequently ground for nutrient analysis. Figure 4 presents representative field conditions of very healthy, moderately healthy, and unhealthy oil palm stands.

Simple linear regression was applied to quantify the relationship between NDVI and field-based indicators. The coefficient of determination (R^2) was used to evaluate model fit, representing the proportion of variance in field observations explained by NDVI (Table 2). This approach is consistent with remote sensing validation studies that emphasize continuous relationships between spectral indices and biophysical variables rather than discrete classification accuracy (Lee et al., 2024; Qin et al., 2021). Overall, the regression-based validation framework demonstrates that NDVI reliably captures spatial variation in oil palm health under the observed plantation conditions.

3.3. Relationship between NDVI and LSU-based nutrient status

Regression analyses indicated positive statistical associations between NDVI and macronutrient concentrations: N ($R^2 = 0.603$), P ($R^2 = 0.575$), K ($R^2 = 0.645$), and Mg ($R^2 = 0.520$), indicating that higher NDVI values are associated with higher nutrient concentrations rather than implying direct causality. The coefficient of determination (R^2) is reported strictly as a measure of model fit, representing the proportion of variance in nutrient concentrations explained by NDVI.

To illustrate these relationships, Figure 5 presents a scatterplot with regression lines for each macronutrient, indicating the sensitivity of NDVI to changes in leaf nutrient status. Additionally, Table 2 summarizes the regression coefficients, *SE*, R^2 , *p*-values, and 95% CI, providing a brief overview of the statistical associations. The entire statistical reporting is presented in a regression framework (β , *SE*, *p*-value, CI, and R^2), ensuring consistency with the analytical approach (Materials and methods, Section 2.6).

Table 2. Summary of linear regression between NDVI and LSU-based nutrient contents (N, P, K, Mg) at Sultra Prima Lestari Ltd. plantation, 2025

Nutrient	Slope (β)	Intercept	<i>SE</i>	R^2	<i>p</i> -value	95% CI Slope
N	2.308	1.764	0.521	0.603	0.001	1.25 – 3.37
P	1.091	-0.066	0.443	0.575	0.003	0.18 – 2.00
K	2.676	-0.009	0.598	0.645	0.0005	1.48 – 3.87
Mg	1.145	0.021	0.487	0.520	0.004	0.15 – 2.14

Note. Simple linear regression was applied, with NDVI as the independent variable and LSU-derived nutrient concentrations as dependent variables. Slope (β) represents the change in nutrient content per unit change in NDVI within the observed range of vegetation conditions. Intercept represents the estimated nutrient content when NDVI = 0. *SE* quantifies the uncertainty of the slope estimate. R^2 indicates the proportion of variance in nutrient concentration explained by NDVI. *p*-value indicates the statistical significance of the slope ($\alpha = 0.05$). 95% CI provides the plausible range of the slope estimate. N and P are expressed as percentage (%), while K and Mg are expressed as mg/kg on a dry weight basis.

