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Exploring Land use and Land cover change in the mining areas of Wa East District, Ghana using Satellite Imagery

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Abstract: Satellite imagery has been widely used to monitor the extent of environmental change in both mine and post mine areas. This study uses Remote sensing and Geographical Information System techniques for the assessment of land use/land cover dynamics of mine related areas in Wa East District of Ghana. Landsat satellite imageries of three different time periods, i.e., 1991, 2000 and 2014 were used to quantify the land use/cover changes in the area. Supervised Classification using Maximum Likelihood Technique in ERDAS was utilized. The images were categorized into five different classes: Open Savannah, Closed Savannah, Bare Areas, Settlement and Water. Image differencing method of change detection was used to investigate the changes. Normalized Differential Vegetative Index values were used to correlate the state of healthy vegetation. The image differencing showed a positive correlation to the changes in the Land use and Land cover classes. NDVI values reduced from 0.48 to 0.11. The land use change matrix also showed conversion of savannah areas into bare ground and settlement. Open and close savannah reduced from 50.80% to 36.5% and 27.80% to 22.67% respectively whiles bare land and settlement increased. Overall accuracy of classified 2014 image and kappa statistics was 83.20% and 0.761 respectively. The study revealed the declining nature of the vegetation and the significance of using satellite imagery. A higher resolution satellite Imagery is however needed to satisfactorily delineate mine areas from other bare areas in such Savannah zones.

Keywords: Land use / Land cover; NDVI; Vegetation; Remote sensing and GIS

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1 Introduction

The need for monitoring and quantifying changes in vegetation cover over large areas using remote sensing data has been well recognized [1, 2]. Remote sensing (RS) and Geographic Information systems (GIS) are important tools for assessing and monitoring environmental impacts due to its synoptic coverage and repetitive coverage of space borne imagery. It helps to detect the changes at various resolutions hence generating information on Land use and land cover (LULC) change. This aids for sound planning and a cost-effective decision making [3, 4]. LULC mapping is therefore one of the important and typical applications of RS. It is a useful tool and has scientific value for the study of human environment interactions, especially in LULC changes [5].

Despite the merits in the use of this technology very little is seen of it in Ghana to assess LULC [6, 7]. Multi date RS data can be used for detection of the LULC changes [8, 9]. There are different types of these satellite images that can be utilized in detecting these changes. Landsat TM with spectral channels is chosen specifically to map vegetation type, soil moisture, and other key landscape features [10]. It has proven useful especially in terms of its availability and cost.

Mining operations in Ghana both from the large and small scale miners are diverse and quite devastating to vegetation and livelihood. The principal elements of the environment (i.e., land, water and air) are affected leaving large tracts of land for farming lost and depriving mining communities of their source of livelihood [11].

There have been several calls from both civil and local authorities on the deleterious effect of legal and illegal mining on the environment in Ghana. Many have argued these negative effects without recourse to scientific quantification of the extent and changes. More of these observations are perceptive and not investigated scientifically.

Lack of spatial information in rural and regional level is one of the main problems for development practitioners, government officials and local level planners. This is even more precarious when it comes to monitoring land use and land cover changes in mining areas of Ghana where the use of satellite imagery is still a challenge. Few of these studies have been carried out in Tarkwa, Obuasi and its environs [12, 13].

The Northern parts of Ghana where there is an upsurge in legal and illegal mining are grey areas yet to be explored using satellite imagery. Normalized Difference Vegetation Index (NDVI) has proven useful in monitoring vegetation at mine areas. Many vegetation indices have been derived based on numerical combinations of red and near-infrared values of remotely sensed data. NDVI values range from −1 to +1. Positive values represent active vegetation, and near-zero or negative values represent other types of materials [14, 15].

Today RS and GIS technology has enabled ecologists and natural resources managers to acquire timely data and observe periodical changes [16]. The Wa East District of Ghana has seen the activities of both legal and illegal mining for some time now. The LULC dynamics in the area is essential to monitor the influence of these activities. Insufficient literature in this area have used qualitative approach to explore social dynamics of the environmental change without recourse to a spatial quantification of the changes. This paper therefore explores the status of Land use and Land cover change in Wa East District using Satellite Imagery.

