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Analysis of forest cover change detection (Remote Sensing and GIS) case area of pyin oo Lwin Township

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Abstract
Remote sensing and GIS can be applied for environmental monitoring and climate change detection. The proposed system is to detect land cover/land use changes especially forest observed in Pyin Oo Lwin township, Myanmar. The required three years (2010, 2014 and 2017) Landsat data of Pyin Oo Lwin are downloaded from United States Geological Survey (USGS). The land cover is classified into four classes: Forest, Vegetation, Water and Other. ArcGIS will be applied as analysis tools for classification and change detection. Maximum likelihood classification and NDVI classification will be applied respectively. Land surface temperature (LST) is an important factor in global climate change studies. Landsat Thematic Mapper and Enhanced Thematic Mapper Plus data of the year 2010, 2014 and 2017 are used to effects of land use/land cover changes on the surface temperature distribution. Land cover maps, land surface temperature and area of land cover changes will be obtained as the result of the system.

Keywords: forest cover change, Remote Sensing, GIS

Introduction

Geographic Information System (GIS) and Remote Sensing (RS) Data are very efficient for obtaining a better understanding of the earth environment [3]. It is the Science and Art of acquiring information and extracting the features in the form of Spatial, Spectral and Temporal about some area or phenomenon, such as forest cover, land cover, urban area, agriculture land, vegetation and water resources [6]. The use of remote sensing data has been of tremendous help in monitoring the changing pattern of vegetation [5].

Remote Sensing and GIS data has many application areas including: urban planning, land cover classification, soil moisture measurement, land surface temperature measurement, forest cover classification, measurement of liquid water content of vegetation, sea ice type classification, snow mapping, oceanography and so on [6]. In this paper, Landsat images of Pyin Oo Lwin township are used to calculate the percentage of versatile features such as forest, vegetation, water and other are presented in this image, and to subsequently make these extracted features available to the public for further analysis in order to avoid any sort of natural disaster like landslide.

Forests have long been regarded as a national treasure in Myanmar especially timber wood. They provide such resources as grazing land for animals, water resources, wildlife habitat, tourism and outdoor recreation areas. They are also important for conserving biodiversity, as they provide a habitat of certain specialized forest related species [12]. However, forest cover today is altered primarily by direct human use and any conception of global change must include the pervasive influence of human activity on land surface conditions and process [10].

Digital image processing of satellite data supports tools for analyzing the satellite image through different mathematical indices and algorithms. Features of land cover are based on reflectance characteristics, and indices are created to highlight the features of interest on the image [2]. There are several indices for highlighting vegetation areas on remote sensing. Normalized Difference Vegetation Index (NDVI) is a common and widely used index [4]. It is an essential vegetation index and widely used in research on global environmental and climate change [4]. It is calculated as a ratio difference between measured canopy reflectance in the near infrared and red bands respectively [9].

The land surface temperature (LST) is the skin temperature of earth surface which can derive from the satellite information or direct measurements in the remote sensing terminology. This is an accurate measurement tool for indicating the energy exchange balance between the Earth and the atmosphere. The combination of forest cover change result with the land surface temperature (LST) can offer useful information to study the forest cover change effects in global climate change [1].

In this study, the effect of forest cover change on the land surface temperature in Pyin Oo Lwin Township is investigated based on the remote sensing analysis.

Study Objectives

- To classify the landsat images into respective classes: water, forest, vegetation and other
- To compare different periods of land use/cover image using Landsats data in the years of 2010, 2014 and 2017 respectively
- To map and monitor the land cover changes especially forest in the region of interest over 3 year periods
- To support in reducing global deforestation with a focus on the Pyin Oo Lwin township
- To identify the land surface temperature change in the study area with the help of remote sensing and Geographical Information System (GIS) for three different time span

Study Area

The study area, Pyin Oo Lwin township is a scenic hill town in Pyin Oo Lwin district, Mandalay Region. It is at an altitude of 3538 ft. It is located in the Shan Highland so that it is so hilly and rare flat land. It is situated at North Longitude 22°2'6.04" and East Longitude 96°27'24.59". It is located 67 kilometers (42 miles) from the east of Mandalay.

