A Hybrid Image Classification Approach to Monitoring LULC Changes in the Mining District of Prestea-Huni Valley, Ghana

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Abstract
Mining and other anthropogenic activities are increasingly destroying forest cover in tropical forest areas of Africa, threating to deplete the entire forest reserves. These depletions not only affect the ecosystems but also have dire implications on global ecological balance and climate. Using Landsat 7 ETM+ satellite images, the study used a combined unsupervised and supervised classification methods to determine the rate of change of the various land use and land cover classes in the mining district of Prestea Huni Valley. The method produced very high accuracies with the least overall accuracy being 95.4272% with a Kappa coefficient of 0.9339. A change detection analysis revealed very significant loss of forest cover as a result of direct mining activities to be 96.78 square kilometres between 2002 and 2015. The results also suggested an overall forest cover loss rate of about 71.63 square kilometres per annum for the periods between 2002 and 2015 which poses a threat to the 493.55 square kilometres of forest cover left in the study area study, if proper monitoring and rehabilitation programmes are not put in place.
Keywords: LULC, Degradation, Hybrid Classification, Surface Mining, Forest Cover, Environment, Landsat ETM+

1 Introduction

Anthropogenic and natural activities have caused various forms of alterations to natural landscape leading to land use and land cover (LULC) changes. These have resulted in different forms of degradation with its resultant adverse effects on arable land, ecosystem, biodiversity, water bodies, greenhouse effects, forestry, ambient climate, and soil amongst others (Ayine 2001; Fonji & Taff 2014; Vittek et al. 2014). According to Malaviya et al. (2010) and Musa & Jiya (2011) the conflict between human interests and nature has been the major factor of LULC changes. Top amongst these conflict of interests are industrialization, urbanization, and intensification of agriculture.

Surface mining, both small and large scale, is one of the most destructive industries that result in massive land use and severe environmental changes in the world. Mining is known to have had adverse effects on land, surface hydrology, groundwater, ambient air and human health (Ogola et al. 2002; Zobrist & Giger 2013). According to Scheueler et al. (2011), the destructive effects of mining activities on the environment and catchment communities can outweigh the socio-economic and infrastructural benefits if strict environmental monitoring and rehabilitation codes are not in place. In early 2006 artisanal surface mining (galamsey) became so popular in the Prestea Huni Valley District (PHVD) that it became a threat to natural forest covers and farm lands. The activities of surface mining continue to degrade forest, farmlands and creeks within the catchment area until now. These activities usually destroy the land without any corrective or rehabilitation obligations. The destructive effects of surface mining on the natural land can span several thousands of hectares which can occur within relatively short time periods. Traditional environmental and land degradation monitoring approaches including surveying have proven to be inadequate for timely and cost effective degradation and LULC change monitoring. Using multispectral optical remote sensing methods, these rapid vast land deformation and changes can be monitored over specific periods to ascertain annual rate of degradation in order to map out effective reforestation, rehabilitation and land restoration strategies by the various stakeholders, regulators, and policy makers (Gupta 2001; Firouzabadi et al. 2008; Weih Jr & Riggan Jr 2010; Zhang & Wang 2014).

In order to manage resource exploitation, whilst protecting the natural environment, LULC classification techniques have been developed to classify, map, quantify and monitor the extents of environmental changes (Anderson 1976; Xiubin 1996; Fonji & Taff 2014). Scholarly studies conducted on LULC have predominantly been based on either supervised or unsupervised classification techniques to classify and quantify detected land use changes. These have been identified to give fairly good accuracies, each with merits and demerits based on feature heterogeneity amongst other factors (Congalton 1991; Hégarat-Mascle et al. 1997; Giacinto et al. 2000; Bruzzone et al. 2002). Due to the relative uniformity in brightness levels across several spectral classes and relative difficulty in identifying very distinct land use classes, a hybrid approach was adopted for this study in order to utilise the merits of both approaches to enhance the overall accuracies of the classification. According to studies conducted by Enderle & Weih Jr (2005) and Omo-Irabor & Oduyemi (2007), accuracies of classification of medium resolution images like Landsat TM/ETM+ can be increased by integrating

both methods. Studies conducted by Kantakumar & Neelamsetti (2015) also used a hybrid method that combined both unsupervised and supervised classification methods by initially identifying "natural" pixel classes within the image without prior knowledge and then using the training data to define the identified classes.
In this study, a hybrid approach is utilised to classify Landsat TM/ETM+ image and detect LULC changes in the study areas over the past two decades as result of mining and other anthropogenic activities.

