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Estimation the Amount of Oil Palm Production Using Artificial Neural Network and NDVI SPOT-6 Imagery

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Abstract:- oil palms industry has strategic role as the biggest contributor for foreign exchange in Indonesia. Meanwhile, Indonesia also the largest producer of oil palms all over the world. However, the productivity value is still less than optimal. Government policy through Presidencial decree Number 8 Year 2018 regarding moratorium/postponement and evaluation on oil palms plantation permit, gives mandate to stakeholders to increase productivity by intensification that needs technological support. The use of remote sensing technology allows the monitoring of oil palms plantation in giving direction for management policy making. This research aims to estimate the remote-sensing based productivity of oil palms plantation by utilizing satellite imagery data of SPOT 6. Method uses in this research is artificial neural network method, one of which detects the plant's life age and analayze through linear regression which involving Normalized Different Vegetation Index (NDVI) value and production to have estimation of production. Results of the research shows that using ANN can predict oil palm plantation life age by 87% of accuracy. Meanwhile, production estimation done using NDVI for estimation of production generated an estimation formula Y = -24391 -766 X1 + 65482 X2

***Keywords**: Production, Oil Palms Plantation, Artificial Neural Network, Spot 6.*

I. INTRODUCTION

Sub-sector of plantation has important role in the contribution of national gross domestic product (GDP) that is of Rp. 429 Trillion in 2016. This exceeded the oil and gas sector which is only Rp. 365 Trillion. Oil Palms hold a crucial role in generating the biggest foreign exchange in plantation sub-sector that is Rp. 260 Trillion or approximately 54% of total of foreign exchange that is generated from 2016, and increased to Rp. 290 Trillion in 2017 (BPS, 2019).

The data shows that oil palm industry has a strategic role for Indonesia. This can be possible also because Indonesia's position with the largest area and production of palm oil in the world. However, there is still a gap between riil production of oil palms with its production potential. At the moment, productivity of oil palms plantation in Indonesia is approximately 2,8 ton CPO/ha/year from 6-7 ton CPO/ha/year potential. Several efforts have been done to increase the productivity, one of which is the application of technology, both in cultivation, mechanism, and other technologies which may support production development.. Government policy through Presidential Decree No. 8 Year 2018 regarding postponement and evaluation on oil palms plantation permit, gives mandate to stakeholders to increase productivity by intensification efforts. This effort needs a proper technological support.

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Development of remote sensing science allows the monitoring of oil palm plantation in giving management policy making. Sharma, et.al. (2017) utilizing remote sensing in agricultural sector, especially in plantation to identify plants suitable to be planted in a particular season. Remote sensing is also an important tools for monitoring in timely manner and give an accurate imagery on agricultural sector with high accuracy of frequency of repetition (Shanmugapriya, et.al., 2019). Remote sensing is an instrument to ease monitoring on performance and development of oil palm plantation productivity. Remote sensing with high resolution will generate precision of data and applicative information which able to monitor the development of oil palm plantation. Wiramoko, et.al. (2016), and Carolita, et.al., (2015), stated that utilization of remote sensing technology in estimating production value using oil palm life age as parameter reach a fairly high level of accuracy.

According to several points above, the use of remote sensing technology has the potential to support monitoring activity in agricultural sector. Production potential of oil palms in affected by some factors including physical factor, plant factor, and management. One of the plant factors which information can be extracted through remote sensing is the life age of the plant. Identification on plant life age can be continued with productivity value, so it can offer economic value which can be used as management monitoring tools for governance of oil palm plantations. This research is conducted to estimate productivity of oil palm plantations based on remote sensing technology through the utilization of SPOT-6 satellite image data.

