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Land Use and Land Cover Detection by Different Classification Systems using Remotely Sensed Data of Kuala Tiga, Tanah Merah Kelantan, Malaysia

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Abstract

Land use and land cover classification system has been used widely in many applications such as for baseline mapping for Geographic Information System (GIS) input and also target identification for identification of roads, clearings and also land and water interface. The research was conducted in Kuala Tiga, Tanah Merah, Kelantan and the study area covers for about 25 km². The main purpose of this research is to access the possibilities of using remote sensing for the detection of regional land use change by developing land cover classification system. Another goal is to compare the accuracy of supervised and unsupervised classification system by using remote sensing. In this research, both supervised and unsupervised classifications were tested on satellite images of Landsat 7 and 8 in the year 2001 and 2016. As for supervised classification, the satellite images are combined and classified. Information and data from the field and land cover classification is utilized to identify training areas that represent land cover classes.Then, for unsupervised classification, the satellite images is combined and classified by means of unsupervised classification by using an Iterative Self- Organizing Data Analysis Techniques (ISODATA) algorithm. Information and data from the field and land cover classification is utilized to assign the resulting spectral classes to the land cover classes.This research was then comparing the accuracy of two classification systems at dividing the landscape into five classes; built-up land, agricultural land, bare soil, forest land, water bodies. Overall accuracies for unsupervised classification are 36.34 % for 2016 and 51.76% for 2001 while for supervised classification, accuracy assessments are 95.59 % for 2016 and 96.29 % for 2001.

1. Introduction

Land cover defines the material on the lands surface such as crops, water, forest and also urban infrastructure. Land cover is an excellent indicator of land use. Land use and land cover (LULC) changes play a major role in the study of global changes (Vitousek, 1992). In particular, land use and land cover (LULC) changes in tropical regions are major concern due to the widespread and rapid changes in the distribution and characteristics of tropical forests (Myers, 1993).

Knowledge of the nature of land use and land cover change and their configuration across spatial and temporal scales is consequently indispensable for sustainable environmental management and development (Turner et al., 1995). Large scale changes are difficult and expensive to quantify through fieldwork. Detection of long term changes in land cover may reveal an idea for the shift in local or regional climatic conditions and analyzing the basis of terrestrial global monitoring (Navalgund et al., 2007).

Remote sensing data are useful for land use and land cover inventory and mapping. Types of land use and land cover detected from remote sensor data are used as the basis for organizing the classification system. The remote sensor acquires a response which is based on many characteristics of the land surface, including natural or artificial cover. The interpreter uses patterns, tones, textures, shapes, and site associations to derive information about land use activities from what is basically information about land cover. Application of remotely sensed data made possible to study the changes in land cover in less time, at low cost and with better accuracy (Kachhwala, 1985) in association with GIS that provides suitable platform for data analysis, update and retrieval (Chilar, 2000). Satellite remote sensing is probably the best way to retrieve this parameter both regionally and globally due to the availability of high resolution, consistent and repetitive coverage and capability of measurements of earth surface conditions (Owen et al., 1998).

The land cover changes are detected by using aerial photographs or by satellite imageries. Before the classification process, it is necessary to prepare images for the study area. Proper geo-reference and standardize

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for the effects of temporal and atmospheric differences between images as well as account for system errors must be taken care (Li et al, 2011). It is also necessary to define the classes to group the landscape. Characteristics constructed must be defined in terms of units and scales that the sensor detected. The national classification systems, such as the U.S. Geological Survey Land Use/Land Cover Classification System (USGS, 1992) can be used to compare the results among similar studies.

There are two ways to characterize the classes. Firstly, the method is called supervised classification that requires the user to locate the desired classes on an image which can be used to train the computer to look for other pixels with similar characteristics. The user selects representative samples for each land cover class in the digital image. Then, the image classification software uses the training sites to identify the land cover classes in the entire image. The second method was using the unsupervised classification which is a statistical algorithm that separates the image pixels into clusters of similar spectral characteristics. Pixels are grouped based on the reflectance properties of pixels. These groupings are called “clusters”. The user identifies the number of clusters to generate and which bands to use. With this information, the clusters were then generated using the image classification software.

