LAND USE MAPPING AND MONITORING IN LAMCHIENGKRAI WATERSHED USING REMOTE SENSING DATA, NAKHON RATCHASIMA, THAILAND

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ABSTRACT: The ability of remote sensing has been significantly contributed to decision makers, planners and managers over the last decades. Satellite data are now available that can be used to map and monitor change from regional to local scales and over multi-temporal scales. Information about land use is a very important component of the development planning process and also other environmental planning and management project. Modifications of land use patterns can affect to environmental conservation and sustainability outcomes. Access to accurate land use maps can assist decision makers and planners to avoid undesirable consequences. The purpose of this study is to present and indicate the growing field of remote sensing as it applies to the mapping and monitoring of land use at a range of spatial and temporal scales. Multitemporal of Landsat 8 imagery dataset of Lamchiengkrai Watershed in year 2015 and 2019 were used. Classification methodology had been employed using machine learning as support vector machine techniques. The study area was categorized into eight different classes, including settlement and built-up, natural forest, paddy field, sugarcane, cassava, corn, post-harvested area, and water body. The importance of land use mapping and monitoring in Lamchiengkrai watershed had been emphasized and discussed. Remote sensing technologies perform an important role in land use mapping and monitoring.

1. INTRODUCTION

1.1 Background and significance of the study

Change detection from remote sensing data is a very challenging research problem. Land use and land cover scenes are composed of many different types of objects, both natural and man-made. Land use and land cover is one of the important and most complex classes to analyze. The processing technique, change categories, and assessment of result had been accomplished worldwide for some decades (Gao F. J. et al., 2016, Zhang, K., et al., 2007, Li, Y. F. et al., 2017, Lv, Z. Y et al., 2018, Hansen and Loveland, 2012, Reddy, C. S., et al., 2014, Altaweel, M. R. et al., 2010, and Salah, H. S et al., 2019). Many researches and the studies of land use classification mapping and monitoring change, includes evaluation of landscape dynamic using remote sensing data and geographic information system are also documented (Townsend, P. A et al., 2009, Sutthivanich, I., 2010, Sutthivanich, I. and Ongsomwang, S., 2015, Scullion, J. J., et al., 2014, Read, J. M and Lam, N. S., 2002, Wan, L., et al., 2015, Sutthivanich, I. and Charungthanakij S., 2015, Moepwint S., et al., 2018). In this paper classification scheme and support vector machine technique were proposed for land use mapping and monitoring in Lanchiengkrai watershed, Nakhon Ratchasima province, Thailand.

1.2 Objectives and Scope of Study

1. To classify land use and land cover using supervised classification and support vector machine technique of Landsat 8 satellite multispectral and ancillary data sets.
2. To assess and evaluate land use change between data set of 2015 and 2019
3. To monitor magnitude of changes between land use classes in the Lamchiengkrai watershed.

2. MATERIALS AND METHODOLOGY

2.1 Study area

The study area is a part of Upper Lamchiengkrai watershed which originated from mountainous area at Bamnet Narong district, Chaiyaphum province. It only locates in Nakhon Ratchasima province. The study area is covered by 3 districts include Theparak (Nong Prue, Nong Waeng, Samnak Takhro, and Wang Yai Thong sub-districts), Dan Khun Thot (Ban Kao, Hin Dad, and Huai Bong sub-districts), and Si Khiu (Kritsana and Wang Rong Yai sub-districts) and covered area of 464.96 sq. km (Figure 1).

