Vol. 13, No. 4 (2024): 1051 - 1063
http://dx.doi.org/10.23960/jtep-l.v13i4.1051-1063

JURNAL TEKNIK PERTANIAN LAMPUNG

ISSN 2302-559X (print) / 2549-0818 (online)
Journal homepage : https://jurnal.fp.unila.ac.id/index.php/JTP

The Use of the Normalized Difference Red Edge (NDRE) Vegetation Index from Multispectral Cameras Mounted on Unmanned Aerial Vehicle to Estimate the Nutrient Content in Oil Palm Leaves

Badi Hariadi[1,3,✉], Hermantoro[2], Andreas Wahyu Krisdiarto[2], Sukarman[3], Tri Haryo Sagoro[3], Septa Primananda[3], Arief Rahmad Maulana Akbar[4], Arief Ika Uktoro[2]

[1] Magister Program in Plantation Management, STIPER Institute of Agriculture, Yogyakarta, INDONESIA.
[2] Department of Agricultural Engineering, Faculty of Agricultural Technology, STIPER Institute of Agriculture, Yogyakarta, INDONESIA.
[3] Wilmar International Plantation, Central Kalimantan Region, INDONESIA.
[4] Agroindustrial Technology Department, Lambung Mangkurat University, INDONESIA.

Article History:

Received : 31 January 2024
Revised : 13 May 2024
Accepted : 26 May 2024

Keywords:

Multispectral Cameras,
Oil Palm,
Leaf Nutrient Contents,
Prediction.

Corresponding Author:
✉ b.hariadi@gmail.com
(Badi Hariadi)

ABSTRACT

This study aimed to develop a prediction model for the nutrient content of N, P, K, Mg, and Ca in oil palm leaves using the Normalized Difference RedEdge (NDRE) vegetation index derived from multispectral camera data. Data acquisition was carried out by an unmanned aerial vehicle (UAV), which was correlated to leaf sample analysis of the 17th frond number. Results showed that simple regression analysis successfully represented nutrient content (N, P, K, Mg, and Ca) based on NDRE values. Based on the MAPE and Correctness values, the nutrient content prediction model for N and P yields reliable results, while for K, Mg, and Ca, they are considered good, with Correctness values of 95.5%, 96.6%, 88.8%, 87.3%, and 90.0% for N, P, K, Mg, and Ca, respectively. The study found that the NDRE vegetation index can be used to predict the nutrient content of oil palm leaves with reliable results in accuracy for N and P, and good accuracy for K, Mg, and Ca. This is a promising finding, as it could lead to the development of a non-destructive and rapid method for monitoring the nutrient status of oil palm trees, with the validation models for N, P, K, Mg, and Ca are yN = 1.1089x - 0.2497, yP = 0.99x + 0.002, yK = 1.204x - 0.1576, yMg = 0.9149x + 0.0183, and yCa = 1.0418x - 0.0218.

1. INTRODUCTION

Oil palm is a plantation commodity that plays an important role in the economic activities of Indonesia, due to its ability to produce vegetable oil that is widely used by various industrial sectors, such as the cooking oil industry, industrial oil, and fuel oil (biodiesel) (BPS, 2022). The importance of the role of palm oil is demonstrated by Indonesia's global leadership as the leading producer of palm oil, with Malaysia in second place (Gregory, 2022).

The high demand for palm oil derivatives to meet the needs of fuel, food, and industry is projected to continue to increase, which could lead to price increases, if not offset by increased production (CPOPC, 2022). Inadequate management factors (CPOPC, 2022), low productivity of oil palm plantations, especially in Indonesia, is one of the causes. The average actual productivity of all oil palm plantations in Indonesia in 2021 was only 3.7 tons/Ha (BPS, 2022), from its potential to reach 8.9 tons/ha of crude palm oil (Fairhurst & Griffiths, 2014; Woittiez et al., 2017).

The implementation of best plantation management practices (Donough et al., 2010), such as nutrient and care management, has been shown to increase oil palm productivity, in terms of both the number and weight of bunches produced (Griffiths & Fairhurst, 2003). On the other hand, poor fertilization management, such as in trees that are not given nitrogen and potassium fertilizers, can reduce oil palm productivity (Woittiez et al., 2017). Nutrient management or fertilization of oil palm plants is essential because of its implications for environmental issues. Excessive use of fertilizers can cause air pollution, soil acidification and degradation, water eutrophication, crop yield reduction, and ultimately threaten the sustainability of environmentally responsible agricultural practices (Yadegari et al., 2020).

The nutrient management of oil palm plants usually begins with leaf nutrient analysis because the leaf nutrient content values can indicate the response of oil palm plants to fertilizer application (Goh, 2004; Prabowo, 2005). Leaf nutrient analysis (Broeshart, 1955), is usually carried out using a chemical analysis method of leaf samples from the 17th frond of oil palm (Von Uexkull, 1991). Leaf sampling on the 17th frond of oil palm is generally carried out in a destructive manner, which should have been avoided by utilizing non-destructive methods (Jayaselan et al., 2017). An example of a non-destructive method is the application of remote sensing technology to obtain oil palm leaf data quickly, especially if supported by high-performance computing technology, the Internet of Things (IoT), and artificial intelligence (AI) (Sastrohartono et al., 2021). This will then be able to streamline the work.

Several studies have used remote sensing data from satellite imagery, such as those from the SPOT-5 satellite, to produce regression models that show the relationship or correlation between the nutrient elements N, P, and K and the vegetation index NDVI (Marzukhi et al., 2016). Other studies have also been conducted to analyze the nutrient levels of N, P, K, Mg, and Ca in oil palm leaves using Landsat-8 OLI/TRIS satellite imagery using SVM, ANN, and Random Forest methods (Kok et al., 2021). Analysis using Sentinel-1-A satellite imagery can provide average MAPE, correctness, and MSE for estimating the nitrogen content of oil palm leaves, which are 9.68%, 90.32%, and 11.03%, respectively (Munir et al., 2022). The analysis of nitrogen nutrient levels in oil palm plants has also been studied using SPOT-7 satellite imagery, using the MSAVI, MTVI1, and TVI vegetation indices, which can produce prediction models with R^2 values above 0.9 (Yadegari et al., 2020).