The standard summaries for the accuracy assessment are the error matrix, the overall accuracy and the Kappa coefficient (Congalton, 1991). Error matrices quantitatively compare the relationship between the classified maps and reference data. Overall accuracy, user’s and producer’s accuracies, and also the Kappa statistic were then derived from the error matrices. The Kappa statistic incorporates the off diagonal elements of the error matrices and represents agreement obtained after removing the proportion of agreement that could be expected to occur by chance. Expert Systems use a combination of remotely sensed and other sources of georeferenced data (Stefanov et al., 2001) to increase the information about mixed pixels to make better classification decisions. Accuracy assessment was critical for a map generated from any remote sensing data. On the other hand, classification accuracy can be improved by using multi-source data (Nizalapur, 2008).

2. Material and Methods

2.1. Study Area

Kuala Tiga is situated nearby Kelantan River. Kuala Tiga is aligned between 5°40’9” N to 5°42’50”N latitudes, and 102°02’37” E to 102°05’18”E longitudes in the south of Tanah Merah District, Kelantan. According to the report issued by the Department of Statistics, the total land area of Kelantan in 2012 is 15,105 km² that make up 4.6% of the total area of Malaysia. In Tanah Merah, the land use is focusing on agriculture. Figure 1 shows land use map of Tanah Merah. Basically, increasing number of people lead to land use changes in the area. This research is important to produce a land use and land cover changes map of Kuala Tiga, Tanah Merah. The demand for standardized land use and land cover data is increase in order to assess and manage areas of critical concern for environmental control and areas such as major residential and industrial development sites. Therefore, it is widely recognized as significant for planning and management purposes as the agencies requiring more detailed land use information to employ more supplemental data.

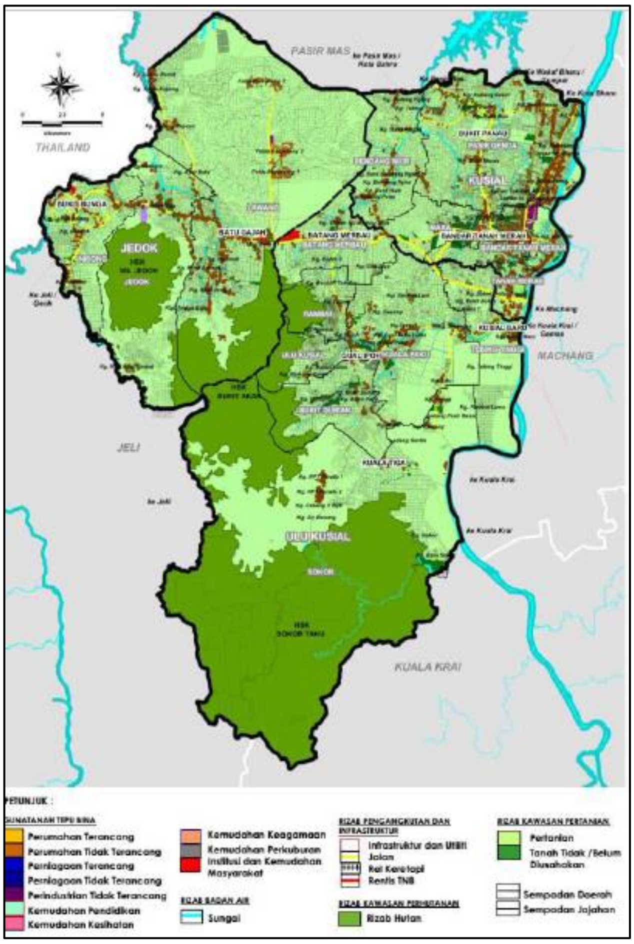

Figure 1: Land use map of Tanah Merah, 2010
(Source: Majlis Daerah Tanah Merah)

2.2. Satellite Imageries

The remotely sensed imagery used for the analysis was acquired from a Landsat 8 Operational Land Imager / Thermal Infrared Sensor (OLI/TIRS) where the image was taken at Path 127, Row 56, on July 3, 2016 (Figure 2 (a)) and a Landsat 7 Enhanced Thematic Mapper Plus (ETM+) where the image was taken on Path 127, Row 56, on May 31, 2001 (Figure 2 (b)). Both images were downloaded from the website of earth explorer of United States (U,S) Department of the Interior U.S.

