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Mapping rubber stand ages in Luangnamtha district (Northern Laos) using NDVI and LSWI from Landsat images

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Abstract

Over the recent past, rubber tree plantations have rapidly expanded across vast tracts of Northern Laos. Remotely assessing rubber stand age is invaluable to monitor and predict the impacts of such an extensive and rapid land use change. This study presents the classification of rubber plantation areas versus non-rubber plantation areas, and the potential of two vegetation indices, namely NDVI and LSWI, for mapping rubber stand ages. Spectral signatures were derived from Landsat OLI images of Luangnamtha district acquired on 5th March and 14th March 2017, including Band 4 (RED), Band 5 (NIR), and Band 7 (SWIR), captured at the time of the year corresponding to the beginning of the foliation of rubber tree, with a spatial resolution of 30m. The work shows that the classification has a high accuracy of 92% and 0.89 for the overall accuracy and the Kappa coefficient, respectively. The producer's and user's accuracies of rubber stand ages were 75-92%, and 75-91% for the three age groups (< 7, 7-12, and > 12 years old). Overall accuracy and Kappa coefficients were 87 and 80%, and 0.79 and 0.67 for NDVI and LSWI indices, respectively. We also found that LSWI values were larger than NDVI when rubber stand age is greater than 7 years old, but NDVI showed better overall accuracy than LSWI at the beginning of the rubber tree foliation.

Keywords: Rubber stand age, Landsat 8 OLI, Google Earth Imagery.

1. Introduction

Rubber tree *(Hevea brasiliensis)* has become an important economic asset for local smallholder producers and governments across Southeast Asia. Following the growing demand for natural rubber and wood products [1 & 2], rubber plantations have expanded rapidly in many parts of mainland Southeast Asia [3]. Today, more than one million hectares have been converted to rubber plantations in the montane regions of Cambodia, Laos, Myanmar, Thailand, Vietnam, and China's Yunnan province and this area is predicted to increase fourfold by 2050 [4]. In Lao PDR, rubber plantations are emblematic of the fundamental changes in agriculture and rural development patterns that the country underwent to improve rural livelihoods, in particular through eradicating shifting cultivation by 2010 [5]. In northern Laos, during the first decade of the 21st century, rubber plantation acreage soared with the largest annual growth rate of 1140.72% [6]. Such extreme land use conversion was triggered by high latex prices following demand from foreign traders and companies in conjunction with supporting government policies [7 & 8]. Under the current situation, the assessment of land use and land cover change at various scales is an essential tool for the sustainable management of natural resources and the environment [9]. The main causes of land use change include a 17.32% population density increase between 2005 and 2015 [10],

urban expansion as well as changes in human activities in response to regional and global economic demand and governmental development strategies implemented to eradicate poverty. The Government of Laos has strongly supported the replacement of subsistence shifting cultivation by cash crop such as rubber trees in the Northern provinces. Such a dynamics has been all the more amplified that latex prices soared by the late 2000s. Therefore, in Northern provinces, a very large share of the farmers have converted their lands to rubber tree plantations, in the perspective of increasing their incomes and improving their livelihoods from latex sales [11]. The expansion of rubber tree plantations in Lao PDR is directly related to the emergence and expansion of capitalism/ free trade in the Mekong sub-region; in this regional context, following the increasing demand for natural rubber since 2005, especially from China, Lao has become a strategic area for rubber production, due to its central location between China, Vietnam and Thailand. Laos has been perceived as a very attractive place to develop rubber plantations because of its abundant available land and cheap labor. The ensuing land use change has had significant impact on the livelihoods of rural people who have become involved in these projects [12]. In Luangnamtha district and province in Northern Laos, at Ban HatNgao smallholders started planting rubber trees in 1994. In the early 2000s, farmers secured high income from latex sales, and therefore rubber plantation boomed, promoted by foreign traders and companies, the Lao Government and by villagers themselves [7 & 8,13]. Subsequently, new projects were initiated by Chinese investors who assisted subsistence farmers from Laos and Burma to replace opium cultivation by cash crops, supplying them with planting materials such as rice, chili, watermelon, and pumpkin in the lowlands, and maize, sugarcane and rubber trees in the uplands [14]. In the Northern parts of Laos, which are predominantly mountainous and where many rural farmers have traditionally been involved in subsistence food production, rapid shift to cash crop cultivation (including maize, cassava, and rubber tree) has offered an opportunity for investors from neighboring countries to engage in diverse forms of contract farming [15].

