Application of SAR data for oil palm tree discrimination

Y W Kee¹, A R M Shariff¹,*, A M Sood² and L Nordin³

¹Department of Biological and Agricultural Engineering, Faculty of Engineering, University Putra Malaysia, 43400 UPM Serdang, Selangor, Malaysia.
²Department of Forest Management, Faculty of Forestry, University Putra Malaysia, 43400 UPM Serdang, Selangor, Malaysia.
³Geoprecision Tech Sdn. Bhd., Lot 2-4 Innovation House, Technology Park Malaysia, Leboh Raya Puchong - Sg Besi 57000 Bukit Jalil, Kuala Lumpur, Malaysia.

rashidpls@upm.edu.my

Abstract. Oil palm tree discrimination is an important step for tree counting. In order for proper planning and management of the plantation, it is important to identify and classify oil palm tree species distinctively from other tree species and weeds. As oil palm trees are green leafy plants, it is difficult to differentiate between oil palm trees and weeds through color classification alone. Tree height can be determined through proper photogrammetric method. However, it is time consuming. SAR data processing is becoming a promising technology in the field of geospatial. Backscatter coefficient value is influenced by the roughness of surface, type of target and moisture content of target. The aim of this research is to utilize L-band ALOS PALSAR-2 dataset and open source C-band Sentinel-1 SAR datasets to discriminate oil palm trees from weeds as there is significant height difference between them. This research determines the backscatter coefficient value range of oil palm trees and weeds, it investigates the suitability of utilizing C-band and L-band SAR data on oil palm tree discrimination. Several existing oil palm field parameters are tested based on the backscatter value of SAR image. The results and discussion of backscatter value ranges between oil palm tree species and weed species will be further discussed in the paper.

1. Introduction
Remote sensing technology and Geographical Information System (GIS) are commonly applied in agriculture and forestry sectors. These technologies provide precise affordable and efficient solution for agricultural and forestry planning, monitoring and management. Oil palm trees discrimination is the most essential steps for tree species classification, oil palm trees counting and aboveground biomass estimation. Traditionally, optical satellite sensors are adapted for oil palm trees classification as shown in the research of [1] and [2]. Other than that, hyperspectral datasets are also becoming more popular for tree type classification due to its capability of providing subtle information for each fine wavelength [3] and [4] are capable to extract oil palm trees information from hyperspectral datasets.

Due to the clouds obscure the view of land use and land cover features from the image, airborne optical sensors are introduced to overcome this limitation. [5] and [6] are adopting Unmanned Aerial Vehicle (UAV) with RGB sensor for oil palm tree counting. Most of oil palm plantation covered the
soil surface with weed to reduce surface runoff. With the present of weed, it increases the difficulty of discrimination from the image due to weed have the color with similar hue as of oil palm trees. Discrimination of oil palm trees with color processing may leads to misclassification. Later on, LiDAR is introducing as it is capable to model 3-dimensional details of trees as well as provide accurate height of the trees. With the help of LiDAR, it can solve the issue of confusion between oil palm trees and weed. [7] is capable to model height of oil palm trees and to estimate the age of oil palm trees by integrating optical satellite data and LiDAR data. [8] also found that oil palm replanting operation could be proper planning with aid of LiDAR and optical datasets. However, it required high operating cost and difficult to interpret of its large size of dataset.

Currently, microwave sensors become a promising approach in the application of remote sensing due to its cloud penetration as well as its capability on obtaining data in all-weather condition and day to night. Besides that, microwave sensor rely on its own energy source unlike the optical sensors which relying on the energy source from sunlight. Boreal forest tree species are successfully separated by using RADAR datasets in the research of [9]-[12]. Even there are many articles are found that L-band sensors are capable for tree types classification, it was disagreed by [9] and [12]. [10] and [12] found that combination of multifrequency and multipolarization is capable to define the tree height and hence the biomass of dry matter. Hence, the aim of this project is introducing L-band ALOS PALSAR-2 dataset to discriminate oil palm trees from its background targets. There are two objectives of this research that are required to achieve which are: (1) to determine the backscatter value of oil palm tree from C-band and L-band SAR data; and (2) to investigate the suitability of utilizing C-band and L-band SAR data on oil palm tree discrimination.

