Multi-Nutrient Mapping in Oil Palm Using Sentinel-2 and Random Forest: A Cost-Efficient Approach for Precision Agriculture

Wiratmoko, D. [1*] and Diana, S.R.[2]

[1]Indonesian Oil Palm Research Institute, Medan, Indonesia

[2]Research Organisation for Governance, Economy, and Public Welfare, PRKP, National Research and Innovation Agency (BRIN), Indonesia

*dhimaswiratmoko@iopri.org and wiratmoko2nd@gmail.com

ABSTRACT

This study developed a cost-efficient multi-nutrient mapping framework for oil palm plantations by integrating Sentinel-2 multispectral imagery, Random Forest (RF) modeling, and Google Earth Engine (GEE). The approach aimed to (i) estimate leaf macronutrients: nitrogen (N), phosphorus (P), potassium (K), and magnesium (Mg) from spectral reflectance data, (ii) evaluate model accuracy, and (iii) assess cost-efficiency compared with conventional nutrient-monitoring methods. Field data collected from a 4,478 ha plantation in North Sumatra, Indonesia served as the ground truth for model training and testing. Only the 10-m Sentinel-2 RGB and NIR bands were used after cloud and shadow masking were applied. RF classification achieved overall accuracies exceeding 90% and Kappa coefficients ranging from 0.85 to 0.89, confirming the robustness of the spectral-based nutrient estimation. Spatial results indicated that N and K levels were generally adequate to slightly excess, whereas P and Mg were predominantly deficient, reflecting the typical nutrient-cycling patterns in tropical oil palm systems. The cost efficiency analysis revealed a 156% improvement compared with the conventional laboratory approach, demonstrating substantial reductions in manpower, time, and material costs. These findings highlight the operational potential of combining remote sensing, machine learning, and cloud computing for large-scale, rapid, and economically sustainable precision nutrient management in oil palm plantations.

Keywords: oil palm, Sentinel-2, random forest, cost-efficiency, precision agriculture, nutrient mapping

Introduction

Oil palm (*Elaeis guineensis*) is a cornerstone of agricultural economies in tropical regions, notably in Indonesia and Malaysia, which collectively account for over 80% of the global palm oil supply (Corley and Tinker, 2016; CPOPC, 2025). Maintaining high and sustainable yields in oil palm plantations depends on effective nutrient management, as imbalances in essential macronutrients such as nitrogen (N), phosphorus (P), potassium (K), and magnesium (Mg) can significantly reduce productivity and long-term soil fertility (Woittiez et al., 2019).

Traditionally, the determination of fertilizer dosage in oil palm plantations relies on manual nutrient monitoring through destructive leaf sampling and laboratory analysis. While this method remains the standard for accuracy, it is costly, labour-intensive, and time-consuming, involving field collection, sample preparation, laboratory processing, and expert interpretation. Consequently, its application across large plantation areas is limited, leading to infrequent nutrient updates and potentially delayed management actions (Fairhurst & Griffiths 2014). These limitations make the current practice inefficient, particularly when timely and spatially detailed nutrient information is required for precision fertilization planning in agriculture.

In contrast, recent advancements in remote sensing (RS)**,** cloud computing platforms, and machine learning (ML) have introduced a cost-efficient, scalable, and non-destructive alternative for monitoring nutrient status and optimizing fertilizer management. Sentinel-2 imagery, with its high spatial resolution (10–20 m) and multispectral coverage across the visible, red-edge, and near-infrared regions, provides valuable indicators of vegetation health and biochemical composition (Gómez et al., 2016). When integrated with Random Forest (RF) algorithms, which are capable of modeling complex nonlinear relationships between spectral signatures and nutrient concentrations, and implemented within cloud computing environments such as Google Earth Engine (GEE), this approach enables rapid large-scale nutrient estimation directly from satellite reflectance data (Belgiu & Drăguţ, 2016; Sirojul et al., 2022; Gorelick et al., 2017). Unlike the traditional approach which delivers nutrient information only after several days or weeks of laboratory processing, RS, ML, and cloud frameworks allow frequent, plantation-wide nutrient mapping at a fraction of the cost.