For decades now, satellite remote sensing has played a crucial role for producing land cover maps and monitoring purposes in the Mekong sub-region [16]. Moreover, remote sensing images have been widely used for rubber mapping in the recent years [16–18]. For example, the Thaichote multispectral bands, NDVI and principal component transformation have been used for mapping rubber tree plantations according to three age classes, namely < 5 years, 5 to 10 years and > 10 years [19]. This work also demonstrated that mature rubber stands of more than 10 years could not be differentiated from the evergreen forest, and that young rubber trees, paddy land and field crops could not be resolved when using multispectral imagery [19]. On the other hand, Thaichote panchromatic imagery can resolve rubber tree spacing of 4x6m to 5x7m which allowed a better discrimination of young rubber tree plantations from other land cover types in Northeast, Thailand [19]. Similarly, multispectral bands and three vegetation indices (NDVI, EVI and SAVI) from high spatial resolution imagery of Pleiades satellite were used as input features for the Sequential Forward Floating Search (SFFS) methods for rubber stand age classification (< 7 years, 7 to 15 years and > 15 years) in Thalang district, Phuket province, Thailand [20]. These results demonstrated that high spatial resolution satellite imagery with the help of SFFS can be used to successfully classify rubber stands age. Accuracies were improved from 94.07% to 94.92% and 96.61% after applying PCA and SFFS, respectively. Moreover, it is anticipated that this methodology can be used as a guideline for rubber tree stand mapping in other areas [20]. Another option for classifying rubber stand ages in mainland Southeast Asia is to apply the Mahalanobis typicality method to spectral signature data from MODIS time-series [3, 21]. Working in Xishuangbanna, Southwest China, Li et al. [22] also proposed a classification of rubber tree ages based on vegetation indices derived from Landsat images. Likewise, time-series of Moderate Resolution Imaging Spectroradiometer (MODIS) associated with Enhanced Vegetation Index (EVI), and short-wave infrared (SWIR) reflectance data were used to classify rubber plantation and forests and to monitor the expansion of rubber tree plantations [23]. In Xishuangbanna, Southern Yunnan province, China, the potential of integrating PALSAR 50m-mosaic images and multi-temporal Landsat images through the analysis of surface reflectance of vegetation indices (NDVI, EVI, and LSWI), to classify rubber tree plantations of different ages was clearly demonstrated [24]. In this study we tested whether spectral signatures of Landsat OLI image acquired in 2017 with a 30-m spatial resolution could be used to derive different vegetation indices useful to classify rubber stand age in Luangnamtha district, Northern Laos.

2. Materials and Methods

2.1 Study area

Luangnamtha district in the Northeast of Luangnamtha province, Northern Laos, lies in the subtropical zone between latitudes of 20˚45’51” to 21˚15’22” N and longitudes of 101˚09’29” to 101˚46’35” E, and covers an area of 214,662 ha (Figure 1). To the North, Luangnamtha district shares border with the People’s Republic of China, while to the East, it neighbors Namor district Oudomxay province, and Nalae district and Viengphoukha / Sing districts, Luangnamtha province, to the South and West respectively. The topography of the study area encompasses approximately 75% of mountainous land, the remainder 25% being plateau and plain, with elevations ranging from 472 m to 1,993 m a.s.l. The weather of Luangnamtha district divides into two seasons,

namely the dry season from November to April, and the rainy season from May to October. The annual average temperature and rainfall are approximately 25°C and 1,420mm, respectively [25]. Most of the district's population is engaged in agriculture related occupations, such as rice, corn, vegetable, cassava and peanut cultivation. However, other agricultural activities of importance in the district include cattle herding, fish and poultry farming, rubber and teak tree cultivation, as well as watermelon, sugarcane, and pepper production. Forest products, including bamboo shoots, mushrooms, rattan, cardamom and ginger are also key sources of income for rural farmers [26]. Besides agriculture, the main industries of Luangnamtha district are wood processing, lignite and copper mining, handicraft production, transportation, and tourism [27].

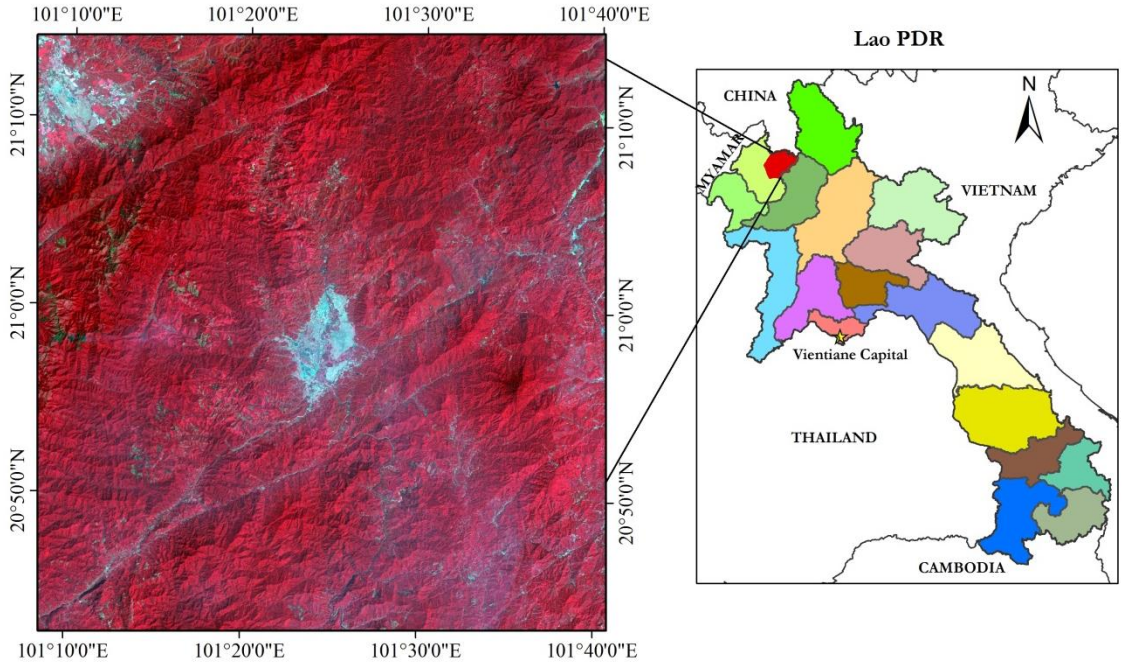


Figure 1 Landsat 8 OLI of the study area, false color composite bands 5 4 3 (Near-infrared/Red/Green) in Luangnamtha district, Northern Laos.

