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The Prediction of Nitrogen, Phosphate, and Potassium Contents of Oil Palm Leaf Using Hand-Held Spectrometer

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ABSTRACT

A hand-held spectrometer can be used to evaluate oil palm (Elaeis guineensis Jacq.) leaf nutrient contents without being destructive. This study aims to develop regression equations and analyze the performance of the prediction models for Nitrogen, Phosphate, and Potassium leaf nutrient contents. The dependent variable in this study was the result of the analysis of nutrient contents in frond number 17 which was carried out in the laboratory, while the independent variable was the leaf reflectance value scanned with a hand-held spectrometer. The Normalized Difference approach is used to create a vegetation index from the combination of reflectance values at two wavelengths. Vegetation index with the highest correlation value to the nutrient content of leaves, is used to make a prediction model for leaf nutrients using the Simple Linear Regression. The regression equations formed to predict the contents of nutrients N, P, and K have high R^2*. The RMSE values of the predicted contents of N, P, and K nutrients, respectively were 0.21, 0.01, and 0.13; and correctness values of those nutrients respectively were 93.29%, 95.5%, and 88.81%.*

1. INTRODUCTION

Plantation is one of the agricultural subsectors that contributes greatly to Gross Domestic Product (GDP), which is around 3.63% of Indonesia's total GDP in 2020 (BPS, 2022). One of the plantation commodities that is very important for the economy in Indonesia is oil palm (*Elaeis guineensis* Jacq.) with its ability to produce vegetable oil which is much needed by the industrial sector (BPS, 2020). Indonesia ranks first as a palm oil producing country by producing more than half of the world's palm oil, followed by Malaysia which produces around a quarter (Gregory, 2022). World demand for palm oil is projected to continue experiencing an upward trend in line with increasing demand to meet biodiesel, food and industrial needs, so that this high demand will trigger price increases because it is not balanced by increased production due to constraints on cultivation factors (CPOPC, 2022).

The average actual palm oil productivity across all palm oil plantations in Indonesia in 2019 was 3.7 ton/ha, with details of 4.4 ton/ha from large state companies and large private companies, and 3.2 ton/ha from smallholder plantations (BPS, 2021), while the potential productivity of palm oil per hectare is around 8.9 ton of crude palm oil (Fairhurst & Griffiths, 2014; Woittiez *et al*., 2017). From this productivity gap, it can be seen that there is still potential to increase the productivity of oil palm plantations in Indonesia.

One way to increase the productivity of oil palm plants is to implement good fertilizer management practices. Nutrition management and good plant care have been proven to increase oil palm productivity, both in terms of the number and weight of bunches produced (Griffiths & Fairhurst, 2003). On the other hand, less effective fertilizer management will result in a reduction in oil palm plant productivity of up to 50%, for example in trees that are not given nitrogen and potassium fertilizer (Woittiez *et al*., 2017).

Accurate fertilizer recommendations can be calculated from the results of leaf nutrient analysis because the response to fertilizer is highly correlated with the leaf nutrient value (Prabowo, 2005). Nutrient analysis of oil palm leaves generally uses chemical analysis methods from leaf samples taken from the frond of oil palm plants at frond number 17 (Von Uexkull, 1991). This method is usually called a destructive method which requires a long time, especially for large plantation areas. Non-destructive methods should be used to speed up this leaf nutrient analysis (Jayaselan *et al*., 2017).

The large area of oil palm plantations requires technological support, such as high performance computing technology, IoT (Internet of Thing), and artificial intelligence, so that plantation management can run effectively and efficiently (Sastrohartono *et al*., 2022). One of them is the SpectraVue CI-710s handheld spectrometer which has the ability to enter a prediction equation for the nutrient content of oil palm leaves with an output that can directly present it in the form of percentage of dry matter (%DM) for each nutrient analyzed. Therefore, researchers intend to develop an equation or model for predicting levels of the nutrient elements Nitrogen (N), Phosphate (P), and Potassium (K) in oil palm leaves using the SpectraVue CI-710s handheld spectrometer, and evaluating the performance of the element prediction model.

2. MATERIALS AND METHODS

The research method used in this research is a quantitative descriptive method. The outline of the research implementation stages is as follows: 1) population and sample determination stage, 2) leaf sampling stage, 3) scanning stage with a handheld spectrometer, 4) leaf nutrient analysis stage in the laboratory, 5) prediction model development stage, 6) the prediction model implementation stage, and 7) the prediction model performance evaluation stage. Figure 1 presented a flow chart of experimental steps.

