Estimation of Calcium, Magnesium and Sulfur Content in Oil Palm using Multispectral Imagery based UAV

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Keywords: Oil Palm, Multispectral Images, Nutrition, UAV.

Abstract: Oil palm is a commodity which contributes to the largest foreign exchange. In Indonesia, the area of oil palm plantations has a large area compared to other commodities. Proper and efficient fertilization is needed to reduce production costs. This study aims to estimate the nutrient content of calcium, magnesium, and sulfur in oil palm plants using UAV-based multispectral cameras. The method used is divided into three stages, data preparation, pre-processing, and data analysis. At the data preparation stage, the things done are leaf sampling, sample coordinate points, and multispectral image capture. In the pre-data processing stage the things done are stitching, georeferencing, and digitizing. The last stage is data analysis like multiple linear regression analysis to get a model of the relationship of multispectral images and actual nutrition of lab test results. The results of this study obtained a model for predicting of calcium content Ca = 0.994+0.00723*GREEN-0.00863*RED EDGE, for magnesium content is Mg = 0.693+0.00531*RED-0.00541*RED EDGE, and for sulfur content is S = -0.222+0.00338*RED EDGE. The results of overall accuracy using a confusion matrix of 66.7% in the calcium model, 63.3% in the magnesium model, and 36.6% in the sulfur model.

1 INTRODUCTION

Oil Palm (Elaeis guineensis Jacq.) is a commodity of plantation crops that contributes to the country's largest foreign exchange because oil palm commodities have high economic value in agribusiness. Palm oil has benefits and advantages compared to other commodity vegetable oils. Indonesia is the country with the largest palm oil production in the world with a contribution of 44.46% of the total world CPO. This contributes to the quite large Gross Domestic Product (GDP) reaching 13.14% in 2017. In Indonesia, the area of oil palm plantations in 2017 according to the Central Statistics Agency (BPS) in 2018 is estimated to reach more than twelve million hectares, so to increase productivity requires proper fertilization. Fertilization on oil palm plants aims to provide nutrient needs for plants so that plants can grow well and be able to produce optimally and produce good quality oil (Adiwiganda and Siahaan 1994). To get the right fertilization results, fertilizer recommendations for the palm oil commodity are needed. Fertilization recommendations are to apply fertilization in a manner and dose that have been determined in the plantation area so that the most efficient absorption of nutrients occurs in plants and can integrate the use of mineral fertilizers and oil palm residues and minimize environmental impacts associated with excessive fertilization such as land degradation (Goh and Hardter 2003). In addition to maximizing the nutrients absorbed, it can also save production costs, because according to Gerendas and Heng (2011) a large proportion of the total production costs is fertilization costs.

Essential nutrients are essential nutrients for plants and their functions cannot be replaced by other elements so plants cannot grow normally if they are not available in sufficient quantities in the soil. The essential nutrients studied in this research are calcium, magnesium, and sulfur. Sudradjat (2016) states that the main macro-nutrients needed by oil palm plants are nitrogen, phosphorus, potassium, and magnesium. While the micro-nutrient that often become obstacles are copper, iron, manganese, and boron.

Chlorophyll greatly affects the level of light reflectance in leaves. The reflectance of plants in visible light (red, green, blue) (400-700 nm) and NIR (700-900 nm) are strongly influenced by chlorophyll and leaf cell structure (Stark et al. 2006). The light

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reflectance pattern can be used to assess plant health conditions related to the available of calcium, magnesium and leaf sulfur nutrients. In this research, parrot sequoia cameras are used to capture the light reflectance of the leaves. The Phantom 4 Pro drone with a Parrot Sequoia camera is used to take multispectral images that can capture 4 color spectrum bands (green, red, red edge, and near-infrared). Table 1 shows the specifications of the Parrot Sequoia camera.

Table 1 Specifications of Parrot Sequoia cameras.

