COMPARISON OF RANDOM FOREST AND CART METHODS FROM LANDSAT-8 IMAGERY IN MAPPING MACRO NUTRIENT CONTENT OF OIL PALM LEAVES IN NORTH SUMATRA PROVINCE, INDONESIA

Dhimas Wiratmoko[1], T. Sabrina Djunita[2], Budiman Minasny[3], and Zulkifli Nasution[2]

[1]Agricultural Science Doctoral Program, Faculty of Agriculture of Universitas Sumatera Utara (USU),
Jl. Dr. A. Sofian No.3, Sumatera Utara, Indonesia
Email : dhimas.wiratmoko@students.usu.ac.id
[2]Faculty of Agriculture Universitas Sumatera Utara,
Jl. Dr. A. Sofian No.3, Sumatera Utara, tdjunita14@yahoo.com
[3]School of Life and Environmental Sciences
C81 - ATP - The Biomedical Building, The University of Sydney

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ABSTRACT: North Sumatra became an important history of the start of the palm oil industry in Indonesia. The development of the industry shows that North Sumatra contributes as the fourth largest province for oil palm plantations and ranks third as the largest producer of crude palm oil (CPO) in Indonesia. The success of oil palm cultivation is strongly influenced by efforts to replace nutrients through fertilization activities. One of the determinations of fertilization needs is done through an approach to nutrient content in oil palm leaves which requires quite expensive costs and a relatively long time to implement. Mapping macronutrient content through a remote sensing approach using Landsat-8 Imagery provides an opportunity for non-destructive analysis to determine leaf nutrient content. This study aims to map and determine the distribution of macronutrients in oil palm leaves in oil palm plantations in North Sumatra Province. The method used in this study is classification using machine learning in the form of random forest (RF) and classification and regression tree (CART). The results of the analysis resulted in the accuracy of macronutrient estimates for oil palm leaves using RF for nitrogen (N), phosphorus (P), potassium (K), and magnesium (Mg) in 2018 of 93.10%; 93.01%; 93.69% and 94.68%, while in 2019 it was 93.24%; 93.61%; 93.56%; and 93.96%. Estimates using CART in 2018 yielded 98.69% accuracy; 98.56%, 98.81%; and 99.76%, while in 2019 it produced an accuracy of 98.57%; 98.88%; 98.97%; and 99.42% for nitrogen (N), phosphorus (P), potassium (K) and magnesium (Mg) nutrients. Based on this, both models are beneficial in spatially estimating the macronutrient content of oil palm leaves through Landsat-8 images.

1. BACKGROUND

Oil palm is an important crop for Indonesia which was able to contribute US$ 18.23 billion in 2018 (BPS, 2019). North Sumatra is the fourth-highest area in Indonesia with an area of 1.5 million hectares and the third-ranked oil production contribution with 5.73 million tons of CPO in 2018 (Directorate General of Estate Crop, 2019). Oil palm productivity is one of the problems. Its management, especially fertilization, strongly influences on oil palm production. Good practices on fertilization management need to consider various factors, the environmental conditions, genetics, and other management. Woittiez et al., (2017) stated that productivity is influenced by various factors, both internal and external. Prabowo et al., (2010), Schaller et al., (2002) approach in assessing fertilizer needs with one factor approach to leaf nutrient status analysis. Leaf nutrients content is one factor in compiling the fertilizer needs for oil palm plantations to obtain production according to their potential. Webb et al., (2011) stated that the factor analysis approach to nutrient status was carried out by comparing it with the critical concentration of nutrient requirements/contents in it. This critical concentration is usually developed through field experiments, so it requires a large amount of money. This condition requires alternative approach methods that can be scientifically justified.

Remote sensing is not something new to the plantation world. Corley and Thinker (2016) stated that remote sensing had been used since the 1990s to determine differences in macronutrient content in oil palm plants using SPOT image data conducted by Naert et al. (1990) and Nguyen et al. (1995). Marzukhi et al. (2016) detected nutrient deficiency in oil palm plants using SPOT-5 image data and the vegetation index method SAVI and NDVI, which, in NDVI, had a higher correlation with R2 of 0.38-0.88 for nutrients N, P, K, and pH. Santoso et al. (2019) predicted nutrients in oil palm leaves by spectrally obtained from spectrometer measurements analyzed using NDVI, GNDVI, SR, MCARI, TCARI, modified MCARI1, MCARI2, N870_1450, N1645_1715, and P1080_1460 followed by PCR analysis. The importance of the nutrient content is needed to map the leaf nutrients content of oil palm through imagery data, which can provide information quickly and accurately to support the accuracy of fertilization. In its development, remote sensing increasingly provides intelligence in classifying various needs from the image it has.