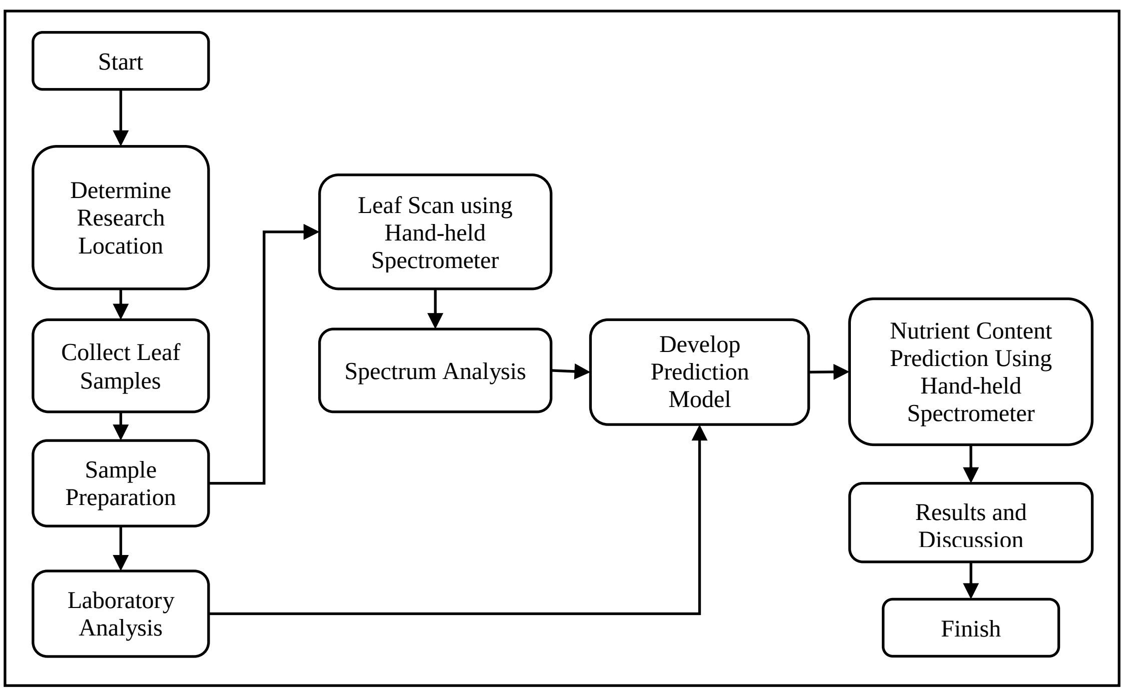

Figure 1. Flow chart of experimental steps

Figure 2. SpectraVue CI-710s leaf spectrometer

2.1. Research Materials

The material used in this research was a sample of oil palm leaves taken from frond number 17. Leaf analysis on frond number 17 is a method commonly used to estimate the status of Nitrogen, Phosphate and Potassium nutrient levels in oil palm plants over 2.5 years, because of its sensitivity to these nutrients (Jayaselan *et al*., 2017; Rendana *et al*., 2015).

2.2. Research Tools

The research tools used in this research included: 1) SpectraVue CI-710s leaf spectrometer (Figure 2); 2) HP ProBook notebook with seventh generation Intel Core i7 processor specifications and RAM with a capacity of 8 GB; 3) Microsoft Excel software to prepare research variable data; 4) Jupyter Notebook software which runs on the Google Chrome application to run the Python programming language; 5) and Python library software: Pandas, scikit-learn, NumPy, Matplotlib, and seaborn.

2.3. Research sites

This research was conducted at one of the oil palm plantations in East Kotawaringin Regency, Central Kalimantan Province from February to March 2023. The soil type at the research location is Entisols with flat to undulating topography. The elevation of the research location ranges from 10-50 meters above sea level.

2.4. Sample Selection

The research was carried out in an area of approximately 6 hectares, with a population of 891 oil palm trees from the planting year in 2017. The criteria for determining the sample were as follows: 1) Blocks of oil palm trees with a uniform planting age of <6 years, with the aim that the handheld spectrometer can reach the fronds without damaging the fronds; 2) Blocks have a variety of plant conditions that can be clearly differentiated with the naked eye, namely having plants that appear yellow or are indicated to be experiencing nutrient deficiencies to plants that appear green or are indicated to be healthy; 3) Samples of 133 oil palm trees were taken at random or around 15% of the total population studied.

2.5. Leaf Sampling

The observed leaf samples were taken from the frond of oil palm tree number 17. In theory, frond number 17 is the most sensitive to indications of the nutrient content N, P, and K (Rendana *et al*., 2015), this is supported by research results others stated that the prediction results for nutrients N, P, and K in frond number 17 gave better results than frond numbers 3 and 9 (Jayaselan *et al*., 2017). However, for young plants (less than 3 years old), leaf nutrient analysis provides better prediction results for frond number 9 (Von Uexkull, 1991).

