ASSESSING THAICHOTE SATELLITE DATA IN SUPPORT OF MAPPING RUBBER TREE PLANTATION IN NORTHEAST THAILAND

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Abstract: Since the past three decades, the rapid expansion of rubber tree plantation has replaced a traditional agriculture and forest reserves in northeast Thailand where the tree was not historically planted. Spatially accurate and reliable information on the rubber tree plantation is needed for better formulating strategic land use planning and understanding its consequences on ecosystem. The study aims to develop a comprehensive methodology for mapping different age groups of rubber tree distribution in the northeast, based on Thaichote satellite data. We used the Thaichote multispectral bands, NDVI and principal component transformation as input parameters. A maximum likelihood method was used to allocate of pixels into the different tree age classes. A transformed divergence was applied to evaluate the training sets of the different age rubber trees and diverse land cover types. The validation was carried out using the Thaichote panchromatic imagery and ground investigation. The mature rubber stands of more than 10 years old could not be differentiated from the evergreen forest. The young rubber tree plantation, paddy land and field crop could not be resolved when using the multispectral imagery. The Thaichote panchromatic imagery is capable of resolving the rubber stands spacing normally 4×6 m to 5×7 m. that allows for better discriminating the young rubber from other land cover types. The methodology for mapping the rubber tree plantation includes an analysis of satellite–vegetation indices, supervised classification, supplemented with visual analysis of the panchromatic imagery.

INTRODUCTION

Since the past three decades expansion of rubber tree plantation in many parts of Southeast Asia and Southern China has rapidly increase. Like the many parts, the upper Northeast Thailand along the Mekong river where rainfall is relatively high, has underwent changes in traditional crops (cassava, sugar-cane and rice). Land use for the traditional crops has been converted to rubber tree which is perennial, non-traditional plant. Attractive price of rubber products in the world market is driving the changes. In 2007/8 the rubber tree plantation reached 447,873 ha or about 2.65 % of the Northeast (Office of Agricultural Economics, 2008). Information about the rubber tree planted areas is of great importance for marketing policy, land use planning and extension program in the region. Moreover the expansion may have significant consequences on the ecosystem when the ecological forest and traditional agriculture are replaced by rubber tree plantation. This occurrence may alter surface water hydrology, lose bio-diversity, enhance soil erosion process and change the way of life.

Remotely sensed data are widely accepted for deriving land cover/land use (LCLU) and cropping areas. A number of works applied satellite-derived indices to map rubber tree plantation and to estimate the extent of different age rubber stands. These works included 1) the establishment of a relationship between the NDVI training areas of FY-3A satellite data and those of Terra-MODIS to extract the spatial rubber tree distribution in Hainan, China (Zongkhun et al, 2010) 2) the vegetation indices(NIR/R, Sqrt(NIR/R) and NIR-R) of Aster data enabling to adequately discriminate crop types and to some extent crop growth stages (Apan et al, 2002) 3) use of NDVI and tasseled cap transformation as input metrics for a Mahalanobis typicality method to estimate the mature and middle age rubber tree in Northeast Thailand (Li et al 2011).In addition, application of the the Karhunen-loeve transformation and the tasseled cap transformation to enhance the Landsat MSS imagery for capturing soil brightness, vegetation and moisture condition provided difference among the LCLU types (Mongkolsawat, 1984)

However, attempt to map the rubber tree plantation in the Northeast was conducted, based on an integration of SPOT data and physical land qualities provided adequate discrimination between the mature and middle age rubber stands (Mongkolsawat et al. 2010). Due to complexity and diversity of vegetation covers in tropical areas especially the Northeast, signature sets of training areas for mature and middle age rubber trees are similar to those of deciduous, evergreen forests. Young rubber tree signature sets are confused with harvested field crops and paddy land, particularly the cloud-free imagery scenes in the region can be acquired after crop harvesting. Our efforts will be placed on applying the satellite vegetation indices as input channels in supervised classification to capture the different types of the LCLU. The study thus aims to develop a comprehensive methodology for mapping different age groups of rubber tree distribution in the northeast, based on Thaichote satellite data.