II. RESEARCH METHOD

A. Research Location

Research object using case study in Plantation Adolina and Pabatu which are located in Serdang Bedagai District and Deli Serdang North Sumatera, respectively. Research location of Plantation Adolina is 3.59455 Latitude and 98.953759 Longitude. Meanwhile, plantation Pabatu is at 3.36126 Latitude and 99.053879 Longitude

B. Type and Source of Data Collection

Type of data used in this research is SPOT 6 satellite imagery data of the recording dated 5 June 2017. Other data used are plant life age data and production year 2017. Another primary data is obtained through discussion and interview with stakeholders related with the survey for validity testing process. Validity test is also done by using groun truth method to compare between interpretation output with real condition on site.

C. Data Analysis

Qualitative and quantitative method approaches used in this research is Artificial Neural Network method from SPOT-6 satellite imagery to differentiate plant's life age.

1. Data Correction

- Radiometric Correction

Radiometric correction is intended to improve the visual quality of the image as well as to fix pixel values that are not suitable with the real spectral radiance. There are 2 steps in radiometric correction, namely equating pixel value range and imagery fusion (pansharpen). This correction change radian value into spectral and then its radians value will be converted to refletion valuue by using FLAASH (Fast Line-odd-sight Atmospheric Analysis of Hypercubes) of ENVI 5.0. software Radiometric correction using FLAASH is done based on the research of (Anderson et al., 2002) using the formula (1) below

$$L = \left(\frac{A\rho}{1-\rho eS}\right) + \left(\frac{B\rho e}{1-\rho eS}\right) + La \ldots\ldots\ldots..(1)$$

Where ρ is pixel surface reflection, ρe means surface reflection average for surrounding area, S is albedo of atmospheric ball, La is backround luminous rays scattered by atmospher without reaching the surface, meanwhile A and B are the variation of surface independent coefficient with atmosphere and geometric conditions.

- *Geometric Correction*

Geometric correction that is used to fix geometric distortion or geometric image error recorded during its imagery that causing mismatch in form, size, and image position with the real condition. The image used in this research has been corrected geometrically in systematic way by the censor from acquisition process from LAPAN Pare-Pare ground segment, so geometric correction is no longer necessary.

2. Transformation of Vegetation Index (NDVI)

Normalized Different Vegetation Index (NDVI) is one of transformations that is commonly used to increase accuracy from multispectral classification output by expecting that the band ratio able to minimize atmospheric errors. Value from this vegetation index is ranged from – 1 to + 1. The (+) number shows green vegetation. This transformation uses red channel and closest infrared channel as its input channel (Danoedoro, 2012). The formula used for NDVI calculation is presented in formula (2) below.

$$NDVI = \frac{NIR - R}{NIR + R} \ldots\ldots\ldots\ldots.(2)$$

Where NIR : infrared reflectance band, and R : red reflectance band.

3. Classification Modelling of Oil Palms Life Age Estimation using Machine Learning

The stages conducted in this modeling are using QGIS software, more details are available below :

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- Compute Image Statistic is a process of calculating global average and deviation standard for each band from remote sensing data and then the output will be saved in XML file format. Output of this process will be used as input for processing.
- Train Images Classifier to normalized sample before the execution.
- Train Images Classifier is a process of traininggiven to remote sensing data with some couple or more input of vector data that has been chosen as classification object. In the process of training, the samples are consists of pixel values on each canal which optionally centered reduced from statistic file with XML format that is generated from Compute Image Statistic process.