Using various algorithms, such as machine learning in remote sensing, is not new. Machine learning is one of the algorithms that are well known and is often used in various classification activities. Chen et al. (2017) compared several algorithms such as logistic models tree, random forest, and classification and regression tree models for estimating the vulnerability of land to landslide events. The results of these studies provide a relatively good performance of the three algorithms used. The random forest has the highest yield compared to the CART and logistic models tree. Khan et al. (2022) used a machine learning algorithm in the form of a random forest, gradient boosting, and a decision tree which provided information that weather fluctuations in the form of rainfall frequency, temperature, and soil moisture in the root zone of the plant had a significant influence on the prediction of oil palm production. Even Rashid et al. (2021) and Xu et al. (2021), even machine learning technology provides a challenge in the study of crop yield production. In addition to the platform methodology used by remote sensing in carrying out classification activities, there have been significant developments.

One of the open source platforms used for this activity is Google Earth Explorer (GEE), which has the advantage of being a cloud computing platform for analyzing earth observation data. GEE has published catalog data, such as Landsat Imagery data which has optimal facilities for large-scale computations (Hansen et al., 2013). The application of the GEE platform in oil palm plantations has been carried out in mapping oil palm plantations, Shaharum et al. (2020) conducted a study to extract information in mapping oil palm over Peninsular Malaysia using Landsat 8 data which was processed through the GEE platform with machine learning algorithms such as support vector machine (SVM), Classification and regression tree (CART), and Random Forest (RF). The three algorithms have good accuracy of 80.08-93.16%. Based on these things, the use of machine learning algorithms in the form of RF and CART, which are processed through the GEE online platform, has not been widely used, so it has excellent potential to be used in estimating the nutrient content of leaves, especially oil palm leaves through spatial prediction. This study aims to map and determine the distribution of macronutrients in oil palm leaves in oil palm plantations in North Sumatra Province.

2. METHODS

2.1 Lokasi Penelitian

The location of this research is oil palm plantations in North Sumatra based on the Indonesian Palm Oil Cover Reconciliation Map in North Sumatra Province (Ministry of Agriculture of the Republic of Indonesia, 2019). The location is at 97° 57’ 16.5” to 100° 24’ 25.7” E and 0° 14’ 55.8” to 4° 17’ 48.2” N.

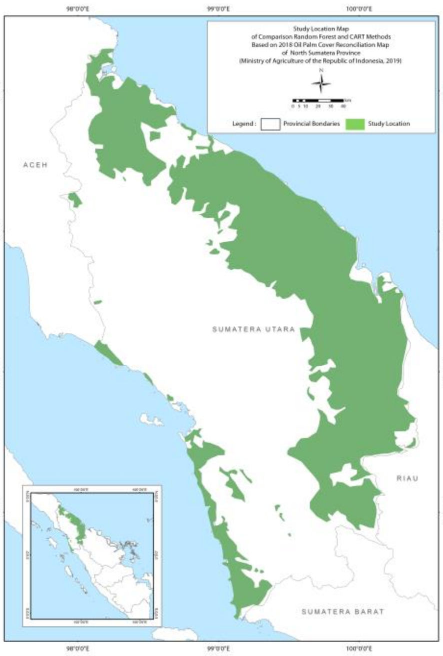

Figure 1. Study Location Map based on 2018 Oil Palm Cover Reconciliation Map
(Ministry of Agriculture of the Republic of Indonesia)

2.2 Data

The primary data used in this mapping is the Landsat-8 OLI archive satellite image data, a joint mission between USGS and NASA obtained through the usgs.gov website. Landsat-8 OLI satellite imagery used with path/row: 127/59, 127/60, 128/58, 128/59, 129/57, 129/58, and 129/059 obtained in the period April 1 to August 31, 2018. Other data is data on the distribution of oil palm plantation points analyzed for leaves in the North Sumatra region. Laboratory analysis of oil palm leaves is in the form of Nitrogen, Phosphorus, Potassium, and Magnesium content.

