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DETECTING NUTRIENT DEFICIENCY IN OIL PALM SEEDLINGS USING MULTISPECTRAL UAV IMAGES

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Abstract: Remote sensing is driving transformation in the palm oil plantation industry with data acquisition and spatial analysis. Rapid identification of nutrients in oil palm plantations using a Remote Sensing approach provides benefits for plantation productivity and operations. The research was carried out at the PT Sampoerna Agro plantation, where 18-month-old oil palm seedlings received different intentional nutrient deficiency treatments. The research method used pixel-based classification algorithms with machine learning and Object-Based Image Analysis (OBIA) based segmentation to identify nutrient deficiencies in oil palm seedlings using multispectral Unmanned Aerial Vehicle (UAV) images. Both techniques were integrated with Random Forest and Support Vector Machine (SVM). The classification results using the OBIA-Random Forest classifier, reached an overall accuracy of 0.421, while the classification results using the OBIA-SVM classifier, reached an overall accuracy of 0.438. Meanwhile, by using the

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pixel-based supervised classification method, with the Random Forest and SVM algorithms, an overall accuracy of 0.413 and 0.438 were obtained. The overall accuracy of both classifiers was low, this is due to several nutrient deficiencies that could not be properly identified. However, nitrogen deficiencies could be identified accurately. Based on this research, the OBIA-SVM classifier has the best overall accuracy for identifying nutrient deficiencies in oil palm seedlings, with an overall accuracy of 0.438.
Keywords: oil palm seedlings; nutrient deficiencies; multispectral; OBIA; Random Forest; SVM.

2020 AMS Subject Classification: 92B05.

1. INTRODUCTION

The development of information and computer technology has influenced the way people view plantation technology. Several things that were previously done manually or conventionally and took a long time can now be processed more quickly and automatically. For example, the method for obtaining spatial data in oil palm plantations is currently starting to use unmanned aircraft (drones). This technology is very promising to be applied and developed according to the topographic and geographical characteristics of Indonesia, especially for large plantation areas such as oil palm plantations. As the largest palm oil-producing country in the world, palm oil is the main commodity for Indonesia's state income and foreign exchange. This is why palm oil has a strategic role in national economic development. Remote sensing is bringing significant innovation to the oil palm industry by bringing positive changes in the way oil palm plantations are managed, enabling more efficient monitoring and better decision-making. Remote sensing allows extensive and comprehensive monitoring of oil palm plantations, satellite and UAV imagery can provide a comprehensive picture of plants and environmental conditions throughout the plantation area. Overall, remote sensing has brought about a transformation in the palm oil industry by increasing efficiency, productivity, and sustainability, while reducing adverse environmental impacts.

Fertilization in the oil palm plantation industry, especially in Indonesia, is one of the most important components that require the largest costs in cultivating oil palm plants, where the cost of fertilizing oil palm plants can reach 24 percent of the total production costs or reach 40 - 60 percent of the total maintenance costs of oil palm cultivation [1]. Fertilization has a significant impact on growth and production. Research studies conducted by Sidhu et al. [2] showed that plots that were fertilized according to requirements had 100% higher productivity compared to control plots that were not fertilized. Purnomo et al. [3] suggested that fertilizer application can increase vegetative growth such as plant height and plant dry weight. Precision Agriculture by utilizing remote sensing technology can reduce costs and increase the effectiveness of oil palm cultivation, especially in mapping/identifying plant nutrient deficiencies.

The use of remote sensing, especially UAVs for identifying agricultural/plantation plant nutrients, especially for oil palm plants, is still minimal. Research trends using UAVs are still dominated by the identification or analysis of vegetation features (such as canopy cover plant height, etc.) [4]. Researchers are currently focusing on examining the use of multispectral in plants to understand the relationship between spectral reflectance and vegetation cover characteristics [5]. Modi & Das [6] revealed that 8 vegetation indexes can be used to detect the green level of leaves, one of them is NDVI. However, the direction of remote sensing-based research, especially using UAV data in the agricultural/plantation sector, is also currently starting to develop toward its use for identifying plant diseases, plant nutritional deficiencies, and for identifying soil nutrients.

