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THE IMPACT OF SURFACE BLUE SAPPHIRE MINING ON LAND USE LAND COVER TYPES IN THE MAMBILA PLATEAU

[*]Mustapha. Z. Karkarna, Yusuf. A. Yusuf and Lawrence. F. Umar

Department of Environmental Management, Bayero University, Kano State, Nigeria

[*]Corresponding author's Email: mzkarkarna@gmail.com

ABSTRACT

Information about patterns of Land use land cover (LULC) changes over time is not only important for a region's management and planning, it is also required for a better understanding of the human dimensions of environmental changes on a regional scale. The study aimed to assess land use land cover change caused by artisanal mining of blue sapphire in some parts of Nguroje district on the Mambila Plateau, Taraba State, Nigeria. A change detection analysis was carried out using QGIS 3.8 and ENVI 5.0 software. Two different methods for change detection were applied; post-classification comparison (PCC) and land cover change detection. The major LULC classes present in the study area include bare land, forest vegetation, built-up areas, water body, agricultural land and grassland. The results of the change detection analysis showed that the natural forest cover 4.91% increased to 11.4% agricultural land decreased from 8.44 % to 6.50%, grassland decreased from 32.65% to 18.1%, built-up areas did not show a significant change, water body decreased from 0.14% to 0.12% while bare land increased from 53.74 % to 63.9 % all between 2007 to 2019 respectively. This study concludes that blue sapphire mining played a major role in natural resources degradation, which results in land-use change. The study suggests that for predicting future land-use change, methodologies are required that integrate and understand the processes affected by socio-economic and bio-physical drivers.

Keywords: LULC, mining, blue sapphire, Mambila, Remote Sensing and GIS

INTRODUCTION

The Mambila plateau is one of the places in Nigeria that is well endowed with abundant natural resources. The plateau is endowed with a semi temperate climate that is suitable for agricultural crop production and livestock rearing, as well as mineral resources (Oruonye, 2015b). Concerns of land use and land cover (LULC) change and soil fertility problems in agricultural systems in Africa are factors that pull the attention of many researchers, and have been winning the interest of top policy makers in recent times. Human population pressure has primarily been the centre of blame for the widespread land use and land cover change and its associated environmental implications (Toh, Angwafo, Ndam, & Antoine, 2018). In developing countries like Nigeria, a large population almost solely depend on natural resource exploitation for livelihood, and with increasingly competing demands for the utilization, development and sustainable management of land resources, LULC changes are very intensive and preoccupying (John & Alaga, 2016). The societal and environmental impacts of mining activity are the focus of greater interest today than ever before (Koruyan et al., 2012). Mining of blue sapphire both surface and subsurface causes enormous damage to the flora, fauna, hydrological circle, land use and soil biological properties of the systems (Hadeel, Jabbar, & Chen, 2011). Opencast mining, which is being given greater importance for present and future mining operations generally, changed the natural topography of the area. These changes may constitute an increase in the groundwater table, and thus a slow sinking of subsurface soils and an unexpected collapse, i.e., subsidence (Padmanaban, Bhowmik, & Cabral, 2017). Large pits are left after mining and large amounts of overburden material excavated during mining is dumped in the vicinity of the mine sites and continuous re-handling of the overburden dumps further modifies the general landscape of the area (Hadeel et al., 2011). The extraction processes and machines used to access mine galleries may produce irreversible damage in soil cohesion and eventually compress soil substrates which may allow groundwater to intrude the surface level, form new water bodies, and cause inundation. This, in turn, leads to several adverse long-term environmental impacts, such as vegetation loss, land use land cover changes, biodiversity loss (Padmanaban et al., 2017). Although remote sensing technology has been available for many years, it has rarely been used for monitoring mining activity (Koruyan et al., 2012). The use of remote sensing coupled with geographic information systems (GIS) provide the most accurate means of measuring the extent and pattern of such changes in landscape conditions over time (Kumar & Pandey, 2013). Remote sensing data can provide information on changes to surface water and land cover over time, which is essential for environmental monitoring in mining areas (Water et al., 2010). With the land use and land cover changes having a significant influence on the ecosystem with impact on biotic diversity, soil degradation, ability of biological systems to support human needs and the venerability of places and people to climatic, economic and socio- political perturbation, understanding these surface processes and predicting the impact on the environment and food production system is necessary for militating against the continuous negative impact of these changes (Gbenga, 2008). This study therefore examines the LULC change caused by artisanal mining of blue sapphire from 2007-2019 in the study area.

Description of the Study Area

The Mambila Plateau is located between latitude 6.8212˚N and 7.3523˚N and longitude 10.7723˚E and 11.5345˚E and covering about 3765 km2 and the adjoining lowland of 1,250 km2 which all constituted Sardauna Local Government (Salako et al., 2016; Garba, Oyieke, Owino, Mwansat & Houmsou, 2018). It is a highland region in Taraba State in North East geopolitical zone of Nigeria. The Mambila plateau consists of scattered settlements over a difficult to access but potentially rich terrain (Adeleke and Oresajo, 2007). The altitude and soils of Mambila suggest that it was once largely forested, anthropogenic pressure (overgrazing, fire, logging etc) has likely lead to a significant loss of old forest (Thia, 2014). However, the plateau is also an important grazing land for livestock in the country. The temperate climate of the plateau supports a wide range of biodiversity (Jerome, Chapman, Iyiola, Calistus, & Goldson, 2011). Mambilla plateau is a land of beauty and wonders, replete with vast arable lands suitable for a wide range of agricultural crops such as maize, guinea corn, banana, plantain, beans (not cowpea), cassava, Irish potato, cocoyam and cash crops such as tea, coffee, kolanut (accumulata), cocoa, avocado pear, soya beans, groundnut, apple and wheat (Oruonye, Ahmed & Ejati 2016). There is a cocoa research institute at Kusuku on the plateau. The forest of the Mambila plateau provides lumberable trees that are felled for timber production and taken to different parts of the state and country for sale. Hence, lumbering is an important economic activity undertaken by the local people (Oruonye, 2015a). According to Mubi and Tukur (2005), basement complex rocks underlay more than two-third of the plateau and dates back to the Precambrian to early Paleozoic era. Meanwhile, the remaining part of the plateau is made up of volcanic rocks of the upper Cenozoic to tertiary and quaternary ages (Igwe, Yakubu, & Ileagu, 2018). These rocks found within the plateau are of volcanic origin, extended from tectonic lines, fissures, etc. These volcanic rocks comprises olivine basalt, basalts suite and trachyte basalt which were found to contain mixtures of amphiboles, pyroxenes with some other free minerals of quartz (Mould, 1960; Omisore & Olorunfemi, 2016). The tertiary basalts are found in the Mambila Plateau mostly formed by trachytic lavas and extensive basalts (Akor, Ukamaka, & Awucha, 2018). The Basalt which is the major rock type in the study area is highly weathered. This is believed to be as a result of the in situ chemical weathering that is common on the Plateau (Omisore & Olorunfemi, 2016).