Data Set

In this study, multi-temporal satellite images used include Landsat ETM Satellite image of 18th January 2010 (Figure 1a), Landsat ETM Satellite image of 13th January 2014 (Figure 1b) and Landsat ETM Satellite image of 16th February 2017 (Figure 1c) respectively and having row and path of 133 and 45. All sensors have spatial resolution of 30. The acquisition dates of the Landsat images employed in this change detection process fall within the same season.

Land Cover Land Use (LCLU) Classification

Land Cover Land Use classes were produced by a supervised classification of the satellite imagery. Maximum likelihood classification was applied using all spectral bands in each satellite image. This is the most widely used classification algorithm [7]. The images of the study area were taken through three stages to produce land cover classes of the study area. These include: (1) extraction of feature; (2) selection of training data (signatures); and (3) selection of suitable classification approaches. The following four land cover and use classes were identified and mapped: forest, vegetation, water and other. The image classification was guided by reconnaissance information gathered from the study field area. The results are shown in Figures 2, 3 and 4 with four classes for 2010, 2014 and 2017 satellite images respectively.

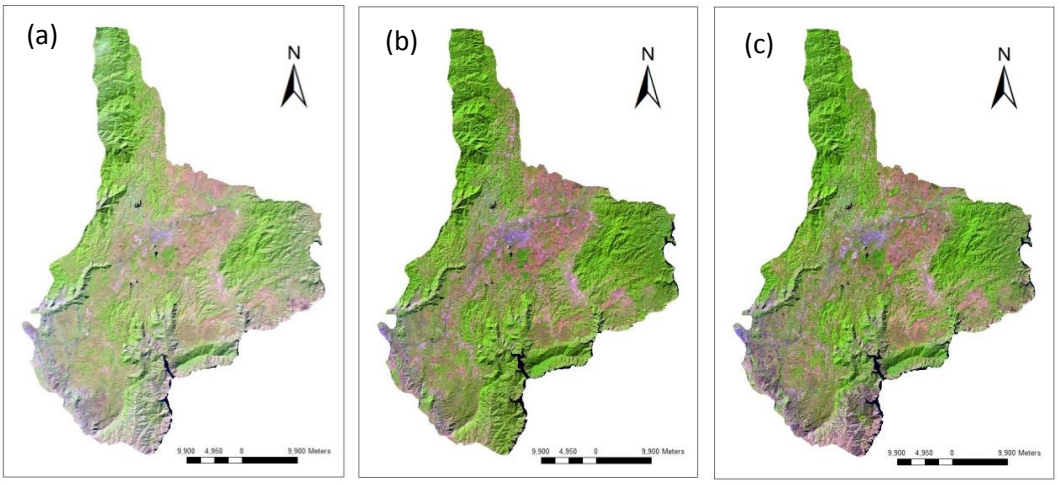

Fig 1: Satellite images of the study area (a, b, c) Normalized Difference Vegetation Index (NDVI)

NDVI is the most commonly used one in spite of the development of many new indices that take into account soil behavior [13]. It is used to distinguish healthy vegetation from non-vegetated areas or form others [7] using red and near infrared reflectance values. NDVI threshold value ranges between -1 to +1 theoretically. The more positive the NDVI, the more green vegetation there is within a pixel [8]. In this study, NDVI was used based on the red band and near infrared band of Landsat and this was derived using expression given in Equation 1.

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

Where, R is the spectral reflectance measurements acquired in the red band, NIR is the spectral reflectance measurements acquired in the near-infrared band.

Classification Accuracy Assessment using Error Matrix

In this research, the classification accuracy was assessed by an error matrix. This is organized as a two dimensional matrix and is derived from a comparison of reference map pixels to the classified map pixels. Among many proposed measurements to improve the interpretation of the error matrix, the Kappa coefficient is one of the most popular measures [16]. The Kappa coefficient expresses the proportion of agreement obtained after removing the proportion of agreement that could be expected to occur by chance [14]. Kappa coefficient is widely adopted because all elements in the classification error matrix and not just the main diagonal, contribute to its calculation and because it compensates for change agreement [17].