Apart from UAV technology, Artificial Intelligence technology has also been used in research in plantations and agriculture. Some research that uses this technology includes tree counting [7], detection of nutrient deficiencies [8–10], fertilizer recommendations [11], and disease detection in plants [12,13]. The remote sensing in this research has also utilized more advanced classification methods such as object-based classification, which is also integrated with machine learning and deep learning algorithms [4,14–18]. Remote sensing was also used to identify plant nutrients, by utilizing multispectral UAV data [19], RGB UAV [20], satellite multispectral data [21,22] which is also integrated with sophisticated machine learning algorithms, including the Random Forest classifier, and Support Vector Machine classifier. Costa et al. [19] identified nutrients in citrus plant leaves using a multispectral UAV which was also integrated with a machine-learning algorithm. The method developed by Costa et al. [19] can properly identify nutrients, both macronutrients and micronutrients on citrus plants. In the application of nutrient identification in oil palm plantations, data [22], utilized Landsat 8 satellite data, the analysis was conducted using oil palm plantation plots as the unit of analysis and also compared the Random Forest, SVM, and MLP algorithms, where the accuracy for Identification of N and K nutrients is good but still unable to identify P, Mg and Ca nutrients.

This research aims to identify nutrient deficiencies in 18 months (about one and half years) old oil palm seedlings using a remote sensing approach on multispectral UAV data. It utilized the object-based classification (OBIA) method that was integrated with the Random Forest (RF) machine learning algorithm and Support Vector Machine (SVM). The results compared object-based classification and pixel-based classification methods.

2. MATERIAL AND METHODS

2.1. Research Location

The research was held at the PT Sampoerna Agro's Nursery, Sukarami, Palembang, South Sumatra, Indonesia. Figure 1 shows the aerial image of the research area. The research objects were oil palm seedlings that were 18 months old. Most of the seedlings have been given certain scenario treatments, to have intentional nutrient deficiencies.

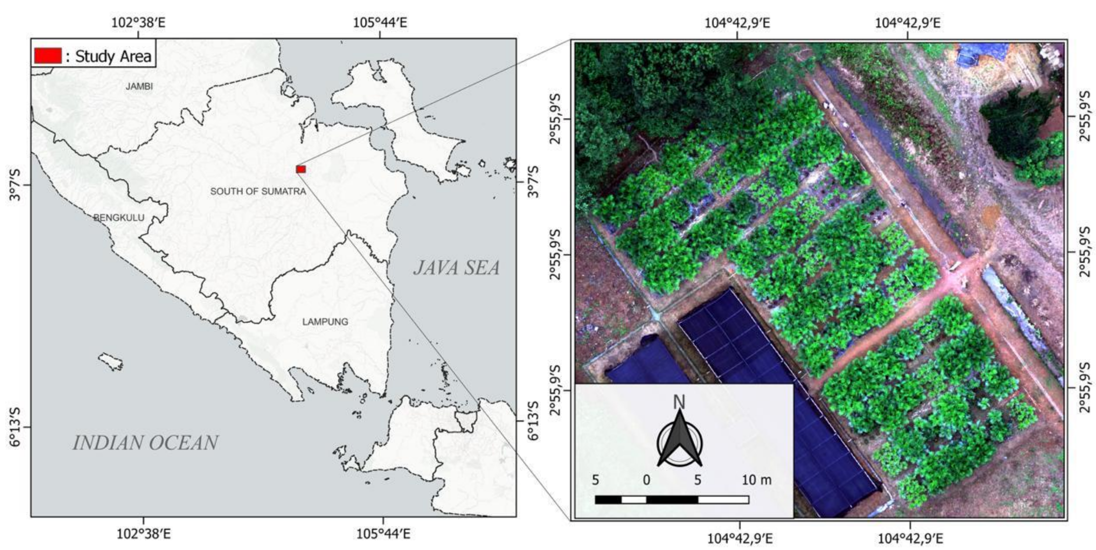

FIGURE 1. The Aerial Image of the Location

2.2. Research Data

2.2.1. Multispectral UAV Data

The data used in this research are based on the aerial multispectral imagery data of PT Sampoerna Agro's nursery plantation. The aerial multispectral imagery data were acquired in September 2022 using DJI Phantom 4 Multispectral UAV. DJI Phantom 4 has 6 CMOS 1/2.9" sensors, consisting of 5 monochrome sensors for multispectral data and 1 RGB sensor for visible waves. All the multispectral bands were used in this study. The specification of the DJI Phantom 4's Multispectral Band Sensor filter is shown in Table 1.

