The Asian Journal of Technology Management Vol. 14 No. 1 (2021): 19-34

Economic Potential of Oil Palm Plantation Using Remote Sensing-Based Technology in Indonesia

Shinta Rahma Diana and Farida
Center for Aerospace Policy Studies, National Institute of Aeronautics and Space (LAPAN), Indonesia
Faculty of Economics and Business, UPI YAI, Indonesia

Abstract. *The productivity of Indonesia's palm oil was considered low when referring to the 14.6 million ha land area in 2019, with the production of national palm oil only reaching 3.2 tons of CPO/ha/year. The uses of remote sensing technology as a means of monitoring and supervising, were expected to increase oil palm production in line with productivity. The purpose of this study was to determine the economic potential based on oil palm plantation productivity, with and without using remote sensing-based technology, as well as other variables likely to affect productivity. Primary and secondary data collection methods were also used in this research. There were three quantitative methods being used in this study, namely (i) Multiple regression model with panel data, (ii) Data Envelopment Analysis (DEA) tool, and (iii) Multinomial logistic regression technique. The results showed that the generated economic potential from the utilization of the remote sensing model, had efficient opportunity value of 10.48, which was higher than the non-usage of the technology. Therefore, the main variables that affected productivity in this study, were fertilizer and labour.*

Keywords: *Efficiency, oil-palm, remote sensing (spot 6), policy, binomial logistic*

1. Introduction

The plantation sector contributed about 429 trillion rupiah to Indonesia's GDP in 2016. This contribution was greater than the oil and gas sector, which contributed only 365 trillion rupiah. In the total plantation sector, the largest contribution came from oil palm production, amounting to 260 trillion rupiah (Bpdpks, 2018). This shows that oil-palm plantations are one of strategic industries for the nation. However, the expansion and development of oil palm plantations should protect the ecosystem's rich biodiversity, which is supported by government regulations and public interventions, caring for the environment (Vijay, Pimm, Jenkins, & Smith, 2016), with the oil product generating food and energy as well. Also, many negative issues threatened the oil-palm commodity, part of which is the low rate of productivity value.

Indonesia is a nation with the biggest oil-palm production around the world, yet its productivity values are low, with estimations showing a 12.9% increase (48.42 million tons) in 2019, compared to 2018 (BPS, 2019). However, productivity of national oil-palm remained very low, as regards the 14.6 million ha land area that produced 3.2 tons CPO/ha per -year, in 2019, with the production level not showing a significant progress within 10 years. According to Rosdiana (2009), the productivity of public plantation in 2008, was around 2.52 ton CPO/ha per year, in Indonesia. Meanwhile, other nations with smaller plantation area have higher productivity values, which are about 8-10 tons/ha per year. Even though Indonesia has a high economic potential from oil palm plantation sector, its implementation is yet to be optimized, and needs serious improvement.

*Corresponding author. Email: shinta.rahmadiana@gmail.com
Received: November 24th, 2020; Revised: December 9th, 2020; Accepted: March 14th, 2020
Doi: http://dx.doi.org/10.12695/ajtm.2021.14.1.2
Print ISSN: 1978-6956; Online ISSN: 2089-791X.

Most studies stated that the utilization of technology is likely to increase productivity (McGuckin, Streitwieser, & Doms, 2006; Sounder, 1989), as it is becoming one of the production factors of an economic unit. An example of technology utilization is the remote sensing, which plays a role in agricultural and oil palm plantation activities. Also, the existence of high-level satellite images, such as spectral, spatial, and temporal, have increased the use of remote sensing in agriculture, such as yield predictions, crops and nutrition monitoring, irrigation management, with diseases and pests control (Sishodia, Ray, & Singh, 2020).

Moreover, remote sensing is used to ease observation performance and productivity development in oil palm plantations. A high-resolution remote sensing generates data precision and useful information, which helps in observing the condition of oil palm plantations. Also, previous studies from Wiratmoko, Hartono, & Murti (2016) and Carolita, Sitorus, Manalu, & Wiratmoko. (2015), stated that remote sensing utilization in estimating production value through plant age, had quite a high accuracy level. Therefore, there is a potential in utilizing remote sensing technology, in order to assist monitoring activity in public and national plantation sectors. Also, the other benefits of remote sensing in agricultural sector, especially plantation, is identification of the most suitable plant for a certain season (Sharma, Liu, Yang, & Shi, 2017). Besides that, it also provides a high accuracy level of description in the agricultural sector, through the use of repetitive frequency and real time monitoring tools (Shanmugapriya, Rathika, Ramesh, & Janaki, 2019).

The effectivity of using remote sensing data to estimate productivity, is considered to be an economic potential value of technology, in order to increase production rate. This overcomes the issue stated by Bappenas (2010), which explained that one of the problems in developing oil palm plantations in Indonesia was due to technological factor.

One of the remote sensing satellites used for oil palm monitoring, is the sensory data of SPOT. Moreover, the utilization of high spatial resolution, SPOT 6 & 7 imagery, provides information related to vegetation objects, which possesses special characteristics, such as coconut, sago, and oil palm trees. Due to the implementation of multispectral classification method, the use of SPOT-6 imagery for oil palm plants, possessed an accuracy of 96.9%. The NDVI (Normalized Different Vegetation Index), MSAVI2 (Second Modified Soil Adjusted Vegetation Index), and PANNDVI (Panchromatic Normalized Different Vegetation Index) transformation methods, also had accuracy values of 83.3%, 78.0%, and 80.74%, respectively (Setyowati and Murti BS, 2015).

Based on Diana et al. (2019a), this study reviews the possibility of economic potential generated from oil palm plantations sector, through the use of SPOT. The application of the remote sensing technology in this research was SPOT-6 (Diana et al. 2019a), to help generate the potential of oil palm plantations productivity level. Also, remote sensing technology is utilized as a tool, to observe or monitor oil palm plantations. Diana et al. (2019a), focused on SPOT technical sector of data utilization for oil palm monitoring, while this manuscript is on the economical aspect.

