Vol. 13, No. 4 (2024): 1216 – 1225 http://dx.doi.org/10.23960/jtep-l.v13i4.1216-1225

JURNAL TEKNIK PERTANIAN LAMPUNG

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

Prediction of Block Production in Oil Palm Plantation Based on Canopy Cover Area and Vegetation Index Using Multispectral Aerial Photographs

Tri Haryo Sagoro[1], Andreas Wahyu Krisdiarto[2,✉], Hermantoro[2]

[1] Master of Plantation Management, Stiper Agricultural Institute Yogyakarta, INDONESIA.
[2] Departement of Agricultural Engineering, Stiper Agricultural Institute Yogyakarta, INDONESIA.

Article History:

Received : 29 September 2024
Revised : 15 October 2024
Accepted : 31 October 2024

Keywords:

Canopy cover area,
Multispectral camera,
NDRE,
NDVI,
Oil palm production.

Corresponding Author:
✉ andre0402@yahoo.com
(Andreas Wahyu Krisdiarto)

ABSTRACT

*This study aims to develop an empirical estimation model of oil palm production through the canopy cover area approach and oil palm vegetation index with multispectral camera technology. The oil palm production estimation method was carried out by comparing the NDVI and NDRE index transformation algorithms. The basis for estimation an area of ± 0.3 ha. The results showed that there is relatively strong relationship between canopy cover area and FFB production (kg) with a coefficient of determination R^2 = 0.573. The results also revealed that NDVI value and the number of FFB have a fairly strong relationship with R^2 of 0.488. The NDRE value correlated to the number of FFB at a strong relationship with R^2 of 0.605. 4) the results of the analysis between NDVI Value and FFB Production (kg) have a strong relationship (r = 0.704) with a coefficient of determination of R^2 = 0.496; 5) the results of the analysis between NDRE Value and FFB Production (kg) have a strong relationship (r = 0.797) with a coefficient of determination of R^2 = 0.635; 6) The NDRE value is the independent variable that provides the best response, both to the Number of FFB and FFB Production (kg); 7) the best regression equation obtained for FFB production (kg) is Y(FFB Production (kg)) = 1153.8– (3621.9*NDRE); and 8) the best regression equation obtained for the number of FFB is Y(Number of FFB) = 113.98 – (379.53*NDRE).*

1. INTRODUCTION

Indonesia is the world's largest producer of palm oil (CPO) with palm oil plantations covering an area of 16.8 million hectares (Yuwono, 2022). Oil palm plantations generally cover large areas, so to carry out productive monitoring, cheaper and more efficient technology is needed (Mirzaeinia *et al*., 2019). The average productivity of Indonesian oil palm plantations in 2019 was recorded by BPS as still being 3.7 tonnes/ha (BPS, 2021), while potentially, palm oil productivity could reach 8.9 tonnes-CPO/ha (Fairhurst & Griffiths, 2014; Woittiez *et al*., 2017). The demand for productivity and efficiency encourages the replacement of time-consuming manual methods with automation or digital ones, for example the use of unmanned aircraft (drones) in collecting spatial data in oil palm plantations (O'Driscoll, 2018). Drone technology has great potential to be developed and applied in Indonesia because it suits the topographic and geographical characteristics of this region (Duffy *et al*., 2018). So far, mapping photos from drones are usually only used to count the number of oil palm trees, while in the science and technology of image processing from remote sensing, the use of multispectral sensors such as infrared, thermal or even hyperspectral has developed.

Some of the important problems in oil palm plantations are technical problems that cause low plant productivity compared to its potential, production costs that are too high due to inappropriate inputs, the application of inefficient methods, and an unorganized administrative system. These problems can be overcome by implementing Precision

Farming (PF). In plantation management, Precision Farming is an information-based technology to support decision making, which includes components such as Remote Sensing, Geographic Information Systems, Global Positioning Systems (GPS), and other related components, in other words, capabilities spatial analysis is needed to carry it out (Rimpika *et al*., 2023).

One application of PF in oil palm plantations is to estimate production per block of oil palm trees. The accuracy of production estimates in oil palm plantation management will determine the right plantation work program, so that the profits achieved can be optimized.

Currently, estimates of palm oil production based on PF imagery which are widely applied in oil palm plantations are based on plant index information derived from Quickbird satellite photos (Balasundram *et al*., 2013; Darmawan *et al*., 2016; Khamis *et al*., 2005; Setyowati *et al*., 2016), as well as Sentinel 2A imagery (Taufik *et al*., 2021). Meanwhile, for other plantation products, for example tea, some use Sentinel 2A (Nurmalasari & Santosa, 2018). The productivity of oil palm plants is also determined by the size of the canopy or leaf area as a photosynthetic surface (Romero *et al*., 2022). A study by (Hardon *et al*., 2008) also showed a positive correlation between leaf area and yield in oil palm plants.

