IDENTIFICATION OF ABANDONED OIL PALM AREAS FROM SATELLITE IMAGES

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ABSTRACT: Abandonment of agricultural land is a global issue; it is a waste of resources and brings a negative impact on local economy. It is also a key factor in certain environmental problems, such as soil erosion and increasing carbon sequestration. In order to address such problems related to land abandonment, their spatial distribution must first be precisely identified. This study utilized the satellite images together with crop phenology information, to identify abandoned oil palm areas. As acknowledged, oil palm is a commercial crop that is important for food value and as a biofuel, along with its other benefits towards human health. Currently, Malaysia cultivates approximately 5.64 million ha of oil palm, where 40% belongs to smallholders. To date, a study to identify abandoned oil palm areas using satellite images is almost non-existent. Conventionally, monitoring of abandoned oil palm lands, especially ones cultivated by smallholders is tedious and time consuming, especially over scattered, large areas. Hence, in this study, the capability of high resolution satellite image via SPOT-6 products to extract abandoned oil palm areas was explored, as was the use of multi-temporal Landsat Operational Land Imager (OLI) imageries to develop the phenology of abandoned oil palm sites. Homogeneity measures derived through SPOT images played a more important role to identify abandoned oil palm than crop phenology characteristics extracted from high spectral resolution of Landsat images. With the advancement of object-oriented classification, monitoring of abandoned oil palm areas can be done semi-automatically with an accuracy of 92%±1%.

1. INTRODUCTION

Oil palm (*Elaeis guineensis*) is one of the world's most important tropical crops and the demand for palm oil has continued for over 50 years (Gutiérrez-Vélez & DeFries, 2013). Oil palm contributes to many positive aspects, such as economy, environment, health, and life (MPOB, 2015) and as one of the most profitable of land uses in humid tropics (Sayer, Ghazoul, Nelson, & Klintuni Boedhihartono, 2012). On the other hand, to ensure high fruit yield, good management is a required on oil palm plantations (Salmiyati, heryansyah, Idayu, & Supriyanto, 2014). After Indonesia, Malaysia is currently the world's second largest oil palm producer (Murphy, 2014), where 60% of the producers are plantation entities and the remaining are under smallholders, including organised and independent smallholders (Abazue, C, Alam, & Begum, 2015). Independent smallholders in particular cultivate oil palm on a small scale and without direct assistance from oil palm related agencies. The challenges faced by smallholders include difficulties to secure capital, difficulties to access good technical advisory, information related to policy and market, difficulties to balance cash crops with food security, and difficulties to cope with market risk (Vermeulen & Goad, 2006), of which these constraints can increase the chances of abandoning their oil palm cultivation.

In the Malaysian context, oil palm is considered abandoned if it has a minimum area of 0.4 hectares, and left idle for more than 3 consecutive years (Department of Agriculture, 2014). Through observations, management activities such as pruning, harvesting, weeding, and fertilisation were also absent; thus, the area tends to be covered by shrubs and bushes, and in a worst-case scenario, the area resembles secondary forest. Hence, this condition is more relevant to the context of smallholders rather than to organised plantations. Abandonment of oil palm is a potential threat to the industry itself, waste the country resources, either through poor agricultural land utilisation or low agricultural production. On the other hand, with limited land to expand, full utilization of existing oil palm areas is better than expanding into natural forest. According to Koh & Wilcove (2008), the conversion of primary or secondary forest to oil palm resulted in significant impact on biodiversity losses and the natural ecosystem (Fitzherbert et al., 2008; Koh & Wilcove, 2008). Economically, each hectare of oil palm is capable of producing 4 tons of palm oil per year, which is equivalent to USD 2,892. In the case of three years of abandonment, the total opportunity losses per hectare area equals at least USD 8,676. Therefore, identifying abandoned oil palm is essential to oil palm policy makers and agencies, such as Federal Land Consolidation and Rehabilitation Agency (FELCRA).