This study was conducted in PTPN IV, North Sumatera, which is the second province contributing to the great production of oil palms in Indonesia, at 5.76 million tons, with Riau in first position at 8.7 million tons. The production location of oil palms in North Sumatera include Labuhan Batu, Asahan, Langkat, and Simalungun districts. Also, the area of oil palm plantations is around 1,201,452.5 Ha, which produces 15,832,922.56 tons of BFF (bunch of fresh fruit). BFF grows in bunches at the crown of the tree, and are very rich in oil. However, the BFF productivity owned by North Sumatera people is still considered to be very low, with estimations between 7 – 10 tons BFF/Ha per year. Also, the potential of BFF production, both to the government and private companies, are up to 20 or 25 tons/Ha per year (LPEI, 2018), indicating the need for massive improvements. Furthermore, North Sumatera is the first region where oil palm is developed in Indonesia (LPEI, 2018). In this supply chain structures, an Oil Palm Research Centre has a role in PT. Perkebunan Nasional (PTPN) IV, which entails making production innovation into major priority. Also, PTPN IV is one of the national oil palm plantations producing BFF, which potentially becomes raw material for palm oil (CPO). Therefore, the production potential of oil palm through the use of a remote sensing technology in a company, is expected to increase productivity and the efficiency of input utilization, in order to maximize the output.

The main objective of this research is to determine the efficiency potential, based on the productivity value of oil palm plantations, with and without using remote sensing technology (SPOT-6), and the variables affecting it.

2. Literature Study/ Hypotheses Development

2.1. Economic Potential of Oil Palm Sector

The economic potential of oil palm are shown from income and manpower aspects (Christiani, Mara, & Naenggolan, 2013). In Economics, production is regarded as a combination process of input utilization into an output (Case and Fair, 2004). This input refers to the use of land resource, manpower, and more, such as, tools and machine, in a production process, with output being classified into products and services. The management use of inputs are used to evaluate output performances, in terms of decision-making, with mathematical relationship also explained in a production function. According to Gordon and Vaughan (2011), production function explained the basis of technology relation or production factors (input), with the generated output.

The commonly used production function is the Cobb-Douglas Equation (Nuryartono, Pasaribu, & Panggabean, 2016). This Cobb-Douglas Equation is a function involving two or more variables, which most times are both dependent and independent (Vilcu, 2011). The input from the Cobb-Douglas production function as an independent variable, varies in each industry, such as (Saraswati, Sari, & Hapsari, 2019) the use of spare parts, rather than manpower. The Cobb-Douglas model is a production function developed in the end of 1920s, and mathematically represented as follow (Hossain & Al-Amri, 2010),

$$Q = AK^{\alpha}L^{\beta}u \tag{1}$$

Where,
Q = output,
K = input for capital,
L = labour,
A = constant,
α and β = positive parameters,
u = the disturbance term.

By transforming into a log, both sides becomes a multiple linear regression. The function further explained that the bigger the A, the more advanced the technology. Moreover, α measures the increase of percentage in Q, due to 1% increment of L, with K being constant. Also, β measures the increase of precentage in Q, due to 1% increment of K, while L remains constant.

A previous study (Ardana and Kariyasa, 2016) used seeds, labour, fertilizer, and pesticide to observe the impact on total production, with multiple ways by which the opportunity of adopting technology is to be utilized. The development of the Cobb-Douglas production function is represented as follows,

$$Y = a_0 S^{a1} L^{a2} F^{a3} P^{a4}\ e \tag{2}$$

Where,
Y = Production total, ton per hectare,
S = Seeds, Rp per hectare,
L = Labour, Rp per hectare,
F = Fertilizer, Kg per hectare,

P = Pesticide, Rp per hectare,
a_0 = intercept from regression function,
aj (j =1, 2, 3, 4) = slope parameters from regression function,
e = error term.

However, productivity function was affected by the price of BFF, the use of fertilizer input, labour, and numbers of oil palm trees. Therefore, all those variables except the product price, are the production factors that determine productivity of oil palm plantation (Bakir, 2007).

Furthermore, another study regarding input of agricultural production factors are seed, climate, soil, fertilizer, and management (PPKS, 2016a). However, the soil element is observed from the nutrients on the leaves. The materials needed to assess agricultural productivity were the measurement from aggregate output and input of its economic value (Alston, Babcock, & Pardey, 2010). Also, productivity inequality between varieties potential and plantation realization have many causative factors, such as the use of fertilizer, non-fertilizer technical culture (pruning, with weeds & harvest management), plants compositions, and efficiency of yield (Saragih, 2017). Moreover, the research of Ismiasih (2018), also observed the factors affecting the technical efficiency (TE) of oil palm plantation productivity in West Kalimantan, which includes numbers of plant ages, productive trees, fertilizers (urea, NPK, and SP36), labour, and artificial pesticide.

2.2. Remote Sensing

Remote sensing activity has already started for quite some times in Indonesia, and also confirmed to provide a very high economical value (generated from data distribution). The economical value generated from data distribution to consumers in Indonesia (remote sensing consumers), showed a profitable condition of a net cash flow (Diana, Hidayat, Rafikasari, Ibrahim, & Farida, 2019b). According to Net Present Value (NPV) calculation in 2017, values of remote sensing activity were up to 19.45 trillion rupiah (Diana et al., 2019b).

Remote-sensing had strong legal arrangements in Indonesia, which were regulated in,

(i) Presidential Instruction (Inpres) No. 6 year 2012, regarding Procurement, Utilization, Quality Control, High Resolution Remote Sensing Satellite Data Processing and Distribution.
(ii) Law of Republic of Indonesia, No. 21 Year 2013, regarding Space in Chapter II Part First, on Article 7 Paragraph 1 b and e, regarding Space Activity and Part Third, Article 15 to 23.
(iii) Presidential Decree of Republic of Indonesia, Number 45 Year 2017, regarding Space Management Master Plan, Year 2016 – 2040.
(iv) Governmental Decree of Republic of Indonesia, Number 11 Year 2018, on Effectuation Procedure of Remote Sensing Activity.

Remote-sensing was defined as an information collected on an object, without having physical contact with the exact entity (Elachi & Van Zyl, 2006). Another definition was expressed as the measurement of an object, through the use of a recording device, with no direct physical contact with the phenomenon being studied (Howard, 1996). Also, a digital remote sensing image refers to a visual representation being obtained, saved, manipulated, and shown in a base binary logic (Danoedoro, 2012).