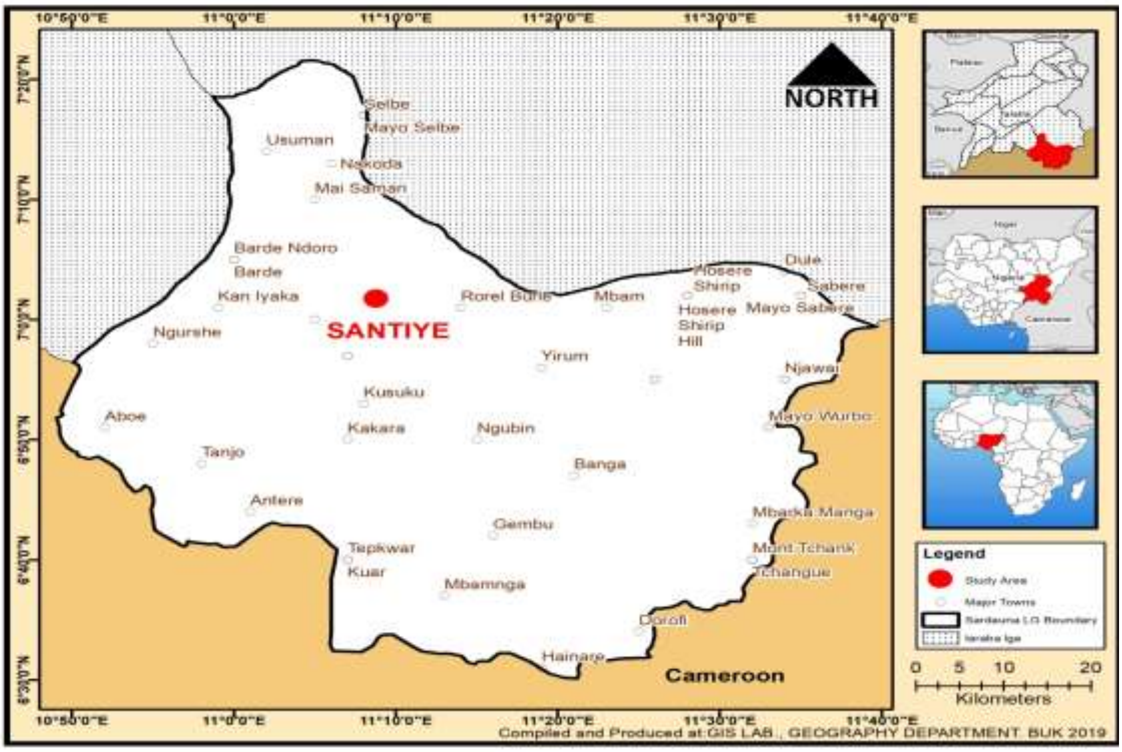

Fig. 1: Map of Sardauna LGA showing the study area
Source: GIS LAB Geography Department BUK (2019)

MATERIALS AND METHODS

Satellite Data

For the purpose of multi-temporal change detection, Cloud-free Sentinel-2, Landsat 8 OLI and Enhanced Thematic Mapper plus 7(ETM+) imagery were used (Table 1).

Table 1: Satellite imagery used for the multi-temporal change detection.

S/No	Satellite sensor	Path/row	Acquisition date	Spectral resolution	Ground resolution (m)
1	Landsat-7 ETM+	186/055	05/01/2007	1-8 bands	30m
2	Landsat-7 ETM+	186/055	02/03/2010	1-8 bands	30m
3	Landsat-8 OLI	186/055	29/11/2013	1-11 bands	15m
4	Sentinel-2	186/055	17/02/2016	1-12 bands	10m
5	Sentinel-2	186/055	11/02/2019	1-12 bands	10m

Sentinel-2 imagery of the study area were acquired for 11/02/2019 and 17/02/2016, Landsat 8 OLI Level-1 imagery for 29/11/2013 and Landsat 7 Enhanced Thematic Mapper Plus (ETM+) Level-I imagery of the area for 02/03/2010 and 05/01/2007 (all path/row 186/055) from the U.S. Geological Survey (USGS) website: http://glovis.usgs.gov were obtained, meaning that they were orthorectified with systematic radiometric and geometric accuracies. The application software used for this study include: ENVI 5.0 Software, Microsoft Excel 2016 and Quantum GIS Version 3.8. Zanzibar (Latest version).
A Handheld Global Positioning System (GPS) was used to obtain the spatial coordinates of LULC classes (Training data) and mining locations. The GPS has developed into an efficient GIS data technology, which allows for users to compile their own data sets directly from the field as part of the 'ground-truthing. In this study, point data was collected using GPS at different points in the field.
The research methodology followed for this research work is illustrated in this Figure.

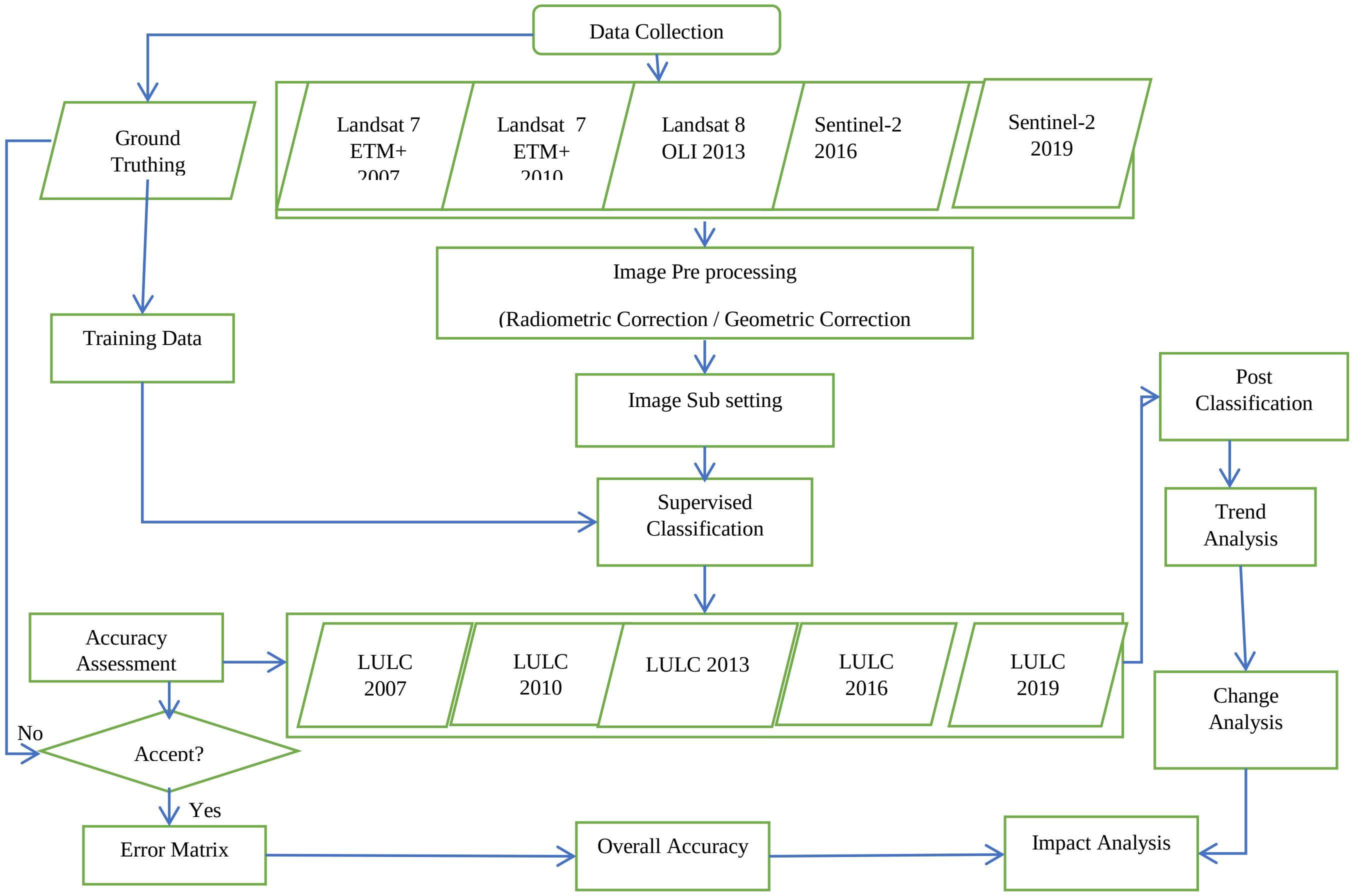

Fig. 2: Flow chart of the Methodology Adopted and modified from (Mayeem, 2016)

Image Pre-Processing

Pre-processing of satellite sensor images before performing change detection is necessary and has the distinctive aims of establishing straight linkage between the data and biophysical phenomena, the subtraction of data acquisition errors and image noise and the masking of contaminated (e.g. clouds) scene fragments (Mayeem, 2016). It is essential to remove atmospheric effects, particularly for change detection experimentation. Mambila plateau is a tropical region with heavy rainfall and cloud cover, hence obtaining images with minimum cloud cover is necessary. For this reason, all the images used in this study were collected during the dry season between January-February with the exception of the image of 2013 which was collected on 29/11/2013 due to unavailability of cloud free image for that same year.

