DISTRIBUTION OF RUBBER PLANTATION AT SURAT THANI USING REMOTE SENSING

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KEY WORDS: rubber plantation, Surat Thani, Landsat

ABSTRACT: In Asia, to be specific Southeast Asian region, countries like Malaysia, Thailand and Indonesia have dominated global rubber cultivation over the last five decades. Rubber tree is one of the major crop and serves as the important commercial crop apart from oil palm plantation. Thailand has been the world's leading rubber producing country since 1995 compare to Malaysia and Indonesia which with an annual increase of four to seven percent per year. The rubber plantations started to expand in the eastern and north-east region of Thailand. In Thailand, rubber production has their own important towards socio-economic. Rubber have become the most cash crop due to its productive value, income from export and job opportunities. The rubber trees are dominantly distributed in Surat Thani provinces. At present, the rubber sector encounters lack of demand and large supplies rubber stock. Natural rubber being replace with synthetic rubber. The price of natural rubber in market also decreasing. To curb the problem, most of rubber plantation holder start to replace their crop to more profitable crop. The changes occur rapidly and lead to massive bare land in the province which in the same time lead to temperature rising. This study is aimed to analyse the spatial distribution of rubber plantation for 2007, 2014 and 2019 in Surat Thani, Thailand. Geospatial data from remote sensors are used to deal with the time and labour consuming problem due to the large spatial coverage and the need of continuous temporal data. Remote sensing images that been used in this study is a Landsat 5 Thematic Mapper (TM) and Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS). The image from optical sensor was used to sense the land cover and further classified for rubber plantation land cover changes. The research has proved that by using remote sensing images showed that specific area of rubber plantation experienced gained, loss and remained unchanged between a desired period.

1. INTRODUCTION

Malaysia, Thailand and Indonesia have dominated global rubber cultivation over the last five decades (Somboonsuke, 2001). Rubber tree is one of the major crop and serves as the important commercial and profitable crop apart from oil palm plantation (Wayne, 2004). According to Somboonsuke (2001), Thailand has been the world's leading rubber producing country since 1995 compare to Malaysia and Indonesia which with an annual increase of 4-7 percent per year. The rubber plantations started to expand in the Eastern and North-east region of Thailand (Wayne, 2004). In Thailand, rubber production has their own important towards socio-economic. Rubber have become the most cash crop due to its productive value, income from export and job opportunities (Jawjit *et. al*, 2010). Among the Asian region, Thailand is the exporter and producer of the natural rubber, and to be specific Surat Thani Province are Thailand's largest source compare to other. Surat Thani consist of nineteen different districts distributed throughout the province. There were no efficient of recent data recorded and being published about the rubber plantation distribution and land cover changes throughout Surat Thani Province.

Accurate and updated finer resolution maps of rubber plantations land cover changes are really needed to assess and understand the implication of rubber plantation on regional ecosystem process (Datta (2012), Fenta *et. al*, (2017), Gong *et. al*, (2009), Li & Fox (2012)). Due to the expanding global and regional markets, traditional agricultural activities and non-agricultural land are convert into commercial-agriculture purposes (Fenta *et. al*, 2017). Most of the mainland in Southeast Asia, the rubber plantation are expanding rapidly which more than one million hectares of land being converted without being monitored which happen in China, Laos, Thailand, Vietnam, Cambodia and Myanmar (Li & Fox (2012), Yi *et. al*, (2013)). The expansion basically are not natural phenomena and were not traditionally grown. Due to the rapid expansion, the original ecosystem and land cover experiencing massive changes that could lead to many issue and environment conflict (Gong *et. al*, 2009). With the distribution data and the together with the impact from the research, the expanding of land used for rubber plantation could be managed well by the government and plantation holder by controlled and monitored it wisely. Ecosystem and environment damaging implication could be curb and reduced in the same time.

