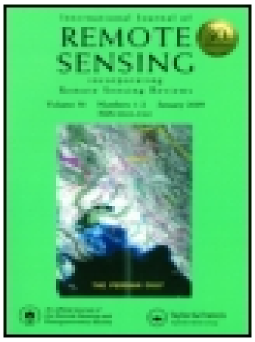

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Assessment of oil palm yield and biophysical suitability in Indonesia and Malaysia

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ABSTRACT

The most crucial technical challenge facing the Malaysian and Indonesian oil palm industry is that the actual yield in the form of Fresh Fruit Bunch (FFB; unit in tonne per hectare (t ha^{-1})) are well below of potential levels and have stagnated over last two decades. Closing this wide yield gap would have a positive impact on the revenue as it increases productivity per hectare and it eventually leads to less pressure on opening new land and mitigates environmental costs of production. With respect to the indispensable need for closing this gap for future prosperity of this industry and sustainable production of palm oil, this study assessed oil palm yield, considering the potential growth of oil palm dependent on the site qualities and actual yield. Firstly, we mapped oil palm plantations combining yearly Advanced Land Observation Satellite (ALOS) Phased Array type L-band Synthetic Aperture Radar (PALSAR) and ALOS-2 mosaics of L-band backscatter, Moderate Resolution Imaging Spectroradiometer (MODIS) reflectance (MOD13Q1), and the MODIS Vegetation Continuous Field canopy cover product (MOD44B); where 10.3 and 6.68 million ha (Mha) of oil palm plantations were mapped, respectively, in Indonesia and Malaysia in 2017. Secondly, the age after planting was estimated at detected plantations using time series of MODIS canopy cover with correlation coefficient (*r*) of 0.68 and Root Mean Square Error (RMSE) of 4.7 years. Thirdly, the biophysical suitability of detected plantations was evaluated considering the spatial-temporal variation of different biophysical criteria. Combining information from second and third steps, we estimated the potential yield at 250 m spatial resolution. The average potential yield in Malaysia ranges between 13.8 t ha^{-1} and 19.3 t ha^{-1} in 2017, where in Indonesia it ranges between 17.8 t ha^{-1} and 21.7 t ha^{-1} in the same year. The actual yield in next step, has been quantified by HH-HV attribute of ALOS PALSAR and ALOS-2 mosaics, where the average actual yield in Malaysia ranges between 14.48 t ha–1 and 20.63 t ha^{-1} and in Indonesia it ranges between 8.49 t ha^{-1} and15.40 t ha^{-1} in 2017. Finally, comparing estimated potential and actual yields, we evaluated oil palm industries' performances where distinct differences were found between two countries. In most of the Malaysian states quantified actual yields were above or at the level of estimated potential yields, whereas in all Indonesian provinces quantified actual yields were well below the potential level. Considering the favourability of environment, among all provinces/states, Sabah, and Sarawak states in Malaysia and Aceh and North Kalimantan provinces in Indonesia

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distinctly differ due to their poor performances from rest of provinces/states. The information on different yields provided in this study are indispensable needs for efficient and accountable policies as it enables governors to directly target specific objectives such as subsidies on fertilizers, productive cultivars, and new technologies for the plantations suffering from low yield. Also, this study provides benchmarks for each province/state for scopes of actual yield improvements for long-term planning.

1. Introduction

Elaeis guineensis known as oil palm is extensively cultivated in South-East Asia, especially in Indonesia and Malaysia (Euler et al. 2016). As of 2018, the global palm oil consumption has reached 30% of the global vegetable oil, and palm oil has turned into the most consumed vegetable oil (USDA 2019). It is expected this increasing demand will continue in future years (Pirker et al. 2016). Due to the significant revenue of the oil palm industry, this sector plays a crucial role in the economic development of Indonesia and Malaysia (Sheil et al. 2009); however, expansion and intensification of this industry have not been robustly managed and caused significant negative impacts (Sheil et al. 2009; Varkkey, Tyson, and Choiruzzad 2018). Apart from the environmental challenges caused by this industry, the most crucial technical challenge of this sector is that the Fresh Fruit Bunch yields (FFB; unit in megagram per hectare (t ha^{-1})) are well below of potential levels and have stagnated over last two decades (Euler et al. 2016; Hoffmann et al. 2017; Barcelos et al. 2015; Woittiez et al. 2017; Varkkey, Tyson, and Choiruzzad 2018). Closing this wide yield gap (YG) would have a positive impact on the revenue as it increases productivity per hectare and it eventually leads to less pressure on opening new land and mitigates environmental costs of production (Benami et al. 2018; Schrier-Uijl et al. 2013). Potential and actual yields are two main components of YG assessment. As a perennial crop, oil palm potential yield is a function of tree's genotype, age, and the biophysical condition of the environment (Hoffmann et al. 2017; Corley and Tinker 2003). While the observed yield at a field which is generally referred to as actual yield, is a function of potential yield coupled with agricultural practices (Dietrich et al. 2012; Sadras et al. 2015). A better understanding of these components is an essential need to identify the key causes of YG, and it introduces the potential scope for raising yields through management changes (Hoffmann et al. 2017; Woittiez et al. 2017). Besides the importance of this information for a range of growers, scientific analysis of YG plays an essential role for accountable policies design and regulations (OECD 2018). Despite this importance, there is a limited number of attempts modelling oil palm yields which are different in their input and output data. However, as oil palm is extended in a considerable spatial heterogeneous area (Lobell 2013), estimated yields using available models neither represent an entire region nor consider a full range of conditions.

So far various space-borne and air-borne remote sensing (RS) data have been used to deal with the heterogeneity of agriculture area for crops' yield assessment (Lobell 2013; Lobell et al. 2015; Franch et al. 2019; Doraiswamy et al. 2005, 2013; Bastiaanssen and Ali 2003).

The biophysical condition of environment for a given crop is evaluated by biophysical suitability assessment methods (sys, van Ranst, and Debaveye 1991). So far, a number of studies used different RS data to assess the biophysical suitability of the environment for different crops (Vasu et al. 2018; Shelia et al. 2019; Mesgaran et al. 2017; Bradford et al. 2017) as well as oil palm (Pirker et al. 2016; Rhebergen et al. 2018; Harris et al. 2013; Mantel, Wösten, and Verhagen 2007; Gingold, Rosenbarger, and Muliastra 2012). Although in all of these studies the biophysical suitability assessment has been introduced as a fundamental step of yield assessment, °C of them discuss the biophysical suitability of environment at existing plantations due to lack of information and challenges in mapping oil palm distributions.

Mapping oil palm distribution relying on optical satellite RS and in particular, the image-based approach has been reported as a challenging task due to the rapid oil palm canopy growth and spectral similarity of this plantation to the other land covers such as natural forest and rubber plantation (Li et al. 2015; Torbick et al. 2016; Víctor and Defries 2013). Relying on the temporal characteristics of optical sensors (phenology-based methods) also introduces some challenges particularly in small fragmented oil palm plantations as it usually uses Moderate Resolution Imaging Spectroradiometer (MODIS) data due to its high temporal resolution (Li et al. 2015). Regardless of the approach, the frequent presence of cloud cover makes it almost impossible to acquire cloud-free images in tropical regions. While the Synthetic Aperture Radar (SAR) can provide images in all-weather and all-time. The Phased Array L-band Synthetic Aperture Radar (PALSAR) has been successfully used in several studies to differentiate oil palm plantations from forest boundaries in local scales (Qin et al. 2016; Li et al. 2015; Wang et al. 2017; De Alban et al. 2018; Reiche et al. 2018; Laurin et al. 2012). Proper training of classifiers, solely based on SAR or optical data on a regional scale is a challenging task due to different conditions, species, and locations. While the combination of SAR and optical data proved to be useful for mapping oil palm plantations (Li et al. 2015; Torbick et al. 2016; Gutierrez-Velez 2013).

Apart from the importance of environmental condition of plantations, tree's age is another crucial layer of information for oil palm yield assessment (Corley and Tinker 2003; Foong et al. 2019; Hoffmann et al. 2017), which RS has proved to provide reliable estimation (Chemura, Van Duren, and Van Leeuwen. 2015; Franklin et al. 2003; Thenkabail et al. 2004; Tan et al. 2013). Despite the successful application of RS on oil palm age determination, most of the studies focus on the characteristics of individual tree stand for local field management using very high-resolution imagery (Srestasathiern and Rakwatin 2014; Fawcett et al. 2019).

Although RS has shown promising applications in oil palm age and biophysical suitability assessment in different studies, °C of those studies have contributed to oil palm yield assessment. Therefore, with respect to the indispensable need for countrywide oil palm yield assessment, the objective of this study is to assess oil palm yields (potential and actual) and their gap by modelling potential yield considering the age and biophysical qualities of plantations and quantifying the actual yield in Indonesian and Malaysian oil palm plantations leveraging publicly available RS datasets and platforms at 250 m spatial resolution.