2 Study Area and Methodology

2.1 Study Area

The Wa East District was carved out of the Wa Municipality in Ghana. It has a territory of about 1,078 km^2, which lies between latitudes 9° 55’ N and 10° 25’ N and longitude 1° 10’ W and 2° 5’ W. The District is remotely located in the South Eastern part of the Upper West Region. The capital is Funsi, about 115 km away from Wa, the Regional capital. The District shares boundaries with Mamprugo-Moaduri District to the North-East, North Gonja to South-East and the Sissala East and West District to the North respectively. The District also Shares borders with Wa Municipal to the West [17].

Temperatures are relatively high, throughout the year, varying between 15°C and 45°C. However, lowest temperatures are recorded in December/January while highest are seen in March/April. Guinea savannah with isolated wood, short thick trees, bushes and grass of variable height constitute the vegetation [18]. The floristic structure is generally diversified. There are several plant species including namely: sheanut (Butyrospermum parkii), baobab (Adansonia digitata) kapok (Ceiba pentandra), dawadawa (Parkia biglobosa), acacia, neem and ebony, mango, cashew and acheapple trees which have a significant economic value. The soil of the District originates mainly from *Precambrian* basement blocks, granite and metamorphic rocks with deposits of the following: Gold, iron, bauxite and clay in Bulenga area. These rocks offer mining opportunities and exploitation opportunities to illegal mine workers called “*galamsey*”. The soils are very fertile and suitable for tuber, crops, leguminous plants cultivation and grazing. The map of the area is shown in Fig 1.

2.2 Methodology

Spatial methods utilizing Landsat Satellite imagery in monitoring change was employed unlike previous studies in the area that have used mostly a qualitative approach. Integrating such methods using GIS and satellite imagery has been widely used in literature [19] though it is new in this area. Supervised *Maximum Likelihood Classification* (MLC) algorithm, more suitable when each class defined has a Gaussian distribution was used in categorizing DN values in the different classes in the study area [20]. Post Classification Change Detection using Land use change matrix; Image Differencing; and Changes in NDVI were used to measure the amount of healthy and declining vegetation in the area. The overall process is outlined in a flow chart shown in Figure 2.

2.3 Data Acquisition

Three Landsat images were downloaded from USGS Global Visualization viewer (http://glovis.usgs.gov) in the dry season with a zero cloud cover. The choice of the dry season is to best distinguish the spectral signatures of the different land-cover types especially bare areas. The images were Two Landsat 5 TM for the years 1991 and 2000 obtained in January 8, 1991 and February 2, 2000. The third image was a 2014 Landsat 8 obtained in January 15, 2014. The images were of Path 195 and Row 053 with spatial res-