TABLE 1. DJI Phantom 4's Multispectral Band Sensor Filter Specification

Spectral Bands	Wavelength Sensor Filter (nm)
Band 1 – Blue	450 ± 16
Band 2 – Green	560 ± 16
Band 3 – Red	560 ± 16
Band 4 – Red Edge	730 ± 16
Band 5 – Near Infrared	840 ± 16

2.2.2. Field Data

The field data used in this study as model training and validation data were plot locations for 18 month-old oil palm seedlings that have received intentional nutrient deficiency treatment scenarios. There were five scenarios of intentional nutritional deficiency, which were:

- F0 scenario was an oil palm plant seedling that received appropriate treatment and did not experience intentional nutrient deficiencies
- F1 scenario was an oil palm plant seedling that intentionally did not receive nitrogen (N) nutrients

- F2 scenario was an oil palm plant seedling, that intentionally did not receive phosphor (P) nutrients
- F3 scenario was an oil palm plant seedling that intentionally did not receive potassium (K) nutrients
- F4 scenario was an oil palm plant seedling that intentionally did not receive magnesium (Mg) nutrients

2.3. Research Methodology

2.3.1. Data Preprocessing

Figure 2 depicts the workflow of this study. The results of aerial imagery acquisition using the DJI Phantom 4 Multispectral drone were then pre-processed by conducted data mosaics. The aerial imagery data mosaic was conducted using Agisoft Metashape software. The mosaic results produced aerial photography images with a spatial resolution of 0.018 meters. The NDVI calculation was then carried out, which then be used as image classification input and to differentiate non-vegetation areas and vegetation areas. NDVI or Normalized Difference Vegetation Index was an index used to compare the greenness of vegetation from aerial imagery. The NDVI value ranges from –1 to +1, where the value (-) indicates water objects or fallow and wetlands, and the value (+) indicates vegetation objects. This parameter was obtained by extracting the infrared band spectral value from the red band in the aerial imagery data. NDVI was used as another input in this classification because this vegetation index has been used quite often for plant health identification purposes and has been proven to be good for identifying plant stressors due to nutrient or water deficiencies [4].