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Figure 2(a): Satellite imagery on 3/7/2016

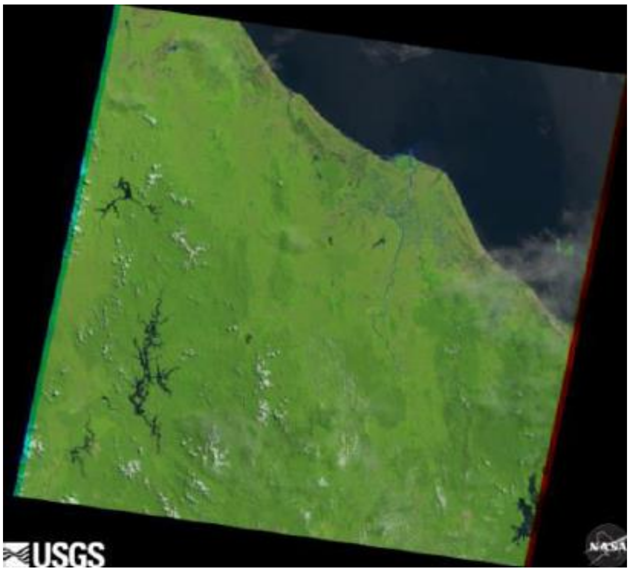

Figure 2(b): Satellite imagery on 31/5/2001

2.3. Geo-referencing

Raw remotely sensed image data that are collected by sensors on satellite platforms or aircrafts are not directly referenced to a known map projection. Thus, the raw data of satellite images Figure 2(a) & 2(b) are geometrically corrected and the projection was set to Universal Transverse Mercator (UTM) projection system, in the zone 32. The spheroid and datum was referenced to WGS84.

2.4. Image Classification and Accuracy Assessment

Before attempting a classification, it is important to define the categories based on the purpose of the study. Accurate classifications are crucial to ensure precise change-detection results. This classification method is carried out using training areas and test data for accuracy assessment. Maximum Likelihood Algorithm method for supervised classification and ISODATA method for unsupervised classification were used to detect the land cover types in Environment for Visualizing Images (ENVI) software. Then, land use and land cover maps are derived with the following five classes: 1. Urban or built-up land, 2. Agricultural land, 3. Bare soil, 4. Forest land, 5. Water. Besides that, the exploratory Normalized Deference Vegetation Index (NDVI) data is applied to distinguish vegetative from non-vegetative features (Equation 1). It is based on the normalized difference between Near-Infra Red (NIR) and Visible Red (VR) and is calculated by,

$$NDVI = \frac{NIR-VR}{NIR+VR} \qquad \text{---------- (Equation 1)}$$

2.4.1. Unsupervised Classification

For unsupervised classification, the satellite images is combined and classified by by using an Iterative Self- Organizing Data Analysis Techniques (ISODATA) algorithm. The algorithm begins with an initial clustering of the data. Each iteration compares the spectral distance of each pixel to the cluster means and assigns them to the closest mean cluster. Then, the cluster means is recalculated, and the pixels are compared, and cluster again based on spectral distance to cluster means in dimensional space. This process is repeated until it meet the specify criteria or reach the maximum number of iteration. The parameters for the unsupervised classification are set to several classes with maximum iterations and a convergence threshold. Information and data from the field and land cover classification is utilized to assign the resulting spectral classes to the land cover classes. The pre-processed imagery was analyzed using unsupervised classification using ISODATA algorithm to enhance the quality of the images and the readability of the features using spatial analysis tools of ENVI. The image analysis is obtained by calculate the changes which is shown in percentage and differentiated by colour.

2.4.2. Supervised Classification

In supervised classification, the satellite images are combined and classified. Information and data from the field and land cover classification is utilized to identify training areas that represent land cover classes. Once the training area is identified, the spectral characteristic across all the image bands are put into the Signature Editor where the signature for the training area can be labelled, evaluated and edited by land cover class. The processes were then incorporated into supervised classification steps.Besides, by using the maximum likelihood classification method, all individual signatures from the training data is utilized.