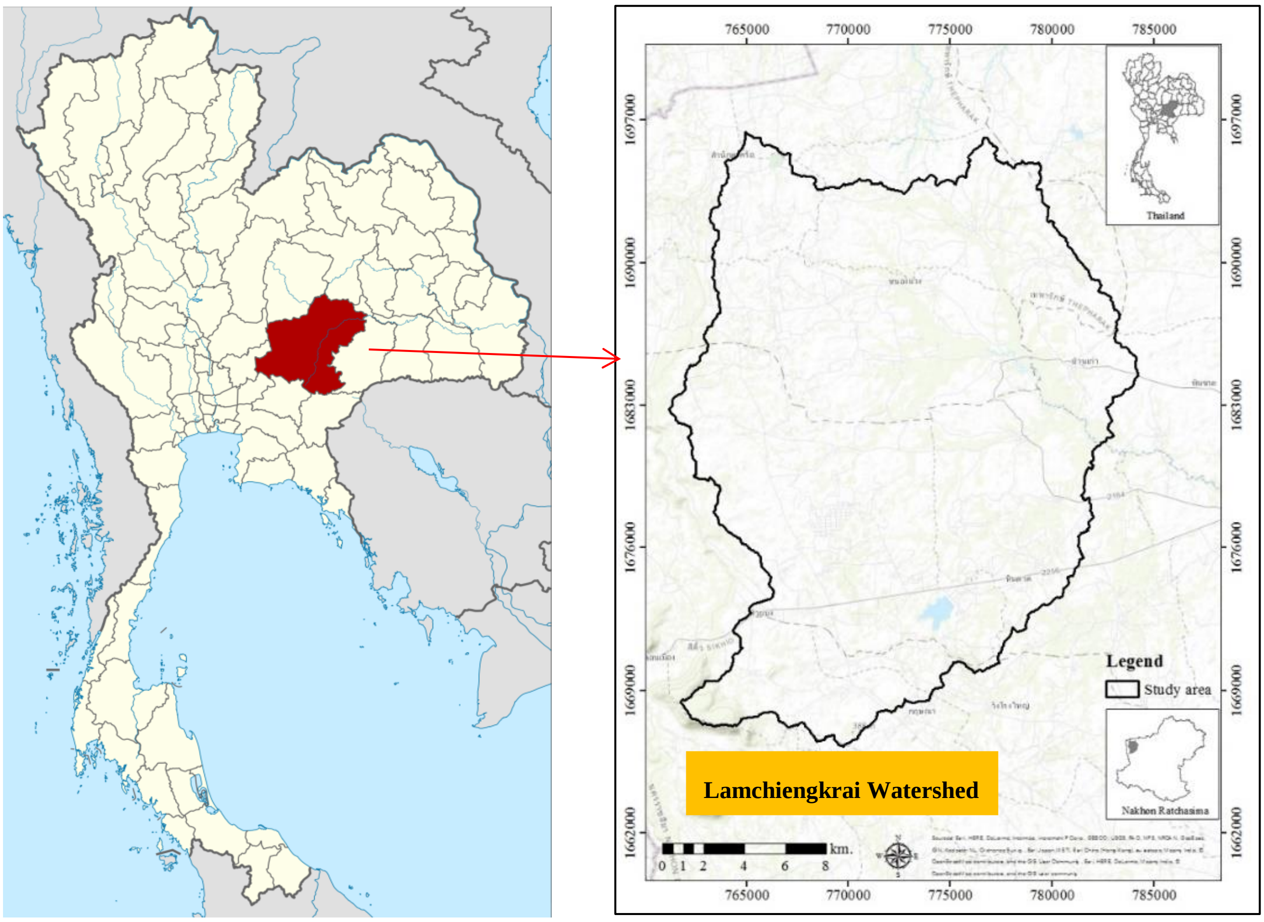

Figure 1 Study area location and boundary (464.96 sq. km)