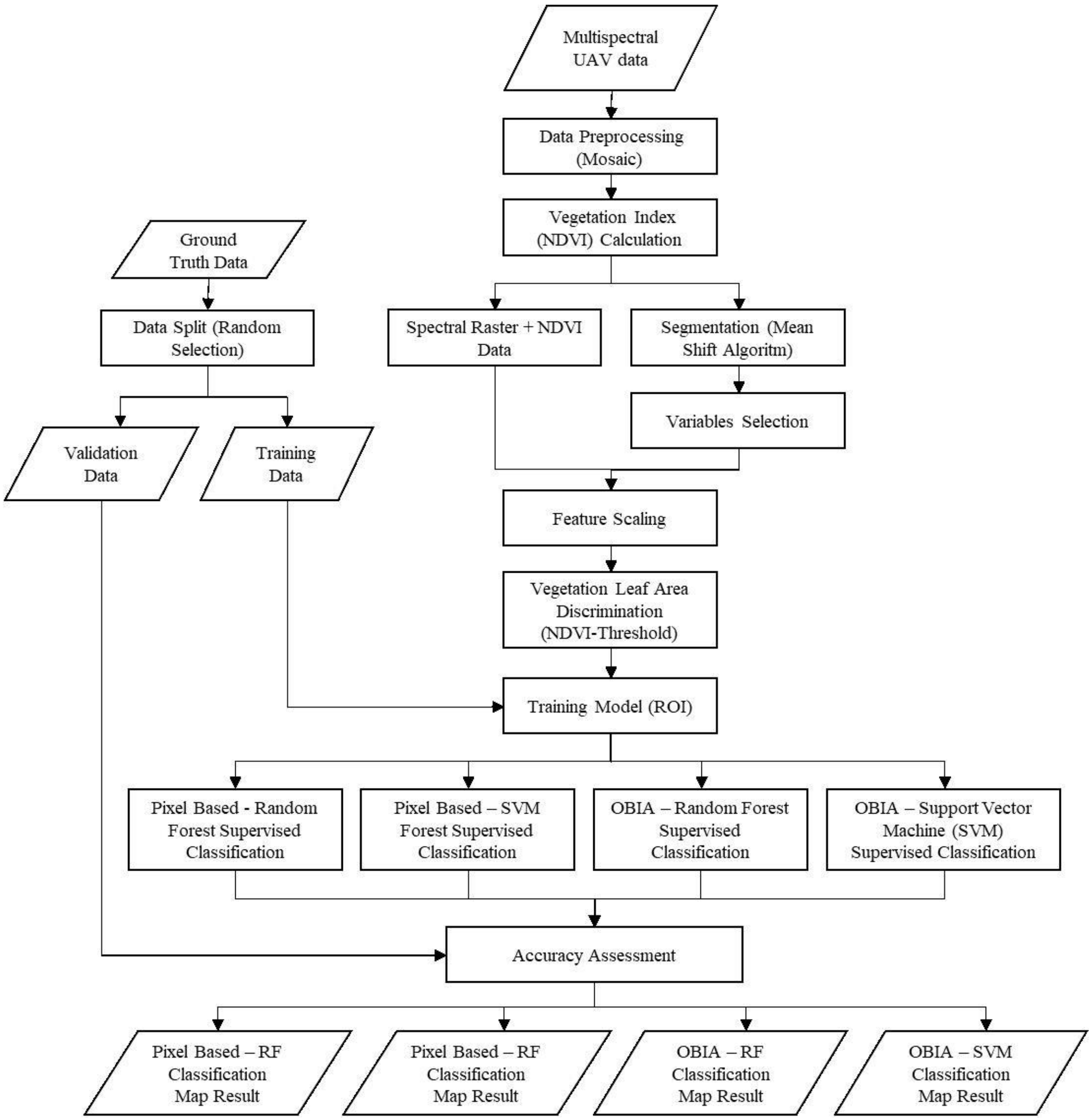

FIGURE 2. The Workflow of the Study

Meanwhile, the results of the Normalized Difference Vegetation Index (NDVI) calculation in the nursery can be seen in Figure 3.

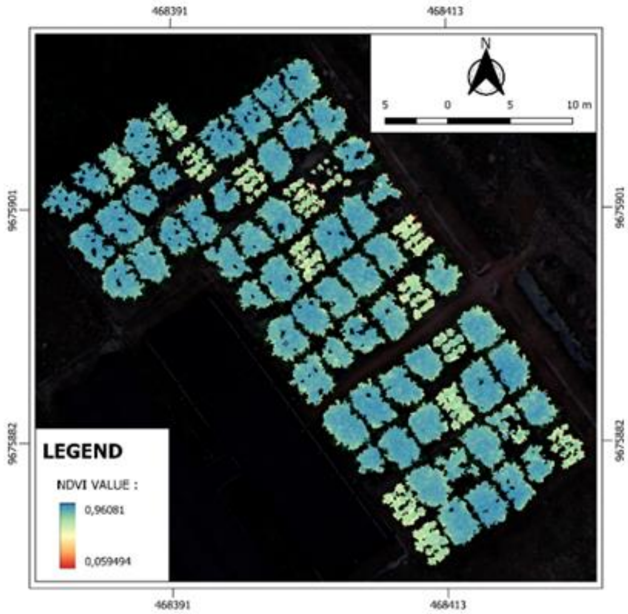

FIGURE 3. NDVI Map of the Palm Oil Nursery

In general, based on the NDVI image in Figure 3, it could be seen that two different ranges of values dominate oil palm seedlings' NDVI value, the first group has a range of NDVI values ranging from 0.12 – 0.38, and the second group of seeds has a range of NDVI values ranging from above 0.38. These two different NDVI groups also have different growth forms, where lower NDVI is found in plants with much smaller leaf canopies, compared to NDVI groups with values above the range. These low-range NDVI values, correlated to the oil palm seedlings, received nitrogen deficiencies treatment. However, NDVI calculations alone were still not enough to detect other different seed management scenarios/nutrient deficiencies in other oil palm seedlings.

2.3.2. Image Segmentation

The OBIA method was chosen due to the reason to make unit analysis of the aerial imagery no longer a single pixel, with the assumption, that leaf segments could minimize identification errors, and would be better as representative of the actual condition of the plant compared to the pixel as unit analysis, where the value of each pixel could vary and would not represent actual plant condition. Segmentation is the stage of dividing raster data into many parts depending on the level of homogeneity of the area or object in the aerial image based on their association with additional attributes such as mean, variance, shape index, textural measures, etc. depending on the segmentation methods [23-24]. The segmentation stage was conducted using the Orfeo-Toolbox plugins in QGIS software using the mean shift algorithm [23].