2 Materials and Methods Used

2.1 Study Location

The Prestea Huni Valley District (PHVD) is in the Western Region of Ghana, in West Africa. The Local Authority District (LAD) is bounded on the north and south by latitudes 5°39’N and 5°21’N respectively, and on the east and west by longitudes 1°53’W and 2°12’W respectively. PHVD is the third largest gold producer in West Africa after Obuasi and Tarkwa districts (over 250 metric tonnes of gold during the last century). The district as one of the nation’s highest rainfall regions has several hectares of tropical forest cover and reserves. It has 2 large scale surface mining operations with over 3,000 workforces, an underground mine and several other small scale mining groups (predominantly artisanal mining groups). The main economic activities in PHVD is mining, agriculture, and trading. Figure 1 below shows a map of the study area.

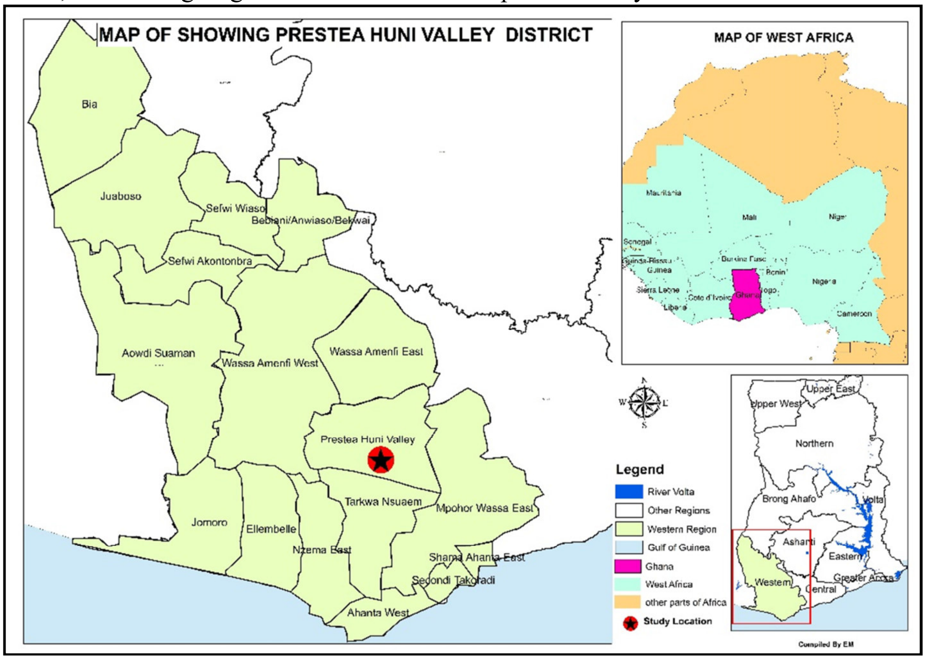

Figure 1: Map showing Study Location

2.2 Data

This study made use of Landsat historical imageries from the Landsat 7 Enhanced Thematic Mapper plus (ETM+). The data was acquired from the United States Geological Survey (USGS) Earth Resource Observation Data Center through the Glovis website. The choice of Landsat data source was made on the basis of extensive continuous imagery archives, higher spectral and spatial resolution, consistency, comparably low cost of acquisition, quality, and frequency of observation which makes it suitable for LULC monitoring and management. Based on the year of comparison identified for this study, Landsat 7 (ETM+) images covering the different time periods (multi-temporal) were used to derive land cover data for 2002, and 2008, and 2015. The image quality was limited to not more than 5% cloud cover. The characteristics considered for the choice of acquired satellite images depended on their technical specifications, which included temporal resolution, spatial resolution, spectral resolution, cloud cover, zenith/nadir angle, sun elevation, swath width, and image size (Lasaponara & Masini 2012; Jones 2015). Table 1 shows meta data and technical specification of images used for the LULC classification and change detection analysis.