2. Methodology

2.1. Study area

Malaysia is located between 0° and 6° N and 99° to 119° E, with an area of 328,657 km^2. Indonesia is located between 5° N and 10° S and 95° to 141° E, with an area of 1,811,569 km^2. Since 90% of Indonesia's oil palm plantations are located on Sumatra and Kalimantan island (*Indonesian Oil Palm Statistics* 2017), to reduce computation time, this study restricted the study area to Kalimantan and Sumatra from Indonesia and whole Malaysia as is shown in Figure 1.

2.2. Overall processing flow

The processing flow in this study consists of four steps of: (1) Mapping oil palm distribution, combining MODIS vegetation continuous fields (MOD44B), MODIS vegetation indices (MOD13Q1) and Advanced Land Observation Satellite (ALOS) Phased Array type L-band SAR and ALOS-2 PALSAR-2 mosaics of L-band backscatter (year 2017); (2) Estimating the year of planting at detected plantations using the time series of MOD44B; (3) Evaluating the biophysical suitability of environment at the detected plantations; and (4) Assessing oil palm yields, comparing oil palm actual and potential yields in 2017 at 250 m spatial resolution. All the processing in this study has been done in Google Earth Engine (GEE), a cloud computing platform which hosts publicly available optical and SAR data archives and is available in Python and JavaScript (http://earthengine.google.org/) (Gorelick et al. 2017). Figure 2 shows the overall flowchart of the study.

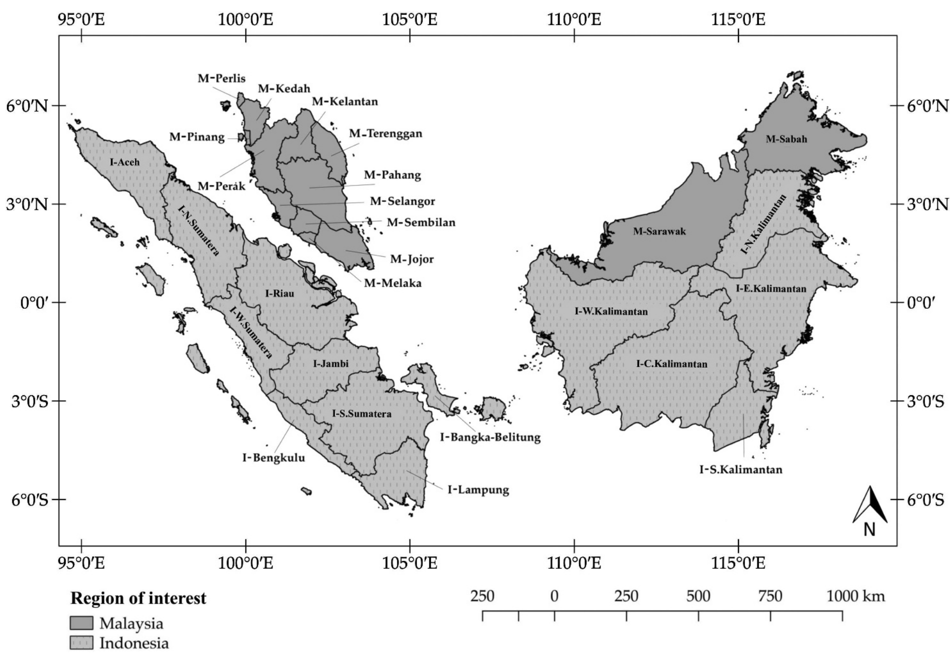

Figure 1. Study Area, where Indonesian provinces have been identified with I and Malaysian states have been identified with M.

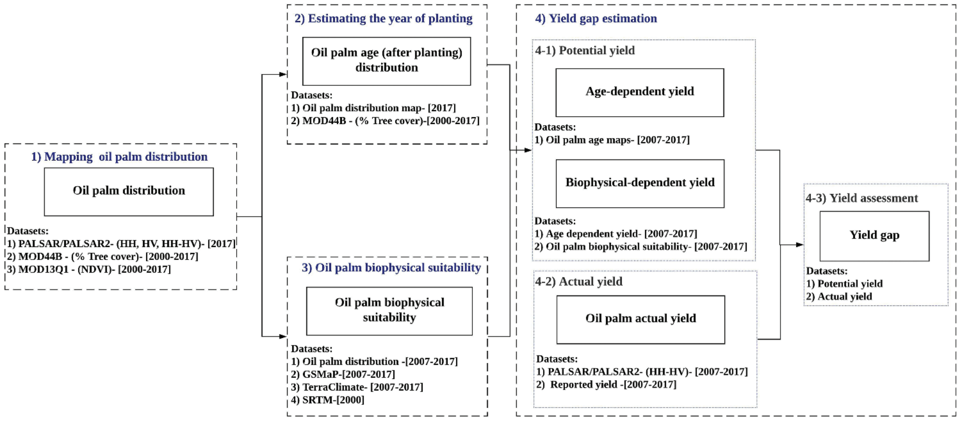

Figure 2. The overall flowchart of the study.

2.3. Mapping oil palm distribution

2.3.1. SAR data pre-processing

This study used ALOS PALSAR/ALOS-2 PALSAR-2 (AP/AP2) global 25 m yearly mosaic data for the year 2017 (Shimada et al. 2014). These data are provided in dual polarization of HH (horizontal transmit and horizontal receive) and HV (horizontal transmit and vertical receive). The refined Lee filter was applied on orthorectified and slope corrected HH and HV bands to reduce inherent speckle noise of SAR data (J. Sen Lee 1986). The digital numbers (DN) values were converted to gamma-naught (γ^0; in decibel, dB) with (1):

$$\gamma^0 = 10 \times \log_{10}\left(DN^2\right) - 83.0 \quad (1)$$

Additional attribute of HH–HV was generated calculating the difference of HH and HV regarding its promising application in oil palm mapping (Qin et al. 2016; Kou et al. 2015). HH, HV, and HH-HV were rescaled into 250 m spatial resolution (consistence with a spatial resolution of MOD44B and MOD13Q1 (discuss in sections 2.3.2 and 2.3.3) to prepare a stacked image for supervised classification.

2.3.2. MODIS vegetation continuous fields (MOD44B) pre-processing

Presence of multiple endmembers in young oil palm pixels (where the oil palm canopy is relatively small) makes mapping of this group challenging at a national scale with extensive heterogeneity using either of optical or SAR sensors. While in mature plantations due to developed and dense structure of the canopy, oil palm plantation can be separated more precisely. To deal with the challenge of mapping young plantations, we relied on the temporal characteristic of MODIS vegetation continuous fields (MOD44B). This product provides yearly information on percentage tree cover at 250 m spatial resolution with Root Mean Square Error (RMSE) of about 10% using monthly composites of Terra MODIS land surface reflectance data (DimiceDimiceli et al. 2015). After removing poor-quality pixels using the quality band, Linear Regression model (LR) has been applied on 17-year time series of percentage tree cover band. The model calculates a linear regression using least square method between the independent variable of time (year) and the dependent variable of percentage tree cover. Due to negative slope values at young plantations in comparison with similar classes, slope component of LR model helps young oil palm be separated from other similar classes in the study area. The slope and offset components of each pixel's regression equation have been used as separated attributes to prepare a stacked image for supervised classification.

2.3.3. MODIS vegetation indices (MOD13Q1) pre-processing

Rubber plantations are also widely found in Malaysia and Indonesia which exhibit similar spectral properties to young oil palm plantations. However, rubber has been reported showing different Normalized Difference Vegetation Index (NDVI) signature during its defoliation (leaf-off) and foliation (leaf-on) periods in comparison with oil palm plantation (Torbick et al. 2016; Kou et al. 2015; Razak et al. 2017; Zhang et al. 2013). Therefore, this study also took this property to differentiate young oil palm from rubber plantations. This study used MOD13Q1 product which provides vegetation indices including NDVI computed from atmospherically corrected bi-directional surface reflectance masked for water, clouds, heavy aerosols, and cloud shadows. Accordingly, first, the monthly characteristic of rubber's NDVI has been checked in a period of 2000–2017 on sample plantations to find defoliation (distinct NDVI drop) and foliation (gradual NDVI increase) periods (JA et al. 2017; Kou et al. 2015). Next, LR model has been applied on 17-year time series of NDVI in the detected foliation and defoliation period of rubber. The slope and offset components of each pixel's regression equation have been used as separated attributes to prepare a stacked image for supervised classification.

2.3.4. Optical-SAR supervised classification

Compiling slope and offset attributes derived from LR model on MOD13Q1 NDVI and MOD44B percentage tree cover, and HH, HV, and HH-HV attributes from AP/AP2, we generated a stacked image (MOD-AP) for year 2017 masked waterbodies to conduct supervised classification. We used the Classification and Regression Trees (CART) method for classification due to its better performance in comparison to the other classifiers in oil palm mapping (J. S. H. Lee et al. 2016). Visually interpreted samples have been randomly selected using Google Earth Pro ('Google Earth Pro') for two classes of oil palm and °C oil palm to conduct supervised classification on MOD-AP. Accordingly, we took about 13,200 and 6200 pixel samples for oil palm class and 14,700 and 2600 pixel samples for no oil palm class, respectively, in Indonesia and Malaysia. Seventy per cent of the samples have been used to train the classifier and 30% used for the accuracy assessment.