2.5. Classification's Accuracy

Error matrix is the most common way to present the accuracy of the classification results. There are three standard criteria that were used to assess the accuracy of the classifications. Firstly, user accuracy indicates the probability that a classified pixel actually represents that

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category in reality. Then, overall accuracy which is the total number of correctly classified pixels divided by the total number of reference pixels (Rogan et al., 2002). Lastly, kappa coefficient measures how much better the classification is compared to randomly assigning class values to each pixel.

3. Results and Discussion

Table 1 shows the land use classification scheme with the description.

Table 1: Land Use Classification

Class	Description
Built-up Land	Areas of intensive use with much of the land covered by structures
Agricultural Land	Land that primarily used for production of food and fiber.
Bare soil	Areas with no vegetation cover, stock quarry, stony areas, uncultivated agricultural lands.
Forest Land	Land that have a tree-crown areal density with trees capable of producing timber or other wood products.
Water Bodies	Areas within the land mass that persistently are water covered.

3.1. Land Use and Land Changes (LULC) of Kuala Tiga, Tanah Merah

Figure 3(a) & (b) show the unsupervised map of LULC of the study area in 2001 and 2016 respectively while supervised map of LULC in year 2001 and 2016 are shown in Figure 4(a) & 4(b).The Kuala Tiga areas are typical of agricultural land. The development pattern was due to the quality of soil that is very fertile due to the water drainage and also the condition of tropical climate and weather in the area that is suitable for vegetation. In this study area, large areas were dominant by plantation such as rubber tree and palm oil tree. Forest class was identified as there were covered with mature trees and other plants that were growing close together in the area. Some of the forest areas were under conservation and preservation. Besides that, there were bare soil areas as there are the areas with no vegetation cover, stony areas and uncultivated agricultural lands or the area of early stage to replant some vegetation such as fruits and vegetables crops. Then, for built up class, most of the land in this study area was categorized as residential, commercial or industrial area. Next, there were water body classes as there are the tributary streams in this study area. This stream is important for drainage and irrigation for people and also for plantation.

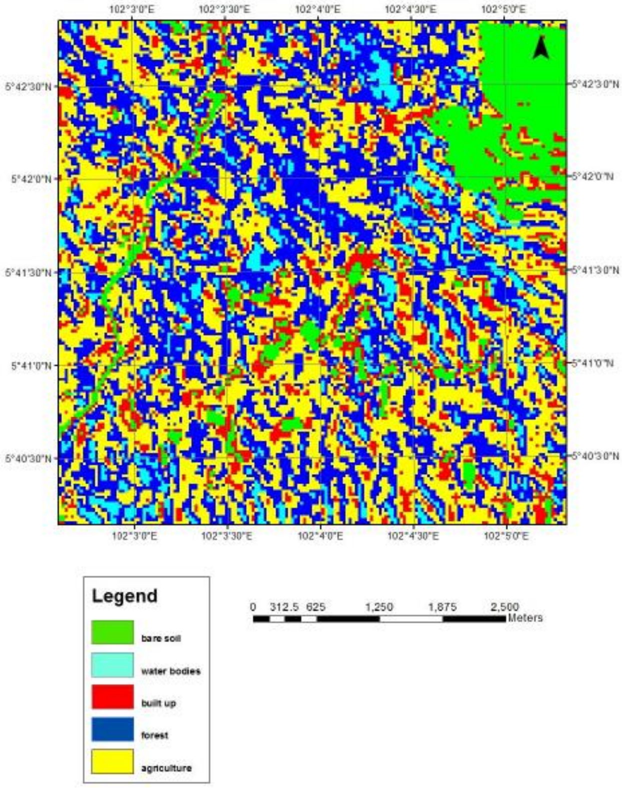

Figure 3(a): Map of Unsupervised LULC of Kuala Tiga in 2001.