The Kappa coefficient is typically between 0 (no reduction in error) and 1 (complete reduction of error). The Kappa values are defined into three groups: a value greater than 0.80 (80%) represents strong agreement, a value between 0,40 and 0.80 (40% to 80%) represents moderate agreement, and a value below 0,4 (40%) represents poor agreement [15]. Kappa was computed using Equation (2). The accuracy and Kappa statistics are summarized in Table 1.

$$K = \frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r}(x_{i+} \times x_{+i})}{N^2 - \sum_{i=1}^{r}(x_{i+} \times x_{+i})} \quad (2)$$

Where N is the total number of sites in the matrix, r is number of rows in the matrix, x_{ii} is the number in row i and column i, x_{i+} is the total for column and x_{+i} is the total for row i. 83 sample points were obtained from the field for accuracy assessment after the classification.

Results and Discussions

In this sector, the results of the supervised classifications using Landsat images are presented. The Kappa statistics and classification accuracy are discussed.

Analysis of LULC Area Change

The supervised maximum likelihood classification of the satellite images yielded three land cover maps of the study area as shown in Figure 2, 3 and 4. After classification, four LULC classes were distinguished: forest, vegetation, water and others.

1) LULC Map from 2010 Landsat Imagery

The supervised classification of the 2010 Landsat image yielded the LULC classes shown in Figure 2(a). These classes were calculated in hectares (ha) based on the count of pixels as shown in Figure 2(b).

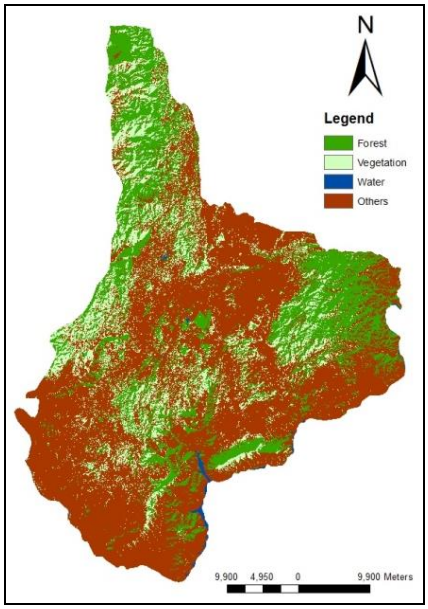

Fig 2(a): 2010 Classified Map of Pyin Oo Lwin Township

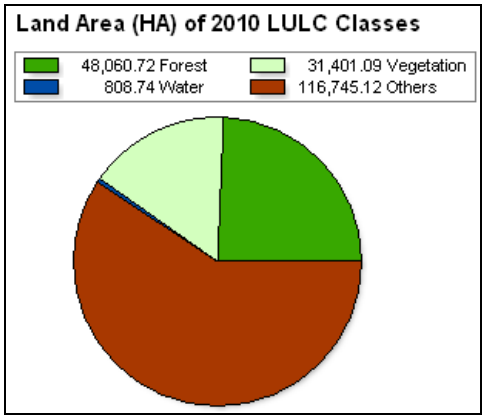

Fig 2(b): Land Area (HA) of 2010 LULC classes LULC Map from 2014 Landsat Imagery.

The supervised classification procedures applied to the 2014 Landsat image yielded land cover map shown in Figure 3(a). These classes were calculated in hectares (ha) based on the count of pixels as shown in Figure 3(b).