Despite its promise, existing studies have often focused on single-nutrient estimation, particularly nitrogen, while other key macronutrients, such as phosphorus (P), potassium (K), and magnesium (Mg), remain less explored (Li et al., 2023). Furthermore, research applying Sentinel-2 imagery and machine learning techniques in oil palm plantations is still limited, despite growing evidence of their potential to improve monitoring accuracy and decision-making efficiency in tropical perennial crops (Baharim et al. 2022; Khan et al. 2021). Oil palm systems exhibit complex canopy structures and nutrient dynamics that differ substantially from those of annual crops, underscoring the need for models specifically tailored to the conditions of perennial plantations.

Simultaneously, the potential of cloud-based platforms, such as the Google Earth Engine (GEE), for large-scale automated data processing has not yet been fully realised in operational plantation management. GEE enables the integration of multi-temporal Sentinel-2 data with advanced algorithms for spatial modeling and monitoring (Amani et al., 2020; Gorelick et al., 2017; Baraldi et al., 2020).

In addition to accuracy, cost efficiency has emerged as a critical consideration for technology adoption. Conventional laboratory-based nutrient diagnosis requires repeated sampling, reagents, and manpower, leading to substantial recurring costs (Fairhurst and Griffiths, 2014; Woittiez et al., 2019). In contrast, a remote sensing-driven framework offers a one-time data acquisition model combined with scalable, cloud-based analytical capabilities. Through the integration of Sentinel-2 imagery, machine learning by Random Forest modeling, and cloud computing, plantations can achieve frequent, spatially explicit nutrient assessments while significantly reducing operational costs, ultimately supporting data-driven fertiliser management and sustainable oil palm production (Baharim et al., 2022; Khan et al., 2021).

Accordingly, this study aimed to develop a multi-nutrient mapping and cost-efficient dosage assessment framework for oil palm plantations by integrating Sentinel-2 imagery, Random Forest algorithms, and Google Earth Engine. The specific objectives are as follows:

(i) Simultaneously estimate multiple leaf nutrient concentrations (N, P, K, and Mg) using Sentinel-2 spectral data.

(ii) evaluate the predictive performance of Random Forest models using both regression and classification accuracy metrics; and

(iii) Compare the operational cost and efficiency between conventional laboratory-based monitoring and the proposed RS–ML approach.

By addressing these objectives, this study demonstrates how satellite-driven analysis can complement and potentially replace conventional nutrient assessment workflows, supporting data-driven fertilizer management and sustainable precision agriculture in the oil palm industry.

Methodology

2.1. Field Data

The study was conducted in an oil palm plantation located in North Sumatra, Indonesia, covering an approximate area of 4,478 hectares. The plantation lies between 3° 03′ 53.52″ N – 3° 10′ 11.52″ N and 99° 26′ 07.19″ E – 99° 30′ 10.15″ E. The estate represents a mature and well-managed plantation, providing an appropriate environment for evaluating the spatial variability of leaf nutrients under operational conditions.

Figure 1 : Study Area

The geographic coordinates of each leaf sampling unit (LSU) were determined using the plantation's spatial block database, allowing precise georeferencing and integration with geospatial layers for subsequent nutrient mapping. Leaf samples collected from selected LSUs were submitted to a certified agronomic laboratory for the chemical analysis of four macronutrients: nitrogen (N), phosphorus (P), potassium (K), and magnesium (Mg).

Laboratory analyses followed standard protocols for oil palm leaf tissue evaluation: the Kjeldahl method for total N, Bray-II extraction and spectrophotometric analysis for available P, and Atomic Absorption Spectrophotometry (AAS) using ammonium acetate extraction for K and Mg. The resulting nutrient concentrations served as ground-truth data for model calibration and validation, functioning as both training and testing datasets in the Random Forest (RF) algorithm implemented within the Google Earth Engine (GEE) platform.

2.2. Imagery Data

Multispectral imagery from the Sentinel-2 mission of the European Space Agency (ESA) was used as the main remote sensing dataset for nutrient estimation. Sentinel-2 provides optical data across 13 spectral bands, of which only the 10 m resolution bands (blue (B2), green (B3), red (B4), and near-infrared (B8)) were selected for this study. These bands were chosen for their high spatial detail and proven sensitivity to canopy colour and structure, which are indirectly related to leaf nutrient status.