2.1 Research Methodology

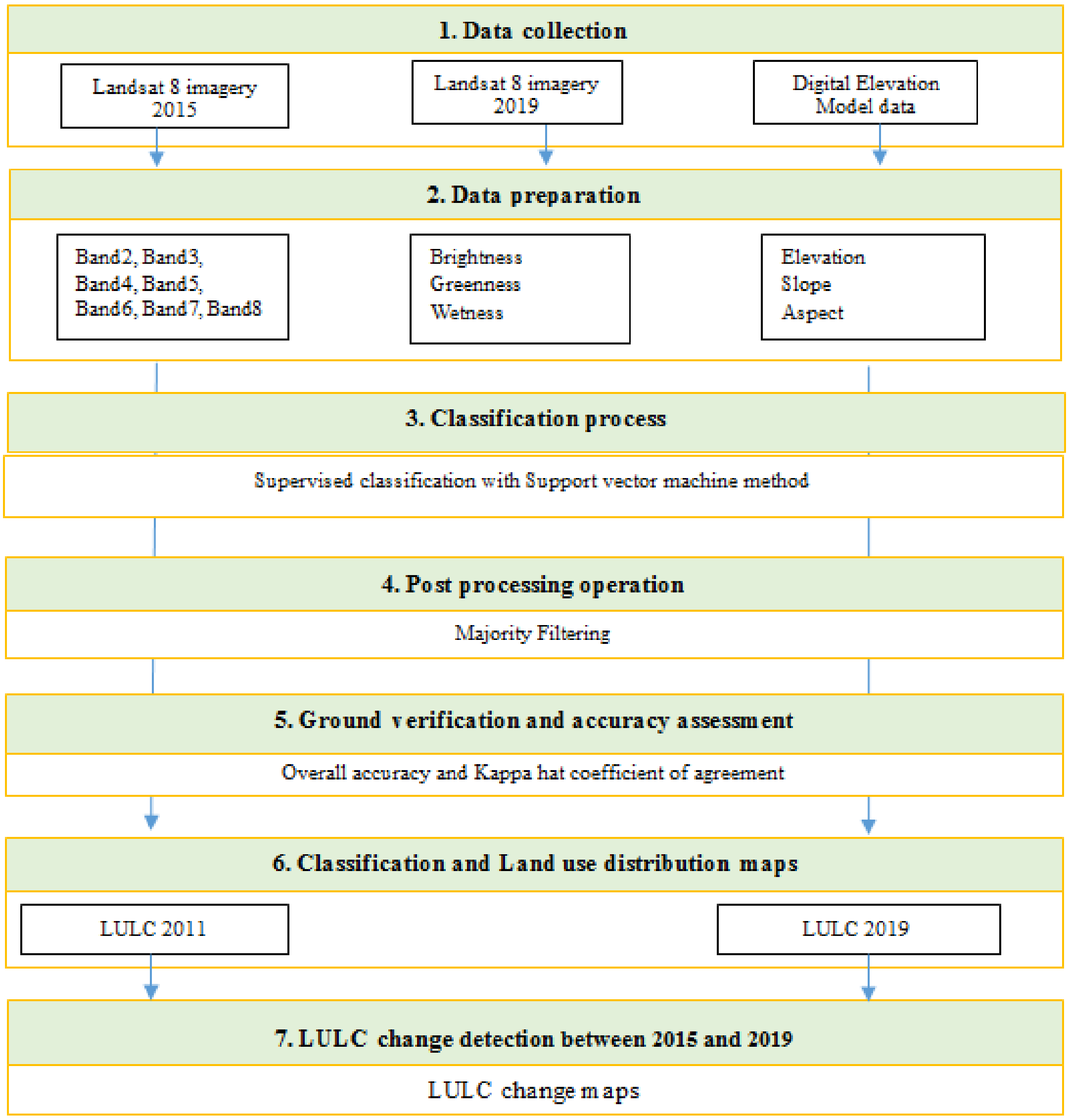

Figure 2 Research Methodology

The research methodology (Figure 2) consists of processes as shown below:

1. Data collection: This study used the Landsat imagery year 2015 and 2019. Satellite images were downloaded from the USGS website (www.earthexplorer.usgs.gov). The first Landsat 8 images were acquired on 2015, and the second Landsat 8 images were acquired on 2019. All acquired data were projected on Universal Transverse Mercator (UTM) with the WGS-84 datum (Table 1).

2. Data preparation: consists of three steps as follows (Table 2 and Figure 3):

(2.1) the derived indices calculation: Landsat 8 images were used to create additional spectral bands included Tasseled Cap with the following equations:

$$Brightness = b1*0.3029+b2*0.2786+b3*0.4733+b4*0.5599+b5*0.508+b6*0.1872 \quad (1)$$

$$Greenness = b1*(-0.2941) +b2*(-0.243) +b3*(-0.5424) +b4*0.7276+b5*0.0713+b6*(-0.1608) \quad (2)$$

$$Wetness = b1*0.1511+b2*0.1973+b3*0.3283+b4*0.3407+b5*(-0.7117) +b6*(-0.4559) \quad (3)$$

Where: b is spectral band

(2.2) the biophysical data: Digital elevation model (DEM) was extracted to elevation (ELE), slope (SLO), and aspect (ASP).

(2.3) dataset preparation: The original Landsat imagery, its derived indices and biophysical data were used in combination.

3. Data classification: The output from process 2 was used for LULC classification using supervised classification and support vector machine method. The LULC classification system which was modified from land use classification scheme of LDD consisted of: (1) Settlement and Build up (SB,) (2) Paddy Field (PF) (3) Cassava (CSV) (4) Sugarcane (SGC), (5) Corn (C), (6) Natural Forest (NF), (7) Water Body (WB) (8) Post-Harvested Area (PHA)

4. Post processing operation: The outputs of land use classification were spatial filtering and defined by majority filtering algorithm.

