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THE EFFECTS OF LARGE-SCALE MINING ON LAND USE AND LAND COVER CHANGES USING REMOTELY SENSED DATA

[1*]Julia Atayi, [2]Amos.T. Kabo-Bah, [3]Komlavi Akpoti
[1]Department of Environmental Management, School of Natural Resources, University of Energy and Natural Resources, P. O. Box 214, Sunyani, Ghana.
[2]Department of Environmental Engineering, School of Engineering, University of Energy and Natural Resources, P. O. Box 214, Sunyani, Ghana.
[3]Earth Observation Research and Innovation Centre, University of Energy and Natural Resources, P. O. Box 214, Sunyani, Ghana.
[*]Corresponding author email: atayijulia@gmail.com

ABSTRACT
Land cover is the natural or basic elements of the environment that link and impacts many parts of the local, regional and global levels of the environment. The study was conducted in two capital districts of the Brong-Ahafo Region which lies within the green belt of Ghana in the moist semi-deciduous forest zone. This research was to assess the effects of large-scale mining on the Land Use Land Cover (LULC) using remotely sensed data. Also, this study tries to find out, total area of the various land use categories, percentage change and annual rate of change of LULC changes as a result of the mining activities from 2005 to 2015. Iterative Self-Organizing Data (ISODATA) under unsupervised classification showed an overall accuracy and kappa coefficient of 80.8% and 0.754 for 2005, 92.8% and 0.908 for 2008, 89.2% and 0.861 for 2012 and 87.6% and 0.841 for 2015 respectively. The results from the LULC analysis showed that, Forest Evergreen was the most dominant land cover type in 2005 with a total area of 1492.93 ha (44.94%), but decreased as the year's increases with increasing built-up areas. The built-up areas which consists of mining areas increased from 316.05 ha (9.51%) in 2005 to 1047.27 ha (31.53%) in 2015. We recommend effective management of degraded areas by incorporating tree planting as this compiles with the 1998 Forest Policy. Concurrent reclamation should be adopted by the mining sectors to achieve a sustainable and successful post-closure outcome. Also decision makers should adopt the use of remote sensing and GIS tools as this would enhance identification of areas that are degraded, their rate and extent.

KEY WORDS: Mining, LULC, Remote Sensing, ANOVA, ISODATA, Landsat image, pattern.

INTRODUCTION
Land cover is the biotic or abiotic features that cover the earth surface, such as water, grassland, bare soil and the forest while Land use is how the land cover is been modified, example recreational area, built up land and agricultural land. The direct result of changes in land cover as a result of human activities especially land use, have changed the physical geographical environment greatly. Land has now become a scarce resource due to the increase in population growth and industrialization (Ahadnejad *et al*., 2009). Mining which is the extraction of minerals from the earth's crust makes a great impact on the landscape, environment and the surrounding communities of the earth especially surface mining. This involves the clearing of large area of the forest and agricultural land and these results in serious deforestation and land degradation. Rapid growth in the mining sector has also attributed to the decrease and degradation of the land, forest cover and the biodiversity, though it serves as a great economic gain for a country economy (Kumar & Pandey, 2013). The mining industry is the second largest industry after agriculture at all scale and regions, and it has played a vital role in the development of civilization from ancient times (Lodha *et al*., 2009). As an example, according to (Aryee, 2001), Ghana's mining sector contributes about 40% of gross foreign exchange earnings, generates some 5.7% of GDP. During mining activities, large vegetation is cleared; huge pits dug to obtain the rocks rich in granite and limestone. The continuous extraction of the natural resources leads to the direct loss of the forest due to the frequent damage of the forest land, removal of the fertile top soil layers, thereby resulting in the shortage of fuel woods, grazing area, increase in soil erosion and air pollution. This situation negatively affects people living within the mining areas (Nzunda, 2013). Dumping of waste rocks in an un-mined environment causes disturbances to the surrounding ecosystem thereby affecting the biodiversity in the area and changing the natural topography of the area. The increase in the global demand of these mineral resources such as Gold, Diamond, Bauxite, Coal etc. have stimulated new mining industries including multinational companies and small-scale miners throughout the world (Bury, 2004). Gold mining activities in the various forest belts is likely to increase in Ghana, as the global demand and the prices for them continues to increase. Accurate information is therefore needed on the rate and impacts of the mining activities on the forest since these activities occur within the remote forest and this also affects biodiversity (Alvarez-Berríos *et al*., 2015). Protecting the global environment is one of the critical problems the world is facing now and this is due to several factors, such as

population increase, depletion of natural resources and the pollution of the environment (Study & Zanjan, 2009). The unplanned changes of the land use have become a major problem because of the absence of logical planning and consideration of environmental impacts (Study & Zanjan, 2009). For the past decades, Remote Sensing (RS) and Geographic Information System (GIS) technologies have been vital tools for mapping the Earth's features, studying the environmental changes in time and space, managing the natural resources. This gives the most accurate means of measuring the extent and pattern of the changes at a particular landscape over time (Kumar & Pandey, 2013). This technology affords a practical means of analysing the changes in the land use pattern at the mine sites at inaccessible places. It has also become possible to get a synoptic coverage of a larger area, in a cost-effective and in a repetitive way.

Assessing land-use and land-cover change has become a central component in the current strategies for managing natural resources and monitoring the environmental changes (Mark & Kudakwashe, 2010). Detection of land cover change has been found applicable in land use change analysis especially in the assessment of the extent of deforestation in a particular area (Dale *et al*., 1993). Therefore viewing the Earth from space has now become a necessity to understand the influence of man's activities on the natural resources over a given period (Zubair, 2006). The focus of this research is to assess the effects of large-scale mining on the land use land cover changes of the Sunyani and Asutifi district in the Brong-Ahafo region of Ghana for 2005, 2008, 2012 and 2015.