Spesifikasi kamera	Parrot Sequoia
Pixel	1.2 mp (1280x960)
Field of View	61.9°
Green band	530 – 570nm
Red band	640 – 680 nm
Red Edge band	730 – 740 nm
Near Infrared band	770 – 810 nm
RGB	400 – 700 nm

Sumber: Parrot SA (2017)

Aerial photography using Unmanned Aerial Vehicles (UAV) is an alternative technology to get more detailed, real-time, fast and cheaper data (Shofiyati, 2011). UAV is a flying robot with remote control that is able to carry payloads according to its purpose and designation. This drone is capable of carrying cameras to photograph and record and can be flown to reach certain locations by remote control by pilots. Many advantages if monitoring is carried out with UAVs, including low investment and operational prices, fast and flexible information acquisition times, and information generated can be more detailed than satellite data. In addition, the UAV in transition flies under the cloud so that its image is cloud free when compared to satellite imagery which depends more on atmospheric conditions (Dony 2014).

This research was conducted to estimate the calcium, magnesium, and sulfur macro-nutrient content of oil palm plants quickly and accurately by utilizing phantom drones 4. Taking images using multispectral parrot sequoia cameras that have high resolution. As well as leaf analysis to determine the nutrient content of calcium, magnesium, and sulfur in oil palm. The results of the image and nutrient content are correlated and interpreted in the form of a model.

2 RESEARCH METHODS

2.1 Time and Location

The study was conducted from February 2019 to April 2019 at the IPB-Cargill Oil Palm Education and Research Plantation, Singasari, Jonggol, Bogor, West Java with coordinates 06^0 28,319' South Latitude, 107^0 01.103' East Latitude and located 116 m above sea level. The research was also conducted at the Bioinformatics Engineering Laboratory of Mechanical and Biosystem Engineering, Faculty of Agricultural Technology, IPB University and Testing Laboratory of the Department of Agronomy and Horticulture, Faculty of Agriculture, IPB University.

2.2 Materials and Tools

The tool used in this research is a computer with i7 processor speed of 2.4 GHz and has 8 GB of RAM. Software used to process data are Microsoft Excel, Microsoft Word, QGIS 2.18, Pix4DMapper, Agisoft PhotoScan, and Minitab 18. Primary data used in this study were leaf nutrition obtained from leaf analysis testing at the Testing Laboratory of the Department of Agronomy and Horticulture, Faculty Agriculture, Bogor Agricultural University. Another primary data used is aerial photography from a 0.076 resolution Parrot Sequoia multispectral camera with the help of a Phantom 4 Pro drone.

2.3 Research Stages

The research began with the preparation phase of the data consisting of leaf sampling, leaf sample coordinate points and Ground Control Point (GCP), and drone image capture. Then the leaf samples were analyzed at the Laboratory to determine the nutrient content used as the dependent variable. The drone image data obtained must be carried out in the pre-data processing stage. This stage consists of photo stitching, georeferencing, and digitization of garden boundaries and canopy of sample plants. The results of the pre-processing data are in the form of reflectant values in each sample plant and will be used as an independent variable. After that the data analysis is processed by multiple linear regression with stepwise methods using independent variables and dependent variables. The results of the regression model are then displayed in the form of an nutrient estimation layer.

2.3.1 Data Preparation Stage

In the data preparation stage, several things are carried out, namely literature study, method determination, discussion, and data collection. After the research planning is done, the data collection stage is carried out. The data collection phase is done by three things, namely sampling, drone imagery, and GCP. Leaf sampling is carried out in a spread where the sample plants are proportionally determined. Guidelines for sampling leaves on oil palm plants based on Winarna et al. (2005) where the leaves used as the main sample must meet a number of provisions, namely they are not the mains of inserts, grow normally, do not lie adjacent to roads or ditches/rivers, do not coexist with insertion trees and are not attacked by pests or diseases.

Leaf samples taken were leaves from the 17th midrib. According to Chapman and Gray (1949) in Pahan (2006) said that the leaves of the 17th midrib are the most sensitive leaves because they show the greatest difference in nutrient levels. In addition, nutrient status on the 17th leaf has a better correlation to crop production when compared to other younger leaves. The leaves of the 17th midrib are taken by six leaflets (three strands on the left and three strands on the right at the meeting point of the two sides of the midrib). Leaves that have been taken are stored in envelopes that have been labeled according to the location of the sample. The selected sample plants were given raffia to indicate the tree was a sample plant. Then the sample plants are marked on GPS which will be used to correct the geometry between the map and the image results. Samples that have been obtained were analyzed for nutrients of calcium, magnesium, and sulfur in the Testing Laboratory of the Department of Agronomy and Horticulture.