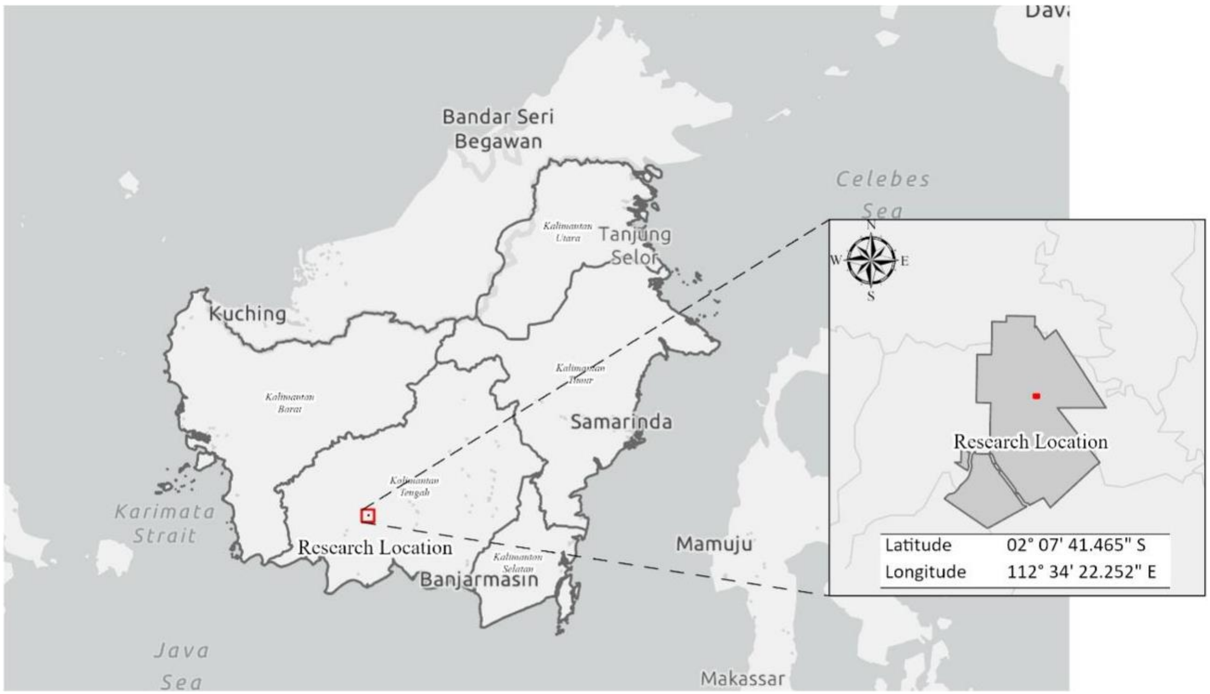

Figure 3. Research location in East Kotawaringin Regency, Central Kalimantan Province (02°07’41,465”S, 112°34’22,252”E)

The method and stages of leaf sampling carried out are as follows: 1) Leaf samples were taken from each oil palm tree sample at frond number 17, from 90 randomly selected oil palm trees; 2) The leaf sample taken is a leaf located in the middle of the frond, which is characterized by the presence of a sharp part on the stem of the frond that faces upwards; 3) 12 leaves were taken, with details of 6 from the right side of the frond and 6 from the left side of the frond; 4) The twelve leaves taken as samples were cut at the base and tip, leaving only the middle part, with a length of approximately 20 cm, and the stem part was removed; 5) Leaf samples that have been cut and the stems removed are then placed in the bag provided and given a sample identification number; 6) Steps 1 to 4 were repeated for all tree samples, until 133 samples were obtained from frond number 17; and 7) All leaf samples were then cleaned of dust and dirt using cotton wool and distilled water, before scanning using a handheld spectrometer and analyzing nutrient levels in the laboratory.

2.6. Spectrometer Scanning

Leaf samples that have been collected and separated into identified bags are then scanned with a handheld spectrometer. Scanning of leaf samples with a handheld spectrometer was carried out directly after taking the leaf samples. Before scanning, leaf samples were cleaned of dust and dirt with distilled water (distilled water). This is done to reduce the possibility of bias caused by instrument reading errors.

The increase in wavelength data when scanning leaf samples was set to increase every 0.6 nm. Based on the equipment specifications document, the SpectraVue CI-710s handheld spectrometer can scan in the wavelength range 360 – 1100 nm (CID Bio-Science, 2023).

The method and stages of scanning leaf samples are as follows: 1) The spectrometer was set using Reflectance scan mode at wavelength range 360 - 1100 nm with wavelength data increment of 0.55 - 0.7 nm, and automatic integration time; 2) Scanning was carried out one by one for each leaf sample and adjusted to the identity of the sample; 3) Out of the 12 leaves taken for each frond, the 2 cleanest leaves were selected for scanning; 4) Scanning of leaf samples was carried out on the abaxial side of the leaf at 3 points or positions, namely at the tip, middle and base of the leaf. Each point was scanned 5 times and averaged.

2.7. Analysis of Leaf Nutrients

Leaf samples that have been cleaned and scanned with a handheld spectrometer were then analyzed for nutrient levels in the laboratory. The methods and stages of analyzing leaf nutrients in the laboratory were as follows: (1) The cleaned leaf samples were placed in an identified envelope and then dried using an oven at a temperature of 80 °C for ±12 h. Drying was carried out to remove water content from plant tissue to stop enzymatic reactions and stabilize the sample (Kalra, 1998). This temperature is safe from loss of N elements, composition changes, and protein changes (Unkovich *et al*., 2008). (2) Dry leaf samples were ground to obtain a smooth sample to ensure homogeneity in the sample (Kalra, 1998). (3) Fine leaf samples were analyzed for levels of the nutrient elements Nitrogen, Phosphate and Potassium using standard procedures at the EMU (R&D) laboratory – Wilmar Central Kalimantan.