METHODOLOGY

Description of the Study Area

The study was conducted in two districts in the Brong-Ahafo region of Ghana; Sunyani and Asutifi (Kenyasi) as indicated in the figure 1 below:

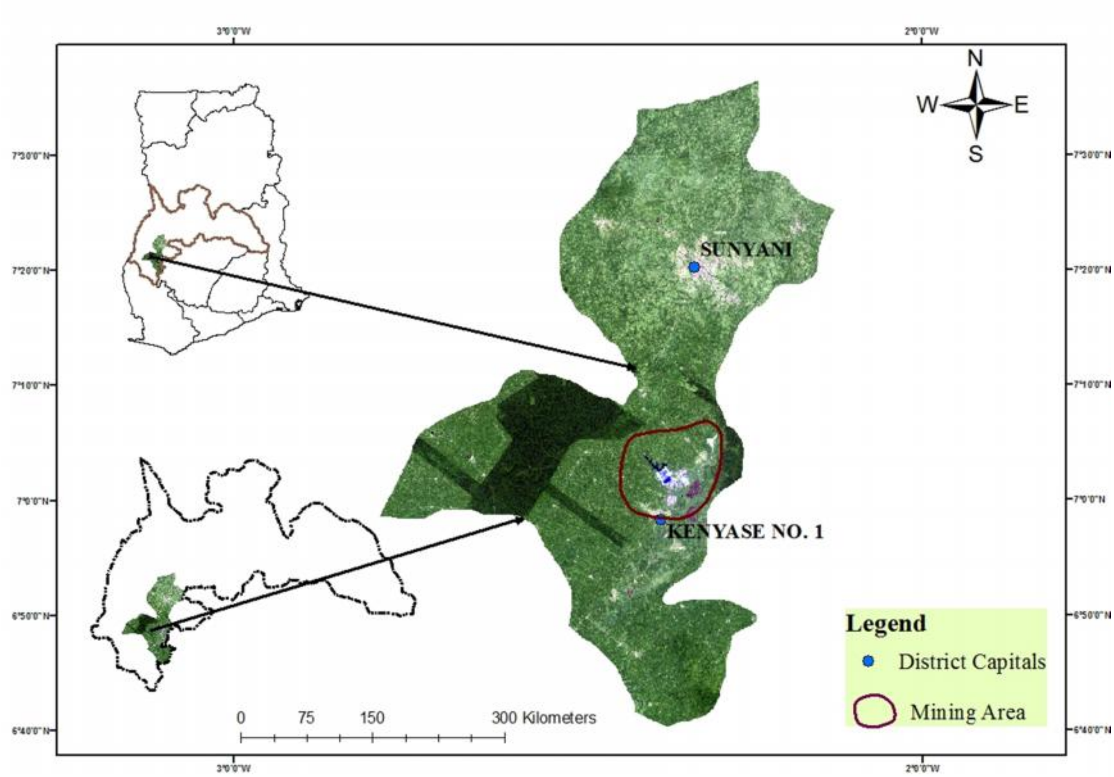

FIGURE 1: Location of the study area

The Sunyani Municipality

Sunyani Municipality is one of the twenty-two (22) districts in the Brong-Ahafo Region of Ghana. Its capital is Sunyani and this lies between latitudes $7^0$19'57.43''N and $7^0$21'41.81"N and longitudes $2^0$19'40.58''W and $2^0$20'51.47''W (PHC, 2014). It shares boundaries with Sunyani West District to the Dormaa District to the West, Asutifi District to the South and Tano North District to the East

The Asutifi District

The Asutifi District is one of the twenty-two (22) Districts in the Brong-Ahafo Region of Ghana and its capital is Kenyasi. It is located between latitudes $6^0$58'8.35''N and $6^0$58'7.55''N and longitudes $2^0$25'13.72''W and $2^0$26'43.56''W (GoG, 2010).The district is one of the smallest in the Brong-Ahafo Region with a total land surface area of 1500 km². The district has a total of 117 settlements in the district and four paramountcy, thus Kenyasi No.1, Kenyasi No.2, Hwidiem and Acherensua (GoG, 2010).

DATA COLLECTION

Spatial Data Collection and Source

In order to determine the effects of large-scale mining on the LULC changes of the study area, spatial data-sets were obtained from Landsat 7 and Landsat 8 archives from U.S Geological Survey (USGS) and ground observations obtained from Google Earth. The Four data sets used for the study, its source and date of acquisition are shown in table 1 below. The Landsat data were obtained from the USGS and Earth Observation database. These imageries were selected based on date of acquisition and its availability. To prevent bias in the data, the images were of the same season free from cloud cover and have the same identifiable features. This gives uniform radiometric and spectral characteristics which helped reduce or prevent seasonal variation in the spectral reflectance of the land cover data-sets (Nzunda, 2013). Also the data were georeferenced to the coordinate system of the study area i.e. WGS84 projection; UTM zone 30N.

