LAND USE CHANGE DETECTION AND ITS IMPLICATION OF THA MAI AREA IN CHANTHABURI PROVINCE USING LANDSAT 8 DATA

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ABSTRACT: Chanthaburi is a province located on the eastern coast of Thailand. The province has long history with rich in natural resources such as forests, precious stones, and abundant soil. The fertile area is resulting in high agricultural productivity and various kinds of orchards. The objective of this study is to detect changes in land use and its implication of Tha Mai area, Chanthaburi province by applying Landsat 8 satellite datasets of year 2011 and 2019 with biophysical data and various indices data in classification process. Maximum likelihood and machine learning methods are employed to classify land use and land cover into seven classes, including urban and built up area, forest area, mangrove forest, orchard, rubber plantation, bare land and water body. The results indicate that the combination of Landsat 8 data, the set of indices (NDVI, MNDWI, and NDBI), elevation, slope and aspect of the classified image year 2011 provided the overall accuracy and the Kappa coefficient at 90.83% and .8762 respectively. While classification of year 2019 showed the overall accuracy and the Kappa coefficient at 91.67 % and 0.8903, respectively. Change detection of land use and land cover of Tha Mai area from 2011 to 2019, the results showed that five classes of land use and land cover had been increased change in their areas and three classes of land use and land cover had been decreased change in their areas. The major change occurred in mixed cultivated area (MC), natural forest (NF), and orchard (OC). The mixed cultivated area (MC) had significantly decreased in its area at 69.48 sq.km, which it decreased from 170.63 sq.km in 2011, to 101.15 sq.km in 2019. The mixed cultivated area was mostly converted to orchard (OC) at 62.68 sq.km., to natural forest at 17.04 sq.km and to urban and build up area at 13.53 sq.km. Meanwhile, the natural forest (NF) was increased from 90.17 sq.km in 2011 to 119.51 sq.km in 2019 and mostly changed to mangrove forest (MF) at 6.61 sq.km., to rubber plantation and tree at 4.30 sq.km and to orchard (OC) at 3.97 sq.km , respectively. Bare land (BL) had been decreased from 45.99 sq.km in 2011 to 26.16 sq.km in 2019 which mostly changed to mixed cultivation area at 18.36 sq.km.

1. INTRODUCTION

1.1 Background and significance of the study

Chanthaburi is a province located on the eastern coast of Thailand. The province has long history with rich in natural resources such as forests, precious stones, and abundant soil. The fertile area is resulting in high agricultural productivity and various kinds of orchards such as durian, rambutan, mangosteen and longan. Chanthaburi is an important food production source in the eastern region, accounting for 60.23 percent of the province's gross domestic product. Land use in Chanthaburi area, mainly consisting of fruit planting areas, accounting for 15.76 percent of all agricultural land in the province. During the past 10 years, Thailand has expanded the demand for durian consumption in the international trade market, resulting in changes in land use patterns from rubber and mangosteen plantation to durian growing areas in Chanthaburi (Office of International Trade Promotion, 2015).

Land use and land cover change (LULCC) is considered as an important tool to assess global change in different spatiotemporal scales (Lambin, 1997). It is a widespread, accelerating, and significant process which is driven by human act actions, and, in many cases, it also drives changes that affect humans (Agarwal et al., 2001). The impacts of LULCC on the sustainability of the ecosystems are becoming increasingly important issues in global changes research. Human actions seem to lead to the greatest changes in the current state of the earth's surface. Geoinformatics technology is a basal and essential technical core of the system for assessing geospatial information and monitoring the environment (Fadhil, 2009). It provides time series data for monitoring land cover change (Lillesand, Kiefer, and Chipman, 2004).

In the past decade, machine learning techniques have been applied via support vector machine to classify satellite imagery data. As a result, data can now be classified very well, although there is a limited as well. Support vector machine is one of the supervised classification methods, which is widely used in work related to pattern recognition. Ninh and Waisurasingha (2017) found that the support vector machine is effective in analyzing Landsat satellite image data at various times. Bahari, Ahmad, and Aboobaider (2014) found that support vector machine methods can be used to classify land use and land cover types in the Selagong state area of Malaysia, with high accuracy and Kappa coefficient representing 97.10% and 96.00%.

This study develops the methods to classify land use and land cover in 2011 and 2019 from Landsat satellite images with the maximum likelihood and support vector machine classification in combination of the secondary data (NDVI MNDWI and NDBI) and biophysical data (height, slope, and aspect) and then change detection method was performed.

1.2 Objectives and Scope of Study

1.2.1 Objectives

1. To classify land use and land cover using the method of Maximum likelihood classification and support vector machine from the multispectral data set of Landsat 8 satellite image data, secondary data and biophysical data.
2. To compare the accuracy of classification and evaluate the data set that is suitable for high accuracy classification.
3. To monitor changes in land use and land cover in Tha Mai District Chantaburi province between 2011 and 2019.

2. MATERIALS AND METHODS

2.1 Study area

Tha Mai District, which is one of the Chantaburi province located in the eastern part of Thailand, with an area of 628.52 square kilometers. The area is flat, uneven, mountainous, and mangrove forest. The soil is sandy soil and has the temperature between 24-33 degrees Celsius, with an average annual rainfall of 3,000 millimeters (Division of Technical and Planning, Tha Mai Subdistrict Municipality, 2011).