The unit (area) of yield or harvest yield evaluation that is currently widely carried out is based on blocks (25-100 Ha). The diverse information in one block is homogenized (homogenized) by calculating the average. This homogenization can eliminate detailed information that is useful for agronomists to evaluate the condition of plants within the block. Therefore, the units of measurement in this study were made in units of harvest *hanca* and fruit collection place (FCP). A harvest *hanca* is defined as an area unit that has been determined to divide the harvester work area in harvesting fresh fruit bunches. With harvest units and FCP, the units evaluated become narrower so that improvement plans can be more focused, for example if there is a case of low yield in a particular block.

This research aims to develop an empirical model for estimating oil palm plantation production per harvest/FCP using a canopy cover area approach and oil palm vegetation index using multispectral camera technology carried by drones. The difference between this research and previous studies is the observation area unit, the use of the MicaSense RedEdge-P multispectral camera, and the creation of an oil palm plantation production estimation model with variables of canopy cover area and vegetation index.

2. MATERIALS AND METHODS

2.1. Tools and Materials

The materials for this research were oil palm planting blocks and oil palm Fresh Fruit Bunches (FFB). The equipment used in this research included hardware DJI Matrice 300 RTK drone with multispectral camera Micasense RedEdge-P. Other hardware include personal computer (PC) unit. The software involved Agisoft Metashape, used for aerial photo data processing, while ArcGIS Pro was used for vegetation index analysis normalized difference vegetation index (NDVI) and normalized difference red edge index (NDRE). Statistical analysis was performed using software SPSS

2.2. Population and Sample

The population in this study were oil palm plants in one oil palm plantation block at PT. MSM, Central Kalimantan with an area of 50-75 ha. The footage in this research is all the damage found in the designated garden blocks. The criteria for determining the population and sample follow the provisions in Table 1.

Table 1. Criteria for determining population and sample

No	Criteria
1.	Block with planting year ≤ 6 years. To ensure that physically there has been no overlap between plant stems.
2.	Blocks that have Entisol soil type. So that it is easy to distinguish the tree canopy from the ground surface background from aerial photos.
3.	Blocks that have the same planting year and soil type.
4.	Determination of harvest hanca, namely 1 harvest hanca for every 2 picul markets (harvesting path), to supply FFB to FCP.

2.3. Research Variables

The research variables consisted of independent variables and dependent variables. The independent variables included canopy cover area, NDVI vegetation index value and NDRE vegetation index value. NDVI (Kim *et al*., 2018) and NDRE (Barnes *et al*., 2000) were chosen because of their good ability to represent vegetation canopy reflectance values well. The dependent variable was oil palm fresh fruit bunches (FFB) production

2.4. Data retrieval

Data collection (variable measurement) was carried out by aerial shooting. Harvesting FFB and weighing FFB was conducted at each FCP. Figure 1 shows steps to complete this research.

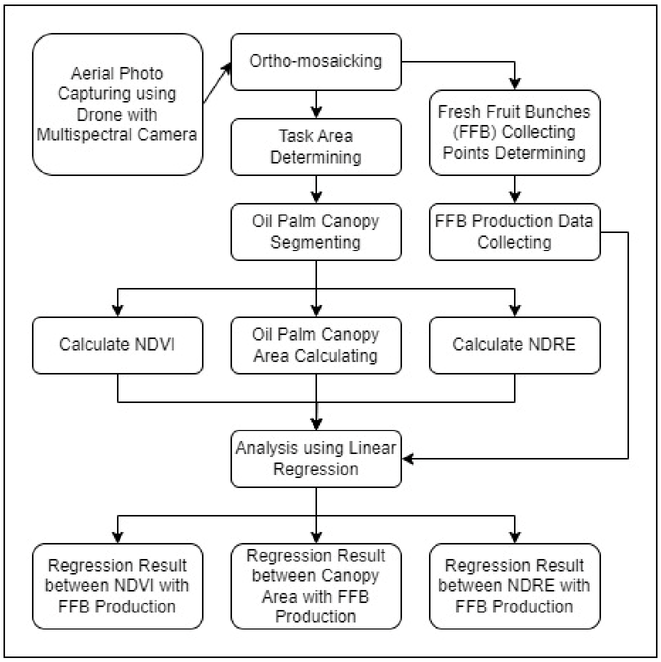


Figure 1. Research stages

2.5. Data Analysis

A linear regression equation was used to describe the relationship between: (a) canopy cover area and FFB production, (b) NDVI vegetation index value on FFB production, and (c) NDRE vegetation index value on FFB production in TPH using SPSS and Microsta software, with the equation as follows:

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

$$\text{NDRE} = \frac{NIR-RedEdge}{NIR+RedEdge} \quad (2)$$

$$Y = \alpha + \beta * \text{ Canopy Cover Area} \quad (3)$$

$$Y = \alpha + \beta * \text{NDVI} \quad (4)$$

$$Y = \alpha + \beta * \text{NDRE} \quad (5)$$

where Y = FFB Production, α = intercept, β = slope. The NDVI and NDRE was resulted from aerial photo processing.