Moreover, remote sensing satellites SPOT 6 & 7 are the most recent generations of OT sensory system with similar specifications, as the only difference are their launching periods. SPOT-6 was launched on September 9th 2012, at Satish Dhawan Space Centre, India, while SPOT-7 was established in 2014. By utilizing a high spatial resolution, SPOT 6 & 7 images were able to provide detailed information related to vegetation object with special characteristics, such as, coconut trees, sago, and palm oil. However, high resolution images of remote sensing are mostly utilized in monitoring and mapping plantations, with forests.

2.3. The role of Technology in Measuring Plantation Productivity

In Indonesia, remote sensing activity had started since 1971, with LAPAN participation in ERS-1 program or the first Landsat. Years later, it was followed by the development of Ground Station data Receiver Tiros-N satellite/NOAA HRPT, and Landsat MSS (Mahsun & Soejoeti, 1976; Wiranto, 1985). However, the utilization of remote sensing data and information had started since the 1990s (Mulyadi, 2009).

Studies abroad have already calculated the amount of values to be generated by utilizing technology in agriculture, plantations sectors, and more. The United States for an instance, through a research conducted by USGS, calculated future values by using remote sensing data and information. The result showed that information from the remote sensing modelling, enabled the agricultural production management to be more efficient, by not sacrificing groundwater quality. Also, the information value of remote sensing is 858 ± 197 million dollars per year, with the future sum of the benefits presently at 38.1 ± $ 8.8 billion dollars. Moreover, when the estimation of benefits from using satellite images was expanded to other parts of the United States, economic value for the nations got higher (USGS, 2013). Presently, the market opportunity for commercial application of remote sensing downstream service in Europe agricultural sector, is estimated at about €34 million (Space.tec partners, 2012). However in Australia, remote sensing contributes around $4.0 billion in 2015 for the GDP (Acil Allen, 2013).

Some of these studies indicated that remote sensing technology provided economic value, both in agriculture and plantations. Remote sensing is a useful tool to monitor the development of oil palm plantations, as it prepares industries for assimilation of technology, such as machinery automation and precision agriculture to reduce cost, with labour dependency to improve productivity (Chong, Kanniah, Pohl, & Tan, 2017). Also, remote sensing is widely used to monitor tropical forests, including further exploration for biomass estimation, mapping, and detecting invasive species changes (Trisasongko & Paull, 2020). Moreover, several studies on the use of remote sensing to predict plantation production, have also been carried out. The measurement of wood production in plantations, through the use of remote sensing data, was carried out by Gao et al. (2016). This study not only measured the potential for timber production using stock volume growth (GSV), it also based on the historical process of the harvested product. Also, the remote sensing method used ALOS PALSAR (Advanced Land-Observing Satellite Phased Array Data L-band Synthetic Aperture Radar) and Landsat-8 OLI (Operational Land Imager) integrated with field data, to estimate age class and GSV of plantations in North China. There was also further use of remote sensing to obtain an estimation of rubber production (Anurogo, Silaban, Nugroho, Mufida, & Pamungkas, 2019), which made use of ASTER imagery, in the visible and nearest IR channel.

2.4. Research Framework

Based on the research of Diana et. al. (2019a), production estimation was carried out through linear regression analysis, which involved plant age factors, and the NDVI average value in the blocks being studied. This study showed that the accuracy value of plant age identification using ANN obtained from SPOT-6/7 image, was 87%, with the production estimation equation formed as,

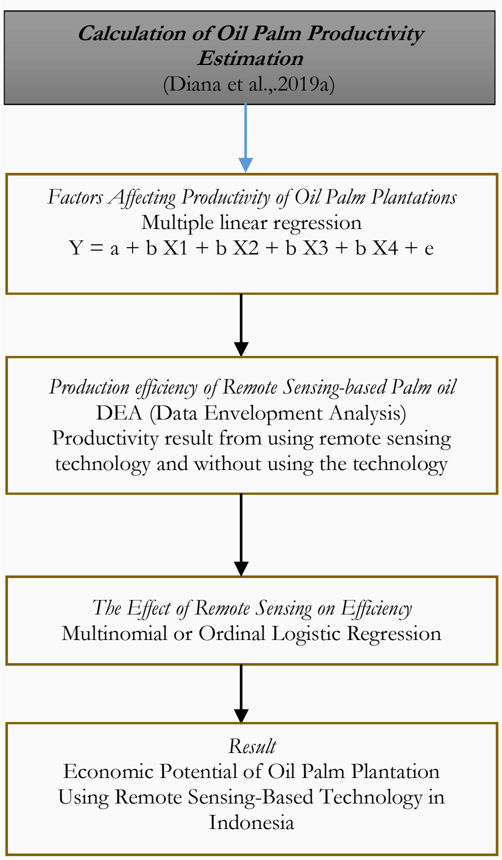
$$Y = -24391-766 X1 + 65482 X2.$$

This production estimation had an 85% accuracy value, with the test result indicating that the remote sensing technology of SPOT 6/7 imagery was capable of estimating oil-palm productivity amount.

This further strengthens the results of a research, which stated that palm oil productivity was generated from the yields of BFF, which through remote sensing technology is likely to accurately estimate production through the planting age approach (Carolita et al., 2015).

Production estimation results based on remote sensing of Diana, et. al (2019a), was being used as a basis for determining the value of efficiency. The input used was based on the Cobb Douglass function, and the basic factors for the production of PPKS book (PPKS, 2016b). The production inputs in this study are the numbers of palm oil tree, labour, fertilizer, and nutrient. Also, palm tree ages resulting from remote sensing technology should be utilized, in order to monitor and determine the amount of fertilizer and workers to be used. Therefore, multiple regression is to used to determine the variables affecting productivity. By using DEA, the level of efficiency are obtained, with the value of potential technology efficiency calculated through the use of logistic regression.

This research framework diagram is described as follows,



3. Methodology

The primary data of this research was directly obtained from SPOT-6 images data, at oil palm plantation PTPN IV Medan, North Sumatera. The base data used by the researcher was planting year and production information of 2017, with validity test through ground truth method, in order to compare between interpretation result and real condition on the field. Also, from the generated prototype, it calculated productivity estimation of oil palm plantation and input variables, which were obtained from the use of remote sensing technology. The production estimation from the prototype was completed using linear regression analysis, which involved plant ages and NDVI average value, on the object being studied. The equation result for linear regression to estimate production outcome is,
$Y = -24391 - 766\ X1 + 65482\ X2$ (Diana et al., 2019a).
However, secondary data was obtained from Factory manual at PTPN IV, in form of productivity and production factors information.