Leaf nutrient analysis of oil palm using remote sensing data from unmanned aerial vehicles has also been the subject of much research. The predictive model for the levels of Ca, Mg, and S nutrients using multiple linear regression statistical analysis can present predicted data with successive accuracies of 66.7%, 63.3%, and 36.6% (Suyuthi et al., 2019). A polynomial multiple regression model of RFE-selected variables is able to predict the nutrient content of N, P, K, and Mg in oil palm leaves with R^2 values of 0.94 to 0.99, adjusted R^2 values of 0.72 to 0.98, and RSE values of 0.0045 to 0.034 (Santoso & Winarna, 2021). In another study, the prediction model for N, P, and K on the 17th frond number and the calculation of vegetation indices from multispectral camera aerial photos can produce accuracies assessed from the correctness values of 95.11%, 95.38%, and 88.65% (Budiman et al., 2022).

The application of remote sensing technology to estimate the nutrient content of oil palm leaves generally utilizes the reflectance value of light from several or many spectral bands and analyzes it statistically with data from the analysis of oil palm leaf samples in the laboratory. Vegetation indices in the form of reflectance ratios or other formulas can be calculated from at least two reflectance values from two spectral bands, depending on the spectral properties of the plant being observed (Mróz & Sobieraj-Żłobińska, 2004).

Vegetation indices, which number in the hundreds of formulas, can be obtained through relatively simple algorithmic calculations that are effective for evaluating vegetation cover qualitatively and quantitatively (Xue & Su, 2017). One example of a vegetation index that can be used for vegetation analysis is the Normalized Difference Red Edge (NDRE) because it can represent the reflectance values of vegetation canopies well (Barnes et al., 2000). NDRE has also been shown to be a sensitive vegetation index for monitoring chlorophyll content in leaves, which is correlated with nitrogen levels (Boiarskii, 2019).

Specific research that utilizes the NDRE vegetation index from a multispectral camera to analyze oil palm plants is still very rare. Therefore, the authors were motivated to conduct this research, which aims to obtain a predictive model for the levels of N, P, K, Mg, and Ca nutrients in oil palm leaves using the NDRE vegetation index obtained from a multispectral camera.

2. MATERIALS AND RESEARCH METHODOLOGY

2.1. Location and Research Samples

Figure 1 provided workflow of this research that was conducted in March 2023 at a palm oil plantation located in Kotawaringin Timur Regency, Central Kalimantan Province, at coordinates 02°07'41"S, 112°34'22"E (see Figure 2(a)). The research site has a flat to undulating topography with Entisols soil type, and is located at an elevation of 10-50 meters above sea level. The research focused on a 6-hectare area containing 891 oil palm trees planted in 2017. The sample selection criteria included only blocks with trees uniformly planted under 6 years ago, to ensure minimal overlap between oil palm canopies. Additionally, we selected blocks exhibiting a clear visual distinction in plant health. This included trees with yellowing foliage, indicative of nutrient deficiency, alongside healthy green trees.

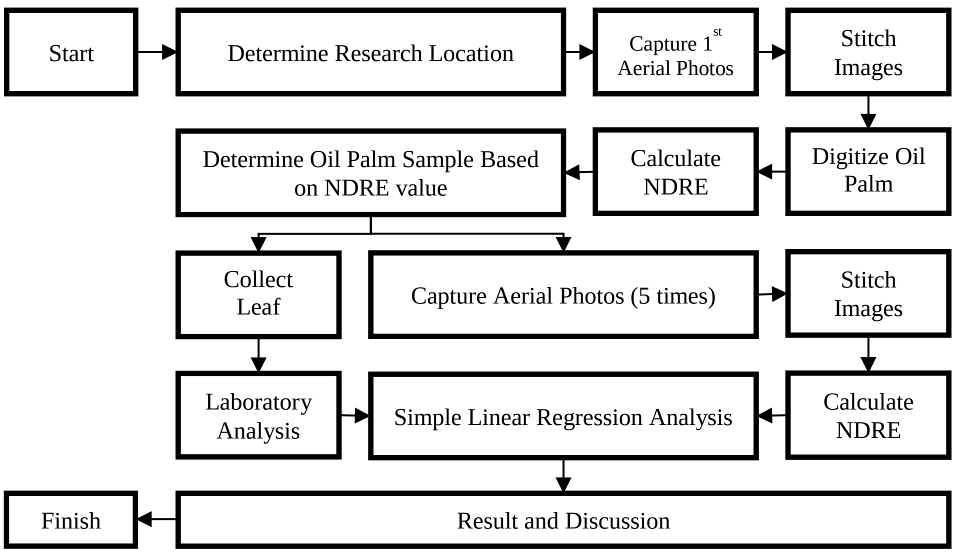

Figure 1. Research workflow

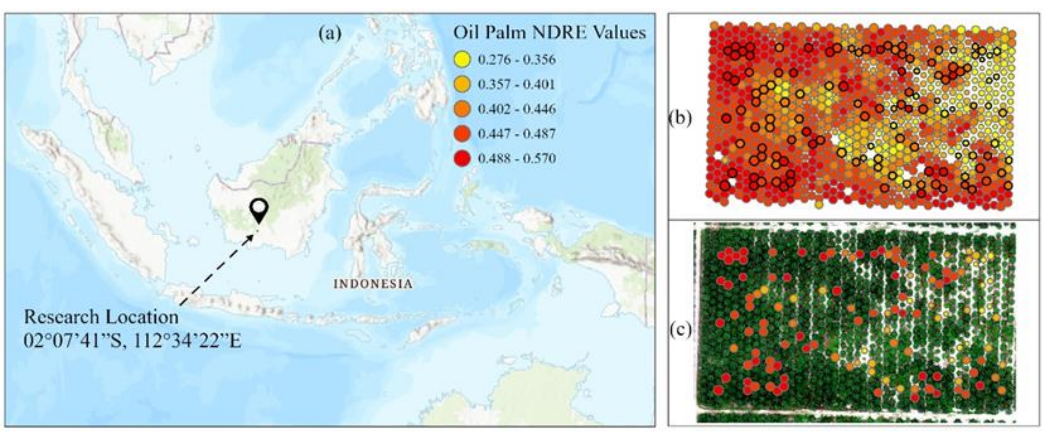

Figure 2. (a) Research location and (b), (c) the distribution of tree samples for research based on the distribution of NDRE value.