2.2 Landsat 8 OLI and Pre-Processing

We used three scenes of the Landsat 8 Operational Land Imager (OLI) at a resolution of 30m and selected images acquired on 5th March and 14th March, 2017 without cloud cover [28]. The images were obtained from the U.S. Geological Survey Earth Explorer Website (http://earthexplorer.usgs.gov/). The characteristics of these images are described in Table 1. All Landsat data were geometrically corrected and calibrated to the Universal Transverse Mercator (UTM), Zone 47N, and WGS 84 Datum. In addition, the Landsat OLI images were converted to Top of Atmosphere (TOA) reflectance [29 & 30], and mosaicked to produce a seamless single image that covers the whole study area using ENVI software (Boulder, Colorado USA).

Table 1. Data characteristics of Landsat images

Data type	Path/Row	Date of acquisition	Spatial resolution	Bands	Bandwidth (μm)	Spectral region
Landsat 8 OLI	130/45	05 March 2017	30m x 30m	1	0.43-0.45	Deep Blue
				2	0.45-0.51	Blue
				3	0.53-0.59	Green
	129/45	14 March 2017		4	0.64-0.67	Red
				5	0.85-0.88	NIR
	129/46			6	1.57-1.65	SWIR
				7	2.11-2.29	SWIR

2.3 Field survey

A field survey was conducted between June and July, 2017, concomitantly with the interview of local people. High resolution Google Earth imagery (Google Earth Pro V 7.1.5.1557. (February 21, 2017). LuangNamtha district and province, Lao PDR. 20°57'40.63"N, 101°24'01.25"E, Eye alt 13.01 mi. CNES/Airbus 2017, DigitalGlobe 2017. http://www.earth.google.com [June 5, 2017]), from which land use types could be precisely and clearly located was used to delineate regions of interest (ROIs), corresponding to 335 sample points (Table 2) for classification and validation of land use types, including forest, rubber plantation, agriculture, and other land (such urban and commercial areas, roads, rivers, and water), these pictures are shown in Figure 3. Moreover, there were 60 ROIs for rubber stand ages, classified into three groups (< 7, 7-12, and > 12 years old) for the purpose of image classification and accuracy assessment (Table 2, and Figure 2). Locations corresponding to these 60 ROIs were inspected as part of our field survey, and age of each corresponding rubber tree stand age was assessed based on interviews of local people conducted at the beginning of foliation phase of rubber tree in 2017.

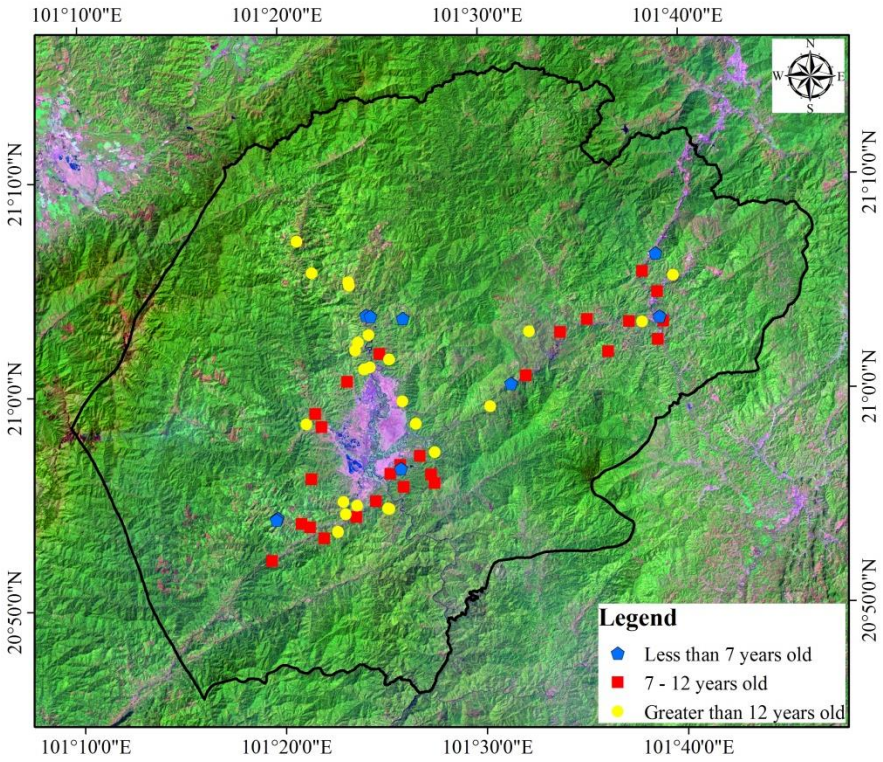
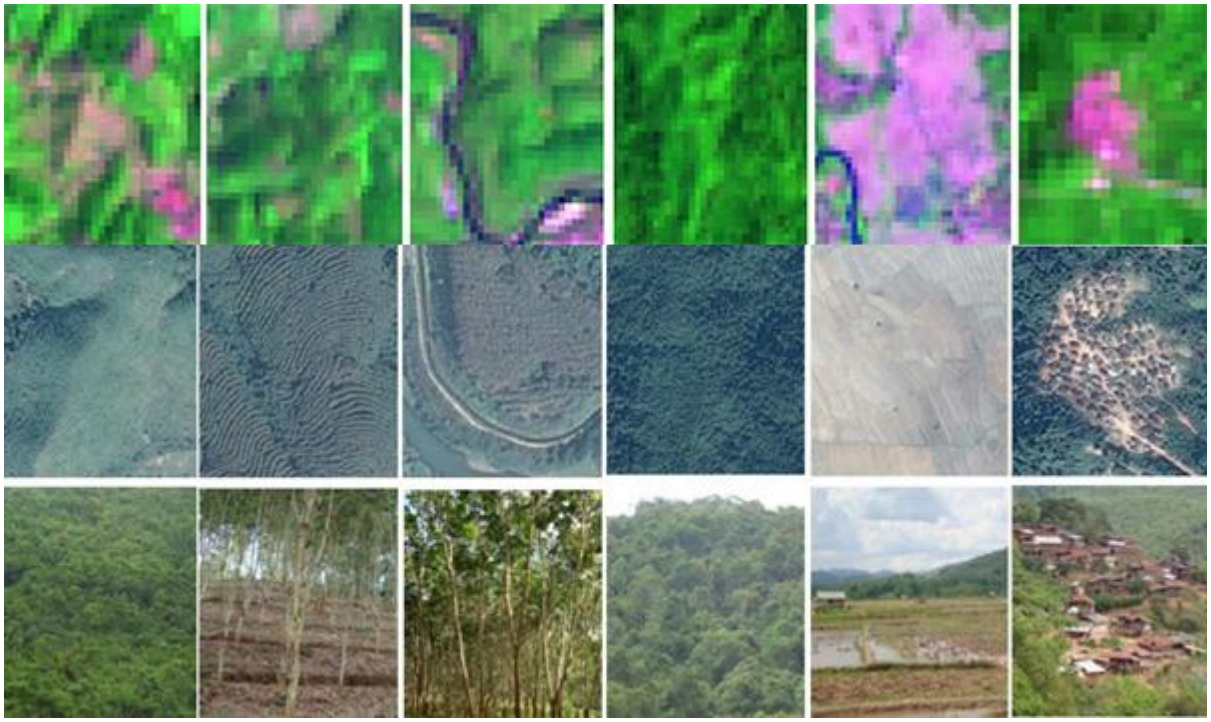


