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Phenology and classification of abandoned agricultural land based on ALOS-1 and 2 PALSAR multi-temporal measurements

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ABSTRACT
Agricultural crop abandonment negatively impacts local economy and environment since land, as a resource for agriculture, is not optimally utilized. To take necessary actions to rehabilitate abandoned agricultural lands, the identification of the spatial distribution of these lands must be acknowledged. While optical images had previously illustrated potentials in the identification of agricultural land abandonment, tropical areas often suffer cloud coverage problem that limits the availability of the imageries. Therefore, this study was conducted to investigate the potential of ALOS-1 and 2 (Advanced Land Observing Satellite-1 and 2) PALSAR (Phased Array L-band Synthetic Aperture Radar) images for the identification and classification of abandoned agricultural crop areas, namely paddy, rubber and oil palm fields. Distinct crop phenology for paddy and rubber was identified from ALOS-1 PALSAR; nonetheless, oil palm did not demonstrate any useful phenology for discriminating between the abandoned classes. The accuracy obtained for these abandoned lands of paddy, rubber and oil palm was 93.33% ± 0.06%, 78% ± 2.32% and 63.33% ± 1.88%, respectively. This study confirmed that the understanding of crop phenology in relation to image date selection is essential to obtain high accuracy for classifying abandoned and non-abandoned agricultural crops. The finding also portrayed that PALSAR offers a huge advantage for application of vegetation in tropical areas.

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1. Introduction

In the Malaysian context, abandoned or idle land is a land dedicated for agricultural purposes but not cultivated for three consecutive years or more. It is common that the land is individually owned and confined a minimum area of 0.4 ha, either continuous or fragmented. It is reported by the Department of Agriculture (2014) that in 2014, a total of 119,273 hectares of arable land in Malaysia are abandoned involving 69,734 locations in Peninsular Malaysia, Sabah and Sarawak. This statistics, however, was obtained through the local district land offices or local leaders by the mean of ground sampling. With the characteristics of these abandoned lands being commonly scattered (Ponnusamy 2013) and small in size, detecting and identifying them create such a huge challenge in terms of cost, time and labour. Besides, with the current practice of identification that relies on the existing land

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records and ground sampling, efficient monitoring of abandoned agricultural lands on the frequent basis is almost impossible due to the fluctuating statistics of abandoned lands caused by the addition of newly abandoned lands or development of the previously abandoned lands (Department of Agriculture 2014).

Identifying abandoned agriculture land is vital due to its influences and consequences on the environment such as soil and water quality, carbon sequestration, biodiversity and nutrient cycling (Benayas et al. 2007; Koulouri and Giourga 2007; Alcantara et al. 2012). In severe cases, abandoned agricultural fields provide fuels for natural wildfire and propagate weeds (Prishchepov et al. 2013). The significance of detecting abandoned lands is economically and environmentally inseparable and hence, becoming a global agenda and part of political discussion (Díaz et al. 2011; Prishchepov et al. 2013). More importantly, from the economic point of view, agricultural land abandonment could be translated into wasteful resources. Since 1980s, Malaysia has been troubled with the issue of land abandonment, until now (Buang 2001). In terms of implication on food production, land abandonment has been identified as among the major problems in local paddy industry (Othman 1992) where production for this staple crop on average, for instance, is only 62% for the period of 2008–2013 (Department of Agriculture 2013b). On the other hand, oil palm is the largest agriculture land use in Malaysia, followed by rubber (Department of Agriculture 2013a). These plantation crops play an important role as a contributor to the gross national income and contribute to more than USD11 billion annually; USD10 billion for oil palm and USD1.6 billion for rubber. Since land availability for expansion of agriculture activities in Malaysia is limited, rehabilitation of abandoned land is essential to ensure the endurance of food crop production and plantation industry.

Remote sensing has undeniably played a vital role for mapping abandoned agriculture worldwide, including the United States (Egbert et al. 2002), Europe (Kristensen, Thenail, and Kristensen 2004; Falcucci, Maiorano, and Boitani 2006) and the former USSR (Bergen et al. 2008; Baumann et al. 2011). However, currently, there is a little attention paid to the study of detecting abandoned agriculture in Malaysia. Previous research conducted by Alcantara et al. (2012) suggested that there are two ways to carry out the mapping and analysis of abandoned agricultural land using remote sensing data: (i) mapping and detecting changes in the land use. This technique involves mapping of the fields that were initially cultivated, which requires archived image prior to the abandonment and later represented by shrublands or grasslands and (ii) mapping the grasslands that have woody growth since the growth of secondary forest is an indicator of natural vegetation. In practice, multi-date remote sensing images have been used to classify land-use classes and consequently detect abandoned agriculture fields (Doug et al. 2000; Amorós-López et al. 2013) based upon the facts that agricultural crops have different planting and harvesting periods. The importance of multi-date images in this study is linked directly to the fact that the phenology of different crop types is conveniently compared (Guerschman et al. 2003; Homer et al. 2004). In relation to this statement, it is important to note that many Malaysian crops are perennials (Economic Planning Unit 2014), including plantation crops such as oil palm, rubber and cocoa, meaning that their sowing and harvesting times that are related to the phenology could be indistinct from one to another. Nonetheless, a recent study conducted by Yusoff and Muharam (2015) illustrated that examination on Landsat OLI (Operational Land Imager) multi-temporal images could reveal rubber unique phenology associated with wintering or defoliation season that was beneficial for discriminating between rubber and non-abandoned rubber lands.

Another main challenge for characterizing the crop phenology through multi-date images is the limited cloud-free images in the tropical areas (Wang et al. 2009). Therefore, the use of non-optical images especially microwave radar becomes necessary for this study. Following this statement, it is essential to investigate to what extent non-optical images could facilitate the mapping and detection of abandoned agricultural fields. In this study, microwave radar data are anticipated not only to provide consistent, periodic data in a reliable manner but also to some degree, provide sub-canopy information in relation to different agricultural lands being abandoned.

Microwave radar has been an important component in the mapping, monitoring, predicting and estimating yield and biomass of agricultural crops such as paddy, rubber and oil palm. The backscattering coefficient from the satellite SAR (Synthetic Aperture Radar) systems has been interpreted for paddy, rubber and oil palm growth monitoring (Toan et al. 1997; Liew et al. 1998; Rosenqvist 1999; Koay et al. 2007; Henderson and Lewis 2008; Bouvet and Le Toan 2011; Miettinen and Liew 2011; Morel, Fisher, and Malhi 2012; Yonezawa et al. 2012; Dong et al. 2013; Dong et al. 2015; Tan et al. 2015; Teng et al. 2015). The SAR data acquired using ERS-1/2 (European Remote Sensing-1/2; Toan et al. 1997; Liew et al. 1998), JERS-1 (Japanese Earth Resources Satellite-1; Rosenqvist 1999), RADARSAT-1/2 (Radio Detection and Ranging Satellite-1/2; Koay et al. 2007; Yonezawa et al. 2012) and ENVISAT ASAR (Environmental Satellite Advanced Synthetic Aperture Radar; Jinsong, Lin, and Pei 2007; Bouvet and Le Toan 2011) have been used to map and monitor paddy growth in the test areas worldwide. On the other hand, Miettinen and Liew (2011) reported that ALOS-1 PALSAR mosaic products have high sensitivity for separating woody plantation such as oil palm and rubber in the Southeast Asian region. Morel et al. (2011) found that ALOS-1 PALSAR has the potential but for precise monitoring, and recommended the utility of multiple temporal images. By integrating PALSAR-based forest baseline map and the multiple temporal Landsat images, Dong et al. (2013) proposed a rapid mapping approach for rubber plantation with a high accuracy; moreover, Dong et al. (2015) applied the approach to map the rubber plantation in a case region of Xishuangbanna and furthermore developed a stand age mapping algorithm.

Therefore, this study was carried out to investigate the capability of ALOS-1 and 2 PALSAR in identifying agricultural abandonment for three crops: paddy, oil palm and rubber. These were the specific objectives to be achieved:

(1) To develop crop phenology of abandoned and non-abandoned lands using multi-temporal PALSAR images and
(2) To develop a methodology for classifying abandoned paddy, rubber and oil palm fields using PALSAR images.

2. Materials and methods

2.1. Study area

The study area for this research was Mukim Sungai Siput and Kuala Kangsar in the Kuala Kangsar district, Perak, Malaysia (Figure 1). The study site covers an area of 96,816 hectares, from 5°5′51″N, 100°48′59″E to 4°39′12″N, 101°28′2″E. The main land cover classes are oil palm, rubber and other crop plantations, secondary forest, grassland, urban and ex-tin mining land, where almost half of the land area is enveloped with primary forest. Soil types in this study area are characterized by either sandy clay, sandy clay loam, sandy loam, sandy or silty clay. The topography in this area is relatively hilly from 18 to 1790 m. The average annual temperature, humidity and daily rainfall of study area are 28.5°C, 86% and 6 mm, respectively (Malaysian Meteorological Department 2015).