METHOD

The study area covers a flourishing rubber tree plantation with relatively high rainfall mostly in Bueng Khan province, Northeast Thailand as shown in Figure 1 Three Thaichote multispectral (MS) scenes and one panchromatic (P) scene were used to identify LCLU and the rubber tree plantation area. We used B1(0.53-0.60 mm), B2(0.62-0.69 mm) and B3(0.77-0.99 mm) of three dates to create the input parameters. The acquisition dates of cloud free images consist of December 24, 2009, January 19, 2011 and February 8, 2011 for the MS and P scenes.

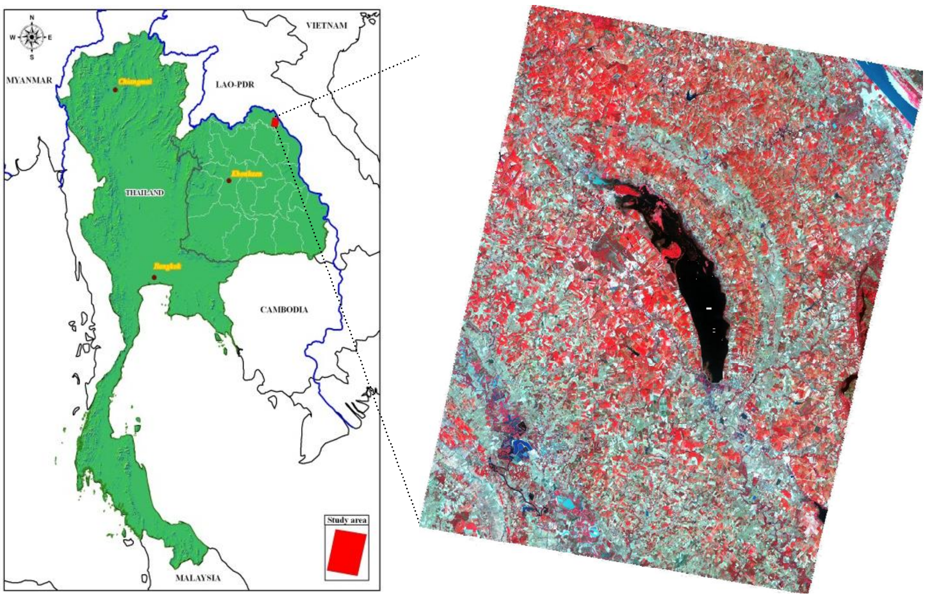


Figure 1: Study Area (Thaichote false colour composite image, Red: B3 Green: B0 Blue: B1)

The Thaichote image scenes were geometrically corrected using 2002 aerial orthophotography and nearest neighbor resampling method.

The Normalized Difference Vegetation Index (NDVI) (Lawrence & Ripple, 1998, Gu et al., 2007.) and Component 2 (CP 2) of the Karhunen-loeve transformation (Richard, 1986), widely used indices of greenness and plant canopy were digitally performed. The NDVI of the Thaichote MS is defined as:

$$NDVI = (B2-B3) / (B2+B3)$$

The B1, B2 and B3 Thaichote data were used as input variables for the Karhunen-loeve transformation to create the CP2. Each image scene had two image sets 1) the B1, B2 and NDVI 2) the B1, B2 and CP2 used for input in the supervised classification. The CP2 for the three different image scenes will be given herein after. This study will provide six classified image outputs, two for each date of the different inputs. Since the main interest of this study was to resolve the rubber tree from other LCLU types, water body was excluded using the B3 image. Three sub-categories were described for the rubber tree ages: young(< 5years), middle age (5-10year) and mature (> 10 year)