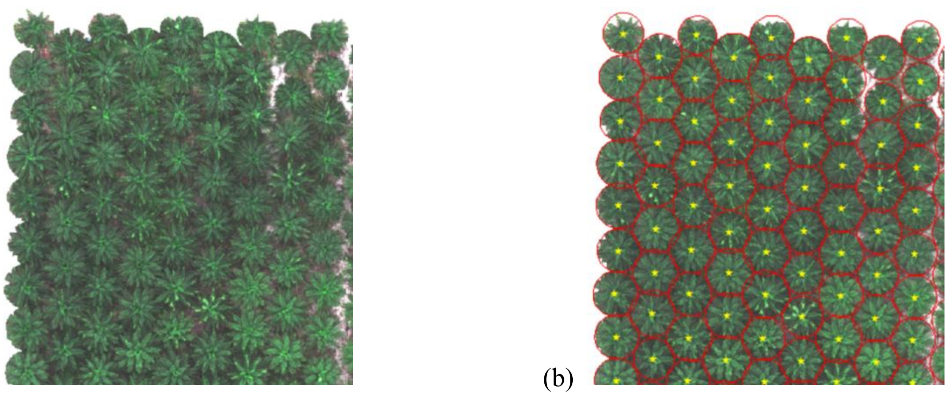
The coefficient of determination R^2 was used to describe the strength of the regression equation, which represents the dynamics of the data between observed variables.

3. RESULTS AND DISCUSSION

The results of photo image acquisition with a multispectral sensor camera produce multispectral aerial photos with a resolution of 7 cm consisting of 6 data bands, namely the Blue band, Green band, Red band, NIR band, Red Edge band and Panchromatic band. The Harvest Density Rate (AKP) reached 105% (more than 100%) in 4 harvest rotations, meaning that all trees in block 531 (Q45) had produced FFB, which totaled 18,136.62 kg.

3.1. Number of Trees and Area of Canopy Cover

The process of providing data on the number of trees and area of canopy cover obtained from RGB (Natural) band aerial photos using ArcGIS Pro Deep Learning Tools software. From the results of image processing, it was found that the number of palm trees in the research object block was 2,010 trees.



(a) (b)

Figure 2. Making a palm tree circle. (a) RGB Composite Image, (b) Palm tree ring image

The shadow effect on the image is removed using the Image Analyst Extension feature in ArcGIS Pro software. Likewise, land objects in photo images are analyzed using the same software, in this case the features contained in the Image Analyst Extension are used to produce a Soil Adjusted Vegetation Index (SAVI) from photo images. The area of canopy cover is obtained from each circle that has been cleaned from the ground background. Figure 3 shows that each palm tree has a canopy cover area in m^2 units (see the SAVIMasked_Area column in Figure 3).

The area of canopy cover per tree was obtained from the calculation results of ArcGIS Pro software. The results of these calculations are presented in Table 2.

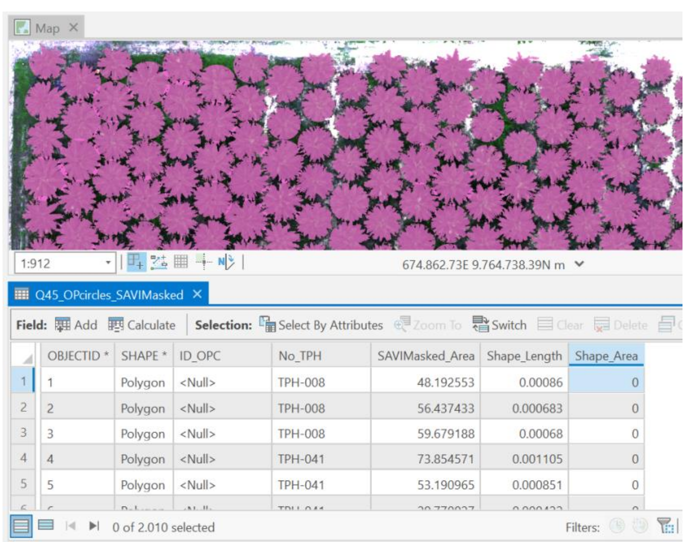


Figure 3. Canopy area per tree displayed using ArcGIS Pro software

Table 2. Canopy area, vegetation index, observations of production quantities, and observations of number of bunches