2.2. Satellite images

We used 23 of ALOS-1 and 2 PALSAR microwave images for the characterization and identification of abandoned land through classification procedure (Table 1). The ALOS-1 and 2 PALSAR data utilized in this study are dual polarized HH (Horizontal transmitting, Horizontal receiving) and HV (Horizontal transmitting, Vertical receiving) L-band that have a spatial resolution of 12.5 m and 6.25 m, respectively. We used product ID H1.5GUA for ALOS-1 which has been corrected for slant range and H2.1GUA for ALOS-2 which has been orthorectified using an SRTM DEM (Shuttle Radar Topography Mission Digital Elevation Model). All data were acquired in fine beam dual mode at a viewing angle of 34.3° and delivered in single-look complex as the normalized backscattering coefficient in slant-range geometry by JAXA (Japan Aerospace Exploration Agency). A standard Universal Transverse Mercator projection (zone 47 N and datum WGS (World Geodetic System)

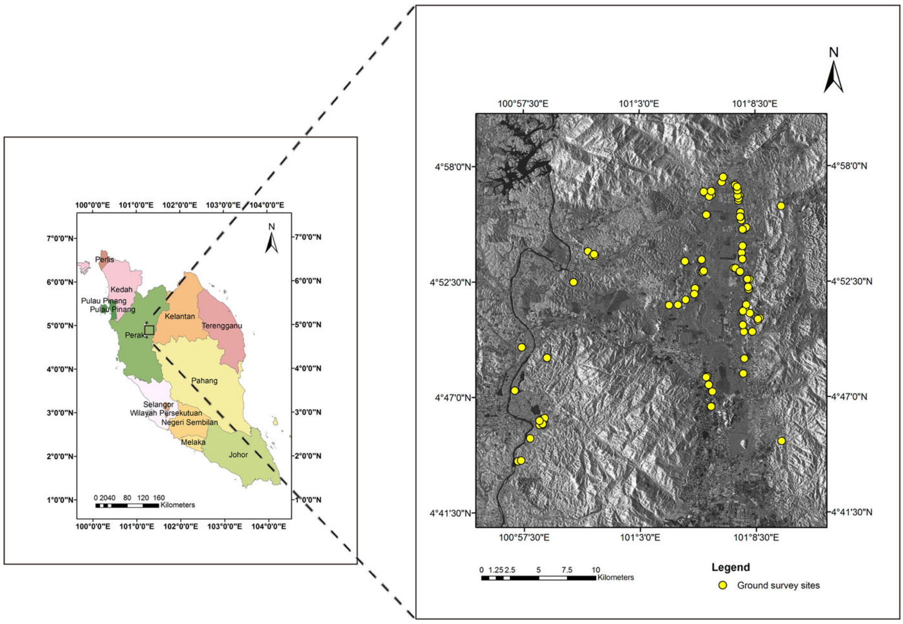

Figure 1. Study area and ground survey sites.

84) was applied to all images. The agricultural land abandonment corresponding to the several image dates is displayed in Figure 2.

2.3. Ground and ancillary data

To assist the classification procedure, we adopted Yusoff and Muharam (2015) who used a historical land-use map produced from the Department of Agriculture Malaysia. The land-use map was

Table 1. Acquisition dates of the images.

Image date	Sensor	Image purpose
28 June 2007	ALOS-1	Crop phenology
30 August 2007	ALOS-1	Crop phenology
13 November 2007	ALOS-1	Crop phenology
30 November 2007	ALOS-1	Crop phenology
29 December 2007	ALOS-1	Crop phenology
30 June 2008	ALOS-1	Crop phenology
17 July 2008	ALOS-1	Crop phenology
15 August 2008	ALOS-1	Crop phenology
30 September 2008	ALOS-1	Crop phenology
17 October 2008	ALOS-1	Crop phenology
20 July 2009	ALOS-1	Crop phenology
18 August 2009	ALOS-1	Crop phenology
4 September 2009	ALOS-1	Crop phenology
3 October 2009	ALOS-1	Crop phenology
20 October 2009	ALOS-1	Crop phenology
23 July 2010	ALOS-1	Crop phenology
21 August 2010	ALOS-1	Crop phenology
7 September 2010	ALOS-1	Crop phenology and classification
6 October 2010	ALOS-1	Crop phenology
23 October 2010	ALOS-1	Crop phenology and classification
21 November 2010	ALOS-1	Crop phenology
8 December 2010	ALOS-1	Crop phenology and classification
13 November 2014	ALOS-2	Classification

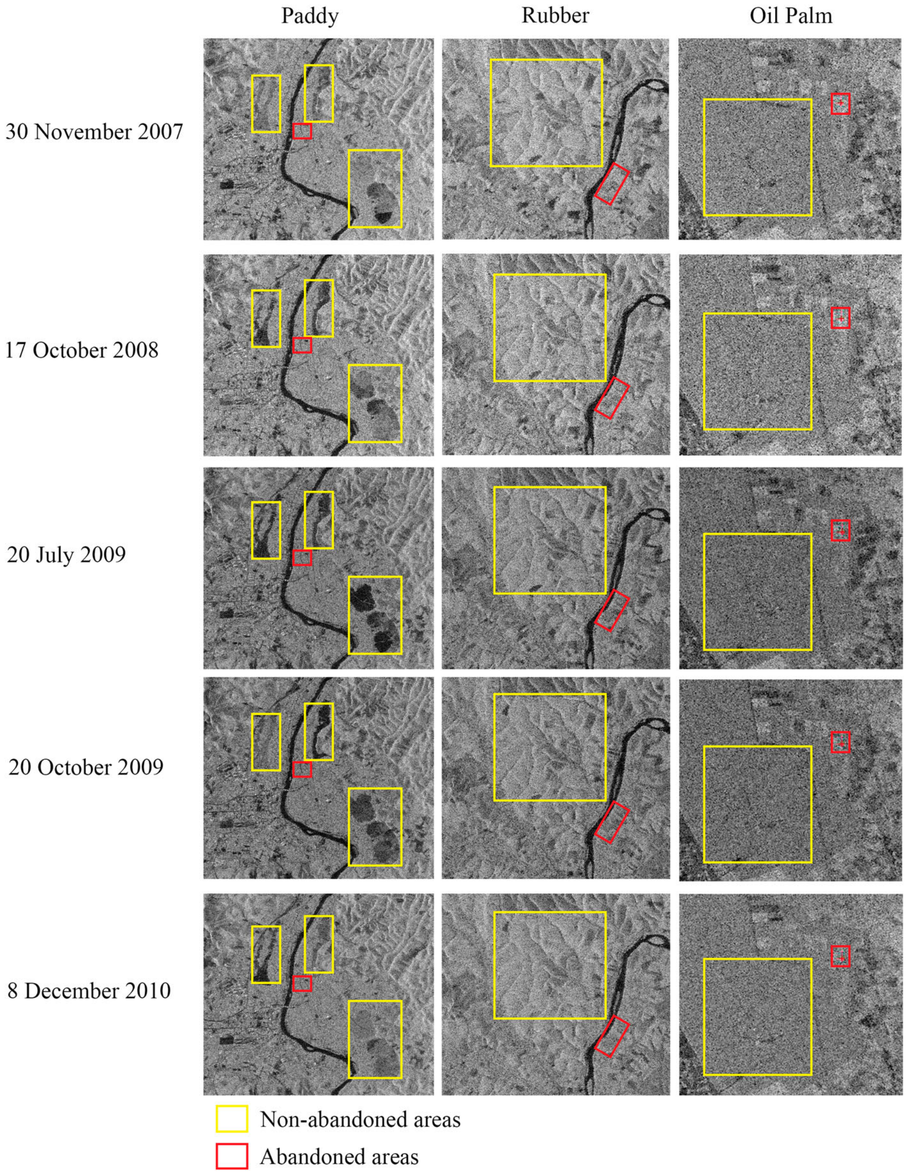

Figure 2. Multi-temporal ALOS PALSAR-1 of several sites of abandoned and non-abandoned agriculture crops.

produced in 2006 in a 1:50,000 scale, based on ground survey and digitized satellite images, with several land-use classes identified as shown in Figure 3. There is an eight-year gap between the ancillary data and satellite imagery, instead of three years of the definition of abandoned land, to ensure that the lands are truly abandoned rather than just poorly managed or unmanaged. A contour map of 10 m interval of the study area was acquired from the Department of Survey and Mapping Malaysia (JUPEM) in order to obtain slope information.

For the purpose of characterizing the crop phenology and assessing the accuracy of the classified map, we conducted different sessions of the ground visit in January, April and November 2014 to collect the locations of different classes of non-abandoned and abandoned agriculture lands. Fundamentally, agricultural classes of our interest are oil palm, rubber and paddy, both abandoned and not. The locations were recorded using a Garmin GPS receiver. In addition, we also used a 1.5 m

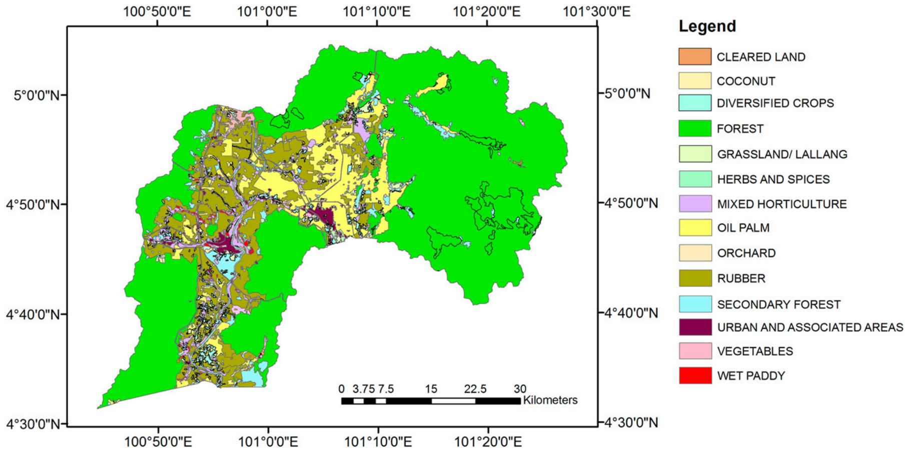

Figure 3. Land-use map (source from Department of Agriculture Malaysia, 2006).

resolution SPOT-6 (Satellite Pour I'Observation de la Terre-6) image acquired on 12 February 2014 to complement the classification accuracy assessment. For paddy, either abandoned or not, we collected 30 locations each, while for rubber, 50 points were collected to represent each abandoned or non-abandoned class, whereas 70 and 30 points for non-abandoned and abandoned oil palm plantations, respectively. Additionally, the characteristics of each class such as ground surface conditions, and crop conditions were recorded to assist in the interpretation of images.