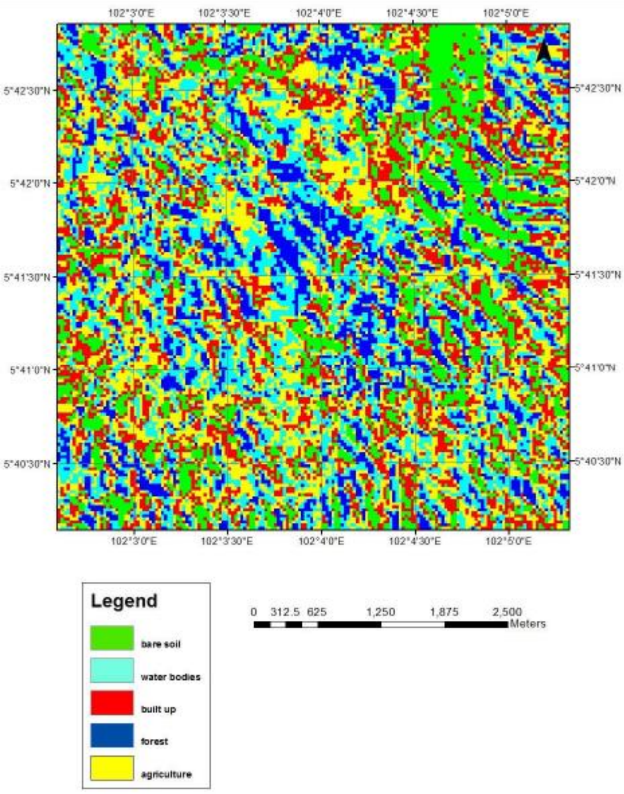

Figure 3(b): Map of Unsupervised LULC of Kuala Tiga in 2016**.**

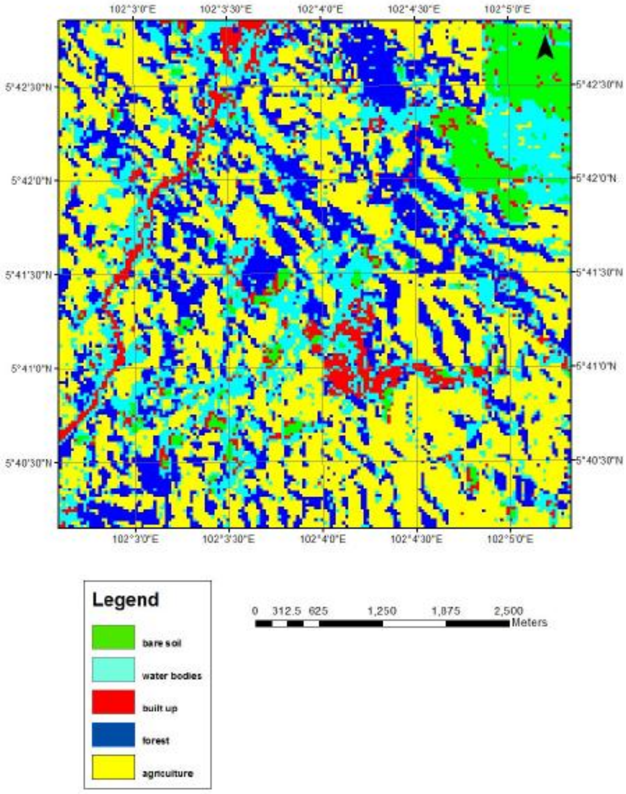

Figure 4(a): Map of Supervised LULC of Kuala Tiga in 2001.