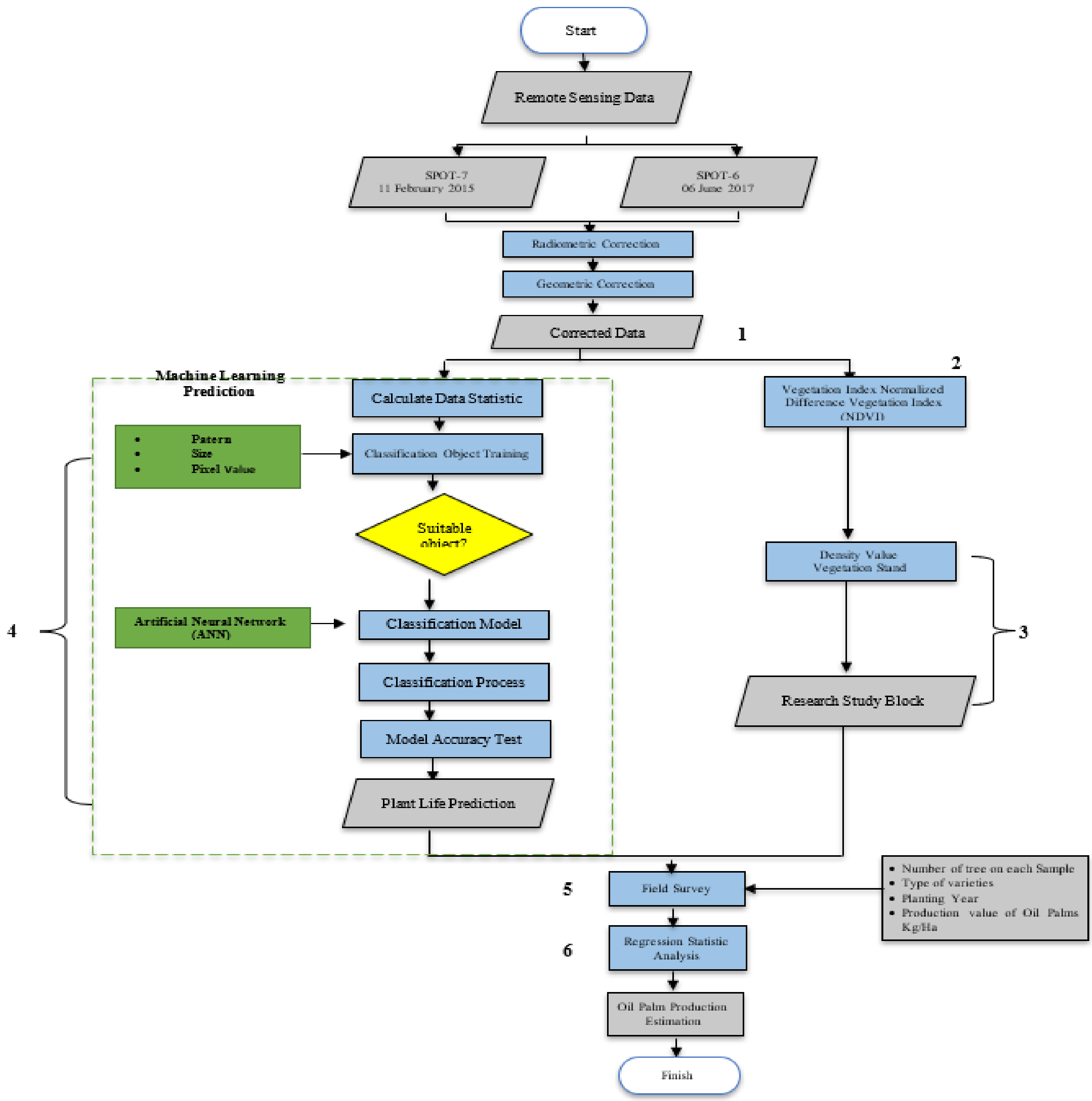

Fig 1:- Stage of Analysis

4. *Modelling of Machine Learning Methode ANN (Artificial Neural Network)*

Artificial Neural Network Artificial (ANN) is one of a techniques of information processing inspired by how the nervous system of human brain cells work in processing an information. This network consists of neuron that is connected by communication network or connector to do its specific function based on weighting between elements (Ismail & Khamis, 2011). ANN has a mathematical model which consist of one set of simple function that are input x, unit output y, and hidden unit z that connect to the output. Eskandarin, et.al., (2010) share an infromation that the hidden unit extracted the useful information and use it to predict the output, so ANN is also commonly known as multi-layer perceptron. Ismail & Khamis, (2011) delivered that network with element input vector xl (1 = 1, 2, ... Ni) is transmitted through connection multiplied by weight, wji, given the hidden unit zi (j = 1, 2, 3,..., Nk) as in the following formula (3) :

$$z_j = \sum_{i=1}^{\infty} w_{jl}x_l + w_{j0} \ldots\ldots\ldots\ldots\ldots (3)$$

Where Nk = Numbers of hidden unit Ni = Numbers of Input unit.