Table 1: Meta data and Technical Specification of Image Used

Western Region				
	Data Set Attribute	Attribute Value		
Meta Data	Landsat Scene Identifier	LE71940562002015EDC00	LE71940562008032ASN02	LE71940562015355ASN00
	Spacecraft Identifier	LANDSAT_7	LANDSAT_7	LANDSAT_7
	WRS Path	194	194	194
	WRS Row	56	56	56
	Date Acquired	2002-01-15	2008-02-01	2015-12-21
Technical Specification	Temporal Resolution	16 days	16 days	16 days
	Spatial Resolution	30m	30m	30m
	Spectral Range	0.45-12.50µm	0.45-12.50µm	0.45-12.50µm
	Cloud Cover	0	0	0
	Number of Bands	8	8	8
	Sensor Type	opto-mechanical	opto-mechanical	opto-mechanical
	Swath	183km	183km	183km
	Image Size	183km x 170km	183km x 170km	183km x 170km
	Sun Elevation	49.20	50.97	51.77
	Sun Azimuth	132.17	126.68	140.77

Source: (USGS, 2014; NASA, 2015)

Landsat 7 ETM+ has archive data on the earth's land over the past three to four decades, creating a historical archive extensive enough for global coverage, yet detailed enough to characterize human-scale processes on a large scale (Jones 2015). Its multispectral characteristics and medium temporal and spatial resolutions makes it especially suitable for LULC change detection covering larger areas. Using the standard 'false colour' composite (bands 4, 3, and 2), the natural colour band combinations (bands 3, 2, and 1), and the 'natural-like' rendition band combinations (bands 7, 4, and 2), a colour image RGB is created to help in the LULC change classification and identification of the various land use classes within the study area.

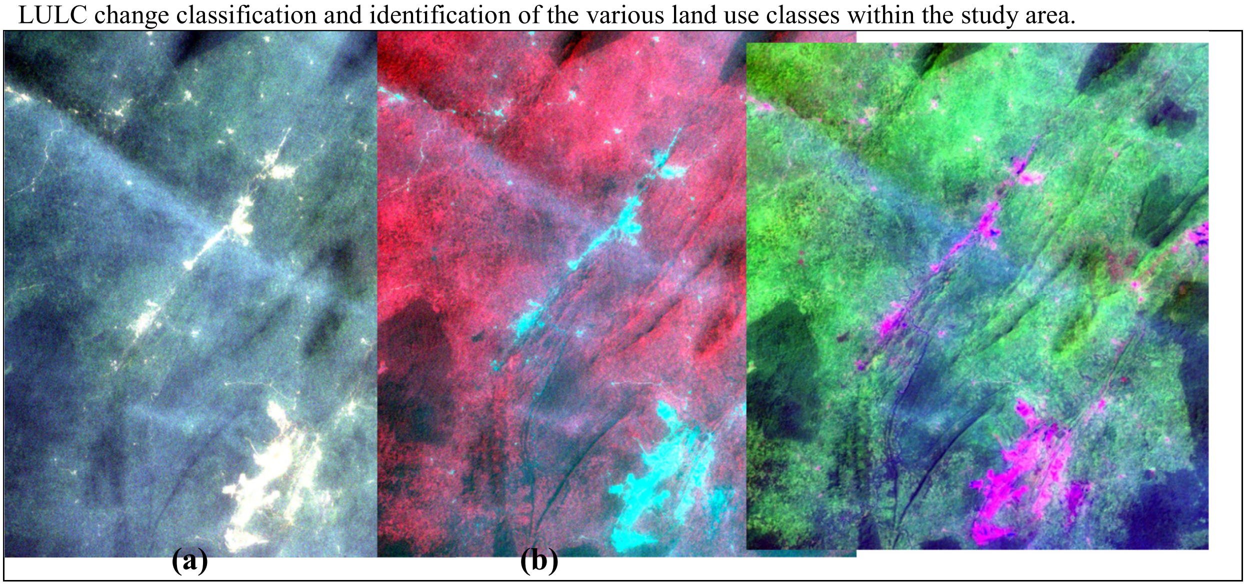

Figure 2: Colour RGB band combinations - the natural colour band combinations (3, 2, 1), 'false colour' composite (4, 3, 2), and the 'natural-like' rendition band combinations (7, 4, 2)

Figure 2 above shows the colour RGB band combinations used for the LULC classification analysis.

Forty (40) ground points' coordinates data (x,y) each of the different LULC classes within the study area were also surveyed using a GPS. These points were used as ground truth data for the supervised classification and accuracy assessment.