2.8. Prediction Model Development

The wavelength range used in this research was the wavelength range of 400 – 900 nm, so that the total number of independent variables analyzed for each leaf sample was 852 variables which were then used to create a vegetation index. There were 3 leaf nutrients analyzed, so that for each leaf sample, there were 3 dependent variables analyzed. Oliveira *et al*. (2019) revealed that there was a strong relationship between leaf nutrition and leaf reflectance (leaf reflectance value), located in the visible and near infrared regions (400 - 900 nm) of the light spectrum. The spectral index was calculated from a combination of 2 independent variables using the Normalized Difference (ND) equation:

$$X = \frac{(\rho_{\lambda\,2} - \rho_{\lambda\,1})}{(\rho_{\lambda\,2} + \rho_{\lambda\,1})} \tag{1}$$

where X is the independent variable in the form of a vegetation index which is formed from a combination of 2 independent variables, namely the reflectance value (ρ) at the first (λ1) and second (λ2) selected wavelengths. So, from 852 independent variables, with a wavelength range of 400 – 900 nm, 362,526 vegetation indices can be formed.

The method used to select the first (λ1) and second (λ2) wavelengths was the brute-force method, to find or select which variable has the strongest correlation with the dependent variable, namely the nutritional content of Nitrogen (N), Phosphate (P), and Potassium (K), oil palm leaves. This brute-force method combines all independent variables (vegetation index) with all dependent variables one by one (Heule & Kullmann, 2017). The interpretation of the correlation coefficient values is as shown in Table 1.

The variables used for analysis were separated into 2 parts, namely 70% training dataset and 30% validation dataset. Making a prediction model using a simple linear regression statistical technique with the equation:

$$Y_N = \alpha_N + \beta_N . x_N \tag{2}$$

$$Y_P = \alpha_P + \beta_P . x_P \tag{3}$$

$$Y_K = \alpha_K + \beta_K . x_K \tag{4}$$

where Y_N, Y_P, and Y_K respectively are the predicted values for the levels of Nitrogen, Phosphate, and Potassium; α and β are the intercept and slope values resulting from the prediction model using simple linear regression; and X is the vegetation index with the highest correlation value. The prediction model was carried out using the Jupyter-Notebook application in a web browser using the Python programming language, utilizing the scikit-learn or sklearn module.

Table 1. Interpretation of correlation coefficient values (Schober *et al*., 2018)

Correlation Coefficient	Interpretation
0.00 – 0.10	Very weak correlation (can be neglected)
0.10 – 0.39	Weak correlation
0.40 – 0.69	Medium correlation
0.70 – 0.89	Strong correlation
0.90 – 1.00	Highly strong correlation

Table 2. Interpretation of MAPE values (Montaño *et al*., 2013)

MAPE (%)	Interpretation
<10	Highly accurate forecasting
10-20	Good forecasting
20-50	Reasonable forecasting
>50	Inaccurate forecasting

The validation dataset was used to test the prediction model formed. Evaluation of the performance of the prediction model used RMSE, MAPE, and Correctness. RMSE (Root Mean Square Error) and MAPE (Mean Absolute Percentage Error) was calculated according to Equation (5) and (6) (Chicco *et al*., 2021):

$$\text{RMSE} = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(X_i - Y_i)^2} \quad (5)$$

The closer the RMSE value is to 0 (zero), the better the performance of the prediction model being built. Conversely, if the RMSE value moves away from 0 (zero) to infinity, the performance of the prediction model is considered poor.

$$\text{MAPE} = \frac{1}{m}\sum_{i=1}^{m}\left|\frac{Y_i - X_i}{Y_i}\right| \quad (6)$$

The closer the MAPE value is to 0 (zero), the performance of the prediction model being built is considered good, conversely, the further the MAPE value is from 0 (zero) to infinity, the performance of the prediction model is considered bad. Interpretation of MAPE values as shown in Table 2.

Correctness is defined as the percentage of accuracy obtained from reducing the error from the MAPE value. The interpretation of the correctness value is that the closer the value is to 100%, the better the performance of the prediction model. Conversely, the closer the correctness value approaches 0% (zero percent), the worse the performance of the prediction model. With correctness, the prediction model that has the best performance can be easily assessed from the highest correctness percentage value. The correctness was calculated using the following (Budiman *et al*., 2022):