5. *Process of Accuracy Test*

Process of accuracy test utilizing the tools from QGIS that is, compute confusion matric. The tools needs initial input data in the form of a model to be tested using matching method with output data from ground truth in vector or raster format. Automatically, the tools compute by generating output in a form of model sparability table in accordance with number of classification. The stage of classification accurac test is conducted using accuracy test method, Kappa coefficient. Kappa coefficient value has a range of 0 to 1, in the process of classificaiton mapping / land cover accuracy value that is acceptable is 85% or 0,85 (Anderson, 1976), 1976). Kappa coefficient is based on consistency of assessment by considering all aspects including producer's accuracy / omission error and user's accuracy /commission error which are generated from matrix error or confusion matrix.

$$OA = \frac{\sum B}{\sum S} \text{ x } 100\% \ldots\ldots\ldots\ldots\ldots (4)$$

Where OA is Overal Accuracy, ΣB is correct amount and ΣS is total sample.

6. *Production Estimation*

Prouction estimation is done by linear regression analysis which involving plant life age factor and NDVI average value on the block under study.

As for the linear regression equation, will be presented in formula 5.

$$Y = a + b1x1 + b2x2 \ldots\ldots\ldots\ldots\ldots\ldots\ldots (5)$$

Where Y is productivity of oil palm plantations (kg/TBS/ha/year), x1 is plant's life age and x2 is NDVI average value in one block plant. Interpretation on correlation value is vary, in this research, using classification done by Sugiyono (2014) whom divided it into 5 (five) classes as presented on Table 1.

Coefficient Interval	Level of Correlation
0,00-0,199	Very low
0,20-0,399	Low
0,40-0,599	Medium
0,60-0,799	Strong
0,80-1,000	Very Strong

Table 1:- Guideline on Correlation Coefficient Interpretation
Source : Sugiyono, 2014

III. RESULTS AND DISCUSSION

A. *Radiometric Correction*

Radiometric correction is done by using FLAASH method (Fast Line-od-sight Atmospheric Analysis of Hypercubes) which is developed by Anderson et.al., (2002). FLAASH is a package of software developed by Air Force Research Laboratory, Space Vehicles Directorate (AFRL/VS), Hanscom AFB and Spectral Sciences, Inc, to support censor analysis, both hyperspectral and multispectral imagery.

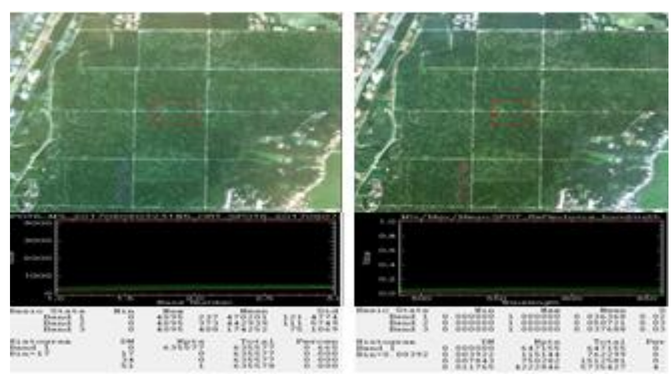

Fig 2:- Output of atmospheric correction: (a) before correction and (b) after correction

Variable used in FLAASH correction is depend on spectral canal used. A, B, S and La value is obtained from MODTRAN-4 calculation using censory viewpoint, sun viewpoint, and surface height average which can be generated from imagery metadata file and height average from Digital Elevation Model data (DEM). According to those data, certain atmospheric model can be derivated such as aerosol model, and visibility value. After getting the object reflectance value, then we normalize spectral value so the value range obtained is 0-1 (Figure 2).