Furthermore, panel data, i.e., the mix of cross section and time series data, were arranged in yearly order, from 2015, 2016, 2017, and 2018. Therefore, this research was an outcome of data series utilization within a certain period of time, while cross sectional information was obtained from 9 afdelings at Adolina and Palbatu PTPN IV Plantations, as study objects.

PTPN IV has 4 districts, with the palm oil sample for plant age prediction obtained by using data images of Adolina and Palbatu. Adolina used afdeling 1 to 7, while palbatu used afdeling 1 and 2, with total points being 25. The research location was also in Serdang Bedagai and Deli Serdang districts, North Sumatera. Also, Adolina and Palbatu Plantations were located at 3.59455 and 3.36126 Latitude, with 98.953759 and 99.053879 Longitude, respectively.

PTPN IV owned thirty business units, which are managing oil palm cultivation, and distributed in 9 districts, namely Deli Serdang, Langkat, Serdang Bedagai, Simalungun, Asahan, Labuhan Batu, Batubara, Padang Lawas, and Mandailing Natal. The plantation owned 1 and 16 units of plasma ranch and oil palm factories, respectively, with capacity up to 635 tons BFF/hour. The process of product flow for raw material procurement came from 3 types of circulations, which are business unit ranch, one main plantation, and the supplier. Moreover, PTPN IV production forged a partnership with smallholder suppliers, in order to supply BFF, including Adolina Business Unit and UD. Mulya Agung Nugraha, CV. Cakrawala, and UD. GINTAR, to meet the capacity of oil palm productivity for the plantation team.

Furthermore, the first step conducted was the assessment of variables affecting productivity and the amount of the efficiency value, through the use of remote sensing technology, compared to its non-usage. The productivity functions are represented in the following,

$$Y = a + b\,X1 + b\,X2 + b\,X3 + b\,X4 + e \tag{3}$$

Given:
Y = Productivity total, ton per hectare
X1 = Numbers of Palm oil Tree
X2 = Labour
X3 = Fertilizer
X4 = Nutrient
a = intercept of function
aj (j=1,2,3, 4) are slope parameters
e for error term

Due to PTPN only using high quality seeds, its variable was not inputted. Also, in relation to the error term, discussion on CO_2 emission variable was carried out, using qualitative approach. Multiple linear regression with panel data, processed with SPSS with selection step of model suitability, was carried out using Chow, Haussnan, and Langrang tests. Afterwards, classic assumption test was also conducted for multi-collinearity. The result of multiple linear regression generated the input variables, which affected the productivity of oil palm plantation.

The second step was to calculate productivity efficiency, by using DEA tool (Data Envelopment Analysis) for both the usage and non-usage of the remote sensing technology. The factors from the multiple linear regression result in the first step and productivity became input and output variables, respectively. Moreover, DEA is a commonly used non-parametric analysis, used to measure technical efficiency relative in various sectors, such as bank (Farida, Osman, Kurniawan Lim, & Wahyuni, 2018), dairy farms (Demircan, Binici, & Zulauf, 2010; Kelly, Shalloo, Geary, Kinsella, & Wallace, 2012), and agricultural regions (Liu, 2015). Therefore, the DEA generated efficiency level of each DMU (Decision Making Unit), with score between 0 to 1. Scale 1 indicated efficiency, while < 1 meant not efficient.

After having each efficiency scores from every DMU, the third step analysis was conducted, determining the productivity efficiency opportunity of oil palm plantation, with and without the use of remote sensing technology. The analysis method used was multinomial or ordinal logistic regression. The result of efficiency from DEA was categorized into three, which are, very, less, and not efficient. Also, most researchers usually use two categories, where dependent variable (Y) are replaced by that of a dummy (between 1 or 0), using binary logistic regression analysis. In multinomial logistic regression, Y variable was provided as 0.1 and 2, with Y = 0 commonly used as comparison. In order to form logit, functions to be compared are Y = 1 and 2, to Y = 0. Also, for independent variable in this research, researchers used a dummy, i.e., score 1 and 0 for usage and non-usage of remote sensing, respectively.

Furthermore, logistic regression model of r nominal has a r-1 logit function. However, when y = 0 as basis category, there are two logit functions as follows,

$$g1(x) = \text{In} \left[\frac{P(y=1|x)}{P(y=0|x)}\right] = \text{In} \left[\frac{\pi 1(x)}{\pi 0\,(x)}\right] \quad (4)$$

$$gr\text{-}1(x) = \text{In} \left[\frac{P(y=r-1|x)}{P(y=0|x)}\right] = \text{In} \left[\frac{\pi r-1(x)}{\pi 0\,(x)}\right] \quad (5)$$

4. Findings and Discussion

4.1. Calculation of Oil Palm Productivity Estimation

The calculation of oil palm production estimation was completed using the research result of Diana et al. (2019a), with productivity value, through the following formula,

Y = – 24391 – 766 X1 + 65482 X2	(6)

4.2. Factors Affecting Productivity of Oil Palm Plantations

This research was conducted at PTPN IV, North Sumatera, precisely Adolina and Palbatu Plantations. In order to answer a question about factors affecting productivity of oil palm, researchers used all available data in Afdeling 1-7 and 1-2 of Adolina and Palbatu Plantations, respectively. The analysis tool being used was multiple linear regression of a 4 years duration data panel (from 2015 to 2018). In order to meet a balanced data panel, sample and blocks of planting year according to purposive sampling, only selected cultivation period objects, which were available for 4 consecutive years. Therefore, for 4 years, from 7 and 2 afdeling at Adolina and Palbatu, 1.412 blocks were obtained.

Furthermore, model estimation test or selection in data panel was being completed to estimate a suitable regression equation model. However, there have been several tests, one of which was the Chow method. This test aimed to select the best approach between Common Effect/Pooled Least Square technique and Fixed Effect Model (FEM). Moreover, from the result of Chow test, a significant cross-sectional F-value was obtained (< 0.05). Afterwards, it was summarized that H_0 was rejected while H_1 was approved, which indicated that Fixed Effect Model (FEM) was more suitable than Common Effect. Next was the Hausman test being conducted, which aimed to compare suitable methods between Fixed and Random Effect Model, for the data panel regression in this research. From the result of the test, the statistics of Hi Square distribution was bigger than its critical value (p-value < 0.05) which indicated significance. Therefore, this result rejected H_0, which indicated that fixed effect model was more suitable for estimation.