Multispectral image capture using a Phantom 4 drone with a Parrot Sequoia camera. Drone flight planning automatically uses the Pix4D Mapper application which is adjusted to the taking land area and hours of time that can be taken by the drone. According to Kasih (2012) the optimum shooting is done in the morning because the effect of reflected light from the sun is still weak. Besides the wind speed in the morning still tends to be low, thereby reducing the risk of UAV shake while shooting which can cause poor quality captured images.

GCP determination aims to reduce errors or changes in position when integrating the results of the image into a map that can make the data change. GCP can be in the form of objects, buildings, or forms of certain locations that can be clearly seen on the image so that the coordinates of the object can be measured to be used as a reference point when uniting images into a complete map. (Adillah 2018). A tool to draw GCP coordinates can be by using a handheld GPS.

2.3.2 Pre-processing Stage

The objectives of the pre-processing stage such as normalization and noise reduction are to produce clean and ready-to-use data (Nanda et al. 2019; Nanda et al. 2018a; Nanda et al. 2018b). At this stage, the stitching and georeferencing process is performed using pix4Dmapper software. The stitching process is basically a combination or combination of two or more different images to create or form one image called a panorama (Kale and Singh 2015). Before stitching, georeferencing needs to be done, namely the process of giving geographic references to raster or images that do not yet have a coordinate system reference. The coordinate reference used is WGS 84 / UTM zone 48S with EPSG: 32748.

Then do bordering of the garden and canopy of the sample plants done using QGIS software. The results of the bordering of the sample plant canopy are used to extract the reflectance value in the form of a digital number at each pixel. The tool used to extract these values is Zonal Statistics on the Raster menu.

2.3.3 Data Analysis Stage

Estimation using multiple linear regression analysis with the stepwise method is performed by Minitab which aims to determine the factors that effect and make a estimation model of calcium, magnesium, and sulfur nutrition. At this stage two types of variables are needed, namely the independent variable and the dependent variable. The independent variable contains the reflectance value data which is the average value of the drone image in the digitizing attribute of the sample plant. While the dependent variable contains the actual calcium, magnesium, and sulfur nutrition data from the 17th midrib nutrient analysis results in the sample plants.

The model obtained is then evaluated to see the strength of the estimator model. The method used to evaluate the model is the Mean Absolute Percentage Error (MAPE). MAPE shows how big the difference between the actual results and the predicted results. Table 2 shows the criteria used to decide the predictive power of an estimator model.

Table 2: Criteria for estimating the strength of the model.

MAPE (%)	Power of prediction
<10	Very Good
10 – 20	Good
20-50	Moderate
>50	Bad

Source: Wang *et al.* (2012)

After that, the nutrient estimation layer is made which contains the estimated nutrient value for each pixel. The estimated nutritional value is the application of the model obtained using the raster calculator tool in the QGIS application. Then the estimate value is classified based on the criteria in Table 3.

Table 3: Nutrition concentration of 17th fronds on the age of oil palm is more than 6 years.

Nutrition	Unit	Deficiency	Optimum	Excess
Ca	%DM	<0.25	0.50-0.75	>1.00
Mg	%DM	<0.20	0.25–0.40	>0.70
S	%DM	<0.20	0.25-0.35	>0.60

Source: Von Uexkull and Fairhurst 1991

The results of the nutrient estimation layer that has been classified will be tested for accuracy to see the size of the miscalculation of nutrient estimates so that it can be determined the percentage of accuracy of nutrient estimation. Accuracy tests are performed using a confusion matrix.