2.4. Estimating the year of oil palm planting

Fresh Fruit Bunch (FFB) is the main product of oil palm tree which different kinds of oils are extracted from its mesocarp and kernel parts (Corley and Tinker 2003). Tree starts producing FFB 3 years after planting. FFB increases rapidly by 10 to 11 years. After that, production reaches to its peak and starts a plateau phase by 18 years after planting. In oil palm older than 18 years old a gradual decline of the yield is expected (Foong et al. 2019; Corley and Tinker 2003).

In this study, in order to estimate the years after planting of the detected plantations, we first determined the year of planting. We assumed that the gap between land clearance (land preparation) and oil palm planting is less than 1 year (Gaveau et al. 2016) and oil palm trees have been planted in the same year of minimum observed tree coverage. Respectively, in the 17-year time series of MOD44B (percentage tree cover band) (2000–2017) masked with detected plantations in 2017, we searched for the year with minimum percentage tree cover in each pixel of oil palm. We considered this year as the year of land clearance which is concurrent with the year of oil palm planting. Figure 3(a) shows a time series of MOD44B percentage tree cover band at an oil palm pixel where the year with a minimum percentage of tree cover (2002) is detected and considered as the year of oil palm planting.

Since usually at the time of land clearance the percentage of tree cover drops to less than 25%, if the detected minimum value on the time series was greater than 25%, we considered that oil palm planting has happened before 2000 (Figure 3(b)) and we assigned the year 1995 as the year of planting, due to the rapid development of oil palm industry in the period of 1990–2000 (Koh and Wilcove 2008). We then compared the detected year of land clearance with 64 visually interpreted samples to check the accuracy of detection. The detected year of planting has been used to estimate the years after planting and also to generate a time series of oil palm's distribution maps (2007–2016) using oil palm distribution map in 2017 (discussed in section 2.3).

2.5. Oil palm biophysical suitability assessment

In this study, the suitability assessment framework suggested by the Food and Agriculture Organization of the United Nations (FAO) has been used. Accordingly, to assess the biophysical suitability of an environment for a given crop, geomorphological suitability, and meteorological suitability are evaluated separately. Integrating geomorphological and meteorological suitability indices, the final biophysical suitability is calculated. In this study, we selected five meteorological and two geomorphological criteria based on a detailed literature review. We defined three different mathematical functions (supplementary material section-a) to transform each of these criteria to rated values ranging from 100 to 0 based on comparison with oil palm requirements introduced by FAO (Table 1) (sys, van Ranst, and Debaveye 1991). The value 100 is assigned to the optimum level of a criterion and 0 is assigned to the minimum level of a criterion. In this study, we used the square root parametric methods to calculate suitability indices as presented in equation 2.

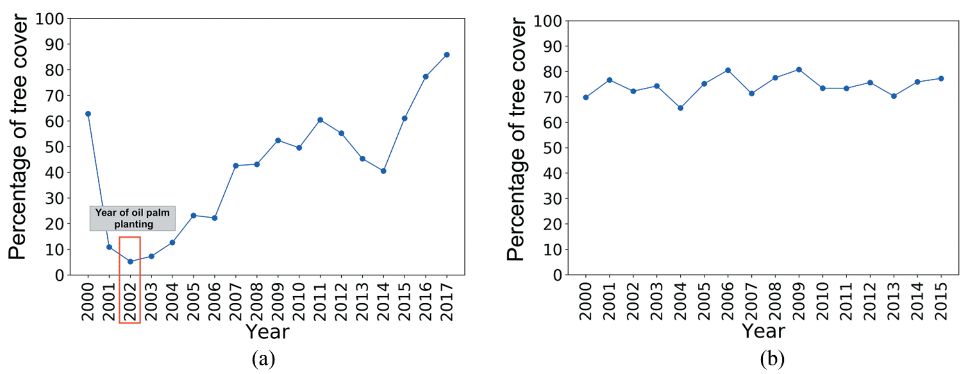

Figure 3. A time series of percentage tree cover at two sample oil palm pixels: (a) Year 2002 is detected as the year of oil palm planting; (b) Oil palm pixel has experienced planting before 2000.

Table 1. Oil palm biophysical criteria used in this study and their suitability ranges.

	Suitability Class 5	Suitability Class 4	Suitability Class 3	Suitability Class 2	Suitability Class 1
Criterion	Perfect	Suitable	Moderate	Marginal	Not suitable
Annual precipitation (mm)	1700–2875 1700–2875	1450–1700 2875–3250	1250–1450 3250–3625	1000–1250 3625–4000	<1000 >4000
Number of dry months (unitless)	0–2	2–3	3–4	>4	>4
Annual mean temperature (°C)	>22	22–20	20–18	<18	<18
Annual maximum temperature (°C)	>27	27–24	24–22	<22	<22
Temperature of the coldest month (°C)	>15	>15	>15	>15	<15
Slope (°)	0–8	8–16	16–30	30–50	>50
Elevation (m)	0–1500	>1500	>1500	>1500	>1500

$$S_i = R_{min} \times \sqrt{\frac{A}{100} \times \frac{B}{100} \times \frac{C}{100} \times \ \ldots} \tag{2}$$

where S_i is a suitability index, R_{min} is the rated value of the most constraining criterion (the minimum-rated value among all criteria), and *A, B, C* are the remaining rated values for rest of criteria. The final biophysical suitability class is calculated according to equation 3.

$$\text{Oil palm biophyical suitability class} = S_M \times S_G \tag{3}$$

Where S_M is meteorological suitability index and S_G is geomorphological suitability index. We assessed the biophysical suitability in years 2007–2017 to capture its temporal variation assuming that meteorological factors vary in different years whereas the geomorphological factors remain consistent.

2.5.1. Meteorological suitability

Based on a detailed literature review (Corley and Tinker 2003; Pirker et al. 2016; Rhebergen et al. 2016; Mantel, Wösten, and Verhagen 2007; Harris et al. 2013; Gingold, Rosenbarger, and Muliastra 2012; Stickler et al. 2007; sys, van Ranst, and Debaveye 1991), in this study five meteorological factors have been selected consisting of annual mean temperature, annual maximum temperature, mean temperature of the coldest month of the year, annual precipitation, and the number of dry months in which plantation receives less than 1000 mm of precipitation.

The optimal temperature condition for oil palm ranges between 22°C and 28°C, and the mean temperature of the coldest month of the year should not be less than 15°C. Besides, the optimal precipitation is 1700–2800 mm per year. This study used TerraClimate dataset for all temperature-related parameters in 4.5 km spatial resolution (Abatzoglou et al. 2018) and Global Satellite Mapping of Precipitation (GSMaP) in about 10 km spatial resolution for two precipitation-related parameters (Kubota et al. 2006). All the meteorological parameters were rescaled to 250 m consistent with oil palm distribution map.

2.5.2. Geomorphological suitability

Oil palm is not sensitive to soil chemical and physical requirements and grows on different types of tropical soils where some of them may not be suitable for other crops (Corley and Tinker 2003). However, the slope limits cultivation due to the increase of planting, harvesting, and maintenance cost. The optimal slope for oil palm cultivation is 0–8° but oil palm also can grow in slope up to 16° (Corley and Tinker 2003). This study used Shuttle Radar Topography Mission (SRTM) (Van Zyl 2001) in 90 m grid cell size for both elevation and slope criteria. All the geomorphological parameters were rescaled to 250 m consistent with oil palm distribution map. Although soil physiochemical attributes affect productivity (such as yield variations in peatland and non-peatland locations), these variables are relatively unstable due to human interventions and yet there is no reliable source of information with sufficient ground data depicting a spatial-temporal variation of these parameters at country scale. Therefore, this study only considered elevation and slope attributes.

2.6. Oil palm yield assessment

In this study, yield assessment consists of four steps. In the first step, oil palm potential yield was estimated considering the biophysical suitability of the environment and age after planting at the detected plantations in time series of 2007–2017. In the second step, actual yield was quantified using AP/AP2 bands and attributes in the same period. In the third step, estimated potential yield for the year 2017 was calibrated based on regression equation between potential and actual yields of years 2007 to 2016 on each oil palm pixel. In the last step, calibrated potential yield in 2017 was compared to quantified actual yield in the same year to assess existing gap in different provinces/states.

2.6.1. Oil palm potential yield estimation

To estimate oil palm potential yield, we first considered the effect of age after planting on FFB production (discussed in section 2.4). Based on (Foong et al. 2019), we transformed the age after planting of each oil palm pixel to its respective FFB yield (Figure 4). We considered this yield as age-dependent yield.