After getting the result that fixed effect model was the most suitable method, the next step was classic assumption test. On the data panel regression, all the classic assumption test were not used in the Ordinary Least Square (OLS) method. The auto-correlation and heteroscedasticity tests were unnecessary in panel data, since both only occurred in time series and cross-section data, respectively. Also, the normality test on data panel was not an obligation, basically not the requirement of BLUE (Best Linier Unbias Estimator). Therefore, the classic assumption test conducted in data panel was the multi-collinearity analysis, with results available in Table 1. Multi-collinearity test aimed to discover whether there was a relation, across independent variables.

Table 1.
Result Of Multicollinearity Test

	X1	X2	X3	X4
X1	1	-0.1418	0.0754	-0.0457
X2	-0.1418	1	-0.2071	0.0390
X3	0.0754	-0.2071	1	0.0015
X4	-0.0457	0.0390	0.0015	1

The result of the multi-collinearity test, showed that there was no independent variable > 0.8. This indicated that there was no multi-collinearity across its independent variables. Also, based on the fulfillment of classic assumption and the chosen model recommendation (fixed effect model), the regression result of FEM on Table 2 is as follows,

Table 2.
Result of Regression (Fixed Effect Model)
Dependent Variable: Y
Method: Panel Least Squares
Date: 11/15/19 Time: 08:22
Sample: 2015 2018
Periods included: 4
Cross-sections included: 353
Total panel (unbalanced) observations: 1411

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	16.45857	1.285266	12.80558	0.0000
X1	-4.69E-05	0.000210	-0.223473	0.8232
X2	0.012198	0.002108	5.785630	0.0000
X3	0.128809	0.068257	1.887112	0.0494
X4	-0.015841	0.060339	-0.262527	0.7930

Effects Specification

Cross-section fixed (dummy variables)

R^2	0.780506	Mean dependent var	19.16415
Adjusted R^2	0.706369	S.D. dependent var	6.023276
S.E. of regression	3.263875	Akaike info criterion	5.418025
Sum squared resid	11228.14	Schwarz criterion	6.746858
Log likelihood	-3465.417	Hannan-Quinn criter.	5.914579
F-statistic	10.52795	Durbin-Watson stat	2.102142
Prob(F-statistic)	0.000000		

According to Table 2, regression result using fixed effect model showed that the coefficient value of determination R-squared 0.78, depicted the affecting contribution provided by the independent variables (X), including number of trees, labour, fertilizer, and nutrient towards Y for 78%. However, the remaining 28% was explained by other variables, which were not in the equation of this research.

During the test for significance of the regression equation simultaneously, the result showed the calculation of F to be 10.53 or > F, with p-value < 0.05, in Table 2. This result indicated that simultaneous equation was significant and suitable to be used for estimation. Furthermore, the data panel estimation technique through the use of fixed effect model, generated a regression equation as follows,

$$Y = 16{,}459 - 0{,}000047X1 + 0{,}0122X2 + 0{,}1288\,X3 - 0{,}0158\,X4 \quad (7)$$

Given
Y= Productivity level of Oil Palm (ton/year)
X1 = Number of trees
X2 = Labour
X3 = Fertilizer
X4 = Nutrient

The result of this equation showed that the number of trees variable (X1), had a p value of 0.8232 or > 0.05. this indicated that the number of trees do not affect the productivity level of oil palm. Also, only productive age of trees seem to affect the productivity level, although one block of the oil palm plantation contains a non-productive tree. Moreover, the age of palm oil became part of the vital problems affecting the fruit bunches (Srestasathiern & Rakwatin, 2014). The ripeness of palm oil trees is about 3 years, with productivity peak attained at the approximate age of 6 to 10 years. However, according to Rizeei, Shafri, Mohamoud, Pradhan, & Kalantar (2018), the calculation of trees was considered an important practice in monitoring and replanting. By discovering the number of trees and its age, the estimation of palm oil output should be carried out in the future.

From the result of the data panel process using fixed effect model, variables affected significantly were X2 (labour) and X3 (fertilizer), because each of them have p-value < 0.05. X2 had a p value of 0,000 or < 0.05, which indicated that labour positively and significantly affected the productivity level. Due to to this outcome, it was clear that the main problem in oil palm plantation sector is the lack of labour, especially for harvesting time, and collection of fresh fruit bunches (Ismail, 2013).

X3 has a p-value of 0.049 or < 0.05, which indicated that fertilizer also positively and significantly affected productivity level. However, X4 variable had a p-value of 0.793 or > 0.05, indicating that nutrient variable does not affect the productivity level of palm oil, as the plantation had a low soil fertility (Goh, Teo, Chew, & Chiu, 1999). Therefore, nutrient element does not truly affect the production of oil palm, compared to fertilizer factor. This further indicated that fertilizer had a crucial role in supporting soil nutrition supply. Also, oil palm absorbed fertilizer in such abundant way, in order to be able to generate a high production output (Comte, Colin, Whalen, Grünberger, & Caliman, 2012). According to Pardamaen (2017), fertilizer contributed about 50-70% of total budget. However, according to Suratin, Karuniasa, & Utomo (2018), it is possible for plantation to have fertilizer efficiency and still be able to generate fresh fruit bunches sustainably, by changing the practice of nutrient element management, and increasing access to certified seeds.

4.3. Production efficiency of Remote Sensing-based Palm oil

Efficiency in this research only measured the efficient level of fertilizer use in general, which is relative on production position, with and without remote sensing technology. Although productivity factors truly get affected by many inputs, this research made fertilizer as limitation in input, and production in output. Moreover, the sample being used in calculating efficiency level was about 114 blocks planting age, with 57 each for both usage and non-usage of remote sensing. However, the use of remote sensing was limited to estimation, which was used to monitor and estimate total production, with the use of fertilizer. Therefore, the estimation of total production and numbers of fertilizer with manual calculation, is available in Table 3.

Also, the number of samples being used in this research were 57 blocks, with the planting year randomly selected from the 7 Afdeling at Adolina plantation, PTPN IV, North Sumatera. The summary of the total remote sensing result is also available on Table 3.

