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ANALYSIS OF THE SPATIAL PATTERN OF OIL PALM TREES IN BLOCKS N39 AND P39 IN PT. NUSANTARA SAWIT PERSADA

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ABSTRACT

Block-level spatial patterning of oil palm is often under-measured for actionable precision management. This study analyzes the spatial pattern of oil palm trees in Blocks N39 and P39 at PT Nusantara Sawit Persada. High-resolution UAV imagery was processed into orthophotos, crowns were automatically detected in eCognition Developer using template matching, and spatial patterns were evaluated with Nearest Neighbor Analysis. The distribution was significantly dispersed (Nearest Neighbor Ratio > 1; Z-score > 97). Morphometric and age variables jointly explained productivity ($R^2 > 0.80$). An integrated workflow combining UAV imagery, eCognition object-based analysis, and Average Nearest Neighbor (ANN) delivers accurate plantation diagnostics and supports data-driven precision management, including block-level planning, targeted fertilization, timely replanting, and harvest scheduling.

A. BACKGROUND

Geography is a science that studies geosphere phenomena with a spatial, ecological, and complex approach to regions (Ariyadi et al., 2023; Bintarto & Hadisumarno, 1982; Yunus, 2010). One of the important aspects of spatial studies is the management and utilization of plantation land, including oil palm (*Elaeis guineensis*), which is a national leading commodity as well as a support for the economy in various regions in Indonesia . (D'Oleire-Oltmanns et al., 2012; Hematang et al., 2021; Liu et al., 2021; Syed Hanapi et al., 2021)The large contribution of oil palm to GDP encourages the need for an efficient, precise, and sustainable plantation monitoring system, especially through the use of UAV-based geospatial technology (*Unmanned Aerial Vehicle).*

The use of UAVs in plantation monitoring has proven to be effective for the rapid and accurate acquisition of spatial data in various tropical regions (Khuzaimah et al., 2022; Liu et al., 2021; J. X. Wong et al., 2023). The aerial imagery generated by the UAV can be processed using Object-Based Image Analysis-based software such as *eCognition Developer* to automatically detect the morphological characteristics of the treetop (Pradiko et al., 2024; Putra & Wijayanto, 2023; Wulandarie et al., 2024).

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One of the techniques used is the *Template Matching*, which has been proven to be able to recognize the visual patterns of palm tree crowns with a high degree of accuracy (Agusman & Saputra, 2025; Hematang et al., 2021; Yudistina et al., 2017).

The visual characteristics of the palm crown, such as the diameter and density of the crown, not only reflect the physiological condition of the plant, but are also closely related to the age of the tree (Agusman & Saputra, 2025; Efendi et al., 2023; Hair et al., 2021; Kwong et al., 2024; Thapa et al., 2025) . Some studies show that as we age, there are significant changes in the size of the crown, trunk height, and diameter of the tree that directly affect the productivity of palm oil (Efendi et al., 2023; Yudistina et al., 2017; Yuniasih & Adji, 2022). Therefore, spatial analysis that considers tree age parameters is crucial for optimizing production and planning for garden revitalization.

The spatial distribution of oil palm trees can be analyzed using the Average Nearest Neighbor (ANN) test to determine whether the pattern is clustered, random, or dispersed (Kwong et al., 2024; Scott & Janikas, 2010; Yang et al., 2024). Identification of these distribution patterns has an important role in evaluating planting efficiency, detecting areas with sub-optimal density, and planning plant care spatially. The importance of spatial analysis in supporting regional management was also emphasized by Lasaiba (2024), especially in areas related to land use and utilization optimization.

Based on this description, this study aims to analyze the spatial distribution pattern of oil palm trees in Blocks N39 and P39 in PT. Nusantara Sawit Persada, East Kotawaringin Regency, by utilizing UAV imagery, *template matching* methods, and spatial analysis using the Average Nearest Neighbor (ANN) test. This research is expected to be a scientific contribution to the development of a precise and efficient geospatial-based agronomic monitoring system, especially in the management of oil palm plantations in Indonesia.