2.3 Clustering of nutrient criteria for oil palm leaves

Oil palm leaf nutrient groupings were carried out using modified criteria set by Uexkull & Fairhust (1991). The nutrient criteria used were at the age of 9-13 years by adjusting the criteria from 3 to 5 standards, namely shallow (VL), low (L), normal (N), high (H), and very high (VH).

Table 1. Nutrient Criteria for Oil Palm Leaves

Hara	Nutrient Content (%)				
	Shalow (VL)	**Low (L)**	**Normal (N)**	**High (H)**	**Very High (VH**
Nitrogen (N)	<2.30	2.30-2.50	2.50-2.70	2.70-2.90	>2.90
Phosphorus (P)	<0.140	0.140-0.155	0.155-0.170	0.170-0.185	>0.185
Potasium (K)	<0.60	0.60-0.80	0.80-1.00	1.00-1.20	>1.20
Magnesium (Mg)	<0.20	0.20-0.23	0.23-0.25	0.25-0.27	>0.27

Source: Uexkull & Fairhust (1991) processed

2.3 Methods and Data Analysis

Processing using machine learning consisting of random forest (RF) and Classification and regression tree (CART) using analysis on Google Earth Engine (GEE). The data needed as sample data and accuracy data are in the form of analysis data on oil palm leaves at 500 points of oil palm plantations in the North Sumatra Province in 2019.