We assumed that this yield will only achieve in the absent of any environmental constraints (only if the biophysical suitability of oil palm pixel is in range of suitability class 5). If biophysical suitability pixel ranges in suitability class 1, then yield 0 was assigned as the potential yield of that pixel (Equation 4).

$$Y_{\text{pot}} = \begin{cases} 0 & \text{if} S_{\text{pixel}} = S_{\text{class1}} \\ \frac{S_{\text{pixel}} \times Y_{\text{Agedependent}}}{S_{\text{class5}} - S_{\text{class1}}} & \text{if} S_{\text{class1}} < S_{\text{pixel}} < S_{\text{class5}} \\ Y_{\text{Agedependent}} & \text{if} S_{\text{pixel}} = S_{\text{class5}} \end{cases} \tag{4}$$

where Y_{pot} is potential yield, S_{pixel} is the suitability of the pixel, S_{class5} is the maximum suitability, S_{class1} is minimum suitability and $Y_{\text{Age-dependent}}$ is the calculated age-dependent yield.

2.6.2. Oil palm actual yield quantification

As oil palm grows, it produces more FFB which are located under the canopy (Corley and Tinker 2003). While from optical sensors it is challenging to estimate FFB, microwaves signals (in particular L-band) have a great chance to penetrate into the upper part of canopy to give more information on its structure (Darmawan et al. 2016). FFB production is also associated with tree height growth, which results in a greater interaction of L-bands signals with the trunk. Therefore, considering the association of different attributes of AP/

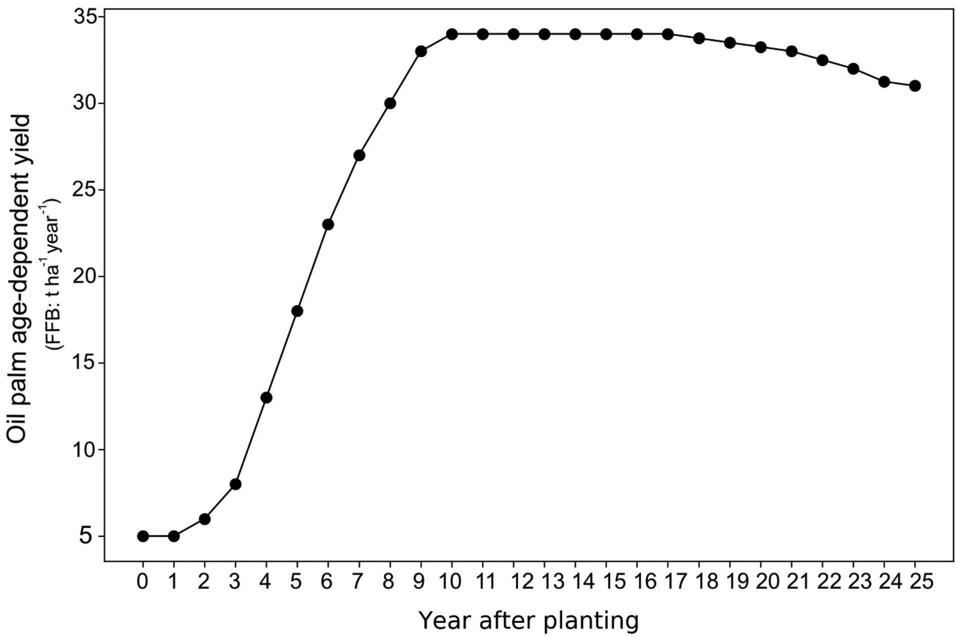

Figure 4. Typical oil palm FFB yield associated with the age of tree after planting (Foong et al. 2019).

AP2 and oil palm tree structure, in this study we used AP/AP2 to quantify oil palm annual actual yield. We used oil palm national statistics of both countries in years 2007–2017 (Malaysian Palm Oil Board; Indonesian Oil Palm Statistics) as an ancillary data to check the association of AP/AP2 attributes and reported yield to quantify actual yield. The statistics report yields in the form of mean provincial FFB (t ha^{-1} year $^{-1}$) which are mainly calculated based on the average values of recorded FFB's weights reached to the mills in each province/state. Despite these data have been previously reported to inherit some degrees of underestimation due to difficulties in harvesting and data collection method (Hoffmann et al. 2017; V. O. Sadras et al. 2014; Burke and Lobell 2017), their spatial-temporal coverage outweighed other field data in national scale studies.

We first masked AP/AP2 HH, HV, and HH-HV attributes in years 2007–2017 with corresponding oil palm distribution maps. Second, we calculated the provincial mean values of HH, HV, and HH-HV over oil palm plantations for 13 Malaysian states and 14 Indonesian provinces for all 7 years. From 189 prepared data for each attribute, 14 outliers have been identified and removed based on the interquartile range method. In 175 data associations of each HH, HV and HH-HV with reported yield have been separately checked using 80% of data as training dataset and 20% of data as testing dataset. In the last step, the regression equation of the best predictor was used to generate the actual yield at oil palm pixels in different years.

2.6.3. Potential yield calibration

Due to the heterogeneity of the study area, different genotypes of oil palm are likely to be planted across the region which have different phenology and yielding characteristics. In order to consider different genotypes and any other possible permanent environmental constraints apart from the considered parameters, yield calibration is one of the critical steps in potential yield estimation (Seidel et al. 2018; Guo, Wenxiang, and Bryant 2019; Van Ittersum et al. 2013). In this study, we calibrated the potential yield based on a least square method where the regression equation of potential yields against actual yields in years 2007–2016 in each pixel of oil palm has been used to calibrate the potential yield in 2017.

2.6.4. Yield assessment

Following Dietrich et al. (2012), in this study, we considered the ratio of actual and potential yields as an indicator of the agriculture practices. In this concept, the actual yield is a function of the agriculture practices together with the potential yield. Respectively, a high actual yield can be the result of implementation of appropriate agricultural practices or high potential yield. Thus, the actual oil palm yield at the location j can be described as a function of two variables of the potential yield and the agricultural practice index (Equation 5).

$$Y_{\text{act},j} = Y_{\text{pot},j} \times \alpha_j \tag{5}$$

where Y_{act} is actual yield at pixel j, Y_{pot} is the oil palm potential yield at pixel j and α is agricultural practice index at same pixel. Therefore, to evaluate the level of the agriculture practice inputs in each province/state, we calculated the ratio between provincial mean actual and potential yields.

3. Results and Discussion

3.1. Oil palm distribution map

Figure 5 shows an average NDVI per month for 200 arbitrary oil palm and rubber pixels through observation years. The points and error bars show samples' median and standard deviation (SD) values. The high SD values in some months show data poor data quality. NDVI showed different characteristics in foliation and defoliation period of rubber (from March to July) in comparison to oil palm plantation (JA et al. 2017). This period was consistent with the reported period in (Zhang et al. 2013) with 1-month time lag which was due to different geographical regions. Accordingly, this period has been used to differentiate oil palm and rubber plantations in the case of partial confusion of young and sparse oil palm plantation with rubber.

AP/AP2 attributes proved to be powerful to separate oil palm plantations from natural forest in confirmation of previous studies (Figure 6) (Qin et al. 2016; Li et al. 2015; Wang et al. 2017; De Alban et al. 2018; Reiche et al. 2018).

The slope and offset of LR on MOD44B percentage tree cover could compensate for the errors raised by the confusion of young oil palm plantations and other dominate vegetations (Figure 6(a)). The HH band proved to be helpful to separate mature oil palm and cocoa plantations which are mainly found in Indonesia (Figure 6(b)). This is due to different trunk structures which results in different HH backscattering characteristics.

CART classifier achieved an overall accuracy of 0.91 and 0.78 with kappa coefficient (k) of 0.98, respectively, in Malaysia and Indonesia. The overall accuracies, k, producer's and user's accuracies for oil palm and no oil palm classes presented in the Table 2. The oil palm

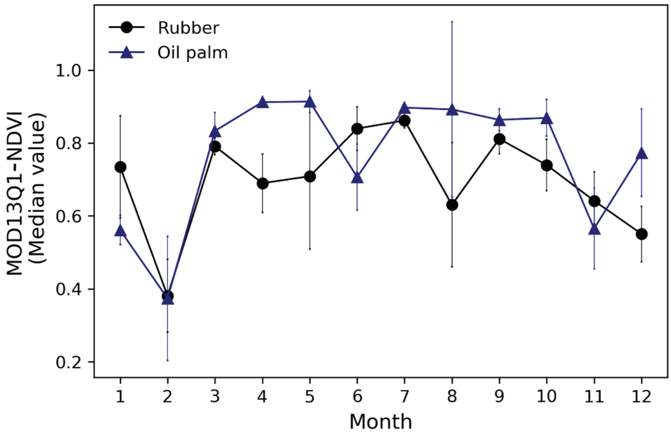

Figure 5. The monthly characteristics of time series NDVI (2000–2017) for rubber and oil palm plantations.