Assessment of Geometric Accuracy of Imagery

The first image processing step is geometric correction (pre-classification approach) which is carried out when the satellite image data are not geo-rectified (Liu and Mason, 2009). Geometric correction handles the errors in the relative locations of pixels. The images used were acquired systematically corrected for sensor geometry and terrain variations to Level 1T by the United States Geological Survey (USGS). Standard Terrain Correction (Level 1T) provides systematic radiometric and geometric accuracy by incorporating ground control points while employing a Digital Elevation Model (DEM) for topographic accuracy. Geodetic accuracy of the product depends on the accuracy of the ground control points and the resolution of the DEM used (http://landsathandbook. gsfc.nasa.gov/data prod/prog_sect11_3.html, 20 July 2016). All images were registered in UTM zone 30N projection under a WGS84 ellipsoid. To ensure minimal errors, the positional accuracy of the images was tested. Fifteen (15) ground control points (GCPs) were commonly identified on both the ground and images which was picked from detectable points (e.g. road junctions) with a handheld GPS in UTM zone 30N projection under a WGS84 ellipsoid. Using ENVI 5.0 software for the geometric correction, it was therefore concluded that the correction undertaken by the USGS is acceptable and can be used for this research.

Ground Truth Data Collection

In order to obtain the training and validation data samples of the image, the field survey was carried out in May 2019 and historical land-use information was collected from farmers and herders who were knowledgeable about land-use change patterns during the respective period (2007-2019). A Hand Held Global Positioning System (GPS) receiver was used according to six LULC classes; 'Bare land', Forest Vegetation', 'Built-Up', 'Water Body,' 'Agricultural land' and 'Grassland'. In all 100 points as ground truth of the study area was obtained and divided into two categories of training (75%) and validation (25%) data sets.

Image Processing

Jensen (2005) states that when conducting process of change detection it is important to work with images from the same sensor as it ensures that data was acquired almost at the same time of the day (important to eliminate diurnal sun angle effects), in addition to the same spectral, spatial, look angle and radiometric resolution. Moreover, in order to obtain improved results from a change detection analysis, the sensor and environmental variables should be minimized as much as possible (Munyati, 2000). For greater accuracy, results largely depend on the geo-referencing of the images to be used and the relationship between the spatial resolution and spatial size of the changes (Munyati, 2000).

Radiometric and atmospheric correction

Radiometric correction is a process used to remove statistical noise and atmospheric extinction affecting image brightness values. Lillesand et al. (2008) state that the process is important due to variations in scene illumination, atmospheric conditions, viewing geometry variations and instrument response characteristics. In this study, the atmospheric correction was carried out with the semi-automatic classification plugin version 6.0 in the QGIS Software version 3.8.3 using Dosi atmospheric correction method.

Image Classification

Navalgund et al. (2007) and Lillesand and Kiefer (2004) define image classification as the process of automatically categorizing all pixels of an image based on their spectral properties into land cover classes. Furthermore, Palaniswami et al. (2006) define image classification as the process of creating thematic maps from satellite imagery. The two primary methods of image classification are supervised and unsupervised classification.

After the pre-processing of the images, the images were stacked for Landsat 7+ using Envi 5.0 and transferred to Q GIS environment. The reflectance of the images and band set was determined. The images were clipped to the study location using the clip multiple raster in the SCP and a training data was carried out. A supervised classification using the maximum-likelihood algorithm was performed using the SCP in QGIS 3.8 software. Algorithms are commonly used in supervised image classification, such as parallelepiped classification, minimum distance classification and maximum likelihood classification. The maximum likelihood approach is, however, the most widely used per-pixel algorithm. This research used the maximum likelihood classification, as it is a preferred algorithm especially in land cover and land-use monitoring approaches, because it assumes that (1) image data are normally distributed and (2) pixels are composed of a single land cover or land-use type. Many research has been conducted using the maximum likelihood classification (Yusuf et al., 2014; Basommi et al.,2015; Pensuk & Shrestha, 2007; Samanta, et al, 2015; Cheruto et al, 2016; Gasu, 2018). The individual images were classified into six different major LULC classes: Bare Land, Built-Up, Forest Vegetation, Grassland, Water Body and Agricultural Land: This method was used to achieve objective one.

Table 1: Definition of LULC classes

Classes Description
Bare land
Non-vegetated areas such as bare rocks, mine pits or areas with very little vegetation cover, where soil exposure is clearly apparent
Forest Vegetation
Land spanning more than 0.5 hectares with trees higher than 5 meters and a canopy cover of more than 10 percent, or trees able to reach these thresholds in situ. It does not include land that is predominantly under agriculture.
Built-Up Areas
These includes residential houses, office buildings, farm stead and other forms of settlement.
Water Body
Water sources which may include Dams, lake, reservoirs, rivers, streams and other sources of water
Agricultural land
Cultivated land Areas currently under crop or land being prepared for raising crops. Physical boundaries are broadly defined to encompass the main areas of agricultural activity and not based on the exact field boundaries.
Grass land
Grassland represents small shrub species and early stage colonizing species.

Accuracy Assessment

Accuracy assessment is an important process that must be completed to determine how correct the classified image is. Jensen (1996) pointed out that if through remote sensing, land use and land cover maps are produced and statistical results are to be useful, then it is important to conduct a quantitative assessment of the classification accuracy. This is important for post-classification change detection analysis. The accuracy of a classification is usually assessed by comparing the classification with some reference data that is believed to accurately reflect the true land cover classes. The overall accuracy is measured by counting how many pixels were classified consistently in the satellite image and on the ground and dividing this by the total number of sample pixels in each class.

To determine the accuracy of the image classification of Landsat 7 for 2007, 2010 Landsat 8 OLI for, 2013 and Sentinel-2 for 2016 images, for which no ground validation data or aerial photograph was available, the equalized random method was used to generate 60 reference points for the whole study area. These points were collected according to the different classes and overlaid on the unclassified image to check if the class given falls into the same spectra as was used to collect the training samples. A comparison of the Landsat classified images was made with the classified Sentinel-2 image for which ground validation points were available. The results of the overall classification accuracy, producer's accuracy and user's accuracies, and Kappa values for each LULC, derived from the error matrix, were used to determine the degree of accuracy of the classification.

LULC Change Detection and Analysis

A Post-classification Comparison (PCC) technique was carried out to evaluate the level of modification in the various LULC types over the 12 years study period (2007-2019). The PCC method is widely used in change detection as many research has been conducted using this method (Abbas, 2012; Cheruto et al., 2016; Gasu, 2018; Merem et al., 2019), In PCC, each date of rectified imagery will be independently classified to fit a common type schema (equal number and type of LULC classes). This method is recognized as the most accurate change detection technique, it detects LULC changes (LULCC) by comparing independently produced classifications of images from different dates (Mayeem, 2016). This technique also readily provides ''from-to'' transfers from one LULC type. In this study, change detection was carried out in ENVI 5.0 software environment using the thematic change workflow.

The process involved the insertion of multi-temporally classified pairs of images for each subset including the classified classes (Bare Land, Built-Up Areas, Forest Vegetation, Grassland, Water Body and Agricultural Land). The output consists of new thematic image maps (2007-2010, 2010- 2013, 2013-2016, 2016-2019 and 2007-2019), a change matrix table and ''from-to'' combinations of class transitions. Change detection maps was visually inspected to determine the areas of LULC change that are caused by mining activities and maps depicting the changes was generated. LULC changes was quantified through statistical tables including changes in terms of area and percentage measures. This method was used to achieve objective two.

RESULT AND DISCUSSION

The results of the classification for the LULC for the years 2007, 2010, 2013, 2016 and 2019 is shown in table 1. As indicated in Table 1, the LULC had six main classes. The area that showed massive increase in water body is the mining site at Santiye which was only visible in the LULC map of 2016. This was as a result of the increased mining of blue sapphire in the area, where mine pits are left open and subsequently filled with underground or rain water. These practices also change water course and increase the overall size of the river within the mine site.