Figure 2 Location of the 60 ROIs used for classification and validation of rubber tree plantations according to tree age; background image is the Landsat 8 OLI with false color composite bands (SWIR/NIR/GREEN).

Table 2. Regions of interest (ROIs) of non-rubber plantation areas and rubber stand ages

No	Land use types	Classification	Validation
1	Non-rubber plantation areas	135	134
2	Rubber plantation areas	32	34
3	Less than 7 years old	4	4
4	7 to 12 years old	13	13
5	Greater than 12 years old	13	13

As shown in Figure 3, forest displayed a makeup very different from that of paddy fields and other land, but similar to that of rubber stands older than 7 years. In the false color composition (Band 7/SWIR; 5/NIR; 4/RED) forest canopy always appeared dark green, while the paddy fields were light purple with dark purple patches, and mixed urban areas dark purple. Rubber plantations older than 7 years displayed mixed light and dark green patches, while rubber stands less than 7 years old appeared dominantly light purple mixed with light green patches. However, the pictures/patterns derived from high spatial resolution Google Earth imagery, and pictures taken in the field revealed obvious differences between the forest, rubber plantations, and other lands in the study area.



(a) (b) (c) (d) (e) (f)

Figure 3 The false color composition (Band 7/SWIR; 5/NIR; 4/RED) of Landsat 8 OLI acquired on 05th and 14th March 2017 (Top row), compared with high resolution images from Google Earth imagery acquired on 21st February 2017 (Middle row); and field pictures took on the July 2017 in Luangnamtha district (Bottom row); (a) rubber tree less than 7 years old; (b) rubber tree between 7 and 12 years old; (c) rubber tree greater than 12 years old; (d) natural forest; (e) paddy field; (f) mixed urban area.

Moreover, there was a good discrimination between natural forest and rubber tree in false color composite based on Landsat 8 OLI image (March 5th and 14th, 2017), with natural forest appearing as light and dark green areas (A) and rubber tree as mixed light green and purple (B).