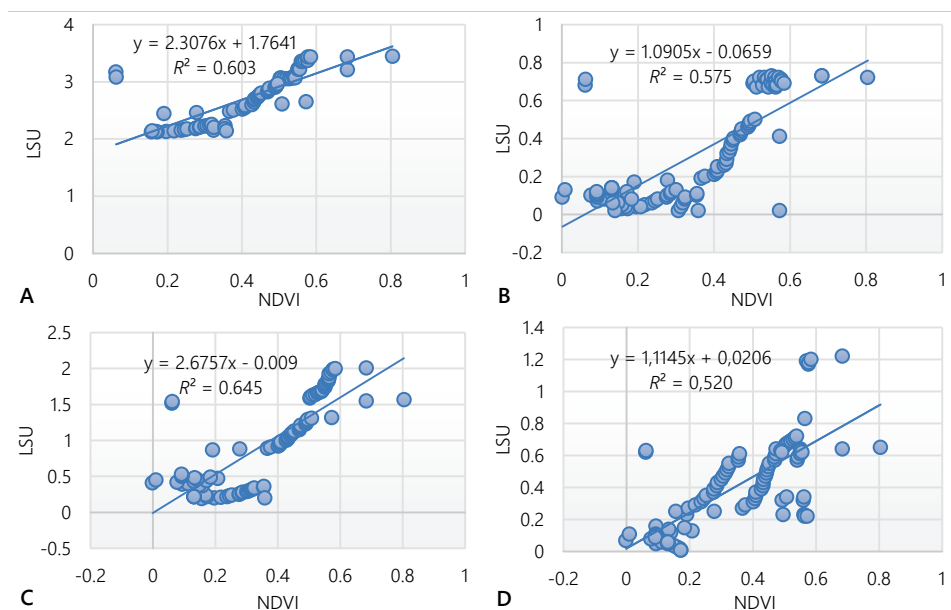


Figure 5. Relationships between NDVI values and LSU-based macronutrient contents at Sultra Prima Lestari Ltd. plantation.

Note. Simple linear regression was used; R^2 is reported as model fit (variance explained). Panel A: Nitrogen (N); Panel B: Phosphorus (P); Panel C: Potassium (K); Panel D: Magnesium (Mg).

This integrated approach enables spatially explicit evaluation of plant nutritional status and supports targeted agronomic interventions at the plantation level. Overall, the regression results demonstrate consistent statistical associations between NDVI and nutrient status, supporting its application as a proxy indicator for spatial variation in oil palm health under the observed conditions.

3.4. Spatial patterns of oil palm health

The NDVI data has exhibited significant variability in terms of oil palm condition across Sultra Prima Lestari Ltd. plantation. *Very healthy* palm trees (indicated by the use of the colour green) are heavily distributed throughout the middle and western portions of the plantation (Division II and Division III). Conversely, *moderately healthy* plants (yellow) and *unhealthy* plants (red) tend to be more prevalent in the eastern portion of the plantation (as shown in Figure 6). This distribution most likely indicates a spatial variability between soil fertility, fertilization, plantation crop age and management intensity across the plantation.

The results of this study show that NDVI derived from Sentinel-2A accurately reflects the spatial variability of oil palm health across a large plantation area. *Very healthy* zones (very high NDVI) were consistently found in areas with a dense canopy and better nutrient conditions as demonstrated through both LSU field measurements reported in Figure 5, and through correlations between the NDVI and the measured nutrient levels found in this study. This reinforces the concept that NDVI is an adequate representation of canopy vigor and vegetation conditions related to nutrients across multiple divisions of a plantation.

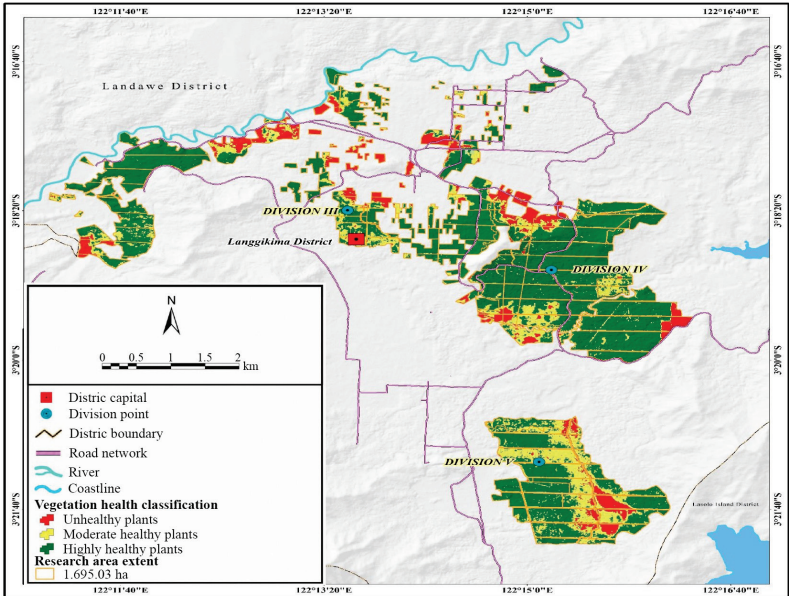


Figure 6. Spatial distribution of oil palm health classes at Sultra Prima Lestari Ltd. plantation based on NDVI derived from Sentinel-2A imagery.