2.4. Image processing

2.4.1. Digital number to backscatter conversion

For the ALOS-1 and 2 images, the processing procedure involved was mainly the conversion of Digital Number (DN) to Normalized Radar Cross Section (NRCS). The conversion of HH (DN_{HH}) and HV (DN_{HV}) backscatter intensities into NRCS (i.e. σ°_{HH} and σ°_{HV}) was conducted based on Shimada et al. (2009) using the following equations:

$$\sigma^{\circ}_{HH} = 10\log_{10}(DN^2_{HH}) - 83, \tag{1}$$

$$\sigma^{\circ}_{HV} = 10\log_{10}(DN^2_{HV}) - 83. \tag{2}$$

The backscatter values of 5×5 pixel associated with the classes of agricultural lands were also extracted for further analysis, where backscatter values were plotted for each agriculture class prior to the investigation on their phenology and abandonment characteristics.

2.4.2. Segmentation and object-oriented classification

The classification method chosen in this research is an object-oriented approach, using eCognition software, which includes segmentation of an image into regions of pixels, computation of attributes for each region to create objects and classification of the objects based on attributes to extract features. The object-oriented algorithm used is a multi-resolution segmentation which locally minimizes the average heterogeneity of image objects for a given resolution. Common parameters that define the object-oriented classification are segmentation scale, ratio of shape/colour and smoothness/compactness (Syed, Dare, and Jones 2005; Aldred and Wang 2011; Dingle and King 2011; Robson et al. 2015). The segmentation scale helps to efficiently delineate object features boundaries, where large segmentation scale resulted in large object features and vice versa (Kassouk et al. 2014). Thus, the selection of appropriate segmentation scale is important to avoid misclassification. After the selection of the most appropriate segmentation scale, the threshold values to discriminate between abandoned and non-abandoned features were chosen based on the visual analysis and trial and error approach using the feature view available in the software. In eCognition, the Assign Class algorithm was used to determine the threshold values that evaluate the probability of an object to belong to a class or not. Once the threshold values were determined, rules were created and executed. If objects were incorrectly classified, adjustment of the thresholds values would be necessary (Gamanya, De Maeyer, and De Dapper 2007). Prior to the classification procedure, PALSAR images were subset according to the types of an agricultural crop by using the land-use map. In other words, the individual classification scheme was performed for each crop.

For the extraction of paddy and abandoned paddy fields, the segmentation scale chosen was 100, with the shape of 0.8 and colour of 0.2, using trial and error approach (Stow et al. 2007; Frohn et al. 2011; Hirata and Takahashi 2011). Since microwave data revealed more information associated with object shape than colour (Smith 2012), the value selected for the former were larger than for the latter. The other two parameters identified were smoothness and compactness the ratio of which was set to 0.5 and 0.5 in order to eliminate bias to any segments (Li et al. 2016). This is followed by identifying the appropriate features and default value of features based on the mean value of the sample objects. Utilization of the time-series images is the key method in identifying annual crops such as paddy due to unique phenology associated with planting seasons such as land preparation, irrigation and crop growth phase (Yusoff and Muharam 2015). Due to the limited availability of ALOS-2 image in 2014, we utilized additional three ALOS-1 images acquired in 2010. By adjusting the backscatter range, we found that a σ^{o}_{HV} value of −23 for the ALOS-2 image acquired in 2014 and −14.70 for the ALOS-1 image dated 7 September, 23 October and 8 December 2010 were the effective thresholds to differentiate between abandoned paddy and paddy areas, since non-abandoned paddy area scattered a lower backscatter value especially during the flooding phase. For these two rules, abandoned paddy field would be identified through values above the thresholds (Table 2) for all the image dates.

In order to discriminate the abandoned from non-abandoned rubber areas, the segmentation parameter chosen was similar to the paddy. ALOS-1 images obtained in 2010 were used to assist visual image interpretation in band combinations of R (ALOS-1, 7 September 2010) G (ALOS-2, 2014) B (ALOS-1, 23 October 2010) as shown in Figure 4(a). In this false colour composite image, patches of abandoned rubber area appeared in purple colour, while non-abandoned rubber area was highlighted in green colour. We found the thresholds to differentiate between abandoned rubber and rubber areas by using a σ^{o}_{HH} value of −8.28 of the ALOS-2 image, where values fell below the threshold were dedicated to identify abandoned rubber. Figure 4(b) shows an example of extracted non-abandoned rubber area by using visual analysis of multi-temporal images as previously mentioned. Optical images captured during the defoliation phase as shown in Figure 4(c), Landsat OLI image dated 4 February 2014 and Figure 4(d), SPOT-6 dated 12 February 2014 confirmed the extraction method of abandoned and non-abandoned rubber areas using multiple PALSAR images.

Table 2. Classification parameters and default value of features.

Class name	Parameters (features)	Threshold value
Abandoned paddy	σ°_{HV} 2014	$\sigma_{HV}2014 > -23.00$
	σ°_{HV} 2010	$\sigma_{HV}2010 > -14.70$
Paddy		'Not Abandoned Paddy'
Abandoned rubber	σ°_{HH} 2014	σ_{HH} 2014 < −8.28
Rubber		'Not Abandoned Rubber'
Abandoned oil palm	σ°_{HH} 2014 Slope	$-5.97 \leq \sigma_{HH}\ 2014 \leq -4.94$ 1 < Slope < 73 Ratio DN_{HV} 2014 ≤ 0.15 Brightness < 2800
Oil Palm		'Not Abandoned Oil Palm'

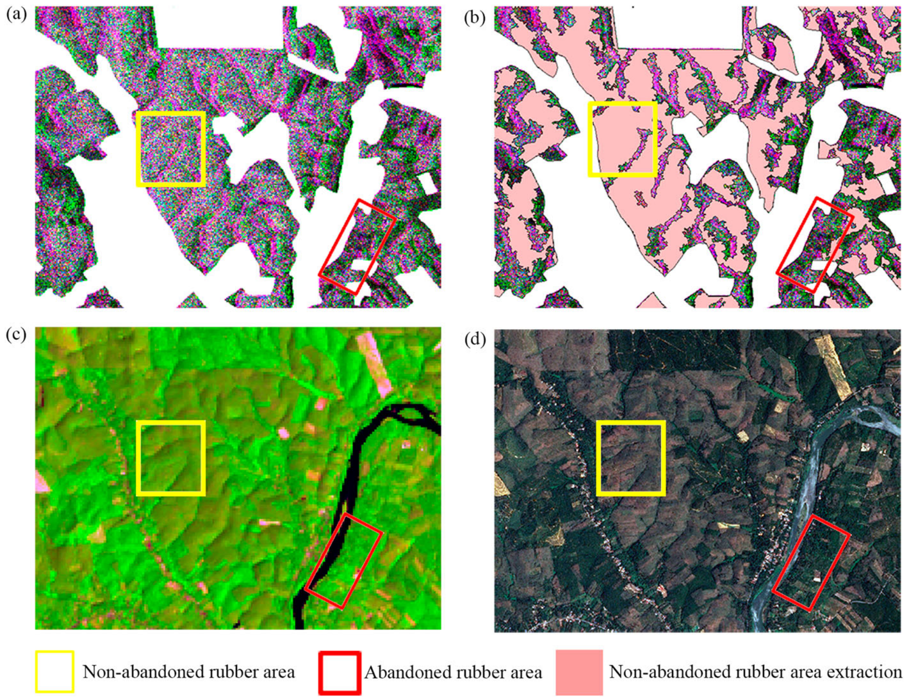

Figure 4. The concept of abandoned rubber and rubber areas identification (a) the purple and green colour composite images produced using band combination of R (ALOS-1, 7 September 2010) G (ALOS-2, 2014) B (ALOS-1, 23 October 2010); (b) extraction of non-abandoned rubber area (shown in coloured polygons); (c) abandoned rubber and rubber areas as validated by Landsat OLI dated 4 February 2014 and (d) abandoned rubber and rubber areas as validated by SPOT-6 dated 12 February 2014.

For the extraction of abandoned and non-abandoned oil palm areas, the segmentation scale chosen was 150, with the shape 0.8 and colour 0.2. The threshold value determined for discriminating abandoned oil palm area from the non-abandoned ones was by using a $\sigma°_{HH}$ value from −5.97 to −4.94 of the ALOS-2 image. $\sigma°$ value smaller than −4.94 is commonly an indicator of buildings, often the plantation offices and worker quarters. Similar to the abandoned paddy field, $\sigma°_{HV}$ values of abandoned oil palm area were higher than the oil palm area. Since oil palms cultivated at hilly area were subject to topographic effect (Morel, Fisher, and Malhi 2012), additional threshold values to accommodate the presence of oil palm cultivation at hilly area were determined: (i) slope is more than 1 and less than 73, (ii) ratio of DN_{HV} is less than 0.15 where the ratio represents the amount that a given image layer contributes to the total brightness, which automatically calculated by eCognition software and (iii) brightness is less than DN value of 2800. For the last two rules, eCognition uses DN value rather than $\sigma°$ value (Syed, Dare, and Jones 2005; Brodský and Borůvka 2006).

Finally, individually classified paddy, rubber and oil palm area polygons were merged and followed by the elimination process of polygons with size less than 0.4 hectares in order to meet the definition of abandoned land.

2.4.3. Accuracy assessment

The accuracy of the classified classes was assessed by using 260 points sampled using the stratified random sampling, with at least 30 points for each class (Canty 2010); 60 points were selected for paddy and 100 points for each rubber and oil palm areas. The producer and user accuracies were used to determine the individual class accuracy while the overall accuracy and kappa statistics indicate the overall accuracy of the classification algorithm. As a complement to the accuracy assessment, standard error, $S(p\hat{})$, which incorporates user and producer accuracies with known area proportions of the map classes, Wi, was also calculated for each class (Olofsson et al. 2014).