TABLE 1: Landsat images used in the analysis of land-cover change

Landsat	Satellite Sensor	WRS Path/Row	Date of Acquisition	Spatial Resolution	Spectral Resolution	Source
1	Landsat 7 TM	195/055	15th January 2005	30m	8 bands	glovis.usgs.gov
2	Landsat 7 TM	195/055	1st January 2008	30m	8 bands	glovis.usgs.gov
3	Landsat 7 TM	195/055	2nd January 2012	30m	8 bands	glovis.usgs.gov
4	Landsat 8 TM	195/055	18th January 2015	30m	11 bands	glovis.usgs.gov

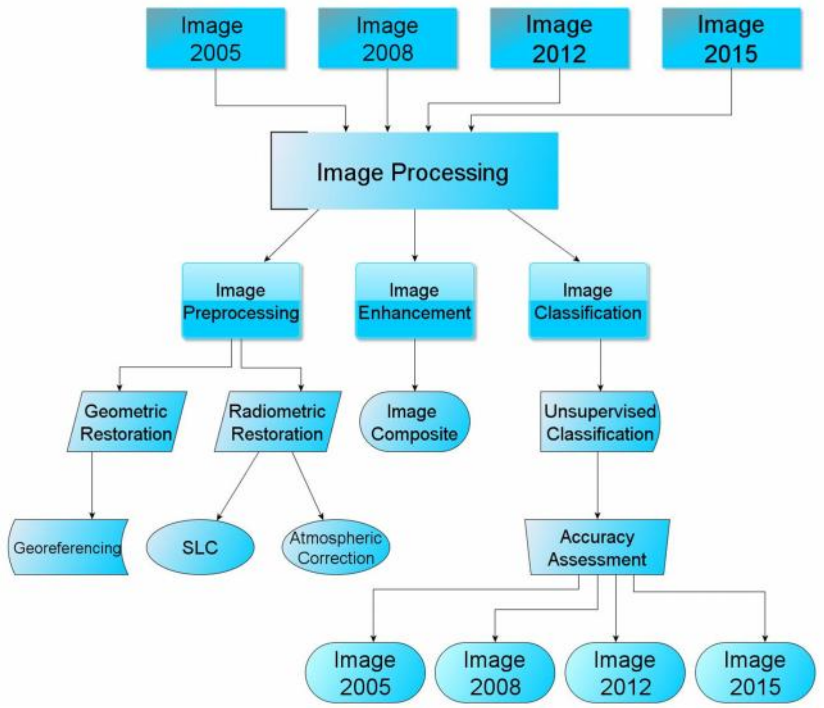

FIGURE 2: Flow chart of the image analysis

DATA ANALYSIS

The acquired Landsat imagery were analysed using ArcGIS 10.2, ENVI 4.7, Google earth and MS Excel. The above flow chart shows a summary figure for the analysis

Image Processing

The methods used in processing the imagery for this study was image restoration/ pre-processing, image enhancement and image classification.

Image Pre-processing

For mapping or analysing the change in the land cover, radiometric and geometric restorations are essential in every remotely sensed data analysis. Geometric restoration gives the accurate orientation of the satellite images, thus geo-referencing of the imagery. The imageries acquired were already geo-referenced from the World Geodetic System (WGS84); they were re-projected to the coordinate system of the study area, i.e. Universal Transverse Mercator (UTM) zone 30 North for Ghana using ArcGIS version 10.2. Radiometric restoration removes or suppresses the degree of spectral differences emanated from each detector causing distortion in the imagery. Some of these distortions are striping, scan line drop-out and atmospheric haze. The data-sets that were mostly affected by these distortions were all the Landsat 7 imageries (i.e. 2005, 2008, and 2012). Land 7 TM developed a faulty scan line corrector in May, 2003 which resulted in scan line drop-out mostly seen as parallel lines in the imagery (O'Neill, 2006). The scan lines in the imagery were removed using the gap-fill method in ENVI version 4.7. Atmospheric corrections were also performed on these imageries to minimize the atmospheric haze caused by variations in the atmospheric conditions between the dates. Atmospheric haze was not completely removed from the imagery due to limited resources but was minimized using ENVI version 4.7.

Image Enhancement

This technique deals with modification or improving the quality of the imagery, making it more suitable as perceived by humans. In order to improve the visibility of the imagery, a colour composite for the imageries were established using Landsat TM bands 4, 3 and 2 (i.e. Nearinfrared, Red and Green) and this gave a false colour composite. False colour composite was chosen because; vegetation mostly reflects in an infra-red colour, thus, they appear in shades of red. Forest evergreen reflects in deep red, forest deciduous in light red, urban areas in cyan blue, soils vary from dark to light brown, and water appears very dark (Ned, 2004). Figure 3 and 4 shows the composite Landsat imagery of the study area in the false colour composite and they were carried out using ArcGIS version 10.2.