One hundred and forty four training sites encompassing the different LCLU types were chosen. (Table 1). Allocation of the sites was based on GPS and the Thaichote P band. Ground observations recorded at each training site consisted of LCLU type, land form, topography, soil, land characteristics and rubber tree canopy and size. Estimates and measurement of the rubber stands were carried out to ensure the observations were as representative as possible. Relationship between image features and the LCLU types was then established, based on the ground observations. On screen selection and calculation of mean vectors for the training areas was performed. Transformed divergences for all input training areas were calculated to measure the separability between the class signatures. Ranging 0-2, the calculated divergence of 0 means inseparable and 2 for totally separable signatures.

Maximum likelihood classifier was applied to assign the pixels to the LCLU class having highest probability. Evaluating the classification was based on the comparison of agreement between the classified images to the ground truth and Kappa coefficient was applied.

Table 1: Number of training areas and pixels used

LCLU	No. of Training areas	No. of Pixels
Young rubber (R1)	22	3108
Middle-age rubber (R2)	19	2050
Mature rubber (R3)	21	1664
Paddy field (PF)	18	1444
Field crop (FC)	13	950
Eucalyptus (EC)	10	2043
Bare soil (BS)	15	1444
Evergreen forest (EF)	10	1169
Deciduous forest (DF)	16	2084

RESULTS AND DISCUSSION

The results obtained from the Karhunen-loeve transformation for the three image scenes in which CP2 used as channel inputs to the processing are shown in Table 2.

Table 2: Eigenvectors of covariance matrix (arranged by rows):

CP	December image scene	January image scene	February image scene
CP1	0.46543 0.75599 0.46027	0.46549 0.75597 0.46025	0.48748 0.55525 0.67384
CP2	-0.24888 -0.38724 0.88775	-0.24745 -0.38814 0.88776	-0.45772 -0.49469 0.73876
CP 3	-0.84979 0.52709 -0.00642	-0.84934 0.52779 -0.00789	-0.74354 0.66856 -0.01300

As mentioned herein above, each image scene with two input channels (B1, B2 & NDVI and B1, B2 & CP2 band set) used to the Maximum likelihood classifier will produce six classified image output. The transformed divergence measures of the training area classes for the six image sets are shown in Table 3 – 5. Among the input channels the February scene gave number of the ambiguous pairs less than those of other scenes as illustrated in Table 6. Reasons behind this are phonological state of rubber stands and forest types, including off-season vegetation and soil moisture condition. The deciduous forest type mostly grown on shallow soil shed their leaves in January .The rubber stands in this region bringing fresh leaves in February lead to higher NDVI values and CP2.The evergreen forest mostly riparian forest found in floodplain with relatively high moisture condition is able to discriminate from the rubber tree stands. Table 6 provides the separability measure summarized from the transformed divergences. The signature sets of R2 and R3 are inseparable from forest and perennial crops for the December (B1, B2 & CP2 band set) and the January band sets scenes. The most useful band sets are the B1, B2 & NDVI of the December and February scenes. These are able to resolve the evergreen forest from the R1and R2.The R1 and R2 are difficult to differentiate from each other, due to similar signature sets. The signature sets of the young rubber plantations (R1) are inseparable from P, C and B LCLU types of the set of bands studied for the December and January scenes. While those of the February scenes are inseparable from the P and C, but separable from the B.

Among the six classified image outputs the February scene with the B1, B2 and NDVI input channel provided the best result in discriminating the rubber tree stands in the study areas (Figure 2).The Kappa Coefficient values representing the agreement between the map outputs and ground truths are 0.665, 0.667, 0.677, 0.627, 0.630 and 0.639 for B1, B2 & NDVI band sets of the December, January, February scenes, B1, B2 & CP2 band sets of the December, January and February scenes respectively.

