Mapping Rubber Tree Growth by Spectral Angle Mapper Spectral-based and Pixel-based Classification Using SPOT-5 Image

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ABSTRACT: Monitoring the rubber tree growth is necessary issue to understand the impacts of changes in Managing land use/land cover. The Malaysian government is interested in increasing rubber latex production. Collecting and analyzing data, and ensuring that such data are up to date to identify the rubber tree stand age distribution is difficult when using the traditional survey method. Per-pixel and spectral-based classification techniques were employed in this study by using the spectral angle mapper classifier approach. SPOT-5 satellite was used as the data source for the classification. The study area was classified into eight classes to estimate the lu/lc. The rubber tree area was subsequently classified into three groups based on age: less than 7, 7 to 25, and more than 25 years; these classes represented the young, middle-aged, and mature rubber trees, respectively. The assessment accuracy of the spectral- and pixel-based approaches was 91% and 77%, respectively. The classification result shows that the spectral-based approach was more accurate and suitable than the pixel-based approach for estimating the rubber tree growth distribution.

1. INTRODUCTION

Monitoring and managing rubber trees by using conventional techniques, such as survey technique, are time consuming, require intensive labor, and difficult in terms of providing real-time data and/or temporal data on the distribution and growth of rubber trees. Finding a new technique that is cheaper and can provide up-to-date geospatial and temporal data on the rubber trees is necessary. Remote sensing and geographic information system (GIS) are currently becoming powerful tools for land use/land cover (lu/lc) identification (Brown, 2007; Zhe and Fox, 2011). Remote sensing and GIS can provide special information on rubber tree distribution based on accurate data that can meet the needs of the government and smallholders (Hurni, 2008; Zhe and Eastman, 2010; Zhe and Fox, 2011).

Recently, remote sensing and GIS have played major roles in managing and monitoring lu/lc (Fox and Vogler, 2005). Several countries, such as Vietnam, Thailand, China, Laos, and Myanmar, plant rubber trees on hundreds of hectares of land (Alan et al., 2009; Mann, 2009). Several studies investigated the distribution of rubber trees in Asia, especially in Yunnan, China, and in Indonesia, Laos, and Thailand (Zhe and Eastman, 2010; Zhe and Fox, 2011). Their research focused on studying the distribution of rubber trees within the age of 7 to 14 years because rubber latex productivity is at its highest at this time (Lobell, 2002; Zhe and Fox, 2011).

Remote sensing and GIS are good spatial tools for rubber tree management. However, the use of spatial tools comes with difficult challenges: (1) collection of ground reference data over a large area will limit the classification approach and lead to over classification and/or misclassification, (2) spectral confusion between the spectral reflectance of rubber tree and tropical evergreen vegetation, and (3) difficulty in identifying young rubber trees less than 4 years of age (Zhe and Fox, 2011). Many classifier approaches that are applied to investigate and identify the distribution of rubber trees used remote sensing and GIS, such as neural networks, decision tree, and support vector machine (Quinlan, 1986; Christopher, 2006; Hayder, 2013), and these approaches revealed more accurate results than the conventional techniques that were used for the same purpose (Civco, 1993; Lippitt et al., 2008; Zhe and Eastman, 2010; Hayder and Alnajjar, 2013). Another research applied Mahalanobis classifier approach to identify the distribution of rubber trees (John, 2007; Sangermano and Eastman, 2007; Hernandez et al, 2008). Zhe and Fox applied Mahalanobis distance approach to estimate and map rubber trees with normalized difference vegetation index data obtained from MODIS and some statistical data (Zhe and Fox, 2012). Data from aerial photographs were used in the study conducted by Jingxiong and Roger (Jingxiong and Roger, 1997), who employed fuzzy classifier to extract fuzzy maps of lu/lc.

This study aimed to identify rubber tree growth through two classifications. The study provides a good statistical assessment using spectral angle mapper classification (SAM) between two approaches (spectral- and pixel-based) with the use of the ENVI software. Moreover, spectral- and pixel-based approaches were compared to identify the most accurate and suitable approach of extracting the thematic map of the land cover of tropical areas and the mapping of the distribution of rubber tree growth. Recommendations were made in monitoring and managing of lu/lc and rubber tree growth estimation.