5. Ground verification and accuracy assessment: The accuracy assessment for the classified land use map was performed based on reference land use data from field survey using overall accuracy and the kappa hat coefficient of agreement. The calculation used equations shown in equation (4) and (5).

$$overall\ accuracy = \frac{\sum_{i=1}^{k} n_{ii}}{N} \quad (4)$$

$$Khat\ coefficient\ of\ agreement = \frac{N\sum_{i=1}^{k} n_{ii} - \sum_{i=1}^{k}(n_{i+} \times n_{+i})}{N^2 - \sum_{i=1}^{k}(n_{i+} \times n_{+i})} \quad (5)$$

6. **Land use change detection in 2015 and 2019**: The output of land use classification in 2015 and 2019 were then used to produce land use change detection with post classification change detection technique to assess land use and land cover changes of the study area.

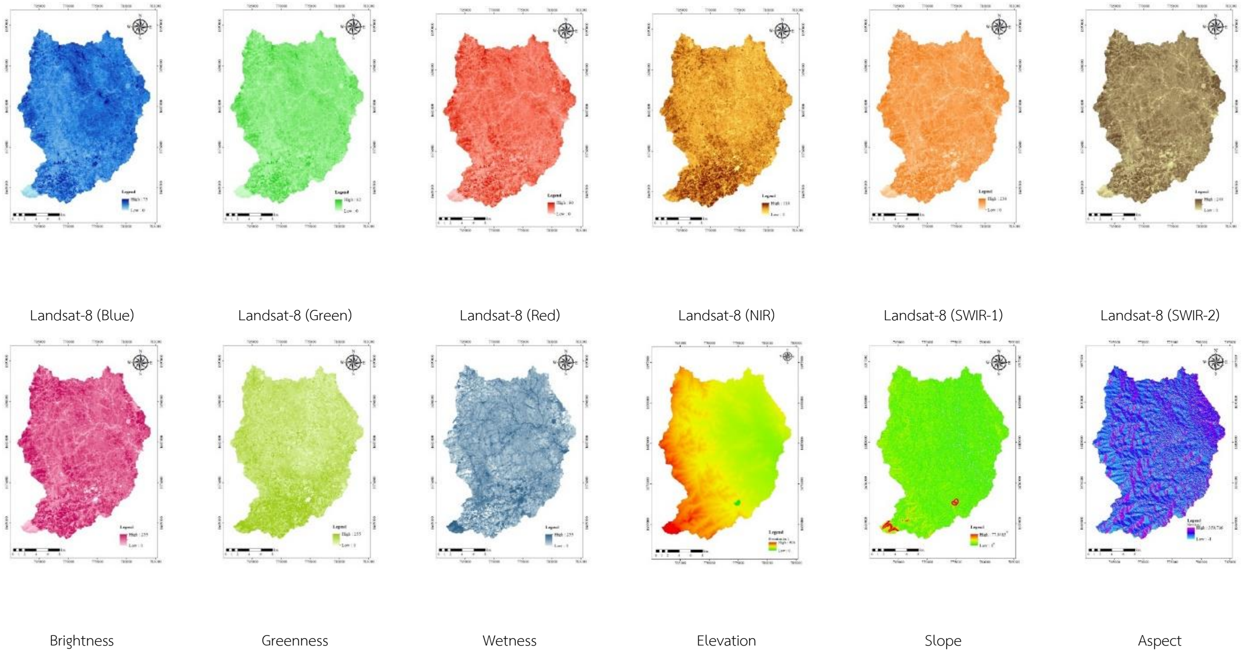

Figure 3 Classification data sets preparation

Table 1 Landsat 8 spectral bands characteristic

Landsat 8		Resolution (m.)
Band	Wavelength (µm.)	
2	0.45-0.51 (Blue)	30
3	0.53-0.59 (Green)	30
4	0.64-0.67 (Red)	30
5	0.85-0.88 (NIR)	30
6	1.57-1.65 (SWIR1)	30
7	2.11-2.29 (SWIR2)	30