3. Results and discussion

3.1. Field characteristics and crop phenology of abandoned and non-abandoned lands

3.1.1. Paddy

Cultivated paddy fields were covered with paddy stands that were partially flooded (Figure 5(a)). In this study area, paddy is planted in two main seasons which are around February and June or July.

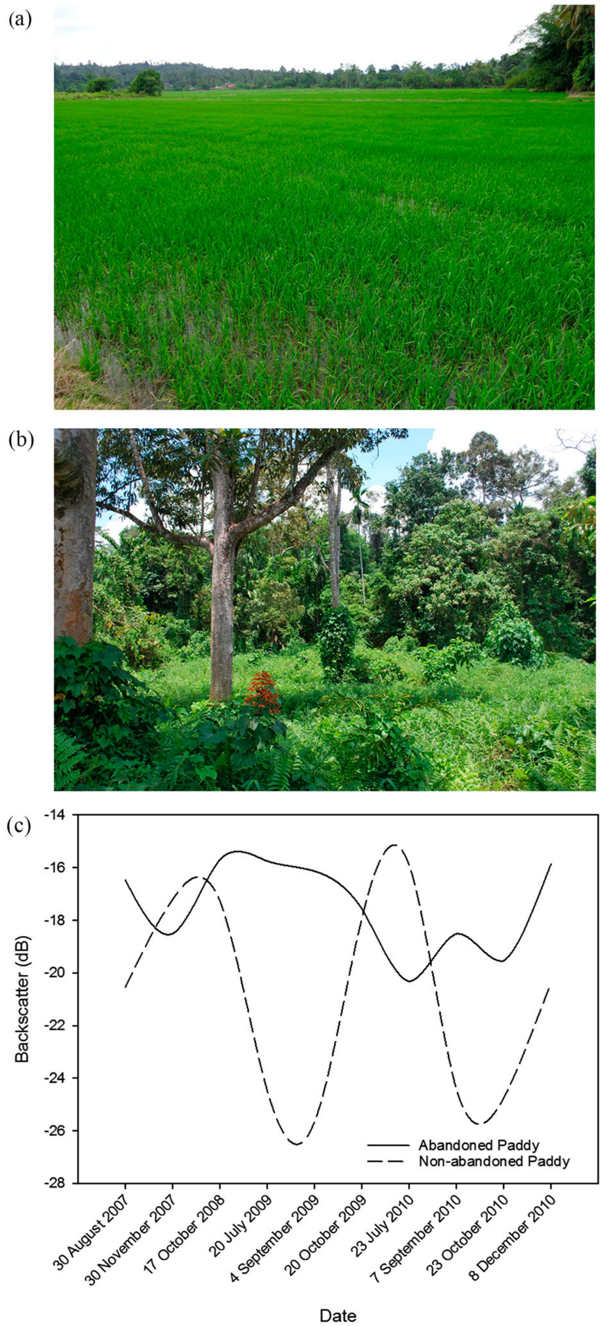

Figure 5. Field characteristics of (a) paddy; (b) abandoned paddy and (c) phenology of abandoned and non-abandoned paddy using 10 series of ALOS-1 PALSAR data.

When farmers began to abandon paddy fields, the area would be initially covered with grasses and shrubs, with some of the fields were still being flooded during planting seasons. Small woody trees were observed in the later stage of abandonment, where the fields were commonly not being flooded anymore. In a worst case scenario, after several years of abandonment, the paddy fields completely turned into a secondary forest (Figure 5(b)).

For the non-abandoned paddy field, ALOS-1 PALSAR data have shown clear phenology (Figure 5 (c)). Beginning from 25 days after transplanting to 80 days after transplanting (head initiation), paddy could be distinguished from other crop types due to very low backscatter, while during maturity period, paddy demonstrates high backscatter value, similar to other crops such as forest and sugar cane (Jinsong, Lin, and Pei 2007). In this study, low backscatter values were recorded for images dated 20 July 2009, 4 September 2009, 7 September 2010 and 23 October 2010 while high values were associated with the remaining six images. Lower backscatter values indicated having more surface or nearly specular reflection while higher backscatter values indicated having more double and volume reflection. The low backscatters were often associated with seedling or irrigation activities where paddy crops were absent, and the area was filled with water, while the high ones often indicate the presence of paddy crops such as during the growth phase (Zhang, Wang, and Zhang 2011). Additionally, it could be observed that the two images taken in October 2009 and 2010 had relatively a huge backscatter difference despite than they were acquired in the same month, indicating differences in the paddy planting stage. Since these paddy areas were planted by smallholder farmers, planting schedule is sometimes adjusted due to circumstances such as water supply and weather condition (Lee, Haque, and Najim 2005; Department of Agriculture 2013b; Ng 2016). On the other hand, the abandoned paddy field had an almost plateau backscatter values throughout the image dates, except for images dated on 30 November 2007 and 23 July 2010. We hypothesized that the declined backscatter values might be due to different incident angles and moisture contents where radar backscatter value highly depends on incident angle, environmental factors such as moisture, topography, and landscape, and vegetation structure (Darmawan, Takeuchi, Vetrita, et al. 2015). Additionally, the values of abandoned paddy field were consistently high throughout the time-series images (Dong et al. 2015; Yusoff and Muharam 2015), indicating the presence of evergreen vegetation, with no seasonal effect characteristic.

Figure 6 demonstrates the importance of time-series images in discriminating between abandoned and non-abandoned paddy areas. The yellow box represents non-abandoned paddy area while the red box represents abandoned paddy area. For non-abandoned paddy area, PALSAR imageries dated 8 December 2010 and 13 November 2014 showed dark objects associated with low backscatter values. Landsat images were used to double-check the activities occurring during that period. By using Landsat OLI images dated 26 December 2010 and 26 November 2014, these areas were found to be covered with water, which was an indicator of irrigation activities. In PALSAR image dated 7 September 2010, non-abandoned paddy area appeared little in difference with abandoned paddy area. The Landsat image confirmed that during this period, the non-abandoned paddy area was covered by soil, and this soil area reflected a high backscatter value in PALSAR image (Zhang et al. 2009). When paddy started to grow, the appearance was much more similar to abandoned paddy area (Yusoff and Muharam 2015). Therefore, the image captured at this stage was not recommended for discriminating between abandoned and non-abandoned paddy areas due to the indifference in crop phenology information reflected through the images.

3.1.2. Rubber

For the rubber class, the crop conditions were comparable, except that the non-abandoned stands were tapped. While the ground surface of the non-abandoned rubber fields was clear from any shrubs (Figure 7(a)), weeds and bushes were evident at the onset of abandonment. At the severe abandonment stage, the floor was completely enveloped with thick bushes and big woody trees that the rubber plantation emerged as a secondary forest (Figure 7(b)).

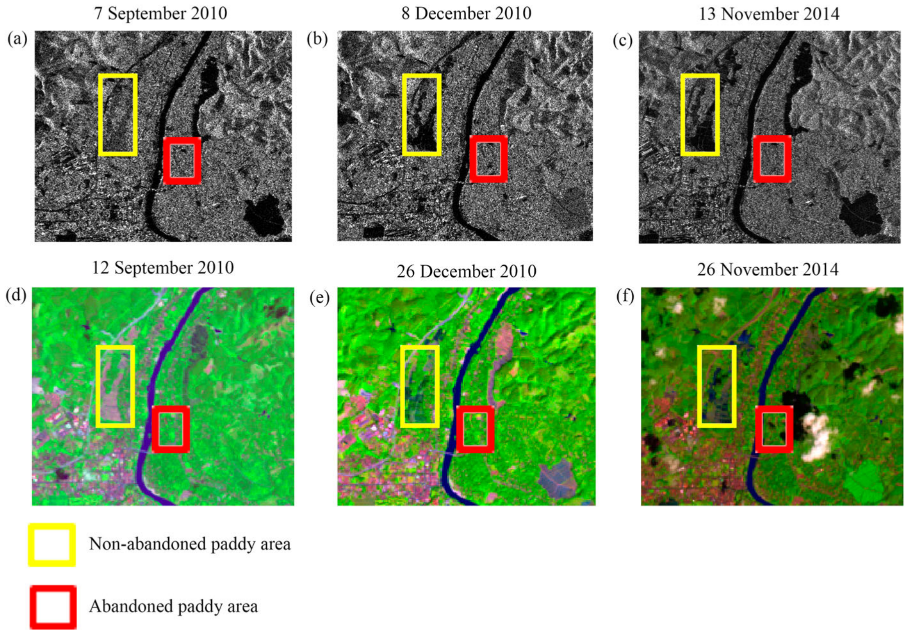

Figure 6. Abandoned paddy and non-abandoned paddy areas shown by multi-temporal of ALOS PALSAR (a–c) and Landsat imageries (d–f).

The hypothesis that abandoned rubber area would illustrate a higher backscatter value than the non-abandoned one due to thicker crops and ground surface conditions was proven valid (Figure 7 (c)). Abandoned rubber area had a higher backscatter value due to inclusion of other vegetation such as shrub and grasses on the ground surface while non-abandoned rubber area had a lower backscattering value as it had only rubber stands. According to Darmawan, Takeuchi, Muharam, et al. (2015), the former raised majority of double bounce reflection while the latter showed a majority of diffuse reflection; this special backscatter characteristic could be used to separate between these two. While Yusoff and Muharam (2015) demonstrated that optical images acquired during defoliation phase or wintering seasons played an essential role in discriminating abandoned and non-abandoned rubber areas, for the ALOS-1 PALSAR data, despite that none of the images were captured during this unique phenology period, the general field conditions were sufficient to differentiate between the abandoned and non-abandoned rubber area classes. In optical remote sensing data, rubber showed low vegetation indices during defoliation stage due to the leaf-off while high vegetation indices during foliation phase or leaf flushing (Fan et al. 2015), which defoliation is an adaptation of rubber trees to dry monsoon (Dong et al. 2013). However, during the determination of threshold value to separate between these two classes it was found that the pattern of the backscatter value was reversed, where non-abandoned rubber area resulted in a higher backscatter value than the abandoned ones. We hypothesized that this condition perhaps occurred due to the segmentation process where features were analysed based on the mean value of the sample objects, rather than individual pixels that were used to construct the phenology graph.