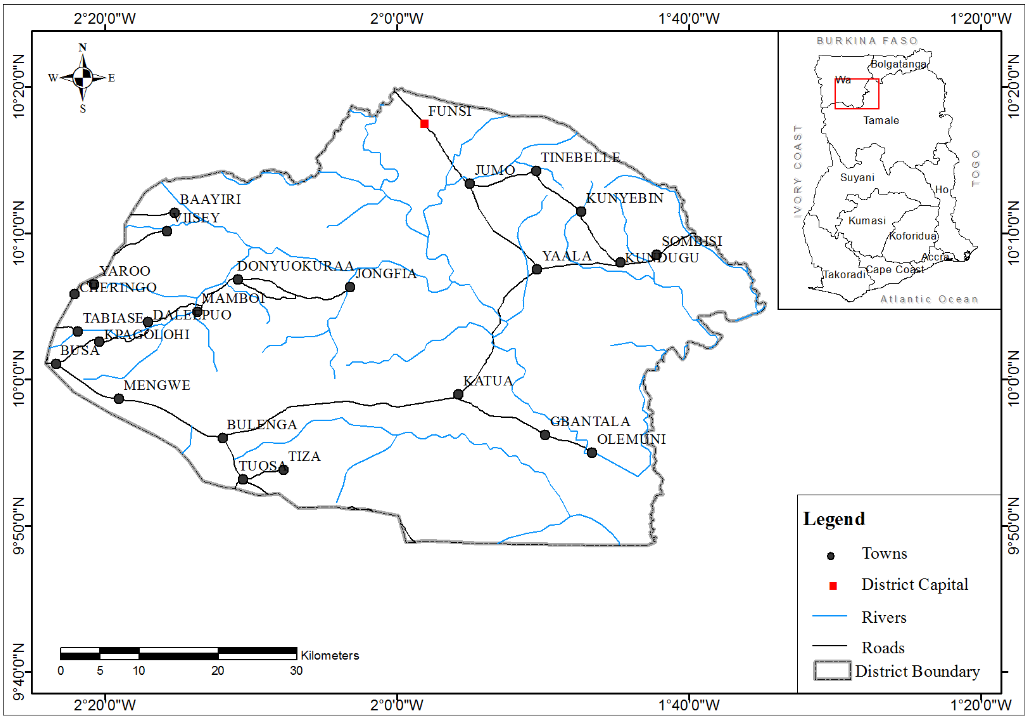

Figure 1: Map of Wa East District

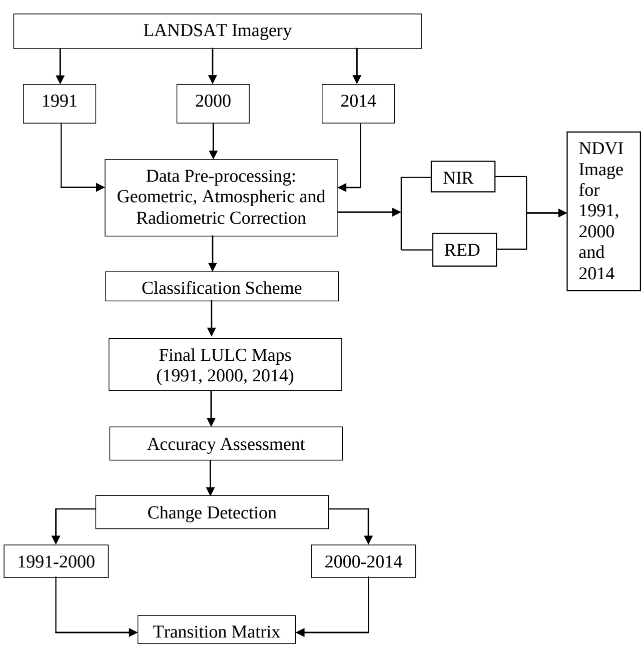

Figure 2: Flow chart on methodology.

olution of 30 x 30 meters. All the data were projected to the same reference system (war office system) of Ghana which is on the Universal Transverse Mercator (UTM) WGS 1984 zone 30N.

(a) Pre-processing

All the three datasets went through Image enhancement. Image georectification and atmospheric correction using ERDAS Imagine software 9.3. Radiometric correction was also employed for detecting changes of surface. Layer stack operations were used to combine the different bands. All bands of image were used for the layer stacking though for the Landsat TM visible to shortwave infrared (bands 1 to 5 and 7 with pixel size 30 m). A shapefile of the study area was then overlaid on each image as the Area of interest (AOI) and a subset obtained.

(b) Classification Scheme

A classification scheme was developed based on the prior knowledge of the study area. Five classes namely: Open Savannah, Closed Savannah, Bare land, Settlements and Water bodies was developed. They were based on the Ghana land use and land cover classification scheme for visual classification of remote sensing data by Agyepong [21] and showed in Table 1 with its associated descriptions. Supervised classification using the *Maximum Likelihood Classification* (MLC) algorithm was then used to classify the images after spectral signatures of the various classes was generated. Two hundred and fifty six (256) ground truth

Table 1: LULC areas covered in Hectares

Code	LULC Categories	Description
1	Open Savannah	Sacred groves/planted woodlots/thick shrubs. This class has less tree cover than the close savannah. It has a tree Population density between 75 and 150 trees per hectare.
2	Closed savannah	These include areas that closely resemble a forest cover and reserved areas; gazetted forest reserves/protected areas and natural growths. It has a tree Population density of more than 150 trees per hectare.
3	Bare Land	Areas of land within and around forest that have no vegetation cover including mining surfaces.
4	Settlements	Towns, Farm house and huts.
5	Water bodies	Rivers, pool of water or dams.

or reference data, which varied given the heterogeneous nature of the study area, were used for both training and evaluation of the map accuracy.

