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Mapping of Mature and Young Oil Palm Distributions in a Humid Tropical River Basin for Flood Vulnerability Assessment

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Abstract. Oil palm is one of the key drivers of economic growth in some regions in the humid tropical countries such as Indonesia. Previous studies show that floods risk at particular river basins in Indonesia will increase in the future due to climate change. This will give negative impacts to the sustainable production of palm oil in the future and subsequently the regions' economy. Discussion on adaptation strategies on this matter is necessary however, the vulnerability of oil palm plantations against floods at river basin scale are still poorly understood. Field surveys for oil palms' vulnerability at such scale is costly in time, labour and resources, and making use of remote sensing is more feasible. The aim of this study is to use remote sensing in assessing oil palm vulnerability against floods at river basin scale. To achieve this objective two oil palm distribution maps which were developed using Sentinel imageries for years 2015 and 2018 allowing young oil palms to be matured under normal condition. To understand the impact of floods to oil palms, a composite of flood extents using radar scenes for years 2016 and 2017 was developed. Our results show that young oil palms are highly vulnerable to floods compared to matured ones. Only 6% of the earlier could survived floods and be matured in time, while most of the matured ones could survive.

1. Introduction

Oil palm plantations are ideally grown in humid equatorial condition [1] and therefore, its expansion rate in the humid tropical region was high. Its rapid expansion in the recent decade has been linked with the rapid deforestation rate in the region [2]. However, a few studies argue that deforestation has happened long before the oil palm expansion and that oil palm plantations were not directly grown in forest cleared lands but on non-forest or degraded forest [3]. Despite the heated debate whether or not the expansion of oil palm is major driver of the deforestation, oil palms are among the key drivers of economic growth and source of income of communities in some regions in the humid tropics.

The humid tropical regions have considerably high annual rainfall where monthly rainfall rate is higher than 100 mm for more than 9.5 months in a year [4]. Particularly, in the Batanghari River Basin, Indonesia, the downstream areas are regularly flooded every year and the society seems to understand how to cope with the current floods. With the higher rate of development, the population increases and so does the need of land for economic activities. Most of the non-flooded lowland areas are currently being used for industrial oil palm plantations and settlements. The societies also grow

small holder plantations in some downstream areas, and with limited land spaces, some gambled by growing plantations in flood prone areas.

Previous studies in the basin show that the flood extent and depth will increase in the future due to climate change, particularly in the downstream area, e.g. [5; 6]. Based on [5] floods in Batanghari River Basin will increase by 2.3 times while the maximum flood depth will increase from 3.7 m to 4.8 m. With the increase of flood risk, it will be more difficult for farmers and plantation owners to cope with floods. That is why it is more likely the favourable location for oil palm will shift to the upstream area. In addition to the higher flood risk in the lowland areas, the increase in the temperature makes higher elevation areas which is currently too cool for oil palm may become suitable for oil palm in the future [7]. This will give higher pressure to the remaining tropical forest which mostly located in high altitude areas. Understanding how to manage the current extent of oil palm plantations under future flood risks is perhaps one of the important steps to prevent further deforestation upstream.

Impact of floods on oil palm plantations has been studied in decades at laboratory or plantation scale. Under normal condition, in average oil palm will be matured and start producing fruits 3 years after plantation. Based on previous studies, these young oil palms (YOP) are likely could not survive prolonged floods [8][9] or floods that is higher than their leaf axils [10]. Oil palms which are older than 3 years are more resilient to floods. However, oil palms which are planted in frequently flooded area has less biological activities than those in area with ideal water table [11] and yields 20-30% less fruits [12; 13]. There are also cases where flooded mature oil palm died due to physical damage (toppled over) [13]. Access for oil palm maintenance and harvesting is also severely affected by floods [13]. Furthermore, the oil palms need to be replanted every 20-25 years to maintain high yield of fruits. With increasing flood risk, future replanting may have lower success rate and it might be challenging to keep the current oil palm extent in the future.