The young rubber stands characterized by diverse covers for which pure pixels are rarely found, mixtures of the intercrops, weeds, grasses and small shrubs are the norm. The Thaichote P band with 2 mm. resolution is the most useful for discriminating the young rubber tree. Figure 3 shows the Thaichote P band in relation to photographs of R1, R2 and R3.

Table 3: Transformed divergence of training areas (December 24, 2009 Scenes)

Input Channels: B1 B2 NDVI

	R1	R2	R3	PF	FC	EC	BS	EF	DF
R1									
R2	1.997								
R3	1.983	0.627							
PF	1.494	1.919	1.747						
FC	0.826	1.998	1.977	1.781					
EC	2.000	1.776	1.971	2.000	2.000				
BS	1.247	2.000	1.999	1.993	1.737	2.000			
EF	2.000	1.801	1.973	1.999	1.999	0.851	2.000		
DF	1.999	1.263	1.538	1.998	1.999	0.454	2.000	0.719	

Average Separability:1.761, Minimum Separability:0.454, Maximum Separability:2.000

Input Channels: B1 B2 CP2

	R1	R2	R3	PF	FC	EC	BS	EF	DF
R1									
R2	1.984								
R3	1.957	0.820							
PF	1.609	1.978	1.701						
FC	0.738	1.880	1.796	1.618					
EC	2.000	1.598	1.932	2.000	1.999				
BS	0.899	1.999	1.996	1.706	1.723	2.000			
EF	1.999	1.407	1.841	1.999	1.992	0.826	2.000		
DF	1.999	0.885	1.257	1.994	1.971	0.427	1.999	0.555	

Average Separability:1.651, Minimum Separability:0.427, Maximum Separability:2.000

Table 4: Transformed divergence of training areas (January 18, 2011 Scenes)

Input Channels: B1 B2 NDVI

	R1	R2	R3	PF	FC	EC	BS	EF	DF
R1									
R2	1.806								
R3	1.718	0.574							
PF	1.237	1.864	1.746						
FC	0.785	1.660	1.507	1.359					
EC	1.977	1.171	1.568	1.999	1.886				
BS	0.999	1.991	1.971	1.745	1.523	1.999			
EF	1.972	1.187	1.653	1.999	1.836	0.649	1.999		
DF	1.940	1.010	1.221	1.981	1.763	0.414	1.999	0.533	

Average Separability:1.684, Minimum Separability:0.414, Maximum Separability:2.000

Input Channels: B1 B2 CP2

	R1	R2	R3	PF	FC	EC	BS	EF	DF
R1									
R2	1.987								
R3	1.963	0.819							
PF	1.628	1.979	1.706						
FC	0.789	1.880	1.798	1.622					
EC	2.000	1.597	1.931	2.000	1.999				
BS	0.928	1.999	1.997	1.742	1.763	2.000			
EF	1.999	1.423	1.850	1.999	1.993	0.823	2.000		
DF	1.999	0.889	1.259	1.994	1.970	0.430	1.999	0.558	

Average Separability:1.659, Minimum Separability:0.430, Maximum Separability:2.000

Table 5: Transformed divergence of training areas (February 08, 2011 Scenes)

Input Channels: B1 B2 NDVI

	R1	R2	R3	PF	FC	EC	BS	EF	DF
R1									
R2	1.983								
R3	1.991	0.690							
PF	1.210	1.913	1.984						
FC	1.245	1.992	1.971	1.555					
EC	2.000	1.997	1.903	2.000	2.000				
BS	1.926	2.000	2.000	1.996	1.998	2.000			
EF	2.000	1.990	1.861	2.000	2.000	1.784	2.000		
DF	1.999	1.685	1.442	1.996	1.995	0.986	2.000	1.946	

Average Separability:1.835, Minimum Separability:0.690, Maximum Separability: 2.000