2. Materials and Methods

2.1. Study Area
The study area is located in Seberang Perak, Perak, Malaysia where its geographical location is lies between latitudes 4° 05’ 56.3288” N & 4° 06’ 50.4958” N and longitudes 100° 53’ 44.9750’ E & 100° 53’ 04.5281” E, comprising 111 ha of oil palm planted area as shown in Figure 1. The age of oil palm planted in the study area is between 9-12 years old. Most of the oil palm trees in this study area are infected with Ganoderma boninense disease and it is the reason of existence of missing oil palm trees in this area.

2.2. Data Used
ALOS PALSAR-2 data and Sentinel-1A data were tested in this project while KOMPSAT-2 high resolution optical satellite image with the acquired date of 23th April 2017 is used as ground truth training and validation data. The details of the SAR images as presented in the Table 1.

| Sensor          | ALOS PALSAR-2            | Sentinel-1A                  |
|-----------------|--------------------------|-----------------------------|
| Polarization    | Full Polarization (HH, HV, VH, VV) | Dual Polarization (VH, VV)  |
| Mode            | High-sensitive Mode      | Interferometric Wide Swath  |
| Wavelength Range| L-band (1.2GHz)          | C-band                      |
| Pixel Spacing   | 3.125m                   | 10m                         |
| Processing Level| Level 1.5                | Level 1                     |
| Product Type    | Geo-referenced Amplitude Image | Ground Range Detected Image |
| Date of Acquisition | 1st May 2017            | 3rd May 2017                |
2.3. SAR Image Pre-processing

Figure 2 depicts the proposed methodology flowchart of SAR image processing. As shown in Figure 2, both ALOS PALSAR-2 data and Sentinel-1A data are subjected to the similar steps of image processing. Speckle filtering and radiometric correction are applied to both datasets. Since ALOS PALSAR-2 L1.5 data has been subjected to geometrical correction, hence, Range Doppler Terrain Correction step is unnecessary for this data.

It is found that Frost filtering was successfully adopted by [13] to estimate AGB of mangrove forest and the same filter is also applied to his research on oil palm related research. Therefore, Frost filter is also used to reduce the speckle noise in this project. [14] stated that kernel size of filter plays an important role in smoothing the image. The bigger size of the window is providing smoother image. In order to preserve the details of the image, appropriate size should be selected for better result. Due to a single pixel size of ALOS PALSAR-2 data is 3.125m, 3×3 of window filter size was selected as the size is similar to the ideal planting distance of oil palm. Meanwhile, 3×3 of window filter size is also applied to Sentinel-1A consider the optimum window size of filtering even the pixel spacing of Sentinel-1A data is larger.

Since both sensors are created and the data are processed by different agencies, the methods of radiometric calibration for both data are slightly different. According to [15], sigma naught of ALOS data or commonly known as backscattering can be obtained by radiometric calibrating using Equation (1). Meanwhile, backscattering value of Sentinel-1A is converting from the gamma-calibrated backscattering coefficient as shown in Equation (2) [16].

\[ \sigma^0 dB = 10 \times \log_{10}[DN^2] - 83 \text{ dB} \]  \hspace{1cm} (1)

\[ \sigma^0 dB = 10 \times \log_{10}[\gamma_i] \]  \hspace{1cm} (2)

where \( \text{DN} \) is the digital number of the ALOS PALSAR-2 data and \( \gamma_i \) is the gamma-calibrated backscattering coefficient of Sentinel-1A data.
2.4. Training Data
Ground truth data was obtained by digitizing from KOMPSAT-2 image. The coordinate of each center of oil palm canopies, weed area and soil area are extracted. Due to trees are mature in this plantation area, the canopies of oil palm trees are overlapping and the diameter of canopies are bigger to the planting distance which is 9m.
Each oil palm tree is expected occupied the ground area with the diameter of 9m. In order to ensure the buffering area is only covering one species target, point buffering with the radius of 3m is introduced to each target point. The backscattering value for each class is extracted from the processed SAR image by using Extract Multi Values tool in ArcGIS. The mean of backscatter value for each polarization for each class is examined.