$$\text{Correctness} = (1 - \text{MAPE})*100\% \quad (7)$$

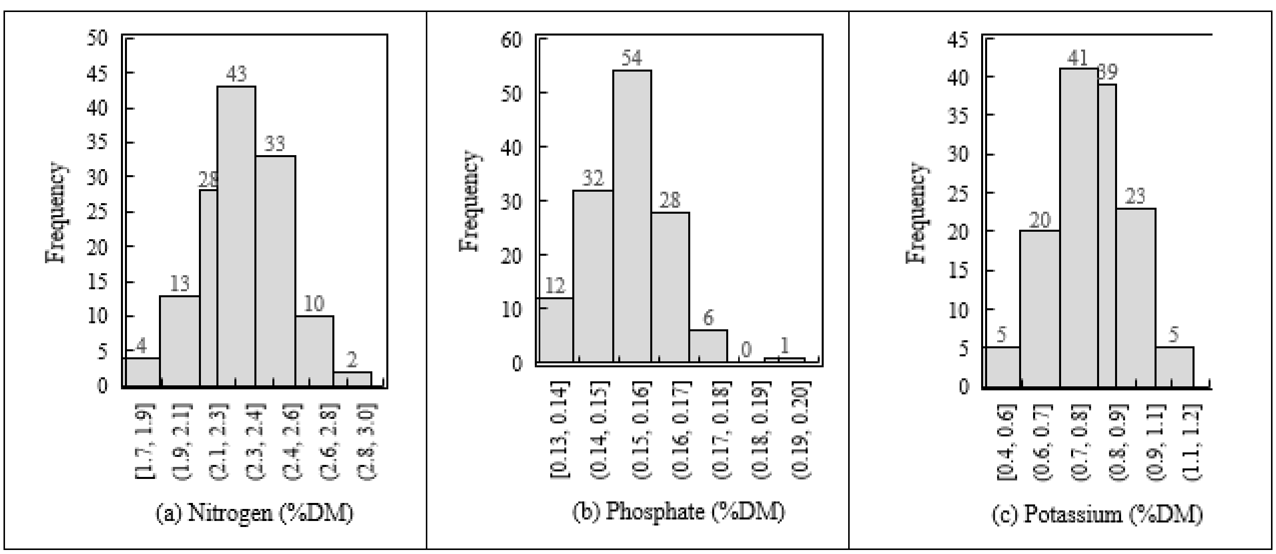

Figure 4. Nutrient content of leaf samples of frond number 17: (a) Nitrogen, (b) Phosphate, (c) Potassium.

3. RESULTS AND DISCUSSION

3.1. Laboratory Analysis of Oil Palm Leaf

Leaf samples were collected from February 15 to March 2 2023. The leaf samples that were collected were then analyzed for the levels of the nutrient elements Nitrogen (N), Phosphate (P), and Potassium (K) in the laboratory. The results of analysis of leaf samples in the laboratory are represented in the form of a histogram in Figure 4. A good dataset can be seen from the shape of the histogram which forms a normal distribution curve or is shaped like a bell (Capili *et al*., 2021). In this research, the dataset resulting from leaf nutrient analysis in the laboratory appears to be normally distributed so it is suitable to be used as a prediction model variable.

3.2. Palm Leaf Sample Scanning

Scans carried out on 133 leaf samples produced reflectance data from wavelengths of 400-900 nm. Figure 5 shows a graphical representation of reflectance data from scanning leaf samples on frond number 17.

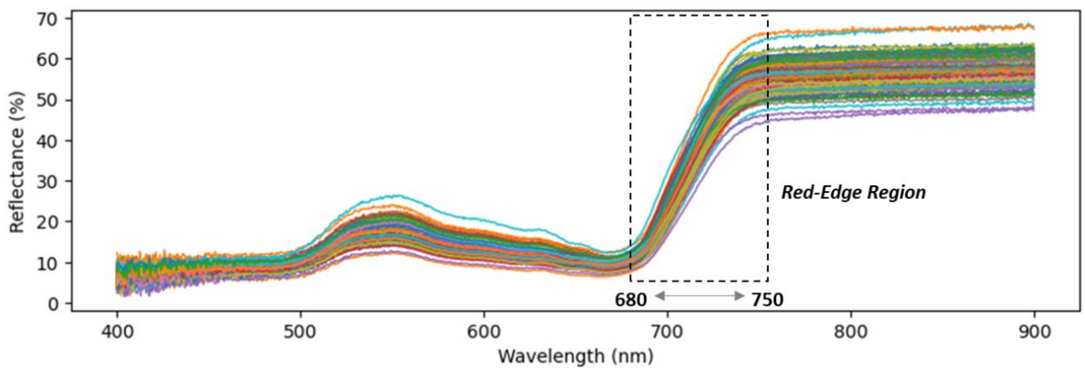

Figure 5. Graph of reflectance values from scanning leaf samples with a handheld spectrometer at frond number 17 and the Red-Edge wavelength range (Horler *et al*., 1983).

3.3. Prediction Model Development

The independent variables chosen to predict the nutrient N were the wavelength pair B733.5 and B723.6 with a correlation coefficient of 0.77; The independent variable chosen to predict the nutrient P is the wavelength pair B721.8 and B715.4 with a correlation coefficient value of 0.69; and the independent variable chosen to predict the nutrient K is the wavelength pair B740.5 and 735.3 with a correlation coefficient value of 0.61. The results of selecting a combination of two wavelengths using this brute-force method are shown in Table 3.

In this study, the vegetation index that provided the highest correlation response was found in the red-edge region of the spectrum with a wavelength range of 670 – 760 nm (Guo *et al*., 2018). In the analysis of N and P nutrients, research on eucalyptus leaves also showed the same thing, namely reflectance from the red-edge region wavelengths gave the highest correlation response, however for K nutrients in the green region range (Oliveira *et al*., 2019).

Table 3. Results of vegetation index selection using the brute-force method to find the highest correlation coefficient for each nutrient.