2. MATERIALS AND METHODS

SAM classifier was applied for the classification of lu/lc by using pixel- and spectral-based approaches. The proposed method started with fieldwork to collect ground reference data with their location and spectral reference data for most of the features located in the study area. Image enhancement was then conducted. The satellite image was already corrected geometrically and radiometrically by the data provider company; the correction is suitable for this research. Training samples were selected from the satellite image for use in the pixel-based classification. The spectral references that were collected from fieldwork were resampled to be suitable with SPOT-5 multispectral bands for use as training samples in the spectral-based classification. The study area was subsequently divided into eight classes (old oil palm, young oil palm, forest, other vegetation, rubber, water bodies, building, and soil), then SAM classifications (pixel- and spectral-based) were conducted. Accuracy assessments were performed after the SAM classifications using the ground samples from fieldwork. The satellite image was masked in preparation for the extraction of the thematic map of the distribution of rubber tree growth. All other features were subsequently clipped, followed by the application of the SAM classifications (pixel- and spectral-based) to map the rubber trees. Finally, accuracy assessment was performed again to determine the most suitable approach of identifying the rubber tree growth. Figure 1 shows the flowchart of the extraction of rubber tree growth.

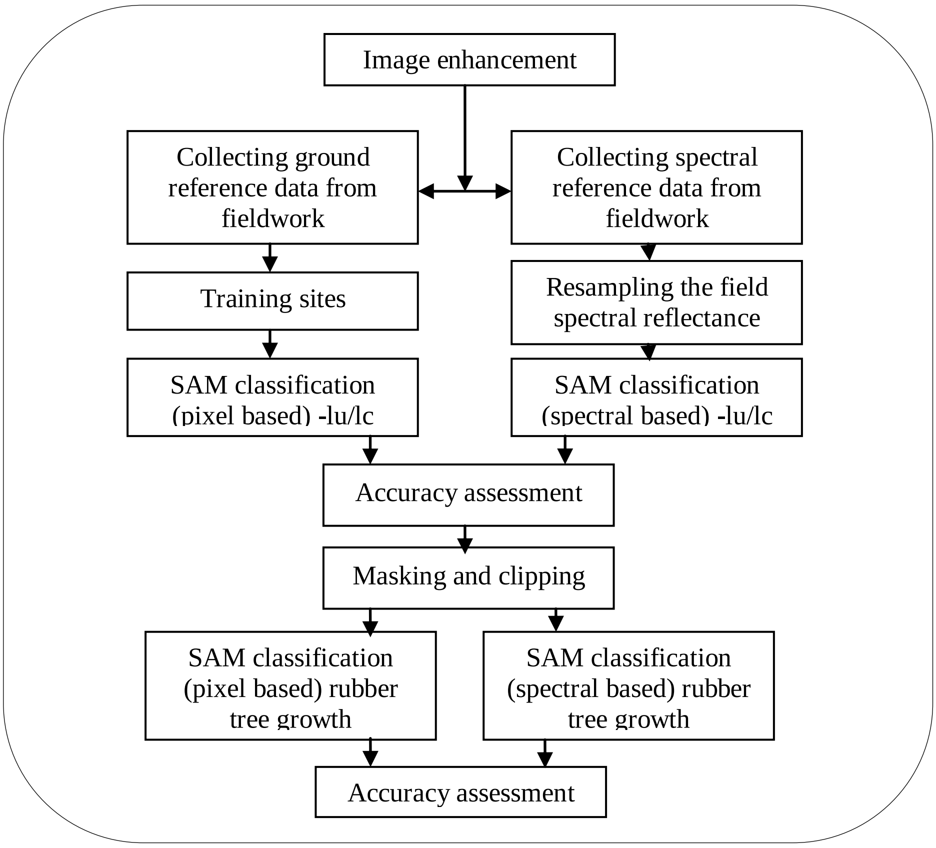

Figure 1 Flowchart of rubber tree growth

2.1 Study Area and Data

Hulu Selangor, Malaysia was the study area and is located between 101°20′57.15″–101°42′41.81″ E and 3°20′31.90″–3°41′54.72″ N over an area of 900 km^2. Figure 2 shows the Hulu Selangor study area.

A SPOT-5 imager was used to investigate the study area. The imager has four spectral bands and one panchromatic band with spatial resolutions of 20 and 10 m, respectively. The SPOT-5 image was captured on August 27, 2007. The image was corrected and registered to the WGS84 datum with the use of Universal Transverse Mercator Zone 47 projection.