(c) LULC Maps

LULC maps for the years 1991, 2000 and 2014 were then produced after editing and finalization. The areas of the classes in Hectares was extracted and used for the statistical analysis. The area in hectares and the percentage change for each year (1991, 2000 and 2014) measured against each land use/land cover type was developed. Percentage change to determine the trend of change was calculated using the relation Percentage change = (Observed change/Sum of change) × 100. A change in the area was indicated as either positive or negative.

(d) Accuracy Assessment

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 2014. Two hundred and fifty six (256) ground truth selected using a stratified random sample was used in the assessment. The overall accuracy values and the Kappa Statistics of the classified image is shown in Table 2. The overall accuracy represents the percentage of correctly classified pixels [22]. It is achieved by dividing the number of correct observations by the number of actual observations. The overall accuracy and kappa statistics was therefore 83.20% and 0.761 respectively as shown in Table 2.

(e) Change detection/Transition Matrix

Image differencing was the method used for the change detection. This stems from the fact that digital numbers in the resultant difference image are often considered to be normally distributed where pixels with small change are observed around the mean [23]. It involves the subtraction of pixels between two co-registered raster datasets to identify areas that have experienced change [24]. The change was therefore obtained using the LULC maps between the years 1991-2000 and from 2000-2014. Transition matrix indicating the respective changes from one class to the other was calculated from 1991-2014 (Table 4).

(f) Normalized Difference Vegetation Index (NDVI)

A widely used indicator for detecting change in land cover is a measure of greenness known as the Normalized Difference Vegetation Index (NDVI) [25]. NDVI was calculated by using spectral enhancement technique for all the classes created for three observation years. It uses the near infrared (NIR) and visible red (RED) to calculate the ratio of the difference in reflectance to the sum of these two as follows: $NDVI = (Near\text{-}infrared - Red) / (Near\text{-}infrared + Red)$.

The NDVI values were therefore computed for the study years involved and the statistics obtained. It ranges from −1 to +1 making interpretation and scaling easy. Positive values represent active vegetation, and near-zero or negative values represent other types of materials. A statistical analysis using minimum, maximum, mean, and standard deviation for each year were determined based on the comprehensive analysis of multispectral signatures and NDVI images.

Table 2: Accuracy Assessment.

Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy	Kappa
Open Savanna	106	112	98	92.45%	87.50%	0.7867
Closed Savanna	57	47	39	68.42%	82.98%	0.781
Bare Ground	61	60	49	80.33%	81.67%	0.7593
Settlement	32	37	27	84.38%	72.97%	0.6911
Water	0	0	0	0	0	0
Total	256	256	213			
Overall Classification Accuracy = 83.20%						
Overall Kappa Statistics = 0.761						

Table 3: LULC areas covered in Hectares.

LULC	**Areas in Hectares**					
	1991	(%)	2000	(%)	2014	(%)
Open Savannah	61455.69	50.80	54067.34	44.69	44212.14	36.55
Closed Savannah	33634.53	27.80	33167.34	27.42	27427.68	22.67
Bare Ground	19947.60	16.49	24288.63	20.08	32215.95	26.63
Settlement	5933.61	4.90	9447.67	7.81	17071.38	14.11
Water	0	0	0	0	44.28	0.04
TOTAL	120971.40	100	120971.00	100	120971.40	100