2.3 Methods

The methodology involved image pre-processing and image classification. The image processing stage of the methodology involved spatial/spectral subsetting and gapfilling. The spatial subsetting process involved cropping out unwanted geographical areas that do not form part of study area. Spectral subsetting on the other hand was used to limit the application of the classification analysis to selected bands of the image. Using the Localized Linear Histogram Match (LLHM) technique, gaps in Landsat 7 ETM+ images with Scan Line Corrector (SLC) off which results in approximately 22% data loss, were filled with data from previously acquired Landsat scene without data gaps (Scaramuzza et al 2004). The process is a two band linear transformation approach which is applied to the "filling" image to adjust it based on the standard deviation and mean values of each band, of each scene. A hybrid approach of both image classification techniques, unsupervised and supervised, were adopted in this study. The first approach involved the use of K-means unsupervised classification method to identify individual pixels to be classified by searching for natural clusters within the dataset. These identified clusters of all pixels in the image were subsequently used as a basis to compare actual LULC classes that are actually present in the study area using land cover maps, and aerial photos to create digitised preliminary training data (Lee & Lewicki 2002). Ground truth training data and the preliminary training data are then used to define the training locations which are representative samples for each LULC class in the image (Foody & Mathur 2004). The supervised classification technique used was the Maximum Likelihood Classification (MLC) which was derived from the Bayes theorem (Strahler 1980; Foody et al 1992; Maselli et al 1994). It is based on the probability that a pixel with a particular feature vector belongs to a particular land cover class based on the training of a visual classifier for four different land use LULC classes (Asmala 2012). The process makes use of a discriminant function to allocate each pixel to the class with the highest likelihood. Class mean vector and covariance matrix are the important inputs to the function and are estimated from the training data of a particular class (Perumal 2010). The LULC classes used for the supervised classification included forest (woodland), light vegetation, disturbed land and settlement, and water bodies. Figure 3 shows the methodological process model adopted for the study.

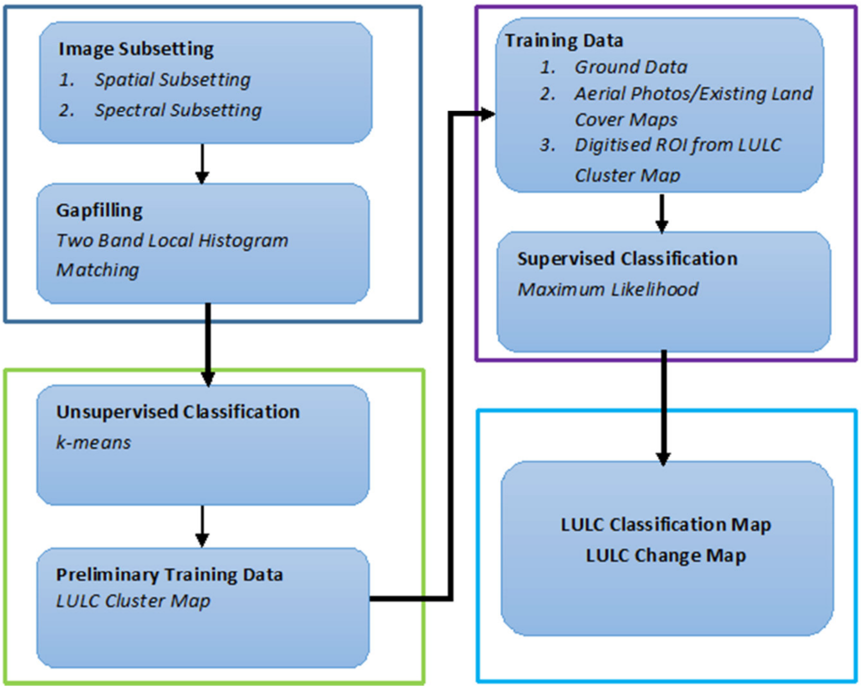

Figure 3: Methodological Model for Study

The purpose of adopting a hybrid approach to classification was to increase the overall classification accuracies. Accuracy assessment simply quantifies how good a classification was done by the classifier. The accuracy of a classification is a validation process conducted by comparing the classification results with ground truth referenced data that accurately reflects the true land-cover of the study area (Brabyn et al. 2014). The accuracy assessment therefore was a representation of the difference between the final supervised classification and the reference data. As result, highly accurate reference data that are randomly distributed over the study area were selected for the assessment while keeping in mind the temporal significance of the reference data to the overall accuracy assessment.

3 Results and Discussion

3.1 LULC Classification and Change Detection

The final LULC classification was used to prepare maps to be used to visualize LULC changes for PHVD and to compare various classes of land cover across the study area. Using maximum likelihood classification, four distinctive land cover classes were chosen for the identification and display of the spectral signatures of land cover/land use types – mining areas/settlement, vegetation, forest, and water bodies. The areas classified as vegetation were mostly either agricultural farmlands or non-agricultural vegetation. The water bodies within the study area were either water in tailings embankments or ponds of water in mined out pits of both large scale corporate mining and artisanal miners. Figure 4 shows the LULC classification across the study area during 2002 and 2008.