Table 2 List of data collection and preparation

Data collection	**Data Preparation**	**Source**	**Year**
Landsat 8 data	Complete	USGS	2019
Administrative boundary	Complete	DEQP	2011
DEM	Complete	USGS	2014
Elevation	Extract from DEM	USGS	2014
Slope	Extract from DEM	USGS	2014
Aspect	Extract from DEM	USGS	2014
Brightness	Create from Landsat data	Landsat data	2015,2019
Greenness	Create from Landsat data	Landsat data	2015,2019
Wetness	Create from Landsat data	Landsat data	2015,2019

3. RESULTS AND DISCUSSION

3.1 Data classification

Results of land use and land cover classification in 2015 and 2019 used supervised classification and support vector machine methods which used multispectral data of Landsat imagery, its derived indices and biophysical data were shown in Figure 4 and Figure 5 respectively. The details of land use and land cover classified maps years 2015 and 2019 were summarized in Table 3 and Table 4.

Table 3 LULC classification 2015 by SVM method

Land use and Land cover Classification types	Year 2015 (sq.km.)
Settlement and Build up	8.4231
Paddy Field	28.8765
Cassava	312.3441
Sugarcane	20.9979
Corn	22.9869
Natural forest	47.2382
Water Body	7.5096
Post-Harvested Area	18.1891
Area total	466.5654

Table 4 LULC classification 2019 by SVM method

Land use and Land cover Classification types	Year 2019 (sq.km.)
Settlement and Build up	13.7758
Paddy Field	21.685
Cassava	299.744
Sugarcane	49.0453
Corn	24.5722
Natural Forest	32.9099
Water Body	7.4728
Post-Harvested Area	17.3604
Area total	466.5654

Table 3 and Table 4, reported land use and land cover classification using supervise classification and support vector machine methods (SVM) of the data year 2015 and 2019. The resulted in 2015 shown that cassava occupied the largest extent over other types in the study area that was 312.34 sq.km. The second majority group was natural forest, paddy field, corn and sugarcane. The group occupied the area of 47.23, 28.87, 20.99, and 22.98 sq.km, respectively. Year 2019, the results indicated that cassava was still a major land cover type in the area, but deceased in its area from 312.34 to 299.74 sq.km. The same as paddy field which was deceased in its area from 28.87 to 21.68 sq.km. Sugarcane had significantly increased in its area from 20.99 to 49.04 sq.km. Similarly, settlement and built up area had changed in extent from 8.42 to 13.77 sq.km. Sugarcane and corn were expanded their area from 20.99 to 49.04 sq.km and from 22.98 to 24.57 sq.km, respectively.