2.5. Image Classification

Maximum Likelihood Classifier is used to classify the image into three classes. In Malaysia, there are numerous large scale of oil palm plantations and the planting area will be planted with only oil palm trees. Hence, most of the plantations have only three main targets in the plantation which are oil palm trees, weed and soil. Maximum Likelihood Classifier calculates the probability that a given pixel belongs to a specific class and the pixel will be allocated to the class where it has the highest probability. [12] is successfully classified boreal forest tree species using Maximum Likelihood Classifier. [17] is also able to obtain high accuracy of forest and oil palm classification by using the same classifier.

2.6. Leaf Area Index, Trunk Height and Biomass

In order to classify accurately, Oil palm related field parameters are calculated based on the invented formulae in the previous researches. The formulae are including leaf area index (LAI) as in Equation (3) and (4), trunk height as in Equation (5) and (6), and aboveground biomass as in Equation (7) – (8). [18] created some field parameters of oil palm as shown in Equation (3) – (8). Both SAR images are applied to the formulae above and further classify using Maximum Likelihood Classifier. The result of the classification is examined.

\[ \text{LAI} = -13.215 + 3.647 \sigma_{L_{HH}}^0 - 0.598(\sigma_{L_{HH}}^0)^2 \]  \( \text{(3)} \)

\[ \text{LAI} = -8.936 + 2.096 \sigma_{C_{VV}}^0 - 0.349(\sigma_{C_{VV}}^0)^2 \]  \( \text{(4)} \)

\[ \text{Trunk Height (m)} = -11.697 + 2.204 \sigma_{L_{HH}}^0 - 0.403(\sigma_{L_{HH}}^0)^2 + 2.39e^{-2}(\sigma_{L_{HH}}^0)^3 \]  \( \text{(5)} \)

\[ \text{Trunk Height (m)} = -8.342 + 1.477 \sigma_{C_{VV}}^0 - 0.255(\sigma_{C_{VV}}^0)^2 + 1.36e^{-2}(\sigma_{C_{VV}}^0)^3 \]  \( \text{(6)} \)

\[ \text{Biomass (t ha}^{-1} ) = -11.856 + 5.47e^{-2} \sigma_{L_{HH}}^0 - 2.49e^{-4}(\sigma_{L_{HH}}^0)^2 + 3.92e^{-7}(\sigma_{L_{HH}}^0)^3 \]  \( \text{(7)} \)

\[ \text{Biomass (t ha}^{-1} ) = -8.349 + 4.23e^{-2} \sigma_{C_{VV}}^0 - 2.15e^{-4}(\sigma_{C_{VV}}^0)^2 + 3.40e^{-7}(\sigma_{C_{VV}}^0)^3 \]  \( \text{(8)} \)

3. Result and Discussion

3.1. Backscattering Value

Table 2 shows the backscattering range for oil palm class and non-oil palm class. Oil palm tree and weed provide different structural attributes and theoretically it should be varying in term of backscatter value. However, weed and soil are combined into one class due to the backscattering signal of weed class is dominant by the soil backscattering. According to [12], the dominant backscattering for low vegetation is the direct backscattering from the ground surface for both L-band and C-band SAR data due to their penetration capabilities.