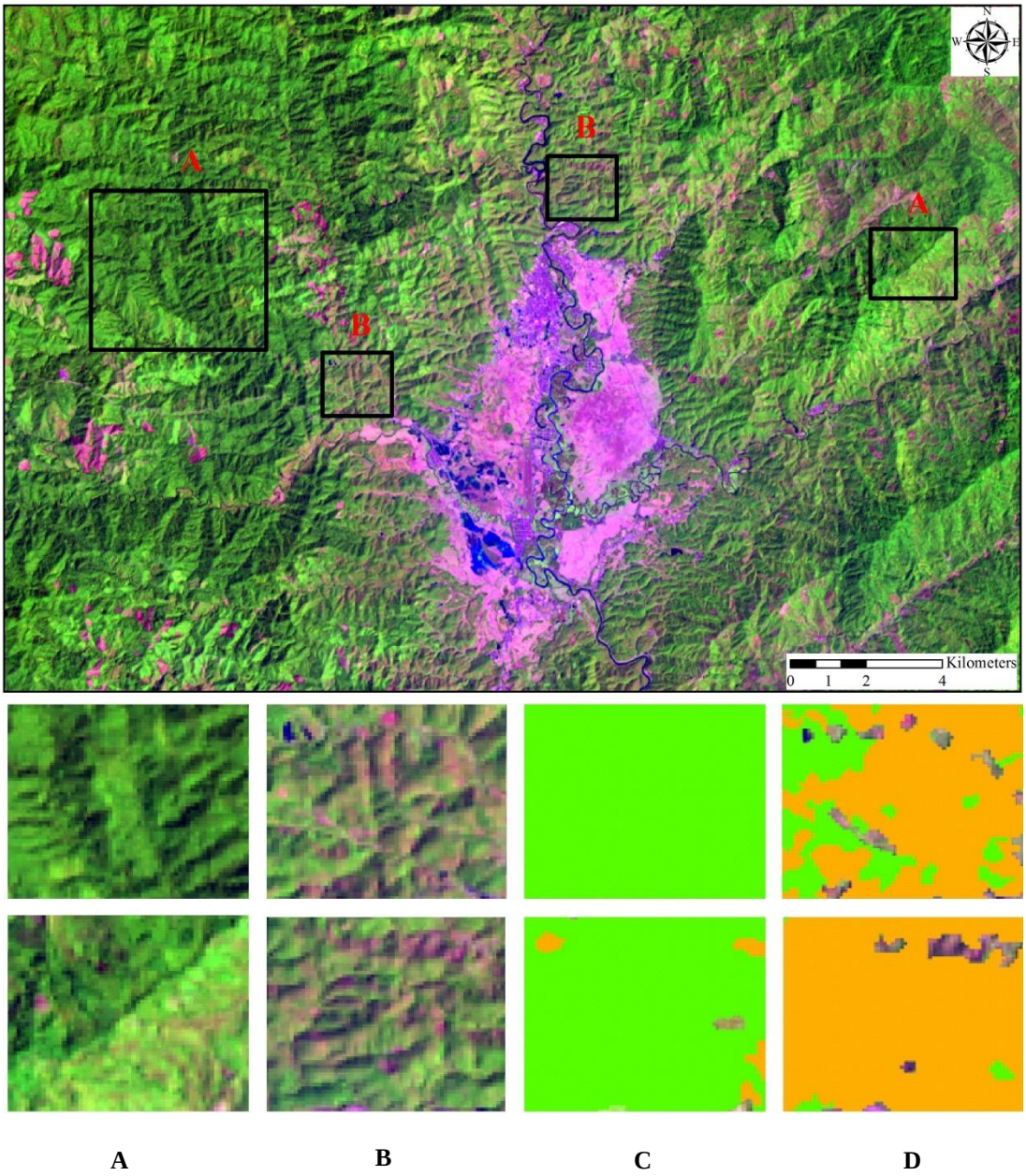


Figure 4 The false color composite the three Bands (Band 6/SWIR; 5/NIR; 4/RED) of Landsat 8 OLI image (March 5th and 14th, 2017). Light and dark green is natural forest (A), purple mixed with light green patches is rubber tree (B). Results of classification of natural forest is (C), and rubber tree plantation (D).

2.4 Image classification

In order to classify the selected Landsat images, we used the supervised classification method with maximum likelihood algorithm [31]. The classification was performed on the basis of the 167 field survey ROIs and visual interpretation of high spatial resolution image of the Google Earth imagery combined with interview of local people at the beginning of the foliation phase of rubber tree i.e. in February 2017 (defoliation occurs between January and February). Rubber tree plantation areas were split out from the other land use types, including forest, agriculture, and other lands or so-called “non-rubber plantation areas”. So, the areas of rubber tree plantation will be used to identify the different rubber stand ages by using the spectral signature derived from the vegetation indices (NDVI and LSWI).

2.5 Vegetation indices

In this study we selected two commonly used indices to identify the different rubber stand ages, namely the Normalized Difference Vegetation Index (NDVI) [30 & 31], and Land Surface Water Index (LSWI) [32] which are calculated based on surface reflectance, using the following equations:

$$NDVI = \frac{P_{NIR} - P_{RED}}{P_{NIR} + P_{RED}} \quad (1)$$

$$LSWI = \frac{P_{NIR} - P_{MIR}}{P_{NIR} + P_{MIR}} \quad (2)$$

where P_{NIR}, P_{RED} and P_{MIR} are the surface reflectance values of neared infrared, red, and shortwave-infrared (band 7) bands in Landsat 8 OLI images.

2.6 Map of different rubber stand ages

Signatures of different stand ages of rubber tree plantations (namely 7 years old, 7 to 12 years old, and greater than 12 years old) at the beginning of foliation phase of rubber tree were determined using the NDVI and LSWI computed for 30 ROIs (Table 2) [32–34]. We then quantified the mean values and ranges values from the spectral signatures values of each class using Extract values to points and Reclassify tools in Spatial Analyst Tools in ArcGIS.