There is previous study from other researcher related to the distribution identification by using various of tools and optical sensor such Landsat 5 TM and Landsat 8 OLI (Barsi *et. al*, (2014), Meti *et. al*, (2008)). The core tools that being used for distribution study are based on GIS application and Remote Sensing to do observations, monitoring and information analysis process because it provided valid and reliable data for distribution and land cover exchange study (Hansen *et. al*, (2008), Shidiq *et. al*, (2014), Zainuddin & Daliman (2020)). Selection of the optical sensor depend on the desire resolution and outcome for the result and usage of multiple technique will produce better results rather using single technique (Barsi *et. al*, 2014). During classification, Maximum Likelihood, Support Vector Machine and Mahalanobis Distance classifier being used in most study and difference classifier have difference ability that compactible to the data used (Song *et. al*, 2000). Certain data suitable for certain classifier and give high overall accuracy in post-classification using Confusion Matrix.

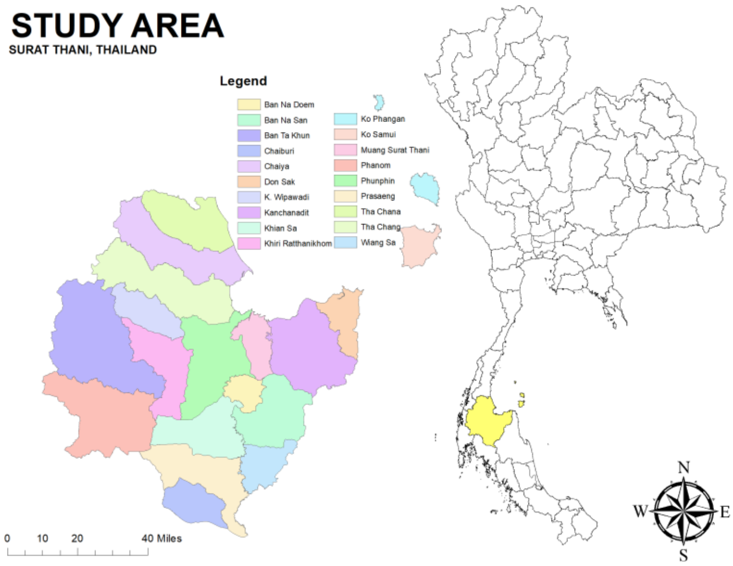


Figure 1 Study area map

2. METHODOLOGY

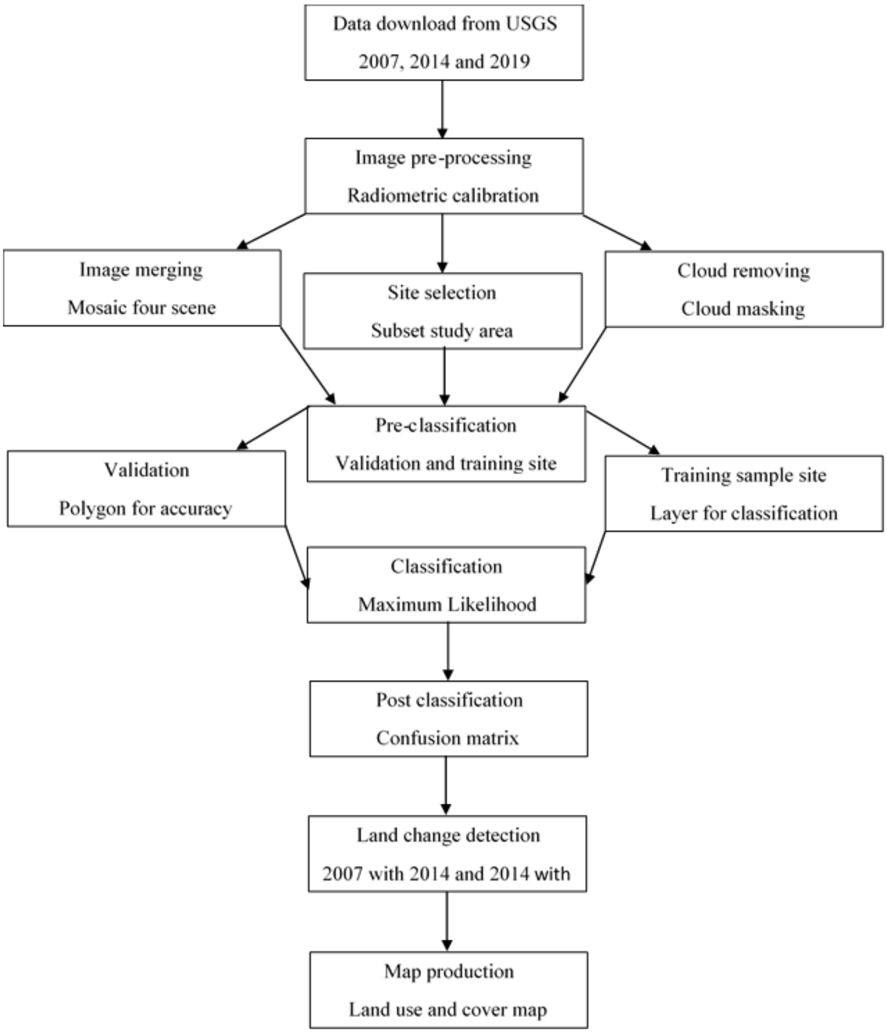


Figure 2 The flowchart of this study.