The sample of oil palm leaves that were studied were taken from the 17th frond number with a total of 123 trees that were selected by stratified random sampling based on the distribution of NDRE representative values, representing approximately 14% of the total population. This was done to ensure that the samples used represented NDRE values from low to high (see Figure 2. (b), (c)). The NDRE equation used is:

$$\text{NDRE} = \frac{NIR - RedEdge}{NIR + RedEdge} \quad (1)$$

where NIR is the reflectance value at the Near Infrared wavelength, and RedEdge is the reflectance value at the RedEdge wavelength.

The 17^{th} frond number is commonly used for analyzing the nutrient content of oil palm leaves in plants older than 3 years (Von Uexkull, 1991), This is because it is more sensitive to indicating the nutrient content of leaf (Rendana et al., 2015), and provides a better indication than the 3rd and 9th frond numbers (Jayaselan et al., 2017). The collected leaf samples (see Figure 4(a)) were then analyzed in the laboratory to obtain the concentrations of the nutrients N, P, K, Mg, and Ca. The data from these laboratory analyses were then used as the dependent variable in the statistical analysis of this study to obtain a predictive model.

2.3. Multispectral Cameras Data

The interaction between electromagnetic waves from the sun and the Earth's surface occurs in four forms: transmission, reflection, scattering, and absorption (Hadi, 2019). Leaf objects also experience these conditions, where on average, plant leaves absorb about 75% of sunlight, reflect it about 15%, and the remaining about 10% is transmitted (Al-Rajab, 2021). The interaction between solar electromagnetic waves and plant leaves can occur naturally due to the presence of chemical components and physical structures in plants. This natural condition occurs to protect plants from damage due to excessive heat by strongly reflecting the infrared spectrum, while for the purpose of photosynthesis, chlorophyll contained in the mesophyll strongly absorbs the blue and red light spectrum, and reflects green light (Al-Rajab, 2021). An illustration of the reflection of electromagnetic waves in the wavelength range of 350-2500 nm on healthy plant leaves is shown in Figure 3. The reflectance data at the blue (475 nm center, 32 nm bandwidth), green (560 nm center, 27 nm bandwidth), red (668 nm center, 14 nm bandwidth), red edge (717 nm center, 12 nm bandwidth), and near-infrared (842 nm center, 57 nm bandwidth) wavelengths of the investigated leaf samples were acquired using a MicaSense RedEdge-P multispectral camera. The camera was carried by the DJI Matrice 300 RTK unmanned aerial vehicle (see Figure 4 (b)), at an altitude of 80 meters above ground level in an area of 6 hectares. Data collection was repeated 5 times to obtain the average value of the vegetation index. The Downwelling Light Sensor (DLS2) was used to correct changes in lighting during flight and the Calibrated Reflectance Panel (CRP2) was used to calibrate digital numbers to reflectance values. The data acquisition method using this camera was adapted to the user guide published by MicaSense.

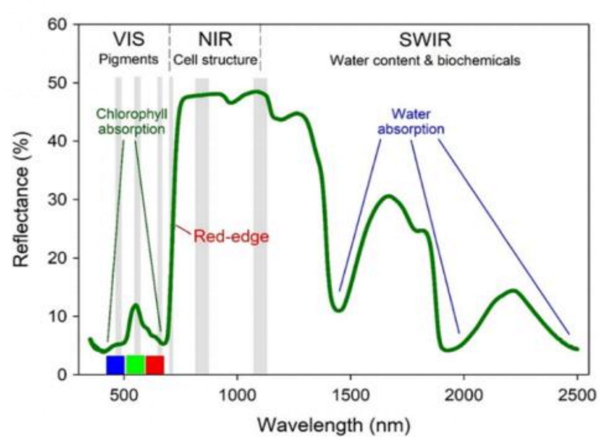

Figure 3. The reflection of electromagnetic waves in the wavelength range of 350-2500 nm on healthy leaves (Cotrozzi, 2022).

The process of radiometric correction and orthomosaic of aerial image data is carried out using the Agisoft Metashape software. After the orthomosaic data from 5 flights have been processed, the digitization of oil palm circles and the analysis of the NDRE vegetation index are then carried out using ArcGIS Pro software. The value used as the independent variable of the study is the average NDRE value within oil palm circles from 5 flights conducted.

(a) (b)

Figure 4. (a) Leaf sampling process on 17th frond number and (b) aerial photography process using a multispectral camera.

2.4. Development of Prediction Models

The development of a prediction model for the nutrient elements N, P, K, Mg, and Ca was carried out using the simple linear regression statistical technique. The simple linear regression equation used is as follows:

$$Y_N = \alpha_N + \beta_N * X \tag{2}$$

$$Y_P = \alpha_P + \beta_P * X \tag{3}$$

$$Y_K = \alpha_K + \beta_K * X \tag{4}$$

$$Y_{Mg} = \alpha_{Mg} + \beta_{Mg} * X \tag{5}$$

$$Y_{Ca} = \alpha_{Ca} + \beta_{Ca} * X \tag{6}$$

where Y_N, Y_P, Y_K, Y_{Mg}, dan Y_{Ca} are the predicted values of the nitrogen, phosphate, potassium, magnesium, and calcium nutrient levels, respectively; α and β are the intercept and slope values; and X is the NDRE value obtained from the processing of multispectral aerial imagery data.

The research dataset with 123 samples was divided into two parts, with 75% of the data used for training and 25% used for validation. Model development was performed using Microsoft Excel software.

2.5. Evaluation of Prediction Models Performance

The performance of a predictive model is evaluated using the following metrics: R Square (R^2) (Chicco et al., 2021), Root Mean Square Error (RMSE) (Chicco et al., 2021), Mean Absolute Percentage Error (MAPE) (Moreno et al., 2013), and Correctness (Budiman et al., 2022). The three were calculated respectively according to the following relations.

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(X_i - Y_i)^2} \tag{7}$$

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Y_i - X_i}{Y_i}\right| x\ 100 \tag{8}$$

$$\text{Correctness} = (1\text{-MAPE})*100\% \tag{9}$$

The closer the R^2 value to 1, the closer the RMSE and MAPE values to 0, and the closer the Correctness value to 100%, the better the performance of the predictive model (Table 1).

Table 1. MAPE interpretation (Moreno *et al*., 2013) dan Correctness (Budiman *et al*., 2022).