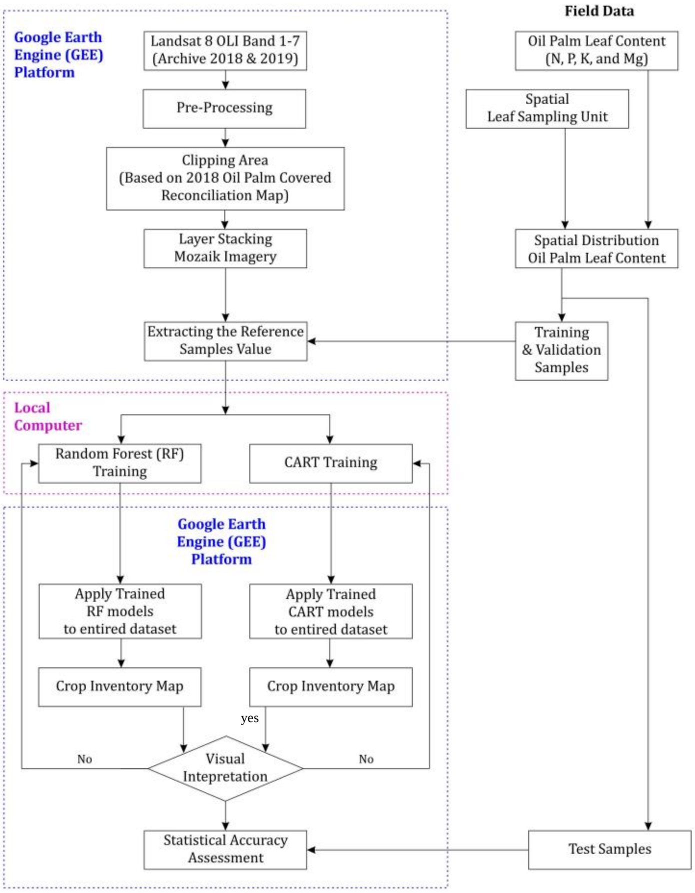

Figure 2. Research Flowchart

3. RESULT AND DISCUSSION

3.1. Klasifikasi Random Forest

Classification of random forest (RF) on Landsat-8 satellite imagery data resulted in the distribution of nitrogen nutrients dominated by low and normal classes. The analysis results show that in 2018 nitrogen nutrients belonging to the inferior class were 790,794 hectares, and the normal class was 584,255 hectares, while in 2019, there was an increase in both classes to 971,605 hectares and 795,161 hectares. The RF analysis for the nutrient content of Phosphorus oil palm leaves is dominated by normal and low classes, namely 1,325.175 ha (normal) and 462.236 ha (low) in 2018. In 2019, there was a decrease in the classification of the nutrient content of normal oil palm leaves to 735,194 ha. and there was an increase in the area with low leaf phosphorus nutrient content. In 2018 the Potassium content of oil palm leaves was dominated by medium and high content, with an area of 765,071 hectares (normal) and 449,762 hectares (high), however in 2019 there was a shift which was dominated by normal and low classes, namely 906.205 hectares and 790,409 hectares. Magnesium nutrient distribution in 2018 was dominated by a shallow and high content of 413.853 hectares and 1,272,050 hectares, while in 2019, the low nutrient content increased to 910.279 hectares, while the high nutrient content decreased to 756,500 hectares. The RF analysis results are shown in Table 1, while the spatial distribution is presented in Figures 2 and 3.

Table 1. Oil Palm Leaf Nutrient Classification Area using Random Forest (thousand hectares)

Class RF	Area (thousand hectares)							
	Nitrogen		Phosphorus		Potasium		Magnesium	
	2018	2019	2018	2019	2018	2019	2018	2019
Shallow (VL)	465.61	188.21	9.53	296.18	79.04	120.55	413.85	910.30
Low (L)	790.79	971.61	462.24	975.24	425.01	790.41	189.92	222.18
Normal (N)	584.26	795.16	1.325.17	735.19	765.07	906.20	78.98	111.57
High (H)	205.22	101.72	258.61	68.40	449.76	220.35	124.22	78.48
Very High (VH)	33.15	22.33	23.48	4.00	360.15	41.52	1.272.05	756.50
Total	2.079.03	2.079.03	2.079.03	2.079.03	2.079.03	2.079.03	2.079.03	2.079.03

Tabel 2. Oil Palm Leaf Nutrient Classification Area using CART (thousand hectares)

Class (CART)	Area (thousand hectares)							
	Nitrogen		Phosphorus		Potasium		Magnesium	
	2018	2019	2018	2019	2018	2019	2018	2019
Shallow (VL)	419.26	257.49	43.15	350.35	121.83	169.31	388.83	388.83
Low (L)	634.31	762.21	511.69	785.60	401.98	627.59	310.41	310.41
Normal (N)	559.55	738.41	982.39	713.86	595.06	764.50	196.78	196.78
High (H)	334.82	252.54	448.65	202.94	497.60	368.36	245.85	245.85
Very High (VH)	131.08	68.39	93.15	26.28	462.55	149.26	937.16	937.16
Total	2.079.03	2.079.03	2.079.03	2.079.03	2.079.03	2.079.03	2.079.03	2.079.03

3.2. Klasifikasi Classification and regression tree (CART)

In the CART analysis for the phosphorus content of oil palm leaves, the normal and low classes were dominated by normal and low classes, namely 982,387 hectares (normal) and 448,647 hectares (low) in 2018. In 2019, there was a decrease in the classification of a normal class of nutrient content of oil palm to 785,595 hectares, and there was an increase in the area with low phosphorus leaf nutrient content to 713,855 hectares. In 2018 Potassium content of oil palm leaves were dominated by medium and high content, with an area of 595,058 hectares (normal) and 497,602 hectares (high). However, in 2019 there was also a shift dominated by normal and low classes of 764,498 hectares and 627,588 hectares. The distribution of magnesium nutrient content in 2018 was dominated by a shallow and high range of 388,827 hectares and 937,155 hectares. In 2019, low nutrient content increased to 657,435 hectares, while high nutrient content decreased to 675,841 hectares. The distribution of nutrients in classification using CART is presented in Table 2, while the spatial distribution is shown in Figures 4 and 5. According to Wu et al., CART is one of the top 10 algorithms in data mining. This algorithm is built through a binary tree framework; this algorithm has a level of data impurity with two classes in taking internal conclusions (Luo et al., 2022).