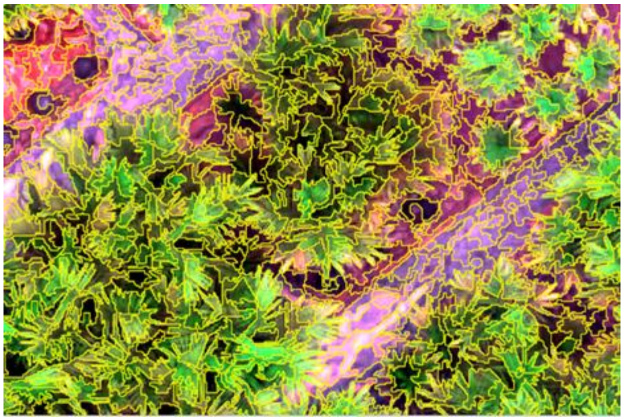

FIGURE 4. An Example of a Segmented Region in the Study Area

Next, based on the NDVI Value, the segmentation data was differentiated between areas of oil palm seedlings and non-vegetation areas, areas that have an NDVI value below zero were no longer included in further processing. This was intended to focus further processing or classification only on the leaf segments of oil palm seedlings, by this research's objectives.

2.3.3. Supervised-OBIA Classification using RF and SVM classifiers

In segmentation-based classification or OBIA, the independent variables used in this research were the mean spectral value, median spectral value, majority spectral value, and standard deviation spectral value, from each of the blue, green, red, red-edge, and near infrared bands, and in addition, the mean value, median value, majority value, and standard deviation value of NDVI which had previously been calculated for each leaf segment. Data normalization or feature scaling was carried out to make all independent variables data as input on the same data scale. Normalization was needed especially when conducting classification using the Support Vector Machine (SVM) algorithm. The SVM classifier used a non-linear approach, employing a radial basis function kernel (RBF). RBF SVM worked by mapping the independent variables as input into a higher-dimensional feature space, where the classes could be separated by a hyperplane, it is proven that RBF SVM could differentiate well between objects [25]. All processing stages in this research used the R programming language and the R studio platform [26]. The training model used in OBIA-supervised classification is in the form of segments/polygons with training data as a reference. The ground truth data were split into training data and data for validation in the OBIA classification with a comparison of 60 to 40 using 3000 leaf segments.

2.3.4. Supervised-Pixel Based Classification using RF and SVM Classifiers

Meanwhile, in pixel-based classification, the reflectance value of each band (blue, green, red, red-edge, near-infrared) and NDVI value were used as the inputs/variables. Feature scaling or data normalization was also conducted at this stage.

2.3.5. Post Processing

The post-processing stage was conducted only on the pixel-based classification results. After the classification results were obtained, post-processing was carried out to generalize the single pixels that were classified among the dominant neighboring pixels, where the single pixel was the dominant pixel class around it. This post-processing stage was conducted using the Majority filter tools in ArcMap 10.8.

3. RESULTS AND DISCUSSIONS

3.1 Supervised Pixel-Based Classification Result

The following are the results of pixel-based classification using the Random Forest (RF) algorithm and the results of Support Vector Machine (SVM) classification as seen in Figure 5.