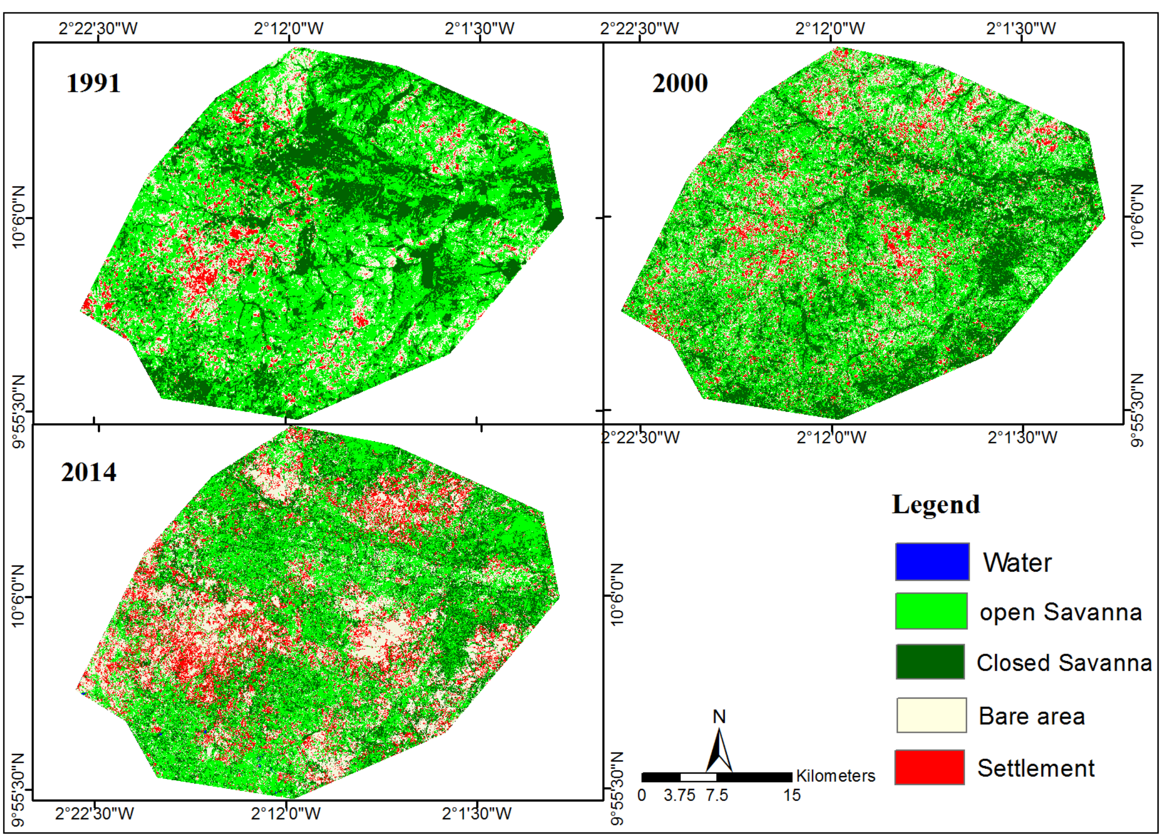

Figure 3: Land use Land cover Map for the years 1991, 2000 and 2014.