Note. Contains adapted data from *Sentinel-2 MSI Level 2-A (Collection 1)* [Data set] (images acquired in June, 2025), by European Union, European Space Agency, and Copernicus, 2021 (<https://dataspace.copernicus.eu/>), CC BY-SA 4.0; *Plantation boundary* [Data set], by Sultra Prima Lestari Ltd., 2025. Copyright 2025 by Sultra Prima Lestari Ltd., adapted with permission; *Geodatabase of Indonesian administrative boundaries (regency/city level)*, *September 2023 edition* [Data set], by Badan Informasi Geospasial, 2023 (<https://tanahair.indonesia.go.id/portal-web/>), in the public domain.

In addition, the raster type classifications of vegetation density and health supported the categorization of NDVI in Table 1 by providing a detailed spatial representation of vegetation structure and vigor across Divisions II–IV (Figure 3). The combination of spatial data allows management to easily identify management zones so that they can apply agronomic practices to specific locations (i.e., localized fertilization or soil management).

4. Discussion

Results obtained in this study suggest that NDVI derived from Sentinel-2A imagery can serve as an accurate indicator of oil palm health at Sultra Prima Lestari Ltd. plantation. The analysis distinguishes three classes of plant health—*very healthy*, *moderately healthy*, and *unhealthy*—indicating that NDVI is capable of detecting differences in canopy density, leaf greenness, and overall plant vigor. This finding is consistent with previous studies highlighting the sensitivity of NDVI to growth conditions in perennial crops (Nuthammachot & Stratoulis, 2023; Yuniasih et al., 2022). With 57% of the plantation classified as *moderately healthy*, the results suggest that although growing conditions are generally adequate, certain areas may still require targeted agronomic intervention to improve overall plantation performance. The presence of *unhealthy* patches (8%) indicates localized stress that may not be captured through conventional field surveys, supporting the value of NDVI for early

detection of vegetation stress at large spatial scales (Figure 6). This is consistent with recent developments in vegetation monitoring using Sentinel-2, including enhanced indices designed to capture subtle canopy variations (Kumar et al., 2025).

Comparison between NDVI and LSU-based nutrient measurements supports the physiological relevance of NDVI. Moderate to strong positive relationships were observed between NDVI and leaf N, P, K, and Mg concentrations, indicating that NDVI reflects plant macronutrient status (Lee et al., 2024; Qin et al., 2021; Zhao & Qu, 2024). The strongest relationships observed for N and P are consistent with their roles in chlorophyll synthesis, leaf development, and overall photosynthetic efficiency. P deficiency can reduce stomatal regulation and transpiration efficiency—both critical for photosynthesis—leading to chlorosis and lower NDVI values. Similarly, N deficiency reduces chlorophyll content and leaf area, resulting in decreased near-infrared reflectance as captured by NDVI.

These mechanisms demonstrate how NDVI integrates multiple aspects of canopy condition into a single spatial indicator of vegetation health (Minarto et al., 2024; Prasvita et al., 2023). However, it is important to note that NDVI is influenced not only by nutrient status but also by factors such as palm age, microclimate, soil properties, shading, and management practices, which were not explicitly controlled for in this study. Previous studies using the Normalized Difference Red Edge Index (NDRE) and advanced regression approaches have similarly demonstrated strong relationships between vegetation indices and nutrient prediction in oil palm systems (Hariadi et al., 2024; Putra et al., 2025). Compared with NDVI, indices such as NDRE may provide greater sensitivity under dense canopy conditions or specific nutrient stress scenarios. Nevertheless, the integration of Sentinel-2 NDVI with field validation offers a cost-effective and operationally practical approach for large-scale plantation monitoring. While earlier studies often relied on visual assessment of canopy condition, this study provides empirical evidence linking NDVI to nutrient status, thereby enhancing its practical relevance for plantation management.