3 RESULT AND DISCUSSION

Overall data were collected on 6 February 2019 at the Cargill IPB Oil Palm Education and Research Plantation. The oil palm plantation, which was cultivated starting in 2012, has an area of 59 hectares which is divided into 5 plantation blocks. There are 3 types of data taken in this study, namely the 17th frond leaf sample, the coordinates of the sampling location and GCP, and the multispectral image. Retrieval of data is done in a day because the data needed is dynamic. Retrieval of image data using a DJI Phantom 4 drone with a Parrot Sequoia multispectral camera. The drone was flown in accordance with the Parrot Sequoia handbook, which is 110 meters above the ground, with a drone speed of 10 m/s and a pause time of 2.1 seconds for shooting. The next step is the pre-processing of data in the form of stitching, georeferencing and bordering. Before that stage aerial photo printing results are selected first using Agisoft PhotoScan then stitching and georeferencing using QGIS. Restrictions on oil palm plantations and sample canopy are done manually using the add feature tool after creating a new polygon layer in QGIS software. Figure 1 and Figure 2 show the results of bordering the sample plant canopy digitized to extract the average value of the digital number (DN) at each pixel. The extraction process is carried out on all layers of stitches using Zonal Statistics in QGIS. Extraction results can be seen in appendix 1.

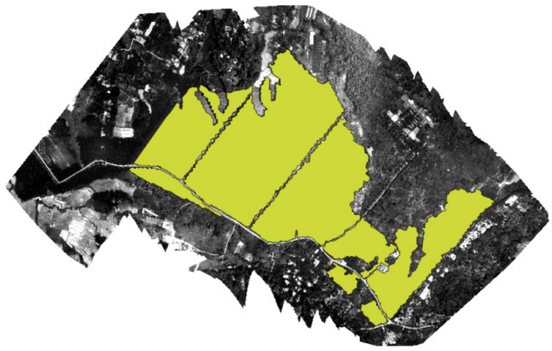

Figure 1: Results of the borderingon oil palm plantations.

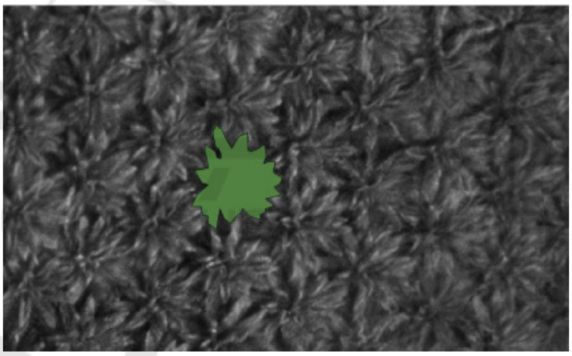

Figure 2: Results of the bordering canopy of sample plants.

Nutrition estimation is represented in the form of mathematical models. Modeling uses the Minitab 18 application with stepwise multiple linear regression analysis. Modeling involves 23 samples from 30 samples. While the remaining 7 samples are used for model validation. The independent variable used is the average DN value of each pixel obtained from the digitized of the plant canopy sample and the dependent variable is the nutrient content of calcium, magnesium, and sulfur laboratory test results. The results of the stepwise multiple linear regression model are as follows:

Ca= 0.994 + 0.00723 GREEN- 0.00863 RED EDGE
Mg= 0.693 + 0.00531 RED- 0.00541 RED EDGE
S = -0.222 + 0.00338 RED EDGE

The model obtained is then predicted with stat> Regression> Regression> Predict. Table 4 shows a comparison of actual and predicted nutrition. Evaluate the model using Mean Absolute Percentage Error (MAPE). Evaluation of the model is done to see how strong the estimation of the model is made. The results of the model evaluation obtained the value of MAPE in the Ca model, Mg model, and the S model respectively 22.72%, 11.62%, and 46.5%. Based on the strength estimation criteria of the model according to Wang et al (2012) in table 2, the evaluation results show that the Ca and S models are categorized as medium and the Mg model is categorized as good. The model obtained is then interpreted in the form of an estimated nutrient layer that has been processed and classified according to table 3. Classification of nutritional assumptions is presented in the form of a color that matches the nutrient content. The red color indicates that the oil palm tree on the grid lacks nutrients, yellow under optimal conditions, green at optimum conditions, light blue at above optimum conditions, and dark blue at excess nutrient conditions. Figure 3 shows the results of the calcium nutrient estimation layer, Figure 4 for magnesium nutrition, and Figure 6 for sulfur nutrition.