Land abandonment is commonly scattered (Ponnusamy, 2013) and widespread (Alcantara et al., 2013); hence, identifying them using ground based method can pose quite a challenge in terms of cost, time, and labor. Therefore, efficient monitoring of abandoned agricultural lands is crucial. Remote sensing technology has been used for the identification of abandoned agricultural lands globally (Milenov et al., 2014; Prishchepov, Müller, Dubinin, Baumann, & Radeloff, 2013; Soukup, Brodsky, & Vobora, 2009) due to its repetitive large coverage (Prishchepov, Radeloff, Dubinin, & Alcantara, 2012) and proven success in monitoring non-accessible areas (Baumann et al., 2011; Ignacio, Laura, Cristian, & Sandra, 2011; Löw, Fliemann, Abdullaev, Conrad, & Lamers, 2015). In oil palm related studies, remote sensing technology has been explored regarding age determination (Chemura, van Duren, & van Leeuwen, 2015) and tree counting (Shafri, Hamdan, & Saripan, 2011). For oil palm, a single-date of satellite imagery might be enough for mapping purposes, due to the fact that no seasonal effects are manifest in the oil palm leaves (Cracknell, Kanniah, Tan, & Wang, 2013). However, there exists almost no research focused specifically on abandoned oil palm.

Thus, in this study, our overarching goal is to explore the capability of high resolution SPOT-6 to identify and classify abandoned oil palm using object-oriented classification. The specific objectives identified were:

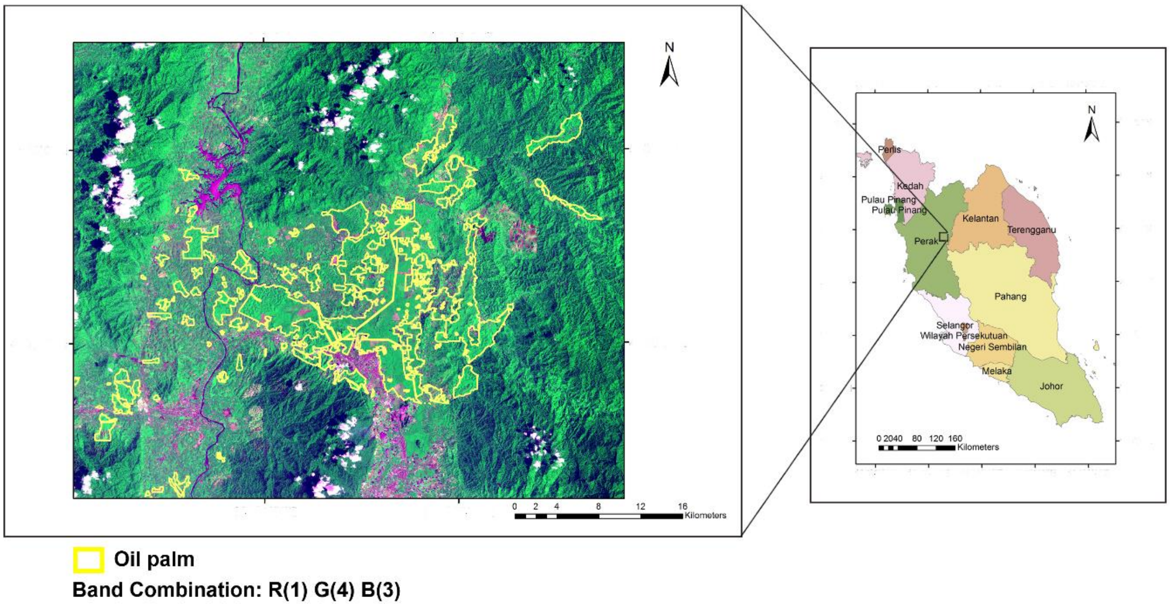
1. To develop crop phenology of abandoned oil palm and non-abandoned oil palm using multi-temporal Landsat OLI images; and
2. To develop a methodology in identifying abandoned oil palm area using SPOT-6 images.