Study area consist of four data scenes that need to be mosaic together to cover all the area needed. Data for 2014 and 2019 are from Landsat Operational Land Imager (OLI) and 2007 from Landsat Thematic Mapper (TM). All the data scenes downloaded from United States Geological Survey (USGS). The differences of the gap year and optical sensor are due to limited availability of data. The land cloud cover of the study area in each scene was not more than 20% (Table 1) (Table 2) (Table3).

Table 1 Landsat data information 2007

Scene	Acquired date	Land cloud cover %
1	03/03/07	10
2	03/03/07	6
3	22/02/07	14
4	06/02/07	0

Table 2 Landsat data information 2014

Scene	Acquired date	Land cloud cover %
1	02/02/14	1.34
2	02/02/14	0.61
3	25/02/14	13.67
4	25/02/14	0.14

Table 3 Landsat data information 2019

Scene	Acquired date	Land cloud cover %
1	07/05/19	15.20
2	04/03/19	6.15
3	11/03/19	16.53
4	18/8/19	2.45

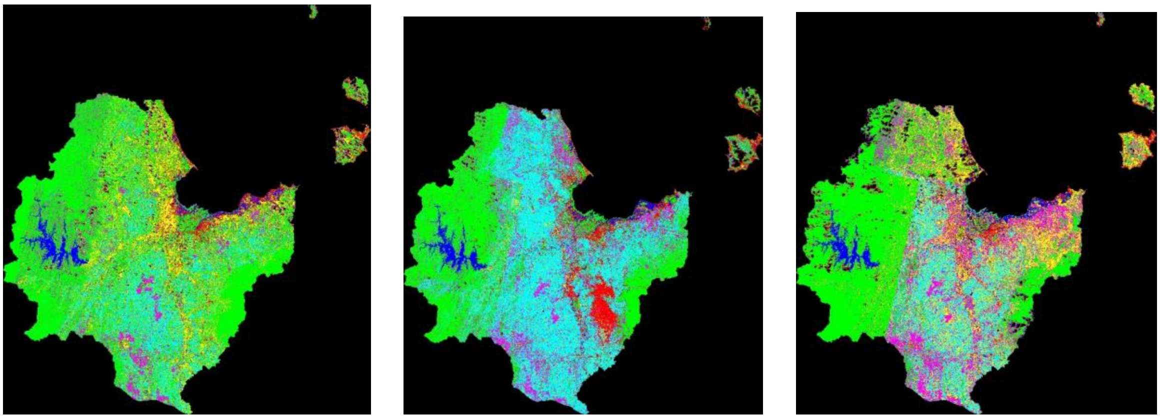
Data need to be corrected by Radiometric Calibration to change from digital number (DN) value to reflectance value for each of the scenes for each year. All the corrected scenes being mosaic together for year 2007, 2014 and 2019. The mosaic images were subsets to the Surat Thani region. Cloud were masked out from the images using region of interest tool threshold.