B. METHOD

This study employed a quantitative descriptive approach using Unmanned Aerial Vehicle (UAV) data to analyze the spatial pattern of oil palm trees at PT Nusantara Sawit Persada, Cempaga Estate, Kota Besi District, Central Kalimantan. The estate spans about 7,000 ha and is divided into roughly 300 blocks. In Stage 1 of a two-stage cluster design, two representative blocks, N39 (planted 2012) and P39 (planted 2014), each about 30 ha with approximately 136 trees per hectare, were purposively selected based on typical 9 × 9 m equilateral-triangle spacing, age classes that capture peak and early-decline productivity, intact administrative boundaries matching UAV footprints, high crown image quality, and consistent maintenance with low topographic disturbance. Block characteristics and population sizes used in the Slovin calculation are summarized in Table 1.

Table 1. Data on Sample Blocks, Planting Area, and Number of Trees

Block	Planting Year	Planting Area (ha)	Number of Trees
N39	2012	30,30	4.120
P39	2014	30,00	4.080

(Source: PT. Nusantara Sawit Persada, 2024)

Based on Table 1, it shows that Blocks N39 and P39 have a uniform planting area and number of trees. These two blocks were chosen because they meet the criteria of plant age and the visual quality of the crown, making them suitable as samples for spatial analysis. The calculation of the number of samples is theoretically based on the Slovin formula as described by Sugiyono (2017), with an error tolerance rate of 5 percent. The formula used is as follows:

$$n = \frac{N}{1 + N(e)^2} \dots\dots\dots (1)$$

where:

n = number of samples

N = total population

e = error tolerance level (5%)

(Source Sugiyono, 2017)

In Stage 2, a field sample for ground-truth morphometrics and productivity was determined using Slovin's formula (Sugiyono, 2017). Using a combined population of 8,200 trees and an effective error tolerance of 0.0527, the resulting sample size was 345 trees, proportionally allocated as 173 in N39 and 172 in P39. Units were selected by simple random or systematic random sampling from the detected point layer, with an interval of about 24 per block.

The Average Nearest Neighbor (ANN) test was applied to the full census of detected trees, whereas the 345-tree sample supported field validation and morphometric and productivity modeling. UAV acquisition and preprocessing were planned in DJI Pilot 2 and executed using a DJI Mavic 3T Enterprise with RTK at 80 m altitude, 80% forward overlap, 70% side overlap, about 5 m s^{-1} flight speed, roughly 2.1 s shooting interval, 7.78 km flight path, approximately 0.31 km^2 coverage, 401 images, and a Ground Sampling Distance of 3.52 cm per pixel.

RTK horizontal and vertical accuracies were better than 2 cm and 4 cm, respectively, during the 08:10–08:20 WITA flight window under partly cloudy, low-wind conditions. Orthophoto and digital surface model (DSM) were produced in Agisoft Metashape Professional v2.2.0.

Individual crowns were identified in eCognition Developer v9.0 using template matching with 20 exemplars per block and a detection threshold of 0.30, then exported as a point vector layer. Spatial distribution patterns were evaluated in ArcGIS Pro v3.4.5 using the Average Nearest Neighbor tool to obtain the Nearest Neighbor Ratio, Z-score, and p-value (Scott & Janikas, 2010; Wang et al., 2022). The outputs inform spatial uniformity, ecological structure, and block-level management implications.

C. RESULTS AND DISCUSSION

C.1. RESULTS

This section summarizes the outcomes of the March 2025 UAV campaign over Blocks N39 and P39 (Cempaga Estate, PT Nusantara Sawit Persada). A high-quality orthomosaic was generated in Agisoft Metashape, individual oil-palm crowns were automatically detected in eCognition using template matching, and the detections were exported as georeferenced point features. Spatial arrangement was then evaluated with the Average Nearest Neighbor (ANN) in ArcMap 10.8 to determine each block's distribution pattern, and block-level productivity summaries were derived from the morphometric classification.

Data Quality Summary

UAV acquisition in March 2025 over Blocks N39 and P39 (Cempaga Estate, PT Nusantara Sawit Persada) produced an orthomosaic with crown-scale fidelity. Flights were automated with consistent overlap/sidelap and RTK positioning, yielding sub-decimeter geolocation suitable for precise crown delineation and downstream statistics. A concise summary of acquisition and orthophoto quality is provided in Table 2.