2. METHODOLOGY

2.1 Study Area

The study was carried out in Kuala Kangsar district in the Perak state of Malaysia. This district is located within 5°5′32″N, 100°50′15″E to 4°42′3″N, 101°18′29″E. Approximately 22,382 hectares or 23% of these areas are cultivated with oil palm trees, indicated by the yellow polygon that overlays with the SPOT-6 image (Figure 1). The oil palm is planted in both flat and hilly areas, with the elevation ranging from 30m to 520m.

Figure 1: Oil palm area in Kuala Kangsar, Perak, Malaysia shown by SPOT-6 image



2.2 Crop Phenology Development

Multi-temporal Landsat OLI imageries with 30 m spatial resolution were utilized in oil palm phenology matrices development, where thirteen series images from 2013 to 2015 were utilized. A systematic archiving of Landsat images was obtained from the United States Geological Survey (USGS). Crop phenology is commonly developed in order to characterize changes in vegetation (Atzberger & Eilers, 2011; Dong et al., 2015; Thayn & Price, 2008). In this study, Normalized Difference Vegetation Index (NDVI) was used to develop the oil palm phenology due to its simplicity and commonly used vegetation index (Atzberger, Klisch, Mattiuzzi, & Vuolo, 2013; Li & Fox, 2012; Yusoff & Muharam, 2015). Ground locations of abandoned and non-abandoned oil palm were used to locate corresponding NDVI values for each satellite image. Ground location on abandoned land and non-abandoned land were collected in January, April and November 2014. We found a total of 27 locations of oil palm, whereas 3 of that locations indicates the abandoned oil palm in this study area. These values were extracted and used to create phenology for abandoned and non-abandoned oil palm. The flowchart of the overall process is shown by Figure 2.

2.3 Identifying Abandoned Oil Palm Area

2.3.1 SPOT-6 Data Collection and Processing

This study used a SPOT-6 satellite image for extraction and classification of abandoned oil palm areas, with the spatial resolution characteristic of 6m and 1.5m for multispectral and panchromatic band, respectively. The image was acquired on 12 February 2014 and orthorectified and geometrically corrected by Malaysian Remote Sensing Agency (MRSA). The oil palm canopy texture was visualized from the SPOT-6 pan-sharpen product, with the combination of panchromatic band (0.450-0.745 μm) and multispectral with four bands, which is blue (0.450-0.520 μm), green (0.530-0.590 μm), red (0.625-0.695 μm) and near infrared (0.760-0.890 μm). This study utilized SPOT-6 products based on their capability, where SPOT-6 multispectral was used for NDVI value extraction, SPOT-6 panchromatic for texture analysis and SPOT-6 pan-sharpen for image segmentation.

2.3.1.1 SPOT-6 multispectral for NDVI value extraction

In many oil palm plantations, non-vegetation features such as roads, workers' houses, oil factories and sometime livestock can also be recognized in satellite images. In addition, oil palm at the replanting stage also may appear as non-vegetation features due to the mixture of soil background values. Therefore, NDVI was used to differentiate between vegetation and non-vegetation areas in this oil palm plantation.

2.3.1.2 SPOT-6 panchromatic for texture analysis

In order to decide which SPOT-6 product was to be utilised, which could either be multispectral or panchromatic, and is capable of discriminating between abandoned and non-abandoned oil palm, we first located in the satellite images abandoned oil palm, non-abandoned mature oil palm, and non-abandoned immature oil palm based on their ground coordinates (Figure 3a and 3b). The SPOT-6 panchromatic image showed the capability to visualize the abandoned oil palm better than the multispectral image due to its spatial resolution. Based upon this advantage, we integrated the textural analysis using the SPOT-6 panchromatic image in the rule-based approach. Texture analysis is found to be useful for imageries with limited spectral bands (Caridade, Marçal, & Mendonça, 2008) and is able to improve classification accuracy (Puissant, Hirsch, & Weber, 2005). For the textured analysis, we selected the homogeneity measure with a 7 x 7 window size (Puissant et al., 2005), which is appropriate for a grid spacing of 9 m between oil palm trees. In Malaysia, oil palm plantation is considered to be a homogeneous area because it is a monocrop (Shafri et al., 2011). Therefore, in Figure 3c, the non-abandoned oil palm area (yellow box) was dominated by white coloured pixels that are highly homogeneous. Meanwhile, the abandoned oil palm area (red box), the homogeneity level decreased due to scrubland and forest re-growth after land abandonment (Ignacio et al., 2011). However, for the non-abandoned young or immature oil palm, the heterogeneity level increased (blue box) due a mixture of spectral signature between oil palm and ground cover (Gutiérrez-Vélez & DeFries, 2013).