Table 3: LULC class statistic for 2007, 2010, 2013, 2016 and 2019

Year	**2007**		**2010**		**2013**		**2016**		**2019**	
Class	**(%)**	**Area (Sq Km)**	**(%)**	**Area (Sq Km)**	**(%)**	**Area (Sq Km)**	**(%)**	**Area (Sq Km)**	**(%)**	**Area (Sq Km)**
1	53.74	355.0	65.9	435.4	49.1	324.5	69.28	457.9	63.9	425.7
2	4.91	3.21	2.87	18.97	16.7	110.4	14.05	9.288	11.4	7.563
3	0.11	0.70	0.15	1.004	0.14	0.977	0.26	1.722	0.09	0.063
4	0.16	1.03	0.14	0.91	0.18	1.202	0.20	1.295	0.14	0.899
5	8.44	55.79	4.59	30.33	6.14	40.56	2.12	13.98	6.50	43.30
6	32.65	215.7	26.4	174.1	25.2	166.6	14.09	93.14	18.1	120.3
Total	100	660.7	100	660.7	97.5	644.3	100	660.9	100	666.5

Where, 1= Bare Land, 2= Forest Vegetation, 3= Built-Up Areas, 4= Water Body, 5=Agricultural Land, 6= Grassland

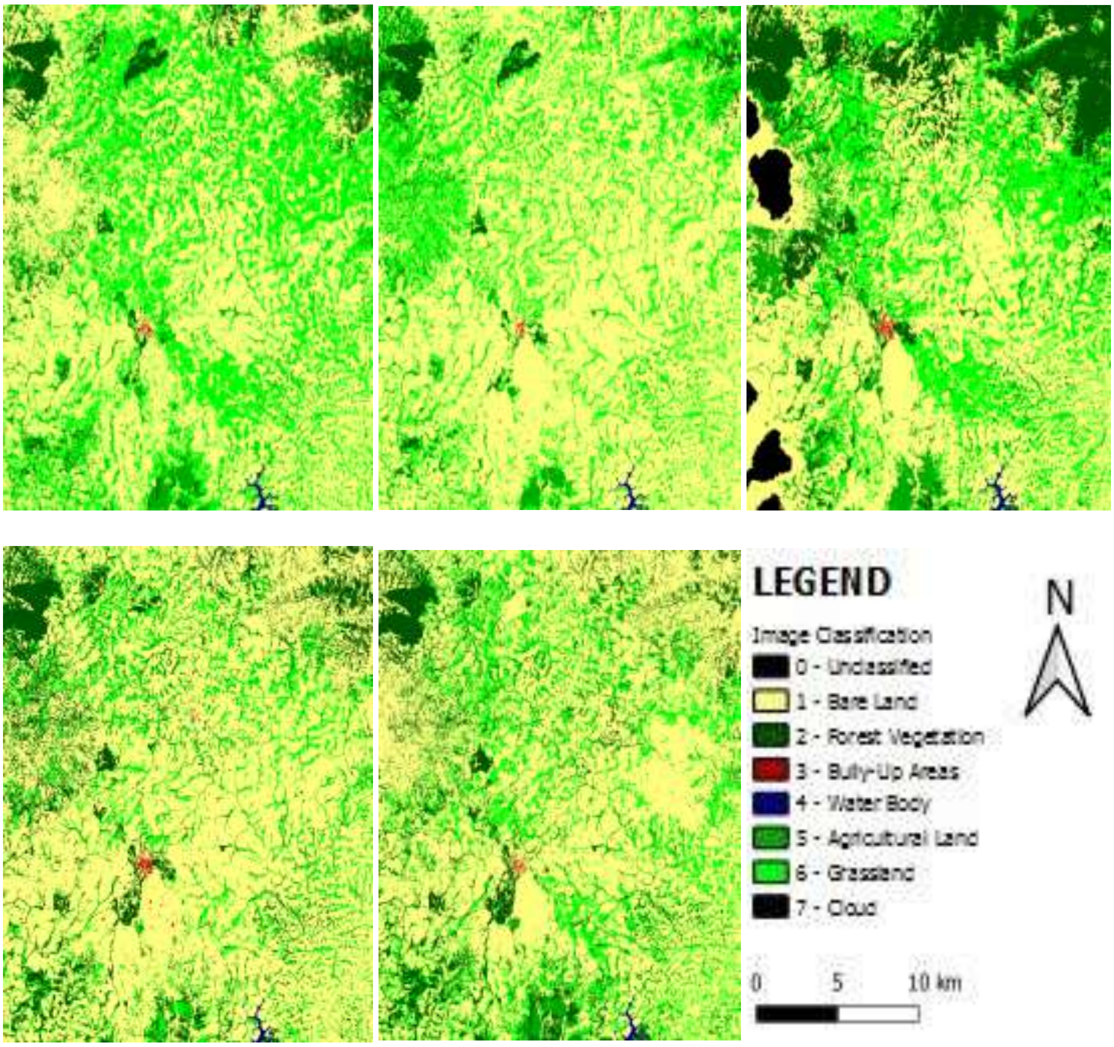

Fig. 3: Maximum likelihood Classification Showing LULC Image for 2007 to 2019

Due to some non-availability of the exact ground truth data for a different year, some limitations for classification and accuracy assessment for Landsat -7, 8 and sentinel-2 data has to be taken into considerations. This is another critical area in validating the accuracy of the classification. In evaluating the user's and the producer's accuracy, a confusion matrix was applied to the most recent classified image in 2019. One hundred and fifty-two (152) ground truth selected using a stratified random sample in the assessment. The overall accuracy values and the Kappa Statistics of the classified image is shown in Table 4.2. The overall accuracy represents the percentage of correctly classified pixels (Basommi et al., 2015). It is achieved by dividing the number of correct observations by the number of actual observations. The overall accuracy and kappa statistics was therefore 89.06754% and = 0.81022 respectively as shown in Table 2.

Table 5: Summary of classification accuracy assessment

Year	2007		2010		2013		2016		2019	
Accuracy type	PA [%]	UA [%]	PA [%]	UA [%]	PA [%]	UA [%]	PA [%]	UA [%]	PA [%]	UA [%]
1	98.04	94.2	87.64	65.9	99.9	92.1	100	90.19	99.9	89.7
2	93.17	99.9	91.09	98.7	92.0	100	100	99.94	100	99.3
3	4.83	100	5.39	94.0	6.60	96.8	3.99	99.88	1.41	99.4
4	100	100	39.49	100	100	100	26.5	99.93	44.4	100
5	99.97	91.2	76.02	86.8	100	83.7	99.6	100	98.1	98.9
6	95.4	96.6	47.74	70.8	100	99.3	100	100	99.5	98.5
Overall accuracy	=89.1									
Kappa hat classification	= 0.81									

Where: PA. = Producer's accuracy; and UA. = User's accuracy, 1= Bare Land, 2= Forest Vegetation, 3= Built-Up Areas, 4= Water Body, 5=Agricultural Land, 6= Grassland

Trend Analysis of Land Use/Land Cover Between 2007 To 2019

During the land use/land cover study of the years 2007, 2010, 2013, 2016 & 2019 we found a trend to change all the classes.

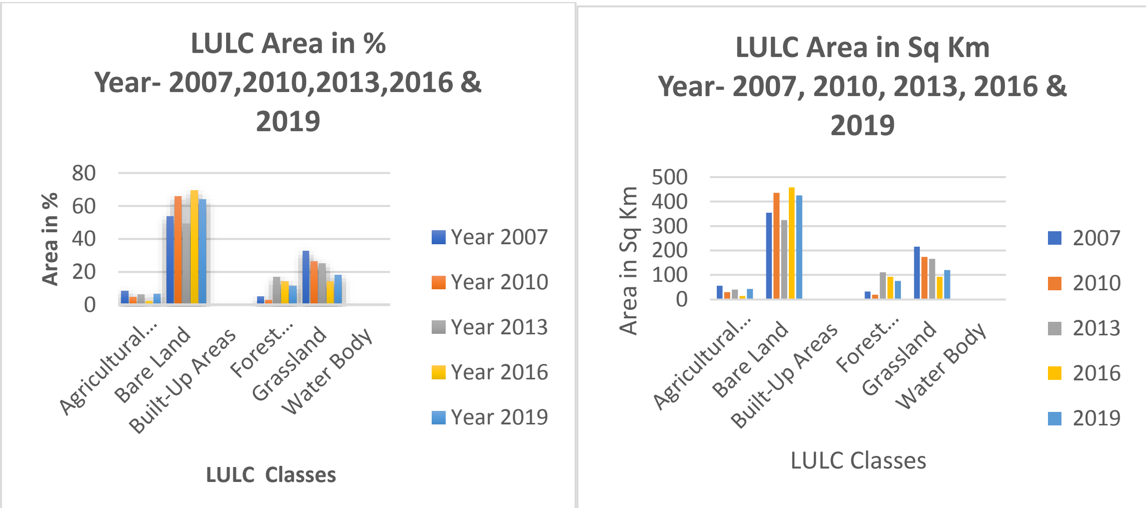

Fig. 5: LULC Area in % and in Sq km between 2007 and 2019

Figure 5 shows that bare land area was 53.74 % (355.04 sq km) in 2007 but it increased 65.90% (435.36 sq km) in 2010 of the total project area and it was coming mostly grassland, agricultural land and water bodies. Between 2010 and 2013, bare land decreased from 65.90% (435.36 sq km) in 2010 to 49.12 % (24.49 Sq km) in 2013 of the total project area which is mostly due to increase in forest vegetation, water body and agricultural land. Furthermore, between 2013 and 2016, bare land increased from 49.12% (324.49 Sq km) in 2013 to 69.28 % (457.93) in 2016 of the total project area, this is coming from the decrease in forest vegetation, agricultural land and grassland. However, between 2016 and 2019, bare land had a slight decrease from 69.28% (457.93) in 2016 to 63.87% (425.72) in 2019 of the total project area which is coming from increase in agricultural land and grassland respectively.