Table 2. Flight and Orthophoto Summary

Metric	Value
Study blocks	N39, P39 (Cempaga Estate)
Acquisition date	March 2025
Platform / positioning	DJI Mavic 3T Enterprise (RTK)
Altitude (AGL)	80 m
Forward overlap / sidelap	80% / 70%
Flight speed	~5 m/s
Number of images	401
Trajectory length	7.78 km
Coverage area	0.31 km²
GSD (orthomosaic)	3.52 cm/pixel
RTK accuracy	< 2 cm (H), < 4 cm (V)
Acquisition window & weather	08:10–08:20 WITA; sunny–cloudy; wind < 5 m/s

(Source: Primary data, UAV flight logs (DJI Pilot 2) and Agisoft Metashape report, 2025)

As summarized in Table 2, the fine ground sampling distance (GSD) and low RTK error under stable conditions provide a robust foundation for accurate crown detection, block-level yield totals, nearest-neighbor statistics, and subsequent regression analyses. Recent UAV photogrammetry studies show that RTK/PPK configurations markedly improve planimetric and altimetric accuracy and camera orientation consistency, thereby enhancing orthomosaic quality for crown-scale analysis (Kostrzewa et al., 2025; Martínez-Carricondo et al., 2023).

Orthomosaic positioning followed RTK solutions reported in the flight logs, with nominal horizontal and vertical accuracies better than 2 cm and 4 cm, respectively. Absolute *orthomosaic* accuracy was not independently verified with *GCP/ICP*, therefore subsequent analyses emphasize relative, block-level metrics that are robust to small absolute shifts.

RTK-enabled UAV mapping can also achieve centimeter-level accuracy while reducing reliance on dense GCP networks in plantation-scale operations (Pilarska-Mazurek & Łoza, 2025).

Automatic Crown Detection (eCognition, Template Matching)

Automatic delineation and counting of individual oil-palm crowns were generated from the orthomosaic using a template-matching workflow in eCognition. Detection outputs were exported as georeferenced point features for subsequent quantitative analyses. A concise per-block summary is provided in Table 3.

Table 3. Automatic Detection of Oil Palm Tree Numbers Using *eCognition Developer*

Block	Planting year	Area (ha)	Template layer	Correlation peak	Threshold	Trees detected
N39	2012	30.3	2	0.335	0.3	4,131
P39	2014	30	2	0.348	0.3	4,080

(Source: UAV Image Analysis using eCognition Developer, 2025)

Based on Table 3, using a 0.30 threshold, template matching on the 3.52-cm GSD orthomosaic produced stable delineations. Blocks N39 and P39 yielded 4,131 and 4,080 crowns, respectively (136.34 and 136.00 trees ha^{-1}). Independent *confusion-matrix* metrics (*precision, recall, F1*) were not compiled for this campaign. As an operational proxy, the detected crown counts closely tracked administrative tallies at the block scale, with minor positive bias plausibly attributable to recent replanting and visually similar non-productive individuals, supporting reliable census and downstream statistics.

The slight positive bias likely reflects recent replanting or visually similar non-productive individuals. Peak correlations (0.335–0.348) indicate a strong crown signal, and the conservative threshold suppresses false positives while retaining sufficient sensitivity for a reliable block-level census and robust downstream spatial and statistical analyses. These outcomes are consistent with recent findings that UAV-based deep-learning detectors can reliably identify and count individual oil-palm trees across a range of canopy densities (Hajjaji et al., 2025; Lee et al., 2024).

Block-Level Oil Palm Production

Per-tree productivity mapping for both blocks reveals clear spatial differentiation across areas and stand ages; its visualization is shown in Figure 1 to provide context before the numerical summary.