Figure 2: Flowchart of the overall process

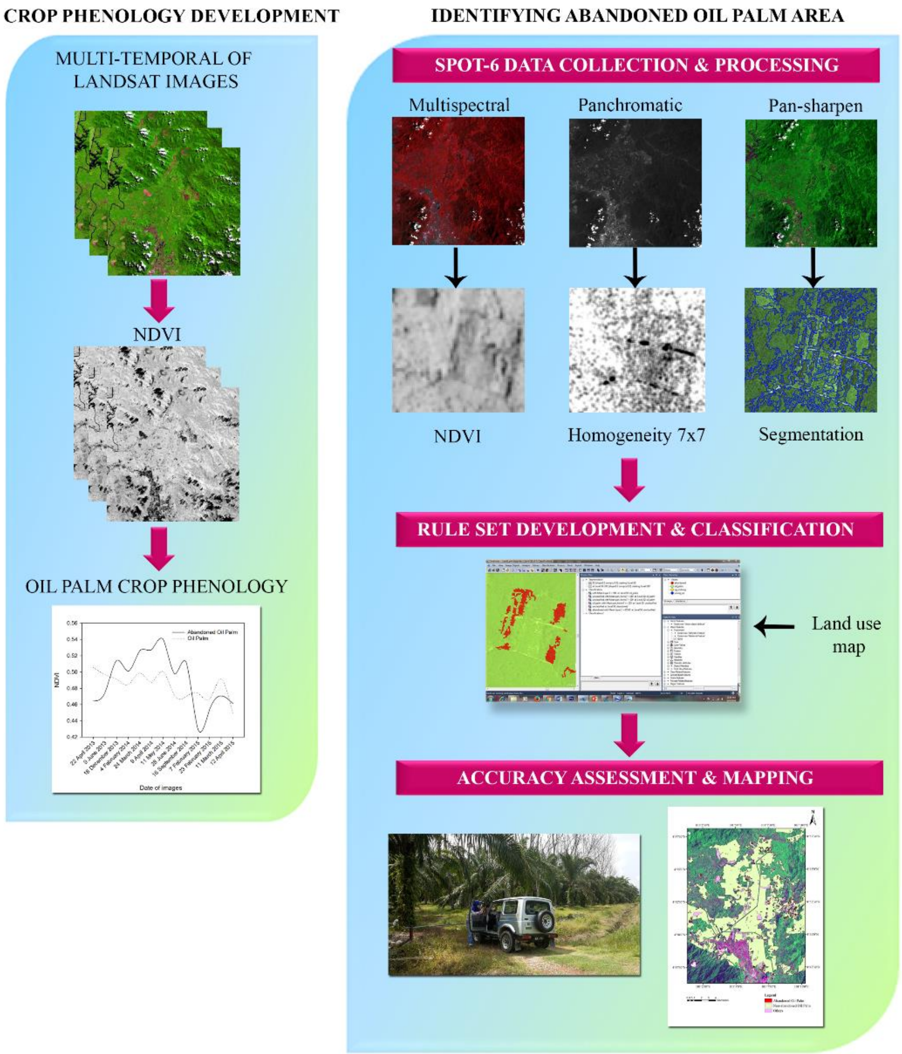
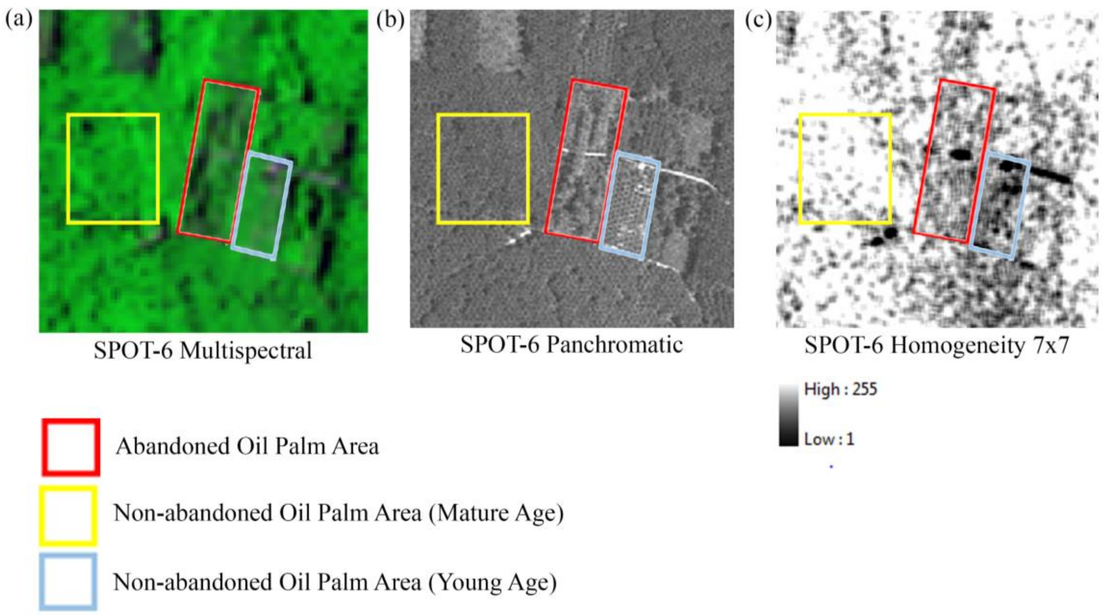