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B. Calculation of NDVI Value

Results of NDVI value on research location get the NDVI value ranged from -0.8 – 1 which inform the information extraction of vegetation object. Low value represents that the object is indicated non-vegetation, meanwhile higher value is a vegetation object. NDVI value that is close to 1 represents a homogeny vegetation object with high level of density.

Fig 3:- Comparison of original colow imagery composite (a) and NDVI value in some part of research location (b)

NDVI value that is used as a reference in sampling by looking at the level of density of plants in one block. Density value is assumed to be able to represent in choosing sample that suit the oil palms planting year. Since it is assumed that spectral value is close to 1 means a plant with high level of chlorophyl/young meanwhile for low value of spectral is assumed to be senile. This fit the statement of Harfield, et.al, (2008) who share NDVI value information which has a role in analyzing cover crops. The number of NDVI will affect the established production.

C. Artificial Neural Network

Calculation output from NDVI will be used as a reference in sampling by looking at density level of trees in one block. Density value is assumed to represent in choosing a sample that fit the oil palm life age. Since it is assumed that spectral value close to 1 means a plant with high level of chlorophyll/young meanwhile for low value of spectral is assumed to be senile. This is not 100% correct, so ground truth method and classification modelling using machine learning is necessary to be done. Machine learning used is ANN.

Vector data used in the training process is a data with polygon topography with attribute information for positive numbers to represent class labels. The name of each class is regulated using parameter “Class Label Field” so the training process and validation of each clas is represented fairly. Model classification class is determined based on planting year distribution that is available in one afdeling andolina and afdeling pabatu area. Model classification making refers to a more general planting year classification that is divide over a lifespan ranging from years 3-5 years, 6-13 years, 14-20 years and 21-25 years.

Identification process of this lifespan classification using an imagery that has been carried out transformation of vegetation index (NDVI), is conducted by identifying density level. Other than looking at NDVI density level on model classification making, it is necessary to pay attention to spatial pattern of each block.

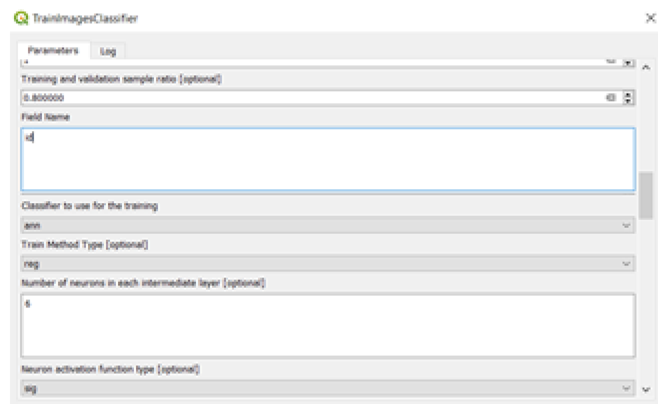

Fig 4:- ANN Process on research location

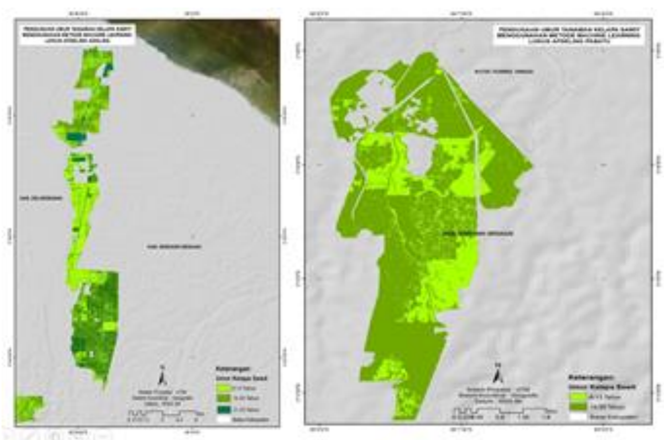

Fig 5:- Output of Analysis of Oil Palms Plantation life age in Adolina and Pabatu plantation

Figure 5 shows the stage of classification model making based on machine learning using ANN Artificial Neural Network Artificial method. The model uses a threshold of 0,8 and neuron 6. The parameter is chosen based on prior testing to get the best model in mahine learning-based classificaiton. ANN output is presented in Figure 7 that classify oil palms plantation into 5 life age groups, from years 3-5 years, 6-13 years, 14-20 years and 21-25 years.