To ensure consistency with the field sampling campaign, imagery was selected based on the best atmospheric and radiometric quality acquired throughout 2024, prioritizing scenes with minimal cloud contamination and optimal surface visibility over the study area. The imagery was obtained as Level-2A surface reflectance products via the Google Earth Engine (GEE) platform, which provides atmospherically corrected data that are ready for analysis.

Pre-processing involved only cloud and shadow masking using the Scene Classification Layer (SCL) and QA60 band to remove the invalid pixels. No temporal compositing or vegetation index derivation was performed; instead, the best quality acquisition was used to preserve the original spectral characteristics. The resulting cloud-free Sentinel-2 reflectance data were spatially sampled at the coordinates of the Leaf Sampling Units (LSUs), producing a dataset that linked each pixel's spectral reflectance values (B2, B3, B4, and B8) to the corresponding laboratory-measured concentrations of nitrogen (N), phosphorus (P), potassium (K), and magnesium (Mg). This dataset was then employed as input for the Random Forest modeling in Google Earth Engine to predict and map the nutrient distribution across the plantation.

2.3. Random Forest Modeling and Accuracy Assessment

The nutrient status of oil palm leaves was modeled using the Random Forest (RF) algorithm implemented within the Google Earth Engine (GEE) environment. Random Forest is a non-parametric ensemble learning algorithm that constructs multiple decision trees and aggregates their outcomes to enhance classification accuracy and model stability (Breiman, 2001). Its robustness against overfitting and ability to handle high-dimensional nonlinear relationships make it particularly suitable for remote sensing applications involving spectral data (Belgiu & Drăguț, 2016; Rodriguez-Galiano et al., 2015).

In this study, an RF model was designed for classification, aiming to categorize each pixel into nutrient status classes deficient, slightly deficient, normal, slightly excess, and excess for four essential macronutrients: nitrogen (N), phosphorus (P), potassium (K), and magnesium (Mg). Nutrient thresholds were defined based on agronomic reference standards derived from laboratory analyses and critical concentration ranges reported in the literature on oil palm nutrition (Fairhurst & Griffiths, 2014; Woittiez et al., 2019).

The model input consisted of Sentinel-2 spectral reflectance values from the 10-meter resolution bands (B2–Blue, B3–Green, B4–Red, and B8–NIR), while the reference labels corresponded to nutrient status classes determined from laboratory results for each Leaf Sampling Unit (LSU). The dataset was randomly split into 70% training and 30% testing subsets using a stratified sampling strategy to maintain a proportional representation across nutrient status categories.

Model parameters, including the number of trees (ntree), maximum depth, and minimum leaf size, were optimized through empirical testing to achieve stable classification performance (Belgiu & Drăguț, 2016). The trained model was subsequently applied to Sentinel-2 imagery to generate plantation-wide nutrient status maps for each macronutrient.
The classification performance was evaluated using a confusion matrix by comparing the model predictions with the laboratory-derived reference classes. Four standard accuracy metrics were computed as follows:

- Overall Accuracy (OA): the ratio of correctly classified samples to the total samples,
- Producer's Accuracy (PA): the probability that a reference sample is correctly identified,
- User's Accuracy (UA): the reliability of each predicted class, and
- Kappa Coefficient (κ): the agreement between classification results and reference data after accounting for random chance.

These accuracy indices provided a quantitative basis for assessing the reliability of Sentinel-2 and Random Forest integration for operational nutrient monitoring in oil palm plantations using cloud-based geospatial processing in GEE (Gorelick et al., 2017).

2.4. Cost-Efficiency Analysis

The efficiency analysis in this study aimed to evaluate the cost-effectiveness of integrating remote sensing (RS), machine learning (ML), and cloud-based processing in oil palm nutrient monitoring compared with the conventional laboratory-based approach. Efficiency is defined as the ratio between output and input, where higher ratios indicate better resource utilization (Cooper et al., 2006; Sherman & Zhu, 2006; Othman et al., 2016).