Input Channels: B1 B2 CP2

	R1	R2	R3	PF	FC	EC	BS	EF	DF
R1									
R2	1.970								
R3	1.991	0.539							
PF	1.337	1.914	1.994						
FC	1.243	1.837	1.932	1.575					
EC	2.000	1.915	1.680	2.000	2.000				
BS	1.866	2.000	2.000	1.994	1.998	2.000			
EF	2.000	1.998	1.839	2.000	2.000	1.533	2.000		
DF	1.997	0.861	1.274	1.982	1.963	0.893	2.000	1.838	

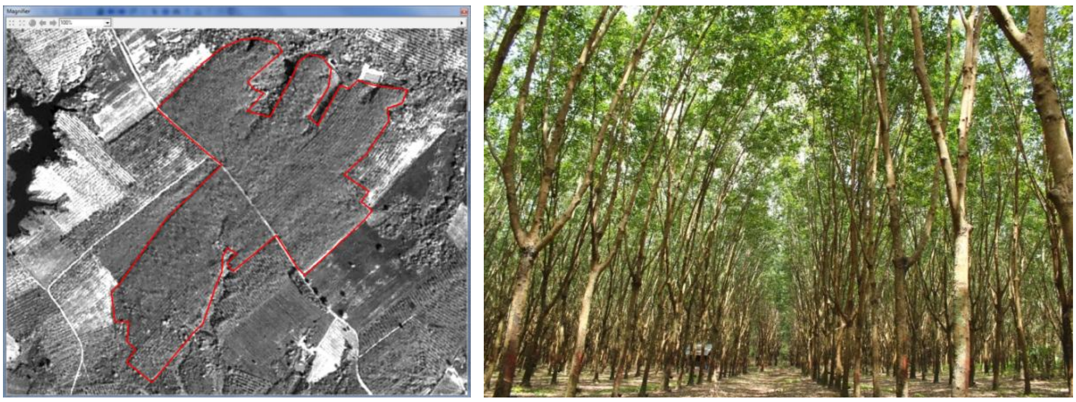
Average Separability: 1.773, Minimum Separability: 0.539, Maximum Separability: 2.000

Table 6: Summary of confusion between rubber tree and other LCLU types

Rubber trees	December		January		February	
	Set of input channels		Set of input channels		Set of input channels	
	B1 B2 NDVI	**B1 B2 CP2**	**B1 B2 NDVI**	**B1 B2 CP2**	**B1 B2 NDVI**	**B1 B2 CP2**
R1	PF, FC, BS	PF, FC, BS	PF,FC,BS	PF, FC, BS	PF,FC	PF, FC
R2	R3, DF	R3, EC, EF, DF	R3, FC, EC, EF, DF	R3, EC, EF,DF	R3, DF	R3, DF
R3	R2, DF	R2, DF, EF	R2, FC, EC, EF, DF	R2	R2, DF	R2, EC, DF

(a) Young rubber stands

(b) Middle-age rubber stands



(c) Mature rubber stands

Figure 3: Thaichote P band imagery and photographs of different ages rubber trees

Acquisition date	Input channels B1 B2 and NDVI	Input channels B1 B2 and CP2
December 2009		
January 2011		
February 2011		