Ground truth method is done to determine the accuracyof the established model in estimating plant life age. Testing process with field survey system by visiting sample of planting year per-block afdeling according to secondary data generated from plantation data. Data of planting year in Plantation Adolina are: 23, 22, 21, 20, 19, 14, 13, 12, 11, 10, 9 and 7 years. The number of plant age variations in plantation Pabatu

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is less than in plantation Adolina, which only consist of 17, 14, 13, 12, 11, and 10 years of planting year.

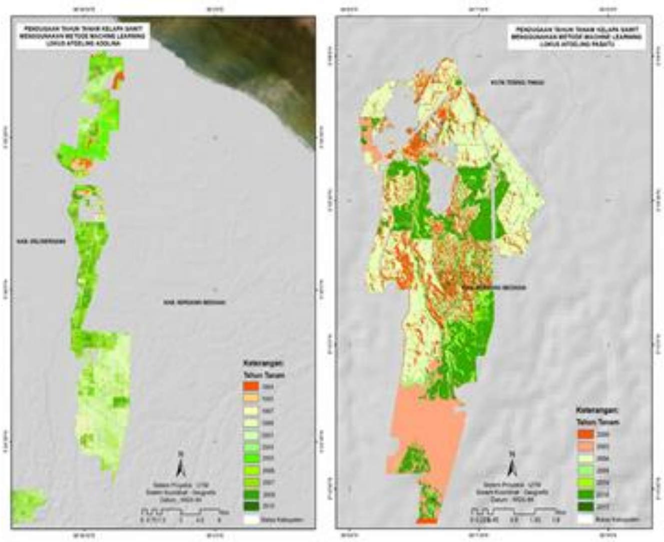

Figure 6. Output ANN after Ground Truth Method

Table 2. Calculation of identification accuracy of plant's life age using ANN method on SPOT 6 imagery at research location.

Accuracy of oil palm life age identification from machine learning using ANN method is generated from SPOT-6 imagery obtained an accuracy value of 87% (Table 2).

Tahun Tanam	0	3	4	5	6	7	8	10	14	16	94	95	97	98	Total Baris	Omisi Pixel (%)
0	20469	0	0	0	0	0	0	0	1365	24	0	0	0	0	21858	6.354652759
3	0	6387241	6478	0	0	250466	52246	5596	0	0	0	0	0	46362	6748389	5.351617994
4	0	0	192433	0	0	0	0	0	0	0	0	0	0	0	192433	0
5	0	0	0	190880	0	15	3407	16387	0	0	0	1392	2	5463	217546	12.25763747
6	0	0	0	0	120943	678	2329	511	0	0	0	0	0	1	124462	2.827368996
7	0	0	0	0	0	365068	9955	0	0	0	0	0	0	1945	376968	3.156766622
8	0	0	0	0	0	30271	159275	2	0	0	0	0	0	179	189727	16.05043036
10	0	0	0	0	0	0	0	56161	0	0	0	0	0	0	56161	0
14	0	0	0	0	0	0	0	0	8887	12958	0	0	0	0	21845	59.31792172
16	0	0	0	0	0	0	0	0	804	62247	0	0	0	0	63051	1.275158205
94	0	0	0	5464	19	420	9	5522	0	0	60231	4922	24	5598	82209	26.73429916
95	0	0	0	1239	0	1	24	1264	0	0	1883	90256	0	0	94667	4.659490636
97	0	0	0	0	0	2674	188	397	0	0	0	7	593	5564	9423	93.63260108
98	0	0	0	0	0	0	0	0	0	0	0	0	0	453597	453597	0
Total Kolom	20469	6387241	198911	197583	120962	649593	227433	85840	9691	75205	62114	96577	619	518709	8168281	
Komisi Pixel (%)	0	0	3.256733	3.392498	0.015707	43.8005	29.96839	34.57479	8.296357	17.23024	3.031523	6.537789	4.200323	12.5527		
Over All Accuracy		87.043														
Perkalian Silang Sampel		4.37477E+13														
Keofisien Kappa		0.624														

