Estimating tree age of rubber stands using spaceborne L-band synthetic aperture radar

B H Trisasongko*, D R Panuju and L O S Iman

Department of Soil Science and Land Resource, Bogor Agricultural University, Jalan Meranti, Dramaga, Bogor 16680, Indonesia; and P4W/CRESTPENT, Bogor Agricultural University, Jalan Pajajaran, Bogor, Indonesia.

*Email: trisasongko@apps.ipb.ac.id

Abstract. Earth-observing data have been employed for plantation’s detection and monitoring within the context of land cover planning. Rising utilization has recently been observed for detailed tree assessment on very specific commodities such as oil palm. In this article, evaluation of spaceborne Synthetic Aperture Radar (SAR) is presented, taking the outstanding benefit of high resolution fully polarimetric data recently available worldwide. Primary goal of the research was to evaluate SAR imagery for the detection of stand age of rubber plantation. We found that coupling fully polarimetric data and Random Forests (RF) as the classifier could yield more than 80% accuracy. This indicates that Earth-observing data serve as potential backbone for mapping and investigating plantations in remote locations.

Keywords: Age prediction; Hevea brasiliensis; Plantation mapping; Random forest; Synthetic Aperture Radar

1. Introduction

Forested lands have been the subject for human exploitation. Precious and invaluable timbers have been the main cause of the exploitation. Although the policy of selected harvesting have long been introduced [1], forest alteration is inevitable. Similarly to Indonesia, to date, forest alteration has largely occurred in developing countries as the base of the nation’s economy. When the forest degradation is severe, conversion to plantations is one of policies taken by governments. In Indonesia, forest alteration is strongly related to the development of plantations, in particular, timber and oil palm estates. Due to their existence in surrounding protected areas, plantations need to be regularly monitored [2].

Multispectral data provide precious information related to the goal, available in coarse, medium and high spatial resolution. Demonstrations are regularly presented in scientific literature, for instance in Brazil [3] and in South East Asia [4]. The use of multispectral imageries, however, imposes specific problems when they are applied in humid tropical regions. Many sites in remote areas of Indonesia are regularly cloud covered, which in turn limit the utility of such imageries. In this respect, SAR provides an alternative for data acquisition as it has less sensitivity to atmospheric condition and capability to acquire images in day or night, nearly all weather situations.
Mapping plantation in Indonesia employing SAR data was implemented with fairly high degree of accuracy [5]. With the aid of fully polarimetric data, the process successfully delineated rubber plantation from other uses [6]. Nonetheless, the paucity of stand age mapping is existent that leads to incomplete information in plantation management.

The aim of this article was, therefore, to evaluate growingly available fully polarised SAR data for stand age mapping of rubber plantation. Specifically, we were interested to investigate the role of SAR data types and their couplings with modern data mining methods.

2. Methodology

2.1. Test site and datasets
Jember (Figure 1) was selected as the test site. Rubber plantation estates are scattered around the Jember city, with majority of them is situated in the southern part of the region. Southern topography was slightly rugged than the northern part of the region. The estates were surrounded by rural settlements, rice and upland agricultural fields and primary forest of the Meru Betiri National Parks.

![Figure 1. Location of the site. Image courtesy Google Earth.](image)

SAR data, dated 31 March 2015, were acquired by the Phased Array-type L-band Synthetic Aperture Radar (PALSAR) sensor in fully polarised mode. The data were supplied by Japan Aerospace Exploration Agency (JAXA) in Single Look Complex format (Level 1.1), allowing the extraction of polarimetric decomposition features alongside the conventional backscatter coefficient. SAR data served as the primary remote sensing data to this research, meanwhile, several multispectral datasets were also available for comparison or target recognition.
In order to support the analysis, field surveys were conducted twice. The first was in January 2015 to arrange permission and to collect reconnaissance ground information. Intensive field survey was done in December 2015, collecting stand age information, cultivar, diameter at breast height (dbh) and height of the trees. In addition, we took vertical photograph to obtain some insight of canopy cover to help interpreting radar scattering properties. Field documentation is presented in Figure 2.

![Field documentation](image)

**Figure 2.** Field documentation.

### 2.2. Pre-processing

Since L-band SAR wave is susceptible to Ionospheric perturbation, fully polarimetric SAR data were firstly investigated to measure one-way Faraday Rotation. In this research, the estimation was accomplished using the Bickel-Bates method [7]. The calculation found that the rotation was generally low, with overall value was less than 5 degrees, a threshold suggested by Wright *et al.* [8]. We then corrected cross-talk effect by using Ainsworth method [9]. The output was resampled to 10-m spatial resolution.

Following conventional practice, HH, HV and VV backscatter coefficients were derived from fully polarimetric SAR data. In addition, we obtained features from Freeman-Durden [10] and Yamaguchi [11] model-based decomposition theorems. All data were subsequently imported into SNAP software for geometric correction using the Range-Doppler Terrain Correction.