Figure 3: Texture analysis



2.3.1.3 SPOT-6 pan-sharpen for image segmentation

In weighing the appropriate segmentation scale, spatial resolution is the main determinant factor (Lian & Chen, 2011; Yu, Cheng, Ge, & Lu, 2011). The higher spatial resolution, the greater the scale, and vice versa (Lian & Chen, 2011). The selected scale greatly influences classification accuracy (Chini, Chiancone, & Stramondo, 2014; Gamanya, De Maeyer, & De Dapper, 2007; Gao, Mas, Kerle, & Navarrete Pacheco, 2011). In order to obtain the optimum segmentation scale, the segmentation process needs to be executed either the by trial-and-error or multi-resolution segmentation approach (Duro, Franklin, & Dubé, 2012; Hirata & Takahashi, 2011; Stow, Lopez, Lippitt, Hinton, & Weeks, 2007; Tian & Chen, 2007). The best segmentation scale is commonly evaluated through visual interpretation (Chen, Su, Li, & Sun, 2009). In this study, segmentation was executed at a level of 50 as an optimum scale considered appropriate with the image size and resolution.

2.3.2 Rule Set Development and Classification

To assist the classification procedure, we utilized a historical land use map produced in 2006 from the Department of Agriculture Malaysia (Yusoff & Muharam, 2015). The 1:50,000 scale land use map was prepared based on a ground survey and digitized satellite images, with several land use classes identified (Yusoff, Muharam, Takeuchi, Darmawan, & Razak, 2016). Only the oil palm boundary was used as a basic for satellite images subset. The selection of backdated year of land use map is according to the definitions of agriculturally abandoned land, which is agricultural land left uncultivated for more than three consecutive years.