MAPE (%)	Correctness (%)	Interpretation
<10	>90	Highly Accurate Forecasting
10-20	80-90	Good Forecasting
20-50	50-80	Reasonable Forecasting
>50	<50	Inaccurate Forecasting

3. RESULTS AND DISCUSSIONS

3.1. Leaf Sample Analysis

The results of the laboratory analysis of leaf samples are presented in the form of a box and whisker plot and a table in Figure 5. The average nutrient content of N, P, K, Mg, and Ca in the studied oil palm leaf samples were 2.35, 0.154, 0.821, 0.372, and 0.756, respectively (see Figure 5). Based on the nutrient sufficiency class (see Table 2), the nutrient content of N and K in the samples studied tended to be in the deficiency-low nutrient sufficiency class, the nutrient content of P tended to be optimum, while for Mg and Ca, it tended to be in the optimum-high nutrient sufficiency class (see Figure 6). It can be seen that the research variable of the nutrient content of oil palm leaves used to analyze the nutrients N, P, K, Mg, and Ca can be said to be still not very diverse, because it is not yet sufficient to represent all nutrient sufficiency classes.

	N	P	K	Mg	Ca
Mean	2.35	0.154	0.821	0.372	0.756
Standard Error	0.0196	0.0008	0.0122	0.0054	0.009
Median	2.36	0.154	0.812	0.373	0.748
Mode	2.38	0.151	0.812	0.338	0.713
Standard Deviation	0.2171	0.0087	0.1354	0.06	0.0994
Sample Variance	0.0471	0.0001	0.0183	0.0036	0.0099
Kurtosis	-0.405	-0.125	-0.322	-0.692	-0.585
Skewness	-0.202	-0.118	0.28	0.201	0.162
Range	1.01	0.044	0.649	0.272	0.438
Minimum	1.87	0.13	0.541	0.249	0.546
Maximum	2.88	0.174	1.19	0.521	0.984
Count	123	123	123	123	123
Confidence Level(95.0%)	0.0387	0.0016	0.0242	0.0107	0.0177

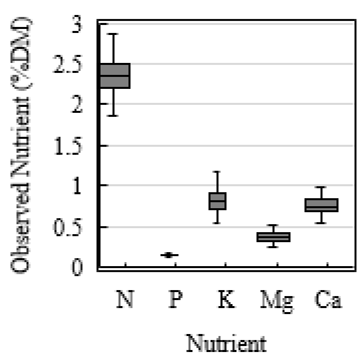

Figure 5. Box and whisker plot and descriptive statistics table of laboratory analysis results for leaf samples.

Table 2. Nutrient Sufficiency Class of oil palm more than 6 years from planting (Fairhurst & Mutert, 1999; Von Uexkull, 1991).

Nutrient	Units	Deficiency	--- Optimum ---		Excess
N	% DM	<2.30	2.40	2.80	>3.00
P	% DM	<0.14	0.15	0.18	>0.25
K	% DM	<0.75	0.90	1.20	>1.60
Mg	% DM	<0.20	0.25	0.40	>0.70
Ca	% DM	<0.25	0.50	0.75	>1.00

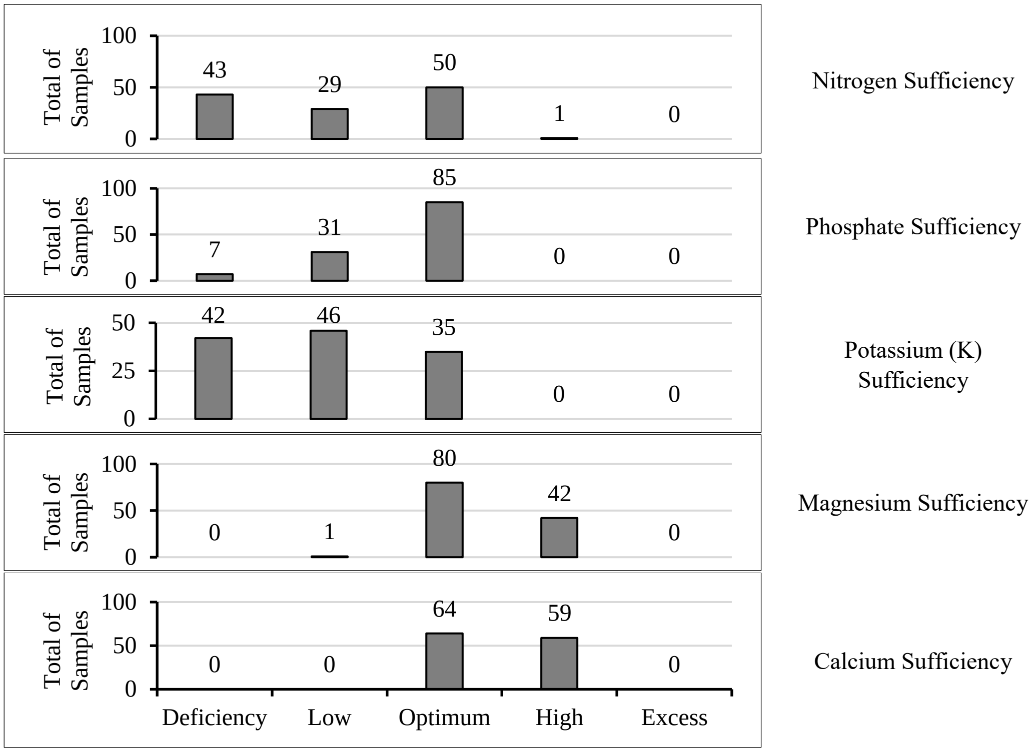

Figure 6. Bar chart of the distribution of research samples by nutrient sufficiency class

	F01	F02	F03	F04	F05	Mean
Mean	0.438	0.44	0.443	0.462	0.456	0.448
Standard Error	0.006	0.006	0.006	0.006	0.006	0.006
Median	0.444	0.449	0.452	0.474	0.466	0.458
Standard Deviation	0.061	0.062	0.062	0.065	0.065	0.063
Sample Variance	0.004	0.004	0.004	0.004	0.004	0.004
Kurtosis	-0.75	-0.73	-0.79	-0.73	-0.78	-0.77
Skewness	-0.32	-0.32	-0.29	-0.43	-0.4	-0.36
Range	0.259	0.27	0.25	0.28	0.26	0.26
Minimum	0.302	0.3	0.311	0.306	0.313	0.307
Maximum	0.561	0.566	0.562	0.589	0.577	0.57
Count	123	123	123	123	123	123
Confidence Level(95.0%)	0.011	0.011	0.011	0.012	0.012	0.011