Table 3.
Result of Remote Sensing Estimation

Information	**Result of Remote Sensing Estimation**	**Manual Result**	**Difference**
Production BFF (ton)	30.347	20.888	(9.459)
Total Fertilizer (ton)	2.188	2.186	(2.3)

The gain of BFF production by using remote sensing, is very useful for PTPN IV, to monitor and assess the reasons production total is lower than standard. From the data being processed and analyzed using DEA in Table 4, results showed that from the total of 114 (remote sensing or manual), there was only one block with score 1 (efficient), 55 blocks at 0.5 – 0.99 (less efficient), and the remaining 58 having less than 0.5 (not efficient).

Table 4.
DEA Output Results

Score	Remote Sensing	Manual	Total	Percentage (%)	Category
1	1	0	1	0.88	Efficient
0.5 – 0.99	42	13	55	48.24	Less efficient
< 0.5	14	44	58	50.88	Not efficient
Total	57	57	114	100	

4.4. *The Effect of Remote Sensing on Efficiency*

The analysis tool being used to observe the effect of remote sensing utilization in efficiency were the multinomial or ordinal logistic regression. The ordinal regression due to dependent variable (Y), is a stratified category data, while multinomial is used, because there are more than 2 categories.

With ordinal scale available on Table 5, dependent variable (Y) has three categories, namely,
1 = efficient,
2 = less efficient,
3 = not efficient.
However, independent variable (X) is a dummy, which is 1 when using remote sensing, and 0 when making use of the manual (no remote sensing).

Table 5.
Ordinal Scale of Efficiency Levels

Scale	Category	Total
1	Efficient	1
0.5 – 0.99	Less efficient	55
< 0.5	Not efficient	58
Total		114

Based on the output of ordinal or multinomial logistic regression, the wellness result of fit test showed that the model was suitable for research. The hypothesis being tested were,

H_0 : Suitable model
H_1 : Non-suitable model

Reject the H_0 when p-value is < 0.05. However, the approved null hypothesis indicated that the model fits the data. The p-value on table 6 showed > 0.05, which approved the decision of the H_0. Therefore, this ordinal logit model was appropriate and suitable.

Table 6.
Model Fit Test Results

Test	Chi-Square	Df	P value
Pearson	0.098481	1	0.754
Deviance	0.186593	1	0.666

Furthermore, on the last part of ordinal logistic regression output on Table 7, concordant value was observed around 57.7%. This showed that varieties of response variables were explained by explanatory factors (X) in the model for about 57.7%, and the remaining discussed by other determinants outside the model.

Also, based on model parameters significance, Wald test was conducted to observe whether a predictor variable was suitable in the model. The hypothesis being used is as follows,

$H_0: \beta_k = 0$

$H_1: \beta_k \neq 0,$

k = 1,2..,

p = numbers of predictor in the model.

Statistics of W test = $\frac{\hat{\beta}_k}{SE\hat{\beta}_k}$, H_0 is rejected when W > $Z_{\alpha/2}$ or p-value < 0. In Table 7, it was observed that variable X had p-value of 0.000, which indicated that X was significantly affecting Y.

Table 7.
Results of Multinomial Logistic/Logit Regression

Predictor	**Odds Coef**	**95% CI SE Coef**	**Z**	**P**	**Ratio**	**Lower**	**Upper**
Const (1)	-6.46775	1.07152	-6.04	0.000			
Const (2)	-1.22125	0.315782	-3.87	0.000			
X	2.34973	0.440500	5.33	0.000	10.48	4.42	24.86

Measures of Association:
(Between the Response Variable and Predicted Probabilities)

Pairs	Number	Percent	Summary	Measures
Concordant	1905	57.7	Somers' D	0.52
Discordant	182	5.5	Goodman-Kruskal Gamma	0.83
Ties	1216	36.8	Kendall's Tau-a	0.27
Total	3303	100.0		

Coefficient interpretation is used for interpreting decision-making or inferences, by looking at the value of estimated ordinal logistic regression model. This coefficient describes slope or changes in Y per-unit of variable on X. Furthermore, the coefficient interpretation of slope is represented in the generated equations of ordinal logistic regression as follows,

g1 (X) = -6,46775 + 2,34973 X dan g2 (X) = - 1,22125 + 2,34973 X.

To interpret parameter coefficient, *odds ratio* (ψ) = exp (β_k), which is being used on independent variable (X). Based on Table 7, the odds ratio for Variable X recorded was 10.48. This was concluded by stating that the opportunity of efficiency through the use of remote sensing, was 10.48 times higher than not using the technology (manual). Remote-sensing technology assists in a more efficient decision-making for oil palm plantation management, through land monitoring (Chong et al., 2017). However, the application/utilization of remote sensing for oil palm is still in the stage of research and development. The collaboration between academics and industry for the sustainability and progress of this utilization, is still difficult to achieve (Hansen et al., 2015).

5. Conclusions

Based on the test results above, this research showed that images from remote sensing technology, SPOT-6, provided economic potential in Oil Palm Plantation, with variables affecting the productivity including fertilizer and labour. Also, the opportunity of efficiency by using remote sensing is 10.48 higher than not using the technology (manual). This research further showed that the use of remote sensing technology from satellite SPOT-6 increased the productivity of oil palm plantations.

Furthermore, remote sensing (SPOT-6/7) was used as a monitoring tool, to optimize the productivity value of oil palm, compared to not using the technology. This strengthens government policies, regarding the importance of using technology. Moreover, it is important to utilize remote sensing technology, in order to provide accurate information/data about the condition of oil palm plantations. This should indirectly prepare the industry for assimilation of technologies, which is likely to be useful for increasing productivity.

Acknowledgments
The authors are grateful for the financial support made available for this research, authorship, and/or publication of this article from Ministry of Research, Technology, and Higher Education of Indonesia. The authors are also grateful to Mr. Robertus Heru Triharjanto, Mr. Agus Hidayat, Intan Perwitasari, Agil Sutrisnanto (Center for Aerospace Policy Studies, National Institute of Aeronautics and Space (LAPAN), Indonesia), Mr. Dhimas Wiratmoko (Indonesian Palm Oil Research Institute), Gusti Darma Yudha (Pustekdata, LAPAN), Syaiful Muflichin Purnama (UGM), that contributed to this research. Also, they are grateful to PT. Perkebunan Nusantara IV, for providing permission to carry out the research in Serdang Bedagai and Deli Serdang Districts, North Sumatra.