Tan et al. [19] reported the backscattering value of oil palm from his research is range of -5dB to -12.5dB for L-band HH polarization and -10dB to -16.5dB for L-band HV polarization. However, the backscattering value of oil palm that obtained from this research has wider range as shown in Table 2. This might be affected by the varying resolution of the data, surface moisture of the area and the way of processing the SAR data.
Table 2. Backscatter Values from ALOS PALSAR-2 and Sentinel-1

| Sensor            | ALOS PALSAR-2 |          | Sentinel-1A |          |
|-------------------|---------------|----------|-------------|----------|
|                   | Oil Palm      | Non-oil Palm | Oil Palm    | Non-oil Palm |
| $\sigma^o_{HH,min}$ (dB) | -16.82        | -13.29   | -           | -         |
| $\sigma^o_{HH,max}$ (dB)  | -1.67         | -1.09    | -           | -         |
| $\sigma^o_{HH,mean}$ (dB) | -8.87         | -8.27    | -           | -         |
| $\sigma^o_{HV,min}$ (dB)  | -25.79        | -26.72   | -           | -         |
| $\sigma^o_{HV,max}$ (dB)  | -10.65        | -11.65   | -           | -         |
| $\sigma^o_{HV,mean}$ (dB) | -16.23        | -18.28   | -           | -         |
| $\sigma^o_{VH,min}$ (dB)  | -27.21        | -20.37   | -16.62      | -15.04    |
| $\sigma^o_{VH,max}$ (dB)  | -10.43        | -12.28   | -10.5       | -11.5     |
| $\sigma^o_{VH,mean}$ (dB) | -16.29        | -17.31   | -13.19      | -13.61    |
| $\sigma^o_{VV,min}$ (dB)  | -18.39        | -16.97   | -8.82       | -9.19     |
| $\sigma^o_{VV,max}$ (dB)  | -4.03         | -5.29    | -3.65       | -4.18     |
| $\sigma^o_{VV,mean}$ (dB) | -10.96        | -11.21   | -6.28       | -6.41     |

3.2. Image Classification

There are four combinations of polarization of L-band ALOS PALSAR-2 were studied in this project which are combination of all polarization (full polarization), combination of co-polarization (HH & VV), combination of cross-polarization (HV & VH) and combination of co- and cross-polarization (HH & HV). Table 3 illustrated the classification result of SAR data. Based on the result, the combination of co-polarization (HH and VV polarizations) gives the highest accuracy of three class classification by providing 77.37% accuracy. [20] found that L-band HH and VV polarization are best for oil palm age classification as both polarizations provide high separability. However, the individual class classification result for non-oil palm class is the lowest among four combinations.

As Sentinel data is provided with dual polarization, the combination of dual polarization is used for classification. It gives the lowest oil palm classification result with 55.95%. The result was incompatible to the previous researches. [9] found that C-band HV polarization is capable to separate different branching geometry tree species which provide high accuracy of forest tree species classification. [12] also proved that C-band provide the greatest difference among the species. Due to low spatial resolution of C-band Sentinel-1A, lesser information is acquired by the SAR image which leads to lower classification accuracy.

3.3. Leaf Area Index, Trunk Height and Biomass

According to [15], LAI of oil palm provide strongest correlation with backscatter value with $R^2$ value of more than 0.81 while trunk height and biomass estimation formulae are capable to provide $R^2$ value of about 0.80. [21] is attempted to get a formula which can relate age of oil palm with backscattering value due to [19] proved that there is high correlation between oil palm tree height and age of oil palm. However, moderate correlation result is acquired throughout his research. Other than that, [20] is capable to prove strong correlation of oil palm biomass versus age of oil palm. It shows that the older oil palms are taller; hence, produce higher biomass.

The classification result of combination of SAR image and field parameter as depicted in Table 4. Combination of L-band HH and VV polarization SAR data with biomass parameter provide the highest accuracy oil palm classification while combination of C-band VH and VV polarization SAR data with trunk height parameter provide the highest accuracy oil palm classification. By comparing the result of Table 3 and 4, result of classification using L-band SAR polarization image itself is better than that of using combination data. The reduction of accuracy for L-band SAR data might be due to
inappropriate formula using for this dataset. The formula created by [18] is depends on his dataset sensors which are JERS-1 (L band) and ERS-1 (C-band). However, it was surprisingly that combination field parameter of C-band SAR data is provide much highest overall accuracy.