According to Mokhtar et al. (2008), efficiency reflects a system's ability to maximize outputs or benefits while minimizing total costs. Hence, the efficiency (E) in this study was determined using the following equation:

$$E = \frac{\text{Output (or Total Benefit)}}{\text{Total Cost}} \times 100\%$$

where:

- Total Cost = Cost of materials (reagents, consumables) + Labor cost + Overhead (logistics, field operations, and computing resources),
- Output = Information or deliverables generated (e.g. nutrient status maps, update frequency, and spatial coverage).

The total Cost in this study refers to the production cost concept as defined in Indonesia's *Statement of Financial Accounting Standards*. Specifically, it follows PSAK No. 14 (Revised 2018), which was updated to PSAK 202 (2024).These standards establish an accounting framework for cost determination, defining the total production cost as the sum of three cost elements**:** direct material cost**,** direct labour cost**,** and overhead cost (or indirect cost) **(**Garrison et al., 2003**)**. Therefore, the total cost represents the overall expenditure required to produce the nutrient distribution outputs (four nutrient maps in this case). Two efficiency scenarios were compared.

1. Conventional Method ($E_{(t-1)}$) — laboratory-based analysis and manual mapping of nutrient distribution.
2. RS–ML Method (E_t) — nutrient status mapping derived from Sentinel-2 imagery processed using Random Forest and Google Earth Engine.

The change in efficiency between the two approaches was quantified as follows:

$$\Delta E = \frac{E_t - E_{t-1}}{E_{t-1}} \times 100\%$$

A positive ΔE indicates improved cost efficiency achieved through the adoption of remote sensing and cloud-based processing. The evaluation included both direct operational savings (e.g. reduced sampling and laboratory costs) and indirect benefits, such as the ability to conduct frequent large-scale monitoring at minimal marginal cost.

However, this simplified efficiency metric may not capture all input–output interactions inherent to complex production systems. As noted by Sherman and Zhu (2006), traditional efficiency ratios can underestimate actual efficiency because of the presence of multiple inputs and outputs. In such cases, the calculated efficiency values tend to be conservative, consistent with the principle of conservatism in accounting practices, which seeks to avoid overstating performance outcomes (Kusumaningtyas and Sri, 2018).

Therefore, while the ratio-based efficiency model provides a practical and transparent comparison framework, future studies may apply more comprehensive approaches such as

Data Envelopment Analysis (DEA) to assess multi-input and multi-output efficiency more rigorously.

Results and Discussion

3.1. Accuracy Assessment of Nutrient Classification

The classification performance of the Random Forest (RF) model for estimating oil palm leaf nutrient status was evaluated using four standard metrics: Overall Accuracy (OA), Kappa Coefficient (κ), producer's accuracy (PA), and user's accuracy (UA). The results are presented in Table 1.

Table 1 : Accuracy metrics of Random Forest classification for nutrient status

Nutrient	Kappa	Overall (%)	Producer (%)	User (%)
N	0.89	93.12	89.47	94.44
P	0.85	90.40	93.31	89.33
K	0.87	92.73	89.09	92.45
Mg	0.87	91.69	97.60	88.40

The model achieved high classification performance across all nutrients, with overall accuracies exceeding 90% and Kappa coefficients between 0.85 and 0.89, indicating a strong agreement between the predicted and observed nutrient classes beyond random chance. Among the macronutrients, nitrogen (N) yielded the highest accuracy (OA = 93.12%, κ = 0.89), reflecting the strong spectral response of chlorophyll-related absorption features in the red and near-infrared bands, which are directly sensitive to N concentrations (Gómez et al., 2016; Li et al., 2023). The phosphorus (P) classification obtained slightly lower accuracy (OA = 90.40%, κ = 0.85), consistent with the limited direct optical sensitivity of P, which is indirectly inferred through canopy vigour and structural indicators (Lizcano-Toledo et al. 2021).

For potassium (K) and magnesium (Mg), both models demonstrated stable performance (κ = 0.87), with Mg showing particularly high producer accuracy (97.6%), indicating that almost all Mg-deficient or adequate areas identified in laboratory analyses were correctly mapped by the RF model. The slightly lower user Accuracy for Mg (88.4%) suggests a minor overestimation in some high-reflectance regions, possibly due to canopy-light scattering effects.