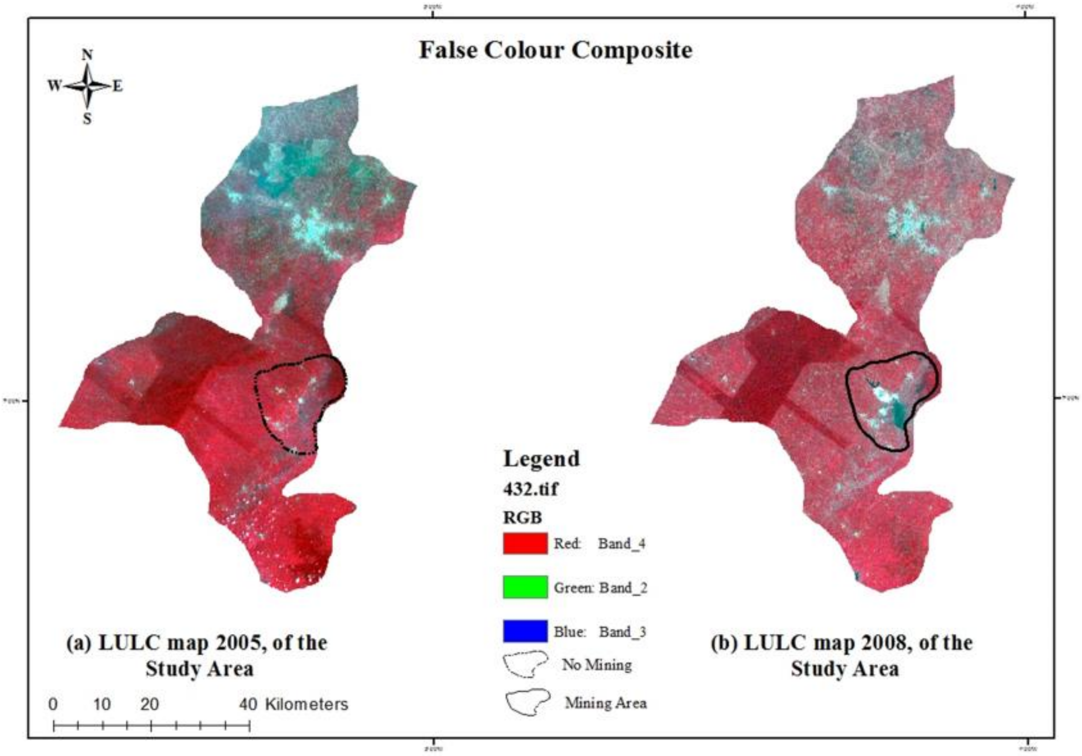

FIGURE 3: Landsat 7 TM of 2005 and 2008 scene of the Study Area

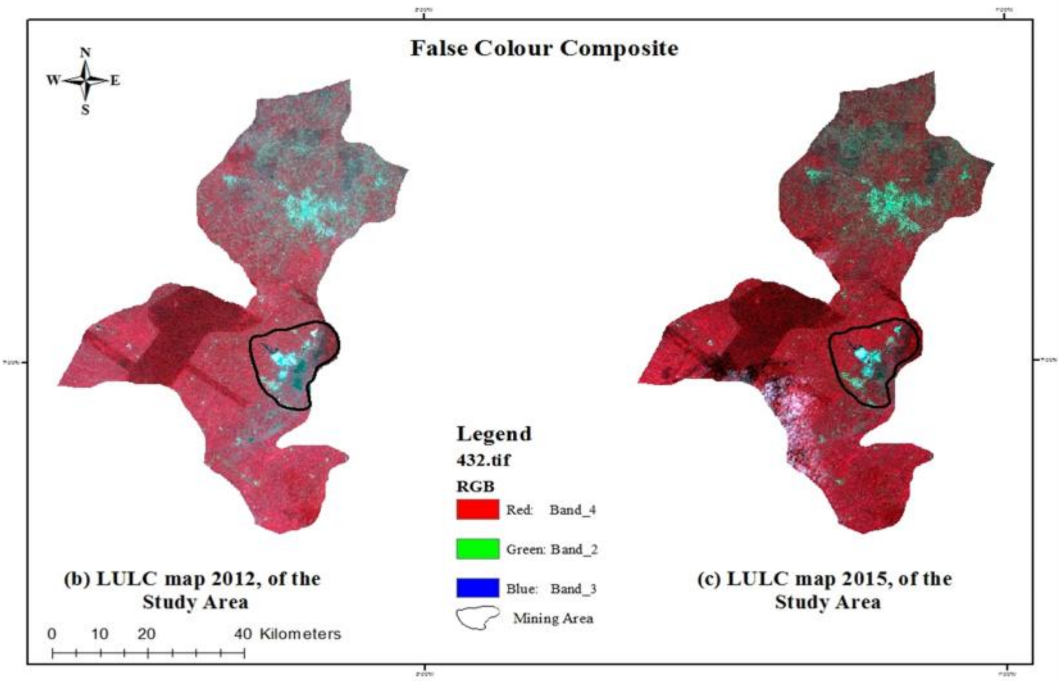

FIGURE 4: Landsat 7 TM & Landsat 8 of 2012 and 2015 scene of the Study Area

Image Classification

The imageries were classified using unsupervised classification method prior to the little knowledge of the study area available at hand. This method involves extracting land cover information from the imagery and it is mostly referred to as clustering. Clustering of the land cover was achieved using an Iterative Self-Organizing Data (ISODATA) or Iterative Self-Organizing Cluster (ISOCLUSTER) algorithm. This groups similar pixels into a unique cluster of specified classes according to statistical determined criteria. The grouped pixels were re-labelled and combined with spectral clusters for informed classes. The main objective for classification was to produce a land cover classes that resemble the actual land cover types of the earth surface (Kashaigili & Majaliwa, 2010). The unsupervised classified imageries also known as thematic map was generated using IsoCluster in ArcGIS version 10.2 and Google Earth as the reference. The classified imageries were grouped into five (5) land cover class prior to the knowledge of the area and this is as shown in table 2 below;

TABLE 2: Description Land Use Land Cover Class

Land Cover Class Name	Description
Forest Evergreen	These are areas covered with trees that do not shed its leaves periodically.
Bare Land	These are areas with less vegetation cover or no vegetation cover.
Forest Deciduous	These are areas covered with Shrubs, Agricultural, Grasslands, and Herbaceous perennials, i.e. those that shed their leaves periodically and are mostly in patches.
Built-Up Areas	These are areas with residential or commercial structures i.e. roads, institutions, mining areas, villages and towns.
Water body	These are areas covered by rivers, ponds, dam etc.