Spatial analysis revealed considerable heterogeneity in oil palm health across the plantation. *Very healthy* areas were predominantly located in the central and western sections, whereas *moderately healthy* and *unhealthy* areas were more common in the eastern regions (Figure 6). This spatial pattern may be influenced by variations in soil fertility, water availability, plantation age, and topographic characteristics such as slope and aspect, which affect drainage, solar radiation, and microclimatic conditions. In addition, differences in management practices, including fertilization and drainage strategies, may further contribute to this variability (Hardanto et al., 2017; Wijaya & Irwansyah, 2023; Yarak et al., 2021). These findings highlight that spatial variability in NDVI is likely driven by both environmental factors and management practices, reinforcing the need for site-specific interventions.

Analysis of plot-scale variability indicates that NDVI saturation did not significantly limit detection capability, as sufficient differentiation was maintained even in high-density canopy areas. This suggests that, when combined with locally calibrated thresholds, Sentinel-2A imagery can effectively capture variability across large plantation areas.

NDVI-based maps have clear practical implications for plantation management. They enable a shift from uniform management strategies toward site-specific interventions, such as targeted fertilization or soil improvement in areas with lower NDVI values. The use of NDVI mapping can enhance operational efficiency, reduce unnecessary input costs, and improve overall productivity. These findings support the integration of remote sensing with field-based physiological measurements, linking environmental variability with management decisions and

contributing to the implementation of precision agriculture in tropical plantation systems (Minarto et al., 2024; Yuniasih et al., 2022).

The combination of moderate-resolution Sentinel-2 imagery with systematic field validation provides a cost-effective and scalable approach for routine plantation monitoring. Although UAV-based approaches and deep learning techniques can deliver high-resolution data, they often require substantial technical expertise and financial investment (Prasvita et al., 2023). In contrast, the methodology applied in this study utilizes freely available satellite data, field validation, and locally calibrated NDVI thresholds, ensuring both relevance and accessibility. This makes the approach particularly suitable for large-scale plantation monitoring in eastern Indonesia, where such applications remain limited (Nuthammachot & Stratoulis, 2023). Furthermore, integrating UAV-based NDRE analysis and advanced regression techniques could complement NDVI mapping, particularly for detecting nutrient stress at finer spatial scales (Hariadi et al., 2024; Putra et al., 2025).

Overall, the findings demonstrate that NDVI is a valid and practical indicator of oil palm health. By linking spectral indices with plant nutrient status and providing spatially explicit insights into plantation variability, this study offers a scalable approach for routine monitoring. The results contribute to improved decision-making in plantation management and enhance understanding of remote sensing applications in tropical agroecosystems.

5. Conclusion

Building on the findings summarized in the abstract, this study confirms that NDVI derived from Sentinel-2A imagery, validated against 94 field plots in Divisions II–IV of Sultra Prima Lestari Ltd., is a reliable indicator of oil palm health. Higher NDVI values corresponded with denser canopies and elevated macronutrient concentrations (N, P, K, Mg), while lower values identified stressed areas. Spatial analysis revealed clear patterns, with *very healthy* palms concentrated in central and western parts of the plantation and *moderate-to-unhealthy* palms in eastern sections. These results demonstrate that NDVI effectively captures intra-plantation variability and provides actionable information for targeted management interventions, such as site-specific fertilization and soil improvement, thereby enhancing resource efficiency and supporting sustainable plantation practices.

From a methodological perspective, combining medium-resolution Sentinel-2 imagery with systematic field validation provides a scalable and practical approach for large-scale, spatially explicit assessments of plantation health. This strategy complements high-resolution UAV or deep learning-based monitoring, enabling operational monitoring over extensive areas without redundancy. Linking NDVI mapping with physiological measurements reinforces the relationship between remote sensing indices and plant nutrient status, supporting informed decision-making and precision management while maintaining clarity and focus on operational applicability.

The limitations of the study included the potential for NDVI to become saturated in very dense canopies and the possibility of undetected or unassessed interfering factors such as micronutrient deficiency, pests, or water stress. Cloud cover also limited data collection sites to Divisions II–IV. Future studies could add the use of EVI and red-edge optical indices as complementary indices to NDVI and employ multi-temporal NDVI series to identify nutritional deficiencies early or seasonal stress more accurately, thus increasing both the operational relevance of predictions and their overall predictive ability.

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