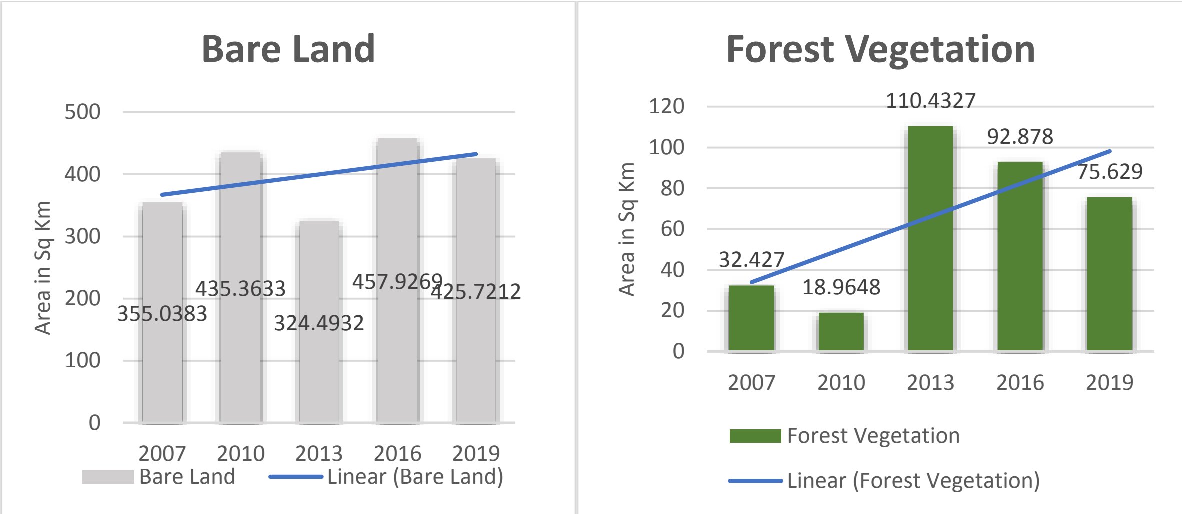

Fig. 6: Trend for bare land and forest vegetation between 2007 and 2019

As illustrated in figure 6 above, in the year between 2007 and 2010, Forest vegetation was 4.91% (32.43 sq km) in 2007 but decreased 2.87% (18.96 sq km) in 2010 of the total project area and it was converted to bare land area, and built-up areas and some part open grassland. However, there was a sporadic increase in forest vegetation from 2.87% (18.96 sq km) in 2010 to16.72% (110.43 sq km) in 2013 of the total project area, this is mostly coming from decrease in bare land area. Moreover, forest vegetation decreased from 16.72 % (110.43 sq km) in 2013 to 14.05% (92.88 sq km) in 2016 of the total project area which is coming from an increase in bare land, water body and built-up area. Similarly, forest vegetation continued decreasing as the years go by from 14.05% (92.88 sq km) in 2016 to 11.35% (75.63 sq km) in 2019 of the total project area, this decrease is coming from sporadic increase in agricultural land and grassland in the project area.

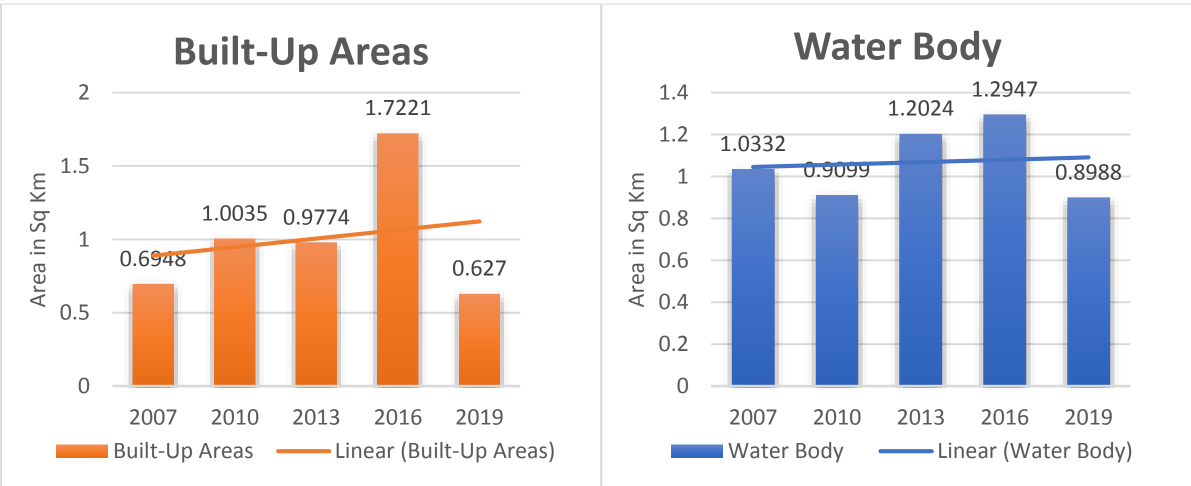

Fig. 7: Trend for built-up areas and water body between 2007 and 2019

Figure 7 above shows that between 2007 and 2010, built-up areas were 0.11% (0.69sq km) in 2007 but gradually increased to 0.15% (1.0 sq km) in 2010 of the total project area, which is due to the conversion of grassland, agricultural land and forest land to built-up areas. However, there was a slight decrease in the amount of built-up areas between 2010 and 2013 from 0.151 % (1.0 sq km) in 2010 to 0.148 % (0.98 sq km) in 2013 of the total project area, this is attributed to the crisis which led to the conversion of this built-up areas to grassland, agricultural land and forest vegetation. Furthermore, built-up areas in 2013 was 0.148% (0.98 sq km) but increased significantly to 0.26% (1.72 sq km) in 2016 of the total project area which is due to the conversion of grassland and agricultural land to built-up areas. However, there was a change in the amount of built-up areas between 206 and 2019, built-up areas decreased significantly from 0.26 % (1.72 sq km) in 2016 to 0.09 % (0.63 sq km) of the total project area, this is due to the conversion of this water bodies to grassland in the study area.

Surface Water body was 0.16% (1.03sq km) in 2007 but it decreased to 0.14% (0.91sq km) in 2010 of the total project area and it was converted into bare land. Between 2010 and 2013 water bodies increased from 0.14% (0.91sq km) in 2010 to 0.18% (1.20 sq km) in 2013 of the total project area and it was due to the decreased in bare land. Similarly, there is a continues increase in water body between 2013 and 2016. Water bodies increased from 0.18% (1.20 sq km) in 2013 to 0.20% (1.29 sq km) in 2016 of the total project area and it was bare land that was converted river. However, there is a significant decrease in the amount of water body within the study area from0.20% (1.29 sq km) in 2016 to 0.13% (0.90 sq km) in 2019 of the total project area, this due to conversion of this water bodies to grassland and agricultural land respectively.

Between 2007 and 2010, water body was % (1.03sq km) in 2007 but gradually decreased to % (0.91 sq km) in 2010 of the total project area, which is due to the conversion of water body to grassland, agricultural land and bare land. However, there was a slight increase in the amount of water bodies between 2010 and 2013 from % (0.91 sq km) in 2010 to % (1.2 sq km) in 2013 of the total project area, this is attributed to the increase in rainfall during this period and conversion of bare land to water body. Furthermore, water body in 2013 was % (1.2 sq km) but increased to % (1.29 sq km) in 2016 of the total project area which is due to the conversion of grassland and agricultural land to water body. However, there was a significant change in the amount of water body between 2016 and 2019, water body decreased from % (1.29 sq km) in 2016 to % (0.90 sq km) of the total project area, this is due to the conversion of this water bodies to grassland in the study area.