3.1.3. Oil palm

The general appearance of field conditions associated with abandoned and non-abandoned agricultural lands is illustrated by Figure 8. For the oil palm class, the most distinct differences between the non-abandoned class and its counterpart were the appearance of the palm canopy and ground surface conditions. Commonly, during the first four years of growth, oil palm canopy is small and the backscatter value is strongly contributed by ground cover. After four years, fronds of adjacent trees overlap and canopy starts to close and finally, at age of 10 and above, leaf area starts to stabilize

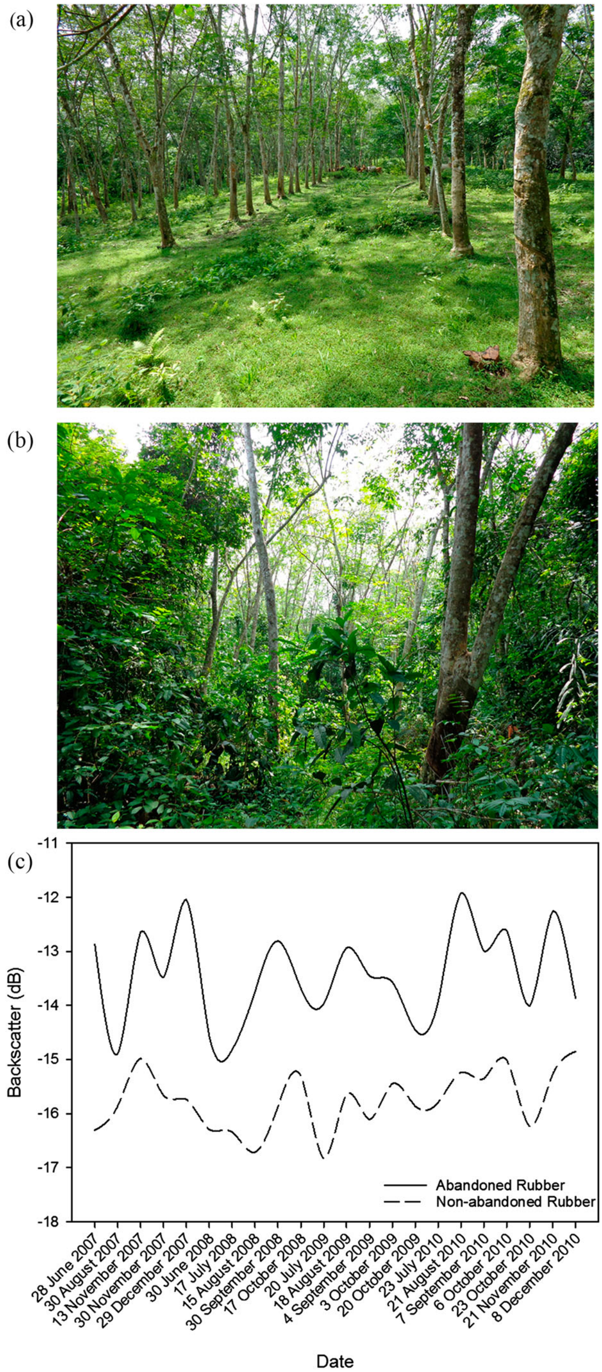

Figure 7. Field characteristics of (a) rubber; (b) abandoned rubber and (c) phenology of abandoned and non-abandoned rubber areas using 22 series of ALOS-1 PALSAR data.

(McMorrow 2001). For the properly maintained oil palms, fronds were pruned and fruit bunches were harvested. A number of fronds were maintained according to oil palm plantation practice, which often around 48. The ground surface was commonly covered with pruned fronds arranged at the frond heaps, and no big shrubs or bushes were observed (Figure 8(a)). On the other hand,

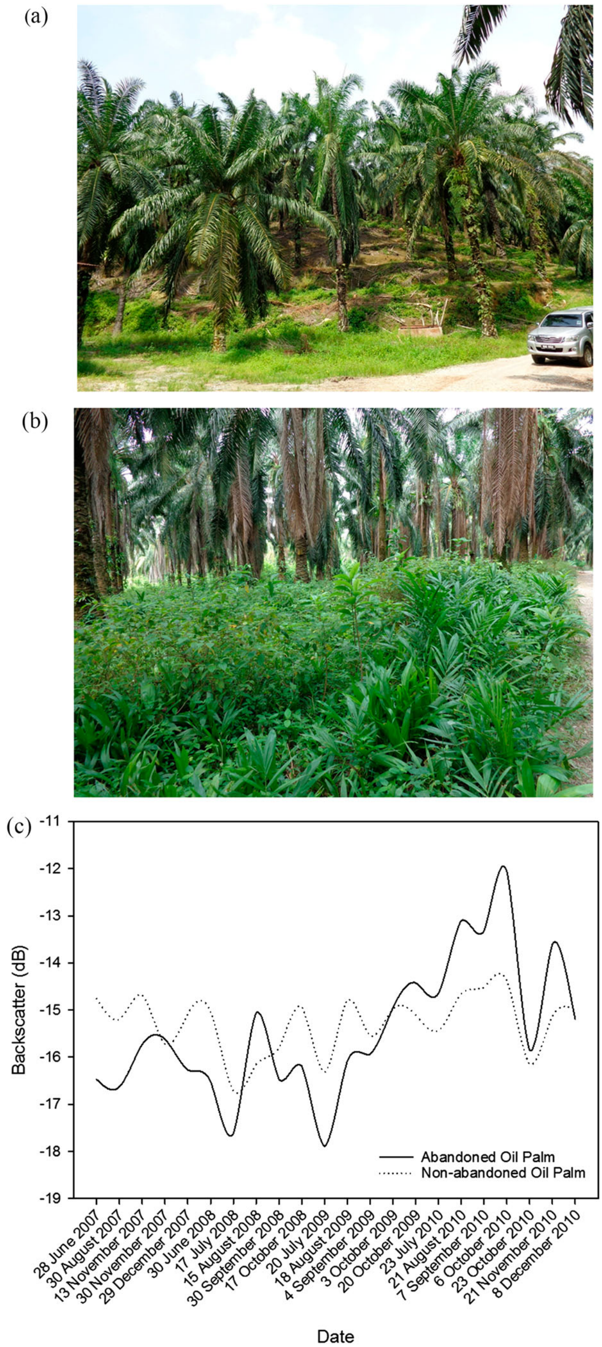

Figure 8. Field characteristics of (i) oil palm; (ii) abandoned oil palm and (iii) phenology of abandoned and non-abandoned oil palm using 22 series of ALOS-1 PALSAR data.

for its counterpart, fronds were not pruned, causing the older fronds to desiccate and dry on the palm trees, and bunches were not harvested. Thick bushes or shrubs and oil palm seedlings of 1 m average height dominated the floor of the abandoned fields (Figure 8(b)).

While we hypothesized that the abandoned oil palm area would raise a higher backscatter value due to the fact that their palm stands had more fronds and non-harvested bunches, that was not the case. This could be due to the saturation of L band signal at high biomass value of oil palm as reported by Morel, Fisher, and Malhi (2012), which is around 88 tonnes ha^{-1}. In general, some random patterns were observed for backscatter value changes for abandoned and non-abandoned oil palm area (Figure 8(c)). There were events where the backscatters of abandoned oil palm area were higher than its counterpart, and vice versa. However, the range of backscatter value for non-abandoned oil palm is small which is 2 dB compared to abandoned oil palm which is 6 dB.

3.2. Image classification and accuracy assessment

The error matrix results of the classification are given in Table 3, indicating the overall accuracy of 83.85% and a kappa statistics of 0.801, whereas Table 4 provides standard error $S(p\hat{})$ for each classification class. Among the three analysed crops, paddy, both abandoned and non-abandoned pair, depicted the highest producer and user accuracies, 93.33% ± 0.06% and 96.67% ± 0.05%, respectively. While these results confirmed the potential of PALSAR images in paddy mapping (Zhang, Wang, and Zhang 2011), distinct phenology between these two classes indirectly contributed to the high separability and hence, classification accuracy. While the accuracy derived from this study was comparable to the ones achieved by Yusoff and Muharam (2015) using multi-temporal Landsat images, PALSAR could offer some advantages due to the fact that the images were cloud-free.

On the other hand, the accuracies of 78% ± 2.32% and 84% ± 2.03% were achieved in the abandoned rubber and rubber classification. While the classification accuracy for the former was slightly lower compared to the result presented by Yusoff and Muharam (2015) who utilized Landsat image obtained during the defoliation phase over the same study area, it is worth noting that even without considering the unique phenology, PALSAR data were still capable of efficiently separating between these two classes. Since cloud cover is a common, inheritable problem in topics, therefore, reliance on optical data captured during the defoliation phase that was inconvenient to obtain could be reduced. Additionally, it was shown that defoliation stage was not necessarily visible in the optical imagery despite being obtained in the defoliation phase (Yusoff and Muharam 2015). On the other hand,

Table 3. Accuracy assessment.