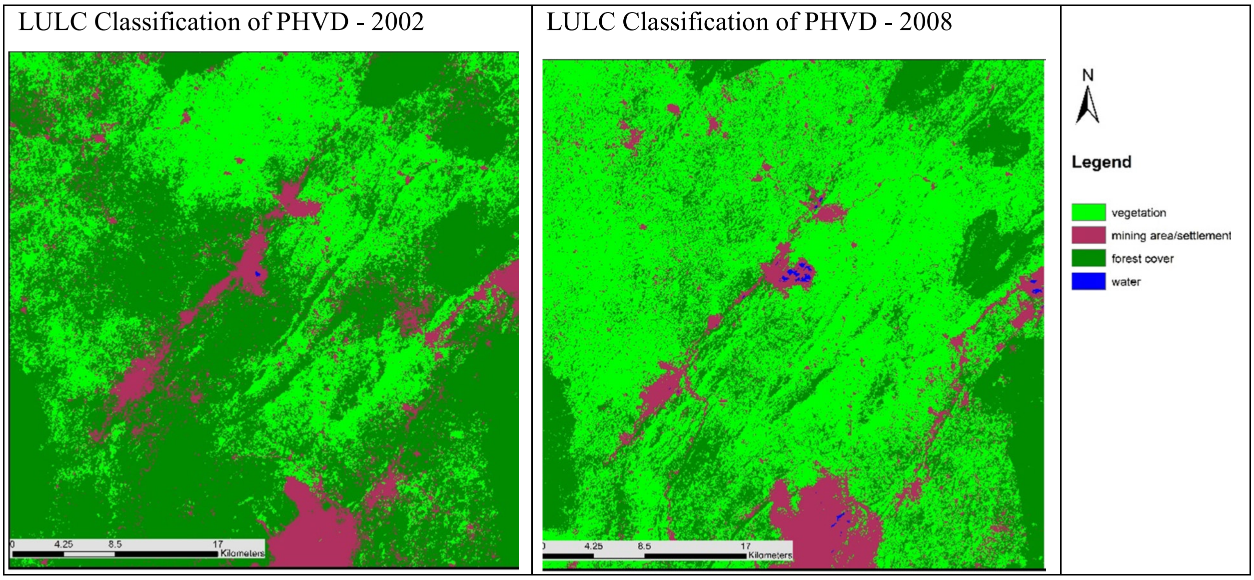

Figure 4: LULC Classification Map of PHVD – 2002 and 2008

Table 2, which is the change detection statistics for the period between 2002 and 2008 shows significant changes in the LULC classes in PHVD with increase in overall vegetation and water by about 786.75 and 2.12 square kilometres respectively. This increase in vegetation cover is primarily due to the conversion of large areas of forest (about 732.59 square kilometres) to agricultural farmlands, clearing of forest for mining activities, and illegal logging of timber species without replacement. Areas of water have increased due to the expansion of tailings water storage facility of a corporate mining operation and also ponding of a few of their mined out pits.

Total loss of forest cover between 2002 and 2008 amounted to about 758.63 square kilometres. This corresponds to forest cover loss of about 126 square kilometres per annum between 2002 and 2008. It can be seen from table 2 that mining activities and urbanisation caused directly very significant degradation of about 101 square kilometres (25.42sq. km in vegetation loss and 75.54sq. km in forest cover loss), representing 16.8 square kilometres per annum of degraded land as a result of mining and urbanisation. However, overall mining and settlement areas reduced from 282.16 square kilometres in 2002 to 251.93 square kilometres in 2008. This may be attributed to rehabilitation of mined out areas by corporate mining organisations with vegetation and vegetation growth as a result of abandonment (114.32 sq. km).

Forest area recovery (15.69 sq. km) was also as a result of planned rehabilitation with forest tree species and forest growth as a result of abandoned agriculture. This reduced resultant degraded land as a result of mining and urbanisation between 2002 and 2008.