### 2.3. Analysis

Both types of data, i.e. backscatter coefficients and model-based decomposition features, were all combined into a single dataset to ease computation. We were interested to observe whether a combined dataset would yield high overall accuracy. Using sampling dataset constructed from field observation, classification procedure was then performed. Training and testing ratio was set into 70:30. We adopted ten-fold cross-validation with three repeats in order to ensure the bias was kept minimum. Table 1 presents R-based statistical models evaluated in this research. Accuracy from the model was then evaluated using overall accuracy.
Table 1. Classification models.

| Model                                | Package    |
|--------------------------------------|------------|
| C5.0                                 | C5.0       |
| Neural Network                       | nnet       |
| Random Forest                        | rf         |
| Support Vector Machine with Radial Basis Function | kernlab    |
| Gradient Boosting                    | xgboost    |

3. Results and discussion

3.1. Scattering variability

Figure 3 presents scattering behavior of L-band radar, dependent to rubber tree age. As shown, vertical co-polarization is less sensitive to stand age. The finding was somewhat different to the earlier result [6], suggesting a further investigation remains important. We need to point out, however, that stand age distribution in Jember was less favorable than the Subang site as described in [6]. Scattering patterns of HH and HV backscatter coefficient appear in agreement with Subang site, although Jember site had shorter dynamic range, i.e. between -11 to -7 dB for HH polarization, while data for Subang spanned from -14 to -7 dB.

Figure 3. Backscatter coefficient variations related to tree age.
To extend previous work [6], an analysis using Freeman-Durden decomposition theorem is presented in Figure 4. The theorem provides a useful measure to characterize the behavior of radar scatterers; hence, allowing further understanding of wave-tree interactions. In very young trees where the rubber canopy was underdeveloped, strong odd (single) bounce mechanism was observed. This indicates that small trees were rarely observable in long wavelength as used in PALSAR sensor. Instead, scattering was dominated by the Earth surface. When canopy was nearly full grown, domination of odd-bounce weakened, indicating that scattering responses of soil was disappearing. Opposing the backscatter of soil surface, fully developed canopy ignited stronger response in volume scattering. The figure indicates that at the age of 4 years old, rubber tree canopy has already developed, and it remains until the end of the whole plant rotation. As depicted from Figure 4, low contribution of double-bounce was indicated from Jember site. Amplified backscatter coefficient usually shown in regular planting scheme was not observable.

![Figure 4](image)

**Figure 4.** Freeman-Durden components, showing contribution of odd-, double-bounce and volume scattering.

### 3.2. Classification outcomes

Result of the analysis presented in the previous section indicated that discrimination of stand age between young (Tanaman Belum Menghasilkan, TBM) and mature (Tanaman Menghasilkan, TM) was generally straightforward. Nonetheless, when detailed information is required, capability of dataset and suitable methods needs to be observed. In this research, fifteen target age classes were used to further investigate potential classifiers for operational mapping. Overall accuracy produced by combined all available features of polarimetric SAR data is presented in Table 2.
Table 2. Overall accuracy.

| Model               | OA (%) |
|---------------------|--------|
| C5.0                | 77.45  |
| Neural Network      | 33.57  |
| Random Forest       | 81.64  |
| Support Vector Machine | 73.60  |
| Gradient Boosting   | 79.20  |

Similar to previous finding [5], Neural network appeared having a problem distinguishing complex problem. Parameter setting was likely to be the cause of this drawback and this should be a topic for investigation in the future research. Support vector machine that previously reported performing comparable to ensemble tree models [6] was shown inferior to discriminate fifteen tree age classes. The best performer among machine learners in this research was ensemble tree-based models, similar to the outcome presented by Panuju et al. [12]. This suggests that enhanced tree-based models coupled by fully polarimetric SAR data could yield a suitable classification map for rubber plantation monitoring.

4. Conclusion
As one of major plantation commodities in Indonesia, rubber needs a suitable monitoring scheme. Multispectral images have a great potential to this requirement with a diversity of spatial resolution and long-term data availability. Nonetheless, cloud cover is somewhat persistent in many parts of Indonesia, suggesting that an alternative for data input is a critical issue. Synthetic Aperture Radar sensors have capability of penetrating cloud cover; hence, suitable for data source. With the advent of fully polarimetric SAR data, a strategy to develop efficient monitoring scheme for plantation is required.

This research demonstrated that coupling fully polarimetric SAR data and some modern machine learning methods could be beneficial to produce fairly high overall accuracy. With the large choice of classification methods, this study indicated that not all methods were suitable. Neural networks, for instance, yielded lowest accuracy. Support vector machine, a competitive machine learning approach, was inferior to ensemble tree-based models. Best performing statistical model in this research was produced by Random forest, yielding 80% accuracy for fifteen discrimination targets.

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