	Abandoned paddy	Paddy	Abandoned rubber	Rubber	Abandoned oil palm	Oil palm	Classification overall	User accuracy
Abandoned paddy	28	1	–	–	–	–	29	96.55%
Paddy	2	29	–	–	–	–	31	93.55%
Abandoned rubber	–	–	39	8	–	–	47	82.98%
Rubber	–	–	11	42	–	–	53	79.25%
Abandoned oil palm	–	–	–	–	19	9	28	67.86%
Oil palm	–	–	–	–	11	61	72	84.72%
Truth overall	30	30	50	50	30	70	260	–
Producer accuracy	93.33%	96.67%	78.00%	84.00%	63.33%	87.14%	–	83.85%

Table 4. Standard error $S(p\hat{})$.

Class	Map area (ha)	Wi	$S(p\hat{})$
Abandoned paddy	683	0.006	0.0006
Paddy	348	0.013	0.0005
Abandoned rubber	16,035	0.260	0.0232
Rubber	14,184	0.294	0.0203
Abandoned oil palm	104	0.425	0.0188
Oil palm	23,145	0.002	0.0171
Others	42,317		
Total	96,816	1	

lower accuracy of abandoned rubber classification was found to be influenced by evergreen perennial trees such as durian (*Durio* sp.) that was mixed with rubber stands.

In the classification of abandoned oil palm and oil palm areas, we achieved the accuracies of 63.33% ± 1.88% and 87.14% ± 1.71%, respectively. Almost one-third of misclassification occurred due to the cultivation of oil palm at the hilly area, where the hilly side facing the radar sensor appeared brighter. For slope angle 30–70°, radar backscatter is dominated by surface roughness (Thomas, Raplh, and Jonathan 2008) which is a similar characteristic of surface roughness for abandoned oil palm area. In future, the combination of optical images is recommended in order to improve the accuracy (Amarsaikhan and Douglas 2004; Morel, Fisher, and Malhi 2012). In addition,

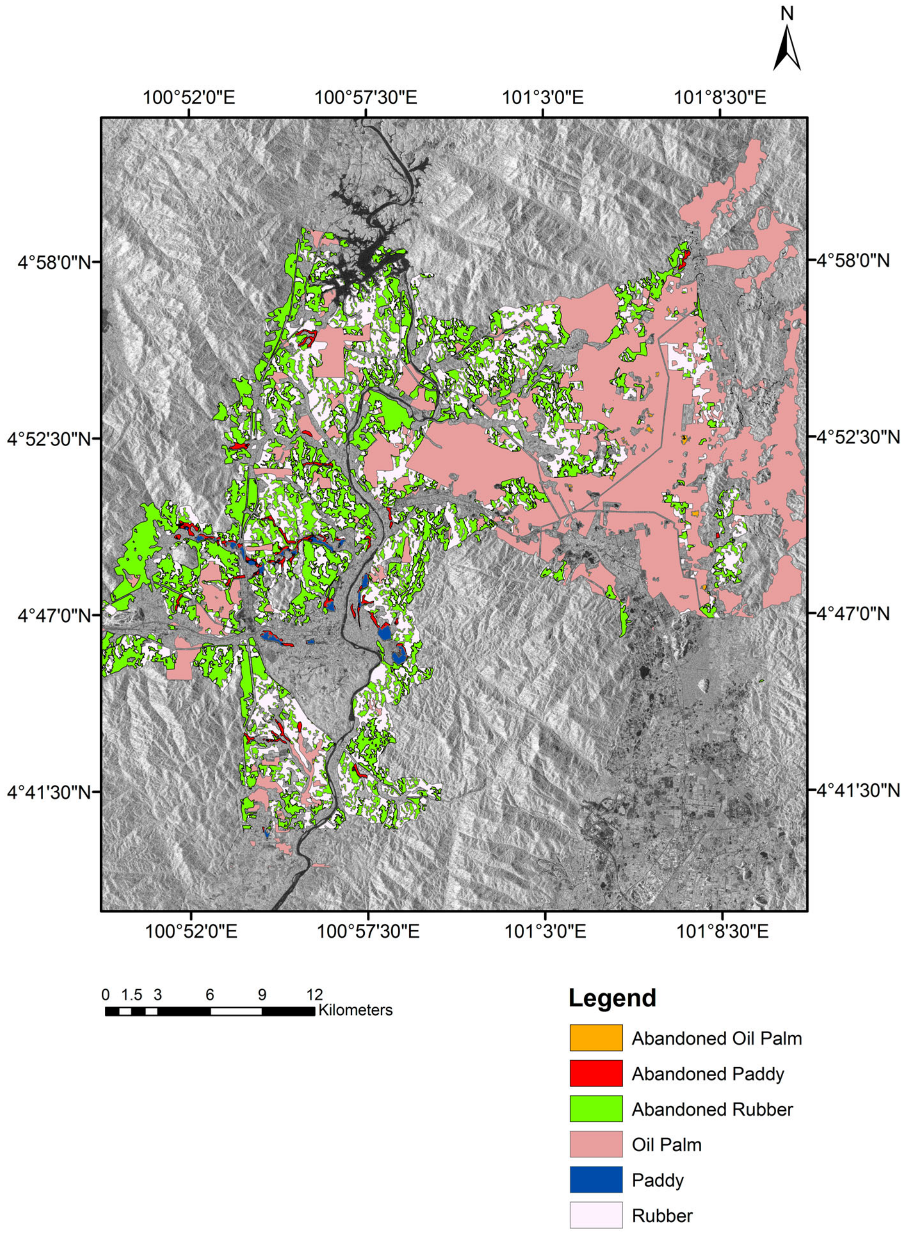

Figure 9. Classification map.

a biomass saturation effect is considered a limitation in radar backscatter, caused by the significant scattering in the foliage (Tan, Kanniah, and Cracknell 2013).

Figure 9 shows the paddy, rubber and oil palm areas, both abandoned and non-abandoned. Thirty-one percentage or 30,219 ha of this area was planted with rubber and slightly more than half of the area was abandoned. The second largest crop area was oil palm with 24% of the total area or 23,249 ha, and 0.04% was left abandoned. Finally, only 1% of the areas or 1031 ha were cultivated with paddy, and 66% went to abandonment. Compared with a study conducted by Yusoff and Muharam (2015) over the same study area, PALSAR gave an 11% extra of abandoned rubber and 14% extra of abandoned paddy areas. We hypothesized that the differences were primarily contributed by the satellite image used in this study. The acquisition dates of PALSAR images were limited to only half of the year, from June to December. While, for a seasonal crop such as rubber and paddy, multi-temporal dates within a year are necessary (Yusoff and Muharam 2015). However, both studies agreed that rubber and paddy areas were left abandoned in this area.

In terms of overall methodology, PALSAR images are capable of identifying abandoned paddy, rubber and oil palm. The advancement of creating rules in object-oriented classification might offer faster feature extraction than the traditional classification method that relies on sample selection. For paddy, at least three multi-temporal images must be used to discriminate between abandoned and non-abandoned classes due to the presence of unique phenology of this crop. Images chosen for the classification must at least be acquired during the planting season to reflect the planting activities such as irrigation and land preparation. For oil palm and rubber, a single image was found to be satisfactory despite no unique crop phenology could be extracted from the PALSAR images. It is vital to note that in this agriculture abandonment study, the threshold values created during the rule-based object-oriented classification have to be adjusted among different set of images and study areas. For instance, in this study we found that two different threshold values were created for identifying abandoned paddy using ALOS-1 and 2 images. This might be due to the different radiometric and spatial characteristics of both data, which according to van den van den Broek, Smith, and Toet (2004) the rules could differ in various situations and not straightforward.

4. Conclusion

This study shows the potential of ALOS-1 and 2 PALSAR images for identification and classification of agriculturally abandoned land. The exploration of radar images is crucial due to cloud cover limitation in optical images. Understanding crop phenology prior to the implementation of classification is essential to identify the agricultural abandonment. The uniqueness of paddy phenology during planting seasons, for instance, provides better delineation between abandoned and non-abandoned paddy area. Nevertheless, despite that none of the multi-temporal ALOS PALSAR images was captured during the defoliation stage, it was still possible to differentiate between the abandoned and non-abandoned rubber areas since there were no overlapping backscatter values for these two classes. Finally, the absence of unique phenology for oil palm imposed difficulties in discriminating between abandoned and non-abandoned areas. The condition was worsened with abandoned oil palm area as a minority area and the characteristic of radar geometry. Abandoned oil palm area appeared brightly as non-abandoned oil palm area cultivated at the hilly area, indicating a similar texture and surface roughness between these two.

In terms of accuracy, multi-temporal ALOS-1 and 2 PALSAR images showed high accuracy in detecting abandoned paddy field with 93.33% ± 0.06%, followed by abandoned rubber land with an accuracy of 78% ± 2.32% where these accuracies were comparable with the study conducted by Yusoff and Muharam (2015). In identifying abandoned oil palm area, ALOS PALSAR was capable of achieving an accuracy of 63.33% ± 1.88%. In addition, this finding proves the relationship between the understanding of phenology and accuracy of classification. The deeper we understand the phenology, the higher accuracy of crop classification, with consideration of the best image selection. Finally, this study confirms the potential of PALSAR as an alternative to optical images for the identification of agricultural crop abandonment.

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References

Alcantara, Camilo, Tobias Kuemmerle, Alexander V. Prishchepov, and Volker C. Radeloff. 2012. "Mapping Abandoned Agriculture with Multi-temporal MODIS Satellite Data." *Remote Sensing of Environment* 124: 334–347. doi:10.1016/j.rse.2012.05.019.

Aldred, D. A., and Jinfei Wang. 2011. "A Method for Obtaining and Applying Classification Parameters in Object-based Urban Rooftop Extraction from VHR Multispectral Images." *International Journal of Remote Sensing* 32 (10): 2811–2823. doi:10.1080/01431161003745590.