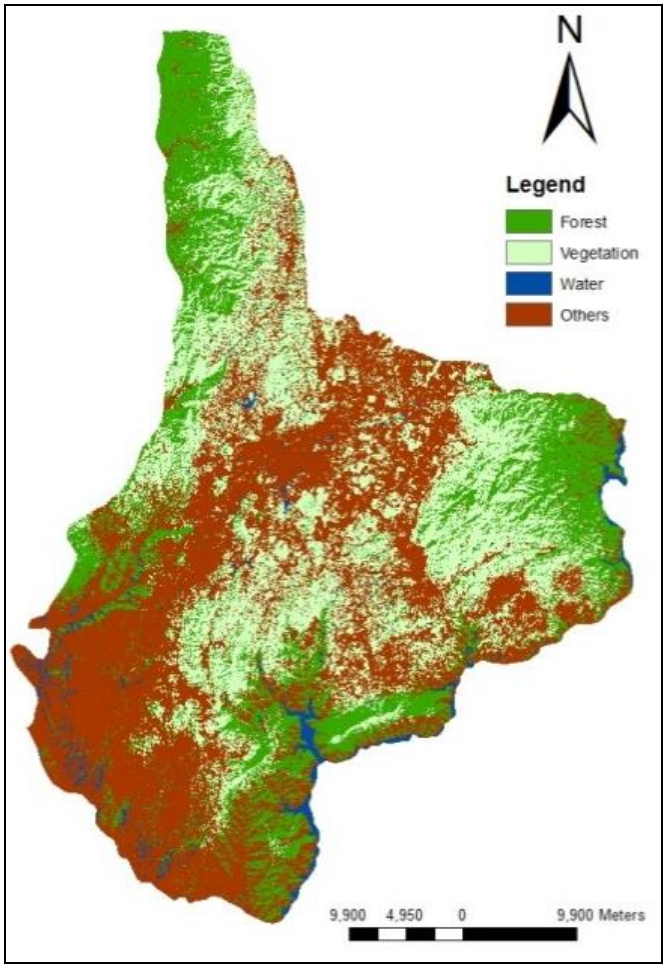

Fig 3(a): 2014 Classified Map of Pyin Oo Lwin Township

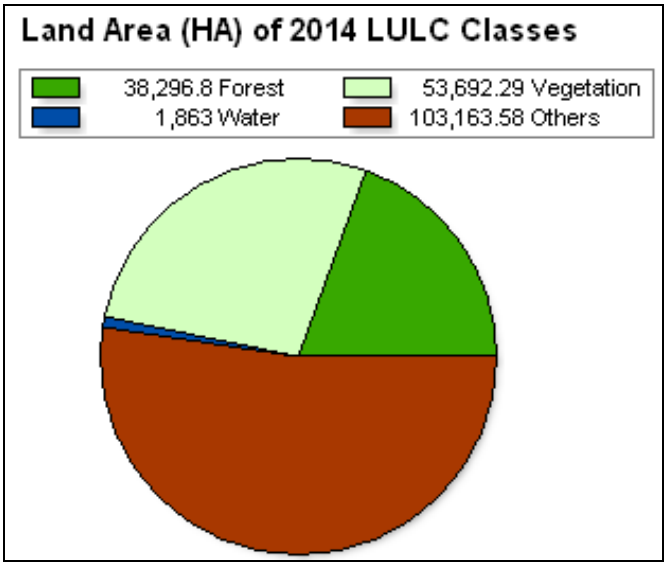

Fig 3(b): Land Area (HA) of 2014 LULC classes

2) LULC Map from 2017 Landsat Imagery

After the classification procedures, the 2017 Landsat image yielded Land cover map as displayed in Figure 4(a). These classes were calculated in hectares (ha) based on the count of pixels as shown in Figure 4(b).