This study proposes to make use of remote sensing to understand the vulnerability of oil palms, particularly the young ones against floods. To achieve this objective, two oil palms distribution maps were developed for the year 2015 and 2018. The distribution maps differentiate immature oil palms from the mature ones (MOP). Under normal condition, the YOP in 2015 will be matured and classified as MOP. To analyze the vulnerability of oil palms under flooding conditions, this study developed composite of floods during 2016-2017. This study aims to answer the following questions:

- What is the percentage of flooded YOP to survive and get matured in time?
- What is the percentage of flooded MOP which can survive?
- What kind of changes to the rest of flooded oil palms which could not survive or matured in time?

2. Materials and methods

2.1. Data and Study Area

2.1.1. Study Area. This study used the Batanghari River Basin (42,960 km^2) as a study area which covers part of Jambi and West Sumatra provinces. The two provinces are among the biggest palm oil contributors in Indonesia. The west part of the basin is mountainous area – part of Bukit Barisan range with the highest peak of 3,805 m a.s.l at Mount Kerinci. However, the largest part of the basin is undulating hills with elevation between 10-100 m a.s.l. [14]. The downstream area is flat swamp areas where the capital of Jambi province and some oil palm plantations are located. The climate in the basin is categorized as humid tropics with average annual rainfall is 2021 ± 247 mm [14] with average monthly rainfall higher than 100 mm. The combination of high rainfall and flat topography makes the downstream part of the basin regularly flooded and people has local wisdom to cope with floods with certain magnitude. Deforestation in the basin took place in the early 1990s and forest area reduced by more than half in 2015. This fact raised concern among the society, particularly on the increase of magnitude and frequency of floods. Earlier studies showed that the combination of deforestation and climate change in the basin will increase the flood risk in the future, e.g. [5; 6; 16].

2.1.2. Data. This study used Sentinel imageries hosted in Google Earth Engine (GEE) to create oil palm distribution maps and composite of floods extents. The optical multispectral images from Sentinel-2 satellites and the Synthetic Aperture Radar (SAR) data collected by Sentinel-1 satellites were used to produce the distribution maps. The composite of flood extent was developed based on the Sentinel-1 SAR data. Specifically, this study used Sentinel-1 SAR Ground Range Detected (GRD) with 10-meter resolution and Sentinel-2 Top-Of-Atmosphere with various spectral resolutions (10, 20 and 60-meter resolution) which are hosted in GEE.

This study collected 5,455 training and validation points (Figure 1) with a visual interpretation over the study area using the high-resolution historical Google Earth orthophotos from year 2015, Sentinel-1 and Sentinel-2 images. The points were collected in Google Earth Pro in kml format. The training points were further processed in ArcMap by assigning classification numbers and converting the format to shapefile to fit requirement to upload in the Google Earth Engine. The classes which were visually distinguished were: 1. Waterbody – 132 points (2%), 2. Settlements – 853 points (16%), 3. Mature Oil Palm – 1,397 points (26%), 4. Young Oil Palm – 902 points (17%), 5. Forest – 873 points (16%) and 6. Other land uses – 1,298 points (24%).
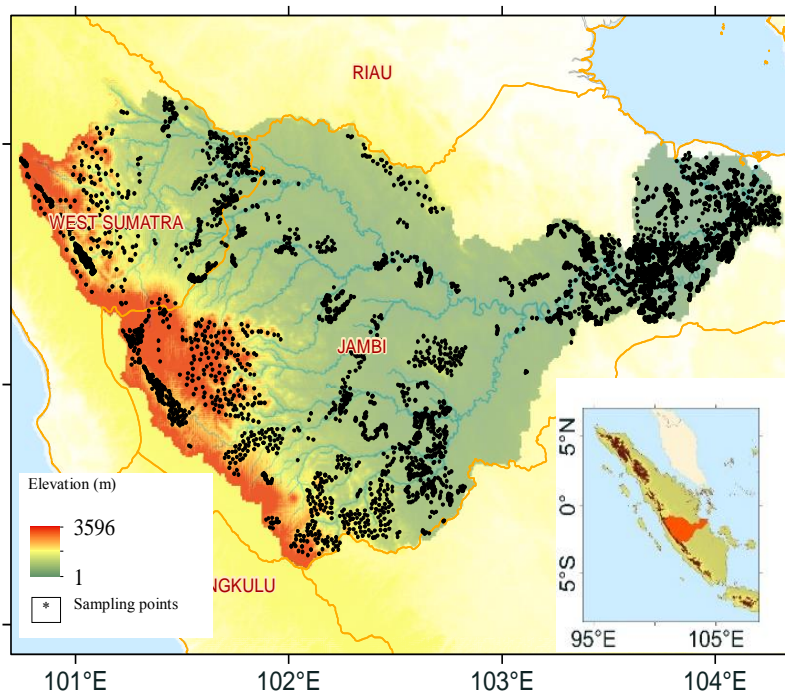