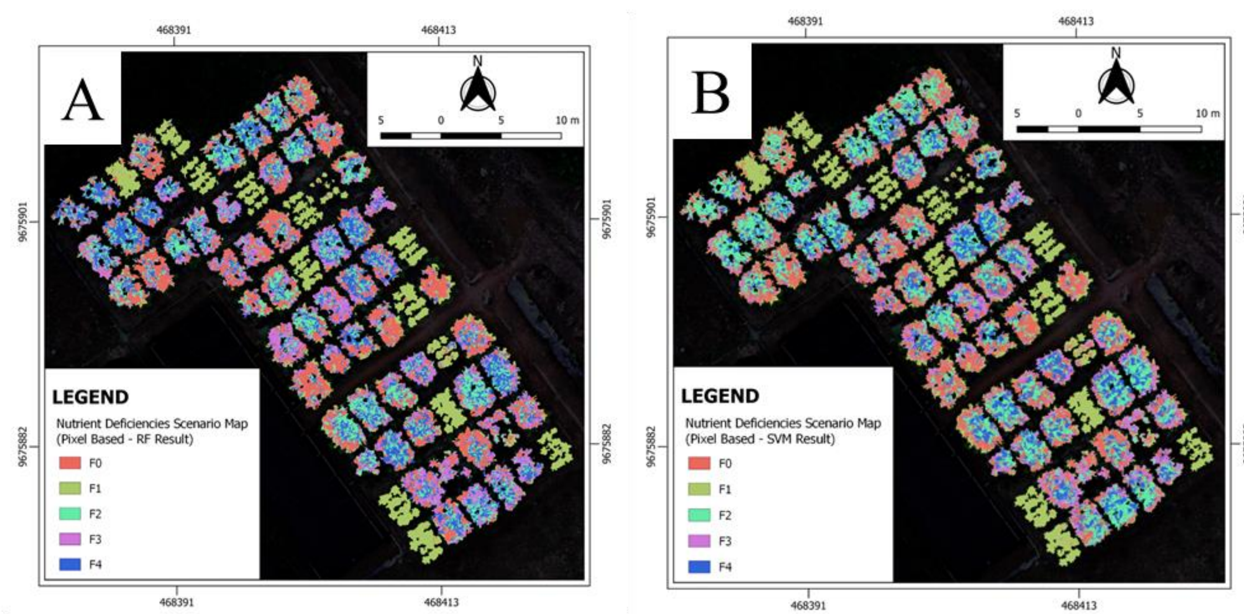

FIGURE 5. Nutrient Deficiency Scenario Map Result of Pixel-Based Classification Using: (A) Random Forest Algorithm (A), and (B) Support Vector Machine Algorithm

In general, and based on visual observation, from the two results of the pixel-based classification in Figure 5, the results obtained by both classifiers, tend to be identical. The two classification results maps can still identify seed plants with nitrogen deficiency scenarios. This result is like Wijaya et al. (2018) research which revealed an elevated level of N accuracy with satellite multispectral imagery [27]. However, both algorithms cannot identify deficiencies in other nutrients such as phosphorus, magnesium, and potassium and in seedlings that have not received nutrient deficiency treatment.

The results of the confusion matrix accuracy test for the OBIA pixel-based classification model [28], both with the Random Forest classifier and the Support Vector Machine classifier, are shown in Table 2 and Table 3.

TABLE 2. Confusion Matrix between the Predicted Pixel Value of RF vs Actual Field Data

		Reference					User Accuracy
		F1	F2	F3	F4	F0	
Predicted	F1	**5778**	685	436	249	817	0.725
	F2	1	**3923**	2276	2380	1950	0.373
	F3	21	2391	**3922**	1973	1541	0.398
	F4	37	2495	2701	**3225**	1605	0.32
	F0	24	3557	2404	2762	**4451**	0.337
Producer Accuracy		**0.985**	**0.3**	**0.33**	**0.3**	**0.43**	
Overall Accuracy		**0.413**					
Kappa Coefficient		**0.28**					

TABLE 3. Confusion Matrix between the Predicted Pixel Value of SVM vs Actual Field Data

		Reference					User Accuracy
		F1	F2	F3	F4	F0	
Predicted	F1	**16006**	1237	1281	1052	2312	0.731
	F2	25	**5285**	3066	5230	3999	0.300
	F3	115	5140	**6421**	5359	3427	0.314
	F4	3	8006	4933	**8319**	2686	0.347
	F0	1095	9552	6946	7904	**15401**	0.377
Producer Accuracy		**0.928**	**0.181**	**0.284**	**0.298**	**0.553**	
Overall Accuracy		**0.412**					
Kappa Coefficient		**0.273**					

Overall, the results of the pixel-based classification of the two classifiers (RF and SVM) were similar, the two classification methods have identical results. The overall accuracy of the pixel-based supervised classification method integrated with the Random Forest classifier reached 0.413, and the overall accuracy of the SVM classifier reached 0.412. Both classifiers were able to identify N deficiency quite well.

3.2. Supervised OBIA Classification Result

The results of the OBIA classification, both with the Random Forest classifier and the Support Vector Machine classifier, are shown in Figure 6.