2.7 Comparison of mean NDVI and LSWI values of the three rubber stand age classes

We applied analysis of variance with Tukey**'**s HSD *post hoc* test to assess whether there were differences in average LSWI and NDVI for different rubber tree age classes, as implemented in the library *agricolae* **(**version 1**.**2-8**)** of R **(**version 3**.**4**.**3**)** [35]**.**

2.8 Accuracy assessment

Validation of the 2017 land use types map was performed using the 168 ROIs derived from field data collection, and visual interpretation the high spatial resolution image of the Google Earth imagery combined with interview local people to assess the non-rubber plantation areas (including forest, agriculture and other land). While the sample of 4, 13 and 13 ROIs for the less than 7 years old, 7 to 12 years old and greater than 12 years old, respectively (Table 2). The overall accuracy, user's and producer's accuracies, and Kappa coefficient [36] were calculated using three functions, including the Extract values to points, Frequency, and Pivot table in ArcGIS (Redland, California, USA).

3. Results and Discussion

3.1 Classification and accuracy assessment results

The resultant classification between rubber tree plantation area and non-rubber tree plantation area map (Figure 5) has a high accuracy based on the validation ROIs. The overall accuracy was 92%, and the Kappa coefficient was 0.89 (Table 3). We found that the rubber tree plantation area was 17,109 ha or equivalent to about 8%, and non-rubber tree plantation area was 197,553 ha or 92% of the district's total area at the beginning of the foliation phase of rubber tree in 2017.

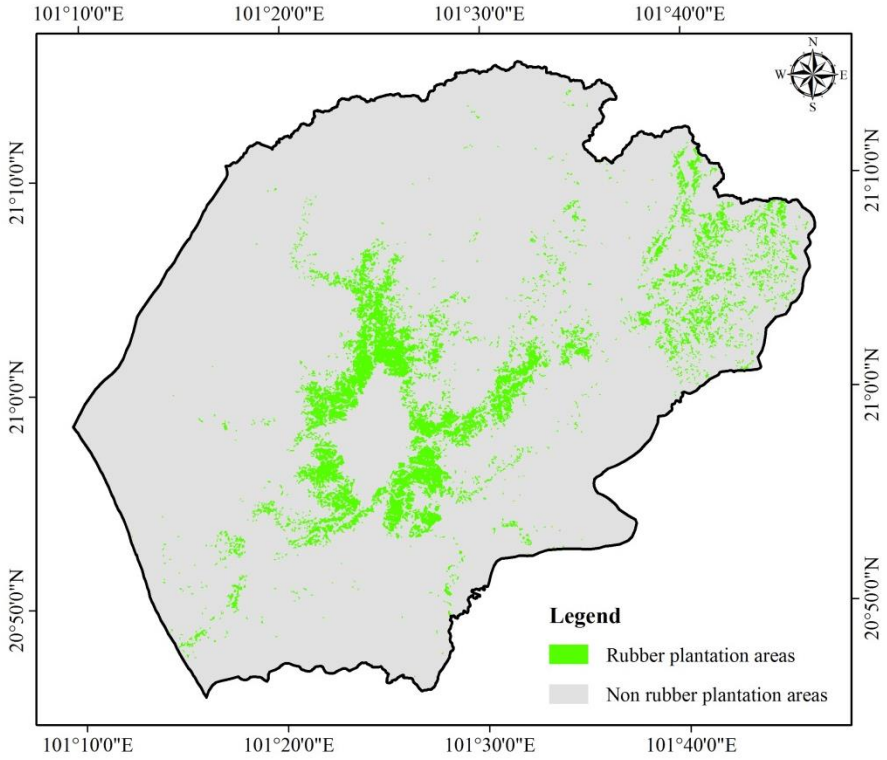


Figure 5 Map of rubber tree plantation areas and non-rubber-plantation areas of Luangnamtha district in 2017

Table 3. Land use types and accuracy assessment of Luangnamtha district

No.	Land use types	ROIs	Area (ha)	Percent (%)	Producer's	User's	Overall accuracy	Kappa coefficient
1	Rubber plantation areas	66	17,109	7.97	86	94		
2	Non rubber plantation areas (forest, agriculture, other land)	269	197,553	92.03	90	88	92	0.89

3.2 Signature analysis and map of different rubber stand ages

The relations between vegetation indices (NDVI and LSWI) and the stand ages extracted from these 30 ROIs indicated differences among their stand ages (< 7, 7-12, and > 12 years old) as shown in Figure 6. However, LSWI values were larger than NDVI values when rubber stand age is greater than 7 years old, but NDVI showed better overall accuracy than LSWI. In addition, an analysis of variance with a *post hoc* Tukey test showed that there were no significant differences **(**$p<0.05$**)** in either mean NDVI or mean LSWI for different rubber tree age classes, although both mean NDVI and mean LSWI tended to increase with increasing rubber age**.** These results are consistent with the results of Dong et al. [37], and Kou et al. [24].