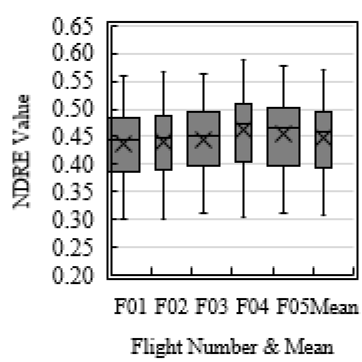

Figure 7. Box and whisker plot and table of NDRE values for each flight and their overall means

3.2. Multispectral Camera Dataset

Unmanned Aerial Vehicle (UAV) flights for aerial photography with a multispectral camera were conducted 5 times within 2 days in February 2023. The results of the aerial photography analysis were then averaged and used as an independent variable in this study. The distribution of the average data of the NDRE vegetation index values of the research samples derived from multispectral camera data, as shown in Figure 2 (c), while the NDRE values for each flight are presented in the form of a box & whisker plot and a descriptive statistics table in Figure 7.

If observed in Figure 7, the NDRE data from aerial photographs of each flight appear to be quite consistent, which is likely due to the relatively similar flight times, i.e., between 9:00 a.m. and 12:00 p.m., with relatively uniform lighting conditions. This is in accordance with the recommendations in the user guide to fly at times with low shadow effects and fly when the sun is clear or overcast without the interference of cloud shadows, and to correct the photos taken by using DLS2 and CRP.

3.3. Prediction Models

In developing predictive models for nutrient content, we analyze the average NDRE value within oil palm circles (Variable X) against laboratory analysis results (Variable Y) using simple linear regression. This method is chosen for its simplicity, ease of interpretation, and computational efficiency, making it ideal for analyzing the relationship between these two variables and identifying a potential linear trend that explains the data (Sarstedt & Mooi, 2014).

A training dataset with 93 samples was used to develop this predictive model. The results of the predictive model development that have been carried out, as shown in Figure 8 below.

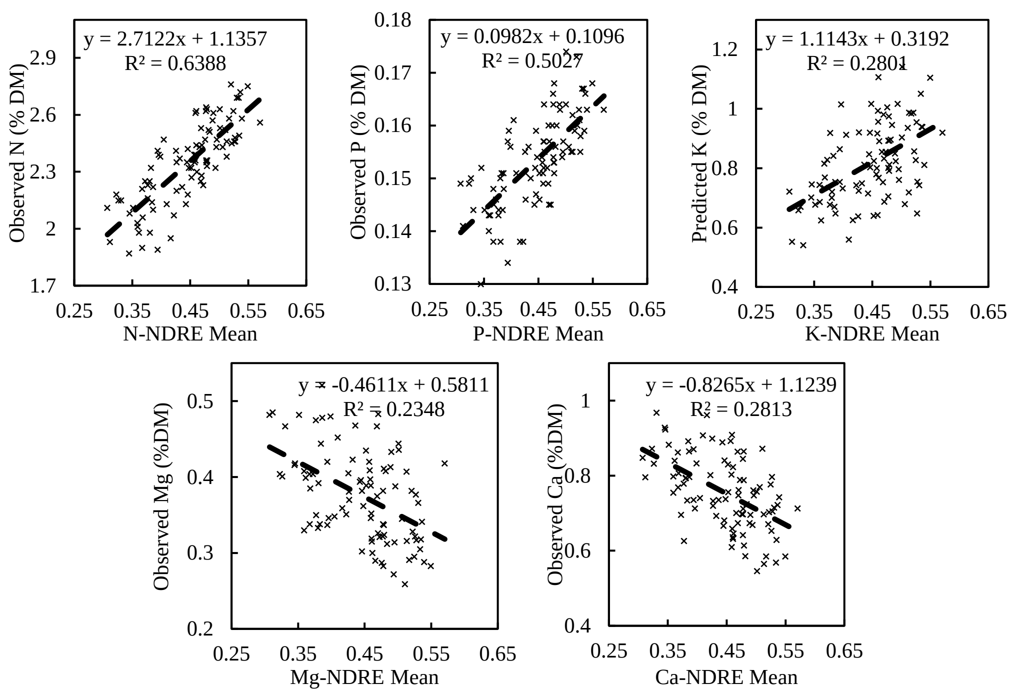

Figure 8. Linear regression plot of the training data.

The following is a simple linear regression equation model for predicting the nutrient content of oil palm leaves that has been successfully developed:

$$Y_{N'} = 1.13567 + (2.71217 * NDRE) \quad (10)$$

$$Y_{P'} = 0.10957 + (0.09821 * NDRE) \quad (11)$$

$$Y_{K'} = 0.31919 + (1.11427 * NDRE) \tag{12}$$

$$Y_{Mg'} = 0.58113 + (-0.46105 * NDRE) \tag{13}$$

$$Y_{Ca'} = 1.12391 + (-0.82647 * NDRE) \tag{14}$$

where $Y_{N'}$, $Y_{P'}$, $Y_{K'}$, $Y_{Mg'}$, dan $Y_{Ca'}$ are the predicted values of N, P, K, Mg, and Ca nutrient contents, respectively, and NDRE is the average NDRE pixel value within oil palm circles obtained from multispectral aerial photo analysis.

In developing predictive models for nutrient content, we pre-process the average NDRE value within oil palm circles (Variable X) according to the following calibration equations: equation (10) for N, equation (11) for P, equation (12) for K, equation (13) for Mg, and equation (14) for Ca. Then, we analyze the pre-processed data against laboratory analysis results (Variable Y) using simple linear regression. From Figure 8, it can be seen that the relationship between the nutrient content of N, P, and K in oil palm leaves with the NDRE value shows a positive relationship, that is, the higher the NDRE value, the higher the nutrient content of N, P, and K. Conversely, a negative relationship occurs between the nutrient content of Mg and Ca with the NDRE value, which can be interpreted that the higher the NDRE value, the lower the nutrient content of Mg and Ca.

3.4. Nutrient Contents Prediction

The developed prediction model was then used to predict nutrient contents using a validation dataset, with a total of 30 samples. The results of the prediction of nutrient contents (N, P, K, Mg, and Ca) of oil palm leaves conducted in this study are shown in Figure 9 and Table 3 below.