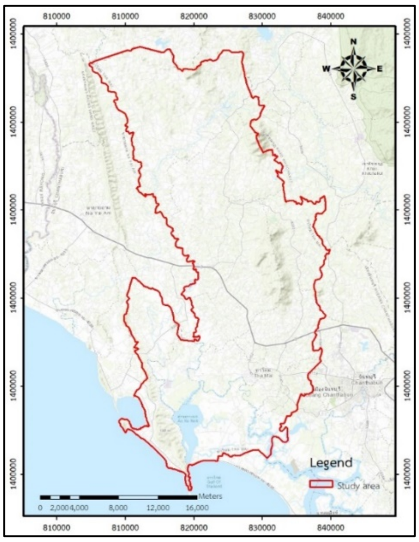

Figure 1 Study area: Tha Mai District, Chantaburi province

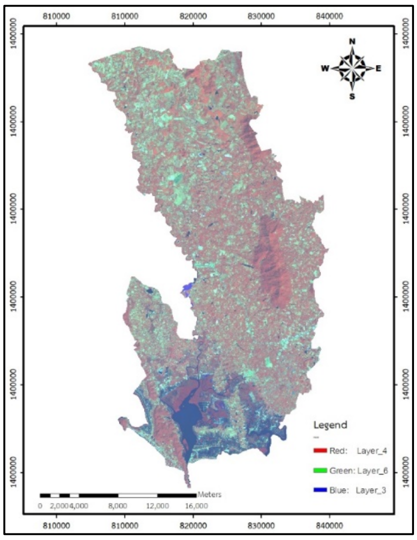

Figure 2 Band 4, 6 and 3 of Landsat 8 imagery

2.2 Research Methodology

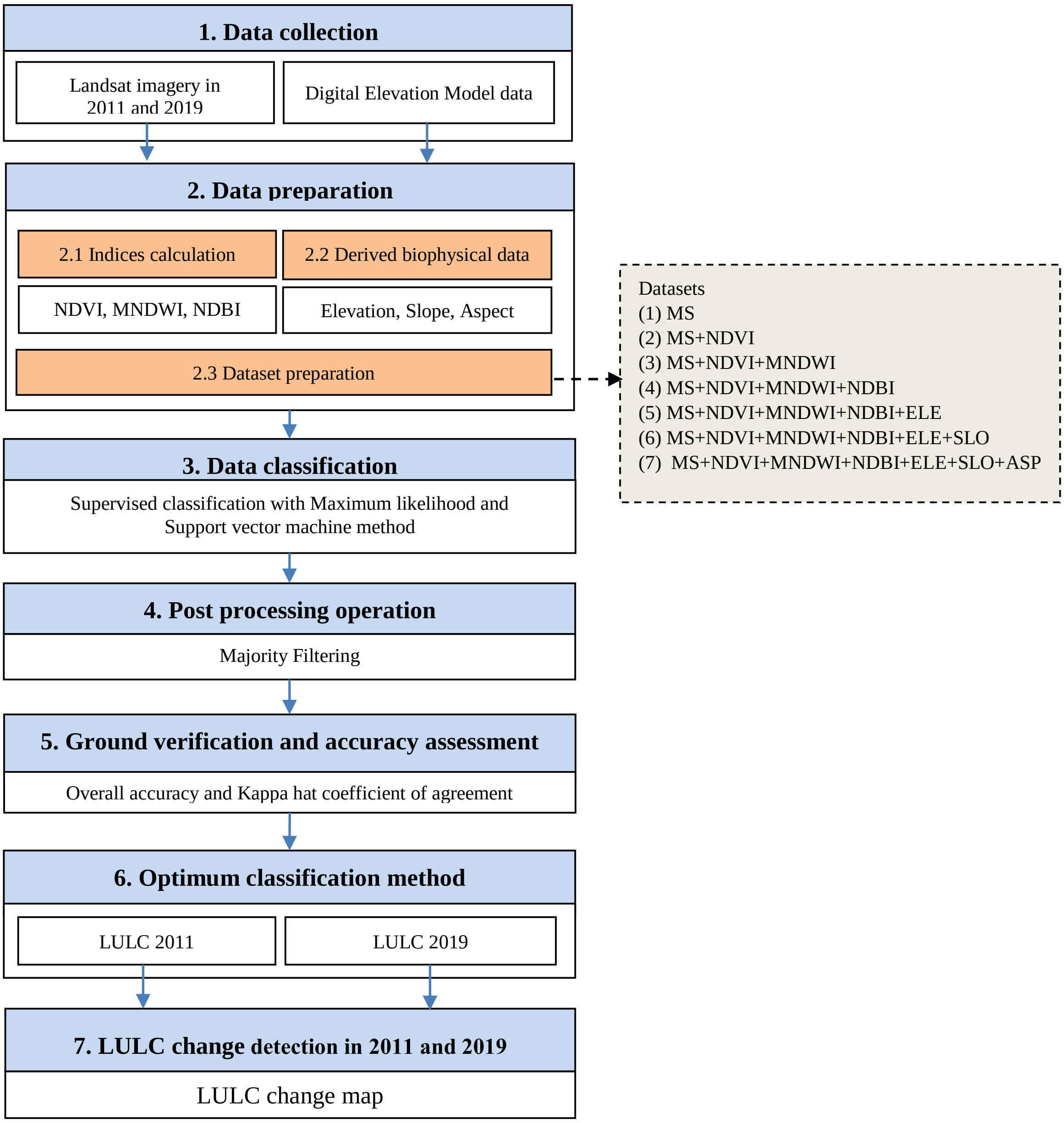

Figure 3 Research Methodology

The details of each process were summarized in the following sections.