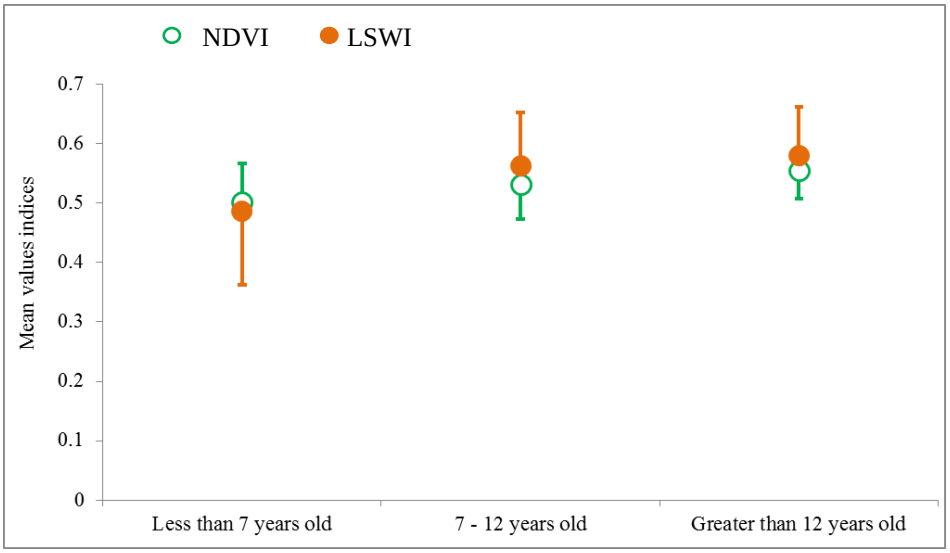


Figure 6 Mean values indices of rubber stand ages of NDVI and LSWI indices, and error bars of less than 7, 7-12 and greater than 12 years old are 0.07-0.12, 0.06-0.09, and 0.05-0.08 of the NDVI and LSWI indices, respectively.

Based on the values of NDVI and LSWI derived from ROIs for the three rubber stand age classes, we found that the total surface area planted with rubber trees less than 7 years old, 7-12 years old and greater than 12 years old were 2,442 and 2,741 ha, and 2,834 and 4,200 ha, and 10,167 and 11,833 ha, respectively (Table 4). As presented in Table 5, producer's accuracies for the three rubber stand age classes were 75 and 80%, 77 and 83%, and 82 and 92% for less than 7 years old, 7-12 years old and greater than 12 years old rubber trees, respectively, for both NDVI and LSWI. User's accuracies were 75 and 80%, and 85 and 91%, and 77 and 86% for rubber stand ages (< 7, 7-12, and > 12 years), respectively. The overall accuracies of this study were 80 and 87%, and the kappa coefficients were 0.67 and 0.79 (Figure 7). We found that the NDVI had higher producer's and user's accuracies than the LSWI. The error matrix for rubber stand ages of varying ages resulted in accuracies of 75 and 91%. In particular, LSWI differentiation produced the lowest user's accuracy of 75% for rubber stand age less than 7 years old.

Table 4. Areas of rubber stand ages obtained from NDVI and LSWI indices of Luangnamtha district

No.	Rubber stand ages	NDVI		LSWI	
		Area (ha)	Percent (%)	Area (ha)	Percent (%)
1	Less than 7 years old	2,442	14.3	2,741	16.0
2	7-12 years old	2,834	16.6	4,200	24.6
3	Greater than 12 years old	11,833	69.2	10,167	59.4

The distributions of rubber plantation areas according to three age groups are presented in Figure 7; these maps depict the presence of large rubber plantation areas surrounding the urban center of Luangnamtha town [6], and along the main roads to the East of Namor district, Oudomxay province, and the Northwest of Sing district, Luangnamtha province across the study area in 2017.