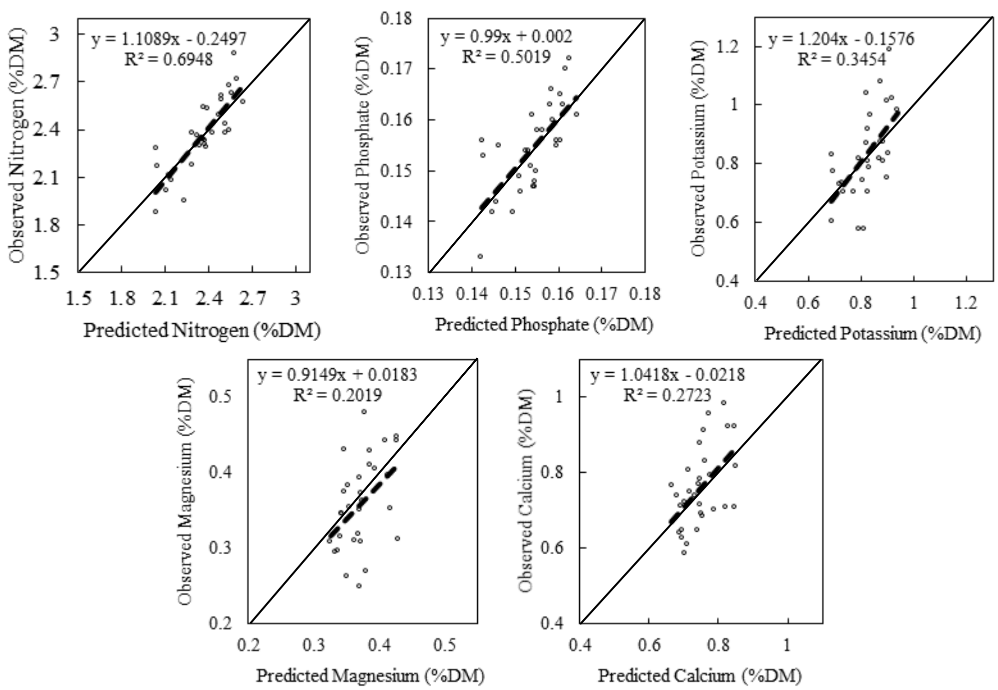

Figure 9. Linear regression results plot.

Table 3. Prediction Model Performance.

	N	P	K	Mg	Ca
R^2	0.69	0.50	0.35	0.20	0.27
RMSE	0.13	0.006	0.12	0.05	0.09
MAPE (%)	4.5	3.4	11.2	12.7	10.0
Correctness (%)	95.5	96.6	88.8	87.3	90.0

In this study, based on the R^2 value generated by the trendline (see Figure 8 and Table 3), it can be seen that the NDRE variable can explain the nutrient content of N, P, K, Mg, and Ca leaves in the following order: 69%, 50%, 35%, 20%, and 27%, while the remaining is explained by other variables that are not present.

The prediction error expressed in RMSE shows that when the successfully developed prediction model is used to predict the nutrient content of N, P, K, Mg, and Ca in oil palm leaves, the range of prediction error for the nutrient content of N, P, K, Mg, and Ca is ±0.13, ±0.006, ±0.12, ±0.05, and ±0.09, respectively, in %DM units.

Evaluation of the performance of the prediction model using the MAPE and Correctness values shows that the prediction error for the nutrient content of N, P, K, Mg, and Ca by the NDRE variable shows MAPE values of 4.5%, 3.4%, 11.2%, 12.7%, and 10%; and Correctness values of 95.5%, 96.6%, 88.8%, 87.3%, and 90%. Based on the interpretation of the MAPE and Correctness values (see Tables 1 and 3), the prediction model for the nutrient content of N and P provides highly accurate forecasting results, while for K, Mg, and Ca, it provides good forecasting results.

In this study, it was found that the changes in chlorophyll content of oil palm leaves can be explained by the NDRE vegetation index. This is related to the relationship between chlorophyll content and N nutrient contents in oil palm leaves. Plants that receive adequate N supply are characterized by high photosynthetic activity and good vegetative growth, which is indicated by dark green leaves. However, plants that experience N deficiency are characterized by yellow leaves, stunted growth, and can lead to crop failure (Nurhayati, 2021). Nitrogen (N) is a mobile nutrient. If the supply of N from the roots is insufficient, the N in the mature leaves will move to supply the younger plant organs. This mobility of N is what makes it easy to visually identify plants that are deficient in N. Specifically, the older leaves will first show signs of deficiency and appear yellow compared to the younger leaves. This is due to the process of hydrolysis (proteolysis), which causes the breakdown of chloroplasts and a decrease in chlorophyll content (Nurhayati, 2021).

The NDRE vegetation index can also explain the P nutrient content in oil palm leaves. The P nutrient affects the length of the fronds, stem circumference, P nutrient content in the 17th frond number (Albari et al., 2018), and the size of the palm fruit bunch (Von Uexkull, 1991). P deficiency is not visible in the leaf color, but rather in the size and shape of the stem, which tends to be stunted, and has short fronds (Von Uexkull, 1991). If we look at the research samples (Figure 6), the condition of the oil palm plants in the study location shows symptoms that tend to experience P nutrient deficiency. In Figure 2 (b) and (c), research samples with low NDRE values tend to be stunted, while research samples with high NDRE values tend to be normal.

The NDRE vegetation index is also can slightly explain the potassium (K) nutrient content in oil palm leaves. Potassium (K) nutrients have an effect on oil palm plants in terms of the number and size of bunches (Von Uexkull, 1991), as well as their tolerance to stress, maintaining leaf function due to its role in maintaining osmotic potential in the regulation of stomata opening and closing, protein synthesis, and increasing N fertilization efficiency (Nurhayati, 2021). Oil palm plants that show symptoms of K nutrient deficiency can be visually observed from their leaves that have orange spotting (Von Uexkull, 1991), have dark green young leaves; while the old leaves show necrosis at the edges and tips of the leaves, as well as necrosis between the leaf veins, and are more susceptible to pest and disease attacks due to extreme climate change. The mobile nature of K nutrients causes the appearance of deficiency symptoms to begin in the older parts of the plant (Nurhayati, 2021).