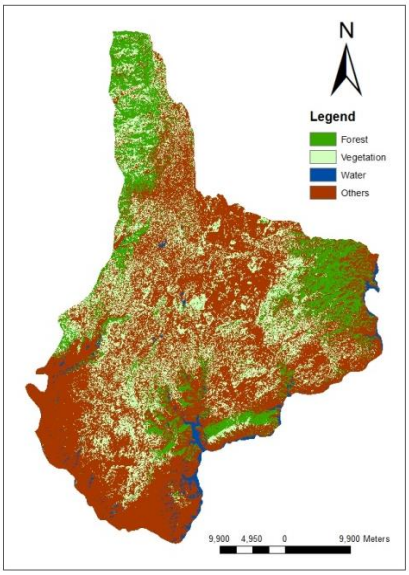

Fig 4(a): 2017 Classified Map of Pyin Oo Lwin Township

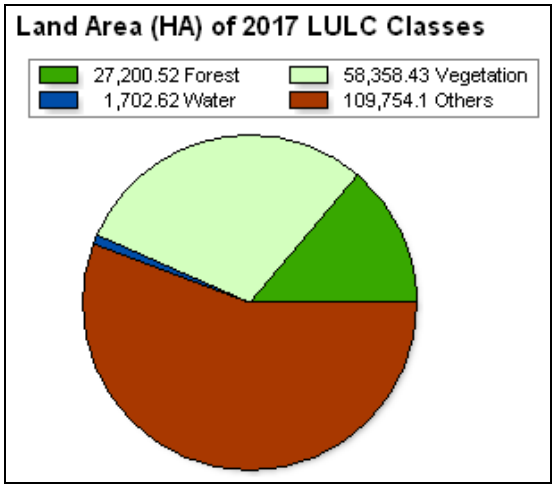

Fig 4(a): Land Area (HA) of 2017 LULC classes

Accuracy Assessment of LULC Classes

Accuracy assessment of the classified image is an important step in image classification. A classification accuracy assessment was performed on the 2017 Landsat image and an assessment report was obtained having error matrix, accuracy totals and a kappa statistics as shown in Table 1. An overall classification accuracy of 96.38% and a Kappa coefficient (overall kappa statistics of 0.9518 was achieved. The Producers accuracy of Forest is 85.71%. The user accuracies of Water is 95.24% and the others is 91.30%. Accuracy assessments were not performed on the 2010 and 2014 images due to unavailability of ground validation and reference points. This has being one of the major problems of remote sensing [11]. Stratified random sampling method could be used to generate reference points for the whole of the study area and to determine the accuracy of classification for these images [11].

Table 1: Summary of Accuracy (%) and Kappa Statistics

LULC	Producers Accuracy	Users Accuracy
Forest	85.71	100
Vegetation	100	100
Water	100	95.24
Others	100	91.30
Overall Classification Accuracy = 96.38% Overall Kappa Statistics = 0.9518		

LULC Change Trend from 2010 to 2017

The trend analysis of Pyin Oo Lwin township reveals a change in size of the four LULC over 7 year period of the study as shown in Table 2. The results indicate that vegetation and water experienced a positive change in area, while forest and others experienced a negative change from 2010 to 2014. From 2014 to 2017, other and vegetation experienced a positive change while forest and water experienced a negative change. Forest experienced the most negative change and Vegetation experienced the most positive change.

Table 2: LULC Change Trend from 2010 to 2017

	Change (ha)	
LULC	2010 to 2014	2014 to 2017
Forest	-9763.92	-11096.28
Vegetation	22291.2	4666.14
Water	1054.26	-160.38
Others	-13581.54	6590.52

Normalized Difference Vegetation Index

The NDVI gave very good results in identifying forest area for data collection and subsequent investigation during fieldwork. Although, it was not tested statistically, but there seems to be no significant difference between the results obtained from the supervised classification and those obtained from NDVI classification.

Analysis of Land Surface Temperature (LST) Change

Land Surface Temperature can be derived from equation 3.

$$LST = T/1+w*(T/p)*\ln(e)) \quad (3)$$

Where LST = Land Surface Temperature, T= Satellite temperature, w = wavelength of emitted radiande (11.5µm), p = h * c / s (1.438*10ˆ-2 mK), h=Planck's constant (6.626*10ˆ-34 Js), s= Boltzamn constant (1.38*10ˆ-23 J/K), c=Velocity of light (2.998*10ˆ8m/s),e=Land Surface Emissivity

Land Surface Temperature maps of the study area as shown in Figure 5, 6 and 7. The Lowest temperature is 12 degree Celsius and highest temperature is 32 degree Celsius in 2010. In 2014, the lowest temperature is 13 degree Celsius and the highest temperature is 37 degree Celsius. In 2017, the lowest temperature is 16 degree Celsius and the highest temperature is 41 degree Celsius.