Nutrient	Correlation Coefficient	Vegetation Index
Nitrogen (N)	0.77	['B733.5 | B723.6']
Phosphate (P)	0.69	['B721.8 | B715.4']
Potassium (K)	0.61	['B740.5 | B735.3']

Note: The Vegetation Index is a combination of 2 wavelengths.

Red-edge is a sharp change in leaf reflectance values in the wavelength range 680 – 750 nm which has a close relationship with the chlorophyll and water content in the leaves (Horler *et al*., 1983) (see Figure 5). Apart from red-edge, the channels related to plants are the green channel which is mostly reflected and received by the human eye, as well as the blue and red channels which are most absorbed by chlorophyll for during photosynthesis (Al-Rajab, 2021). In this research, it can be seen that the red-edge channel, which has the characteristic of reflecting more light, turns out to be a channel that has a moderate to strong correlation with the levels of leaf nutrients N, P, and K, when compared to channels that are mostly absorbed by leaves, such as blue and red channels. So the red-edge channel proves to be very relevant and can produce a strong correlation or relationship with leaf nutrients.

The nutrient N has an influence on leaf area, leaf color, sheath growth rate, and photosynthesis results. N nutrient deficiency usually occurs in oil palm plants in sandy or flooded areas (Von Uexkull, 1991). The characteristics of the soil type at the research location tend to be sandy and light in color, which indicates that the soil has low organic matter. Soil with low organic matter will give a brighter color appearance when compared to soil with a high organic matter content which tends to be dark in color, the presence of which greatly influences the physical and chemical properties of the soil. These soil color characteristics can be used as a basis for predicting soil organic matter content (Sastrohartono *et al*., 2021). Therefore, the impact of the lack of soil organic matter is that, to the naked eye, some plants at the research location look yellow and others look greener. This research sample included variations in leaf color, so this is what is likely to cause the correlation coefficient value of the nutrient N with the vegetation index to show a strong relationship.

Likewise with the nutrient P. The nutrient P has an influence on plant growth rate, stem diameter, frond length, and the size of the bunch. Unlike N, P deficiency does not show visible symptoms from leaf color, but can be seen from the size and shape of the stem, tending to be stunted, and short fronds (Von Uexkull, 1991). If observed at the research location, the shape and size characteristics of the oil palm plants sampled were stunted, indicated to have a P deficiency, and there were also samples that were not dwarf or normal. This may be the reason why the correlation coefficient value between the nutrient P and the vegetation index shows a moderate relationship (Table 3).

The influence of the K nutrient on oil palm plants is on the number and size of the bunches. Symptoms of K nutrient deficiency usually appear on oil palm leaves which experience orange spotting (orange spots) (Von Uexkull, 1991). In this study, the relationship between the nutrient K and the vegetation index showed a moderate relationship.

Prediction model was developed using the Simple Linear Regression method, so that a successful prediction model was developed for each nutrient and frond number in the form of a linear regression model, as follows:

$$Y_N = 1.034647 + 15.77955 * X_N \tag{8}$$

$$Y_P = 0.094865 + 0.722499 * X_P \tag{9}$$

$$Y_K = 0.338618 + 18.9094 * X_K \tag{10}$$

where $X_N = \frac{(\rho_{\lambda\,733,5} - \rho_{\lambda\,723,6})}{(\rho_{\lambda\,733,5} + \rho_{\lambda\,723,6})}$; $X_P = \frac{(\rho_{\lambda\,721,8} - \rho_{\lambda\,715,4})}{(\rho_{\lambda\,721,8} + \rho_{\lambda\,715,4})}$; and $X_K = \frac{(\rho_{\lambda\,740,5} - \rho_{\lambda\,735,3})}{(\rho_{\lambda\,740,5} + \rho_{\lambda\,735,3})}$.

3.4. Prediction Results of Oil Palm Leaf Nutrients

Prediction of the nutrients Nitrogen (N), Phosphate (P), and Potassium (K) of oil palm leaves was carried out on the validation dataset. From a total of 133 samples for each tree and frond, the number of validation datasets was 40 samples or 30% of the total samples collected. The prediction results for the nutrients Nitrogen (N), Phosphate (P), and Potassium (K) are as shown in Figure 6. Meanwhile, the performance of the prediction model is as shown in Table 4.

The equation and trend line $y = ax + b$ produced by the scatter plot of observed and predicted nutrient content values (see Figure 6), shows a tendency to provide good prediction results for predicting Nitrogen nutrient levels. This is shown by the trend line which is tangent to the 45° curve line. This is different from the results of predicted levels of the nutrient elements Phosphate and Potassium. The prediction results for these two nutrients show a tendency to provide smaller prediction values or under estimates, where the predicted results for the levels of the nutrient elements Phosphate and Potassium tend to be smaller than the observed values. This is shown by the trend line which is above the 45° curve.