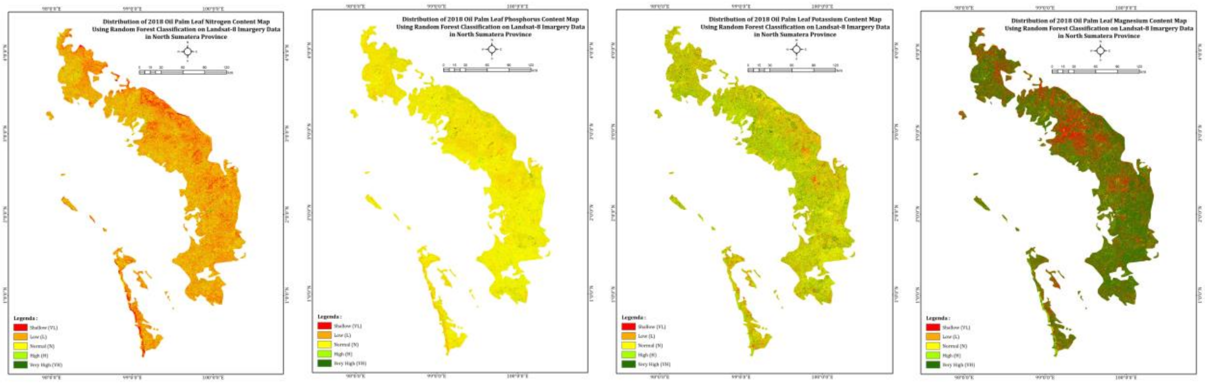

Figure 2. Distribution of the 2018 Oil Palm Leaf Nutrition using Random Forest Analysis

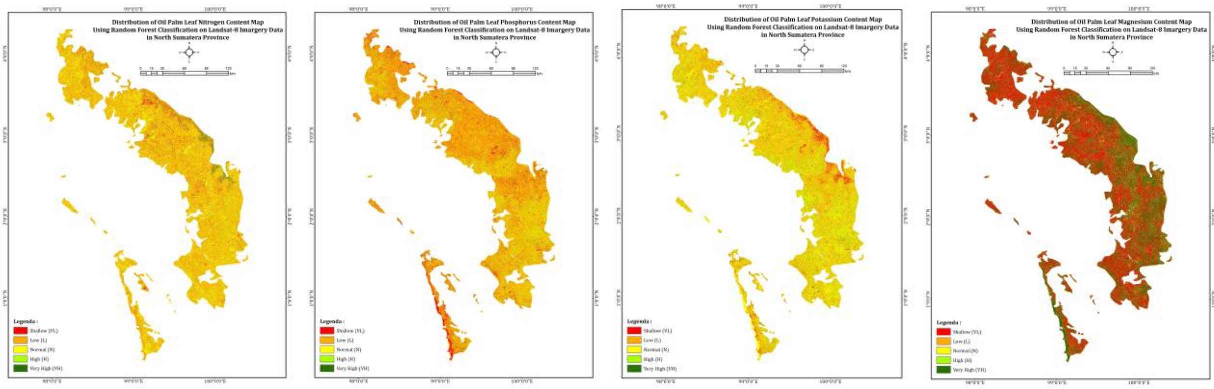

Figure 3. Distribution of the 2019 Oil Palm Leaf Nutrition using Random Forest Analysis