Component 1: Data collection

This study used the Landsat imagery in year 2011 and 2019. Satellite images were downloaded from the USGS website (www.earthexplorer.usgs.gov). The first Landsat 5 images were acquired on January 18, 2011, and the second Landsat 8 images were acquired on January 24, 2019. All acquired data were projected in Universal Transverse Mercator (UTM) with the WGS-84 datum (Table 1).

Table 1 Characteristics of Landsat 5 and 8 in this research (USGS, 2015)

Landsat 5		Landsat 8		Resolution (m.)
Band	Wavelength (μm.)	Band	Wavelength (μm.)	
1	0.45-0.52 (Blue)	2	0.45-0.51 (Blue)	30
2	0.52-0.60 (Green)	3	0.53-0.59 (Green)	30
3	0.60-0.69 (Red)	4	0.64-0.67 (Red)	30
4	0.77-0.90 (NIR)	5	0.85-0.88 (NIR)	30
5	1.55-1.75 (SWIR1)	6	1.57-1.65 (SWIR1)	30
7	2.08-2.35 (SWIR2)	7	2.11-2.29 (SWIR2)	30

Component 2: Data preparation

Data preparation consists of three steps as follows:

(2.1) the derived indices calculation: The derived Landsat imagery image was used to create additional spectral bands included NDVI, MNDWI and NDBI using following equations:

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

$$MNDWI = \frac{GREEN-SWIR}{GREEN+SWIR} \quad (2)$$

$$NDBI = \frac{SWIR-NIR}{SWIR+NIR} \quad (3)$$

Where:

GREEN is Brightness value of Band 2 of Landsat-5 and Band 3 of Landsat-8;
RED is Brightness value of Band 3 of Landsat-5 and Band 4 of Landsat-8;
NIR is Brightness value of Band 4 of Landsat-5 and Band 5 of Landsat-8;
SWIR is Brightness value of Band 5 of Landsat-5 and Band 6 of Landsat-8.

(2.2) the derived biophysical data: DEM was used to extract study area and elevation (ELE), slope (SLO), and aspect (ASP) respectively.

(2.3) dataset preparation: The original Landsat imagery and its derived indices and biophysical data were used to create 7 datasets for classifying LULC in year 2011 and 2019: (1) Multispectral data (MS) (Band 1-5, and 7 in 2011 and Band 2-6 in year 2019), (2) MS and NDVI, (3) MS, NDVI and MNDWI, (4) MS, NDVI, MNDWI, and NDBI, (5) MS, NDVI, MNDWI, NDBI, and elevation, (6) MS, NDVI, MNDWI, NDBI, elevation, and slope, and (7) MS, NDVI, MNDWI, NDBI, slope, elevation, and aspect.