Table 2: Change Detection Statistics 2002 - 2008

CHANGE DETECTION 2002 TO 2008 - Area (Square Kilometers)						
	Initial State					
Final State	Vegetation	Mined areas/settlement	Forest	Water/Ponds	Row Total	Class Total
Vegetation	541.36	114.32	732.59	0.00	1388.27	1388.27
Mined areas/settlement	25.42	150.90	75.54	0.07	251.93	251.93
Forest	34.67	15.69	687.31	0.00	737.67	737.67
Water	0.06	1.26	0.87	0.10	2.28	2.28
Class Total	601.52	282.16	1496.30	0.16	0.00	0.00
Class Changes	60.16	131.26	808.99	0.07	0.00	0.00
Image Difference	786.75	-30.23	-758.63	2.12	0.00	0.00

Table 3: Summary Statistics of LULC Change Detection 2002 - 2008

Summary Comparison of LULC Change Detection 2002 - 2008								
Land Cover(LC) Classes	2002 LUlC Area		2008 LULC Area		Area Change from 2002 - 2008		Annual Rate of Change 2002 - 2008	
	Sq. Km	%	Sq. Km	%	Sq. Km	%	Sq. Km/yr	%
Vegetation	601.52	25.27	1,388.27	58.33	+ 786.75	+ 130.79	+ 131.13	+ 21.80
Mined areas/settlement	282.16	11.85	251.93	10.58	- 30.23	- 10.72	- 5.04	- 1.79
Forest	1,496.30	62.87	737.67	30.99	- 758.63	- 50.70	- 126.49	- 8.45
Water	0.16	0.01	2.28	0.1	+ 2.12	+ 1284.15	+ 0.35	+ 214.03
Total	2,380.15	100.00	2,380.15	100.00				

From the LULC classification map in figure 5 and the change detection statistics table 4, there was further reduction in forest cover in the study area and corresponding increase in vegetation, mining and settlement areas, and water.

Overall vegetation/agricultural land cover in PHVD increased by 201.95 square kilometres (14.55%). From table 5, overall mining and settlement areas increased by 14.43 square kilometres (5.73%). Vegetative cover loss due to mining and settlement areas was 100.15 square kilometres and forest cover loss attributable to mining and settlement was 27.76 square kilometres. Total degraded land as a result of mining and settlement for the period between 2008 and 2015 was 127.91 square kilometres. This represented an annual degradation between the periods as 16.00 square kilometres. Table 5 also shows an overall change of 27.74 square kilometres in water and pond areas which indicates an annual increment of 3.47 square kilometres. These are attributable mainly to mined out pits that have been filled with rainwater and the expansion of the Bogoso surface mine tailings water storage facility. Total degradation liability as a result of mining and settlement for the study area therefore amounted to 42.17 square kilometres as of December 2015. Total forest cover continued to be depleted at an alarming rate of 30.52 square kilometres per annum over the 8 year period between 2008 (January) and 2015 (December).