The result of nutrient estimation layer is performed by accuracy test using a confusion matrix. In the confusion matrix the predicted nutrition of the model results is compared with the actual nutrition of the lab test results. From the results of the accuracy-test using a confusion matrix, Overall Accuracy obtained in the nutrients of calcium, magnesium, and sulfur was 66.6%, 63.3%, and 36.7%. According to Jaya (2015) a good accuracy value is an accuracy value that has reached a score of> 85%, so the estimation of calcium and magnesium nutrients has moderate accuracy and for sulfur has poor accuracy.

Table 4: Comparison of actual nutrition and prediction of the 17th midrib leaf laboratory results.

Sample	Magnesium (%DM)		Kalsium (%DM)		Sulfur (%DM)	
	Actual	Prediction	Actual	Prediction	Actual	Prediction
1A	0.36	0.296	0.51	0.643	0.15	0.231
1B	0.34	0.296	0.69	0.594	0.17	0.282
1C	0.19	0.304	0.53	0.616	0.17	0.266
1D	0.32	0.316	0.82	0.668	0.13	0.193
1E	0.32	0.284	0.69	0.622	0.43	0.264
2A	0.32	0.383	0.39	0.621	0.18	0.193
2B	0.42	0.356	0.59	0.642	0.14	0.218
2C	0.32	0.378	0.69	0.649	0.13	0.184
2D	0.41	0.390	0.91	0.658	0.40	0.167
2E	0.39	0.353	0.79	0.651	0.17	0.203
2F	0.35	0.351	0.68	0.638	0.17	0.233
2G	0.34	0.379	0.67	0.683	0.07	0.156
2H	0.44	0.386	0.42	0.668	0.09	0.181
3A	0.40	0.357	0.48	0.632	0.46	0.220
3B	0.38	0.370	0.68	0.603	0.40	0.265
3C	0.36	0.424	0.82	0.671	0.16	0.125
3D	0.30	0.375	0.79	0.615	0.14	0.236
3E	0.40	0.385	0.61	0.633	0.22	0.192
3F	0.41	0.389	0.66	0.661	0.34	0.157
3G	0.47	0.355	0.62	0.647	0.23	0.202
3H	0.45	0.416	0.55	0.629	0.20	0.182
3I	0.41	0.461	0.60	0.582	0.23	0.218
3J	0.49	0.458	0.51	0.583	0.28	0.221
3K	0.44	0.410	0.70	0.570	0.19	0.286
3L	0.33	0.375	0.67	0.591	0.36	0.263
4A	0.48	0.362	0.56	0.608	0.26	0.247
4B	0.50	0.423	0.72	0.634	0.10	0.147
4C	0.37	0.387	0.87	0.625	0.17	0.169
4D	0.43	0.413	0.45	0.619	0.15	0.165
4E	0.40	0.382	0.52	0.577	0.15	0.243