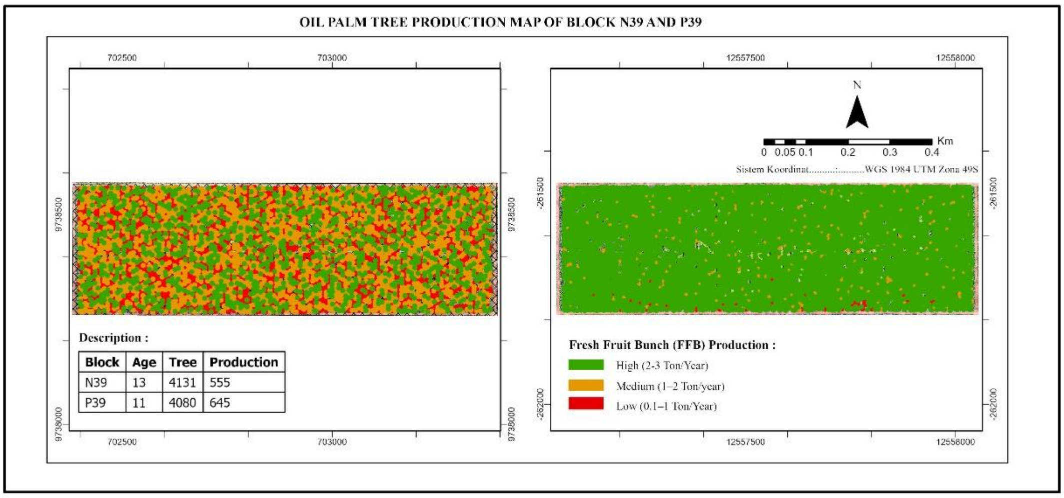


Figure 1. Map of Oil Palm Production Block N39 and Block P39 at PT. Nusantara Sawit Persada

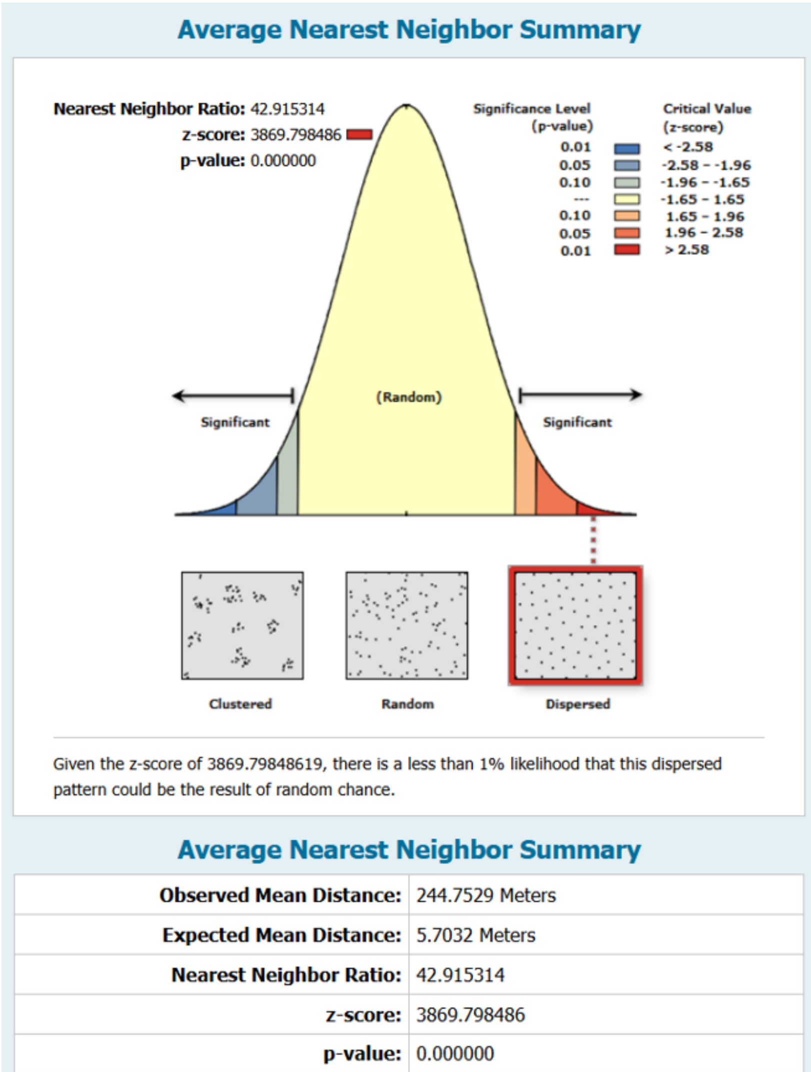
(Source: Productivity Segmentation Results and UAV Image, 2025)

Figure 1 provides spatial context for the block-level yield statistics. Using approximately 5 cm ground-resolution UAV workflows, which are effective for deriving quantitative yield or maturity indicators from georeferenced imagery (Puttinaovarat et al., 2024), the results are as follows: P39 contained 4,080 detected palms and produced 645 t FFB per year, averaging 158.09 kg per tree per year, whereas N39 contained 4,131 detected palms and produced 555 t FFB per year, averaging 134.35 kg per tree per year (for example, 555,000 kg ÷ 4,131 = 134.35). Relative to N39, P39 delivered an additional 90 t per year (+16.2%) and 23.74 kg per tree per year (+17.7%). The difference aligns with stand age, with P39, approximately 11 years old, near peak production and N39, approximately 13 years old, entering early decline, indicating more stable management performance in P39.