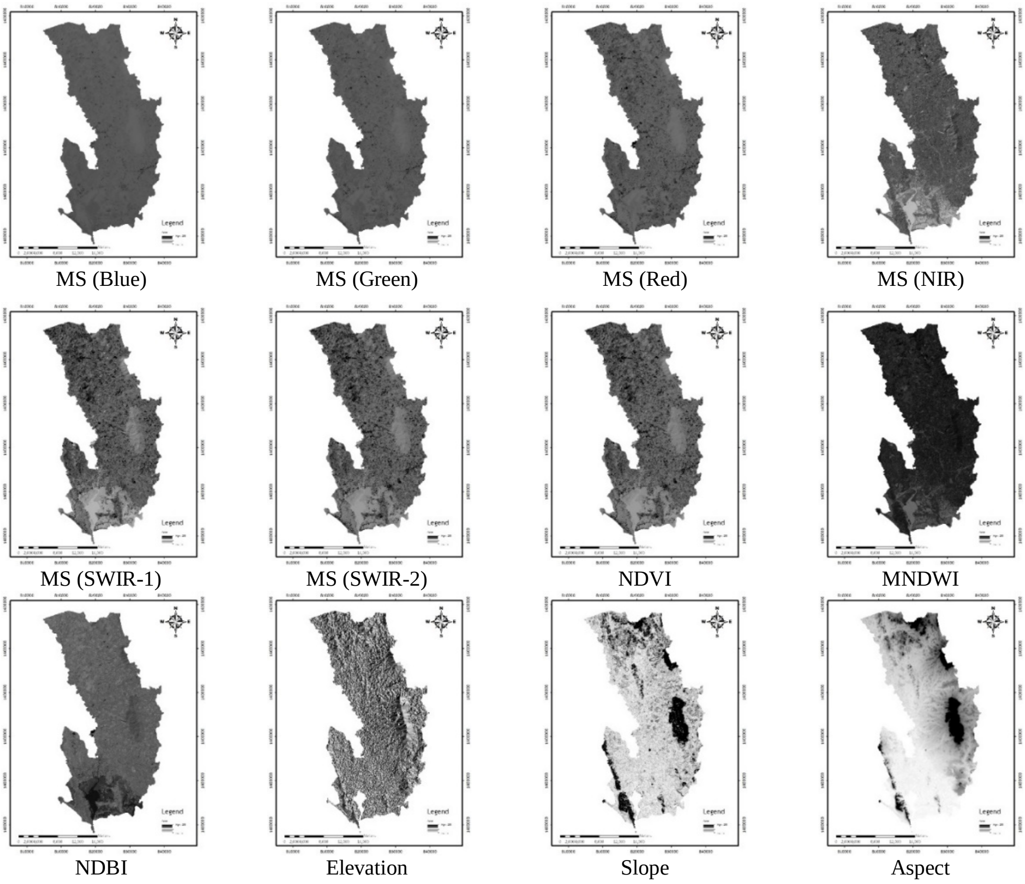

Figure 4 Landsat imagery and its derived indices and biophysical datasets

Table 2 List of data collection and preparation

Data collection	Data Preparation	Source	Year
Landsat 5 data	Completeness checking	USGS	2011
Landsat 8 data	Completeness checking	USGS	2019
Administrative boundary	Completeness checking	DEQP	2011
DEM	Completeness checking	USGS	2014
Elevation	Extract from DEM	USGS	2014
Slope	Extract from DEM	USGS	2014
Aspect	Extract from DEM	USGS	2014
NDVI	Create from Landsat data	Landsat data	2011,2019
MNDWI	Create from Landsat data	Landsat data	2011,2019
NDBI	Create from Landsat data	Landsat data	2011,2019

Component 3: Data classification

The output from process 2 was used for LULC classification using supervised classification with Maximum likelihood and Support vector machine method in ENVI 4.4 software. The LULC classification system which was modified from land use classification scheme of LDD consisted of: 1) Urban and built-up area (UB), 2) Orchard (OC), 3) Rubber plantation and Tree (RT), 4) Natural forest (NF), 5) Mangrove forest (MF), 6) Mix cultivated area (MC), 7) Water body (WA), and 8) Bare land (BL).

Component 4: Post processing operation

The output of LULC classification was used to spatial filtering by majority filtering algorithm.

Component 5: Ground verification and accuracy assessment

The accuracy assessment for the classified LULC map was performed based on reference LULC data from field survey using overall accuracy and kappa hat coefficient of agreement.

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

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

Component 6: Optimum classification method

The optimum classification method was compared in each dataset to evaluate optimum dataset for land use and land cover classification in year 2011 and 2019.

Component 7: LULC change detection in 2011 and 2019

The output of the optimum LULC classification in 2011 and 2019 were used to produce LULC change detection with post classification change detection technique to assess land use and land cover changes of the study area.

3. RESULTS AND DISCUSSION

3.1 Data classification

Results of land use and land cover classification in 2011 and 2019, by Maximum likelihood and Support vector machine methods that used multispectral data of Landsat imagery and its derived indices and biophysical data of the seven datasets were shown in Figure 5 and 6 respectively, and the details of land use and land cover areas classified from all data sets years 2011 and 2019 were summarized in Table 3 - 6.

Table 3 LULC classification by MLC method 2011

LULC	Dataset						
Types	1	2	3	4	5	6	7
UB	100.18	69.41	61.71	61.32	56.87	54.42	46.22
OC	147.36	148.08	145.07	157.88	145.20	176.85	204.79
RT	21.12	24.48	29.03	14.27	21.73	17.91	4.58
NF	70.61	80.39	89.43	93.22	96.72	72.47	98.70
MF	24.45	17.53	16.41	16.45	16.66	15.92	14.86
MC	142.82	179.15	167.15	166.79	171.46	166.10	121.33
WA	81.02	60.13	77.28	76.64	77.43	77.67	70.94
BL	40.97	49.35	42.45	41.96	42.45	47.19	67.11
Total	628.52	628.52	628.52	628.52	628.52	628.52	628.52

Table 4 LULC classification by SVM method 2011

LULC	Dataset						
Types	1	2	3	4	5	6	7
UB	58.77	52.73	57.38	60.03	59.73	59.24	61.06
OC	197.54	175.38	187.00	173.39	169.58	171.18	180.63
RT	5.84	6.78	10.27	12.83	9.55	6.35	5.91
NF	88.70	106.25	92.15	104.60	93.01	101.87	90.18
MF	31.37	31.18	31.76	31.60	30.97	31.68	34.69
MC	161.63	171.14	167.98	166.21	170.82	172.82	170.63
WA	42.38	44.50	40.87	38.99	38.68	39.11	39.43
BL	42.28	40.55	41.11	40.88	56.17	46.27	45.99
Total	628.52	628.52	628.52	628.52	628.52	628.52	628.52