By using histogram analysis, the NDVI threshold between vegetation and non-vegetation was set to be 0.31 (Table 1). In identifying non-abandoned oil palm, we employed a red band of SPOT-6 pan to sharpen the image. The mean of the red value below 390 was used to separate non-abandoned oil palm from abandoned ones. Non-abandoned oil palm, which is considered to be healthy plants, greatly absorbs red energy due to chlorophyll production (Thomas, Raplh, & Jonathan, 2008). However, there were still unclassified non-abandoned oil palm using this single rule. Therefore, a second rule developed from SPOT-6 panchromatic homogeneity 7x7 was created. As shown in Figure 3c, the non-abandoned mature oil palm area had a high homogeneity value while non-abandoned immature oil palm areas were highly heterogeneous. Therefore, the threshold value above 200 and below 150 were used to extract non-abandoned oil palm. Finally, abandoned oil palm area was declared as not non-abandoned oil palm and non-vegetation, where the rules for abandoned oil palm were the opposite of those derived for the aforementioned classes.

Table 1: Rule set identified to extract abandoned oil palm, non-abandoned oil palm and others features

Rule set	Purpose
with NDVI < 0.31 at Level 50: Others	To extract non-vegetation and others features
with Mean Red < 390 at Level 50: non-abandoned oil palm	To extract non-abandoned oil palm area
unclassified with Mean homogeneity 7x7 < 150 at Level 50: non-abandoned oil palm	To extract non-abandoned immature oil palm area
unclassified with Mean homogeneity 7x7 > 200 at Level 50: oil palm	To extract non-abandoned mature oil palm area
unclassified at Level 50: abandoned oil palm	To extract abandoned oil palm

2.3.3 Accuracy Assessment and Mapping

The accuracy of the classification maps derived from SPOT-6 was assessed by a set of 256 points using stratified random sampling (Canty, 2010); 52 points were selected for abandoned oil palm, 151 points for non-abandoned oil palm and 53 points for others feature. All of the sample points were generated automatically from ERDAS Imagine and were examined individually. The ground locations were collected during field trips were used as a basis to identify the characteristics of abandoned oil palm from satellite images. Besides using ground truth data, the assessment was also visually assisted through inspection using high resolution images from Google Earth (Latifovic et al., 2012; Rahman et al., 2013) dated 26 April 2014, to obtain the optimum sample size. For instance, non-vegetation classes could be clearly identified from Google Earth due to their colour (Google Earth: R (3), G (2), B (1)) and shape. For non-abandoned oil palm, individual oil palm trees could be clearly identified, especially at an immature stage. Moreover, abandoned oil palm appeared in dark green colour due to high crop density and species mixture, as well as low sun penetration (Celis & Jose, 2011). Therefore, Google Earth was utilised to differentiate between abandoned and non-abandoned oil palm due to the differences shown by the crop texture where the former resembles secondary forest. The user and producer accuracy, kappa statistic and overall accuracy were then calculated for each class (Olofsson, Foody, Stehman, & Woodcock, 2013).

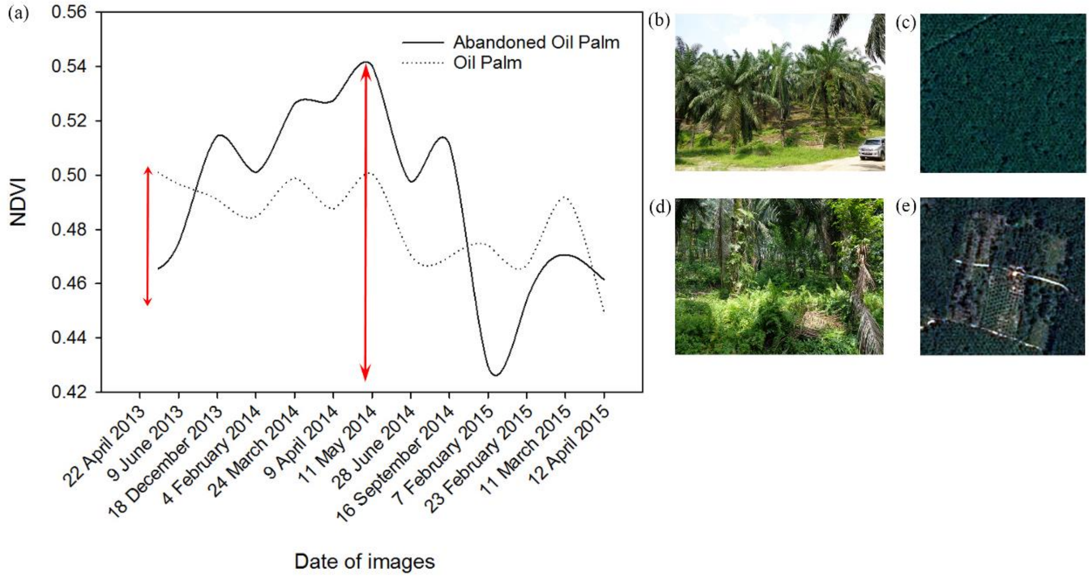
For mapping purposes, the polygon area of less than 0.4 hectares was eliminated. The individual layer was then updated, and the final map classes identified were abandoned oil palm, non-abandoned oil palm and others.