Figure 1. Location of training and validation points
in the Batanghari River Basin, Indonesia.

We visually distinguished oil palm to other plantations from its distinct eight-pointed star from a bird's eye view [16]. The oil palm plantations, particularly the industrial ones have distinctive pattern of dense harvest tracks or roads which make it easier to locate over a large area.

In this study, we aimed to map young oil palms younger than 3 years which are vulnerable to prolonged floods [8]. [17] defined the relationship between age of oil palm and their Crown Projected Area in m^2 (CPA)

$$EA = 0.59 + 0.15\ CPA \tag{1}$$

where *EA* is the estimated oil palm age in years. Based on eq.1 the *CPA* for young oil palm of three years old is 16 m^2. Therefore, we collected samples for young oil palm classification from plantations with average *CPA* less than 16 m^2 (see figure 2 for example of oil palms with *CPA* less than 16 m^2). *CPA* was measured using the Google Earth Pro ruler tool during sample collection.

Figure 2. (left) Young oil palm in Batanghari River Basin taken in
November 2017 (Photo: K. Yamamoto) and (right) Google
Earth high-resolution historical orthophotos from August 2019.

2.2. Algorithm Overview
To assess the vulnerability of oil palm against floods, two oil palm distribution maps with 3 years gap (2015 and 2018) were developed. Under normal condition, the YOP will be matured in 2015. In order to analyse changes in oil palm distribution due to flooding, one composite map of all floods in 2016 and 2017 was developed..

2.2.1. Algorithm for oil palms classification. We carried out the whole processing chain in Google Earth Engine except for sample collection and post-classification process. First, we created cloudless composites of Sentinel-1 and Sentinel-2 images for year 2015 and 2018 which are hosted in Google Earth Engine [18]. The Sentinel-1 composites are based on median values of daily images during one-year period for year 2015 and 4-month period (June-October) for year 2018. The Sentinel-2 composites are using daily images of three-year period (2015-2017) to create composite of year 2015 and one-year period to create composite of year 2018. The compositing period was set into three-year period for Sentinel-2 in the year 2015 since that is the minimum window size to create a cloud-free composite in the Batanghari River Basin. However, one-year period is sufficient to create cloud-free composite in the year 2018. The Sentinel-1 scenes were pre-processed using the Sentinel-1 Toolbox in Google Earth Engine for thermal noise removal, radiometric calibration and terrain correction. To create the cloud-free composite of Sentinel-2, we first masked the daily images using bit 10 (for cloud) and bit 11 (for cirrus) of QA60 band. Then, we further masked the cloud using cloud-score algorithm adapted for Sentinel-2 [19].

Since oil palm has distinctive patterns, the use of median filter and Grey-Level Co-Occurrence Matrix (GLCM) [20; 21] which can capture the texture of surrounding cells may improve the accuracy [15]. In this study, we used these textural analysis as additional predictive bands for oil palm classification (method 2) and compared the classification results without the use of texture analysis (method 1). Predictive bands used in both methods are listed in Table 1. Ideally, we should select predictive bands using all original bands and use feature selection process to pick the best predictive bands. However, in this study we just used some selected features based on [22] i.e. median filter with kernel size 5, GLCM Sum Average, GLCM max correlation coefficient, GLCM correlation, GLCM difference variance, GLCM contrast and GLCM cluster shade, all with kernel size 10. Table 1 summarize the difference between the two methods.