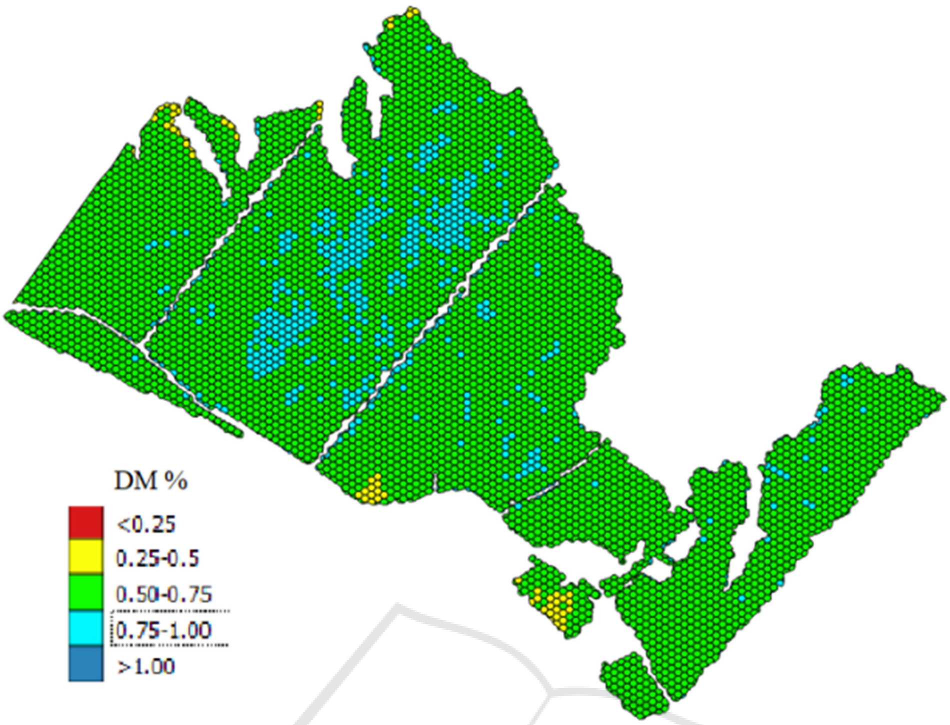

Figure 3: The calcium nutrient estimation layer.

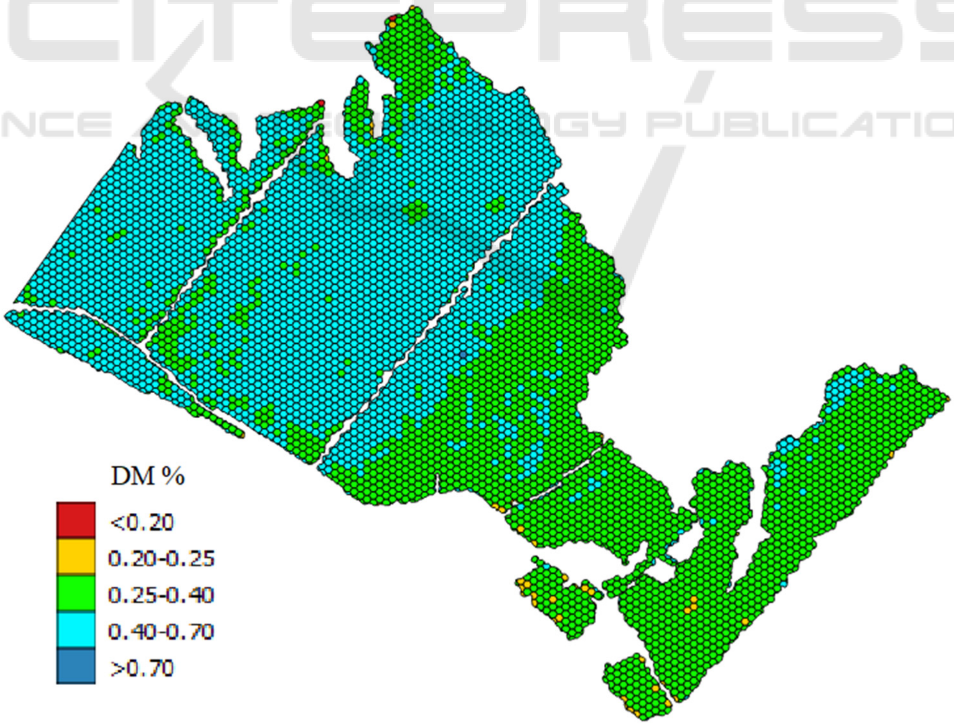

Figure 4: The magnesium nutrient estimation layer.