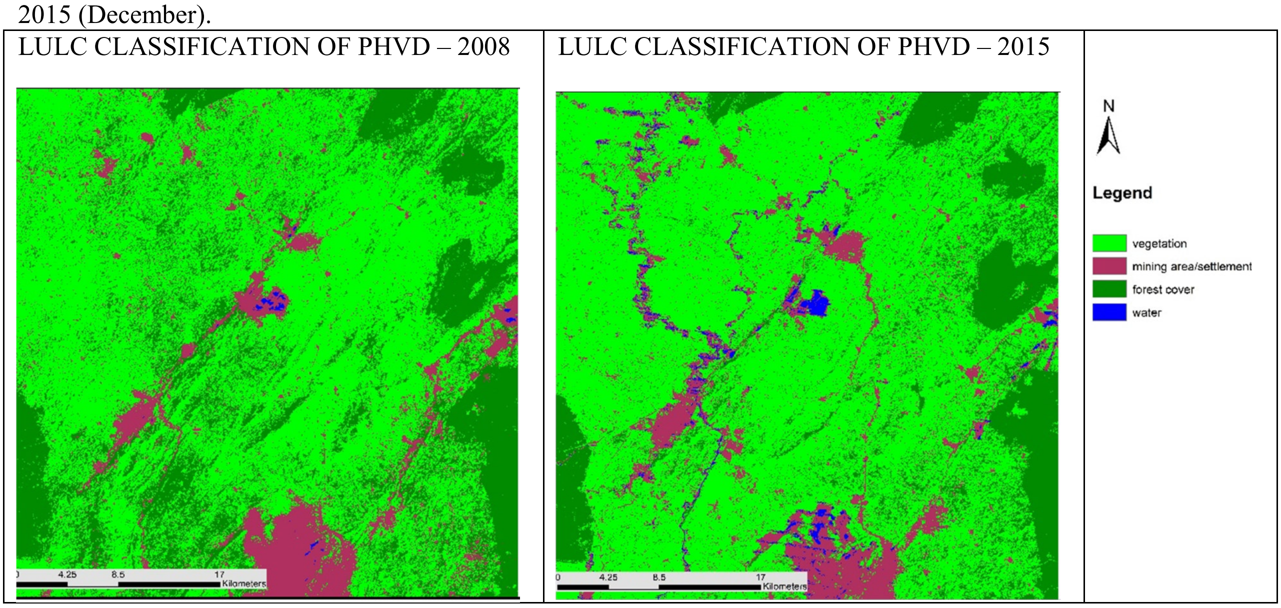

Figure 5: LULC Classification Map of PHVD – 2008 and 2015

Significant areas of forest cover (306.83 sq. km) was lost to agricultural farmlands and other vegetation outgrowths. This accounts for about 41.60 per cent of forest cover loss between 2008 and 2015. Total effective forest cover loss between January 2008 and December 2015 was 244.12 square kilometres (339.97 sq. km loss and 95.85 sq. km gain)

Table 4: Change Detection Statistics 2008 - 2015

CHANGE DETECTION 2008 TO 2015 - Area (Square Kilometers)						
	Initial State					
Final State	Vegetation	Mined areas/settlement	Forest	Water/Ponds	Row Total	Class Total
Vegetation	1192.62	90.73	306.83	0.04	1590.22	1590.22
Mined areas/settlement	100.15	138.11	27.76	0.35	266.36	266.36
Forest	86.90	8.95	397.70	0.00	493.55	493.55
Water	8.60	14.14	5.39	1.89	30.02	30.02
Class Total	1388.27	251.93	737.67	2.28	0.00	0.00
Class Changes	195.65	113.82	339.97	0.39	0.00	0.00
Image Difference	201.95	14.43	-244.12	27.74	0.00	0.00

Table 5: Summary Statistics of LULC Change Detection 2008 - 2015

Summary Comparison of LULC Change Detection 2008 - 2015								
Land Cover(LC) Classes	2008 LUlC Area		2015 LULC Area		Area Change from 2008 - 2015		Annual Rate of Change 2008 - 2015	
	Sq. Km	%	Sq. Km	%	Sq. Km	%	Sq. Km/yr	%
Vegetation	1,388.27	58.33	1,590.22	66.81	+ 201.95	+ 14.55	+ 25.24	+ 1.82
Mined areas/settlement	251.93	10.58	266.36	11.19	+ 14.43	+ 5.73	+ 1.80	+ 0.72
Forest	737.67	30.99	493.55	20.74	- 244.12	- 33.09	- 30.52	- 4.14
Water	2.28	0.1	30.02	1.26	+ 27.74	+ 1216.78	+ 3.47	+ 152.10
Total	2,380.15	100.00	2,380.15	100.00				

Though the change detection statistics showed a decrease in mining area/settlement by 5.04 square kilometres per annum between 2002 and 2008, there was however an increase in mining areas between 2008 and 2015 by almost 5.27 square kilometres (1.80 sq. km – increment in mining area and 3.47 sq. km – increment in ponded mined out pits). Also in the periods between 2002 and 2008, 130.1 square kilometres (86.16%) of mining areas were covered with vegetation or forest cover as opposed to 99.68 square kilometres (72.17%) of vegetative or forest cover of mining areas for the period between 2008 and 2015. This represented an annual class change of mine land rate of 21.68 square kilometres between 2002 and 2008 as opposed to 12.46 square kilometres per annum for 2008 to 2015. The statistics suggest a reduction in rehabilitation efforts between 2008 and 2015, however the increase in uncontrolled artisanal mining contributes largely to the observed increase in degraded lands. Mining activities can be thought of having a rippling effects on all the four main LULC changes within the study area. Most farmers who lose their agricultural lands to mining activities (25.42 sq. km in 2002 to 2008 and 100.15 sq. km in 2008 to 2015) encroach into forest zones to continue with their farming. This further causes a reduction and conversion of forest cover to agricultural farmlands. Some mining activities also take place within the forest zones (75.54 sq. km in 2002 to 2008 and 27.76 sq. km in 2008 to 2015) which also cause direct forest cover loss and degradation of land. The figure 6 below shows a graphical representation of the LULC changes.