These findings confirm that Sentinel-2 spectral reflectance, when integrated with Random Forest classification under a cloud-computing framework (GEE), can effectively predict multi-nutrient status in oil palm plantations with high reliability and minimal misclassification. Consistent Kappa coefficients across nutrients also demonstrate model robustness and generalizability for operational nutrient-mapping applications (Belgiu & Drăguț, 2016; Gorelick et al., 2017).

3.2. Nutrient Status Distribution and Intepretation

The nutrient status classification derived from Sentinel-2 imagery and Random Forest (RF) modeling revealed clear spatial variability of nitrogen (N), phosphorus (P), potassium (K), and magnesium (Mg) across the 4,478 ha oil palm plantation. The distribution of each nutrient class is presented in Table 2.

Table 2 : Areal distribution of nutrient status classes

Nutrient Content Class	Nitrogen		Phosphorus		Potassium		Magnesium	
	Area (ha)	%	Area (ha)	%	Area (ha)	%	Area (ha)	%
Deficient	–	–	1,809	40	–	–	3,032	68
Slightly Deficient	137	3	1,549	35	192	4	118	3
Normal	1,636	37	1,121	25	902	20	–	–
Slightly Excessive	2,705	60	–	–	2,972	66	626	14
Excessive	–	–	–	–	411	9	702	16
Total	**4,478**	**100**	**4,478**	**100**	**4,478**	**100**	**4,478**	**100**

Nitrogen (N)

The spatial distribution of nitrogen showed that 60% of the plantation area fell within the *slightly excess* category, followed by 37% *in the normal category*, and only 3% *in the slighty deficient category*. This pattern indicates a generally adequate N supply across the plantation blocks, consistent with fertilization practices that focus on maintaining canopy vigour and leaf greenness. The strong performance of Sentinel-2 spectral bands, particularly in the red and near-infrared regions, contributed to the high classification accuracy in nitrogen prediction, as these bands are directly sensitive to chlorophyll absorption (Gómez, White, & Wulder, 2016). The predominance of slightly excess N corresponds to higher productivity zones, in accordance with the results reported by Fairhurst and Griffiths (2014).

Phosphorus (P)

Phosphorus exhibits a contrasting pattern, with 75% of the area classified as *deficient* or *slightly deficient*, and only 25% categorized as *normal*. This widespread P deficiency reflects the limited mobility and high fixation capacity of phosphorus in acidic tropical soils, leading to low availability of oil palm roots (Lizcano-Toledo et al., 2021). The spectral sensitivity of phosphorus is generally indirect and derived from its influence on canopy development, rather than direct absorption features. These results highlight the importance of site-specific P management and improved fertilizer formulations to overcome soil fixation and enhance the nutrient use efficiency (NUE).