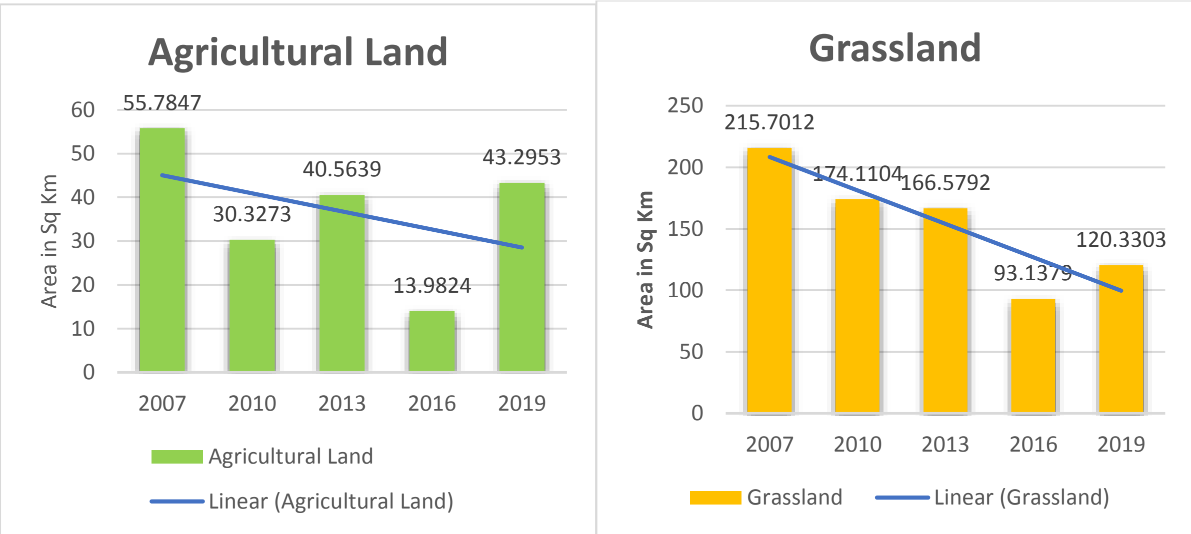

Fig. 8: Trend for agricultural land and grass land between 2007 and 2019

As illustrated in figure 4.5 above, between 2007 and 2010, agricultural land area was 8.44% (55.78 sq km) in 2007 but it decreased significantly to 4.59% (30.33 sq km) in 2010 of the total project area and it was coming mostly from bare land expansion. Between 2010 and 2013, agricultural land increased from 4.59% (30.33 sq km) in 2010 to 6.14% (40.56 Sq km) in 2013 of the total project area which is mostly due to conversion of bare land to agricultural land. Furthermore, between 2013 and 2016, agricultural land decreased from 6.14% (40.56 Sq km) in 2013 to 2.12% (13.98sq km) in 2016 of the total project area, this is coming from the conversion of agricultural land to bare land. However, between 2016 and 2019, bare land had a slight decrease which resulted to increase in agricultural land from 2.12% (13.98 sq km) in 2016 to 6.50 % (43.29 sq km) in 2019 of the total project area.

Grass land showed a linear decrease throughout the study period except for 2019 which is a recovery phase. Between 2007 and 2010, grass land area was 32.65% (215.70 sq km) in 2007 but it decreased significantly to 26.35% (174.11 sq km) in 2010 of the total project area and it was coming mostly bare land expansion built-up area. Between 2010 and 2013, agricultural land increased from 26.35% (174.11 sq km) in 2010 to 25.21% (166.58 sq km) in 2013 of the total project area which is mostly due to conversion of grassland to agricultural land. Furthermore, between 2013 and 2016, grass land continued to decreased from 25.21% (166.58 sq km) in 2013 to 14.09% (98.14 sq km) in 2016 of the total project area, this is coming from the continues conversion of grass land to bare land. However, between 2016 and 2019, grass land showed a significant increase from 14.09% (98.14 sq km) in 2016 to 18.05% (120.33 sq km) in 2019 of the total project area, this is due to the conversion of bare land in the mine site to grass land.

Thematic Change Detection

The post-classification comparison (PCC) technique is the most straightforward method of change detection. It depends on the comparison of independently produced classified images by properly coding the classification results for time 1 and time 2 (Singh, 1989) and the output produces a change map that indicates a complete matrix of change (Table 4.3).

Post-classification comparison provides "from-to" information. Actual change can be obtained by a direct comparison between classified images from one date with that obtained on another date. Temporal changes that have occurred between the two dates can be measured by performing a change matrix (Table 4.3). The data obtained from change matrices was further used to calculate rate of change in each LULC class using the following formula as the changes were not linear (Puyravaud 2003).

$r = [1/(t1 - t2)] \times \left[In(\frac{A2}{A1})\right]$

Where, r is the rate of LULC Change, and A1 and A2 are the Land Use land cover class cover at the time t1 and t2, respectively (Weng 2002). This model analyses two qualitative LULC images from different dates and produces a transition matrix, which determines the likelihood for a cell or pixel to change from a LULC class in every other category from time 1 to time 2 (Houet & Hubert-Moy 2006).

Table 7: Change analysis in % and Area (Sq Km) between 2007 and 2019

Year	**2007-2010**		**2010-2013**		**2013-2016**		**2016-2019**		**2007-2019**	
LULC changed class	**%**	**Area(Sq Km)**	**%**	**Area(Sq Km)**	**%**	**Area(Sq Km)**	**%**	**Area(Sq Km)**	**%**	**Area(Sq Km)**
1	65.9	48.3737	50.37	47.6596	69.7	449.3897	63.92	421.604	63.92	421.783
2	0.39	0.2831	16.71	11.9646	4.1	26.5079	5.93	39.1112	9.32	61.4749
3	2.48	1.8241	0.43	0.3057	9.5	61.1371	5.32	35.0898	1.94	12.7824
4	0.15	0.1115	0.15	0.1115	0.3	1.7216	0.1	0.6269	0.1	0.6269
5	0.14	0.1011	0.19	0.1029	0.2	1.2884	0.13	0.8404	0.12	0.8423
6	4.6	3.3697	6.3	1.591	2.1	13.3966	6.49	42.7983	6.5	42.8134
7	26.35	19.3456	25.86	18.5488	14.1	90.8057	18.12	119.5574	18.1	119.5698
Total	100	73.4088	100	80.2841	100	644.247	100	659.628	100	659.8927

Where 1= Bare Land expansion, 2= Forest Regeneration, 3= Deforestation, 4= Built-Up Areas expansion, 5= Water Body expansion, 6= Agricultural Land expansion, 7= Grassland expansion