3 RESULTS AND DISCUSSION

3.1 Crop Phenology

As seen in Figure 4a, the NDVI value for abandoned oil palm were higher than oil palm in several Landsat images, especially in year 2014. This might due to the higher heterogeneity characteristic of abandoned crops or perhaps due to higher crop diversities and species (Zhang, Dang, Tan, Wang, & Zhang, 2010). However, several images, especially in 2015, showed that the NDVI values for the abandoned oil palm were completely the opposite. Because oil palm is a perennial crop with no seasonal effect in the leaves, the unique phenology is not manifested distinctively, such as is found with rice paddy and rubber tree areas (Yusoff & Muharam, 2015). After 10 years of age, the growth of oil palm starts to stabilize or become stagnant (Tan, Kanniah, & Cracknell, 2013). Therefore, the NDVI range is not as wide as for the abandoned oil palm as indicated by the red and blue arrows, respectively in Figure 4a. Figure 4b depicts the properly managed oil palm plantation and this condition is reflected in SPOT-6 image in Figure 4c, which shows the crops' pattern was homogeneous (Cracknell et al., 2013; Shafri et al., 2011). However, for the abandoned oil palm, Figure 4d demonstrates that the area resembled secondary forest, in which its ground was covered by bushes and was unmanaged. The condition was well reflected in the SPOT-6 image, where the heterogeneity of the crop pattern was highly visible, as shown in Figure 4e.