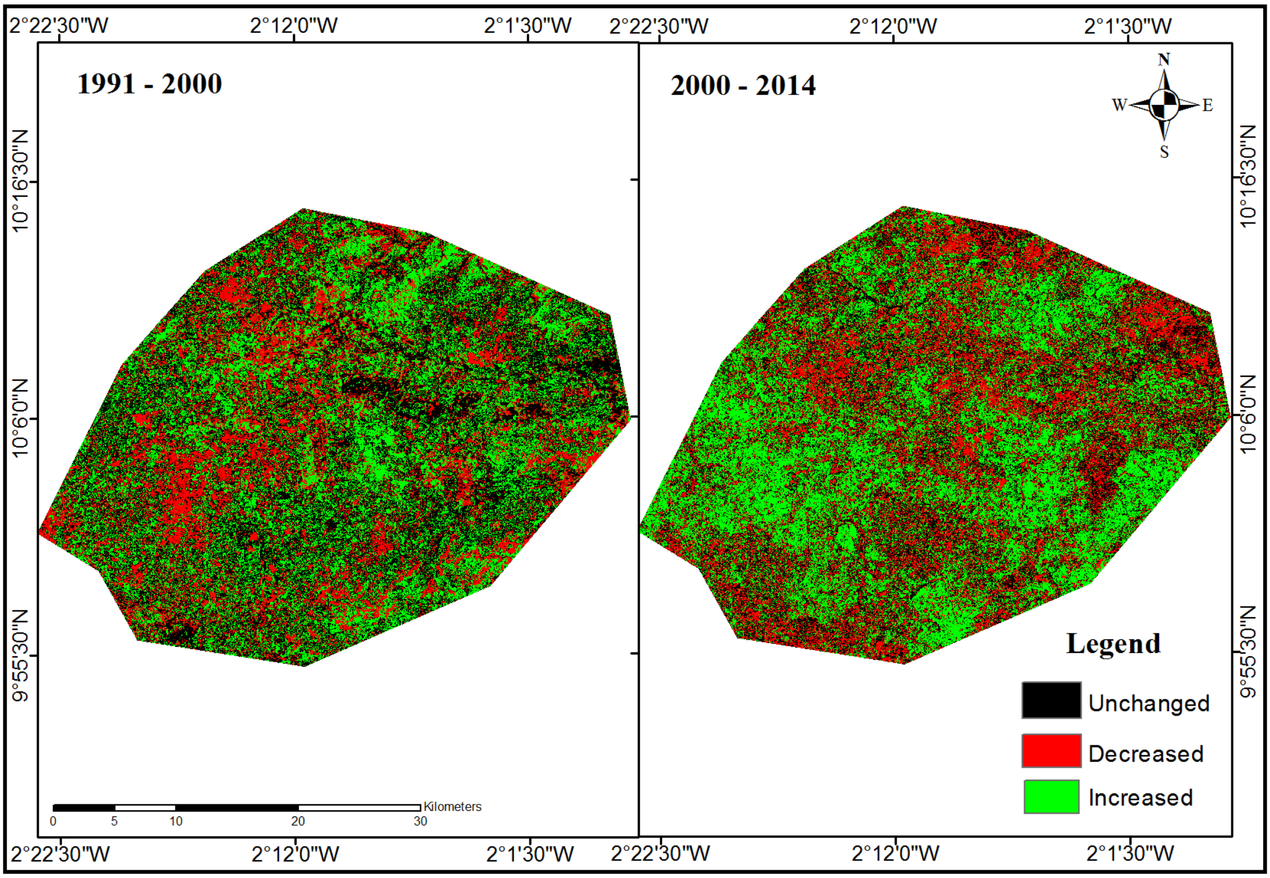

Figure 4: Image Differencing Map.

3 Results and Discussion

The results of the classification for the LULC for the years 1991, 2000 and 2014 is shown in Figure 2. As indicated in Table 1, the LULC had five main classes. The area covered by water was visible in the LULC map of 2014 only. This was as a result of some Dams and dug outs construction in the district of recent times.

Figure 3 and Table 3 clearly shows significant changes in LULC in the case study area. In the South Western part, from 1991 to 2000 settlement and bareground decreased whiles from 2000 to 2014 settlement and bareground increased. This increase in settlement and baregrounds can be associated to increase in socio economic activities in the study area. The socio economic activities in the area is mainly farming and quite recently the activities of small scale and large scale mining. According to the Ghana Statistical Service(GSS) report for 2010, 94 percent of households in the district engaged in agriculture and their household dwellings largely rural [26]. Also, the Ghana News Agency (GNA) report 2013 showed mining concessions and illegal mining activities having increased in the study area from the year 2000. The report links gold exploring concessions belonging to Azumah Resources Limited, Castle Minerals and Carlie Minerals, all in the Wa East District taken over by illegal miners whose activities were impacting negatively on the environment and water bodies [27].

The activities of mining 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. Studies in Talensi-Nabdam District of Ghana have witnessed higher number of migrants, both locals and foreigners, especially in the mining communities of recent times [28]. They put up temporal structures as place of residence and are usually drifted towards the mine sites. The increase in population and increase in mining activities which implies conversion of other LULC classes into Settlements and baregrounds could be a reason for the general increase in the settlement and baregrounds LULC across the study area.

Open Savannah is the most dominant class throughout the three years. This is consistent with studies car-

Table 4: Change matrix from 1991–2014.

1991–2014	Open Savannah	Closed Savannah	Bare ground	Settlement	Water	TOTAL
Open Savannah	**23339.25**	14227.74	15868.17	8010.72	9.81	61455.69
Closed Savannah	15441.03	**10035.9**	5518.17	2607.39	32.04	33634.53
Bare ground	4419.81	2678.04	**8162.64**	4684.95	2.16	19947.6
Settlement	1012.05	486	2666.97	**1768.32**	0.27	5933.61
Water	0	0	0	0	**0**	0
Total	44212.14	27427.68	32215.95	17071.38	44.28	**120971.43**

Table 5: Image Differencing Statistics.