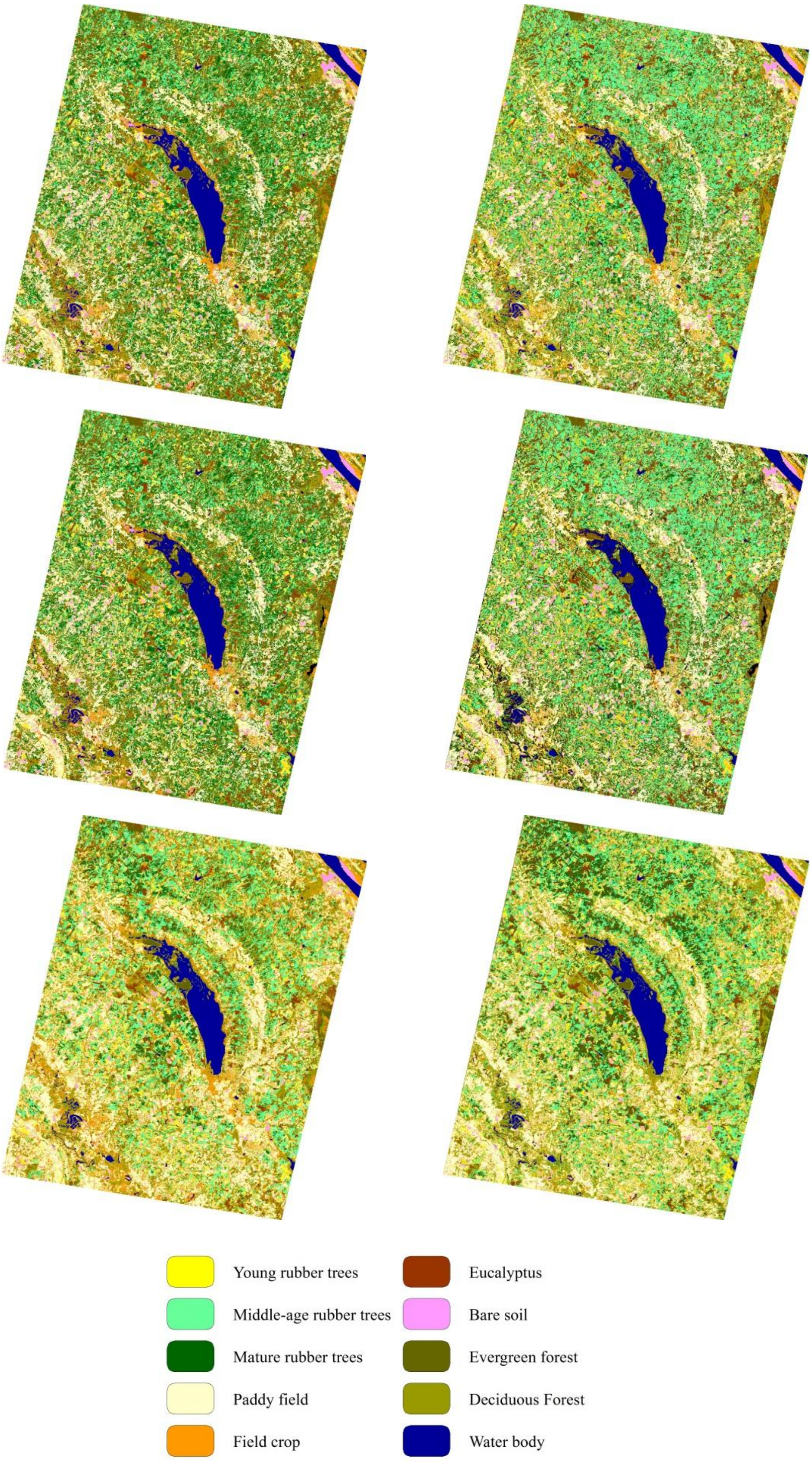


Figure 2: Classified image outputs of the three image scenes with different input channels

CONCLUSIONS & DISCUSSION

The mature rubber stands of more than 10 years old could be differentiated from the evergreen forest with selected acquisition dates and set of bands. The young rubber tree plantation, paddy land and field crop could not be resolved when using the multispectral imagery. The Thaichote panchromatic imagery is capable of resolving the rubber stands spacing normally 4×6 m. to 5×7 m. that allows for better discriminating the young rubber from other land cover types. The methodology for mapping the rubber tree plantation is an integrated image processing, including an analysis of satellite–vegetation indices, supervised classification, supplemented with visual analysis of the panchromatic imagery. For bettering the discrimination of signature sets, clear identification of phonological states of rubber stands and forest types is suggested. An integration of physical land characteristics in the analytical process helps enhance the result reliability.

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