FCP	Number of Trees	Canopy Cover Area (m^2)	NDVI	NDRE	FFB Production (kg)	Number of Bunches
FCP-001	44	2,679	0.886	0.508	768	78
FCP-002	44	2,551	0.887	0.494	654	80
FCP-003	44	2,292	0.870	0.464	575	77
FCP-004	44	2,208	0.867	0.477	694	80
FCP-005	44	2,193	0.870	0.470	506	63
FCP-006	44	2,267	0.870	0.482	731	82
FCP-007	44	2,018	0.865	0.469	587	68
FCP-008	44	1,813	0.855	0.423	347	44
FCP-009	44	1,781	0.850	0.409	385	49
FCP-010	44	1,472	0.836	0.362	197	24
FCP-011	44	1,476	0.834	0.373	201	27
FCP-012	44	1,534	0.837	0.383	191	28
FCP-013	43	1,715	0.846	0.402	207	23
FCP-014	43	2,172	0.865	0.436	474	51
FCP-015	44	2,242	0.870	0.437	407	51
FCP-016	44	2,068	0.866	0.422	390	50
FCP-017	44	2,125	0.860	0.413	261	32
FCP-018	44	1,816	0.852	0.408	177	23
FCP-019	43	1,775	0.847	0.404	194	23
FCP-020	42	1,998	0.859	0.412	201	29
FCP-021	42	2,191	0.871	0.422	372	53
FCP-022	42	2,232	0.872	0.429	337	43
FCP-023	43	2,451	0.876	0.442	372	43
FCP-024	31	1,781	0.895	0.485	299	40
FCP-025	33	1,954	0.869	0.426	268	36
FCP-026	43	2,306	0.862	0.391	515	66
FCP-027	41	1,989	0.850	0.371	375	50
FCP-028	41	1,818	0.852	0.374	232	36
FCP-029	40	1,939	0.857	0.395	177	25
FCP-030	41	1,764	0.848	0.362	99	16
FCP-031	41	1,861	0.855	0.376	217	26
FCP-032	43	2,013	0.859	0.398	323	41
FCP-033	44	1,922	0.853	0.380	277	35
FCP-034	42	1,886	0.852	0.372	243	29
FCP-035	41	1,632	0.846	0.356	211	26
FCP-036	42	1,819	0.845	0.364	202	24
FCP-037	40	1,673	0.848	0.374	115	15
FCP-038	42	1,780	0.853	0.391	197	28
FCP-039	42	1,960	0.867	0.437	195	28
FCP-040	40	1,868	0.867	0.440	453	65
FCP-041	41	2,027	0.869	0.447	421	60
FCP-042	41	1,897	0.858	0.400	398	52
FCP-043	40	1,930	0.861	0.420	568	72
FCP-044	38	1,910	0.873	0.451	443	51
FCP-045	41	2,132	0.878	0.481	434	52
FCP-046	42	2,322	0.883	0.485	563	64
FCP-047	40	2,404	0.889	0.488	982	104
FCP-048	38	2,272	0.882	0.494	701	71
Total	**2010**	**95,927**			**18137**	**2233**

3.2. Extent of Canopy Cover on FFB Production

LAI is widely used as a reference parameter for modeling environmental systems to demonstrate production (Parker, 2020). The results of the correlation and regression analysis between Canopy Cover Area and FFB Production, obtained a value of r = 0.757, which can be interpreted that these two variables have a positive and strong linear relationship (Sarwono, 2006; Wibowo, 2012), In addition, The coefficient of determination R^2 obtained was 0.573 (see Figure 4), which means that FFB production (kg) can be explained by the variable tree cover area, with a determination or influence value of 57.3%, while the rest is influenced by other variables not included in this research.

This is in accordance with research results (Hardon *et al*., 2008; Squire, 1984), where LAI has a positive relationship (r = 0.669) with FFB production, meaning that the higher the leaf area index, the heavier it will be. Total FFB produced by the block. However, 25 - 34% is influenced by other factors, for example topography, rainfall and dead oil palm trees. Garden productivity is also influenced by nitrogen and potassium fertilization in each block (Woittiez *et al*., 2017). Several other studies have indicated that LAI can reflect production, for example reported by Hashimoto (2023) for rice plants and by Sandoval (2024) for Lotus plants. In line with this, Räsänen (2020) also reported that LAI modeling provided moderate-good results for the total biomass produced.