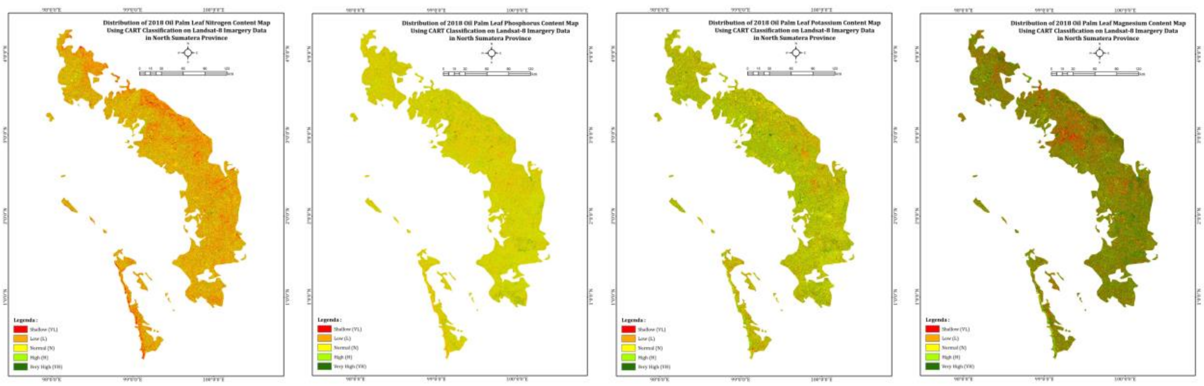

Figure 4. Distribution of the 2019 Oil Palm Leaf Nutrition using CART Analysis

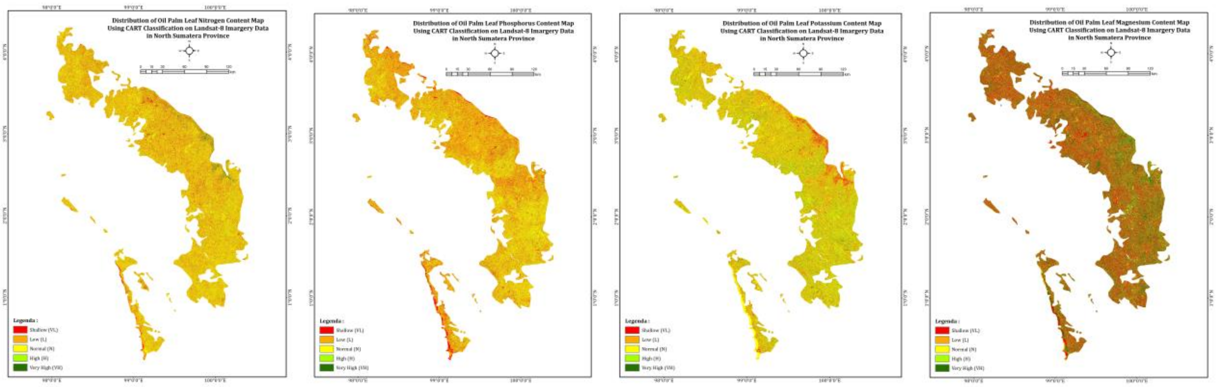

Figure 5. Distribution of the 2019 Oil Palm Leaf Nutrition using CART

3.3. Comparison of Random Forest and Classification and regression tree (CART)

The distribution of nutrient content of oil palm leaves using both RF and CART algorithms produces almost similar classification results. Nutrient distribution classification conditions in both algorithms have relative proportion values. The analysis shows that in 2018 nitrogen nutrients used RF, which was classified as a shallow class of 465.61 thousand ha (22.40%) and CART covering an area of 419.26 thousand ha (20.17%), while the low class using RF covering an area of 790.79 thousand ha (38.04%) and CART surrounding an area of 634.31 thousand ha (30.51%). Normal type in the analysis using RF obtained an area of 584.26 thousand ha (28.10%), and CART an area of 559.55 thousand ha (26.91%), high class in RF got an area of 205.22 thousand ha, while CART obtained 334.82 thousand ha (16.10%). In the very high class, there are 33.15 thousand ha (1.59%) for RF and 131.08 thousand ha (6.30%) using CART. Likewise, with the data generated from the two algorithms in 2019, the shallow class obtained an area of 188.21 thousand hectares (9.05%) and 257.49 thousand hectares ha (12.39%). In the low category, the site is 971.61 thousand hectares (46.73%) for RF and 762.21 thousand hectares (36.66%) for CART. In the normal type, the classification area is 795.16 thousand hectares (38.25%) for RF and 738.41 thousand hectares (35.52%). For the high nutrient classification, it is 101.72 thousand hectares (4.89%). And 252.54 thousand hectares (12.15%). Meanwhile, for very high nutrient content, the area was 22.23 thousand hectares (1.07%) for RF and 68.39 thousand hectares (3.29%) for CART.

Table 3. Comparison of RF and CART analysis for nitrogen nutrient classification

Class	Oil Palm Nitrogen Leaf Content Distribution Area (thousand hectares)							
	2018				2019			
	RF	%	CART	%	RF	%	CART	%
Shallow (VL)	465,61	22,40	419,26	20,17	188,21	9,05	257,49	12,39
Low (L)	790,79	38,04	634,31	30,51	971,61	46,73	762,21	36,66
Normal (N)	584,26	28,10	559,55	26,91	795,16	38,25	738,41	35,52
High (H)	205,22	9,87	334,82	16,10	101,72	4,89	252,54	12,15
Very High (VH)	33,15	1,59	131,08	6,30	22,33	1,07	68,39	3,29
Total	2.079,03	100,00	2.079,03	100,00	2.079,03	100,00	2.079,03	100,00