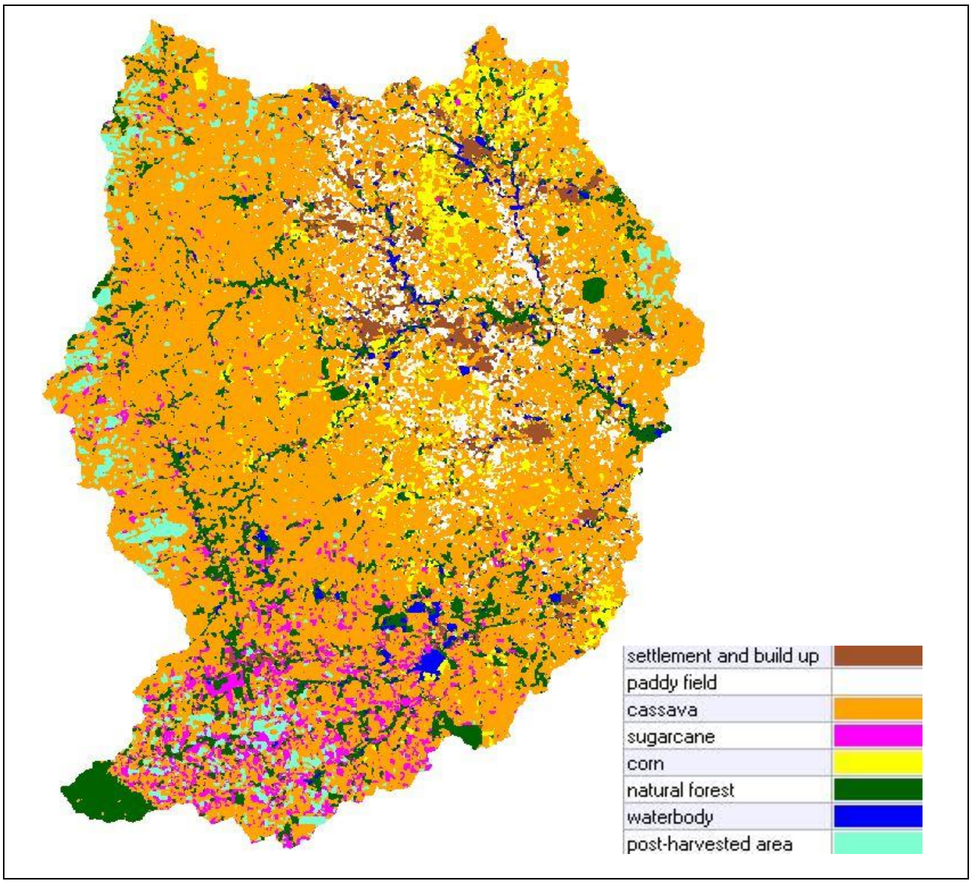

Figure 4 LULC classification map 2015 by SVM method

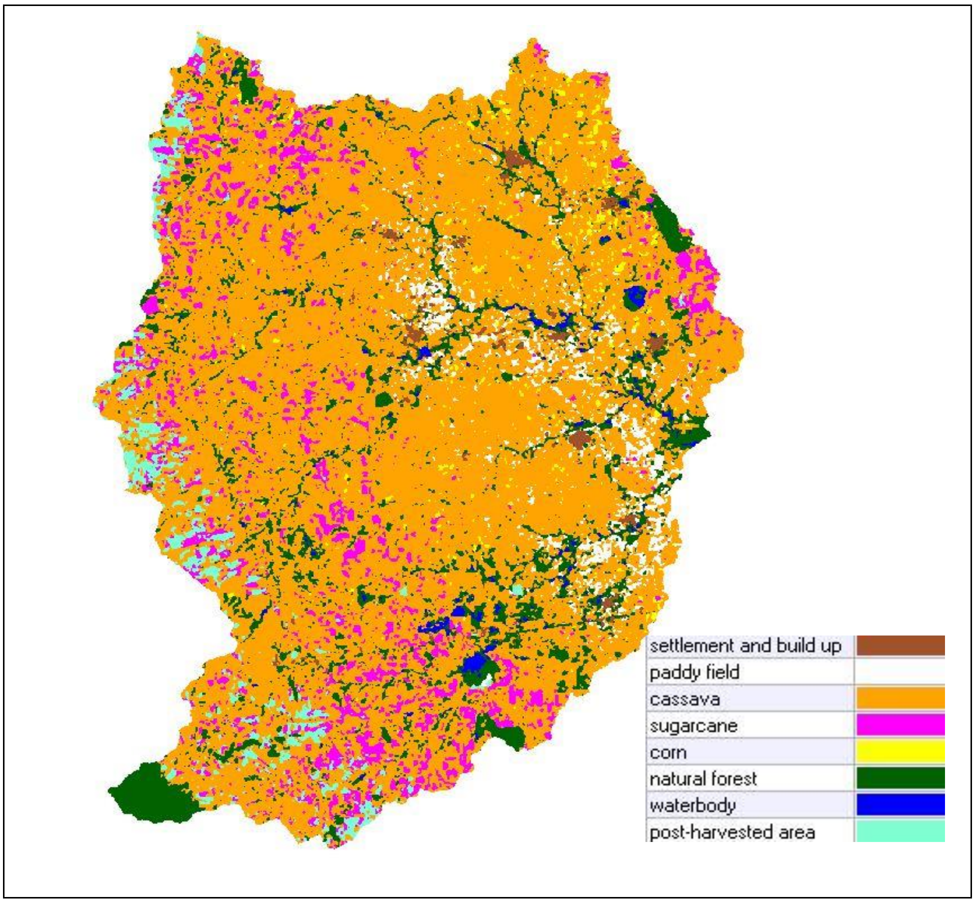

Figure 5 LULC classification map 2019 by SVM method

3.2 Land use classification accuracy assessment

The accuracy assessment of land use and land cover classification used the 120 reference random points to validate the accuracy. The number of reference random point calculation based on the theory of probability of binomial distribution and stratified random sampling. The overall accuracy and the Kappa coefficient were processed and the results as shown in Table 5 and Table 6.