### Table 3. Confusion Matrix of Maximum Likelihood Classification of SAR Data

| Type of Sensor | Ground Truth (Percent) | Overall Accuracy |
|----------------|------------------------|------------------|
|                | Oil Palm | Non-oil Palm | Total |
| ALOS PALSAR-2  |           |              |       |
| Full Polarization (HH, HV, VH &VV) | 76.40 | 24.29 | 73.05 | 76.35% |
| Oil Palm       | 23.60    | 75.71        | 26.95 |
| Total          | 100.00   | 100.00       | 100.00 |
| Co-polarization (HH & HV) | 65.80 | 23.16 | 63.06 | 66.51% |
| Oil Palm       | 34.20    | 76.84        | 36.94 |
| Total          | 100.00   | 100.00       | 100.00 |
| Cross-polarization (HH & VV) | 78.03 | 32.20 | 75.08 | 77.37% |
| Oil Palm       | 21.97    | 67.80        | 24.92 |
| Total          | 100.00   | 100.00       | 100.00 |
| Cross-polarization (HV & VH) | 65.02 | 31.07 | 62.84 | 65.27% |
| Oil Palm       | 34.98    | 68.93        | 37.16 |
| Total          | 100.00   | 100.00       | 100.00 |
| Co-polarization (HH & HV) | 56.84 | 55.56 | 56.75 | 55.95% |
| Oil Palm       | 43.16    | 44.44        | 43.35 |
| Total          | 100.00   | 100.00       | 100.00 |

Even C-band SAR data combination provide highest overall accuracy, it is unable to accurate classify non-oil palm class. Resolution of the image might be the main reason lead to misclassification. Due to the spatial resolution of Sentinel-1A data is 10m, the large pixel might be included two species target in one pixel. Other than that, backscattering is highly sensitive to surface moisture. Misclassification might be due to high precipitation during the image acquisition period.

#### 3.4. Recommendation for Future Works

Precipitation highly affects the backscattering value due to high surface moisture. Therefore, rainfall data should be taking into consideration to improve the accuracy of the results. Besides that, shorter wavelength such as X-band should be tested as it is believed that shorter wavelength signal provides more information on the canopy of trees due to its low penetration capability.

#### 4. Conclusion

Oil palm discrimination is the part of tree counting image processing process. In order to delineate individual tree crown, classification of oil palm and non-oil palm classes correctly have to be done. Based on the findings, L-band ALOS PALSAR-2 provides better accuracy of oil palm classification compared to C-band Sentinel-1A. 77.37% accuracy of oil palm classification result is obtained based on HH and VV polarization of L-band ALOS PALSAR-2. However, L-band full polarization ALOS PALSAR-2 gives the least misclassification percentage.
Field parameter formulae were applied to the image. It improved the C-band SAR data classification but slightly reduce the accuracy of L-band SAR data. However, severe misclassification on non-oil palm class resulted on the C-band SAR data. There are many factors that contribute to misclassification such as resolution of data and parameters affecting the backscattering value such as moisture content.

Table 4. Confusion Matrix of Maximum Likelihood Classification Based on Field parameters

| Type of Sensor | Ground Truth (Percent) | Overall Accuracy |
|----------------|------------------------|------------------|
|                | Oil Palm | Non-oil Palm | Total |               |
| R:HH, G:VV, B:LAI |          |              |       |               |
| ALOS PALSAR-2 |  R:HH, G:VV, B:Trunk Height |          |              |       |               |
| R:HH, G:VV, B:Biomass |          |              |       |               |
| R:VH, G:VV, B:LAI |          |              |       |               |
| R:VH, G:VV, B:Trunk Height |          |              |       |               |
| R:VH, G:VV, B:Biomass |          |              |       |               |

Acknowledgement
We would like to thank KARI to provide KOMPSAT data for the data validation. We would also express our gratitude to JAXA who provide ALOS PALSAR-2 data. Lastly, we are appreciated ESA that provide open source Sentinel-1 SAR data.

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