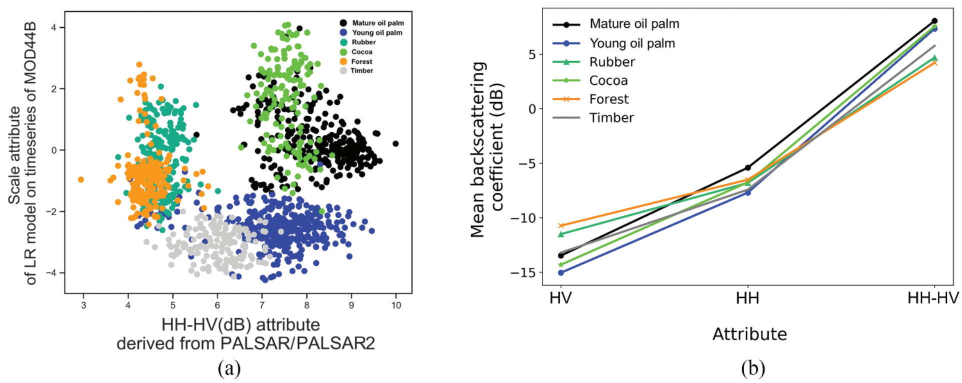

Figure 6. Performance of different optical and SAR attributes in separating dominant vegetations in the study area: (a) The scatter plot shows how dominated vegetations were separated using scale component of LR model on MOD44B combined with HH-HV attribute of AP/AP2; (b) The Line plot shows how HV, HH, and HH-HV mean backscattering values of dominate vegetations are differ from each other.

Table 2. Oil palm classification's confusion matrix in Malaysia and Indonesia.

	Oil palm	No oil palm	User's accuracy
A) Confusion matrix of oil palm classification in Malaysia			
Oil palm	1693	167	0.91
No oil palm	82	698	0.89
Producer's accuracy	0.95	0.88	
Overall accuracy	0.91	*k*	0.98
B) Confusion matrix of oil palm classification in Indonesia			
Oil palm	3578	382	0.79
No oil palm	1467	2943	0.91
Producer's accuracy	0.71	0.89	
Overall accuracy	0.78	*k*	0.98

user's and producer's accuracies in Indonesia are less than Malaysia. This is due to different characteristics of oil palm industry in both countries which leads to more sparse and fragmented patches of land smaller than 7 ha in Indonesia (Varkkey, Tyson, and Choiruzzad 2018; Craw 2019).

Taking a moderate spatial resolution of 250 m introduced some challenges in mapping these small patches (Li et al. 2015). Also, the extensive heterogeneity of study area made proper training of classifier challenging which effected the classification accuracy. Additionally, fine-resolution images in Google Earth Pro which have been used for visual interpretation, were often obtained from different dates, which considering rapid land cover changes in the study area, is another source of the misclassification.

The total area under oil palm plantations in Malaysia in 2017 was estimated to be 6.68 million ha (Mha) and 10.39 Mha in Sumatra and Kalimantan territory of Indonesia. Comparing the area under oil palm plantations in each province/state with a national statistic, in all Malaysian states, our study showed overestimation except Sarawak state. Similar overestimation in Malaysian case has been reported in (Cheng et al. 2019); where oil palm plantations have been mapped using ALOS-1/2 PALSAR-1/2. Along with the accuracies of classification, these overestimations are also attributed to the reliability of the national statistics (in particular case of Sarawak) and the method of measuring the area (pixel counting). In the case of Indonesia both under and over estimation were observed (Figure 7). This is due to partial instability of coarse spatial resolution in the cases of small and fragmented plantations where other endmembers are observed in a pixel.

3.2. The year of oil palm planting

In this study, in order to detect the year of planting, we assumed that the year in which land has been cleared is the same year of oil palm planting. Therefore, we searched for the year with minimum tree cover on the time series of MOD44B masked by oil palm distribution in 2017. The detected year with minimum tree cover showed correlation coefficient (r) of 0.68 with RMSE of 4.7 years against observed values (Figure 8(a)). Assigning the year 1995 to all old plantations which have been planted before year 2000, increased the RMSE, while for the samples observed in year 2000–2017 the RMSE was 3.3 years. Considering the year 1995 as the year of planting at old plantations, however, does not strongly affect potential yield estimation as those plantations have already entered the plateau phase in which yield has less variation with tree ageing. The estimated years after planting in this study (RMSE of 4.7 years) showed reasonable accuracy in comparison with a similar study (McMorrow 2001), where RMSE of 3.9 years was reported for estimation using a linear regression of the age after planting and all reflective bands of Landsat Thematic. Our estimation also showed acceptable results in comparison with (Chemura, Van Duren, and Van Leeuwen. 2015) where the authors used WorldView2 to determine the age after planting from an empirical relationship between tree age and crown projection (RMSE 1–13 years depending on the age of the tree).

In this study, we used the year of planting as a benchmark to generate the time series of oil palm distribution maps (2007–2016) at 250 m spatial resolution using the oil palm map of 2017. Figure 8(b) shows the estimated area under oil palm plantations plotted against reported area from national statistics in both countries (Indonesian Oil Palm Statistics; Malaysian Palm Oil Board). Due to lack of data at provincial level in years 2007–2010, the

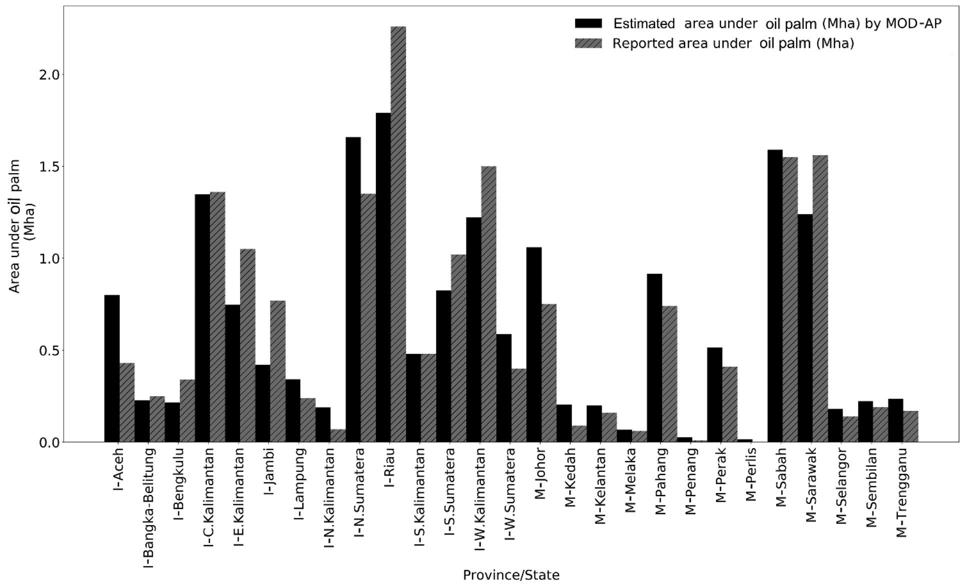

Figure 7. The estimated and reported area under oil palm plantations in 2017 at each province/state in Indonesia and Malaysia (unit in million ha (Mha)) (Indonesian Oil Palm Statistics 2017, Malaysian Oil Palm Statistics 2017).

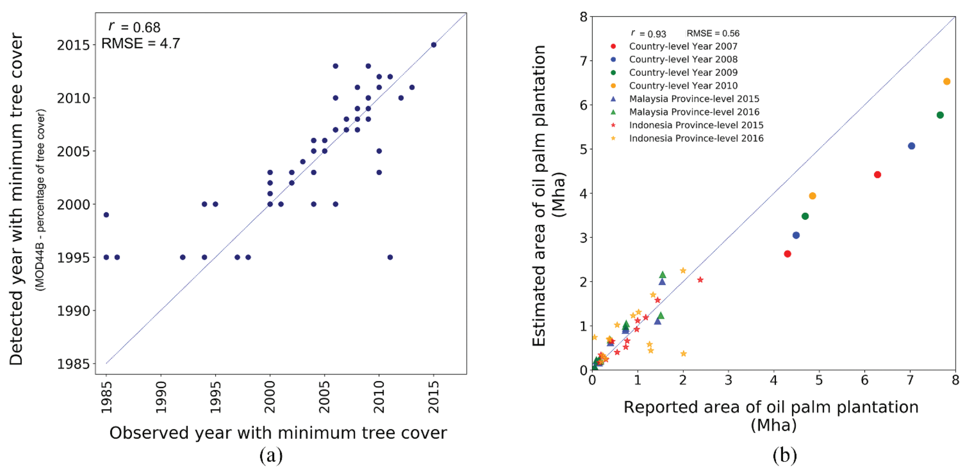

Figure 8. (a) Detected year of minimum tree cover vs the observed year of land clearance at 64 visually interpreted samples. (b) The estimated area under oil palm plantations vs reported area in years 2007–2017, with the RMSE of 0.5 (Mha) for all plotted data in all years.

area under oil palm in these years have been compared at the country level. The RMSE of estimated area in all data in the period of 2007–2016 was 0.5 million ha and R^2 was 0.9.