Table 5 LULC classification by MLC method 2019

LULC Types	Dataset 1	2	3	4	5	6	7
UB	32.64	129.93	87.62	95.03	95.97	88.39	88.15
OC	395.92	298.85	332.08	258.02	302.49	315.38	275.16
RT	11.12	11.38	11.60	12.09	11.71	10.83	11.35
NF	81.54	96.37	86.11	98.84	98.75	101.26	137.49
MF	15.39	22.43	20.48	22.85	22.93	21.01	21.92
MC	29.10	14.06	59.17	86.53	47.21	59.89	59.54
WA	48.00	21.53	26.19	32.56	31.47	28.05	28.62
BL	14.81	33.99	5.27	22.60	17.98	3.72	6.29
Total	628.52	628.52	628.52	628.52	628.52	628.52	628.52

Table 6 LULC classification by SVM method 2019

LULC Types	Dataset 1	2	3	4	5	6	7
UB	48.95	65.85	56.9	62.89	60.15	70.55	73.92
OC	307.9	300.2	318	298.7	290.7	219.7	204.78
RT	22.78	26.99	22.75	33.27	29.32	29.41	27.69
NF	56.89	58.44	52.16	57.45	59.67	106.6	119.51
MF	20.67	16.21	18.15	18.5	18.19	23.94	39.55
MC	107.8	98.62	103.6	100.8	88.95	116.4	101.15
WA	40.24	40.98	37.25	36.28	36.19	36.7	35.76
BL	23.24	21.27	19.75	20.68	45.4	25.11	26.16
Total	628.5	628.5	628.5	628.5	628.5	628.5	628.52

From Table 3 and 4, it was found that all data sets of multispectral data of Landsat imagery and its derived indices and biophysical data provide complete classification of all types of land use and land cover in year 2011, including 1) Urban and built-up area (UB), 2) Orchard (OC), 3.) Rubber plantation and Tree (RT), 4) Natural forest (NF), 5) Mangrove forest (MF), 6) Mix cultivated area (MC), 7) Water body (WA), and 8) Bare land (BL), as shown in Figure 5. Similarly, from Table 5 and 6, it was found that all data sets of multispectral data of Landsat imagery and its derived indices and biophysical data provide the same classification for all types of land use and land cover in year 2019.