Accuracy Assessment

The ideal knowledge for accuracy assessment was from the fact that it is essential for every classified imagery results, due to the fact that classified imageries are deemed inaccurate to be used for its intended purpose or as a decision tool. This helps in determining the feasibility of the classified image depending on the acceptable level of error in the imagery. The accuracy level of a map is determined by selecting reference points identified in the imagery which are evenly distributed and by comparing it with the test pixel or corresponding reference location of a ground observation. Equal number of text pixels selected for the reference point is not advisable as some classes may have larger number than the others, hence the larger the class, the more the test pixels. The reference points were randomly distributed in the imagery and generated using ArcGIS version 10.2 and further exported to MS Excel to determine the accuracy. The data exported were used to determine the error matrix *i.e.* the kappa coefficient (k), overall accuracy, commission error (user's accuracy) and omission error (producer's accuracy), of the images classified. Overall accuracy is the total accuracy of the classified images. Commission error (user's accuracy) is the probability of a specific class to be incorrectly classified on the map, whiles Omission error (producer's accuracy) is the probability of a specific class is incorrectly classified on the ground. Kappa coefficient (K), gives a discrete multivariate technique used in accuracy assessment, thus K>0.80 gives a strong accuracy or agreement of the class assessed, 0.40-0.80 is average and <0.40 is poor (Maps & GIS Library, 2014). The formulae given below were used to determine the kappa coefficient, overall accuracy, user's and producer's accuracy respectively;

$$K = \frac{N \sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r} (x_{i+} X\, x_{+i})}{N^2 - \sum_{i=1}^{r} (x_{i+} X\, x_{+i})} ....(4)$$

Where; N is the total number of observations in the matrix
r is the number of rows in the matrix
x_{ii} is the number of observations in row i and column i
x_{+i} is the total for row i
x_{i+} is the total for column I (Jensen, 2014).

$$Overall\ accuracy = \frac{Total\ number\ of\ individual\ pixels\ correctly\ classified}{Total\ number\ of\ \text{classified cells}}\ x\ 100.................(5)$$

$$User's\ accuracy = \frac{Total\ number\ of\ correctly\ classified\ individual\ cell(row)}{Total\ number\ of\ pixel\ in\ a\ given\ class\ (row)}\ x\ 100..................(6)$$

$$\text{Producer'}s\ accuracy = \frac{Total\ number\ of\ correctly\ classified\ individual\ cells(column)}{Total\ number\ of\ classified\ pixel(column)}\ x\ 100.....(7)$$

Change Detection and Analysis

Change detection measures the changes that have occurred in a particular area over a period of time. In this study, post classification method was used to determine the cover change, annual rate of change and the percentage annual rate of change between the imageries *i.e.* 2005-2008, 2008-2012 and 2012-2015. These were done by using Ms Excel and the rate of change for the different land covers estimated based on the following formulae used by (Kashaigili & Majaliwa, 2010);

$$Percentage\ Change = \frac{Area_{i\ year\ x+1} - Area_{i\ year\ x}}{\sum_{i=1}^{n} Area_{i\ year\ x}}\ x\ 100...................................(8)$$

$$Annual\ rate\ of\ change = \frac{Area_{i\ year\ x+1} - Area_{i\ year\ x}}{t_{years}} \qquad (9)$$

$$\%Annual\ rate\ of\ change = \frac{Area_{i\ year\ x+1} - Area_{i\ year\ x}}{\sum_{i=1}^{n} Area_{i\ year\ x}\ x\ t_{years}}\ x\ 100 \qquad (10)$$

Where; $Area_{i\ year\ x+1}$ = area of land cover (i) for the second date or the following date

$Area_{i\ year\ x}$ = area of land cover (i) for the first date/ initial date

$\sum_{i=1}^{n} Area_{i\ year\ x}$ = the sum of the land cover area for the first date

t_{years} = the number of years between the first and second imagery date.

RESULTS & DISCUSSION

Accuracy Assessment

The accuracy of the classified imageries was determined by generating 250 reference points to obtain an error matrix using the formulas in equation 1-9. The results obtained are summarised in table 3 below for the four periods of the study area.

TABLE 3: Summary of Overall Accuracy and Kappa coefficient (k)

Year	Classified Image	Overall Accuracy (%)	Overall Kappa coefficient (k)
2005	Landsat 7 TM	80.8	0.754
2008	Landsat 7 TM	92.8	0.908
2012	Landsat 7 TM	89.2	0.861
2015	Landsat 8	87.6	0.841

As shown in table 3 above, the highest overall accuracy for the four period of the study was 92.8% in 2008 whereas the lowest was 80.5% in 2005. The highest kappa coefficient was 0.908 and the lowest was 0.754. The lowest accuracy was obtained in 2005 image classification because of the low quality of the imagery as a result of clouds and the scan lines in the imagery and this led to misclassification of the LULC.