These quantitative results provide a stronger basis than color-only map interpretation and frame the spatial-pattern metrics reported next. These block totals correspond to 18.32 t/ha in N39 (555 t over 30.3 ha) and 21.50 t/ha in P39 (645 t over 30.0 ha), consistent with near-peak stand age in P39. P39 outperforms N39 (21.50 vs 18.32 t/ha; +23.74 kg/tree/year), indicating a consistent, age-driven productivity premium that warrants harvest prioritization in P39 and diagnostics/replanting planning in N39.

Average Nearest Neighbor (ANN)

Average Nearest Neighbor (ANN) statistics were used to classify the spatial arrangement of detected palms into clustered, random, or dispersed based on the Nearest Neighbor Ratio (NNR), Z-score, and p-value; its visualization is shown in Figure 2.



Observed Mean Distance:	244.7529 Meters
Expected Mean Distance:	5.7032 Meters
Nearest Neighbor Ratio:	42.915314
z-score:	3869.798486
p-value:	0.000000

Figure 2. Z-Score Value Distribution and Spatial Distribution Pattern Classification Based on Nearest Neighbor Analysis
(Source: ArcMap 10.8 Analytics Output, 2025)

Figure 2. Z-Score Value Distribution and Spatial Distribution Pattern Classification Based on Nearest Neighbor Analysis. With reference to Figure 4, the block-level metrics are summarized in Table 4.

Table 4. Results of Nearest Neighbor Distribution Pattern Analysis

Block	NN Ratio	Z-Score	P-Value	Distribution Pattern
N39	1.807883	98.418	< 0.001	Dispersed
P39	1.801237	97.90885	< 0.001	Dispersed

(Source: Primary Data Analysis, 2025)

Interpretation of Table 4. Extremely large *Z*-scores are expected under a design-driven, regular 9 × 9 m spacing with thousands of points, because the standard error of the test statistic shrinks as *n* increases. The dispersed classification (*NNR* > 1, *p* < 0.001) therefore reflects regular plantation layout rather than stochastic aggregation. These results indicate a design-driven plantation structure rather than stochastic clustering or randomness.

Productivity Morphometry Relationship

Multiple linear regression was used to relate per-tree productivity to Height, Trunk Diameter, Crown Size, and Age; bivariate trends are illustrated in Figure 1–2. Scatterplots of Age, Height, Diameter, and Crown vs Productivity. A model fit summary by block is provided in Table 5 (standardized coefficients and *p*-values can be listed in Table 5. Standardized Coefficients (β) and p-values of the Multiple Regression Models in the appendix).

Table 5. Value of Determination Coefficient (*R-Square*) between Height, Crown, Diameter, Age and Tree Productivity

Tree Productivity			
Block	**Planting Year**	***R-Square***	**Power of Correlation**
N39	2012	0,800	Very Powerful
P39	2014	0,805	Very Powerful

(Source: Primary Data Analysis, 2025)

Interpretation of Table 5. The models explain a large share of productivity variance at block scale, indicating that structural and age-related morphometrics provide strong predictive signals for yield. The closely matched fits across blocks suggest stable behavior of the predictors under differing stand ages, while any remaining unexplained variance is likely attributable to non-structural factors (e.g., physiology, soil–moisture heterogeneity) beyond canopy geometry. These results support the operational use of crown/structure-based indicators for block-level yield monitoring and targeted management.

C.2 DISCUSSION

UAV-based object detection with eCognition reliably delineated individual oil-palm crowns and yielded counts that track administrative records, with minor discrepancies plausibly arising from recent replanting or visually similar nonproductive individuals. The workflow captures detailed canopy geometry that is highly informative for block-level monitoring, while it does not directly represent internal physiological status or age history (Liu et al., 2021; Y. Bin Wong et al., 2023).