3.3. Oil palm biophysical suitability assessment

Combining the meteorological and geomorphological suitability indices, a time series (2007–2017) of biophysical suitability has been generated. Accordingly, in almost all the study area precipitation-related parameters (number of dry months and annual precipitation) are the least favourable factors for optimal oil palm growth. This is in agreement with Oettli, Behera, and Yamagata (2018) in the case of Malaysia where the author emphasized on the pronounced effect of precipitation among the other meteorological factors on FFB yield. In highly elevated regions, equal contribution of all three factors limits oil palm optimal growth. This is due to high correlation of elevation and temperature in a tropical region, where per 1000 m of elevation, temperature declines around 6°C (Pirker et al. 2016). In Central and East Kalimantan (refer to Figure 1 for the location of each province/state), combination of precipitation and temperature limitations is counted as a constrain for oil palm growth. Considering all meteorological and geomorphological factors, Lampung and North Kalimantan provinces in Indonesia and Sembilan and Johor states in Malaysia have been identified as the least biophysically favourable locations for oil palm plantations. While in contrast, Central, and West Kalimantan in Indonesia and Sarawak and Penang in Malaysia are the most favourable locations for this cultivation.

3.4. Oil palm yield estimation

3.4.1. Oil palm potential yield

The average potential yield in Malaysia in 2017 ranges between 13.8 t ha–1 and 19.3 t ha^{-1}, where in peninsular Malaysia it ranges between 13.5 t ha–1 and 18.1 t ha^{-1}. In Sabah and Sarawak, the average potential yield ranges between 20.2 t ha–1 and 20.8 t ha^{-1}. The estimated potential yields are well consistent with Oettli, Behera, and Yamagata (2018), in which the authors introduce a statistical climate-based model for Malaysia to predict oil palm yield using local atmospheric variable together with large-scale clime indices (such as ENSO). The maximum country-level potential yields had less than 0.5 (t ha^{-1}) differences in both studies, while the minimum potential yield showed 5.1 (t ha^{-1}) less in our study. Integrating the age after planting into potential yield estimation is the main reason for observed partial disagreement between both studies. However, as it was discussed in section 2.4, considering the age of plantation is a crucial step in oil palm potential yield estimation which has not been considered in the mentioned study.

The average potential yield in Indonesia in 2017 ranges between 17.8 t ha–1 and 21.7 t ha^{-1}, where in Sumatera it ranges between 17.1 t ha–1 and 21.7 t ha^{-1}, and in Kalimantan it ranges between 18.8 t ha–1 and 21.4 t ha^{-1}. We compared our estimated potential yields with an estimation of PALMSIM (Simulating potential growth and yield of oil palm) model introduced in Hoffmann et al. (2014) at eighth sample locations in Indonesia (Figure 9).

PALMSIM takes a simple physiological approach to estimate the upper ceiling of the oil palm potential yield which is determined by solar radiation and it is in absent of any other environmental limiting factors such as water limitation (Hoffmann et al. 2014). Therefore, in all locations PALMSIM showed overestimations on average of 19.8 t ha^{-1} year^{-1} in comparison with our estimations. This discrepancy was expected as PALMSIM authors also emphasized on the importance of consideration of the water limitation in future studies (Hoffmann et al. 2014). In Euler et al. (2016), the authors considered 75–80% of

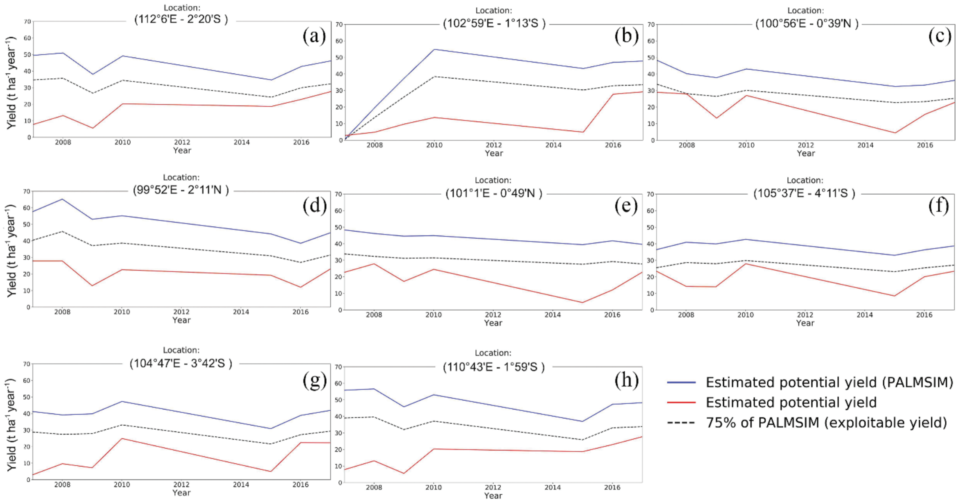

Figure 9. Comparison of estimated potential yields in this study and PALMSIM model in sample locations (a-h) in different years.

PALMSIM estimations as the oil palm exploitable yield for yield assessment in smallholder plantations in Jambi province in Indonesia. Comparing 75% of PALMSIM estimations with our study, 7.3 t ha^{-1} underestimation on average was realized in this study in all locations in 2017 (when our potential yield model was calibrated based on previous years). In both studies, however, the annual variation of potential yield showed similar patterns, which confirms the reasonable performance of our proposed methodology in capturing the effect of annual variations of meteorological factors on oil palm FFB yield. This similarity in pattern is mainly due to the covariance effect of temperature and solar radiation.

Figure 10 shows provincial potential yield in Indonesian and Malaysian provinces/ states in 2017. Respectively, the highest potential yields were captured at Bangka-Belitung, Bengkulu and West Sumatera in Indonesia and Sabah, Sarawak, and Perak in Malaysia. And the lowest potential yields were captured in Lampung and South Sumatera in Indonesia and Perlis and Terengganu in Malaysia. Considering the uncertainty levels embedded of input datasets, the uncertainty of 4.6 t ha^{-1} was estimated for potential yield estimation (supplementary material section-b).

3.4.2. Oil palm actual yield

We checked the association of provincial mean values of AP/AP2 HH, HV, and HH-HV with reported provincial yield separately using 80% of data as training data and 20% of data as testing data. Accordingly, HH-HV attribute showed the highest correlation of 0.5 at training data (Figure 11(a)), and 0.53 in testing data. The RMSE of estimated actual yield from HH-HV attribute was 2.9 t ha^{-1} year^{-1} with a mean value of 13.38 t ha^{-1} year^{-1}. The better association of HH-HV and reported yield are due to the characteristics of oil palm growth model, in which, as oil palm gets older, it produces more FFB which are located under the canopy (Corley and Tinker 2003). This structure leads to more volume scattering and greater HV value in high yield trees (Shabdin et al. 2017). This production is always associated with an increase in the height of tree, which together results in greater HH-HV. A weaker

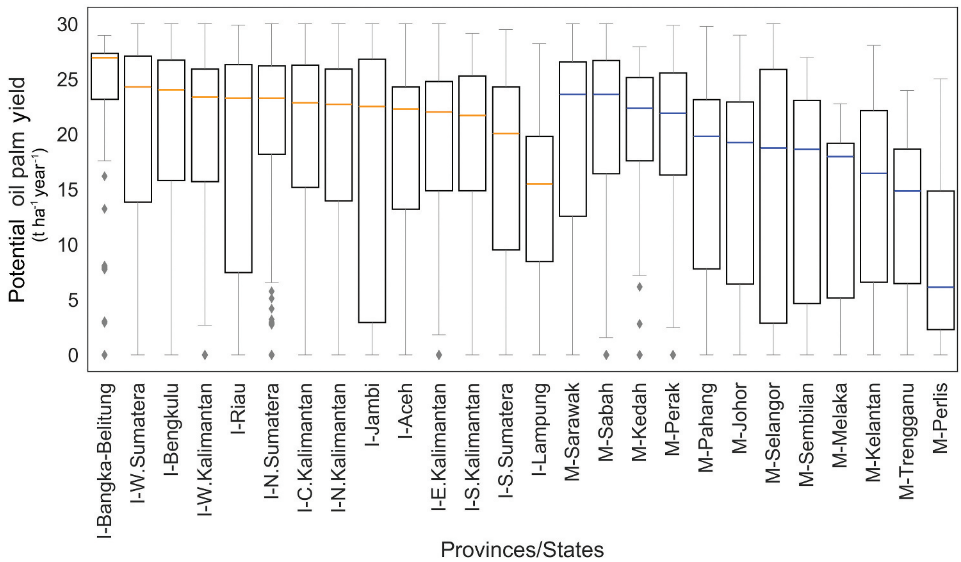

Figure 10. Provincial potential yield in Indonesian and Malaysian provinces/states in 2017 (sorted descending). The median potential yields for Indonesian provinces have been shown in orange and Malaysian states have been shown in blue. The error bars show the standard deviation of potential yield in each province/state. Indonesian provinces have been identified with I and Malaysian states have been identified with M.

correlation has been observed in the case of HV and HH bands (Figure 11(b and c)). The weak correlation of HH values and reported yields are due to the fact that apart from the FFBs, structure of canopy shows some differences in a different stage of growth and environmental conditions (Corley and Tinker 2003) which results in wide ranges of volume scattering. It is difficult to observe any association between reported yields and HH values, which is due to the fact that oil palm's height grows in whole tree life even in the over mature stage when the FFB production declines (Corley and Tinker 2003).