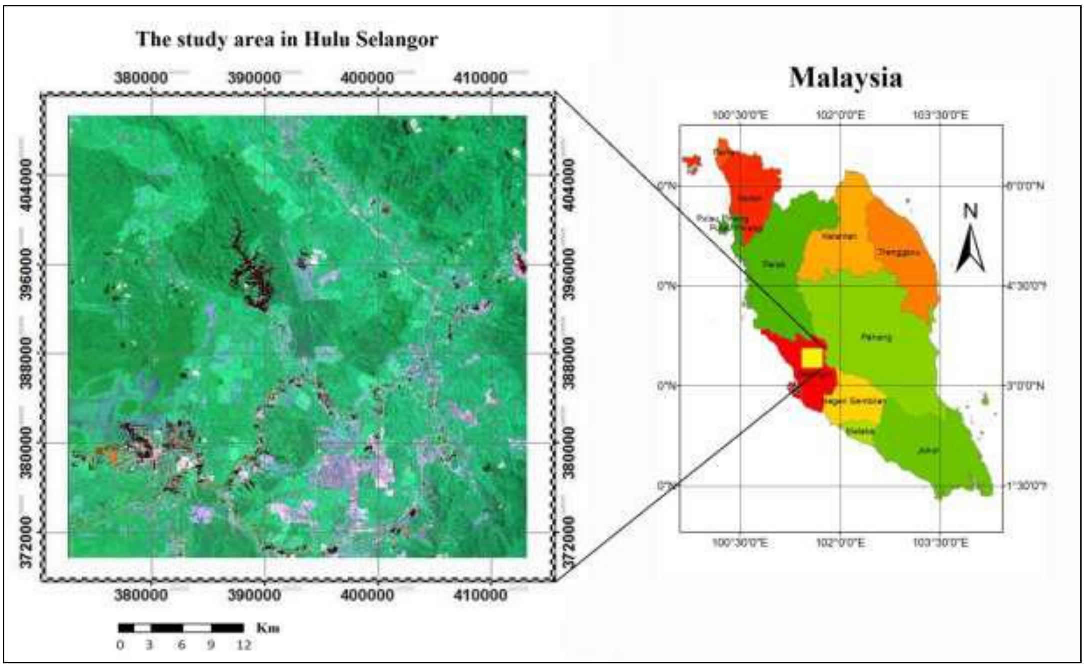

Figure 2 Study area of Hulu Selangor, Malaysia.

Two types of ancillary data were used to assist in the fieldwork and image interpretation to obtain initial information on the rubber tree locations. The first used a Rawang district topographic map with a scale of 1:50,000. The second used a shapefile data generated on April 14, 2009.

2.2. Collecting ground reference data (fieldwork)

The first step in the fieldwork was the collection of the ground reference data, which is an important step in many remote sensing and GIS applications. These references should be collected from the study area to assess the classification (John, 2007). Garmin 76CSX global positioning system was used to collect the ground reference data of the features that are related to each class located in the study area. Reference data were collected with their locations, especially the rubber trees whose ages were also recorded, for use in the confusion matrix (John, 2007; Alan et al., 2009; Zhe and Fox, 2011; Hayder, 2013). The size of each ground reference data was at least 50 m^2. The ground reference data and spectral reflectance of all the classes were collected on May 15, 2012. The datum that was used in collecting these references was the WGS84 ellipsoid that was converted to the Kertau (RSO) Malaysian datum. The second step in the fieldwork was the collection of the spectral reflectance of the features that were mostly distributed in the study area for application into the classification approach to extract the thematic map of lu/lc. The spectral reflectance of rubber trees' spectral measurements was collected on May 15, 2012. The spectral reflectance data were collected by using the Stellar Net Spectroradiometer with a wavelength that ranges from (400 – 1100) nm for use in the accuracy assessment. Three spectral signatures were plotted for rubber trees that represent the mature, middle-aged, and young rubber trees. After plotting the spectral reflectance of rubber trees over green band. The mature rubber had the highest reflectance among all types of rubber trees. Identifying the spectral response of the mature rubber trees in the wavelength of the red band was possible. By contrast, the middle-aged and young rubber trees have similar spectral reflectance response at the end of the red band wavelength. However, all the categories of rubber trees had inconsistent spectral reflectance at the wavelength of near-infrared band