Table 2. Calculation of identification accuracy of plant's life age using ANN method on SPOT 6 imagery at research location.

D. Calculation of Oil Palms Productivity Estimation

Calculation of oil palms productivity estimation is done by using formula 5. The results of multiple linear regression obtained as an estimation formula as follows:

$$Y = -24391 - 766\,X1 + 65482\,X2 \ldots\ldots(6)$$

Where Y is productivity of oil palm plantation (kg/ha/year), X1 is plant's life age (year) and X2 is NDVI value. This formula has a correlation coefficient value (R) of 0.71 and determination coefficient ($R^{2)}$ of 0.51. This is in accordance with results according to Sugiyono, (2014) classified as having a strong corelation level that is 85%.

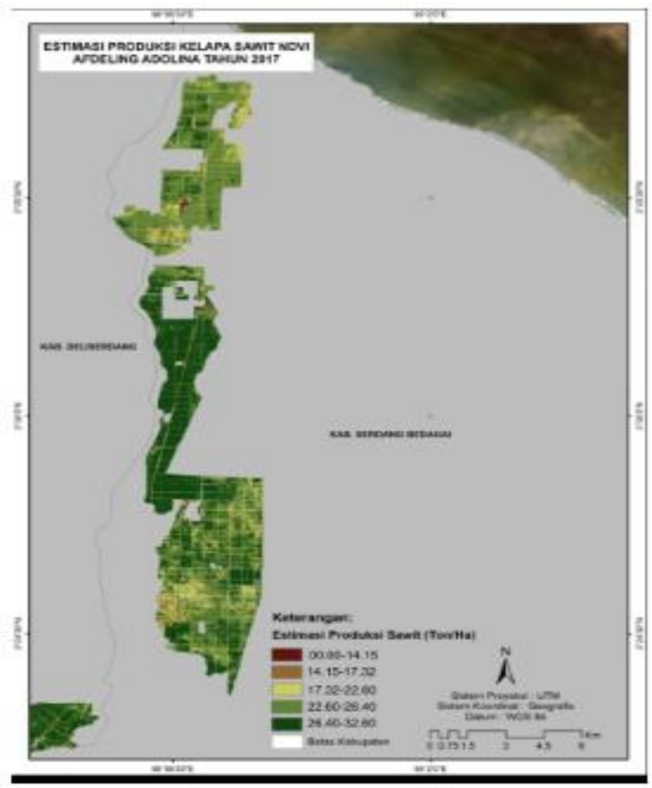

Fig 7:- Map of Estimated Oil Palm Production

IV. CONCLUSION

1. The result of accuracy value of oil palms identification output by using ANN method which is generated from SPOT-6 imagery, is 87%.
2. Equation of a formed production estimation is as follows:
$$Y = -24391 - 766\,X1 + 65482\,X2$$

The generated estimation of production has accuracy value of 85%

3. According to the test result, it shows that remote sensing technology through SPOT-6 imagery can be used to estimate productivity value of oil palms. Therefore, it can support the effort to increase the intensification as a proof of implementing government policy that is stated in Presidential Decree No. 8 Year 2018. This is also can be used by oil palms industry as a tool to monitor the management of oil palms plantation. The results of this study also support the research of Diana, et al (2019),

about the direct use of remote sensing technology that can provide high economic value.

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