Table 1. Predictive bands used in oil palm classification.

Method 1	Method 2
2 bands of Sentinel-1	2 bands of Sentinel-1
13 bands of Sentinel-2	13 bands of Sentinel-2
Normalized Difference Vegetation Index (NDVI)	Median filter for Sentinel-1 bands (kernel size 5)
NDVI texture (standard deviation, kernel size 5)	GLCM for 9 Sentinel-2 bands (kernel size 10)

The classification process consists of three parts i.e. sampling process, training process and classification process. We used composites of 2015 for sampling and training process and then used the classifier to classify composites for 2015 and 2018. Before the sampling process, we randomly split the collected sample points (figure 1) into two parts. Half of the samples were used as trainer and half were used for validation. In the sampling process, the trainers took information of predictive bands of the pixel where they are located. These trainers were then used to create classifier using the Random Forest (RF) classification (training process). We used random forest (RF) parameters from [23] for maximum tree depth (100) and variable per split (4). The classifier was then used to classify land use from composites of 2015 and 2018 images.

We assessed the accuracy of each method (with and without texture analysis) and sampling resolution with kappa coefficient and overall accuracy. We only performed validation for classification in the year 2015.

We improved the general appearance of the classification by removing the salt and pepper effect through post-classification processing. The process was carried out in ArcMap 10.5 using ArcGIS Spatial Analyst. We carried out the following process:

1. Filtered the classified output using Majority Filter tool;
2. Smoothed the class boundaries and clump the classified output using Boundary Clean tool;
3. Removed the small isolated regions (less than 150 pixels) using the Region Group, Set Null and Nibble tools.

2.2.2. Algorithm for composite of floods extents. The composite of flood extents was developed with daily images of Sentinel-1 SAR GRD. We used flood mapping method based on [24] by using change detection method. In this method, in principal the difference of backscatter values of two images – image before floods and image during floods - were used to define flood extent.

One Sentinel-1 image can only cover part of the basin and to cover the whole basin we combined (mosaic) images during 15 days period. The 'before floods image' were developed using mosaic from images in August 2016 (dry season period). The 'during floods images' were created by creating mosaics of images from December 2016 to April 2017. Before calculating the difference, we filtered the speckles by smoothing with circle radius of 250 m. The difference was calculated by dividing vertical polarization (VV) values of 'during flood image' with 'before flood image'. The flood extent was areas with difference higher than 1.15. This threshold value was obtained through calibration process using available flooding photos. We then refined the results by excluding 'permanent and perennial water extent' (JRC Global Surface Water Mapping Layers, v1.2), floods on slope higher than 5% (WWF HydroSHEDS Void-Filled DEM, 3 Arc-Seconds), and flood extent with neighbourhood pixels less than 8. We then merged all flood extents from every half-month mosaic images as composite of floods during December 2016 to April 2017.

3. Results and Discussion

This study shows that oil palm distribution maps at river basin scale can be obtained with accuracy of 85% using method 1, however the use of texture analysis the accuracy increases to 86%. This