2.3. Spectral Angle Mapper (pixel and spectral-based)

SAM classifier was selected for the spectral classification to create the thematic map of the pixels of imagery by using dimensional angle to match the reference spectra. This type of classification is defined as follows: if small angles between the two spectrums reveal high similarity, then the DNs have the same class; and if high angles between two vectors show low similarity, then the DNs will not be in the same class. The SAM method is not affected by solar illumination factors because the angle between two vectors is independent of the vectors' lengths (Kruse et al., 1993). SAM takes the arccosine of the dot product between the test spectrums to a reference spectrum (De and Clevers, 2004; Richards, 2013). This kind of classification was conducted to describe the lu/lc of the study area in the first stage, then to identify the rubber tree growth by using the pixel- and spectral-based approaches. The classification was conducted by using the training sites that were previously generated for the eight classes in the per-pixel classification and the resampled spectral reflectance for spectral-based classification.

2.4. Accuracy Assessment

Accuracy assessment is the last step for this current study. It is important to assess the result of the remote sensing classification. User accuracy calculation evaluated the map user accuracy of the classification. Kappa coefficient value should be computed. Kappa coefficient was used to identify if the value from the error matrix was better than random class assignment (Jensen, 2005; Lillesand and Kiefer, 2009; Su, et al., 2009).

3. RESULT AND DISCUSSION

3.1. Land cover estimation by using SAM (per-pixel and spectral based)

The two different SAM classification approaches were used to estimate the land cover map of the study area in Hulu, Selangor. The study area was mapped to identify the area of rubber trees. The SAM (per-pixel) classification was the first classification approach used to obtain the thematic map of land cover for the study area. The results show that the rubber tree area almost had a good classification result, but with some overlap with the forest area. In addition, the forest and oil palm overlapped. The water bodies, urban area, and soil had quite good identification and representation. The results were due to the fact that most of the study area was covered by plants that had almost the same spectral reflectance. The assessment accuracy of the classification indicated that the overall accuracy was 59% and the Kappa coefficient was 0.36, which reflects the difficulties in using the pixel-based SAM classifier to identify the land cover in tropical areas; such difficulties are related to the similar spectral responses of tropical plants (Zhe and Fox, 2011). The resampled spectral reflectance was used on the training sites to perform the spectral-based SAM. The result improved, as did the identification of the different classes in the study area compared with the result of the pixel-based SAM classifier. The accuracy assessment of this classification based on the confusion matrix indicated an overall accuracy of 84% and a Kappa coefficient of 0.65, which provides this research with better results than the previous ones. The spectral-based approach was more accurate in this study because the study area was covered with tropical plant species. Thus, the plants had similar spectral responses. Therefore, using the pixel-based approach to classify this area was difficult and inaccurate. By contrast, using the spectral-based approach facilitated the identification of the study area's land cover because the spectral-based approach considered the spectral response of each feature it classified in the study area, and each feature is known to have a unique spectral reflectance (De and Clevers, 2004; Jensen, 2005; Richards, 2013)

3.2. Determination of Rubber Tree Age Stand

3.2.1. Clipping and masking rubber tree area

The next stage after acquiring the land cover map of the study area was to estimate and map the distribution of rubber tree growth also by using the SAM classifier with pixel- and spectral-based approaches. The rubber trees were divided into the following three classes in this step based on the productivity of latex: < 7, 7 to 25, and > 25 years. The satellite SPOT-5 image was clipped by using the shapefile of the land cover map to extract only the area that was covered with rubber trees for use in classification and identification of rubber tree growth in the study area. The satellite image was subsequently masked to remove any other features.

3.2.2. SAM pixel-based classifier

SAM pixel-based classification was used first to extract the thematic map of rubber ages. The classification was conducted after the training sites of each class (mature, middle-aged, and young) of rubber trees were selected based on stand age. Ground reference data were used in the confusion matrix to examine the accuracy of the pixel-based classification; the overall accuracy of pixel-based SAM was 77%, and the Kappa coefficient was 0.80.

3.2.3. SAM classifier (spectral based)

Spectral based SAM classification was used to extract the thematic map of rubber trees that covered the study area in Hulu Selangor by using the training sites that were previously generated from the spectral reflectance that were collected from fieldwork. The spectral response of the rubber tree was resampled to be suitable for the wavelength of SPOT-5 image bands. After the classification, the accuracy assessment was calculated by using the confusion matrix. The accuracy assessment results indicates 91% overall accuracy and a Kappa coefficient of 0.85.