Amarsaikhan, D., and T. Douglas. 2004. "Data Fusion and Multisource Image Classification." *International Journal of Remote Sensing* 25 (17): 3529–3539. doi:10.1080/0143116031000115111.

Amorós-López, Julia, Luis Gómez-Chova, Luis Alonso, Luis Guanter, Raúl Zurita-Milla, José Moreno, and Gustavo Camps-Valls. 2013. "Multitemporal Fusion of Landsat/TM and ENVISAT/MERIS for Crop Monitoring." *International Journal of Applied Earth Observation and Geoinformation* 23: 132–141. doi:10.1016/j.jag.2012.12.004.

Baumann, Matthias, Tobias Kuemmerle, Marine Elbakidze, Mutlu Ozdogan, Volker C. Radeloff, Nicholas S. Keuler, Alexander V. Prishchepov, Ivan Kruhlov, and Patrick Hostert. 2011. "Patterns and Drivers of Post-socialist Farmland Abandonment in Western Ukraine." *Land Use Policy* 28 (3): 552–562. doi:10.1016/j.landusepol.2010.11.003.

Benayas, José M. Rey, Ana Martins, José M. Nicolau, and Jeniffer J. Schilz. 2007. "Abandonment of Agricultural Land: An Overview of Drivers and Consequences." *Perspectives in Agriculture, Veterinary Science, Nutrition and Natural Resources* 2 (57). doi:10.1079/pavsnnr20072057.

Bergen, K. M., T. Zhao, V. Kharuk, Y. Blam, D. G. Brown, L. K. Peterson, and N. Miller. 2008. "Changing Regimes: Forested Land Cover Dynamics in Central Siberia 1974 to 2001." *Photogrammetric Engineering and Remote Sensing* 74 (6): 787–798.

Bouvet, Alexandre, and Thuy Le Toan. 2011. "Use of ENVISAT/ASAR Wide-swath Data for Timely Rice Fields Mapping in the Mekong River Delta." *Remote Sensing of Environment* 115 (4): 1090–1101. doi:10.1016/j.rse.2010.12.014.

Brodský, Lukáš, and Luboš Borůvka. 2006. "Object-oriented Fuzzy Analysis of Remote Sensing Data for Bare Soil Brightness Mapping." *Soil & Water Research* 1: 79–84.

van den Broek, A. C., A. J. E. Smith, and A. Toet. 2004. "Land Use Classification of Polarimetric SAR Data by Visual Interpretation and Comparison with an Automatic Procedure." *International Journal of Remote Sensing* 25 (18): 3573–3591. doi:10.1080/01431160310001654400.

Buang, Amriah. 2001. "Privatizing the Rehabilitation of Idle Agriculture Land in Malaysia: Feedback from the Malay Folks." *Pertanika Journal of Social Sciences and Humanities* 9 (2): 103–112.

Canty, Morton J. 2010. *Image Analysis, Classification, and Change Detection in Remote Sensing*. 2nd ed. With Algorithms for ENVI/IDL. Boca Raton, FL: Taylor and Group.

Darmawan, S., W. Takeuchi, F. M. Muharam, and M. H. A. Razak. 2015. Investigation of Scattering Mechanisms on Agricultural Land Abandonment based on Decomposition of ALOS PALSAR Data. *Monitoring of Global Environment and Disaster Risk Assessment from Space: the IIS Forum Proceedings* 23: 137–140.

Darmawan, S., W. Takeuchi, Y. Vetrita, K. Wikantika, and D. K. Sari. 2015. "Impact of Topography and Tidal Height on ALOS PALSAR Polarimetric Measurements to Estimate Aboveground Biomass of Mangrove Forest in Indonesia." *Journal of Sensors* 2015: 1–13. doi:10.1155/2015/641798.

Department of Agriculture, Malaysia. 2013a. "Booklet Statistik Tanaman 2013". www.doa.gov.my/c/document_library/get_file?uuid=6e657e5c-21c4-4967-8e84-8b3a67dae933&groupId=38371.
Department of Agriculture, Malaysia. 2013b. "Paddy Statistic of Malaysia 2013." Accessed February 25, 2015. http://www.doa.gov.my/c/document_library/get_file?uuid = cef1fc5b-0adf-437d-a80e-f3136ee8b968&groupId = 358510.
Department of Agriculture, Malaysia. 2014. "Idle Land Information." Accessed January 12. http://www.doa.gov.my/maklumat-tanah-terbiar.
Department of Agriculture, Malaysia. 2006. *Land Use Map*. Malaysia: Department of Agriculture.
Díaz, G. Ignacio, Laura Nahuelhual, Cristian Echeverría, and Sandra Marín. 2011. "Drivers of Land Abandonment in Southern Chile and Implications for Landscape Planning." *Landscape and Urban Planning* 99 (3–4): 207–217. doi:10.1016/j.landurbplan.2010.11.005.
Dingle, Robertson Laura, and Douglas J. King. 2011. "Comparison of Pixel- and Object-based Classification in Land Cover Change Mapping." *International Journal of Remote Sensing* 32 (6): 1505–1529. doi:10.1080/01431160903571791.
Dong, Jinwei, Xiangming Xiao, Bangqian Chen, Nathan Torbick, Cui Jin, Geli Zhang, and Chandrashekhar Biradar. 2013. "Mapping Deciduous Rubber Plantations through Integration of PALSAR and Multi-temporal Landsat Imagery." *Remote Sensing of Environment* 134: 392–402. doi:10.1016/j.rse.2013.03.014.
Dong, Jinwei, Xiangming Xiao, Weili Kou, Yuanwei Qin, Geli Zhang, Li Li, Cui Jin, et al. 2015. "Tracking the Dynamics of Paddy Rice Planting Area in 1986–2010 through Time Series Landsat Images and Phenology-based Algorithms." *Remote Sensing of Environment* 160: 99–113. doi:10.1016/j.rse.2015.01.004.
Doug, R. Oetter, Warren B. Cohen, Mercedes Berterretche, Thomas K. Maiersperger, and Rober E. Kennedy. 2000. "Land Cover Mapping in an Agricultural Setting using Multiseasonal Thematic Mapper Data." *Remote Sensing of Environment* 76: 139–155.
Economic Planning Unit. 2014. "Prime Minister's Department Malaysia." Accessed February 17, 2015. http://www.epu.gov.my/en/statistic-of-major-agriculture-product.
Egbert, Stephen L., Sunyurp Park, Kevin P. Price, Re-Yang Lee, Jiaping Wu, and M. Duane Nellis. 2002. "Using Conservation Reserve Program Maps Derived from Satellite Imagery to Characterize Landscape Structure." *Computers and Electronics in Agriculture* 37: 141–156.
Falcucci, Alessandra, Luigi Maiorano, and Luigi Boitani. 2006. "Changes in Land-use/Land-cover Patterns in Italy and their Implications for Biodiversity Conservation." *Landscape Ecology* 22 (4): 617–631. doi:10.1007/s10980-006-9056-4.
Fan, Hui, Xiaohua Fu, Zheng Zhang, and Qiong Wu. 2015. "Phenology-based Vegetation Index Differencing for Mapping of Rubber Plantations Using Landsat OLI Data." *Remote Sensing* 7 (5): 6041–6058. doi:10.3390/rs70506041.
Frohn, R. C., B. C. Autrey, C. R. Lane, and M. Reif. 2011. "Segmentation and Object-oriented Classification of Wetlands in a Karst Florida Landscape using Multi-season Landsat-7 ETM+ Imagery." *International Journal of Remote Sensing* 32 (5): 1471–1489. doi:10.1080/01431160903559762.
Gamanya, Ruvimbo, Philippe De Maeyer, and Morgan De Dapper. 2007. "An Automated Satellite Image Classification Design using Object-oriented Segmentation Algorithms: A Move towards Standardization." *Expert Systems with Applications* 32 (2): 616–624. doi:10.1016/j.eswa.2006.01.055.
Guerschman, J. P., J. M. Paruelo, C. Di Bella, M. C. Giallorenzi, and F. Pacin. 2003. "Land Cover Classification in the Argentine Pampas using Multi-temporal Landsat TM Data." *International Journal of Remote Sensing* 24 (17): 3381–3402. doi:10.1080/0143116021000021288.
Henderson, Floyd M., and Anthony J. Lewis. 2008. "Radar Detection of Wetland Ecosystems: A Review." *International Journal of Remote Sensing* 29 (20): 5809–5835. doi:10.1080/01431160801958405.
Hirata, Yasumasa, and Tomoaki Takahashi. 2011. "Image Segmentation and Classification of Landsat Thematic Mapper Data using a Sampling Approach for Forest Cover Assessment." *Canadian Journal of Forest Research* 41 (1): 35–43. doi:10.1139/x10-130.
Homer, C., C. Huang, L. Yang, B. Wylie, and M. Coan. 2004. "Development of a 2001 National Land-cover Database for the United States." *Photogrammetric Engineering and Remote Sensing* 70 (7): 829–840.
Jinsong, Chen, Hui Lin, and Zhiyuan Pei. 2007. "Application of ENVISAT ASAR Data in Mapping Rice Crop Growth in Southern China." *IEEE Geoscience and Remote Sensing Letters* 4: 431–435.
Kassouk, Zeineb, Jean-Claude Thouret, Avijit Gupta, Akhmad Solikhin, and Soo Chin Liew. 2014. "Object-Oriented Classification of a High-Spatial Resolution Spot5 Image for Mapping Geology and Landforms of Active Volcanoes: Semeru case study, Indonesia." *Geomorphology* 221: 18–33. doi:10.1016/j.geomorph.2014.04.022.
Koay, Jun-Yi, Chue-Poh Tan, Ka-Sing Lim, Saiful Bahari bin Abu Bakar, Hong-Tat Ewe, Hean-Teik Chuah, and Fellow Jin-Au Kong. 2007. "Paddy Fields as Electrically Dense Media: Theoretical Modeling and Measurement Comparisons." *IEEE Transactions on Geosciene and Remote Sensing* 45: 2837–2849.
Kou, Weili, Xiangming Xiao, Jinwei Dong, Shu Gan, Deli Zhai, Geli Zhang, Yuanwei Qin, and Li Li. 2015. "Mapping Deciduous Rubber Plantation Areas and Stand Ages with PALSAR and Landsat Images." *Remote Sensing* 7 (1): 1048–1073. doi:10.3390/rs70101048.