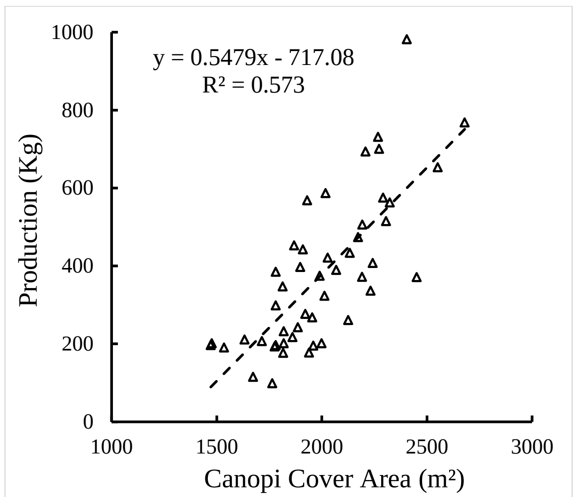


Figure 4. Regression graph between canopy cover area and FFB production

3.3. NDVI and NDRE values for the number of FFB

Normalized Different Vegetation Index (NDVI) is an index that describes the level of greenness of a plant. The vegetation index is a mathematical combination of the red band and the Near-Infrared Radiation (NIR) band. NDVI can be used as an indicator of the presence and condition of vegetation. NDVI calculations are based on the principle that green plants grow very effectively by absorbing radiation in the visible light spectrum (Photosynthetically Active Radiation), while green plants highly reflect radiation from the near infrared region. The NDVI value from the spectral pattern concept based on this principle uses only red band images. Previous research reporting the relationship between NDVI and palm oil productivity was reported by Diana *et al.* (2019), where using an Artificial Neural Network (ANN) obtained an accuracy of up to 80%. Meanwhile, Taufik *et al.* (2021), compared the results of processing Sentinel-2A satellite imagery with the NDVI transformation algorithm to estimate palm oil production, getting an accuracy of 76.8%.

The results of the correlation and regression analysis between the NDVI value and the number of FFB, obtained an *r* value of 0.699, which means that the relationship between the two variables is quite strong, where a positive correlation can be interpreted as meaning that the higher the NDVI value, the more fruit will be harvested. Apart from that, a determination coefficient value of 0.488 was obtained, which means that the NDVI variable can explain the number of FFB or has an effect of 48.8%, the rest is influenced by other variables not included in this research.

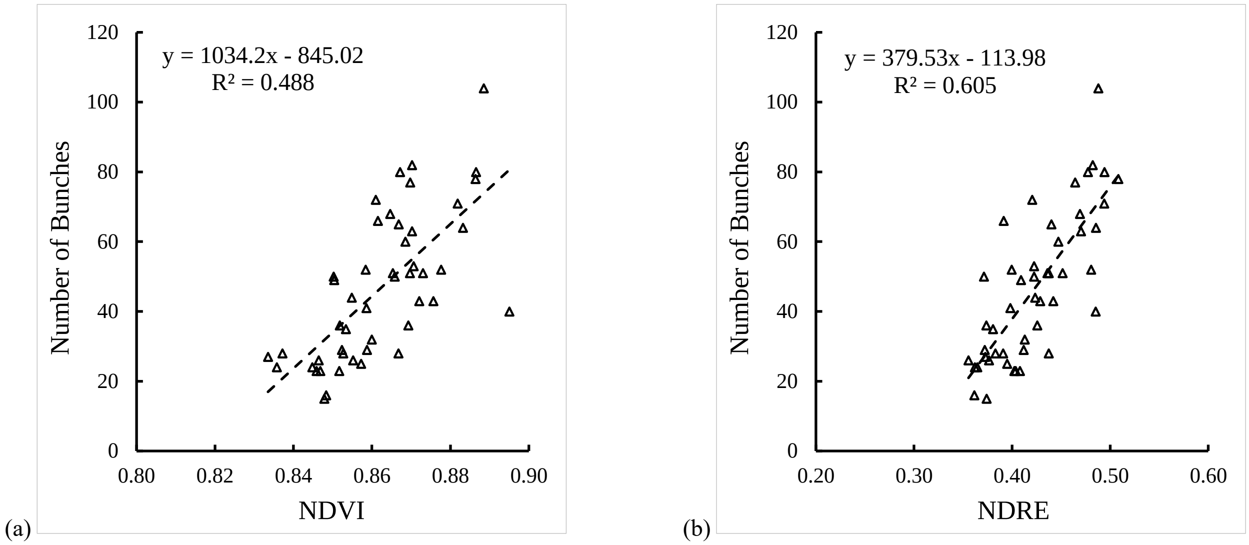


Figure 5. Regression graph: (a) NDVI value vs. number of FFB; (b) NDRE value and number of FFB

The NDRE (Normalized Difference Red Edge) index is an index that can be analyzed via a camera sensor. Sensors with NDRE have the ability to analyze the chlorophyll content of a plant from the greenness of the leaves. NDRE can also read the variability of leaf area and the effect of a plant seen from its soil background. A high NDRE value indicates a high level of leaf chlorophyll content.