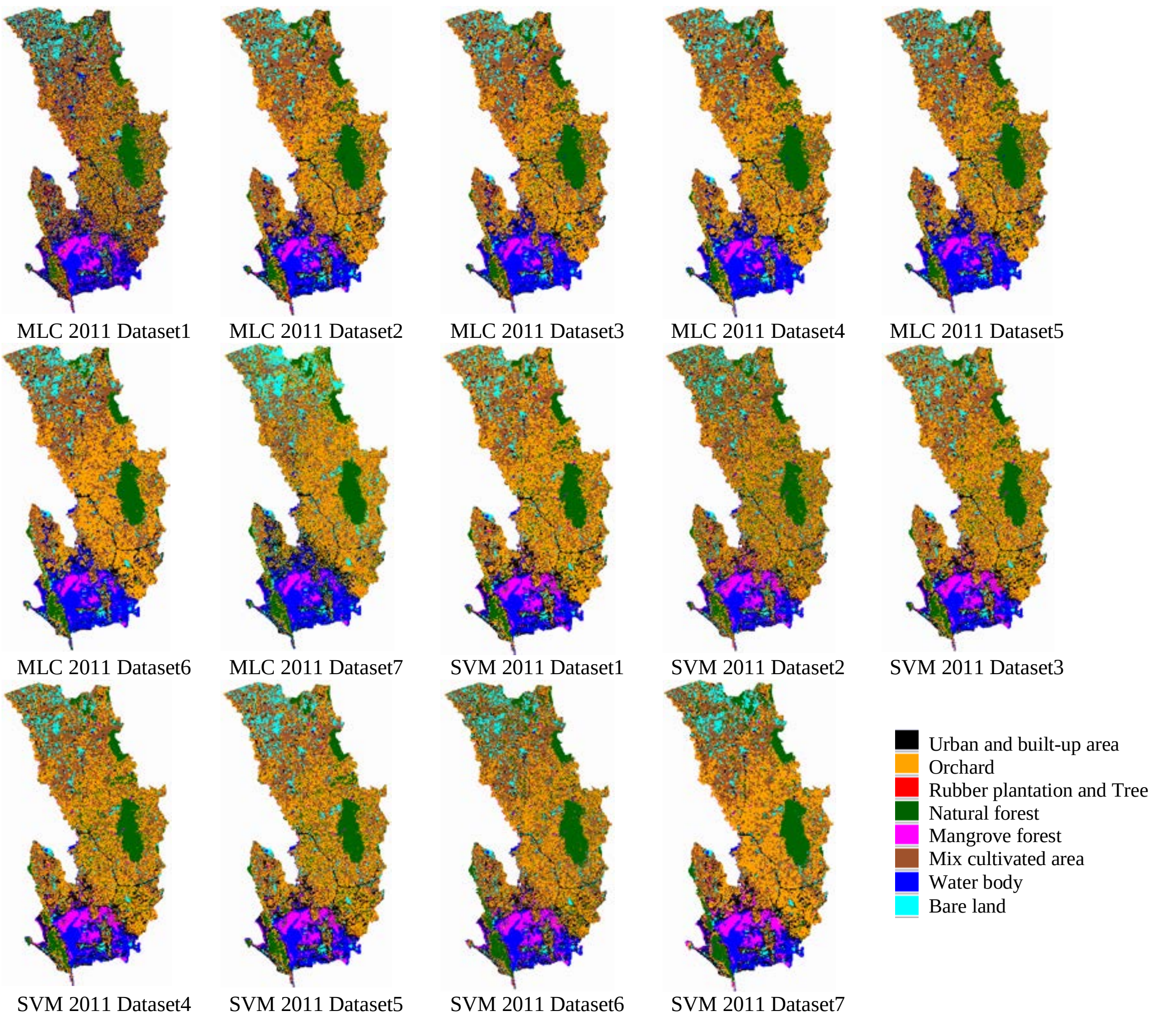

Figure 5 LULC classification map by MLC and SVM methods 2011

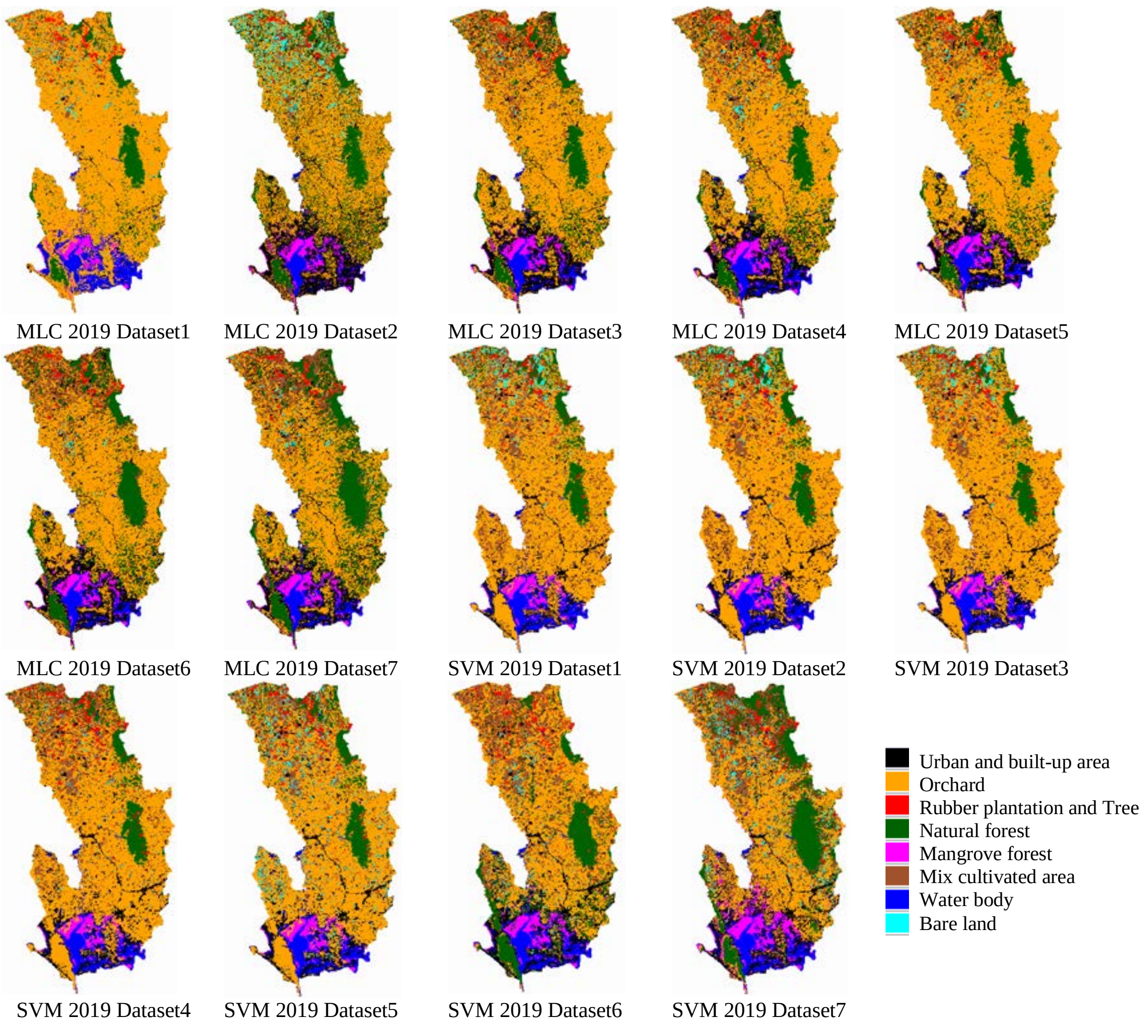

Figure 6 LULC classification map by MLC and SVM methods 2019

3.2 Accuracy assessment results for land use and land cover classification

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 points calculated 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 7 and 8.