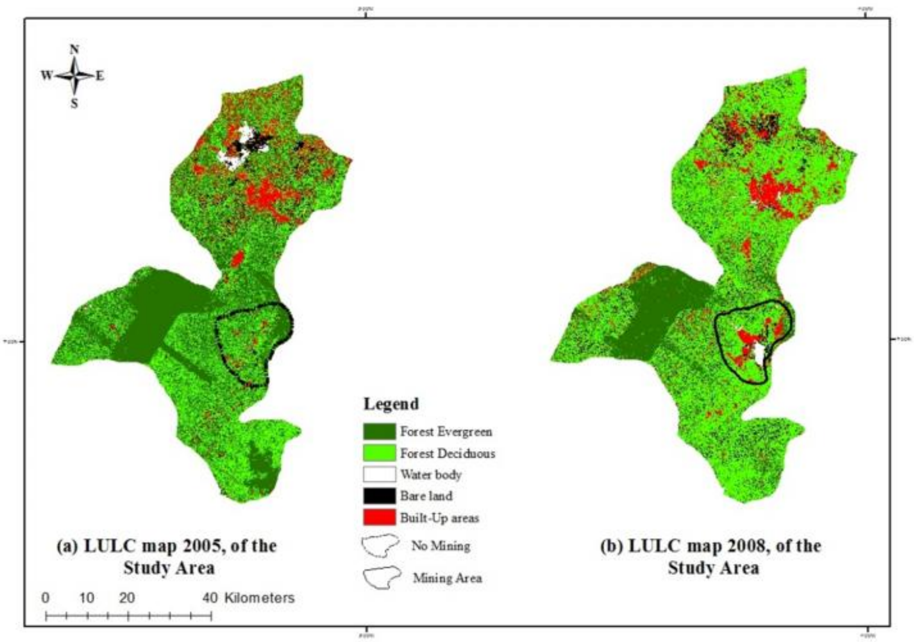

FIGURE 5: Land Use Land Cover map, 2005

Land Use Land Cover Classification from 2005-2015

The Landsat images for the study area were classified in order to identify the changes in the cover between the four periods, i.e. 2005, 2008, 2012 and 2015 respectively and this yielded four LULC maps from the satellite images. Five (5) land cover classes i.e. Forest Evergreen, Forest Deciduous, Bare land, Built-up areas and Water Body were identified. The land use land cover analysis is presented in maps and tables as shown in figures 5, 6 and tables 4, 5 and 6 respectively.

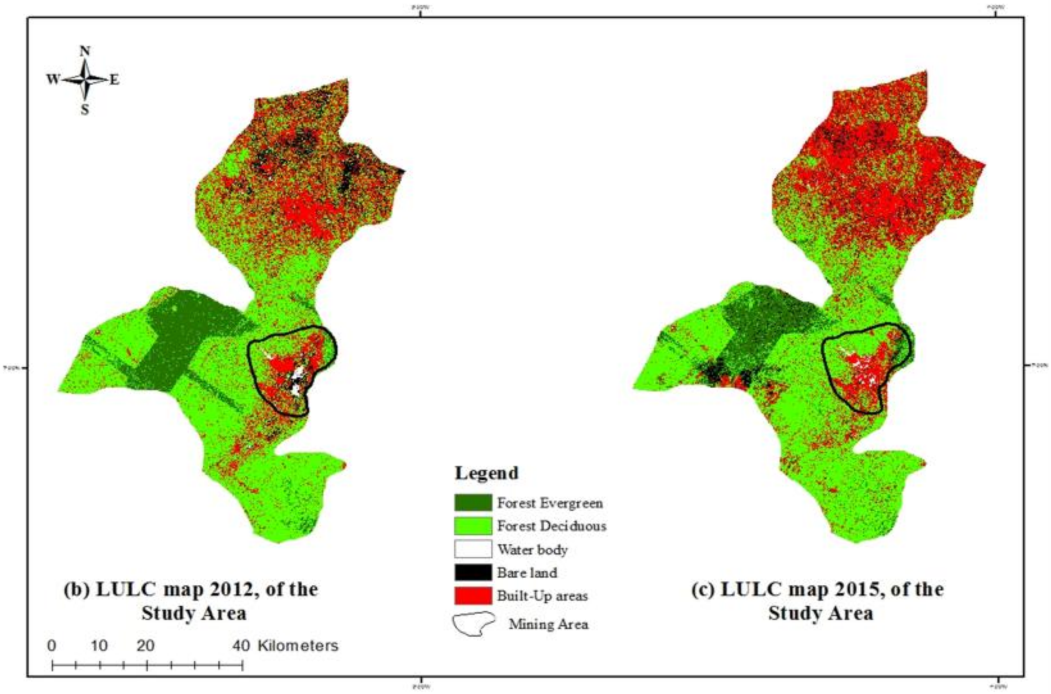

FIGURE 6: Land Use Land Cover map, 2008

LULC Change between 2005-2015

The various land use land cover classes for 2005, 2008, 2012 and 2015 were analysed to determine the area covered by each class quantitatively. The LULC area, area of change and the rate of change between 2005-2008, 2008-2012, 2012-2015 and 2005-2015 that have occurred in the study area were analysed and presented in table 3, 4 and 5 respectively for the four (4) classified maps as shown in the previous section. From 2005-2008 as shown in table 4, the forest evergreen and water body decreased by 26.11% and 0.36% respectively, whiles forest deciduous, bare land, built-up areas and increased by 21.74%, 3.51% and 1.22% respectively. For the second period (2008-2012) shown in table 5 above in the previous section, forest evergreen and water body still by decreased by 7.36%, 0.61% and built-up areas increasing by 15.09%. During the second period, forest deciduous and bare land which increased in the first period decrease tremendously by 6.28% and 1.29% respectively. For the third period (2012-2015) shown in table 6 above in the previous section, forest evergreen, forest deciduous, bare land and water body still decreased by 1.28%, 3.66%, 0.61% and 0.15% respectively whiles built-up areas continued to increase by 5.70%. The results are also presented in annual rate of change (ha/yr**)** and percentage annual rate of change (%/yr) in table 4, 5 and 6, these were determined using the formula in equation 8, 9 and 10 in the previous section. In 2005-2008, forest deciduous, bare land and built-up areas increased by 240.75ha/yr (7.25%/yr), 38.86ha/yr (1.17%/yr) and 13.51ha/yr (0.41%/yr) and forest evergreen and water body decreasing by 289.14ha/yr (8.70%/yr), 3.99ha/yr (0.12%/yr). For 2008-2012, most of the land covers of the study area decreased whiles land use (built-up areas) was increasing. Thus forest evergreen, forest deciduous, water body, bare land were decreasing in rate by 61.41ha/yr (1.84%/yr), 52.15ha/yr (1.57%/yr), 1.34ha/y (0.04%/yr), 10.72ha/yr (0.32%/yr) respectively whiles built-up areas were increasing by 125.34ha/yr (3.77%/yr). From 2012-2015 result, there was a continuous reduction in the forest evergreen, forest deciduous, bare land, water body by 14.19ha/yr (0.43%/yr), 40.56ha/yr (1.22%/yr), 1.64ha/yr (0.05%/yr), 6.71ha/yr (0.20%/yr) whiles built-up areas continued to increase by 63.10ha/yr (1.90%/yr).