Table 5 Accuracy assessment of LULC classification 2015 by SVM method

Classified Data	Accuracy assessment of LULC classification 2015									Producers Accuracy	Users Accuracy
	SB	PF	CSV	SGC	C	NF	WB	PHV	Row Total		
SB	5	0	0	0	0	0	0	0	5	100.00%	100.00%
PF	0	8	3	1	0	0	0	0	12	72.73%	66.67%
CSV	0	3	33	5	0	0	0	0	41	82.50%	80.49%
SGC	0	0	0	14	0	0	0	0	14	70.00%	100.00%
C	0	0	1	0	14	0	0	0	15	100.00%	93.33%
NF	0	0	1	0	0	14	0	0	15	100.00%	93.33%
WB	0	0	0	0	0	0	5	0	5	100.00%	100.00%
PHA	0	0	2	0	0	0	0	11	13	100.00%	84.62%
Column Total	5	11	40	20	14	14	5	11	120		
Overall Classification Accuracy = 86.67%											
Overall Kappa Statistics = 0.8364											

Note: Settlement and build up (SB) / Paddy field (PF) / Cassava (CSV) / Sugarcane (SGC) / Corn (C) / Natural forest (NF)/ Water body (WB) / Post-harvested area (PHV)

The results of the accuracy assessment of land use and land cover classification 2015 showed that the overall accuracy was 86.67 percent and the Kappa coefficient was 0.8364. While in 2019, the overall accuracy was 87.50 percent and the Kappa coefficient was 0.8477.

Table 6 Accuracy assessment of LULC classification 2019 by SVM method

Classified Data	Accuracy assessment of LULC classification 2019									Producers Accuracy	Users Accuracy
	SB	PF	CSV	SGC	C	NF	WB	PHV	Row Total		
SB	4	0	1	0	0	0	0	0	5	100.00%	80.00%
PF	0	7	0	0	0	0	0	0	7	77.78%	100.00%
CSV	0	2	31	3	6	0	0	0	42	93.94%	73.81%
SGC	0	0	0	18	1	0	0	0	19	81.82%	94.74%
C	0	0	0	0	15	0	0	0	15	68.18%	100.00%
NF	0	0	1	1	0	13	0	0	15	100.00%	86.67%
WB	0	0	0	0	0	0	5	0	5	100.00%	100.00%
PHA	0	0	0	0	0	0	0	12	12	100.00%	100.00%
Column Total	4	9	33	22	22	13	5	12	120		
Overall Classification Accuracy = 87.50%											
Overall Kappa Statistics = 0.8477											

Note: Settlement and build up (SB) / Paddy field (PF) / Cassava (CSV) / Sugarcane (SGC) / Corn (C) / Natural forest (NF)/ Water body (WB) / Post-harvested area (PHV)

3.3 Land use change detection in Lamchiengkrai watershed between 2015 and 2019

Change detection of land use and land cover of Lamchiengkrai watershed from 2015 to 2019, the results showed that the major change occurred in cassava (CSV), natural forest (NF), and corn field (C). The cassava had significantly changed in the area of 57.91 sq.km, which mostly converted to sugarcane (SGC) at 25.78 sq.km. Meanwhile, natural forest (NF) was the second magnitude changed at 20.76 sq.km which mostly converted to cassava area at 14.97 sq.km. In corn field trend had been changed to cassava at 9.12 sq.km. and post-harvested area at 2.01 sq.km. Similarly, paddy field had highly transformed to cassava at 15.17 sq.km. In post-harvest area, changes occurred in crop field classes such as sugarcane, cassava, and corn, which mostly it was converted to sugarcane. The minor change appeared in water body and settlement and build up area at 1.90 sq.km and 2.96 sq.km, respectively. Figure 6 and Table 7 illustrated result of land use change detection in Lamchiengkrai watershed between 2015 and 2019. The total area of changed in Lamchiengkrai watershed was 133.40 sq.km and the area of no changed was 333.17 sq.km.