The average actual yield in Malaysia in 2017 ranges between 14.48 t ha–1 and 20.63 t ha^{-1}, where in Sabah and Sarawak it ranges between 16.41 t ha–1 and 18.50 t ha^{-1}. The average actual yield in Indonesia in the same year ranges between 8.49 t ha–1 and 15.40 t ha^{-1}, where in Sumatera it ranges between 8.49 t ha–1 and 15.40 t ha^{-1}, and in Kalimantan it ranges between 8.63 t ha^{-1} to 17.25 t ha^{-1}.

3.4.3. Oil palm yield assessment and agricultural practice level

We checked the discrepancy of potential and actual yields in each province/state. Accordingly, states of Sarawak and Sabah were identified with noticeable YG between potential and actual yields in comparison with the other states in Malaysia. Similarly, provinces of Aceh, North, and West Kalimantan in Indonesia showed a distinct gap in comparison with other provinces. Figure 12 shows the estimated gap in 2017, where the pixels with positive YG (actual yield is greater than potential yield) are presented in blue colour and negative gap (actual yield is less than potential yield) are presented in red colour.

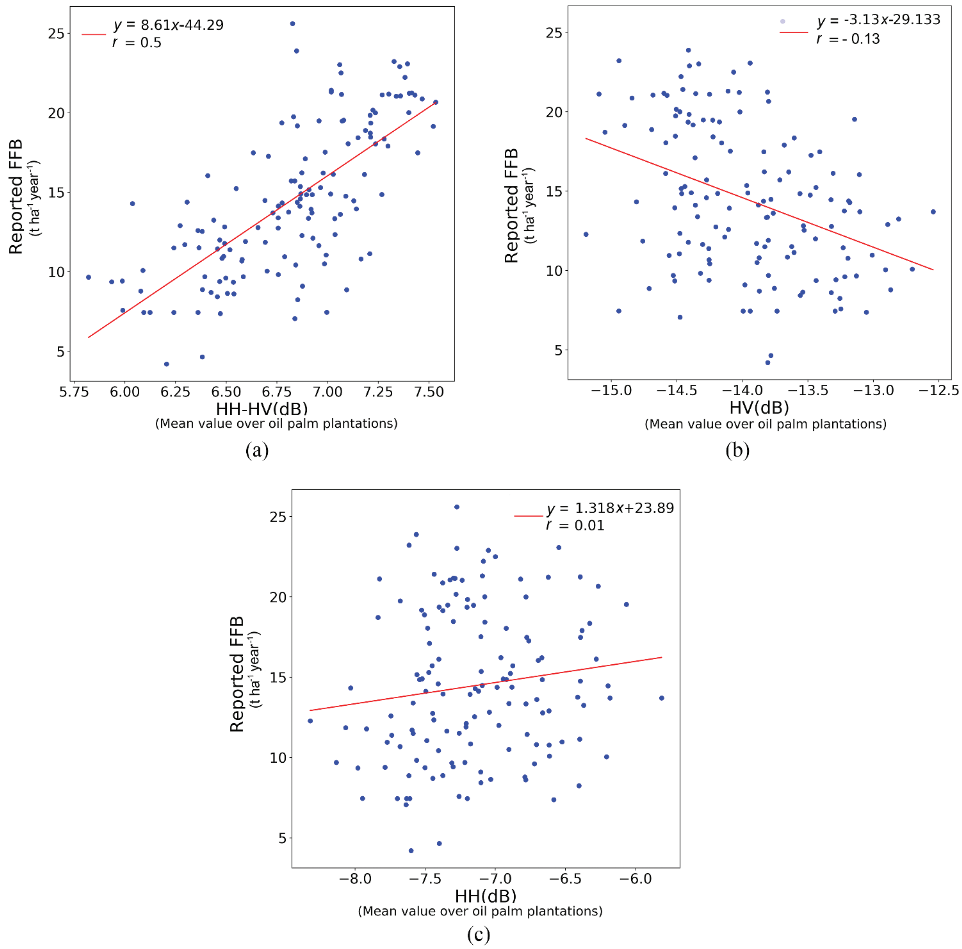

Figure 11. Reported yields plotted against the provincial mean of (a) HH-HV, (b) HV and (c) HH values over oil palm plantations. Each point shows the mean values for different provinces/states in different years at the training dataset.

In this study, oil palm yields exhibit spatial patterns in which the yields tended to be more similar for pixels that are close together than the pixels that are farther from each other. The dependency of yield variable to its location can be measured by different spatial autoregressive models which was not the measured in this study.

As it was discussed in section 2.6.4, the actual yield is a function of the agriculture practices together with the potential yield. Therefore, considering the ratio of actual and potential yields, we calculated the agriculture practice index (α). While in this study, the potential yield was considered to be a function of limited number of biophysical variables together with the age of plantation; the quantified actual yield is a function of far more variables at the plantation which some can be controlled by human practices such as pests, diseases, terrain correction, resistance genotypes, and supplementary water resources. Accordingly, resistance genotype to drought, supplementary water resource, and proper land preparation can potentially improve the actual yield in a given situation.

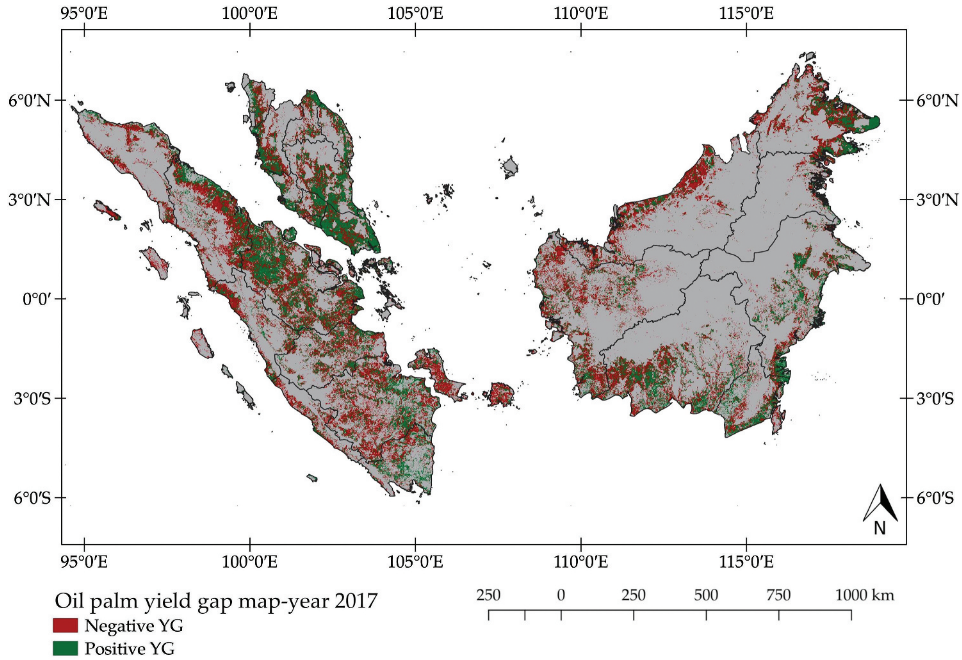

Figure 12. Estimated oil palm yield gap in Indonesia and Malaysia in 2017. pixels with positive yield gap (actual yield greater than potential yield) are presented in blue colour and negative gap (actual yield less than potential yield) are presented in red colour. Estimated oil palm yield gap in Indonesia and Malaysia in 2017. pixels with positive yield gap (actual yield greater than potential yield) are presented in blue colour and negative gap (actual yield less than potential yield) are presented in red colour.

While in contrast, the present of pests, diseases, or any other environmental constraining factors can reduce productivity.

Accordingly, pronounced differences were observed at provincial level between Indonesian and Malaysian oil palm sectors (Figure 13) where the majority of states in Malaysia were identified with α of greater than one, whereas all the provinces in Indonesia showed α of less than one. This characteristic was also reported in Varkkey, Tyson, and Choiruzzad (2018) where based on the national indicators the authors emphasized that Malaysia and Indonesia have developed almost adverse paths to satisfy the global palm oil demand. Accordingly, Malaysia has invested more efforts and resources into intensification which resulted in higher yield at a unit of area, while Indonesia has been more in favour of the expansion of the area.