The results of the classification of Phosphorus nutrient content in 2018 were obtained for very low, low, normal, high, and very high classes covering an area of 9.53 thousand hectares (0.46%), 462.24 thousand hectares (22.23%), 1.325.17 thousand hectares (63.74%), 258.61 thousand hectares (12.44%), and 23.48 thousand hectares (1.13%) for RF, while for CART an area of 43.15 thousand hectares (2.08%), 511.69 thousand hectares (24, 61%), 982.39 thousand hectares (47.25%), 448.65 thousand hectares (21.63%), and 93.15 thousand hectares (4.48%). In 2019, the total area of Phosphorus nutrient content of oil palm leaves for very low, low, normal, high, and very high classes was 79.04 thousand hectares (3.80%), 425.01 thousand hectares (20.44%), 765.07 thousand hectares (36.80%), 449.76 thousand hectares (21.63%), 360.15 thousand hectares (17.32%) for RF, while for CART an area of 169.31 thousand hectares (8.14%), 627.59 thousand ha (30.19%), 764.50 thousand hectares (36.77%), 368.39 thousand hectares (17.72%), and 149.26 thousand hectares (7.18%).

Tabel 4. Comparison of RF and CART analysis for phosphorus nutrient classification

Class	Oil Palm Phosporus Leaf Content Distribution Area (thousand hectares)							
	2018				2019			
	RF	%	CART	%	RF	%	CART	%
Shallow (VL)	9,53	0,46	43,15	2,08	79,04	3,80	169,31	8,14
Low (L)	462,24	22,23	511,69	24,61	425,01	20,44	627,59	30,19
Normal (N)	1.325,17	63,74	982,39	47,25	765,07	36,80	764,50	36,77
High (H)	258,61	12,44	448,65	21,58	449,76	21,63	368,36	17,72
Very High (VH)	23,48	1,13	93,15	4,48	360,15	17,32	149,26	7,18
Total	2.079,03	100,00	2.079,03	100,00	2.079,03	100,00	2.079,03	100,00

The results of the classification of Potassium nutrient content in 2018 were obtained for very low, low, normal, high, and very high classes covering an area of 79.04 thousand hectares (3.80%), 169.31 thousand hectares (8.14%), 425.01 thousand hectares (20.44%), 765 .07 thousand hectares (36.80%), 449.76 thousand ha (21.63%) and 360.15 thousand hectares (17.32%) for RF, while for CART an area of 169.31 thousand hectares (8.14 %), 627.59 thousand hectares

(30.19%), 764.50 thousand hectares (36.77%), 368.36 thousand hectares (17.72%), and 149.26 thousand hectares (7.18%). In 2019, the total area of Potassium nutrient content of oil palm leaves for very low, low, normal, high, and very high classes was 9.53 thousand ha (0.46%), 462.24 thousand hectares (22.23%), 1,325.17 thousand hectares (63. 74%), 258.61 thousand hectares (258.61%), 23.48 thousand hectares (1.13%) for RF, while for CART an area of 43.15 thousand hectares (2.08%), 511.69 thousand hectares (24.61%), 982.39 thousand hectares (47.25%), 448.65 thousand hectares (21.58%), and 93.15 thousand hectares (4.48%).

The results of the classification of the magnesium nutrient content in 2018 were obtained for very low, low, normal, high, and very high classes covering an area of 413.85 thousand hectares (19.91%), 189.92 thousand hectares (9.13%), 78 .98 thousand hectares (3.80%), 124.98 thousand hectares (3.29%), and 1,272.05 thousand hectares (61.18%) for RF, while for CART an area of 388.83 thousand hectares (18, 70%), 310.41 thousand hectares (14.93%), 245.85 thousand hectares (11.83%), and 937.16 thousand hectares (9.76%). In 2019, the total area of Phosphorus nutrient content in oil palm leaves for very low, low, normal, high, and very high classes was 910.30 thousand hectares (43.78%), 222.18 thousand hectares (43.78%), 111.57 thousand hectares (5.37%), 78.48 thousand hectares (3.77%) and 756.50 thousand hectares (36.39%) for RF, while for CART an area of 657.44 thousand hectares (31 .62%), 334.41 thousand hectares (16.08%), 219.42 thousand hectares (10.55%), 191.92 thousand hectares (9.23%), and 675.84 thousand hectares (32, 51%).