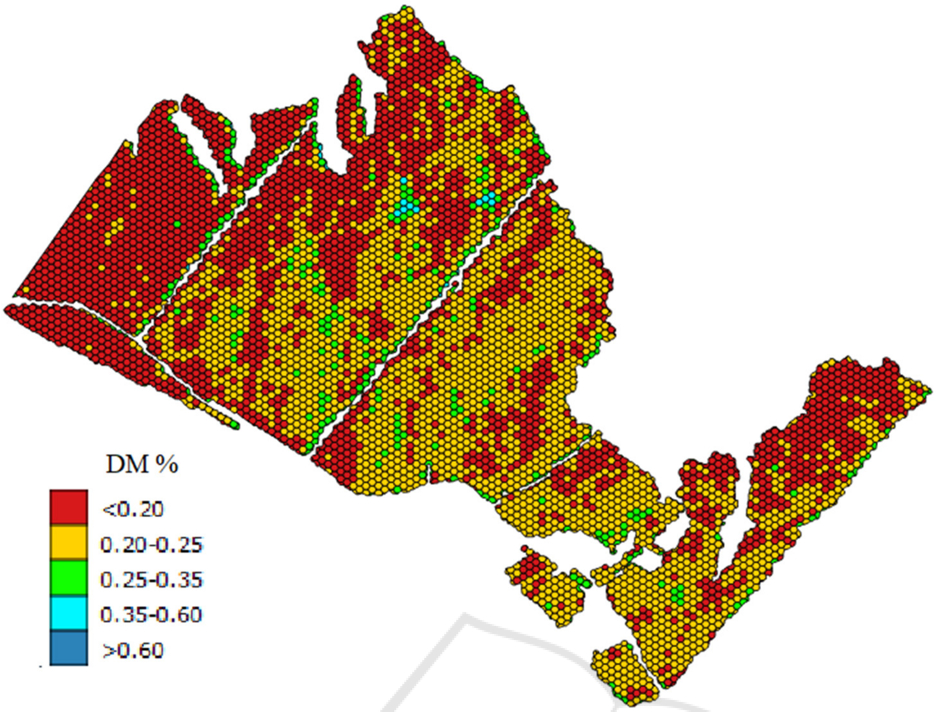

Figure 5: The sulfur nutrient estimation layer.

4 CONCLUSION

The nutritional estimation model was made by using stepwise multiple linear regression analysis. The independent variable used is the average multispectral reflectance value in the form of a digital number in the canopy of the sample plant and the dependent variable used is the nutrient content of calcium, magnesium, and sulfur on the 17th midrib leaf obtained from analysis in the testing laboratory of the Department of Agronomy and Horticulture, IPB. The model obtained from multiple regression analysis for calcium nutrition is Ca= 0.994 + 0.00723 *GREEN - 0.00863*RED EDGE, for magnesium nutrition is Mg= 0.693 + 0.00531*RED - 0.00541 *RED EDGE, and for sulfur nutrition is S= -0.222 + 0.00338*RED EDGE . Evaluate the model using Mean Absolute Percentage Error (MAPE). MAPE values in the Ca, Mg, and S models are respectively 22.72%, 11.62%, and 46.57%. The results of the model evaluation show that the strengths of the Ca and S models are in the moderate category and the Mg model is in a good category. While the accuracy of the nutrient estimation layer using confusion matrix obtained Overall Accuracy value for estimating calcium nutrition by 66.7%, magnesium nutrition by 63.3%, and sulfur nutrition by 36.7%. The results show the accuracy of estimation of calcium and magnesium nutrition including moderate grade, while the estimation of sulfur nutrition is poor.

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APPENDIX

Digital number values of digitization of the sample plant canopy.

Sample	Green	NIR	Red	Red Edge
1A	97.696	150.290	55.234	126.499
1B	99.226	162.430	60.269	128.360
1C	107.011	158.916	62.020	128.823
1D	100.055	149.172	54.509	120.953
1E	101.391	162.627	55.288	125.934
2A	92.608	131.776	71.301	127.583
2B	110.319	123.704	75.585	139.960
2C	103.668	124.700	73.264	132.114
2D	104.833	123.975	73.732	129.730
2E	107.398	130.823	70.143	133.121
2F	118.497	135.772	75.499	137.183
2G	112.261	130.371	69.891	125.834
2H	122.389	129.942	77.669	131.776
3A	107.613	133.104	73.033	134.595
3B	125.211	138.418	85.341	141.739
3C	102.690	124.847	73.835	121.059
3D	114.509	134.506	80.459	137.144
3E	103.420	133.144	73.862	128.594
3F	101.884	131.221	69.520	123.551
3G	105.717	133.299	69.451	131.241
3H	108.704	131.464	80.579	128.028
3I	121.342	135.507	97.446	132.733
3J	122.091	132.585	98.171	135.082
3K	134.299	137.072	99.472	146.368
3L	114.651	134.315	84.555	141.575
4A	111.116	137.428	77.785	136.967
4B	90.891	131.026	72.818	119.278
4C	79.805	129.379	66.129	122.606
4D	85.741	126.997	73.204	123.770
4E	96.247	141.433	77.157	131.028