LULC Difference	LULC (2014–2000)	LULC (2000–1991)
Increased (%)	25.53	21.89
Unchanged (%)	56.38	62.35
Decreased (%)	18.09	15.75

Table 6: Summary statistics of NDVI values.

Values	Summary statistics of NDVI values		
	1991	2000	2014
Minimum	−0.3	−0.62	−0.08
Maximum	0.48	0.33	0.11
Mean	0.04	−0.02	−0.02
Standard Deviation	0.05	0.04	0.02

ried out in the Upper West Region where the study area is based [29, 30]. From Table 3, it can be seen that Open Savannah decreased from 50.80% to 36.55% from 2001 to 2014 and Closed Savannah also reduced from 27.80% to 22.67% from 2001 to 2014. These reductions in Savannah vegetation can also be attributed to population increase in the study area. This is clearly shown in the change matrix provided in Table 4.

The change matrix shows how a total of 5,483.86 Ha of Open Savannah was converted to Settlements (4,419.81 Ha) and Bare ground (1012.05 Ha) reducing Open Savannah from 61455.69 Ha in 1991 to 44212.14 Ha in 2014. Furthermore, Table 4 clearly shows a total conversion of 3164.04 Ha of Closed Savannah of the study area to Settlement (486 Ha) and Bare ground (2678.04 Ha) reducing Closed Savannah from 33634.53 Ha in 1991 to 27427.68 Ha. Population increase exerts pressure on dwindling vegetation cover and it also leads to increase in settlement and bare areas. Settlement increased from 4.9% to 14.11% from 1991 to 2014. Similar studies in Shiwalik hills also attributed land-use and land-cover change to the increase in population size and per-capita requirement of natural resources [31].

Mining activities is another significant driver to the decrease in Open and Closed Savannah lands in the study area. The area is characterized by mining activities especially around Bulenga, Donfia, Mengwe and Donyoukuraa enclave. The instance of loss of vegetation in mining areas is not new [32]. In comparison with other studies in Brazil, Venezuela Tanzania and Zimbabwe, there has been evidence to prove that mining activities has a considerable effect on loss of vegetation [33–35].

The issue of wildfires common in the area studied also accounts for the loss in vegetation and increase in bare areas. A spatio-temporal analysis of wild fires in the savannah zone of the Northern parts of Ghana attest to the above [36]. The use of multispectral images in this study is also highlighting the rate at which the relatively forested areas like the Close Savannah is gradually turning to Open savannah and Bare areas. This raises alarm in these areas were large concession of mining has begun though not in full force like the other mine areas in Ghana.

Figure 4 shows all changes from 1991–2000 and 2000–2014. Table 5 also shows the statistics of change in LULC classes based on increase or decrease and LULC that remained unchanged. From Table 5 56.38% (1991 to 2000) and 62.35% (2000-2014) of LULC classes remained unchanged, whiles 25.53% and 21.89% of LULC classes increased and 18.09% and 15.75% of LULC classes decreased respectively for 1991 to 2000 and 2000 to 2014.

NDVI values for the various years 1991, 2000 and 2014 was derived and showed in Figure 5. This was essential in correlating the NDVI results with the LULC maps generated in the study area. The values as from the years 1991 to 2014 changed from −0.302 to −0.063 and from 0.478 to 0.108 signifying a reduction in the health of green vegetation in the area.

Table 6 shows the amount of greening or healthy vegetation has reduced from a mean of 0.04 to −0.02 just as in Figure 3. A healthy vegetation normally ranges from the