Table 7 Accuracy assessment of LULC classification using MLC and SVM methods 2011

dataset	MLC 2011		SVM 2011	
	Overall Accuracy (%)	**Kappa hat Coefficient (%)**	**Overall Accuracy (%)**	**Kappa hat Coefficient**
1	77.50	0.7059	79.17	0.7219
2	77.50	0.7061	80.00	0.7398
3	78.33	0.7196	80.83	0.7502
4	79.17	0.7293	83.33	0.7837
5	82.50	0.7670	85.00	0.8047
6	86.67	0.8179	88.33	0.8437
7	86.67	0.8183	90.83	0.8762

From Table 7 showing the results of the accuracy assessment of land use and land cover classification 2011 by MLC method, which provided an overall accuracy between 77.50 - 86.67 percent and the Kappa coefficient was between 0.7059 - 0.8183. The SVM method which provided an overall accuracy of 79.17 - 90.83 percent and the Kappa coefficient was between 0.7219 - 0.8762. The comparison of land use and land cover classification accuracy of all 7 dataset, it was found that the dataset 7, which was the combination of multispectral, NDVI, MNDWI, NDBI, elevation, slope, and aspect of vector support machine method provided the highest accuracy. The overall accuracy was 90.83% and the Kappa coefficient was 0.8762. The error matrix was shown in Table 8.

Table 8 Error matrix of dataset 7 using SVM method 2011

Classified Data	**Reference Data**								**Total**	**Producers Accuracy**	**Users Accuracy**
	UB	OC	RT	NF	MF	MC	WA	BL			
UB	7	0	0	0	0	0	0	0	7	100.00%	100.00%
OC	0	48	1	0	0	2	0	1	52	96.00%	92.31%
RT	0	0	3	0	0	0	1	0	4	50.00%	75.00%
NF	0	0	1	5	0	0	0	1	7	100.00%	71.43%
MF	0	0	0	0	5	0	0	0	5	100.00%	100.00%
MC	0	2	0	0	0	27	0	1	30	93.10%	90.00%
WA	0	0	1	0	0	0	7	0	8	87.50%	87.50%
BL	0	0	0	0	0	0	0	7	7	70.00%	100.00%
Total	7	50	6	5	5	29	8	10	120		
Overall Classification Accuracy = 90.83%											
Overall Kappa Statistics = 0.8762											

3.3 Evaluation of classification methods and suitable datasets for LULC classification

The results of the accuracy assessment of land use and land cover classification of 2011, it was found that the combination of multispectral data, NDVI, MNDWI NDBI, elevation, slope and aspect of the support vector machine methods provided highest accuracy was at 90.83 percent and the Kappa coefficient was at 0.8762 percent. It was the most suitable dataset for classification of land use and land cover. As well as the results of the accuracy assessment of land use and land cover classification in 2019, it was found that dataset 7 of support vector machine classifying methods provided the highest overall accuracy was at 91.67% and the Kappa coefficient was at 0.8903 (Table 9 and 10).

Table 9 Accuracy assessment of LULC classification using MLC and SVM methods 2019

dataset	**MLC 2019**		**SVM 2019**	
	Overall Accuracy (%)	**Kappa hat Coefficient (%)**	**Overall Accuracy (%)**	**Kappa hat Coefficient**
1	80.83	0.7344	80.83	0.7391
2	81.67	0.7532	81.67	0.7504
3	81.67	0.7556	82.50	0.7617
4	82.50	0.7626	85.83	0.8084
5	83.33	0.7745	88.33	0.8429
6	85.83	0.8112	89.17	0.8583
7	86.67	0.8246	91.67	0.8903

Table 10 Error matrix of dataset 7 using SVM method 2019

Classified Data	**Reference Data**								**Total**	**Producers Accuracy**	**Users Accuracy**
	UB	OC	RT	NF	MF	MC	WA	BL			
UB	7	0	0	0	0	0	0	0	7	100.00%	100.00%
OC	0	50	2	0	0	0	0	0	52	100.00%	96.15%
RT	0	0	19	0	0	0	0	0	19	86.36%	100.00%
NF	0	0	1	5	0	0	0	0	6	100.00%	83.33%
MF	0	0	0	0	5	0	0	0	5	100.00%	100.00%
MC	0	0	0	0	0	11	0	5	16	84.62%	68.75%
WA	0	0	0	0	0	0	8	0	8	100.00%	100.00%
BL	0	0	0	0	0	2	0	5	7	50.00%	71.43%
Total	7	50	22	5	5	13	8	10	120		
Overall Classification Accuracy = 91.67%											
Overall Kappa Statistics = 0.8903											