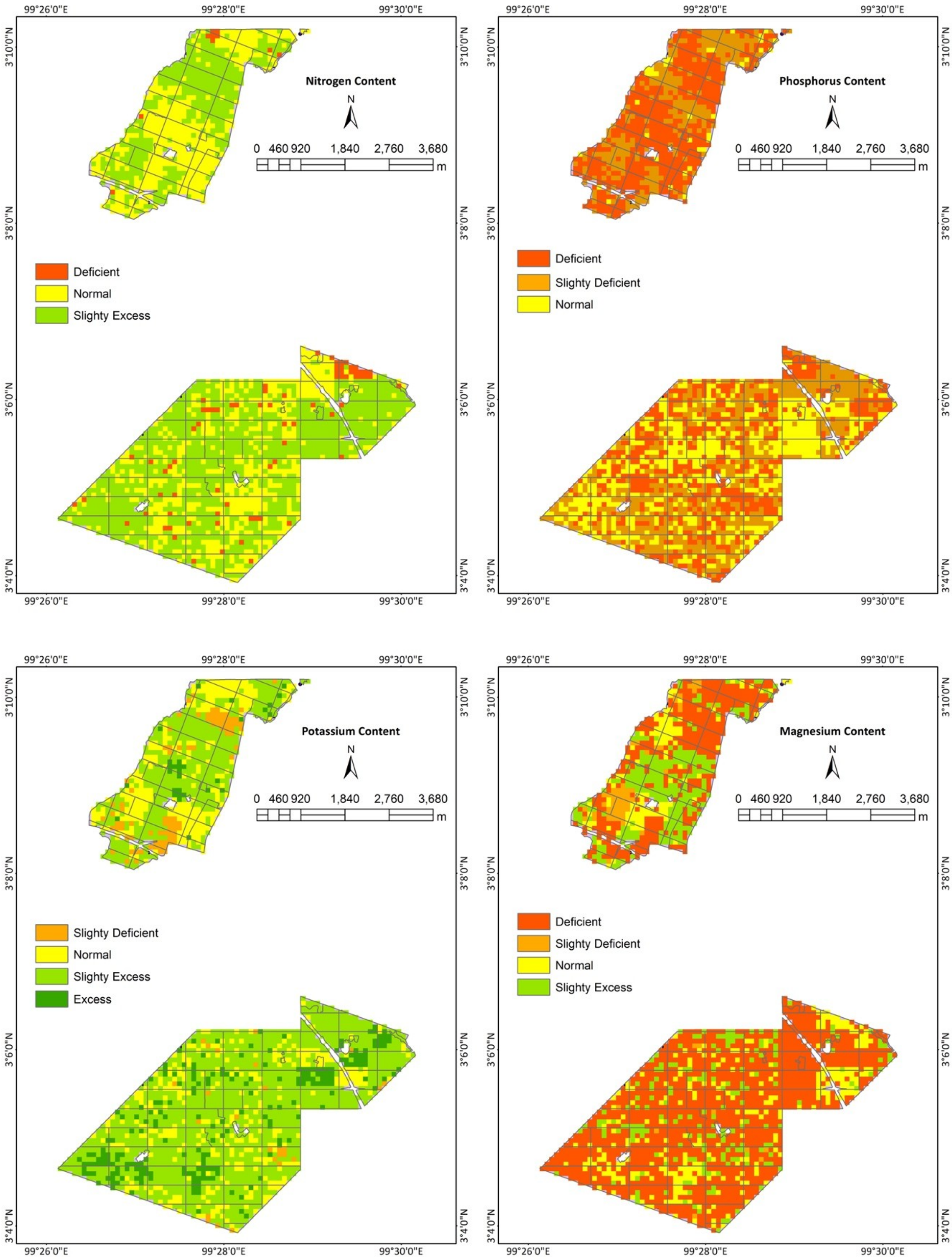

Figure 2 : Leaf Nutrient Status (nitrogen, phosphorus, potassium, and magnesium)

Potassium (K)

For potassium, 66% of the area was categorized as *slightly excessive*, 20% as *normal*, and 13% as *slighty deficient* or *excessive*. The excess-K zones corresponded to better-drained blocks with higher fertilizer application rates, whereas the deficient areas were associated with low-permeability soils where nutrient leaching was limited. These results are consistent with previous findings that K variability in oil palm plantations can be effectively mapped using multispectral data, as K influences canopy reflectance through leaf turgor and structure (Khan et al., 2021).

Magnesium (Mg)

Magnesium status showed a predominance of *deficient* (68%) and *slightly deficient* (3%) zones, with smaller proportions of *slightly excess* (14%) and *excess* (16%) zones. The observed Mg deficiency is likely related to K–Mg antagonism, where high K uptake suppresses Mg absorption, a well-known physiological effect in oil palm nutrition. This antagonistic relationship has been widely reported in plantation systems with high KCl inputs (Fairhurst & Griffiths, 2014; Khan et al. 2021). Mg deficiency highlights the need to adjust the fertilizer balance to maintain optimal cation ratios for sustained productivity.

The classification results demonstrated that Sentinel-2-based Random Forest modeling effectively captured nutrient heterogeneity at the plantation scale. Overall, nitrogen and potassium levels were adequate to slightly excess, whereas phosphorus and magnesium were substantially deficient. The generated nutrient maps provide actionable insights for spatially targeted fertilizer recommendations, supporting the implementation of precision nutrient management strategies to improve cost efficiency and sustainability in oil palm cultivation.