TABLE 4: LULC Change between 2005 and 2008

Class Name	LULC (2005)		LULC (2008)		LULCC (2005-2008)			
	Area (Ha)	Area (%)	Area (Ha)	Area (%)	Area Change (ha)	% Cover Change	Annual rate of change (ha/yr)	%Annual rate of change (%/yr)
FE	1492.93	44.94	625.52	18.83	-867.41	-26.11	-289.14	-8.70
FD	1282.03	38.60	2004.28	60.34	722.25	21.74	240.75	7.25
WB	37.08	1.12	25.11	0.76	-11.97	-0.36	-3.99	-0.12
BL	193.62	5.83	310.21	9.34	116.59	3.51	38.86	1.17
BA	316.05	9.51	356.59	10.73	40.54	1.22	13.51	0.41
TOTAL	3321.71	100.00	3321.71	100.00	0	0	-0.01	0.01

Forest Evergreen (FE), Forest Deciduous (FD), Water Body (WB), Bare Land (BL), Built-Up Areas (BA).

TABLE 5: LULC Change between 2008 and 2012

Class Name	LULC (2008) Area (Ha)	Area (%)	LULC (2012) Area (Ha)	Area (%)	LULCC (2008-2012) Area Change (ha)	% Cover Change	Annual rate of change (ha/yr)	%Annual rate of change (%/yr)
FE	625.52	18.83	380.95	11.47	-244.57	-7.36	-61.14	-1.84
FD	2004.28	60.34	1795.69	54.06	-208.59	-6.28	-52.15	-1.57
WB	25.11	0.76	19.77	0.59	-5.34	-0.16	-1.34	-0.04
BL	310.21	9.34	267.34	8.05	-42.87	-1.29	-10.72	-0.32
BA	356.59	10.73	857.96	25.83	501.37	15.09	125.34	3.77
TOTAL	3321.71	100.00	3321.71	100.00	0	0	-0.01	0

Forest Evergreen (FE), Forest Deciduous (FD), Water Body (WB), Bare Land (BL), Built-Up Areas (BA).

TABLE 6: LULC Change between 2012 and 2015

Class Name	LULC (2012) Area (Ha)	Area (%)	LULC (2015) Area (Ha)	Area (%)	LULCC (2012-2015) Area Change (ha)	% Cover Change	Annual rate of change (ha/yr)	%Annual rate of change (%/yr)
FE	380.95	11.47	338.38	10.19	-42.57	-1.28	-14.19	-0.43
FD	1795.69	54.06	1674.01	50.39	-121.68	-3.66	-40.56	-1.22
WB	19.77	0.59	14.85	0.45	-4.92	-0.15	-1.64	-0.05
BL	267.34	8.05	247.20	7.44	-20.14	-0.61	-6.71	-0.20
BA	857.96	25.83	1047.27	31.53	189.31	5.70	63.10	1.90
TOTAL	3321.71	100	3321.71	100	0	0	0	0

Forest Evergreen (FE), Forest Deciduous (FD), Water Body (WB), Bare Land (BL), Built-Up Areas (BA).

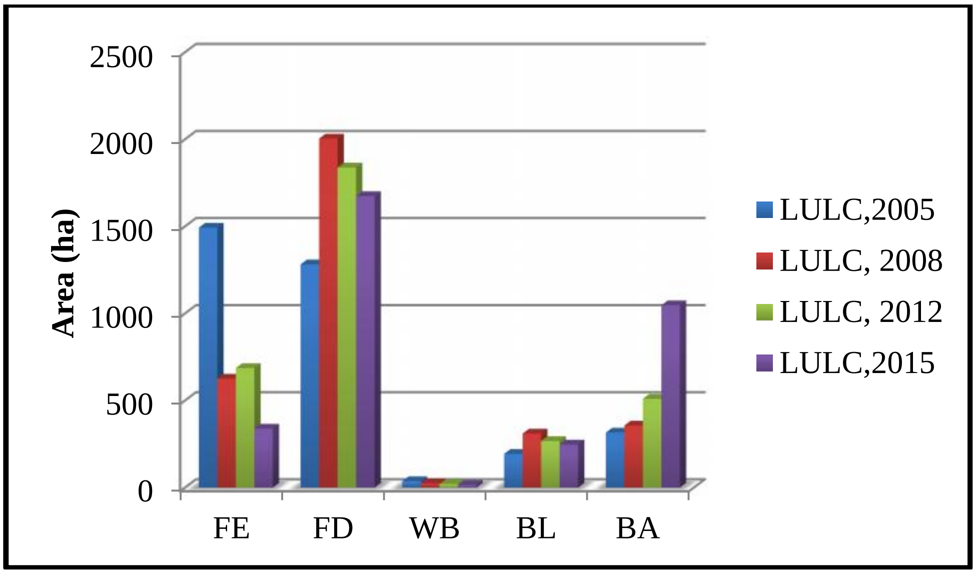

FIGURE 7: The trend of the Land Use Land Cover Changes

Considering the trend for Forest Evergreen over the years between 2005 and 2015 with respect to the percentage area covered as shown in figure 8, the trend shows a strong negative correlation of r^2=0.88 as there was a gradual decrease in the percentage area coverage over the years. Therefore, as the years increase, the percentage area coverage of the Forest Evergreen decreases. However, the Forest Deciduous shows a weak positive correlation i.e. r^2=0.385 over the years. The results also indicate a strong positive correlation r^2=0.969 over the years between 2005 and 2015 in relation to the percentage area covered by built-up areas. The trend shows that as the year's increase, the percentage area covered by the built-up areas increases. Comparatively, the trend of Bare land was weakly positive r^2=0.285 in correlation over the years. This shows a sharp increase from 2005-2008 and a gradual decrease from 2008-2015. The percentage area covered by water body over the years between 2005 and 2015 showed a strong negative correlation of r^2=0.967.