The NDRE vegetation index can slightly explain the levels of Mg and Ca nutrients in oil palm leaves. Although Mg nutrients are present in small concentrations, ranging from 0.1% to 0.4%, they play an important role in plants as a component of chlorophyll molecules in all green plants, metabolic processes, and protein synthesis. In general, Mg content is higher in old leaves than in young leaves. Symptoms of Mg deficiency are characterized by the occurrence of chlorosis or yellowing in the interveinal areas of old leaves, stiffness, easy damage, curling, and easy to fall off. Due to the mobility of Mg nutrients, deficiency symptoms can be seen starting from old leaves and then moving to younger leaves (Nurhayati, 2021). The antagonistic relationship between K and Mg nutrients can affect oil palm productivity, because when the availability of one nutrient increases, it can inhibit the absorption of other nutrients (Xie et al., 2021). In Figure 6, this condition shows evidence that the samples studied experienced the impact of the antagonistic relationship between K and Mg, where the high absorption of Mg nutrients in the leaves caused low absorption of K nutrients in the plant.

In this study, it was found that NDRE vegetation index can slightly explain the Ca nutrient content in oil palm leaves. Ca in plants plays a role in regulating a number of metabolic processes, including plant response to the environment and growth regulators; and plays an important role in cell elongation and maintaining membrane structure in plants. Ca deficiency causes abnormal formation of storage tissues. In photosynthesis, Ca deficiency causes the initial products of photosynthesis to be less available to support respiration that occurs outside the chloroplasts. The nature of Ca that is not easily mobile makes it important to maintain a continuous supply of Ca for normal fruit growth and development; and will affect developing plant parts (meristems), such as young leaves that experience uneven chlorosis (Nurhayati, 2021).

The visual appearance of plants when they are deficient in nutrients and when they are in optimal nutrient conditions can be used as a basis to explain that the NDRE vegetation index can explain its influence on the nutrient or nutrient content of oil palm leaves. The condition of oil palm plants in the research location, which tends to be deficient in N, P, and K nutrients, is not unrelated to the soil condition in the research location, which tends to be sandy and light in color, indicating that the research location has low clay and organic matter content, so its water retention capacity is also low (Afandi et al., 2017), resulting in suboptimal nutrient absorption by plants (Albari et al., 2018).

4. CONCLUSIONS AND SUGGESTIONS

The study reveals that the NDRE vegetation index, obtained from multispectral aerial images, effectively predicts the nutrient content of oil palm leaves. Specifically, it forecasts nitrogen and phosphorus with reliable results in accuracy and potassium, magnesium, and calcium with good accuracy. The predictive power is quantified by R^2 values ranging from 20% to 69%, RMSE values between ±0.006 and ±0.13, MAPE values from 3.4% to 12.7%, and correctness from 87.3% to 96.6%. The regression equations for each nutrient show how NDRE influences their levels, indicating a reliable method for non-destructive nutrient monitoring in oil palms.

Based on the characteristics of the samples, which tend to be deficient in N, P, and K nutrients, and tend to be optimum in Mg and Ca, there is potential to improve the performance of the prediction model by increasing the number of samples and ensuring that the distribution of the samples is balanced from deficient to excessive. This is to ensure that the leaf nutrient prediction model that is formed is analyzed from samples that represent the entire variation in the nutrient sufficiency conditions of oil palm plants. In addition, it is also necessary to conduct an analysis using other independent variables besides the NDRE vegetation index, so that the vegetation index that is able to predict the level of oil palm leaf nutrients with the best performance can be known.

REFERENCES

Afandi, F.N., Siswanto, B., & Nuraini, Y. (2017). Pengaruh pemberian berbagai jenis bahan organik terhadap sifat kimia tanah pada pertumbuhan dan produksi tanaman ubi jalar di Entisol Ngrangkah Pawon, Kediri. *Jurnal Tanah dan Sumberdaya Lahan*, ***2***(2), 237–244. https://jtsl.ub.ac.id/index.php/jtsl/article/view/134.

Albari, J., Supijatno., & Sudradjat. (2018). Peranan pupuk nitrogen dan fosfor pada tanaman kelapa sawit (*Elaeis guineensis* Jacq.) belum menghasilkan umur tiga tahun. *Buletin Agrohorti*, ***6***(1), 42–49. https://doi.org/10.29244/agrob.v6i1.16822.

Al-Rajab, J.M. (2021). Chapter 2 - Solar radiation and its role in plant growth. Lecture note on *Agro-Hydrometeorology*. Al-Mustansiriyah University, Baghdad-Iraq: 8 pp.

Hadi, B.S. (2019). *Penginderaan Jauh Pengantar ke Arah Pembelajaran Berpikir Spasial, Fisrt*. Yogyakarta: UNY Press.

Barnes, E., Clarke, T.R., Richards, S.E., Colaizzi, P., Haberland, J., Kostrzewski, M., Waller, P., Choi, C., Riley, E., & Thompson, T.L. (2000). Coincident detection of crop water stress, nitrogen status, and canopy density using ground based multispectral data. *5th International Conference on Precision Agriculture, Bloomington*, 16-19 July 2000, 1-15.

Boiarskii, B., & Hasegawa2, H. (2019). Comparison of NDVI and NDRE indices to detect differences in vegetation and chlorophyll content. *Journal of Mechanics of Continua and Mathematical Sciences*, spl1(4). https://doi.org/10.26782/jmcms.spl.4/2019.11.00003.

BPS (Badan Pusat Statistik). (2022). *Statistik Kelapa Sawit Indonesia 2021 – Indonesian Oil Palm Statistics 2021*. Badan Pusat Statistik, Jakarta: 139 pp.

Broeshart, H. (1955). The Application of Foliar Analysis in Oil Palm Cultivation. [*Thesis*], Wageningen University.

Budiman, R., Seminar, K.B., & Sudradjat. (2022). The estimation of nutrient content using multispectral image analysis in palm oil (*Elaeis guineensis* Jacq). *IOP Conference Series: Earth and Environmental Science*, ***974***(1), 012062. https://doi.org/10.1088/1755-1315/974/1/012062.

Chicco, D., Warrens, M.J., & Jurman, G. (2021). The coefficient of determination r-squared is more informative than SMAPE, MAE, MAPE, MSE and RMSE in regression analysis evaluation. *PeerJ Computer Science*, ***7***, e623. https://doi.org/10.7717/peerj-cs.623.