Before the classification process, pre-classification was needed which consist of validation and training sample site. Training sample site were prepared on the image of each year to train the system with the desired layer of class. There was 7 class type and each class consist of 40 polygons with 60-80 pixels each polygon in order to increase the accuracy of the classification (Song *et. al*, 2000) (Table 4).

Table 4 Training sample site and validation polygon for 2007, 2014 and 2019

Type	Number of polygon	Amount of pixel each polygon	Eye of elevation m
Bare	40	60 – 80	190 – 200
Forest	40	60 – 80	190 – 200
Oil	40	60 – 80	190 – 200
Rubber	40	60 – 80	190 – 200
Urban	40	60 – 80	190 – 200
Water	40	60 – 80	190 – 200

Validation polygon was prepared using the Google Earth Pro to do the region of interest for all the 6 class type. The polygon was drawn on the same elevation at 190-200 m to fix the size of the polygon .



(a) 2007 (b) 2014 (c) 2019

Figure 3 Classification map based on Maximum Likelihood Coefficient

Maximum Likelihood Coefficient (MLC) algorithm has been used on all the training samples to make the classification. From all the training sample site, MLC produce map that differentiate all land use and cover as the desired class type represented by difference colour (Figure 3). Bare as yellow, forest as green, oil as magenta, rubber as cyan, urban as red and water as blue.

confusionmatrixmlc14 - Notepad

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Confusion Matrix: C:\fyp\2014\classification\mlc\mlc14subsetmask

Overall Accuracy = (553/741) 74.6289%

Kappa Coefficient = 0.6949

	Ground Truth (Pixels)				
Class	EVF:Layer:	foEVF:Layer:	baEVF:Layer:	oiEVF:Layer:	ruEVF:Layer: ur
Unclassified	5	13	0	12	7
forest [Green	118	0	20	24	0
bare [Yellow]	0	64	0	0	16
oil [Magenta]	13	1	74	0	0
rubber [Cyan]	5	9	3	68	0
urban [Red] 2	5	16	0	12	67
water [Blue]	0	7	0	0	1
Total	146	110	97	116	91

Figure 4 Confusion matrix MLC 2007

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Confusion Matrix: C:\fyp\2007\classification\mlc\mlc07cliptrymosaic6_3subsetmask

Overall Accuracy = (205/272) 75.3676%

Kappa Coefficient = 0.5471

	Ground Truth (Pixels)				
Class	EVF:Layer:	baEVF:Layer:	foEVF:Layer:	oiEVF:Layer:	ruEVF:Layer: ur
Unclassified	2	0	0	0	0
bare [Yellow]	5	2	0	2	1
forest [Green	1	154	5	7	0
oil [Magenta]	0	31	10	4	0
rubber [Cyan]	0	0	0	1	0
urban [Red] 2	4	3	0	0	4
water [Blue]	0	0	0	0	0
Total	12	190	15	14	5

Figure 5 Confusion matrix MLC 2014

mlc19confusionmatrix - Notepad

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Confusion Matrix: C:\fyp\2019\classification\mlc\mlc19subsetmask

Overall Accuracy = (525/743) 70.6595%

Kappa Coefficient = 0.6446

	Ground Truth (Pixels)				
Class	EVF:Layer:	baEVF:Layer:	foEVF:Layer:	oiEVF:Layer:	ruEVF:Layer: ur
Unclassified	3	0	0	4	14
bareland [Yel	57	7	2	32	2
forest [Green	0	92	15	39	0
oil [Magenta]	0	30	78	9	0
rubber [Cyan]	0	3	0	42	0
urban [Red] 2	22	7	0	0	74
water [Blue]	1	10	2	0	0
Total	83	149	97	126	90

Figure 6 Confusion matrix MLC 2019

The classification was validated by post classification confusion matrix using the ground truth region of interest's that have been prepared during validation polygon using Google Earth Pro. The process was done to check the accuracy of the classification (Figure 4) (Figure 5) (Figure 6). The data indicated in form of overall accuracy and kappa coefficient. As long as the overall accuracy exceeded 70% and kappa coefficient exceeded 0.4 the classification considered as high accuracy due to huge study areas (Song *et. al*, 2000). The study area also consists of islands that have a massive cloud cover that lead to low accuracy due to masking and shadow. Difference date of data acquired also effect the classification because lack of blend during mosaic.