3.4. NDVI Value of FFB Production

The results of the correlation and regression analysis between the NDVI value and Production (kg), obtained an r value of 0.704, which means that the relationship between the two variables is strong, where a positive correlation can be interpreted as meaning that the higher the NDVI value, the heavier the fresh fruit bunches will be. which is harvested. Apart from that, a coefficient of determination value of 0.496 was obtained, which means that the NDVI variable can explain FFB production or has an effect of 49.6%, the rest is influenced by other variables not included in this research. These results are in accordance with the research results of Diana *et al.* (2019) and Taufik *et al.* (2021) which show a positive correlation between NDVI and crop production.

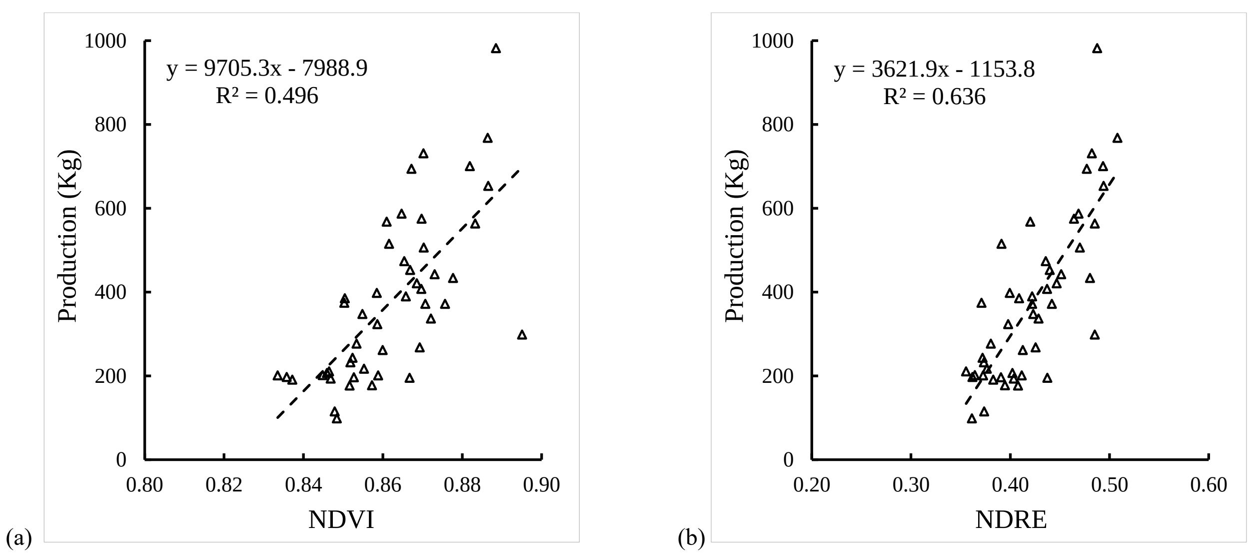


Figure 7. Regression graph: (a) NDVI values vs. FFB production; (b) NDRE value vs. FFB production

3.5. NDRE on FFB Production

The results of the correlation and regression analysis between the NDRE value and Production (kg), obtained an r value of 0.797, which means that the relationship between the two variables is strong, where a positive correlation can be interpreted that the higher the NDRE value, the heavier the fresh fruit bunches will be, which is harvested. Apart from that, a determination coefficient value of 0.636 was obtained, which means that the NDRE variable can explain FFB production or has an influence of 63.6%, the rest is influenced by other variables not included in this research. Positive correlation values like this were also obtained by Macedo *et al*. (2023) when predicting corn crop production using NDRE.

The correlation values and coefficient of determination, both between NDVI and the amount of FFB and NDRE with an amount of FFB of this size, are considered reasonable, because they are in accordance with research conducted by (Sukarman *et al*., 2022), which shows that water deficit causes a decrease in oil palm productivity. Therefore, the amount of FFB is greatly influenced by the water deficit experienced by oil palm trees, starting from the flower initiation phase to the fruit phase towards maturity (Woittiez *et al*., 2017). Apart from that, it is also supported by the statement (Pahan, 2015), that fruit production (kg) of oil palm is related to the fertility and growth rate of the plant. The interesting thing that can be obtained is that in this research it was also found that the NDRE value can provide a better response when compared to the NDVI value, both when used to estimate the amount of FFB and estimate FFB production (kg).