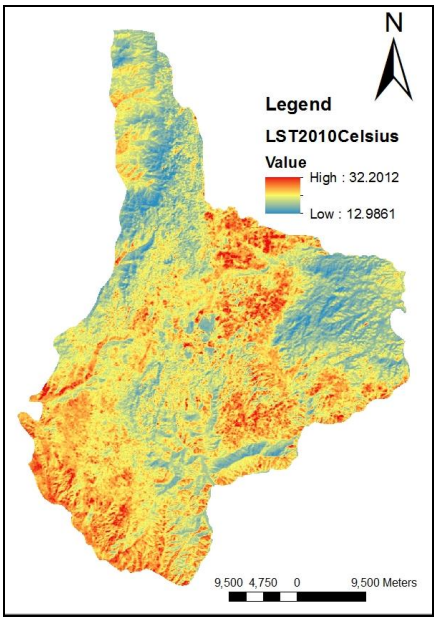

Fig 5: Land Surface Temperature for 2010

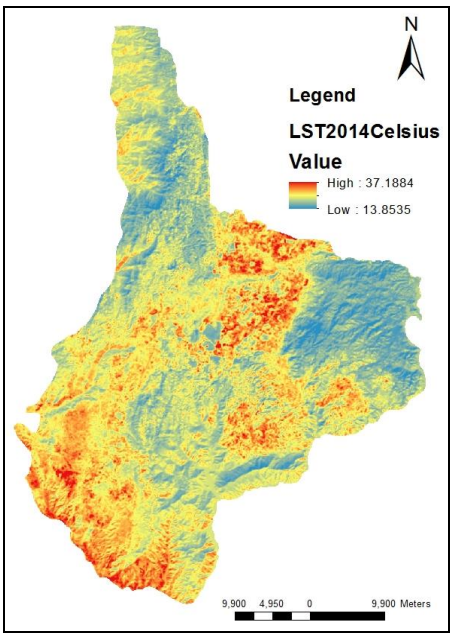

Fig 6: Land Surface Temperature for 2014

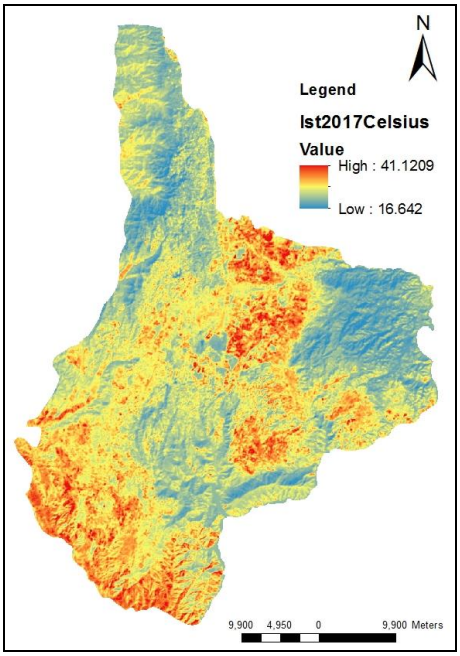

Fig 7: Land Surface Temperature for 2017

Conclusions

The main LULC types identified in this study are forest, vegetation, water and others. The relationship between the forest covers and its associated LULC cases were investigated and various maps were developed. It was observed that forest cover has changed remarkably from the period of 2010-2017. This decrease in the forest cover has been as a result of anthropogenic activities in the study area. As a result of significant decreasing forest cover in Pyin Oo Lwin from 2010 to 2014, there is a dramatic increasing temperature during these years.

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