Koulouri, M., and Chr Giourga. 2007. "Land Abandonment and Slope Gradient as Key Factors of Soil Erosion in Mediterranean Terraced Lands." *Catena* 69 (3): 274–281. doi:10.1016/j.catena.2006.07.001.

Kristensen, L. S., C. Thenail, and S. P. Kristensen. 2004. "Landscape Changes in Agrarian Landscapes in the 1990s: The Interaction between Farmers and the Farmed Landscape. A Case Study from Jutland, Denmark." *Journal of Environmental Management* 71 (3): 231–44. doi:10.1016/j.jenvman.2004.03.003.

Lee, Teang Shui, M. Aminul Haque, and M. M. M. Najim. 2005. "Scheduling the Cropping Calendar in Wet-seeded Rice Schemes in Malaysia." *Agricultural Water Management* 71 (1): 71–84. doi:10.1016/j.agwat.2004.06.007.

Li, Manchun, Lei Ma, Thomas Blaschke, Liang Cheng, and Dirk Tiede. 2016. "A Systematic Comparison of Different Object-Based Classification Techniques Using High Spatial Resolution Imagery in Agricultural Environments." *International Journal of Applied Earth Observation and Geoinformation* 49: 87–98. doi:10.1016/j.jag.2016.01.011.

Liew, Soo Chin, Suan-Pheng Kam, To-Phuc Tuong, Ping Chen, Vo Quang Minh, and Hock Lim. 1998. "Application of Multitemporal ERS-2 Synthetic Aperture Radar in Delineating Rice Cropping Systems in the Mekong River Delta, Vietnam." *IEEE Transactions on Geosciene and Remote Sensing* 36: 1412–1420.

Malaysian Meteorological Department. 2015. "Monthly Weather Bulletin." Accessed May 29,2015. http://www.met.gov.my/.

McMorrow, J. 2001. "Linear Regression Modelling for the Estimation of Oil Palm Age from Landsat TM." *International Journal of Remote Sensing* 22 (12): 2243–2264. doi:10.1080/01431160117188.

Miettinen, Jukka, and Soo Chin Liew. 2011. "Separability of Insular Southeast Asian Woody Plantation Species in the 50 m Resolution ALOS PALSAR Mosaic Product." *Remote Sensing Letters* 2 (4): 299–307. doi:10.1080/01431161.2010.520345.

Morel, Alexandra C., Joshua B. Fisher, and Yadvinder Malhi. 2012. "Evaluating the Potential to Monitor Aboveground Biomass in Forest and Oil Palm in Sabah, Malaysia, for 2000–2008 with Landsat ETM+ and ALOS-PALSAR." *International Journal of Remote Sensing* 33 (11): 3614–3639. doi:10.1080/01431161.2011.631949.

Morel, Alexandra C., Sassan S. Saatchi, Yadvinder Malhi, Nicholas J. Berry, Lindsay Banin, David Burslem, Reuben Nilus, and Robert C. Ong. 2011. "Estimating aboveground Biomass in Forest and Oil Palm Plantation in Sabah, Malaysian Borneo using ALOS PALSAR Data." *Forest Ecology and Management* 262 (9): 1786–1798. doi:10.1016/j.foreco.2011.07.008.

Ng, Casey. 2016. "What it means to be a Farming Smallholder in Malaysia." *UTAR Agriculture Science Journal* 2 (1): 40–48.

Olofsson, Pontus, Giles M. Foody, Martin Herold, Stephen V. Stehman, Curtis E. Woodcock, and Michael A. Wulder. 2014. "Good Practices for Estimating Area and Assessing Accuracy of Land Change." *Remote Sensing of Environment* 148: 42–57. doi:10.1016/j.rse.2014.02.015.

Othman, P. 1992. "Land Abandonment in the Rice Sector: An Economic Analysis." *Journal Ekonomi Malaysia* 26: 21–45.

Ponnusamy, R. 2013. Director, Research and Development Division, Felcra Berhad, Kuala Lumpur, Malaysia, Felcra Plantation Services Sdn. Bhd.

Prishchepov, Alexander V., Daniel Müller, Maxim Dubinin, Matthias Baumann, and Volker C. Radeloff. 2013. "Determinants of Agricultural Land Abandonment in Post-Soviet European Russia." *Land Use Policy* 30 (1): 873–884. doi:10.1016/j.landusepol.2012.06.011.

Robson, Benjamin Aubrey, Christopher Nuth, Svein Olaf Dahl, Daniel Hölbling, Tazio Strozzi, and Pål Ringkjøb Nielsen. 2015. "Automated Classification Of Debris-Covered Glaciers Combining Optical, SAR and Topographic Data in an Object-based Environment." *Remote Sensing of Environment* 170: 372–387. doi:10.1016/j.rse.2015.10.001.

Rosenqvist, Ake. 1999. "Temporal and Spatial Characteristics of Irrigated Rice in JERS-1 L-band SAR Data." *International Journal of Remote Sensing* 20 (8): 1567–1587. doi:10.1080/014311699212614.

Shimada, Masanobu, Osamu Isoguchi, Takeo Tadono, and Kazuo Isono. 2009. "PALSAR Radiometric and Geometric Calibration." *EEE Transactions on Geoscience and Remote Sensing* 47 (12): 3915–3932.

Smith, Randall B. 2012. "Interpreting Digital Radar Images." MicroImage. Accessed June 2016. http://www.microimages.com/documentation/Tutorials/radar.pdf.

Stow, D., A. Lopez, C. Lippitt, S. Hinton, and J. Weeks. 2007. "Object-based Classification of Residential Land Use within Accra, Ghana Based on QuickBird Satellite Data." *International Journal of Remote Sensing* 28 (22): 5167–5173. doi:10.1080/01431160701604703.

Syed, Sohel, Paul Dare, and Simon Jones. 2005. "Automatic Classification of Land Cover Features with High Resolution Imagery and Lidar Data: An Object-Oriented Approach." SSC2005 Spatial Intelligence, Innovation and Praxis: The national biennial Conference of the Spatial Sciences Institute, Melbourne: Spatial Sciences Institute.

Tan, Longfei, Yan Chen, Mingquan Jia, Ling Tong, Xin Li, and Lei He. 2015. "Rice Biomass Retrieval from Advanced Synthetic Aperture Radar Image based on Radar Backscattering Measurement." *Journal of Applied Remote Sensing* 9 (1): 097091. doi:10.1117/1.jrs.9.097091.

Tan, Kian Pang, Kasturi Devi Kanniah, and Arthur Philip Cracknell. 2013. "Use of UK-DMC 2 and ALOS PALSAR for Studying the Age of Oil Palm Trees in Southern Peninsular Malaysia." *International Journal of Remote Sensing* 34 (20): 7424–7446. doi:10.1080/01431161.2013.822601.

Teng, Khar Chun, Jun Yi Koay, Seng Heng Tey, Ka Sing Lim, Hong Tat Ewe, and Hean Teik Chuah. 2015. "A Dense Medium Microwave Backscattering Model for the Remote Sensing of Oil Palm." *IEEE Transactions on Geosciene and Remote Sensing* 53 (6): 3250–3259.

Thomas, M. Lillesand, W. Kiefer Raplh, and W. Chipman Jonathan. 2008. *Remote Sensing and Image Interpretation*. 6th ed. Hoboken, NJ: John Wiley.

Toan, Thuy Le, Florence Ribbes, Li-Fang Wang, Nicolas Floury, Kung-Hau Ding, Jin Au Kong, Masaharu Fujita, and Takashi Kurosu. 1997. "Rice Crop Mapping and Monitoring Using ERS-1 Data Based on Experiment and Modeling Results." *IEEE Transactions on Geosciene and Remote Sensing* 35: 41–56.

Wang, K., S. E. Franklin, X. Guo, Y. He, and G. J. McDermid. 2009. "Problems in Remote Sensing of Landscapes and Habitats." *Progress in Physical Geography* 33 (6): 747–768. doi:10.1177/0309133309350121.

Yonezawa, Chinatsu, Masahiro Negishi, Kenta Azuma, Manabu Watanabe, Naoki Ishitsuka, Shigeo Ogawa, and Genya Saito. 2012. "Growth Monitoring and Classification of Rice Fields using Multitemporal RADARSAT-2 Full-Polarimetric Data." *International Journal of Remote Sensing* 33 (18): 5696–5711. doi:10.1080/01431161.2012.665194.

Yusoff, N. M., and F. M. Muharam. 2015. "The Use of Multi-Temporal Landsat Imageries in Detecting Seasonal Crop Abandonment." *Remote Sensing* 7 (9): 11974–11991. doi:10.3390/rs70911974.

Zhang, Yuan, Cuizhen Wang, Jiaping Wu, Jiaguo Qi, and William A. Salas. 2009. "Mapping Paddy Rice with Multitemporal ALOS/PALSAR Imagery in Southeast China." *International Journal of Remote Sensing* 30 (23): 6301–6315. doi:10.1080/01431160902842391.

Zhang, Yuan, Cuizhen Wang, and Qi Zhang. 2011. "Identifying Paddy Fields with Dual-polarization ALOS/PALSAR Data." *Canadian Journal of Remote Sensing* 37 (1): 103–111. doi:10.5589/m11-016.