4. CONCLUSION

Based on the results of the analysis in this research, it can be concluded that: 1) the results of the analysis between Canopy Cover Area and FFB Production (kg) have a strong relationship (r = 0.757) with a coefficient of determination value of $R^2 = 0.573$; 2) the results of the analysis between the NDVI value and the number of FFB have a fairly strong relationship (r = 0.699) with a coefficient of determination value of $R^2 = 0.488$; 3) the results of the analysis between the NDRE value and the number of FFB have a fairly strong relationship (r = 0.778) with a coefficient of determination value of $R^2 = 0.605$; 4) the results of the analysis between the NDVI value and FFB production (kg) have a strong relationship (r = 0.704) with a coefficient of determination value of $R^2 = 0.496$; 5) the results of the analysis between the NDRE value and FFB production (kg) have a strong relationship (r = 0.797) with a coefficient of determination value of $R^2 = 0.635$; 6) The NDRE value is the independent variable that provides the best response, both to the number of FFB and FFB production (kg); 7) the best regression equation obtained for FFB production (kg) is Y(FFB Production (kg)) = 1153.8– (3621.9*NDRE); and 8) the best regression equation obtained for the number of FFBs is Y(Number of FFBs) = 113.98 – (379.53*NDRE).

ACKNOWLEDGMENTS

The author thanks DRTPM Kemdikbudristek for research funding support through the Postgraduate Master's Thesis scheme, and PT. Mentaya Sawit Mas (MSM), Wilmar Group, for facilitating research locations and materials.

REFERENCES

Balasundram, S.K., Memarian, H., & Khosla, R. (2013). Estimating oil palm yields using vegetation indices derived from quickbird. *Life Science Journal*, ***10***(4), 851–862.

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

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

Darmawan, S., Takeuchi, W., Haryati, A., Najib, A.M.R., & Na'aim, M. (2016). An investigation of age and yield of fresh fruit bunches of oil palm based on Alos Palsar 2. *IOP Conference Series: Earth and Environmental Science*, ***37***, 012037. https://doi.org/10.1088/1755-1315/37/1/012037

Diana, S.R., Sutrisnanto, A., Purnama, S.M., Perwitasari, I., Yudha, G.D., & Farida, F. (2019). Estimation the amount of oil palm production using artificial neural network and NDVI SPOT-6 imagery. *International Journal of Innovative Science and Research Technology*, 4(11), 548-554.

Duffy, J.P., Pratt, L., Anderson, K., Land, P.E., & Shutler, J.D. (2018). Spatial assessment of intertidal seagrass meadows using optical imaging systems and a lightweight drone. *Estuarine, Coastal and Shelf Science*, ***200***, 169–180. https://doi.org/10.1016/j.ecss.2017.11.001

Fairhurst, T.H., & Griffiths, W. (2014). *Oil Palm: Best Management Practices for Yield Intensification*. International Plant Nutrition Institute (IPNI), Malaysia: 180 pp.

Hardon, J.J., Williams, C.N., & Watson, I. (2008). Leaf area and yield in the oil palm in Malaya. *Experimental Agriculture*, ***5***(1), 25–32. https://doi.org/10.1017/S0014479700009935

Hashimoto, N., Saito, Y., Yamamoto, S., Ishibashi, T., Ito, R., Maki, M., & Homma, K. (2023). Relationship between leaf area index and yield components in farmers' paddy fields. *AgriEngineering*, ***5***(4), 1754–1765. https://doi.org/10.3390/agriengineering5040108

Khamis, A., Ismail, Z., Haron, K., & Mohammed, A.T. (2005). Nonlinear growth models for modeling oil palm yield growth. *Journal of Mathematics and Statistics*, ***1***(3).