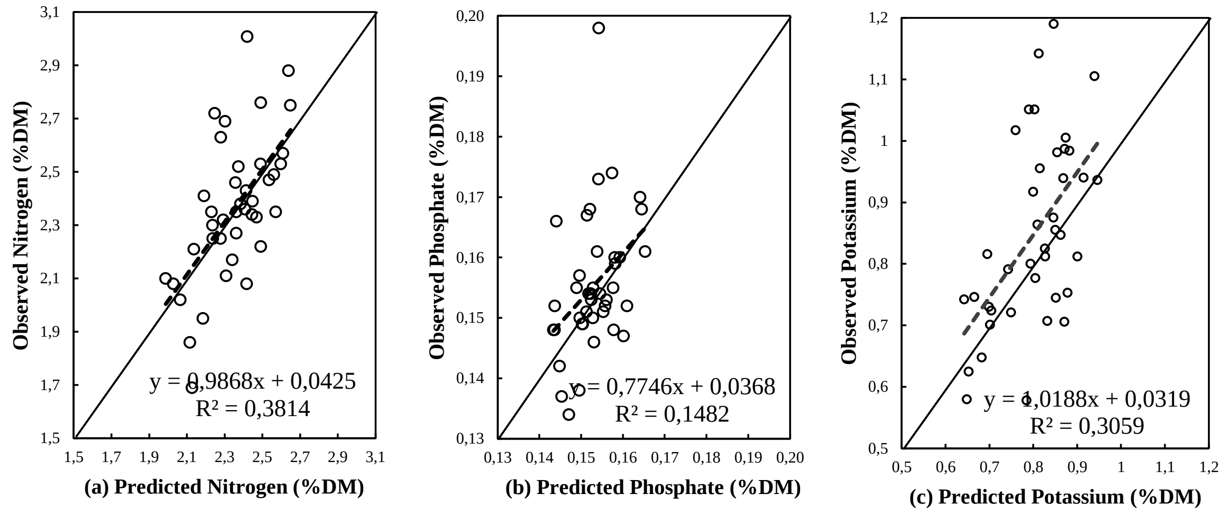

Figure 6. Graph of prediction results for nutrient: (a) Nitrogen (N), (b) Phosphate (P), and (c) potassium (K).

Table 4. Prediction Model Performance

Ntrient	RMSE	MAPE	Correctness (%)
Nitrogen (N)	0.21	0.07	93.29
Phosphate (P)	0.01	0.04	95.50
Potassium (K)	0.13	0.11	88.81

Note: MAPE is used to assess the accuracy of a prediction model and is usually converted into a percentage (MAPE*100%). The smaller the MAPE value, the more accurate the prediction model developed (Montaño *et al*., 2013).

The R^2 value produced by the trend line in the predicted results of Nitrogen, Phosphate and Potassium nutrient levels is 0.3814, 0.1482 and 0.3059 respectively. It can be interpreted that the independent variables used in this research can only explain the levels of the nutrients Nitrogen, Phosphate and Potassium respectively at 38.14%, 14.82% and 30.59%, while the rest is explained by other variables outside the variables mentioned. used in this research.

To evaluate the performance accuracy of the prediction model, apart from using the 45° line curve approach and the R2 value, it can also be evaluated using MAPE and Correctness. High accuracy of the prediction model is evaluated through a MAPE value of <10% (less than 10%) (Montaño *et al*., 2013) (see Table 2) or a Correctness value of >90% (more than 90%) (Budiman *et al*., 2022). Meanwhile, the accuracy of a good prediction model is evaluated through MAPE values ranging between 10% - 20% or Correctness values ranging between 80% - 90%. In this study, the accuracy of the prediction model was carried out using the Correctness approach for the nutrients N, P and K, where the Correctness values for the nutrients N and K showed very good accuracy, as assessed by the Correctness values of N and P respectively 93.29% and 95.50%, while for the nutrient K it shows good accuracy with a Correctness value of 88.81% (Table 4).

4. CONCLUSION AND SUGGESTION

4.1. Conclusion

In this research, the prediction model for oil palm leaf Nitrogen nutrient levels tends to give good results which can be seen from the trend line which is tangent to the 45° curve, while the prediction model for Phosphate and Potassium nutrient levels tends to under estimate as indicated by the trend line for both elements, those that are above the 45° line curve. From the R^2 value formed by the trend line of observed values (Y-axis) against predicted results (X-axis), it can be interpreted that the independent variables used in this research can only explain the levels of the nutrients Nitrogen, Phosphate and Potassium respectively at 38 .14%, 14.82% and 30.59%, while the rest is explained by other variables outside the variables used in this research. The developed prediction model can produce RMSE values from the predicted N, P, and K nutrient levels of 0.21, 0.01, and 0.13, respectively. Meanwhile, the correctness values for the predicted levels of N, P, and K nutrients were 93.29%, 95.5%, and 88.81%, respectively. The regression equation formed to predict levels of the nutrients N, P, and K respectively is respectively:

$$Y_N = 1.034647 + 15.77955 * \frac{(\rho_{\lambda\ 733,5} - \rho_{\lambda\ 723,6})}{(\rho_{\lambda\ 733,5} + \rho_{\lambda\ 723,6})}$$

$$Y_P = 0.094865 + 0.722499 * \frac{(\rho_{\lambda\ 721,8} - \rho_{\lambda\ 715,4})}{(\rho_{\lambda\ 721,8} + \rho_{\lambda\ 715,4})}$$

$$Y_K = 0.338618 + 18.9094 * \frac{(\rho_{\lambda\ 740,5} - \rho_{\lambda\ 735,3})}{(\rho_{\lambda\ 740,5} + \rho_{\lambda\ 735,3})}$$

This equation can then be used as algorithm input on the SpectraVue CI-710s handheld spectrometer to estimate the nutrient content of oil palm leaves in frond number 17 in %DM units.