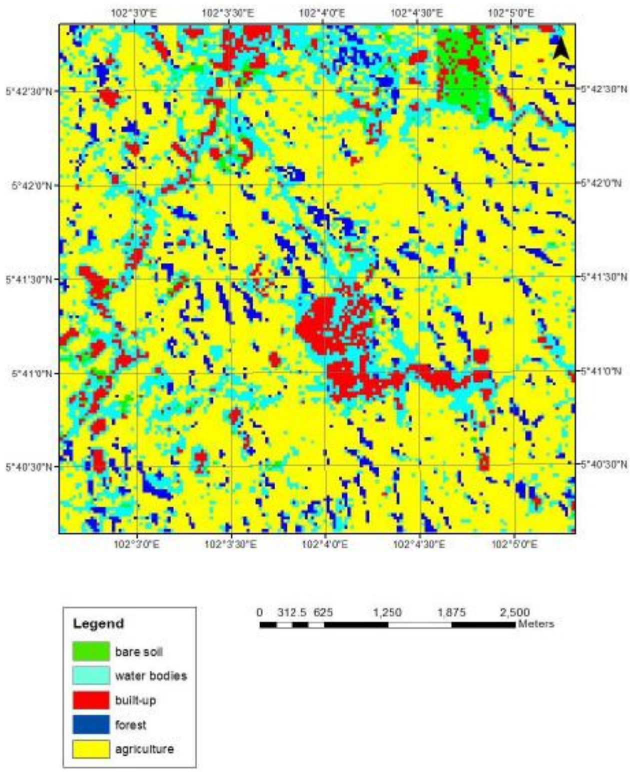

Figure 4(b): Map of Supervised LULC of Kuala Tiga in 2016

3.2. Change Detection

The LULC classification results for the years 2016 and 2001 are summarized in Table 2. From 2001 to 2016, water bodies area, built up area and bare soil area were increased in 4.11 km², 2.68 km², and 1.12 km² respectively. On the other hand forest and agriculture areas were decreased in 5.41 km², and 2001, this number increased and became 5.13 km² in 2016. On the other hand there was a decrease number in forest areas in which those areas decreased from 9.11 km² to 3.70 km².

Table 2: Summary of Landsat 8 OLI/TIRS and Landsat 7 ETM+ classification area statistics for 2001 and 2016 (unsupervised classification)

Class	2001		2016		Relative Changes	
	km^2	%	km^2	%	km^2	%
Forest	9.11	36.29	3.70	14.74	-5.41	- 21.55
Water bodies	1.70	6.77	5.81	23.15	4.11	16.38
Agriculture	9.39	37.41	6.89	27.45	-2.5	-9.96
Built up	2.45	9.76	5.13	20.44	2.68	10.68
Bare soil	2.45	9.76	3.57	14.22	1.12	4.46
Total	**25.1**	**100**	**25.1**	**100**	**-**	**-**

Table 3 summarized the changes in LULC over the past decade for supervised classification. It shows an increased growth rate on agriculture and built up areas for about 18.94 % and 1.08 % respectively. However, water bodies, forest and bare soil classes have shown a decreased amount of changes for about 2.42 %, 17.37 % and 3.23 % in the area.

Table 3: Summary of Landsat 8 OLI/TIRS and Landsat 7 ETM+ classification area statistics for 2001 and 2016 (supervised classification)

Class	2001		2016		Relative Changes	
	km^2	%	km^2	%	km^2	%
Forest	6.11	24.32	1.75	6.97	-4.36	-17.37
Water bodies	5.37	21.39	4.76	18.97	-0.61	-2.42
Agriculture	10.87	43.31	16.37	65.25	5.5	18.94
Built up	1.39	5.54	1.66	6.62	0.27	1.08
Bare soil	1.36	5.42	0.55	2.19	-0.81	-3.23
Total	**25.1**	**100.0**	**25.09**	**100.0**	**-**	**-**

Figure 5 and 6 shows the change detection of image classification based on percentage and area in the study area. Change detection on agriculture and forest class show the greatest changes compared to other classes of bare soil, water bodies and built up that shows slightly different amount of changes.

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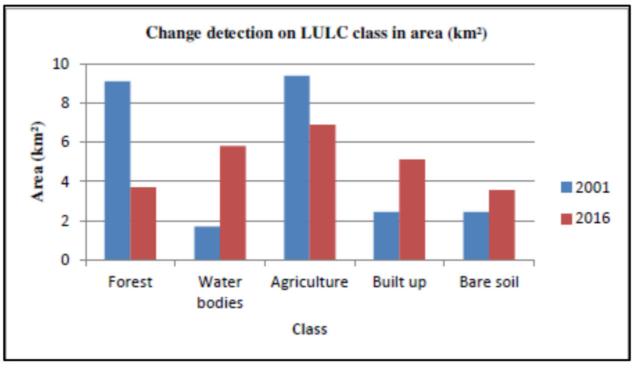

Figure 5: Change detection of LULC class in area (unsupervised classification)

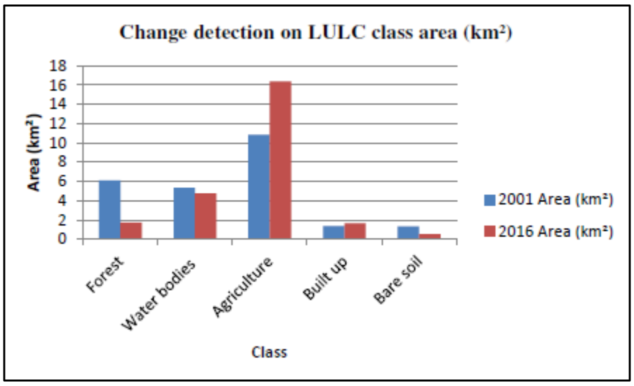

Figure 6: Change detection of LULC class in area (supervised classification)