References

Acil Allen (2013).*The economic value of earth observation from space: A review of the value to Australia of Earth observation from space. Acil Allen.* Retrieved from http://www.acilallen.com.au/cms_files/ACILAllen_Earth2013.pdf.

Alston, J. M., Babcock, B. A., & Pardey, P. G. (2010). *The shifting patterns of agricultural production and productivity worldwide*. Midwest Agribusiness Trade Research and Information Center.

Anurogo, W., Silaban, R. D., Nugroho, C. B., Mufida, M. A. K., & Pamungkas, D. S. (2019, October). Pixel-based Remote Sensing Data Processing for Estimating Rubber Plantations Productivity. In *2019 2nd International Conference on Applied Engineering (ICAE)* (pp. 1-5). IEEE.

Ardana, I.K., Kariyasa, K. (2016).Influence of Technological Innovation and Use of Production Input on Productivity of Oil Palm in West Kalimantan Province. *Jurnal Penelitian Tanaman Industri, Jurnal Littri* 22(3), 125-134.

Bakir, L.H. (2007). *Kinerja perusahaan inti rakyat kelapa sawit di Sumatera Selatan: analisis kemitraan dan ekonomi rumah tangga petani.* Eprint.unsri.ac.id

Bappenas. (2010). Kebijakan dan Strategi dalam Meningkatkan Nilai Tambah dan Daya Saing Kelapa Sawit Indonesia secara Berkelanjutan dan Berkeadilan. *Naskah Kebijakan (Policy Paper). Direktorat Pangan dan Pertanian, Kementerian Perencanaan Pembangunan Nasional/Badan Perencanaan Pembangunan Nasional (BAPPENAS).* Desember 2010.

Bpdpks. (2018). *Sawit Kontributor Utama PDB Indonesia. Bpdpks.* Retrived from https://www.bpdp.or.id/Sawit-Kontributor-Utama-PDB-Indonesia

BPS. (2019). *Indonesia Oil Palm Statistics.* Retrived frrom https://www.bps.go.id/publication/2020/11/30/36cba77a73179202def4ba14/statistik-kelapa-sawit-indonesia-2019.html

Case, E. K., & Fair, C. (2004). *Prinsip-Prinsip Ekonomi Makro*. Edisi Kelima, Cetakan Kesatu. Jakarta: PT. Indeks.

Christiani, E., Mara, A., & Naenggolan, S. (2013). Peranan Perkebunan Kelapa Sawit dalam Pembangunan Ekonomi Wilayah di Kabupaten Muaro Jambi. *Jurnal Sosio Ekonomika Bisnis*, *16*(2), 63-73.

Carolita, I., Sitorus, J., Manalu, J., & Wiratmoko, D. (2017). Growth profile analysis of oil palm by using SPOT 6 the case of North Sumatra. *International Journal of Remote Sensing and Earth Sciences (IJReSES)*, *12*(1), 21-26.

Chong, K. L., Kanniah, K. D., Pohl, C., & Tan, K. P. (2017). A review of remote sensing applications for oil palm studies. *Geo-spatial Information Science*, *20*(2), 184-200.

Comte, I., Colin, F., Whalen, J. K., Grünberger, O., & Caliman, J. P. (2012). Agricultural practices in oil palm plantations and their impact on hydrological changes, nutrient fluxes and water quality in Indonesia: a review. *Advances in Agronomy*, *116*, 71-124.

Demircan, V., Binici, T., & Zulauf, C. R. (2010). Assessing pure technical efficiency of dairy farms in Turkey. *Agricultural Economics-Czech*, *56*(3), 141-148.

Diana, S. R., Purnama, S. M., Dharma, G., Sutrisnanto, A., Perwitasari, I., & Farida, F. (2019a). Estimation the Amount of Oil Palm Production Using Artificial Neural Network and NDVI SPOT-6 Imagery. *International Journal of Innovative Science and Research Technology*, *4*(11), 548-554.

Diana, S. R., Hidayat, A., Rafikasari, A., Ibrahim, I. M., & Farida, F. (2019b). Economic Assesstment of Satellite Remote Sensing Data in Indonesia: A Net Present Value Approach. *International Journal of Economics and Financial Issues*, *9*(1), 140-146.

Danoedoro, P. (2012). *Pengantar Penginderaan Jauh Digital.* [Introduction to Digital Remote Sensing]. Yogyakarta: Penerbit Andi.

Elachi, C., & Van Zyl, J. J. (2006).*Introduction to the Pyhsics and Techniques of Remote Sensing.* New York: Wiley & Sons.

Farida, F., R Osman, I., Kurniawan Lim, A., & Wahyuni, N. (2018). The efficiency of formal microfinance in Indonesia: using data envelopment analysis application. *Iranian Economic Review*, *22*(3), 787-810.

Gao, T., Zhu, J., Deng, S., Zheng, X., Zhang, J., Shang, G., & Huang, L. (2016). Timber production assessment of a plantation forest: An integrated framework with field-based inventory, multi-source remote sensing data and forest management history. *International journal of applied earth observation and geoinformation*, *52*, 155-165.

Goh, K. J., Teo, C. B., Chew, P. S., & Chiu, S. B. (1999). Fertiliser management in oil palm: Agronomic principles and field practices. In: *Fertiliser management for oil palm plantations,* 20-21, September 1999, ISP North-east Branch, Sandakan, Malaysia: 44 pp.

Gordon, D., & Vaughan, R. (2011). The Historical Role of the Production Function in Economics and Business. *American Journal of Business Education*, *4*(4), 25-30.

Hansen, S. B., Padfield, R., Syayuti, K., Evers, S., Zakariah, Z., & Mastura, S. (2015). Trends in global palm oil sustainability research. *Journal of cleaner Production*, *100*, 140-149.

Howard, J. A. (1996). *Remote Sensing of Forest Resources: Theory and Application*, London: Chapman & Hall.

Hossain, M. Z., & Al-Amri, K. S. (2010). Use of Cobb-Douglas production model on some selected manufacturing industries in Oman. *Education, Business and Society: Contemporary Middle Eastern Issues*, *3*(2), 78-85.