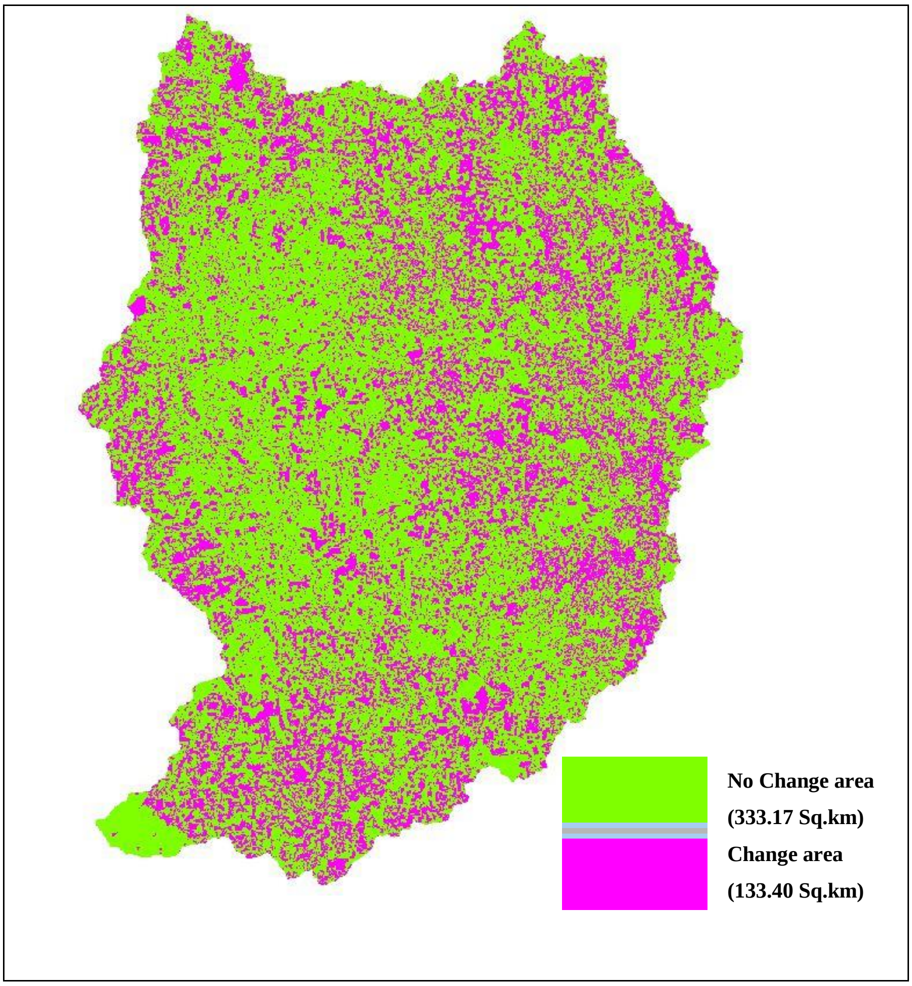

Figure 6 Land use change detection map between 2011 and 2019

Table 7 Result of Land use and land cover change detection between 2011 and 2019

LULC area in 2015 (sq.km.)	LULC area in 2019 (sq.km.)								Total (sq.km)	LULC change (sq.km)
	SB	PF	CSV	SGC	C	NF	WB	PHV		
SB	5.47	0.27	1.09	0.01	0.29	0.84	0.45	0.01	8.42	2.96
PF	1.94	15.17	10.10	0.12	1.16	0.37	0.01	0.01	28.88	13.71
CSV	3.51	5.71	254.44	25.78	12.08	3.71	0.18	6.92	312.34	57.91
SGC	0.04	0.05	7.35	11.24	0.85	0.00	0.00	1.46	21.00	9.75
C	0.09	0.19	9.12	1.02	9.13	0.58	0.85	2.01	22.99	13.86
NF	1.60	0.23	14.97	1.23	1.05	26.48	0.38	1.31	47.24	20.76
WB	0.07	0.07	0.83	0.00	0.01	0.92	5.61	0.00	7.51	1.90
PHA	1.06	0.00	1.84	9.65	0.00	0.01	0.00	5.64	18.19	12.55
Total	13.78	21.69	299.74	49.05	24.57	32.91	7.47	17.36	466.57	133.40

Note: settlement and build up (SB) / paddy field (PF) / cassava (CSV) /sugarcane (SGC) /Corn (C) / natural forest (NF)/ water body (WB) / post-harvested area (PHV)

4. CONCLUSIONS

Land cover change detection based on remote sensing images and ancillary data sets plays an important role in mapping and monitoring land use and land cover changed in Lamchiengkrai watershed, Nakhon Ratchasima province, Thailand. This classification scheme and classify technique can guide other practitioners in choosing appropriate classification and change detection methods to achieve their goals as well as suggesting new research efforts. In comparison to several widely used change detection methods, the proposed approach can produce a land cover change map with a competitive accuracy.

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