3.3. Error Matrix

The accuracy of the classification can be described in terms of both producers (omission) and user's accuracy (commission). Producer's accuracy describes the amount of a landscape category correctly classified on the classification image, while user's accuracy describes the probability that a category on the classification image will be correct when used on the ground. To display users and producers accuracy, an error matrix is used. Tables 4(a) represent the results of the unsupervised process while Table 4(b) indicates error matrix of the supervised classification in year 2001 and 2016. Both results in water bodies show the lowest accuracy score. However, if there is a quite high accuracy score of classes, it indicates that the classification process was done as expected.

Table 4(a): Results on producer accuracy and user accuracy in 2001 and 2016 in percentage (unsupervised classification)

Class	2001		2016	
	Producer accuracy	User Accuracy	Producer accuracy	User Accuracy
Water bodies	0.81	2.59	31.15	25.53
Built up	24.76	13.97	15.92	5.16
Bare soil	93.49	52.12	56.58	8.67
Forest	71.94	48.29	99.79	47.31
Agriculture	63.80	73.81	32.49	77.20

Table 4(b): Results on producer accuracy and user accuracy in 2001 and 2016 in percentage (supervised classification)

Class	2001		2016	
	Producer accuracy	User Accuracy	Producer accuracy	User Accuracy
Water bodies	91.28	100.00	82.70	98.08
Built up	100.00	100.00	99.12	99.12
Bare soil	100.00	95.92	98.99	97.51
Forest	97.76	99.48	97.89	99.90
Agriculture	73.33	15.07	80.00	19.67

3.4. Accuracy

In this study, 27888 polygons for Landsat 8 OLI/TIRS and 28054 polygons for Landsat 7 ETM+ were randomly selected to assess classification accuracy. All two classification dates achieve overall accuracies 36.34 % for 2016 and 51.76% for 2001 (Table 5). Kappa coefficient for 2016 and 2001 are 0.1515 and 0.3349. Table 6 represents the results on accuracy assessment in percentage for 2016 and 2001. There is about 1567 polygons for Landsat 8 OLI/TIRS and 1620 polygons for Landsat 7 ETM+ that were randomly selected to assess classification accuracy. All two classification dates achieve overall accuracies 95.59 % for 2016 and 96.29 % for 2001. Kappa coefficient for 2016 and 2001 are 0.9158 and 0.9365.

Table 5: Accuracy assessment of unsupervised classification

Year	**2016**	**2001**
Satellite image	Landsat 8 OLI/TIRS	Landsat 7 ETM
Overall Accuracy	(10140/27888) = **36.34 %**	(14522/28054) = **51.7645 %**
Kappa Coefficient	0.1515	0.3349

Table 6: Accuracy assessment of supervised classification

Year	**2016**	**2001**
Satellite image	Landsat 8 OLI/TIRS	Landsat 7 ETM
Overall Accuracy	(1498/1567) = **95.59 %**	(1560/1620 = **96.29%**
Kappa Coefficient	0.9158.	0.9365

4. Conclusion

Based on the study in Kuala Tiga, Tanah Merah, the area was covered by hilly to undulating landform. The area mostly covered with vegetation or plantation of palm oil trees and rubber trees which is the main source of economy in this area. The study of LULC has showed the recent advancements in remote sensing and GIS technologies that provide tools for mapping and detecting land use and land cover changes. Based on the observation and the study of LULC, the general trend of the study area is decreasing in forest but increasing in agriculture and built up activities. This is due to the increasing in number of human population that leads the scarce for resources.Besides that, the major problem of accuracy assessment was getting the aerial images into some projection. Thus, satellite imageries were used as it

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is easier to get, cheap, but it has lower resolution as the pixels of the images might have counted as misclassified. Moreover, inexperienced user to identify and classify the classes in pixels unit can contribute to the misclassified pixels.

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