3.3. Cost-Efficiency Evaluation

In this study, we assessed cost efficiency to determine the most effective method for mapping multiple essential leaf nutrients, including nitrogen (N), phosphorus (P), potassium (K), and magnesium (Mg), in oil palm plantations. An innovative approach using Sentinel-2 multispectral imagery and the Random Forest algorithm within the Google Earth Engine (GEE) platform was designed to produce five nutrient maps (*nutrient map*) that support optimised fertiliser use and sustainable palm oil production.

Efficiency was used as an indicator to evaluate whether the proposed technology could replace the conventional method commonly applied for nutrient monitoring. According to Farhana et al. (2013), cost efficiency reflects the ability to achieve cost savings when producing a product or performing an organizational activity. Efficiency measures the relationship between resource inputs and outputs and assesses whether resource utilization generates high economic value.

3.4.1. Cost Components and Comparison

The conventional approach required a total cost of Rp 94,255,548, consisting primarily of field labor (Rp 26,135,548) and laboratory analysis (Rp 68,120,000). This method involves extensive sampling and destructive chemical testing, which are both time-consuming and operationally expensive. In contrast, Table 4 summarizes the production cost using the Remote Sensing (RS)-based approach, which integrates Sentinel-2 data processing in GEE with Random Forest modeling.

Table 3.: Represents the total cost incurred in monitoring nutrient distribution using the conventional (without RS) method.

Conventional Method (Without RS)	Unit	Quantity	Unit Cost (Rp.)	Total (Rp.)
Direct Labor Cost :				
Field sampling labor	*Man-Days*	*262*	*99,754*	*26,135,548*
Laboratory analysis	*Sample*	*262*	*260,000*	*68,120,000*
Total Production Cost				96,255,548

Source: Processed data (2025)

Table 4. : Presents the total cost incurred in monitoring nutrient distribution Remote Sensing based method

RS Based Method	Unit	Quantity	Unit Cost (Rp.)	Total (Rp.)
Raw Material Cost :				
GEE subscription	*Year*	*1*	*8,500,000*	*8,500,000*
Direct Labor Cost :				
Technical Expert	*Man-Days*	*2*	*1,355,013*	*2,710,27*
Field sampling labor	*Man-Days*	*65,5*	*99,754*	*6,533,887*
Laboratory analysis	*Sample*	*65,5*	*260,000*	*17,030,000*
Overhead Cost :				
Computer rent	*Month*	*1*	*2,000,000*	*2,000,000*
Total Production Cost				36,733,914

The total cost for the RS-based method was Rp 36,773,914, including raw materials (Rp 8,500,000), direct labor (Rp 26,273,914), and overhead (Rp 2,000,000). This represents a reduction of approximately 61% compared with the conventional approach.

3.4.2. Efficiency Calculation

The efficiency was calculated using the following formula:

$$E = \frac{\text{Output}}{\text{Total Cost}} \times 100\%$$

Assuming equivalent output quality between both methods, the ratio of cost efficiency between the conventional and RS-based approaches was 1:2.56, indicating a 156% increase in cost efficiency when applying remote-sensing technology. This finding implies that producing the same outputs (five nutrient maps) required significantly less cost and time using Sentinel-2 and GEE. Multispectral satellite data and machine learning algorithms enable higher productivity per unit cost by minimizing repetitive field sampling and laboratory analysis. The RS-based approach also enhances the effective use of resources by combining automation, scalability, and rapid data access to deliver actionable insights. Consequently, this method provided greater economic value per unit of input, confirming a higher operational efficiency than conventional practices.

These results are consistent with the conceptual framework of cost efficiency measurement described by Cooper et al. (2006) and Mokhtar et al. (2008), emphasizing that technological innovation enhances productivity by reducing resource inputs while maintaining output quality. Furthermore, following Sherman and Zhu (2006), the calculated ratio should be interpreted conservatively, as some unquantified benefits (e.g. time savings, spatial coverage, and analytical repeatability) may further enhance the true efficiency value.