concludes that Sentinel 1 and 2 can be used to discriminate young and mature oil palm in a large river basin with satisfactory results. However, we expected that the use of texture analysis will give higher improvement in the classification as was performed by [22]. Yet, in this study it only gives about 1% improvement. The reason might be because the selection of additional predictive features was not based on feature selection method.
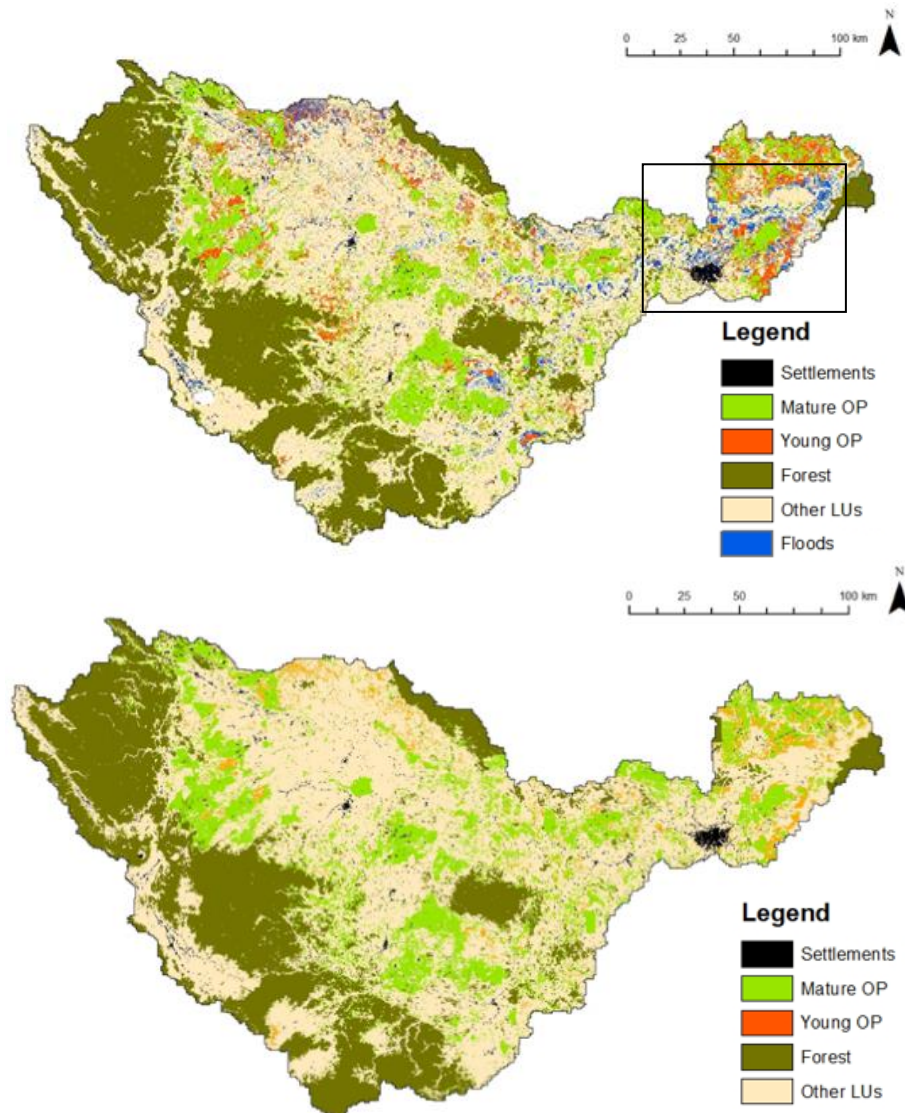

Figure 3. Map of oil palm distribution for year 2015 (with floods in 2016-2017) (upper) and 2018 (bottom). The box in the upper figure is the downstream area used in figure 4.

Figure 3 shows the classification maps after post-classification processing. In the year 2015, based on the classification map, the oil palm plantation is 21% of the area Batanghari River Basin or about 8,902 km^2 and this area did not change much in 2018 (reduced by 2%). In figure 3 (upper), we also included composites of floods extent obtained from Sentinel-1 images during 2016-2017. The floods during 2016 to 2017 flooded 2% of oil palms in the basin or about 181 km^2. The flooded oil palms consist of mostly YOP (79%). These results show that the current oil palm plantations (which consist

of mostly MOP) are mostly located in area free of floods. However, there are attempts to expand the oil palms in flooding area (indicated by higher portion of flooded YOP).