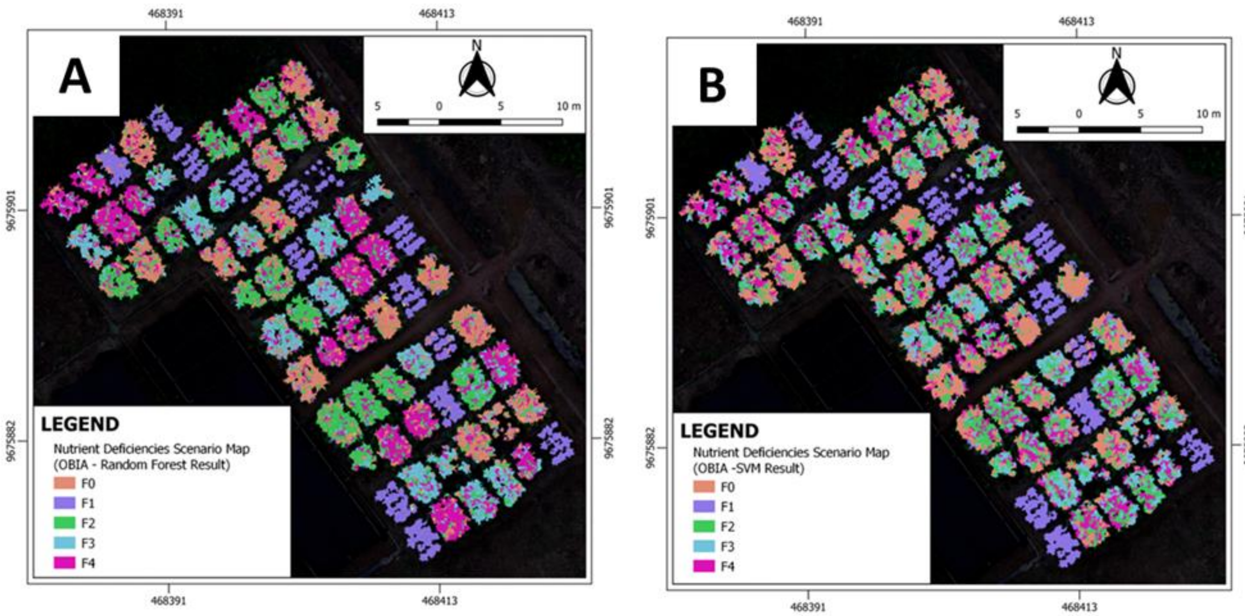

FIGURE 6. Nutrient Deficiency Scenario Map Result of OBIA Classification Using: (A) Random Forest Classifier, and (B) Support Vector Machine Classifier

Of all the intentional nutrient deficiency scenarios, the one that could be identified very well was the F1 scenario, which was the oil palm seedlings that were not given nitrogen nutrients. Unfortunately, misclassification still occured in many leaf segments of oil palm seedlings and can be clearly seen on the map.

Similar to the results of pixel-based classification. Nitrogen deficiency results could be well identified by the Random Forest and Support Vector Machine algorithms. Oil palm seedlings with nitrogen nutritional deficiency, experience stunted growth, and their leaves are more yellow than other seedlings, this makes the NDVI value of seedlings in the F1 scenario low.

Apart from the nitrogen (F1) nutrient deficiency scenario, the classification models (both pixel-based and also OBIA classification) are inconsistent in identifying other nutrient deficiencies. This could be caused by limitations in multispectral data for identifying nutrient deficiencies.

This limitation could be observed in the following spectral reflectance value curve in Figure 7.