3.4 Land use and land cover change detection in Tha Mai District Chanthaburi province between 2011 and 2019

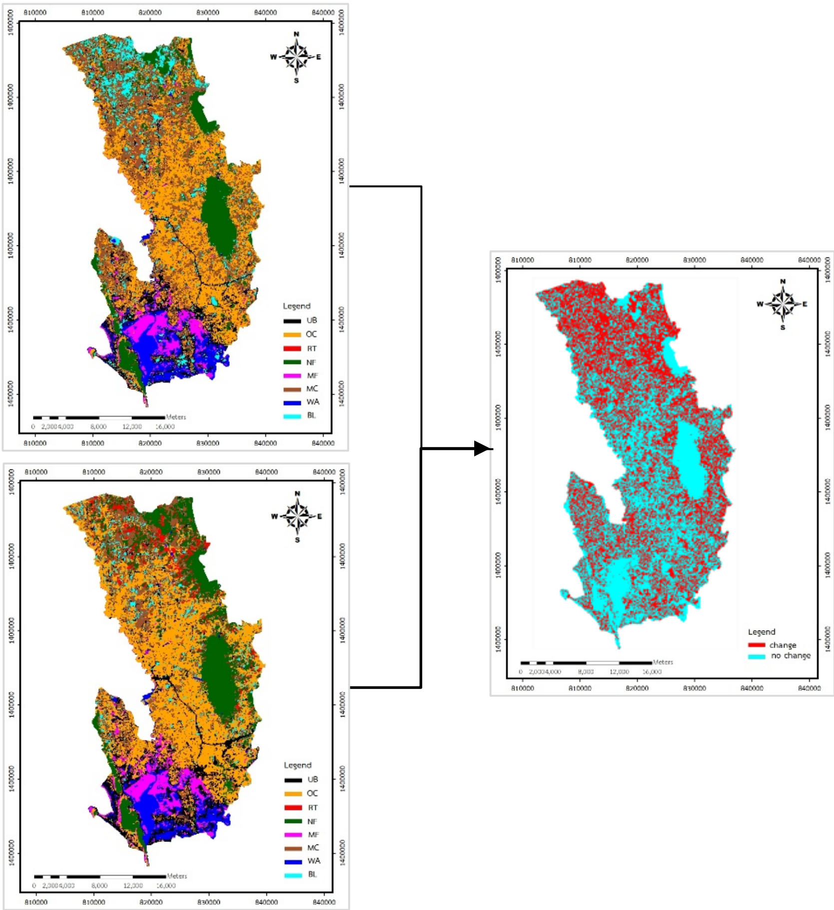

Figure 7 LULC Change detection map of between 2011 and 2019

Table 11 Result of Land use and land cover change detection between 2011 and 2019

LULC area in 2011 (sq.km.)	LULC area in 2019 (sq.km.)								Total	LULC change
	UB	OC	RT	NF	MF	MC	WA	BL		
UB	35.75	8.77	0.19	2.55	5.67	5.17	2.16	0.79	61.06	12.86
OC	8.96	122.19	4.43	21.44	2.78	16.97	0.26	3.60	180.63	24.15
RT	0.09	1.01	3.86	0.57	0.00	0.28	0.01	0.08	5.91	21.78
NF	0.64	3.97	4.30	73.34	0.52	6.61	0.05	0.75	90.17	29.34
MF	2.80	0.99	0.01	0.41	26.76	0.36	3.32	0.06	34.70	4.85
MC	13.53	62.68	9.69	17.04	0.59	52.89	0.29	13.91	170.63	-69.48
WA	6.51	0.33	0.00	0.20	3.12	0.51	28.73	0.04	39.43	-3.67
BL	5.65	4.83	5.20	3.96	0.11	18.36	0.95	6.94	45.99	-19.83
Total	73.92	204.78	27.69	119.51	39.55	101.15	35.76	26.16	628.52	

Change detection of land use and land cover of Tha Mai area from 2011 to 2019, the results showed that five classes of land use and land cover had been increased change in their areas and three classes of land use and land cover had been decreased change in their areas. The major change occurred in mixed cultivated area (MC), natural forest (NF), and orchard (OC). The mixed cultivated area (MC) had significantly decreased in its area at 69.48 sq.km, which it decreased from 170.63 sq.km in 2011, to 101.15 sq.km in 2019. The mixed cultivated area was mostly converted to orchard (OC) at 62.68 sq.km., to natural forest at 17.04 sq.km and to urban and build up area at 13.53 sq.km. Meanwhile, the natural forest (NF) was increased from 90.17 sq.km in 2011 to 119.51 sq.km in 2019 and mostly changed to mangrove forest (MF) at 6.61 sq.km., to rubber plantation and tree at 4.30 sq.km and to orchard (OC) at 3.97 sq.km , respectively. Bare land (BL) had been decreased from 45.99 sq.km in 2011 to 26.16 sq.km in 2019 which mostly changed to mixed cultivation area at 18.36 sq.km.

4. CONCLUSION

The study findings indicate that the combination of Landsat 8 data and ancillary data such as the set of indices (NDVI, MNDWI, and NDBI), elevation, slope and aspect of the classified image year 2011 provided the overall accuracy at 90.83% and the Kappa coefficient at .8762. While the classification of year 2019 showed the overall accuracy at 91.67 % and the Kappa coefficient at 0.8903. Change detection of land use and land cover of Tha Mai area from 2011 to 2019 revealed that the major change occurred in mixed cultivated area (MC), natural forest (NF), orchard (OC), and bare land (BL). The mixed cultivated area (MC) had significantly changed which mostly converted to Orchard (OC). Meanwhile, orchard (OC) was the second magnitude of increasing changed and mostly converted to natural forest. Bare land mostly had been changed to mixed cultivated area (MC). The combination of Landsat 8 and ancillary data sets integrated with new classifiers improved classification result.

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