Cotrozzi, L. (2022). Spectroscopic detection of forest diseases: a review (1970–2020). *Journal of Forestry Research*, ***33***(1), 21–38. https://doi.org/10.1007/s11676-021-01378-w.

CPOPC. (2022). *Palm Oil Supply and Demand Outlook Report 2022*.

Donough, C., Witt, C., & Fairhurst, T. (2010). Yield Intensification In Oil Palm Using Bmp As A Management Tool. *International Plant Nutrition Institute (IPNI) Southeast Asia Program, Penang.*

Fairhurst, T.H., & Griffiths, W. (2014). Oil Palm: Best Management Practices for Yield Intensification. *International Plant Nutrition Institute (IPNI), Singapore.*

Fairhurst, T., & Mutert, E. (1999). Interpretation and management of oil palm leaf analysis data. *Better Crops International*, ***13***(1), 48-51.

Goh, K. (2004). Fertilizer recommendation systems for oil palm: Estimating the fertilizer rates. *Proceedings of MOSTA Best Practices Workshops: Agronomy and Crop Management, Malaysian Oil Scientists and Technologies Association, Kuala Lampur*, 235-268.

Gregory, M. (2022). *Palm Oil Production, Consumption and Trade Patterns: The Outlook From an EMU Perspective*. Fern. 1C Fosseway Business Centre, Stratford Road, Moreton in Marsh, GL56 9NQ, UK.

Griffiths, W., & Fairhurst, T. (2003). Implementation of best management practices in an oil palm rehabilitation project. *Better Crops International*, ***17***.

Jayaselan, H., Nawi, N., Ismail, W., Shariff, A., Rajah, V., & Arulandoo, X. (2017). Application of spectroscopy for nutrient prediction of oil palm. *Journal of Experimental Agriculture International*, ***15***(3), 1–9. https://doi.org/10.9734/JEAI/2017/31502.

Kok, Z.H., Shariff, A.R.B.M., Bejo, S.K., Kim, H.T., Ahamed, T., Cheah, S.S., & Wahid, S.A.A. (2021). Plot-based classification of macronutrient levels in oil palm trees with landsat-8 images and machine learning. *Remote Sensing*, ***13***(11), 2029. https://doi.org/10.3390/rs13112029.

Marzukhi, F., Elahami, A.L., & Bohari, S.N. (2016). Detecting nutrients deficiencies of oil palm trees using remotely sensed data. *IOP Conference Series: Earth and Environmental Science*, ***37***, 012040. https://doi.org/10.1088/1755-1315/37/1/012040.

Moreno, J.J.M., Pol, A.P., Abad, A.S., & Blasco, B.C. (2013). Using the R-MAPE index as a resistant measure of forecast accuracy. *Psicothema*, ***25***(4), 500–506. https://doi.org/10.7334/psicothema2013.23.

Mróz, M., & Sobieraj-Żłobińska, A. (2004). Comparison of several vegetation indices calculated on the basis of a seasonal SPOT XS time series, and their suitability for land cover and agricultural crop identification. *Agricultural Crops*, ***7***, 39–66.

Munir, S., Seminar, K.B., Sudradjat, Sukoco, H., & Buono, A. (2022). The use of random forest regression for estimating leaf nitrogen content of oil palm based on sentinel 1-a imagery. *Information*, ***14***(1), 10. https://doi.org/10.3390/info14010010

Nurhayati, D.R. (2021). *Introduction to Plant Nutrition*. UNISI Press.

Prabowo, N.E. (2005). Penggunaan diagnosa daun untuk rekomendasi pemupukan kelapa sawit. *Prosiding Pertemuan Teknis Kelapa Sawit 2005: Peningkatan Produktivitas Kelapa Sawit Melalui Pemupukan dan Pemanfaatan Limbah PKS*. Medan, 19-20 April 2025.

Rendana, M., Rahim, S.A., Idris, W., Lihan, T., & Ali Rahman, Z. (2015). A review of methods for detecting nutrient stress of oil palm in Malaysia. *Journal of Applied Environmental and Biological Sciences*, ***5***, 60–64.

Santoso, H., & Winarna, W. (2021). The Exploration of The Oil Palm Leaf Nutrients Content Using Unmanned Aerial Vehicle and Multispectral Camera. *Jurnal Penelitian Kelapa Sawit*, ***29***(1), 49-62. https://doi.org/10.22302/iopri.jur.jpks.v29i1.145.

Sarstedt, M., & Mooi, E. (2014). *Regression Analysis In A Concise Guide To Market Research* (pp. 193–233). https://doi.org/10.1007/978-3-642-53965-7_7.

Sastrohartono, H., Suparyanto, T., Sudigyo, D., & Pardamean, B. (2021). *Prediction of Soil Organic Matter Levels with Image Processing 2 and Artificial Neural Networks Using Mobile Phones*.

Suyuthi, M., Seminar, K., & Sudradjat. (2019). Estimation of calcium, magnesium and sulfur content in oil palm using multispectral imagery based UAV. *Proceedings of the 2nd SEAFAST International Seminar*, 127–134. https://doi.org/10.5220/0009978701270134

Von Uexkull, H.R. ; F.T.H. (1991). *The Oil Palm: Fertilizing for High Yield and Quality*. International Potash Institute.

Woittiez, L.S., van Wijk, M.T., Slingerland, M., van Noordwijk, M., & Giller, K.E. (2017). Yield Gaps in Oil Palm: A Quantitative Review of Contributing Factors. *European Journal of Agronomy*, ***83***, 57–77. https://doi.org/10.1016/j.eja.2016.11.002

Xie, K., Cakmak, I., Wang, S., Zhang, F., & Guo, S. (2021). Synergistic and antagonistic interactions between potassium and magnesium in higher plants. *The Crop Journal*, ***9***(2), 249–256. https://doi.org/10.1016/j.cj.2020.10.005.

Xue, J., & Su, B. (2017). Significant Remote Sensing Vegetation Indices: A Review of Developments and Applications. *Journal of Sensors*, ***2017***(1), 1–17. https://doi.org/10.1155/2017/1353691.

Yadegari, M., Shamshiri, R.R., Shariff, A.R.M., Balasundram, S.K., & Mahns, B. (2020). Using SPOT-7 for Nitrogen Fertilizer Management in Oil Palm. *Agriculture*, ***10***(4), 133. https://doi.org/10.3390/agriculture10040133.