3.5. Implications for Precision Nutrient Management

The integration of Sentinel-2 multispectral imagery, Random Forest (RF) modeling, and cloud-based processing in Google Earth Engine (GEE) demonstrates strong potential as an operational framework for precision nutrient management in oil palm plantations. The results of this study confirm that the approach is both technically accurate and economically efficient, providing plantation managers with timely, data-driven insights for spatially optimized fertilizer applications.

The classification accuracy achieved for the four macronutrients (N, P, K, and Mg) was consistently above 90%, with kappa coefficients ranging from 0.85 to 0.89. This high performance indicates that reflectance data from the 10 m Sentinel-2 RGB–NIR bands are sufficient to discriminate nutrient-status classes without the need for additional vegetation indices or temporal composites. These findings are consistent with those of Li et al. (2023) and Belgiu & Drăguț (2016), who demonstrated that RF models can effectively extract biochemical variability using limited but information-rich spectral inputs.

From an operational perspective, the generated nutrient-status maps provide actionable information on spatial variability across the plantation blocks. Identifying zones of deficiency or excess allows site-specific fertilization, reducing over-application while maintaining productivity. Such optimization not only improves fertilizer efficiency but also mitigates nutrient leaching and runoff, which are key environmental concerns in tropical plantation ecosystems (Woittiez et al. 2019; Lizcano-Toledo et al. 2021).

The cost efficiency analysis further supports the practical advantages of the RS–ML approach. With an estimated 156% improvement in cost efficiency compared with the conventional field-and-laboratory method, the integrated system markedly reduces the time, manpower, and material expenditure required for nutrient monitoring. Leveraging free Sentinel-2 imagery and cloud-based computation enables repeated large-scale assessments at minimal incremental costs. This scalability makes the system highly suitable for both corporate plantations and regional monitoring programs, where traditional methods remain logistically demanding and financially restrictive (Cooper et al. 2006; Mokhtar et al. 2008).

Overall, this study highlights how the synergy of remote sensing, machine learning, and cloud computing can transform traditional plantation management into a precision-driven, sustainable, and cost-effective system. Future research should focus on integrating temporal Sentinel-2 composites and ancillary datasets, such as soil properties, yield maps, and climatic variables, to refine nutrient-prediction models and enable dynamic, adaptive decision-making for fertilizer scheduling and environmental stewardship.

Conclusion

This study successfully developed a cost-efficient multi-nutrient mapping framework for oil palm plantations by integrating Sentinel-2 multispectral imagery, Random Forest (RF) modeling, and cloud-based processing in Google Earth Engine (GEE). The approach effectively addressed the key objectives of (i) estimating multiple macronutrients, namely, nitrogen (N), phosphorus (P), potassium (K), and magnesium (Mg) using spectral information from Sentinel-2 imagery, (ii) evaluating classification accuracy and model reliability, and (iii) assessing the cost-efficiency of remote sensing–based monitoring compared to conventional laboratory methods.

The results demonstrated that RF classification achieved high accuracy (overall > 90%) and strong agreement (kappa 0.85–0.89) for all nutrients, even when using only the 10 m RGB–NIR bands. This confirms that Sentinel-2 spectral data, when properly modeled, can capture the biochemical variability of oil palm canopies without requiring additional vegetation indices or temporal composites.

Spatial analysis revealed that nitrogen and potassium levels were generally adequate or slightly excessive, whereas phosphorus and magnesium deficiencies were widespread,emphasizing the need for site-specific nutrient management. The resulting nutrient maps provide a practical decision-support tool for optimizing fertilizer dosage, improving nutrient use efficiency, and reducing environmental impacts.

From an economic perspective, the RS–ML framework improved cost efficiency by 156% compared with the conventional field-and-laboratory approach, significantly lowering monitoring expenses while maintaining the analytical accuracy. This confirms that remote sensing combined with machine learning and cloud computing offers a scalable, rapid, and sustainable alternative for the operational monitoring of nutrients in large-scale plantations.

In summary, this study demonstrates that the integration of Sentinel-2 imagery, Random Forest modeling, and GEE can transform conventional nutrient-management practices into a precision, data-driven system, enabling both productivity gains and resource optimization in the oil palm sector.

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