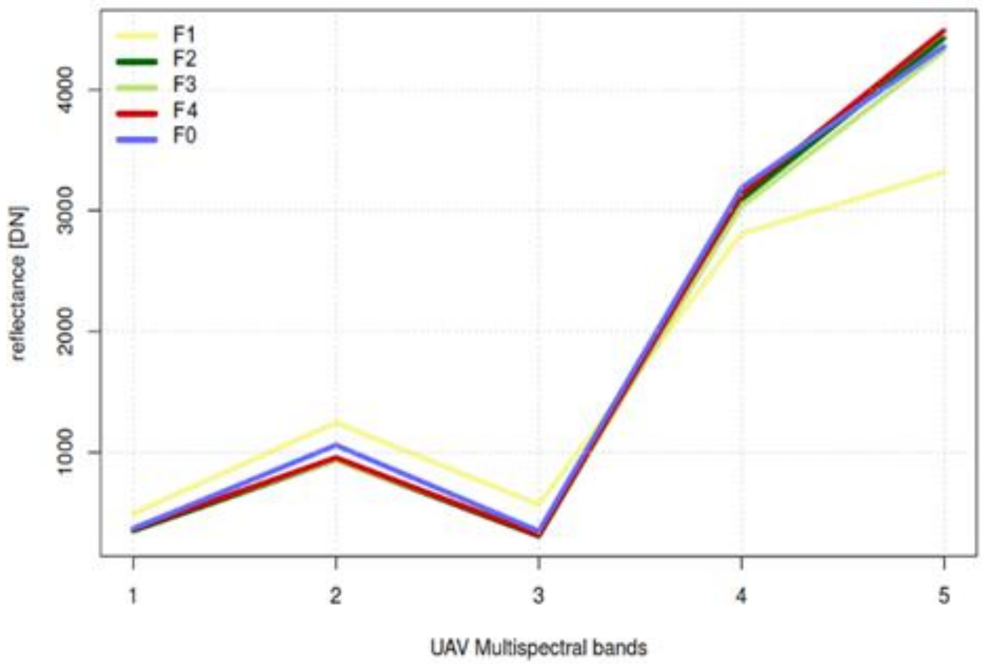

Figure 7. Average Reflectance Value (DN) Curves of the Five Bands for Each Nutrient Deficiency Scenario

Based on Figure 7 the average reflectance value curves could be observed, the reflectance values of seedlings that experience nitrogen nutrient deficiency (F1) are quite different from other seedlings. However, other nutrient deficiencies cannot be distinguished by multispectral aerial imagery, this would contribute to the deficient performance of classification of other nutrient deficiencies.

The accuracy test results of the OBIA classification model, both with the Random Forest algorithm and the Support Vector Machine algorithm, can be seen in the following Table 4 and Table 5.

TABLE 4. Confusion Matrix between Predicted Leaf Segment Value of OBIA-RF and Actual Field Data

		Reference					User Accuracy
		F1	F2	F3	F4	F0	
Predicted	F1	**166**	9	5	8	23	0.787
	F2	4	**69**	45	64	44	0.305
	F3	0	55	**73**	51	45	0.326
	F4	1	51	52	**83**	55	0.343
	F0	3	63	44	70	**113**	0.386
Producer Accuracy		**0.95**	**0.28**	**0.3**	**0.3**	**0.4**	
Overall Accuracy	**0.421**						
Kappa Coefficient	**0.251**						

TABLE 5. Confusion Matrix between Predicted Leaf Segment Value of OBIA-SVM and Actual Field Data

		Reference					User Accuracy
		F1	F2	F3	F4	F0	
Predicted	F1	**163**	4	5	2	5	0.911
	F2	0	**83**	53	70	49	0.325
	F3	1	37	**70**	57	39	0.343
	F4	1	68	56	**59**	34	0.271
	F0	7	77	38	69	**149**	0.438
Producer Accuracy		**0.95**	**0.31**	**0.32**	**0.23**	**0.54**	
Overall Accuracy	**0.438**						
Kappa Coefficient	**0.292**						

In general, the results of the classification of the two algorithms are not much different, here it could be observed, that both algorithms are unable to identify deficiencies in the phosphorus, magnesium, and potassium nutrient deficiencies, and in seed plants that have not undergone treatment. However, the classification results from OBIA integrated with SVM are better in identifying nutrient deficiencies compared to the Random Forest method, with the overall accuracy of OBIA-SVM reaching 0.4381 and the overall accuracy of OBIA-RF reaching 0.4214. Meanwhile, the identification of nitrogen nutrient deficiencies was able to achieve a producer accuracy of 0.95 and a user accuracy of 0.787, while in classification using the SVM algorithm, a producer accuracy of 0.95 was obtained and a user accuracy reached 0.91.

4. Conclusions

This research discusses the potential for using multispectral UAV data to identify nutrient scenarios for oil palm seedlings. The classification that has been carried out in this research, whether using OBIA or pixel-based, is not capable of identifying nutrient deficiencies, P, K, Mg, and distinguishing them from those that do not experience nutrient deficiencies in 18 months (about one and half years) old oil palm seedlings. Limitations in this research may be caused by, among other things, the limited spectral resolution of UAV data. However, it is worth noting that UAV multispectral data using either pixel-based classification or object-based classification could be used to identify nitrogen deficiencies in oil palm seedlings. More research is needed to identify nitrogen deficiencies in old/mature oil palm plants. The best method for classifying nutrient deficiencies in oil palm seedlings is the object or segment-based classification method (OBIA) using the SVM algorithm with an overall accuracy of 0.438.

Conflict of Interests

The authors declare that there is no conflict of interest.

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