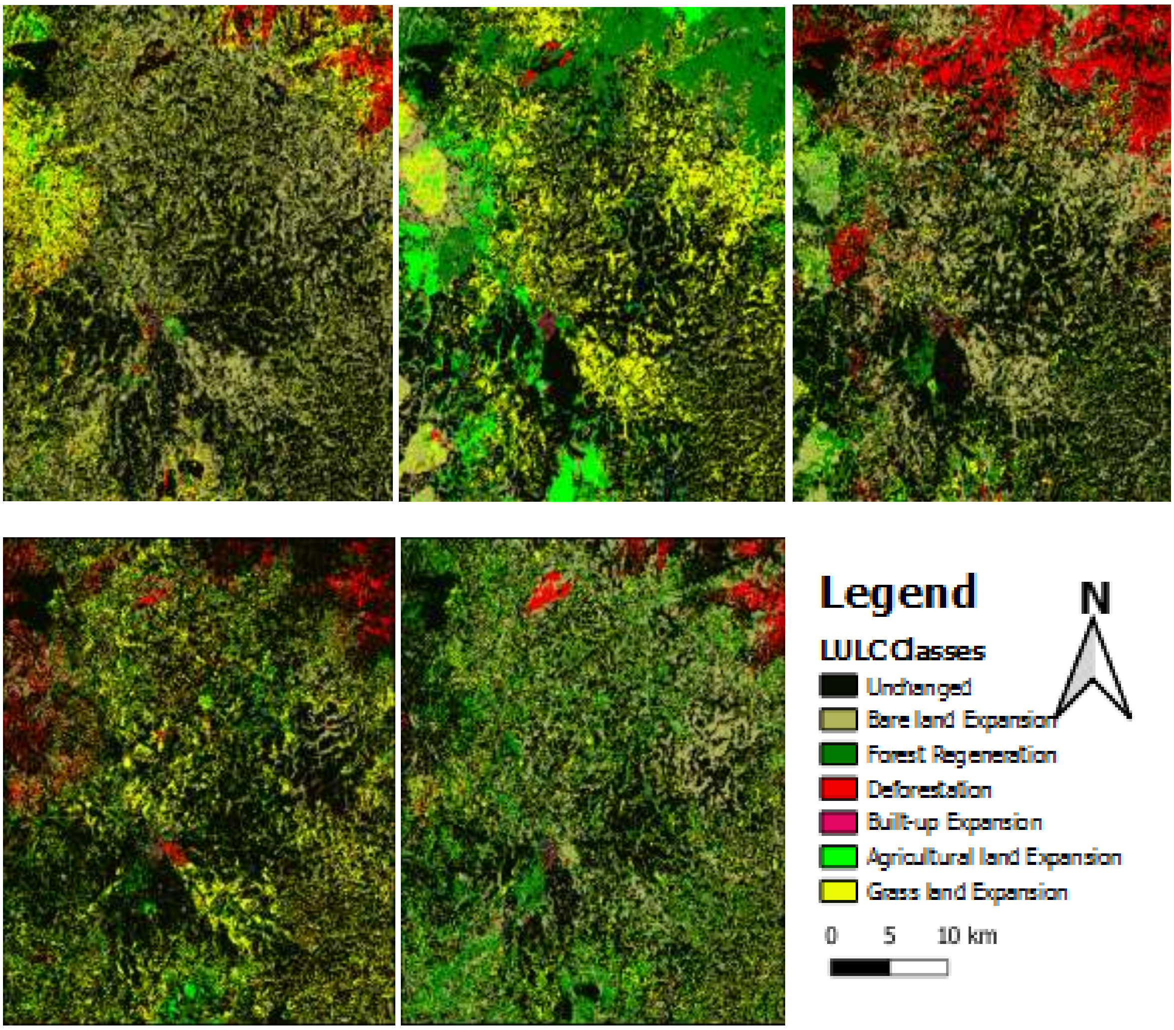

Fig. 8: Change Detection Image from 2007 to 2019

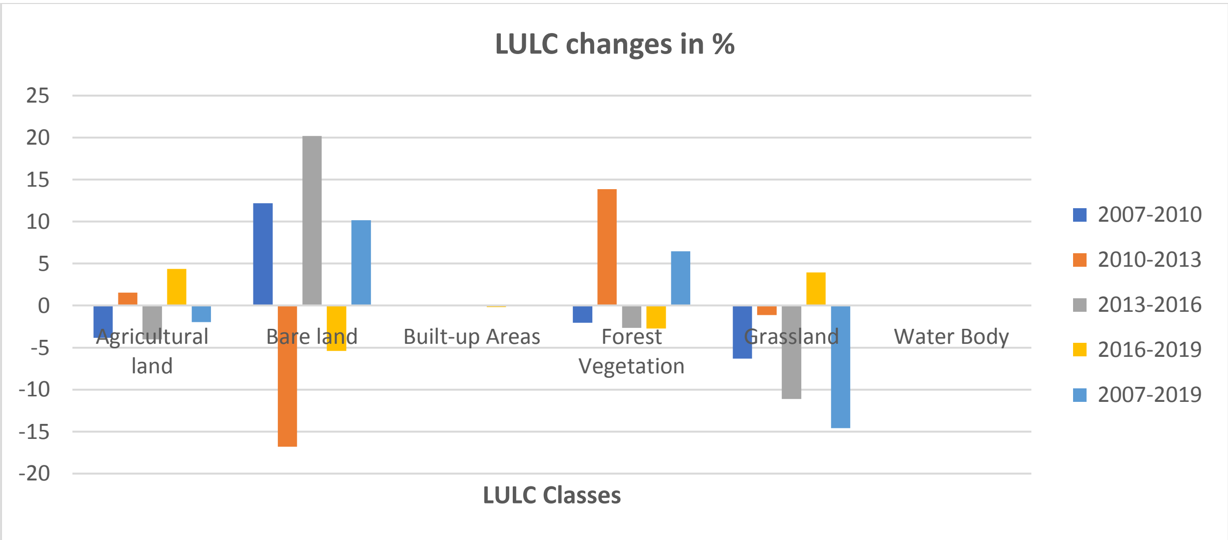

Figure 9: LULC changes in percentage between 2007 and 2019

Analysis of change detection between 2007 and 2010

Figure 6, 7 and Table 3 clearly shows significant changes in LULC in the study area. In some part of the district, between 2007 and 2010, bare land represented the highest percentage of coverage. This indicates that mining and other land degradation activities were the main course of this large portion. The dynamic change of natural vegetation cover shows that forest land significantly decreased from 4.91% in 2007 to 2.87% in 2010, this degradation in natural forest is a result of wood logging for timber and fire wood production that led people to forest exploitation as the main source of income. However, built-up areas showed a slight increase from 0.11% in 2007 to 0.15% in 2010, while water bodies showed a slight decrease form 0.16% in 2007 to 0.14% in

2010 and agricultural land decreased significantly in 2007 from 8.44% to 4.59% in 2010, these decrease in agricultural land was as a result of people venturing in to wood logging/deforestation instead of farming. Grassland comprised the second highest percentage in the study area, this means that animal grazing is the second largest use of the2 land in the study area. However, there was a decrease in the grassland from 32.65% to 26.35% in the two respective years. Moreover, bare lands and built-up areas increased in 2010. The increase in bare land can be attributed to the conversion of forest to bare land as a result of people abandoning their farmlands and engaging in wood logging while the increase in built-up areas can be attributed to increase in income level of the inhabitants.

However, the increase in bare land has led to a decrease in forest vegetation, water body, agricultural land and grassland area from 4.91% to 2.87%, 0.15% to 0.14%, 8.44% to 4.59%, and 32.65 % to 26.35 % in the two years respectively.

Analysis of change detection between 2010 and 2013

The LULC changes for the period between 2010 and 2013, as indicated in table 3 above shows an increase in the natural vegetation cover. Agricultural land as well as natural forests increased from 4.59 %, 2.87% to 6.14% and 16.72 % respectively. This is due to a good rainy season during this period as shown by the LULC map of 2016. This indicates that the environment had begun to recover from land degradation in the previous year.

There was an increase in water bodies from 0.14 % to 0.18 % in this period, while there was a significant decrease in bare land from 65.90 % in 2010 to 49.12 % in 2013. This can be interpreted that some of the bare land were converted into natural vegetation, agricultural land and grazing lands as these is a period in the raining season where there is vegetation growth throughout the area. However, grassland shows a slight decrease in 2013. This is due to demand for food and fodder, which led to over-cultivation and increase over grazing by animals in recent times and because some parts of the satellite image about 2.28% were covered by cloud in this year which tend to cover most areas covered by grassland in the study area.

Between 2010 and 2013 there was no significant change in the amount of built-up areas as it decreases from 0.15% in 2010 to 0.14% in 2013. This may be due conflict during this period in some parts of the district which led to burning down of properties worth millions of Naira.

Analysis of change detection between 2013 and 2016

The LULC changes between the period of 2013 and 2016 as indicated in table 3 above showed an up rise in the amount of bare land form 49.12% in 2013 to 69.28% in 2016, this happens to be the highest increase in percentage of bare land throughout the study period. This can be attributed to the high increase in mining activities in this period which saw high amount increase of open/abandoned mine pits especially in the mining sites. 2016 witness the largest mining activities in the study area, this led to reduction in agricultural activities from 6.14% in 2013 to 2.12% in 2016, and this is because most of the youths leave their homes to go for mining in the mining areas leaving behind the aged groups and women to farming. This activity also saw the rebirth of deforestation, forest vegetation has reduced from 16.72% in 2013 to 14.05% in 2016. As human and animal populations have increased in recent years due to migration/influx of people and environmental degradation resulting in high demand on food and shelter, this led to logging for timber and firewood which was on high demand during this period as this migrants tends to build roofs over themselves and firewood was transported from this villages to the mining site because of high demand for food. However, built-up areas and water body saw an increase from 0.14%, 0.18% in 2013 to 0.26%, and 0.20% in 2016 respectively. Mining activities leads to migration in most mining communities, it therefore leads to an influx of people and the increase in the settlement pattern of the area. The increase in water body was only seen in the LULC map of 2016 which was as a result of the ASM activities in the study area, this mine pits are left open and filled with both underground and rain water since the mine site is located along a river. This saw the increase in the size of water body around the mining site.