Digging into possible reasons for these differences, we noticed a negative correlation ($r = 0.25$) between the agriculture practice index in each province/state and population of the smallholders (Figure 14(a)). The correlation suggests the greater the population of smallholder, the smaller the agriculture practice index, and consequently wider YG. This confirms other literature in which smallholders have been reported to suffer from a set of agronomic and institutional limitation affecting their productivity (Euler et al. 2016; Cramb 2013; Corley and Tinker 2003). Although the observed correlation was week, the pattern was clearer in the case of Indonesia provinces. In 2017, smallholders hold about 46% of

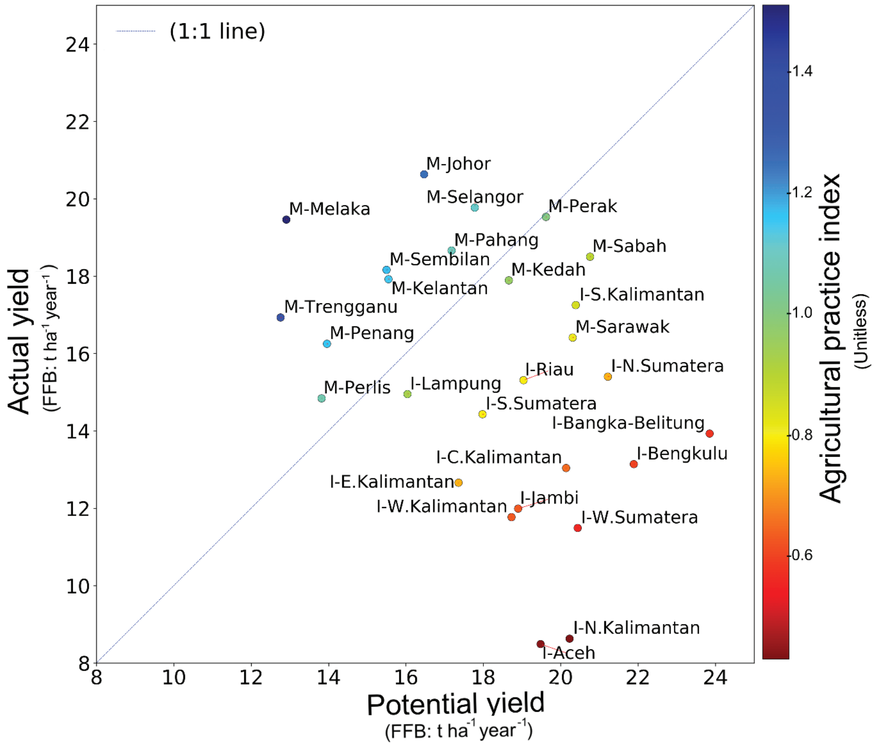

Figure 13. Agriculture Practice Index in different provinces/states in Indonesia and Malaysia in 2017. Indonesian provinces have been identified with I and Malaysian states have been identified with M.

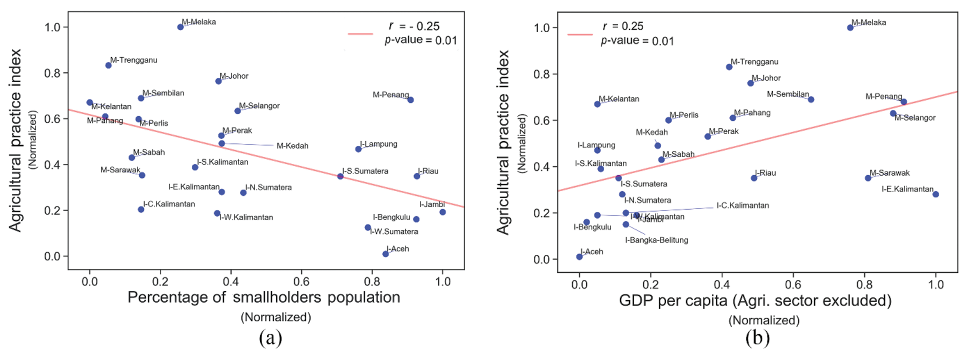

Figure 14. The relationship observed between (a) population of smallholders and (b) GDP per capita with agriculture practice index in different provinces/states in Indonesia and Malaysia. All the values have been normalized to maximum and minimum. The population of smallholders data in Indonesia and Malaysia was retrieved from (Indonesian Oil Palm Statistics 2017) and (Malaysian Palm Oil Board Malaysian Oil Palm Statistics 2017). The GDP data in Indonesia and Malaysia were retrieved from (BPS-Statistics Indonesia 2017) and (Department of Statistics Malaysia 2017).

the area under oil palm plantations in Indonesia which is equivalent to 12.3 Mha (Craw 2019; Indonesian Oil Palm Statistics 2017), where independent smallholders (who manage their plantations without being under the supervision of any mill or organization) include the majority of this population (Craw 2019). However, Malaysian smallholders hold about

39% of the area under oil palm plantations in 2017 (equals to 2.3 Mha) (Malaysian Palm Oil Board Malaysian Oil Palm Statistics 2017), where independent smallholders contribute for 16.9% of this area (nearly 1Mha). Therefore, the area under independent smallholders' plantations is distinctly different in both countries. Less productivity is a common characteristic of this group of growers. This resulted in a clearer negative correlation between the population of smallholders and the agriculture practice index in the case of Indonesia in contrast to Malaysia.

We also noticed a positive correlation ($r = 0.25$) between the agriculture practice index and Gross Domestic product (GDP) per capita (Figure 14(b)). Since the agriculture sector highly contributes to provinces/states' GDP, to avoid the covariance effect we only considered service and industry as main sources of GDP. Although the observed correlation was week, it confirms that the greater economic advancement can provide better agricultural practices which consequently it will lead to yield improvements (Euler et al. 2016). This pattern was clearer in the case of Malaysian states due to more investment of Malaysia on technical-based intensification which relies on economical advancements (Varkkey, Tyson, and Choiruzzad 2018).

Given this fact that, in both countries, the population of smallholders is expected to grow due to the limited suitable area for future expansion of large plantations (Pirker et al. 2016), according to observed correlations, we emphasize on the importance of policies and initiatives which support smallholders to be more equipped with better agriculture practices and technologies. Provided information in this research enables governors to directly target specific objectives such as subsidies on fertilizers, productive cultivars, and new technologies to support this group of growers to improve their productivity.

4. Conclusion

This study assessed oil palm potential and actuals yields and their gap in each province/state in Indonesia and Malaysia leveraging publicly available RS datasets and the computing power of GEE in processing. Considering potential growth of oil palm dependent on the site qualities and age of plantations, the average potential yield in Malaysia ranges between 13.8 t ha–1 and 19.3 t ha^{-1}, whereas in Indonesia it ranges between 17.8 t ha–1 and 21.7 t ha^{-1} in 2017. The actual yield in next step, has been quantified by HH-HV attribute of AP/AP2, where the average actual yield in Malaysia ranges between 14.48 t ha–1 and 20.63 t ha^{-1} and in Indonesia it ranges between 8.49 t ha–1 and 15.40 t ha^{-1} in 2017. Uncertainty of potential yield estimation was 4.64 t ha^{-1} year^{-1} and actual yield was 2.9 t ha^{-1} year^{-1}.

YG in different magnitude was observed in all Indonesian provinces, notably in Aceh, and North Kalimantan. Sabah and Sarawak states in Malaysia were also identified with relatively distinct YG in comparison with other states. However, in comparison with the Indonesian provinces, the magnitude of YG was smaller in Malaysia. In general, having lower potential in yield, majority of Malaysian states achieving higher actual yields at plantations which was in contrast with Indonesian case. Decomposing the effect of biophysical suitability of environment and age after planting on oil palm yield, the observed YG was attributed to the level of agriculture practice implementations. Higher economic advancement and a smaller population of the smallholders showed to be effective to improve the actual yields. In this study remotely sensed data showed great capacity to model potential and actual yields and provided a spatial distribution of each of those yields. However, for future studies following concern need to be addressed:

(1) Oil palm distribution should be precisely mapped to retrieve accurate information on actual yield and other characteristics involved in potential yield estimation. Here, we would like to particularly emphasize on difficulties in the detection of newly planted plantations due to small canopy coverage and presence of other endmembers in each pixel; as well as old oil palm plantations, where detection is challenging due to signal saturation. Finer spatio-temporal resolution is expected to improve the quality of mapping oil palm plantations.
(2) The association of L-band SAR HH-HV attribute with reported yield has been used to quantify actual yields. However, the reported data have been previously noted to inherit some degrees of underestimation due to their collection method (Hoffmann et al. 2017; Sadras et al. 2014; Burke and Lobell 2017). Therefore, accurately collected actual yield data in different locations will help to improve RS derived measurements.
(3) The potential yield in this study was estimated considering different meteorological and geomorphological parameters along with the growing model of oil palm. Although the biophysical criteria have been selected based on a detailed literature review but considering the extensive heterogeneity of the study area estimation of the potential yield could remain as a source of debate. Also, our estimation is in the case of absence of any other limiting factors such as pest, disease, or soil constraints, while, potential yield may differ in the case of the presence of each of these constraints.
(4) To estimate the year of planting, we assumed that oil palm trees have been planted in the same year of land preparation, however, we noticed on average three years' time lag between the year of land clearance and oil palm planting in some locations (Gaveau et al. 2016) which is needed to be address in the future studies. On this, we would like to highlight the importance of ancillary information on the age of plantations. Oil palm age information is a crucial missing information layer in oil palm yield assessment in both countries. Future studies in large scale oil palm age detection are expected to provide useful information on YG management.

We hope this study can contribute to sustainable production of palm oil as it provides useful benchmarks for improving the yield. This information are indispensable needs for efficient and accountable policies as it enables governors to directly target specific objectives such as subsidies on fertilizers, productive cultivars, and new technologies for specific plantations suffering the most from low yield.

Disclosure statement

No potential conflict of interest was reported by the authors.

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