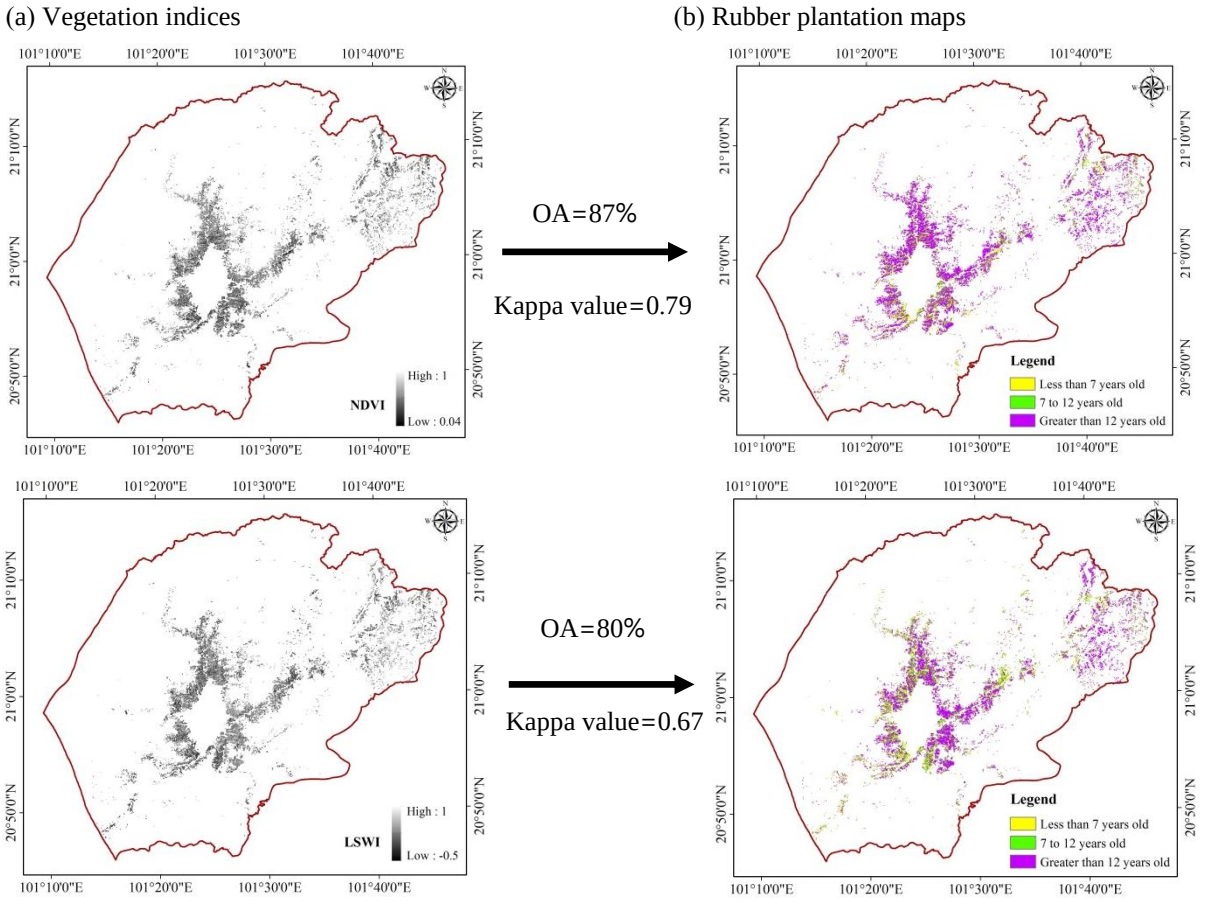


Figure 7 (a) NDVI and LSWI indices derived from the Landsat 8 OLI images acquired on 05th and 14th March 2017; (b) maps of rubber stand ages extracted from two vegetation indices (NDVI and LSWI) based on the ROIs to identify the rubber stand ages of three groups (< 7, 7-12, and > 12 years old), at the beginning of the foliation of the rubber tree in 2017.

Table 5. Accuracy assessment of land use types between NDVI and LSWI indices.

Rubber stand ages		Reference data			Total	User's accuracy (%)
		< 7 years old	7 - 12 years old	> 12 years old		
NDVI index						
Classified data	< 7 years old	4	0	1	5	80
	7 - 12 years old	1	10	0	11	91
	> 12 years old	0	2	12	14	86
	Total	5	12	13	30	
	Producer's accuracy (%)	80	83	92		
LSWI index						
Classified data	< 7 years old	3	1	0	4	75
	7 - 12 years old	0	11	2	13	85
	> 12 years old	1	2	10	13	77
	Total	4	14	12	30	
	Producer's accuracy (%)	75	79	83		

The results obtained in this study demonstrated that in Luangnamtha district, both NDVI and LSWI vegetation indices can be used to classify rubber stand ages. The accuracies of classification maps produced in this study are lower than the overall accuracies of 92-96% found in previous studies in Xishuangbanna, China [24,33] with kappa coefficients of 0.84 to 0.92. On the other hand, our results are consistent with Kou et al. [24], which, for rubber stand ages mapping derived from 30m Landsat 5/7 TM/ETM+ images reported an overall accuracy of 85%, and a kappa coefficient of 0.78. One difficulty specific to the rubber stand ages of Northern Laos is that they occur in a variety of terrain, often rugged, such as along main roads, across mountains, and that tree spacing is highly variable depending on location (which is influenced by land owners choices, labour costs, and exploitation techniques, all knowledge that needs to be documented in consultation with farmers and government agencies). Moreover, it must be noted that the training ROIs used for both classification and accuracy assessment were derived from the Google Earth imagery, and the information about rubber stand ages was obtained from interviewing local people, as in case of many other studies [3, 20–21,24]. Yet, most of these training regions of interest are sparsely represented in most remote sensing products, especially the representative training sites of each rubber stand ages, even when we collected interview data from local people, results could often not be overlaid in some parts of study area, due to data quality and availability as well as algorithm design. Consequently, some sparse forest areas or bush fallow are likely to be misclassified with rubber plantation areas due to their small and sparse canopies and low height in the field. Further, landscape conditions such as slopes, aspects and elevations may affect backscatter coefficient of Landsat images. Therefore, LSWI is likely to effectively separate among rubber stand ages better than NDVI in terms of mean ranges values when rubber stand age is greater than 7 years old at the beginning of the foliation phase of the rubber tree in Luangnamtha district in 2017.

4. Conclusion

The study presented in this paper illustrates the classification of rubber tree plantation areas versus non-rubber-plantation areas, and the potential for using differences in vegetation indices (NDVI and LSWI) to map rubber stand ages, using multi-temporal Landsat OLI images. The results demonstrated that rubber plantation areas and non-rubber plantation areas had a high overall accuracy of 92% and a Kappa coefficient of 0.89. While producer's and user's accuracies of rubber stand ages were 75-92%, and 75-91% for three groups (< 7, 7-12, and > 12 years old), and overall accuracies were 80 and 87% and Kappa coefficient was 0.67 and 0.79, respectively for both NDVI and LSWI indices. In addition, this study found that, although neither mean LSWI and NDVI values of rubber stand of the three considered age classes ages differed significantly from each other, they tended to increase for ages greater than 7 years, and permitted image classification with high overall accuracy (higher with NDVI than LSWI), at least at the beginning of the foliation phase of the rubber trees.

5. Acknowledgements

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6. Conflict of Interest

No conflict of interest are declared

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