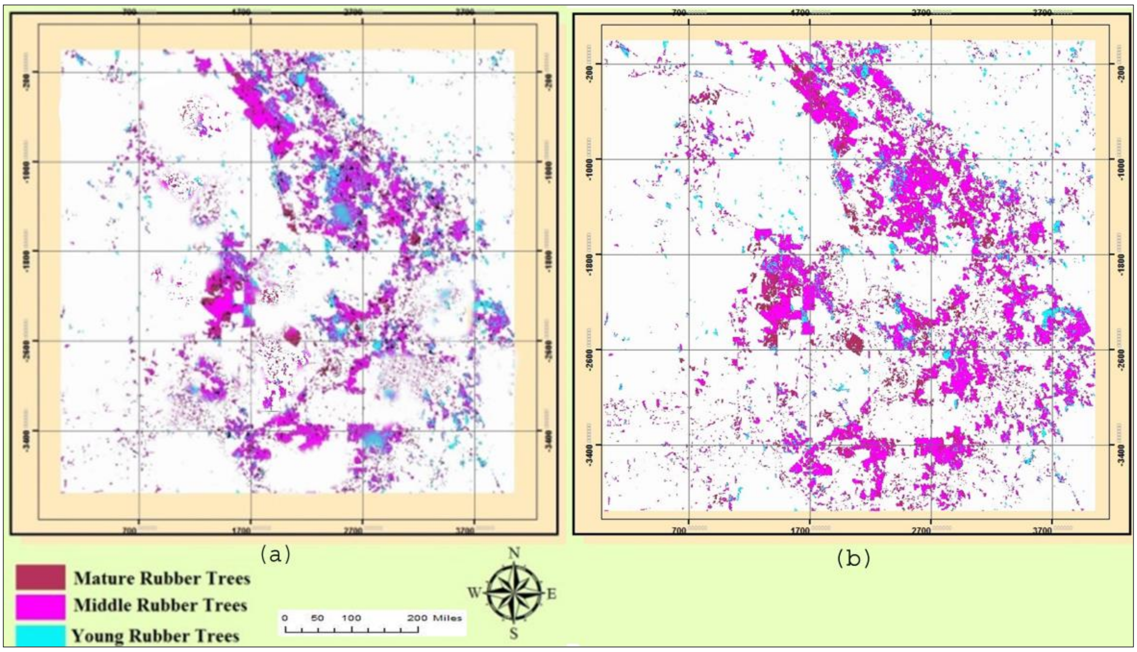

Figure 3 (a) Rubber tree growth map (a) Rubber tree growth map by using pixel-based SAM (b) the thematic map of rubber tree growth by using spectral-based SAM.

The classification accuracies were compared after conducting all types of classifications to determine which of the techniques had the highest accuracy and was most appropriate for classifying a tropical forest covered with rubber trees. The result of the comparison showed that the spectral-based SAM classification was the most accurate classifier that was suitable for classifying tropical forest and identifying rubber tree distribution based on age stand. The spectral-based SAM classification of different tropical forest plantation species reached an accuracy of 84%, whereas the pixel-based SAM achieved 59% accuracy in estimating the land cover map. The accuracy assessment of the distribution of rubber tree growth by using spectral- and pixel-based SAMs was 91% and 86%, respectively. The Kappa coefficients for lu/lc from spectral- and pixel-based SAMs were 0.65 and 0.36, respectively, and the Kappa coefficients for rubber tree growth from spectral- and pixel-based SAMs were 0.87 and 0.80, respectively.

Table 1 Comparison between the classifiers' results

Classifier	accuracy %	kappa coefficient
Spectral-based SAM – lu/lc	84%	0.65
Pixel-based SAM – lu/lc	59%	0.36
Spectral-based SAM – rubber	91%	0.87
Pixel-based SAM – rubber	77%	0.80

4. CONCLUSION

Rubber tree stand age mapping using SPOT-5 satellite data was conducted in Hulu Selangor, Malaysia through pixel- and spectral-based SAM classification approaches to estimate the thematic map of lu/lc. The same approaches were applied to identify the distribution of rubber based on age stand in the study area. Fieldwork was conducted to collect ground reference data to apply in result accuracy assessment. Evaluation was conducted by calculating the confusion matrix with the collected ground reference data. The results of this research show that using spectral-based SAM classification will yield more accurate results and will suitably classify tropical areas and identify rubber tree growth with the SPOT-5 satellite. The rubber ages were divided into three classes: < 7, 7 to 25, and > 25 years. Attempts will be made in the future to generate a spectral library to use as a standard for classification tasks.

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