Ismail, A. (2013). The effect of labour shortage in the supply and demand of palm oil in Malaysia. *Oil Palm Industry Economic Journal*, *13*(2), 15-26.

Ismiasih, I. (2018). Technical efficiency of palm oil production in West Kalimantan. *Habitat*, *28*(3), 91-98.

Kelly, E., Shalloo, L., Geary, U., Kinsella, A., & Wallace, M. (2012). Application of data envelopment analysis to measure technical efficiency on a sample of Irish dairy farms. *Irish Journal of Agricultural and Food Research 51*(1), 63-77.

Liu, K. (2015). Application of DEA method in the evaluation of agriculture economic efficiency. *Journal of Chemical* *and Pharmaceutical Research*, *7*(3), 997-1000.

LPEI (2018). Analisa Rantai Pasok (Supply Chain) Komoditas Unggulan Ekspor Indonesia: Minyak Sawit. *Indonesia Eximbank Institute, Lembaga Pembiayaan Ekspor Indonesia (LPEI).*

Mahsun, I., & Soejoeti, Z. (1976). *Proyek Pemanfaatan Satelit Tele Deteksi Sumberdaya alam/Proyek Telsa*. Jakarta: LAPAN.

McGuckin, R. H., Streitwieser, M. L., & Doms, M. (1998). The effect of technology use on productivity growth. *Economics of Innovation and New Technology*, *7*(1), 1-26.

Mulyadi, K. (2009*). Pemanfaatan Data Inderaja untuk Pemantauan Sumberdaya Alam dan Lingkungan*. Jakarta: Massma Publishing.

Nuryartono, N., Pasaribu, S. H., & Panggabean, P. N. K. (2016). Total factor productivity analysis of oil palm production in Indonesia. *Journal of Economics and Financial Issues*, *6*(4), 1570-1577.

Pardamaen, M. (2017). *Kupas tuntas agribisnis kelapa sawit: Mengelola kebun dan pabrik kelapa sawit secara efektif dan efisien*. [Exploring oil palm agribusiness: Managing oil palm plantations and mills effectively and efficiently]. Jakarta: Penebar Swadaya.

PPKS (2016a).*Pedoman Norma Kerja Perkebunan Kelapa Sawit Pada Lahan Mineral, Buku 1.*

PPKS (2016b). *Pedoman Norma Kerja Perkebunan Kelapa Sawit Pada Lahan Mineral, Buku 2.*

Rizeei, H. M., Shafri, H. Z., Mohamoud, M. A., Pradhan, B., & Kalantar, B. (2018). Oil palm counting and age estimation from WorldView-3 imagery and LiDAR data using an integrated OBIA height model and regression analysis. *Journal of Sensors*, *2018,* 1-13.

Saragih, B. (2017). Produktivitas sumber pertumbuhan minyak sawit yang berkelanjutan. Palm Oil Technical Meeting (PTKS). Retrived from http://www.iopri.org/wp-content/uploads/2017/07/I-01.-Makalah-Prof-Bungaran-Saragih-Produktivitas.pdf

Saraswati, D., Sari, D. K., & Hapsari, D. (2019, May). The applications of Cobb-Douglas Production Function in remanufacturing industry. In *IOP Conference Series: Materials Science and Engineering* (Vol. 528, No. 1, p. 012055). IOP Publishing.

Setyowati, H. A., & Murti BS, S. H. (2015). Aplikasi Citra Spot-6 Berbasis Transformasi Indeks Vegetasi untuk Estimasi Produksi Kelapa Sawit (Elaeis Guineensis Jacq) (Kasus Perkebunan Kelapa Sawit PT. Tunggal Perkasa Plantations, Air Molek, Kabupaten Indragiri Hulu, Propinsi Riau, Sumatera). *JurnalBumi Indonesia*, *4*(4), 1-7.

Shanmugapriya, P., Rathika, S., Ramesh, T., & Janaki, P. (2019). Applications of remote sensing in agriculture-A Review. *International Journal of Current Microbiology and Applied Sciences*, *8*(1), 2270-2283.

Sharma, A., Liu, X., Yang, X., & Shi, D. (2017). A patch-based convolutional neural network for remote sensing image classification. *Neural Networks*, *95*, 19-28.

Sishodia, R. P., Ray, R. L., & Singh, S. K. (2020). Applications of remote sensing in precision agriculture: A review. *Remote Sensing*, *12*(19), 3136.

Souder, W. E. (1989). Improving productivity through technology push. *Research-Technology Management*, *32*(2), 19-24.

Space.tec partners (2012). *Assessing the Economic Value of Copernicus: "European Earth Observation and Copernicus Downstream Services Market Study"*, Retrived from http://www.copernicus.eu/sites/default/files/library/GMES_GIO_LOT3_PublishableExecutiveSummary_final.pdf.

Srestasathiern, P., & Rakwatin, P. (2014). Oil palm tree detection with high resolution multi-spectral satellite imagery. *Remote Sensing*, *6*(10), 9749-9774.

Suratin, A., Karuniasa, M., & Utomo, S. W. (2018). Is sustainable oil palm production possible for smallholders?. *Journal of Environmental Science and Sustainable Development, 1*(1), 25-39.

Trisasongko, B. H., & Paull, D. (2020). A review of remote sensing applications in tropical forestry with a particular emphasis in the plantation sector. *Geocarto International*, *35*(3), 317-339.

USGS. (2013).*What is the Economic Value of Satellite Imagery?* Retrieved from https://pubs.usgs.gov/fs/2013/3003/fs2013-3003.pdf.

Wiranto A. (1985). LAPAN. *Special Edition of LAPAN Journal*.

Wiratmoko, D., Hartono, H., & Murti, S. H. (2016). Worldview-2 Imagery Vegetation Index Calculation for Oil Palm Yield Estimation. *Jurnal Penelitian Kelapa Sawit*, *24*(3), 143–156.

Vijay, V., Pimm, S. L., Jenkins, C. N., & Smith, S. J. (2016). The impacts of oil palm on recent deforestation and biodiversity loss. *PloS one*, *11*(7), e0159668.

Vîlcu, G. E. (2011). A geometric perspective on the generalized Cobb–Douglas production functions. *Applied Mathematics Letters*, *24*(5), 777-783.