Figure 4: Crop phenology of non-abandoned and abandoned oil palm



3.2 Image Classification and Accuracy Assessment

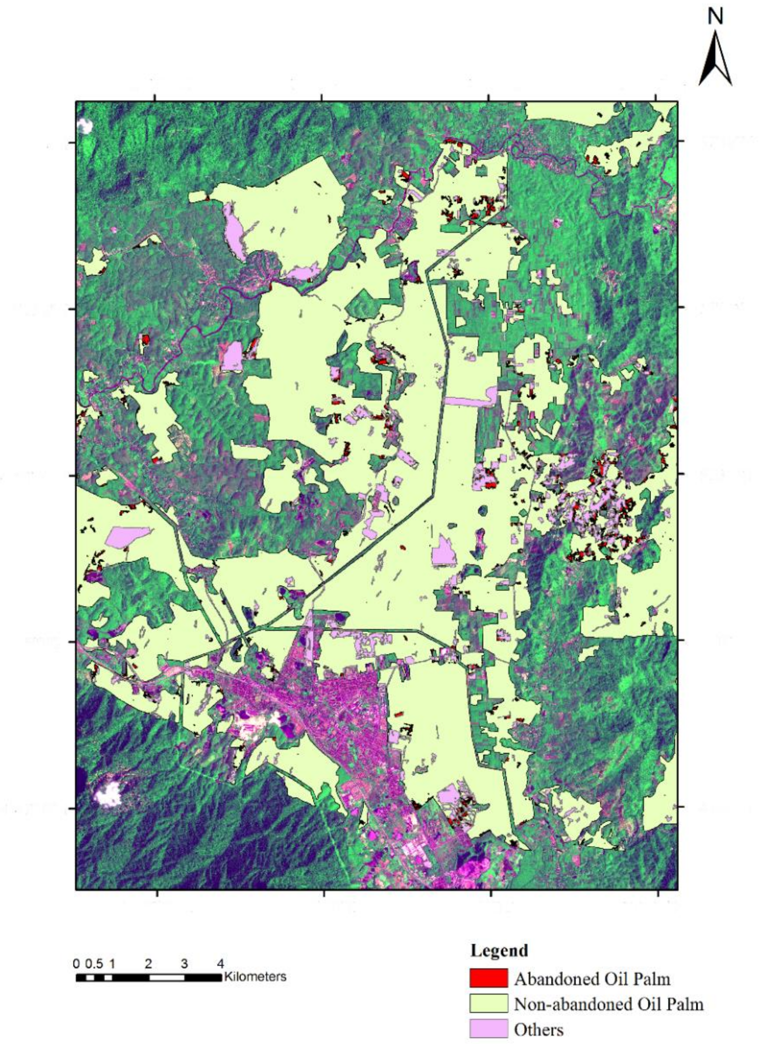
With the advancement of the rule-based method, classification can be done in a semi-automated manner, which eliminates the need for sample collection and is less time consuming. In this study, we extracted the classes by hierarchy. Firstly, non-vegetation with a 100% accuracy obtained, secondly non-abandoned oil palm (mature and immature individually) with accuracy of 96% ± 1% and finally the abandoned oil palm area with achievable accuracy up to 92% ± 1% (Table 2). Most of the misclassification for abandoned oil palm occurred at hilly areas, which is subject to the topographic effect (Morel, Fisher, & Malhi, 2012), where the non-abandoned immature oil palm cultivated at these areas were wrongly identified to be abandoned oil palm. Additionally, four points of abandoned oil palm were misidentified as non-abandoned due to their characteristics that resembled forest, where this misclassification occurred at hilly areas as well. Hence, additional rules during the feature extraction procedure concerning the cultivation of oil palm at hilly areas are required.

The final classification map as shown in Figure 5, which demonstrates the distribution of abandoned oil palm, non-abandoned oil palm and other features in this study area. Evidently, the distribution of abandoned oil palm are scattered (Ponnusamy, 2013) and widespread (Alcantara et al., 2013), and therefore, strongly justifies the advantages of using remote sensing technology in identifying abandoned areas.

Table 2: Accuracy assessment

	Abandoned Oil Palm	Non-abandoned Oil Palm	Others
Abandoned Oil Palm	46	4	-
Non-abandoned Oil Palm	6	147	
Others	-	-	53
Total	**52**	**151**	**53**
User's	92%	96%	100%
Producer's	88%	97%	100%
Overall		**96%**	

Figure 5: Classification map



4. CONCLUSION

This study shows the utilization of multi-temporal Landsat OLI images to develop crop phenology of abandoned oil palm and non-abandoned oil palm. Contradict with seasonal crops such as paddy field and rubber trees, the crop phenology of abandoned oil palm and non-abandoned oil palm is not straightforward. However, since oil palm is a perennial crop, the growth is slower than seasonal crops, especially when oil palm is at its maturity stage. Therefore, the NDVI range between multi-temporal images is smaller than the abandoned oil palm. In terms of texture, non-abandoned oil palm at a mature age gave a higher value of homogeneity than abandoned oil palm. On the other hand, for non-abandoned immature oil palm, the results were reversed due to the open canopy and the ground cover effect.

In terms of accuracy, this study also shows the capability of SPOT-6 imagery in identifying abandoned oil palm areas with an accuracy of 92% ± 1%. With the development of the rule set, the classification was done without having to collect training samples, required less time consuming activities and was semi-automated. We found that 3% of this oil palm plantation area was left abandoned; certainly, land abandonment is a waste of country resources.

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