3. RESULTS AND DISCUSSION

From Figure 7 and 8, clearly shown that the changes of land cover either other land cover to rubber or rubber to other land cover happen enormously within just several year gap.

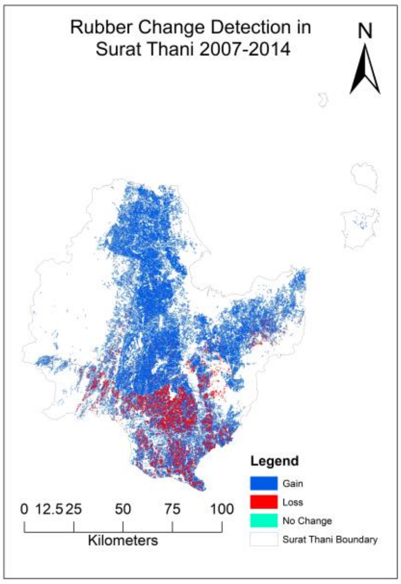

Figure 7 Rubber change detection in Surat Thani 2007-2014

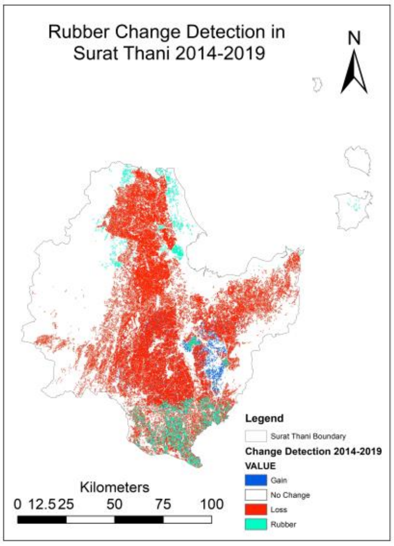

Figure 8 Rubber change detection in Surat Thani 2014-2019

Table 5 Area of rubber land cover

Years	2007 km^2	2014 km^2	2019 km^2
Area	1064.7261	4360.6883	511.6082

Table 6 Area changes of rubber land cover

Type of changes	2007-2014 km^2	2014-2019 km^2
Gain	4003.7013	446.8116
No change	3046.0260	230.6612
Loss	707.0508	4295.8917

Based on the result obtained, in period between 2014-2019 the area of rubber experienced a massive and significant loss compare between gaining and remained as rubber (Table 5) (Table 6). Vice versa for 2007-2014 which rubber area have a huge number of gained and clearly significant differentiated with loss and no change (Table 5) (Table 6). The detail of rubber plantation distribution in Surat Thani, have to be improve and update for future reference.

4. CONCLUSION

This study was conducted to identify rubber plantation distribution in Surat Thani, Thailand. Results from the GIS application showed specific area of rubber plantation that experienced gained, loss and remained as rubber between a desired period. The worrying part are, when the area loss of rubber plantation being left as bare land and massive rubber plantation being cut down in short period. It will lead to a lot of natural disaster such as rise of land temperature, flash flood and other. Future studies should consider other factors such as land surface temperature to improve the results obtained in this study.

ACKNOWLEDGMENT

I acknowledge Universiti Malaysia Kelantan and Prince of Songkla University for providing funding, facilities and opportunity to conduct the study. I also acknowledge both of my supervisor Asst. Prof. Dr. Sunisa Suchat and Dr. Shaparas Daliman for giving advice and support this study. I would like to thank to Fateen Nabilla Rasli for the guidance along the study.

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