Kim, D.-W., Yun, H. S., Jeong, S.-J., Kwon, Y.-S., Kim, S.-G., Lee, W.S., & Kim, H.-J. (2018). Modeling and testing of growth status for chinese cabbage and white radish with UAV-Based RGB imagery. *Remote Sensing*, ***10***(4). https://doi.org/10.3390/rs10040563

Macedo, F.L., Nóbrega, H., de Freitas, J.G.R., Ragonezi, C., Pinto, L., Rosa, J., de Carvalho, M.A.A.P. (2023). Estimation of productivity and above-ground biomass for corn (*Zea mays*) via vegetation indices in Madeira Island. *Agriculture*, ***13***(6), 1115. https://doi.org/10.3390/agriculture13061115

MicaSense Series. (2023). *RedEdge-P*. https://ageagle.com/wp-content/uploads/2022/08/AgEagle-RedEdge-P-Brochure-EN.pdf

Mirzaeinia, A., Hassanalian, M., Lee, K., & Mirzaeinia, M. (2019). Energy conservation of V-shaped swarming fixed-wing drones through position reconfiguration. *Aerospace Science and Technology*, ***94***, 105398–105404. https://doi.org/10.1016/j.ast.2019.105398

Nurmalasari, I., & Santosa, S.H.M.B. (2018). Pemanfaatan citra sentinel-2A untuk estimasi produksi pucuk teh di sebagian Kabupaten Karanganyar. *Jurnal Bumi Indonesia*, 152(3), 28.

O'Driscoll, J. (2018). Landscape applications of photogrammetry using unmanned aerial vehicles. *Journal of Archaeological Science: Reports*, ***22***, 32–44. https://doi.org/10.1016/j.jasrep.2018.09.010

Pahan, I. (2015). *Panduan Teknis Budidaya Kelapa Sawit.* Penebar Swadaya Grup.

Parker, G. G. (2020). Tamm review: Leaf Area Index (LAI) is both a determinant and a consequence of important processes in vegetation canopies. *Forest Ecology and Management*, ***477***, 118496. https://doi.org/10.1016/j.foreco.2020.118496

Räsänen, A., Juutinen, S., Kalacska, M., Aurela, M., Heikkinen, P., Mäenpää, K., Rimali, A. & Virtanen, T. (2020). Peatland leaf-area index and biomass estimation with ultra-high resolution remote sensing. *GIScience & Remote Sensing,* 57(7). https://doi.org/10.1080/15481603.2020.1829377

Rimpika., Anushi., Manasa, S., Anusha, K.N., Sharma, S., Thakur, A., Shilpa., & Sood, A. (2023). An overview of precision farming. *International Journal of Environment and Climate Change*, ***13***(12). https://doi.org/10.9734/ijecc/2023/v13i123701

Romero, H.M., Guataquira, S., & Forero, D. (2022). Light interception, photosynthetic performance, and yield of oil palm interspecific OxG hybrid (*Elaeis oleifera* (Kunth) Cortés x *Elaeis guineensis Jacq*.) under three planting densities. *Plants*, ***11***(9), 1166. https://doi.org/10.3390/plants11091166

Sandoval, A.P., Acoltzi, S.X., Calzada, R.T., de los Santos, G.G., Vázquez, P.Á., & Ávila, J.G.A. (2024). Índice de área foliar e indicadores de productividad forrajera de Lotus corniculatus L. en diferentes contenidos de humedad del suelo y estaciones del año. *Revista Mexicana De Ciencias Pecuarias*;***15***(1),17-31. https://doi.org/10.22319/rmcp.v15i1.6472

Sarwono, J. (2006). *Metode Penelitian Kuantitatif & Kualitatif.* Graha Ilmu.

Setyowati, H.A., Murti, B.S.S.H., & Widyatmanti, W. (2016). Yield estimation comparison of oil palm based on plant density coefficient variation index using spot-6 imagery in part of Riau. *IOP Conference Series: Earth and Environmental Science*, ***37***, 012038. https://doi.org/10.1088/1755-1315/37/1/012038

Squire, G.R. (1984b). *Light Interception, Productivity and Yield of Oil Palm*. Palm Oil Institute of Malaysia, Kuala Lumpur, 72 pp

Sukarman, Saidy, A.R., Rusmayadi, G., Adriani, D.E., Primananda, S., Suwardi., Wirinata, H., & Fitriana, C.D.A. (2022). Effect of water deficit of ultisols, entisols, spodosols, and histosols on oil palm productivity in Central Kalimantan. *Sains Tanah – Journal of Soil Science and Agroclimatology*, ***19***(2), 180-191. https://dx.doi.org/10.20961/stjssa.v19i2.6545

Taufik, V.V., Sukmono, A., & Firdaus, H.S. (2021). Estimasi produktivitas kelapa sawit menggunakan metode NDVI (normalized differnce vegetation index) dan ARVI (atmospherically resistant vegetation index) dengan citra sentinel-2A (Studi kasus : beberapa wilayah di Provinsi Riau). *Jurnal Geodesi Undip*, ***10***(1), 153–162.

Wibowo, A. E. (2012). *Aplikasi Praktis SPSS Dalam Penelitian (Vol. 1)*. Gaya Media.

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