4.1. Suggestion

The handheld spectrometer used in this research has the ability to enter the obtained N, P and K regression equations. With this capability, the regression equation entered into this tool can be updated when there is a regression equation with better performance analysis results. The R^2 value in this research is still low, so it can be interpreted that this prediction model still has a big opportunity to be further developed in further research.

REFERENCES

Al-Rajab, J. M. (2021). Solar Radiation and its Role in Plant Growth. In *Agro-Hydrometeorology*.

BPS. (2020). *Statistik Kelapa Sawit Indonesia 2019*. Jakarta: Badan Pusat Statistik.

BPS. (2021). *Statistik Kelapa Sawit Indonesia 2020*. Jakarta: Badan Pusat Statistik.

BPS. (2022). *Statistik Kelapa Sawit Indonesia 2021*. Jakarta: Badan Pusat Statistik.

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

Capili, N.I.F., Marilla, J.F., Montes, K.M.S., & Villaseñor, F.C. (2021). Spatial variability model for water quality assessment of the physicochemical parameters and the water quality index of laguna lake and its tributaries. *Journal of Physics: Conference Series*, ***1803***, 012006. https://doi.org/10.1088/1742-6596/1803/1/012006

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

CID Bio-Science. (2023). *Leaf spectroscopy for rapid non-destructive plant stress measurement*. https://cid-inc.com/plant-science-tools/leaf-spectroscopy/ci-710-miniature-leaf-spectrometer/ (Accesed on 25 July 2023).

CPOPC. (2022). *Palm Oil Supply And demand Outlook Report 2022*.

Fairhurst, T.H., & Griffiths, W. (2014). *Oil Palm: Best Management Practices for Yield Intensification*. International Plant Nutrition Institute, South East Asia Program (IPNI SEAP), Canada. ISBN: 978-983-44503-1-1.

Gregory, M. (2022). *Palm Oil Production, Consumption and Trade Patterns: The Outlook from an EU Perspective*. FERN, Brussels, Belgium: 19 pp.

Griffiths, W., & Fairhurst, T. (2003). Implementation of best management practices in an oil palm rehabilitation project. *Better Crops International*, ***17***(1), 16-19.

Guo, B.-B., Zhu, Y.-J., Feng, W., He, L., Wu, Y.-P., Zhou, Y., Ren, X.-X., & Ma, Y. (2018). Remotely estimating aerial n uptake in winter wheat using red-edge area index from multi-angular hyperspectral data. *Frontiers in Plant Science*, ***9***, 675. https://doi.org/10.3389/fpls.2018.00675

Heule, M.J.H., & Kullmann, O. (2017). The science of brute force. *Communications of the ACM*, ***60***(8), 70–79. https://doi.org/10.1145/3107239

Horler, D.N.H., Dockray, M., & Barber, J. (1983). The red edge of plant leaf reflectance. *International Journal of Remote Sensing*, ***4***(2), 273–288. https://doi.org/10.1080/01431168308948546

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

Montaño, J., Palmer, A., Sesé, A., & Cajal, B. (2013). Using the R-MAPE index as a resistant measure of forecast accuracy. *Psicothema*, ***25***, 500–506. https://doi.org/10.7334/psicothema2013.23

Oliveira, L.F.R. de, Santana, R.C., & de Oliveira, M.L.R. (2019). Nondestructive estimation of leaf nutrient concentrations in eucalyptus plantations. *CERNE*, ***25***(2), 184–194. https://doi.org/10.1590/01047760201925022631

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., Abd Rahim, S., 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.

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*.

Sastrohartono, H., Suryotomo, A. P., Saifullah, S., Suparyanto, T., Perbangsa, A. S., & Pardamean, B. (2022). Drone application model for image acquisition of plantation areas and oil palm trees counting. *2022 International Conference on Information Management and Technology (ICIMTech)*, 167–171. https://doi.org/10.1109/ICIMTech55957.2022.9915223

Schober, P., Boer, C., & Schwarte, L.A. (2018). Correlation coefficients: Appropriate use and interpretation. *Anesthesia & Analgesia*, ***126***(5), 1763–1768. https://doi.org/10.1213/ANE.0000000000002864

Kalra, Y.P. (Editor) (1998). *Handbook of Reference Methods for Plant Analysis*. CRC Press. Boca Raton, FL: 287 pp.

Unkovich, M., Herridge, D., Peoples, M., Cadisch, G., Boddey, B., Giller, K., Alves, B., & Chalk, P. (2008). *Measuring Plant-associated Nitrogen Fixation in Agricultural Systems*. Australian Centre for International Agricultural Research (ACIAR).

Von Uexkull, H.R. ; Fairhurst, T.H. (1991). The Oil Palm: Fertilizing for High Yield and Quality. *IPI Bulletin 12*. International Potash Institute, Worblaufen-BernlSwitzerland: 79 pp.

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