Table 5. Comparison of RF and CART analysis for potassium nutrient classification

Class	Oil Palm Potassium Content Distribution Area (thousand hectares)							
	2018				2019			
	RF	**%**	**CART**	**%**	**RF**	**%**	**CART**	**%**
Shallow (VL)	296,18	14,25	350,35	16,85	121,83	5,86	121,83	5,86
Low (L)	975,24	46,91	785,60	37,79	401,98	19,34	401,98	19,34
Normal (N)	735,19	35,36	713,86	34,34	595,06	28,62	595,06	28,62
High (H)	68,40	3,29	202,94	9,76	497,60	23,93	497,60	23,93
Very High (VH)	4,00	0,19	26,28	1,26	462,55	22,25	462,55	22,25
Total	2.079,03	100,00	2.079,03	100,00	2.079,03	100,00	2.079,03	100,00

Tabel 6. Comparison of RF and CART analysis for classification Magnesiun content

Class	Oil Palm Magnesium Leaf Content Area (thousand hectares)							
	2018				2019			
	RF	**%**	**CART**	**%**	**RF**	**%**	**CART**	**%**
Shallow (VL)	413,85	19,91	388,83	18,70	910,30	43,78	657,44	31,62
Low (L)	189,92	9,13	310,41	14,93	222,18	10,69	334,41	16,08
Normal (N)	78,98	3,80	196,78	9,46	111,57	5,37	219,42	10,55
High (H)	124,22	5,98	245,85	11,83	78,48	3,77	191,92	9,23
Very High (VH)	1.272,05	61,18	937,16	45,08	756,50	36,39	675,84	32,51
Total	2.079,03	100,00	2.079,03	100,00	2.079,03	100,00	2.079,03	100,00

Tabel 7. Overall Accuracy

Nutrient Status	2018		2019	
	RF	CART	RF	CART
Nitrogen	93,11	98,69	93,24	98,57
Phosphorus	93,01	98,56	93,61	98,88
Potassium	93,69	98,81	93,56	98,97
Magnesium	94,68	99,76	93,96	99,42
Average	93,62	98,96	93,59	98,96

Based on these data, the results of the classification of the leaf nutrient content of Nitrogen, Phosphorus, Potassium, and Magnesium using the RF and CART algorithms have similar results. The results of a statistical test through a T-test yielded a t-value of 0.0385, so there was no significance in the area classified using RF and CART against the five classes of nutrient content classification of oil palm leaves, namely Nitrogen, Phosphorus, Potassium, and Magnesium. The accuracy of the classification is measured through the accuracy of the classification correctness owned by the GEE platform. The accuracy measurement results show that the two algorithms' accuracy value is very high, with an accuracy value of 93 to 99%. The accuracy values for each category and each nutrient content are presented in Table 7. The results of the accuracy of the two algorithms CART algorithm has higher accuracy than RF. The results of the CART accuracy are between 93.24 to 99.42%, while the RF has an accuracy of 93.11 to 93.96%. Based on several kinds of literature comparing RF and CART, the results are not different, and the accuracy of CART is higher than that of RF. Lou et al. (2022) said that the CART classification has a greater accuracy rate of 97.33%, while RF has an accuracy rate of 92.59%. This is reinforced by the results of research conducted by Guo et al. (2022), which analyzed changes in the Maize distribution in Heilongjiang Province, China, which gave a higher CART accuracy value, which was 97.17, and the RF algorithm was 95.23%. Based on this, the RF and CART algorithms can predict the macronutrient content of oil palm leaves. CART algorithm has a higher capability than RF.

4. CONCLUSION

The study based on Landsat-8 satellite imagery data processing combined with the GEE platform by utilizing machine learning algorithms in the form of random forest (RF) and classification and regression trees (CART) to predict the macronutrient content of oil palm leaves has a high overall accuracy rate. This prediction follows the study of Lou et al. (2022) and Guo et al. (2022), which contributes to the CART algorithm being higher than RF. Development studies are needed to enrich the analysis using other machine learning algorithms to get consistent results.

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