Generally, from the results, forest evergreen, forest deciduous, and water bodies were decreasing as the built-up areas increased. The increased depletion rate of the general land cover indicated that, human population and mining activities were immensely destroying the vegetation cover. However, the mining activity is the main reason for the tremendous changes in the study area. This is because, these activities are linked to both direct and indirect changes of the land cover especially in areas where the operations are being carried out. These have substantial effects on the land cover land use of which the forest is the greatest victim because these mineral resources are embedded within the soils in which they are found. The loss of the forest cover was due to the random and rampant clearing of the forest for mining activities (surface mining) especially those mostly found on the mountainous areas in the Asutifi district. This indirectly has affected the water bodies as most of them had their source from these mountainous and forested areas leading to their drying up as these vegetation covers are cleared. Built-up areas were increasing because of increase in population and also immigrants from far and near have come to settle at the location of the mining operation for work and trade purposes. Though, mining activities boosts a country's economy, it leaves a negative impact on land cover because it is a function of time that results in direct and indirect effects on different land use and land covers. This however, confirms the studies conducted by (Opoku-Ware, 2010; Pandit, 2011; Kumi-Boateng *et al*., 2012 and Nzunda, 2013) who concluded that, increase in populations and mining activities and the changes in the land use/land cover were mutually related to each other.

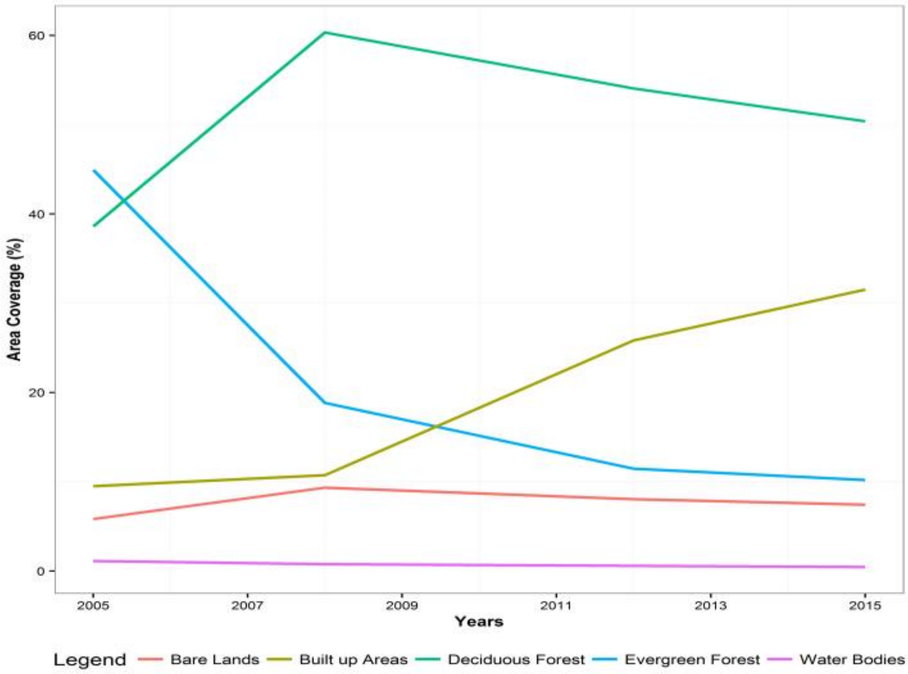

FIGURE 8: Forest Evergreen with respect to the percentage area covered

CONCLUSION

The study revealed that considerable portion of the land cover especially the forest evergreen area was converted to forest deciduous, built-up areas, bare lands during the period of 2005-2015 at the Sunyani Municipality and the Asutifi district. Unsupervised classification method was used to delineate five (5) LULC classes (forest evergreen, forest deciduous, water bodies, bare lands and built-up areas). The highest overall accuracy for the classified imageries for the four periods was 92.8% with a kappa coefficient of 0.908 in 2008 whiles the lowest was 80.8% with a kappa coefficient of 0.754 in 2005. From the results, Forest Evergreen areas were decreasing as the years increased showing a strong negative correlation of r^2=0.88 whiles Forest Deciduous areas showed a weak positive correlation of r^2=0.385. Built-up areas increased as the years pass-by showing a strong positive correlation of r^2=0.969 whiles Bare-land areas showed a weak positive correlation of r^2=0.285 over the years, showing a sharp increase from 2005 to 2008 and a gradual decrease from 2008 to 2015. The water body cover also showed a strong negative correlation of r^2=0.967 indicating a decrease in the area cover as the years increases. Also, the results show that, Forest Evergreen was the dominant land cover type in 2005 with a total area of 1492.93 ha (44.94%), but decreased as the years increases with increasing built-up areas. The built-up areas which consists of mining areas increased from 316.05 ha (9.51%) in 2005 to 1047.27 ha (31.53%) in 2015. Bare lands also decreased from 310.21 ha (9.34%) in 2008 to 247.20 ha (7.44%) in 2015. The water body also decreased from 37.08 ha (1.12%) in 2005 to 14.85 ha (0.45%) in 2015. This is attributed to the decline in the forest area, as most of the water bodies find their source from these areas. The forest deciduous areas were increasing because of the inability of the native tree species to regenerate and most of these areas were colonised by herbaceous species. The land use/land cover types keep changing at an alarming rate in the study area as the population and mining activity increases. However, if the current trend of degradation of the environment continues without putting measures to curb the situation at hand, there could be an imbalance in the ecosystem.

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