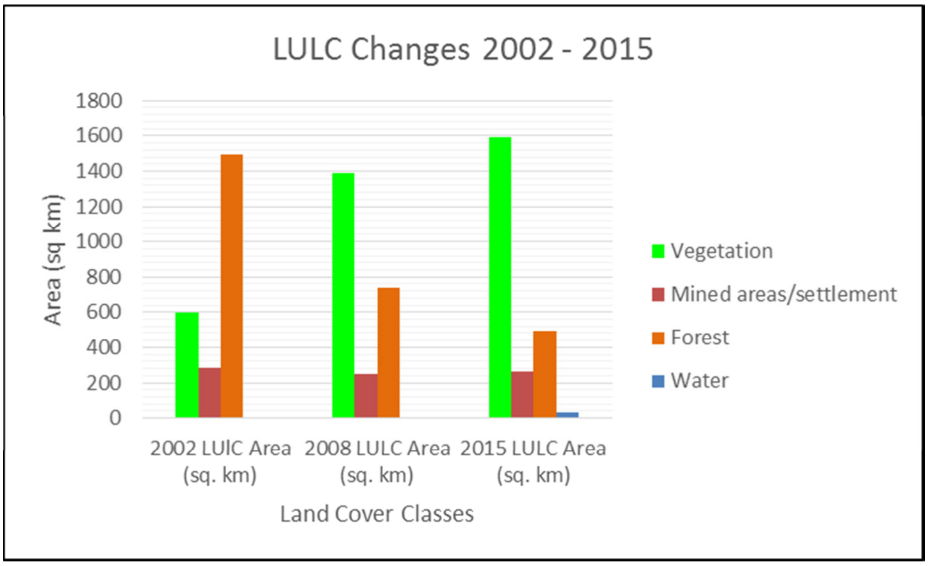

Figure 6: LULC Changes – 2002 to 2015

3.2 Accuracy Assessment

Using the class confusion matrix, an appraisal of the performance of the classifier was done to show the number per class of well classified and mislabelled instances. The salient measures of accuracy were the overall accuracy expressed as a percentage of the total number of pixels classified correctly and the kappa coefficient which is an estimation of agreement in categorical data by extracting the actual percentage expected by chance from the correctly classified percentage (Landis & Koch, 1977). Table 6 shows the accuracy assessment of the classification for each of the 3 different years classified showing the overall accuracies and their corresponding kappa coefficients. The combined classification approach was very useful and produced very good classification accuracies.

Table 6: Summary LULC Accuracy Assessment

	LULC Accuracy Assessment	
Year	**Overall Accuracy (%)**	**Kappa Coefficient**
2002	96.0691	0.9350
2008	95.4272	0.9339
2015	95.8346	0.9370

4 Conclusion

The significant increase in both vegetation, and mine and settlement areas are as result of the vast decrease in forest cover between 2002 and 2015. Only about 30% of the existing forest cover of 2002 exists in 2015 with about 62% direct loss to vegetation and farming and about 6% direct loss to mining and settlement. Whiles farming and other anthropogenic activities have contributed to the fast depletion of the forest cover, mining has also accounted for a significant amount of the depletion. Vegetation and farming areas loss to mining was about 14% of the entire mined area and forest cover loss accounted for about 36% which is more than twice the loss of farmlands to mining activities. This shows the distructive effect of these artisanal mining activities on forest cover. The continous cycle of farmers relocating farmlands by clearing forest areas for new farms to make up for mining land take, affects forest areas most as seen in studies also conducted by Scheueler et al. (2011). The environmental and forest cover liabilities caused by mining, industrilisation and urbanisation need to be properly monitored and reported to create awareness on the extent of degradation and destruction within these communities. Most artisanal mine land takes, are aboadoned to allowed vegetation growth, but this practice does not assure effective land restoration and rehabilitation. The study shows an alarming continous reduction in forest cover which has various environmental implications on the study area including reduction in capacity to sequester carbon, susceptibility to soil erosion, biodiversity losses, ecological imbalance, and climatic changes (Fonji & Taff, Using satellite data to monitor land-use land-cover change in North-eastern Latvia, 2014). The continous monitoring of reduction of forest cover is therefore important for mining regulators, environmental protection agency, town and country planning, various stake holders and the government to take a proactive approach in monitoring and enforcing mining and development laws to manage and conserve the fast depleting forest cover within the study area and the region at large. Concessions of mining companies are therefore needed to be properly demarcated and their mining areas monitored to determine the annual rates of LULC changes as a result of their operations and charged to effectively restore lost forest cover. Small scale artisanal mining should be properly regulated and regulators should also ensure their adherance to mining and environmental rehabilitation laws.

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