Prior work consistently supports the use of high-resolution UAV imagery for plantation mapping under varying canopy densities. Object-based analysis combined with modern deep learning has proven effective for crown identification and automatic census at the block scale, providing a robust methodological backbone for operational mapping in estates (Zheng et al., 2021).

Beyond classical template matching, advances in detection pipelines continue to improve robustness. Normalized cross-correlation enhances pattern sensitivity in dense stands, and recent real-time detectors that run efficiently on edge devices enable practical, routine field deployment with rapid feedback loops for managers (Farhan et al., 2025; Shaikh et al., 2024; Syed Hanapi et al., 2021).

Average Nearest Neighbor (*ANN*) indicates a clearly dispersed arrangement that aligns with regular 9 × 9 m spacing. This pattern is consistent with dispersed crown layouts reported for large-scale estates using high-resolution remote sensing, reinforcing that plantation design, rather than stochastic aggregation, dominates the small-area spatial structure (Wibowo et al., 2022).

Morphometric predictors derived from crowns, stems, and height proxies jointly explain a substantial share of yield variation, supporting crown-based inference as a practical signal for block-level productivity. While this strengthens the case for geospatial, data-driven management, residual uncertainty remains where structure alone cannot fully capture physiological status.

Several constraints warrant consideration. RGB imagery primarily describes canopy geometry and texture, not internal health, chlorophyll, moisture, or latent disease. Detection accuracy is sensitive to template definitions and threshold values, which can elevate false positives near young replanting. These issues should be addressed through stratified ground verification and standard reporting of precision, recall, and F1 scores, complemented by uncertainty analysis (Farhan et al., 2025; Putra & Wijayanto, 2023).

In comparative perspective, the detection and modeling outcomes observed here fall within commonly reported ranges for crown-based inference in oil-palm estates. For context, an edge-deployed YOLOv8 system achieved 95.6 percent precision, 93.3 percent recall, and 98 percent mAP@0.5 (Farhan et al., 2025). Studies leveraging object-based analysis and deep learning on large estates have reported F1-scores in the mid- to high-90s for crown detection, which is consistent with our results (Putra & Wijayanto, 2023; Wibowo et al., 2022). Differences across studies are plausibly driven by canopy density, age structure, sensor configuration, and verification effort (Putra & Wijayanto, 2023).

Future work should integrate multispectral vegetation indices, such as NDVI or GNDVI, to complement canopy geometry with physiological signals related to chlorophyll and stress, thereby reducing ambiguity inherent to RGB-only assessments (Kurihara et al., 2022; Putra & Wijayanto, 2023).

Combining crown features, DSM-derived vertical structure, and vegetation indices within modern machine-learning pipelines, for example YOLO-family detectors for localization and Random Forest or gradient-boosting regressors for yield estimation, is expected to enhance robustness and predictive accuracy (Farhan et al., 2025).

From a management standpoint, UAV-enabled health surveillance can be extended to early-warning layers that flag stress and disease hot-spots. Such layers support targeted interventions for fertilization, pest control, and replanting, improving timeliness and resource allocation in precision agronomy while aligning with evidence from plantation-scale UAV monitoring (Ahmadi et al., 2022; Ong et al., 2023).

In sum, a crown-centric, UAV-based workflow provides operational value for spatial monitoring and decision support. Its effectiveness is maximized when paired with spectral health indicators, rigorous accuracy reporting, and cross-block validation, ensuring generalizable insights that translate into actionable, block-level management improvements.

D. CONCLUSION

This study analyzed the spatial pattern of oil palm trees in Blocks N39 and P39 at PT Nusantara Sawit Persada using UAV imagery and object-based processing in eCognition. Nearest Neighbor Analysis revealed a significantly dispersed distribution, consistent with the 9 × 9 m planting system applied in the field. Morphometric variables, namely age, height, trunk diameter, and crown size, were strongly associated with productivity (R-square = 0.800 across blocks), indicating that spatial and crown-based indicators are effective proxies for block-level yield. These findings show that spatial- and morphometric-based approaches can accurately describe plantation structure and productivity and support geospatial, data-driven agronomic management. This approach can be scaled up for large-plantation monitoring and for informing policy decision-making in sustainable palm-oil management.

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