Most of the flooded MOP survived in 2018 (52%), only 2% changed to YOP (replanted). The remaining part of flooded MOP (44%) changed into other land uses. On the other hand, only 6% of the flooded YOP can survive and matured in 2018. The remaining flooded young oil palms changed into other land uses (59%) such as bare lands (abandoned) or has slow growth (remains young) (35%). We verified some of the changes with the use of Google Earth historical orthophotos which cover both years, however not all changes could be validated. Figure 4 shows examples of changes in flooded YOP.
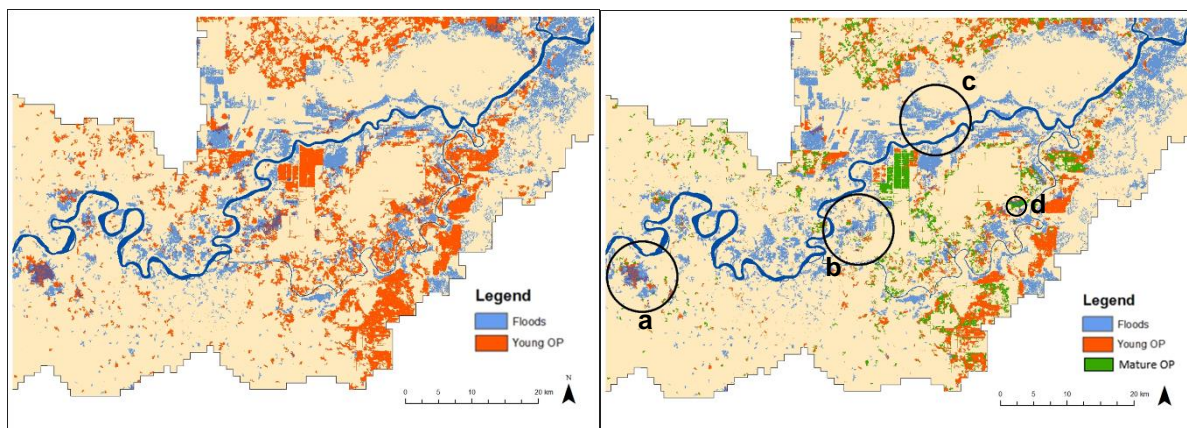

Figure 4. Detailed comparison of flooded YOP in downstream area (location can be viewed in Figure 3) in 2015 (left) and situation in 2018 (right). (a) YOP remains young in 2018, (b) and (c) YOP changed into other LUs and (d) survived OP.

These results show that we can use remote sensing to understand the vulnerability oil palms against floods at river basin scale using time series oil palm distribution maps and composite of floods extents. Furthermore, there is potential use of the time series oil palm distribution maps such as to understand the shifting of oil palms in the basin. The percentage of oil palm plantation in downstream area (after the confluence of Batanghari River) in 2018 is larger (20%) than in the upstream area (18%). However, the percentage of new young oil palms (changed from forest, settlements or other land uses) in the upstream area is a little bit higher (13%) than in downstream area (11%). More time series maps can support this argument, but this indicates that the oil palm plantations started to shift to upstream area.

4.   Conclusions

This study assessed the use of remote sensing to assess the vulnerability of oil palms against floods by using time series oil palm distribution maps at river basin scale and composite of floods extents. Cloudless composites of Sentinel-1 and 2 can be used to classify young and mature oil palms in the Batanghari River Basin, Indonesia with satisfactory accuracy (85%). The use of texture analysis as additional predictive bands improved the accuracy by 1%.

Based on this study, the oil palm area between 2015 and 2018 did not change much. Most of oil palm plantations are located in flood free area, however there are some attempts of opening new plantation sites in the flooded area. The flooded MOP has much higher survival rate (52%) than the YOP (6%). Only 2% of the flooded MOP became YOP in 2018, probably were replanted. However, there were 35% of the YOP remains young in 2018. These oil palms could be replanted or has slower growth (could be matured in time). The change of flooded oil palms to other land uses, however, results in significant portion (44% for MOP and 59% for YOP).

This study demonstrates that remote sensing can be used in assessing the vulnerability of oil plams against flood, including the survivability of young and matured oil palms after flooding. However,

other changes such as when oil palms were converted to other land uses should be further clarified through communications with farmers or oil palm plantations companies.

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