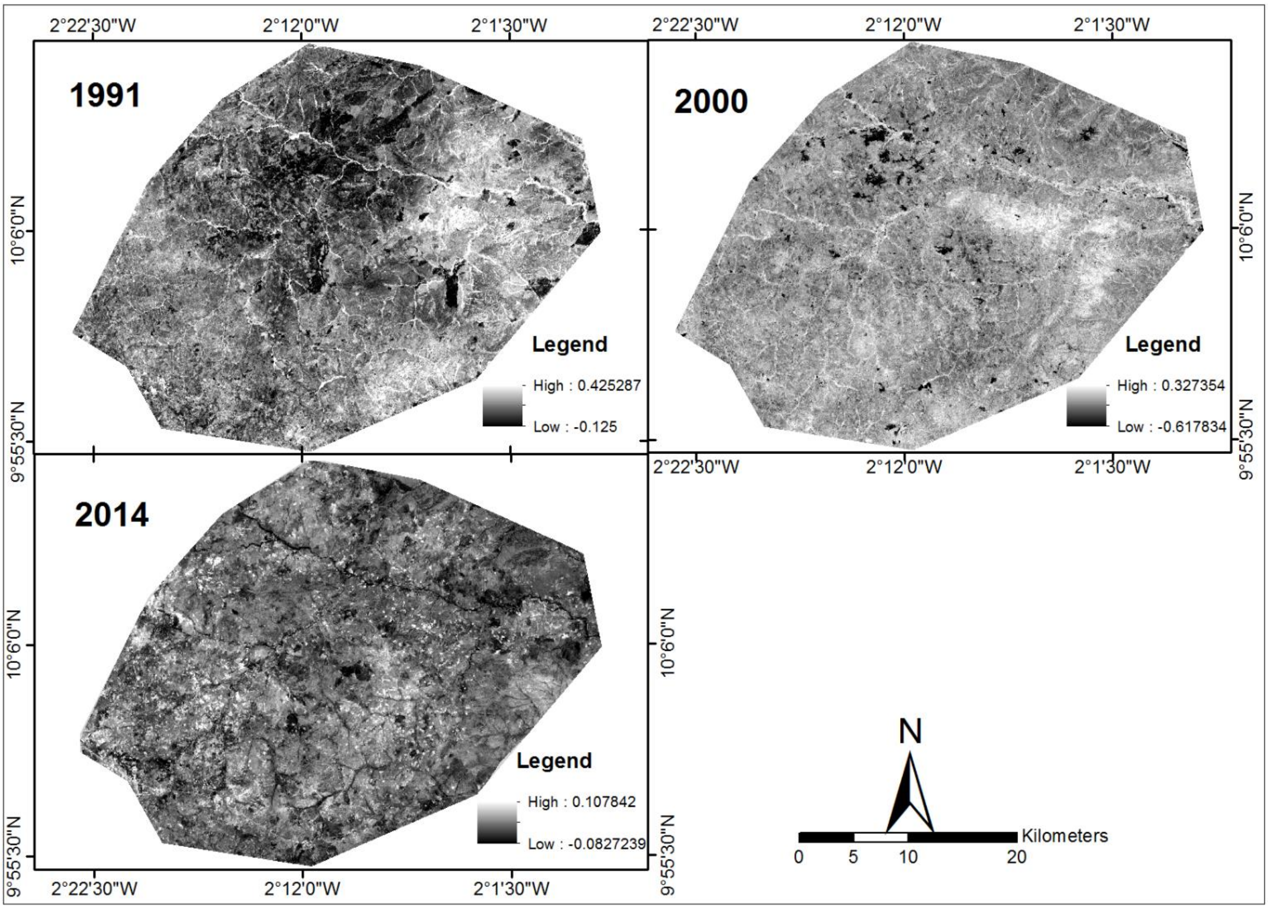

Figure 5: NDVI values for the years 1991, 2000 and 2014.

positive values close to 1. Similar studies within the region using NDVI showed evidence of remarkable land degradation and reduction in vegetation in the Upper East, Upper West and Northern Regions of Ghana [37].

4 Conclusion

This paper focuses on LULC changes in an area characterized by the influx of Gold mining activities to ascertain the LULC changes. The dominant LULC class was Open Savannah. The results clearly show that Open Savannah and Closed Savannah are reducing whereas Settlement and Bare areas are increasing. The other vegetative methods mainly NDVI and Image differencing have also shown a great loss or reduction in the amount of healthy vegetation in the area. The use of this approach in the area is novel as it has clearly demonstrated the potential of GIS and remote sensing techniques in measuring the change pattern of LULC in the area characterized by the influx of mining. There is therefore the need to obtain very high resolution satellite images to delineate the mine areas and quantify the real impacts of the mines specifically. The outcome of this research is raising concerns of decreased vegetation in a mining area. It would therefore help in specifying models of land-use change. It would aid in future projections as well as enable the Minerals Commission of Ghana and the Environmental Protection Agency (EPA) fashion out policy for potential environmental changes in the study area.

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