Moreover, grassland has shown a massive decreased from 25.21 % in 2013 to 14.09 % in 2016, this means that herders were greatly affected by this mining activities during this period. On the other hand, bare land increased in 2016 in comparison to 2013, 2010 and 2007 where constituted 53.74%, 65.90%, 49.12 % and 69.28%, respectively. This was as a result of over grazing, decrease in natural vegetation cover and mining in the study area.

Analysis of change detection between 2016 and 2019

The year 2016 to 2019 is a recovery phase for some part of the district where bare land showed a decrease from 69.28% in 2016 to 63.87% in 2019 as illustrated in table 4.3 above, this can be attributed to the suspension of ASM by the government of Taraba State, the closure of the ASM came with so many conflicts where people were chased away and the whole built-up areas were brought down to the ground level. This singular act has contributed to the increase in the percentage coverage of grassland from 14.09% in 2016 to 18.05% in 2019. When an extraction and supply of blue sapphire area is covered, mined areas are left abandoned, which in due course of time are covered sometimes by water but mostly by grasses that can grow in the harsh edaphic conditions. However, the closure of ASM by the government and the recent several conflict between communities and Fulani herdsmen in the study area which saw the creation of an Air force containment in the study area led to the massive decrease in built-up areas from 0.26% in 2016 to 0.09% in 2019 especially in Santiye Maayo mine site. Furthermore, water body indicated a decrease from 0.20% in 2016 to 0.14% in 2019. Forest vegetation kept decreasing from 14.05% in 2016 to 11.35% in 2019, this may be attributed to continuous use of fire wood by the locals and logging for timber. However agricultural activities had a drift from 2.12% in 2016 to 6.50% in 2019 which can be said that agriculture is beginning to maintain its position as one of the most important livelihood activity in the study area, this is because many of the youths that were engaged in mining activities have no other source of livelihood and resorted back to agriculture after the closure of the mine by the government. This in turn will burst crop productivity in the study area. Increase in water body was more pronounced in LULC map of 2016 particularly at Santiye Maayo mine site, this was as a result of the increase in size of the river due to excavation within the river bank and the increased number of abandoned mine pits filled with water in the area, but this water body saw a decrease from 0.20% in 2016 to 0.14% in 2019. This can be attributed to the increased coverage of grassland and deposits of sediments which reduces the size of the river. During the study, the researcher observed that most of the abandoned mine pits where covered in grasses and the main river passing through the area drastically reduced in size due to high deposit of sediments along the river bank.

Analysis of change detection between 2007 and 2019

Table 4 above shows that bare land Between the year 2007 and 2019, showed a significant increase where 11.22 sq km of bare land area was converted to forest vegetation between these seasons, similarly, 0.5 sq km, 0.21 sq km 14. 86 sq km and 114.46 sq km of built-up areas, water body, agricultural land and grassland respectively replaced bare land area in the total project area. However, bare land area maintained about 280 sq km thereby increasing the rate of bare land expansion from 53.74% (3355.0383 sq km) in 2007 to 63.87% (425.7212 sq km) in 2019. This massive increase in bare land area can be attributed to overgrazing by animals, ASM and deforestation in the study area.

Forest vegetation between 2007 and 2019 showed a significant change. The result shows that 18.29sq km, 22.60sq km and 13.83 sq km of forest vegetation were converted to bare land, agricultural land and grassland respectively. However, another 0.006 sq km, 0.009 sq km of forest vegetation was converted to built-up areas and water body thereby leading to deforestation rate of 1.9% (12.7824 sq km) between 2007 and 2019. Although the rate of deforestation was said to have been very high in-between the years therefore 2019 was said to be a recovery phase for forest resources. Furthermore, forest vegetation expanded by 19.53 sq km increasing the total amount of forest regeneration to 9.32% (61.4749 sq km) of the total project area. This is because some of these forest trees are mostly Eucalyptus species used for timber production except for the Ngel-Nyaki forest reserve, the other forest at Yelwa and some others. Most of these forest trees are harvested for timber and later replanted or allowed to regenerate.

Built-up areas between 2007 and 2019 did not show a significant change, 0.39 sq km, 0.015 sq km, 0.019sq km, 0.05sq km, 0.006 sq km of built-up areas where converted to bare land, forest vegetation, agricultural land and grassland respectively while built- up areas expanded by 0.15 sq km to maintain the current amount of built-up areas as 0.1% (0.6269 sq km) of the total project area. This lack of change was as a result of the demolition of the built-up areas at santiye mayo and the Fulani-Mambila clashes in-between these years that rendered so many people homeless. However, there were great amount of increase in built-up areas in-between the years.

Water Body between 2007 and 2019 did no show a significant change, although 0.03 sq km, 0.006 sq km, and 0.002 sq km of water bodies were converted to bare land, forest vegetation and agricultural land thereby reducing the amount of water body expansion to 0.12 sq km of the total project area. Meanwhile, water body maintain 0.08 sq km between these seasons, this is attributed to the pressure on water resource by grazing animals, increased human population and mining activities within these years.

Agriculture land saw a significant decrease between 2007 and 2019. However, 10.9360 sq km of agricultural land was maintained during this period, 11.1474 sq km, 0.49 sq km, 0.002 sq km and 20.2282 sq km of agricultural land was converted to bare land, forest vegetation, built-up areas, water bodies and grassland respectively, thereby reducing agricultural land to 6.5% (42.8134 sq km). These decrease in agricultural land was due to the abandonment of agricultural activities to mining and other livelihood activities by the communities.

Grass land however indicates a significant decrease between 2007 and 2019. Grass land maintained 66.8931 sq km of the total project area during these years meanwhile 1.0452 sq km, 0.009 sq km. 0.009 sq km and 7.2997 sq km 0f grassland where converted to bare land, forest vegetation, built-up areas and agricultural land respectively there by decreasing the amount of grass land to 18.1% (119.5698 sq km) of the total project area. These significant decrease in the amount of grassland in the study area was as a result of overgrazing, mining, agricultural activities, building construction and other land use activities within the study area.

Impact Analysis

The Blue sapphire mining is the biggest natural resources found on the plateau. The ASM activities affects the land use and land cover that causes environmental impact. Day by day it has been increased and it's affecting the environment directly.

From the study of satellite image during the years of 2007, 2010, 2013, 2016 and 2019, through collateral data and field verification we had findings following assessment and impact on Land use and land cover

a. Due to ASM, large pits are left over.
b. A large amount of overburden material excavated during ASM is dumped in the vicinity of the mine sites.
c. Flow of silt from overburden dumps causes degradation of land and disruption of water flow.
d. Creation of meanders and change in river course due to the deposit of sediments from washing of the overburden material especially at Santiye mayo (river)
e. Destruction of grazing lands by mining activities.

CONCLUSIONS

The major land-use classes in the study area where found to be bare land, forest vegetation, built-up areas, water body, agricultural land and grass land. The study identified that land-use change in the study area is driven by both physical and biophysical, especially mining and agricultural production, human settlement development (housing), deforestation; and human factors, such as population growth and conflict. As a result of natural resource degradation, grass land, which represented 32.65 percent of all land in 2007, has been cleared and converted into bare land, which amounted to 26.4 percent, 25.2 percent, 14.09 percent and 18.1 percent in 2010, 2013, 2016 and 2019, respectively. Whereas, bare land area increased from 53.74 percent in 2007 to 65.9 percent, 49.1 percent, 69.28 percent and 63.9 percent in 2010, 2013, 2016 and 2019, respectively. The study was successfully able to detect LULC change and concluded that forest cover and bare land has increased between 2007 and 2019 and has replaced grass land. The study reveal that the major land-use changes occurred between 2010-2013 and 2013-2016, as instances of mining and migration from all over the country and even outside the country took place, as well as conflict in the latest period, which led to the overexploitation of natural resources.

The applicability of maximum likelihood classification methods in multi-temporal satellite imagery change detection studies was demonstrated. The study proved that the maximum likelihood classification provided an accurate means to quantify, map, and analyse changes over time in LULC. The study concludes that remote sensing can be used to support some criteria and indicators for land use/ land cover monitoring. Specifically, the study successfully uses optical satellite remotely sensed images (i.e. Landsat-7 ETM+, Landsat 8-OLI and Sentinel-2 data) to detect change in LULC in the study area.

As such, the levels of grass land have decreased significantly. This can be attributed to environmental degradation, mining, overgrazing and due to an increase in human population as a result of migration in recent years.

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