IMPACT OF MINING ON VEGETATION COVER: A CASE STUDY OF PRESTEA HUNI-VALLEY MUNICIPALITY

BY

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DECLARATION

I hereby declare that this research was carried out by me, Biney Nathaniel (PG9264817) in the Department of Geometric Engineering, Kwame Nkrumah University of Science and Technology, Ghana, under the Supervision of Dr. Isaac Dadzie, and that no previous submission for Degree of this University or elsewhere has been made. The works of other authors which served as sources of references and information have been duly acknowledged.

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DEDICATION

I dedicate this work to the cherished memory of my parents Mr. Francis Kofi Biney and Madam Victoria Essien.

ACKNOWLEDGEMENTS

I first and foremost appreciate and give all glory to the Most High God.

The success of a project of this nature depends on the contribution of many people; especially those who spent time and share their thoughtful criticism and suggestions to improve this project.

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ABSTRACT

Land use and land cover (LULC) change, also known as land cover change is a general term for the human and physical modification of the earth's terrestrial surface. LULC changes are the direct and indirect consequences of human actions to secure essential resources for a successful livelihood. It has therefore become very necessary to analyze such changes for the effective management of natural resources and the protection of our environment to ensure its continuous existence and usage. Anthropogenic factors such as urbanization, mining and population increase in the Prestea Huni-Valley Municipality are causing rapid changes to LULC. These factors and others are putting a lot of pressure on the forest vegetation and this has dire consequences on the availability and protection of the vegetative cover. In view of this, the study focused on assessing the impact of mining on vegetation cover with particular focus on Prestea Huni-Valley Municipality. Multi-spectral satellite images of the study area from 1986 to 2016 were spatially analyzed to identify the LULC change patterns. Modelling and analysis of these images were performed using Erdas Imagine Software and R. Six LULC classes were identified including: forest, open vegetation, cultivated areas, bare lands, built-up and mine sites. The results showed that during the period under study (1986-2016) there have been losses in forest, cultivated land and open vegetation while bare lands, built-up and mine sites have seen substantial increases. Also, an annual rate of change of 5% was realized within the 30-year period under study.

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LIST OF ABBREVIATIONS AND ACRONYMS

LULC	Land use land cover
LULCC	Land use land cover Change
FAO	Food and Agriculture Organization
WWF	World Wildlife Fund
CO_2	Carbon Dioxide
MMDAs	Metropolitan, Municipal and District Assemblies
USGS	United States Geological Survey
GloVis	Global Visualization Viewer
FRI	Forestry Research Institute
ESA	European Space Agency
Cci	Climate Change Initiative
AOI	Area of Interest
TM	Thematic Mapper
ETM	Enhanced Thematic Mapper
LCM	Land Cover modeler

CHAPTER ONE

INTRODUCTION TO THE RESEARCH

1.1 BACKGROUND TO THE STUDY

Mining is a valuable economic industry that boosts the GDP of any nation. Due to the location of these valuable resources (in the earth crust) accessibility comes with a whole lot of negative impact on the environment that host it (Siachoono, 2010; URT, 2010; Festin *et al.,* 2019). It involves the clearing of vegetation to access the soil and rocks containing the minerals which significantly alters the biological and physical component of the earth crust. Mining operations are thus a source of great economic gain on the livelihoods but on other hand contribute to serious threats to the environment, due to the reduction of forest cover, land degradation, air and water pollution and ultimately reduction in biodiversity (IGF, 2018; Festin *et al.,* 2019). The GDP of Ghana has recently been thriving on the service industry as competition for land due to growing small-scale mining has also affected the agriculture sector (GSS, 2012; Addo *et al.*, 2014).

Deforestation which is a major consequence of mining is on the rise at a rate of about 5 % (USGS, 2018) in Ghana. However, specific location analyses have reported higher deforestation rates especially in location of intense small-scale mining (Kusimi, 2008; Schueler *et al.,* 2011; Kumi-Boateng *et al.,* 2012; Awotwi *et al.,* 2018) as well as places under intense agriculture activities (Agyarko, 2001; Ayivor and Gordon, 2012; Bessah *et al.,* 2019a). Globally, deforestation was estimated to be about 29.7 million hectares in 2016 (University o9f Maryland, 2016). A major impact of deforestation is the release of greenhouse gases (estimated at 15% of total GHG's emissions) which is fueling the current climate change globally.

Mining contributed to about 10% of deforestation in the Amazon within a ten-year period (2005 - 2015). The impact of mining induced deforestation has been found to be more extensive than within the demarcated zone for mining (Sonter *et al.,* 2017).

Ghana is the leading West African country with a long standing record of gold production. Most of the gold deposits in the country are located in the Western region due to the underlying rock material of the region. The recent rise in small-scale illegal mining has had a significant impact on many natural resources in the region. Two main natural resources which were at risk are forest and rivers.

1.2 STATEMENT OF THE PROBLEM

Extensive intense deforestation has been reported to be taken place in the Ankobra River Basin of Ghana (Kusimi, 2008; Schueler *et al.,* 2011; Kumi-Boateng *et al.*, 2012). The main factors driving this change were mining, agriculture expansion and urbanisation. Prestea Huni-Valley Municipal is currently experiencing an increased migration due to the expansion of the mining industry. This has negatively affected agriculture activities in the Municipal. The extent to which the dynamics of mining and agriculture is impacting the land cover in the area is yet to be scientifically investigated and reported although observations of inhabitants suggest a decline in forest due to these human-induced activities.

Mining, especially small-scale (both legal and illegal) in the area is creating competition for land and putting pressure on land cover. The operation of open cast mining has led to the clearing of large portions of high density forests in the Prestea Huni-Valley Municipal. Although these mining companies make an effort in reclaiming the land by replanting, the natural ecosystem of the area is altered, and thus causes destruction to biodiversity. The condition is worsened by small-scale mining. Erosion and pollution of water bodies are common experiences in the area due to the bare lands created from small-scale mining activities in the Municipal (Wassa West District Assembly, 2004).

The assessment of land use change and its transitions would provide a lead on which land cover is currently under a threat of extinction by human activities through the intensity of change provided by this study. The spatial extent of changes from the land use land cover maps would help with afforestation and land reclamation intervention plans while the predicted changes in future would inform policy makers on which land cover must be protected most to preserve biodiversity. Furthermore, the future land use change maps, could serve as basis to control the sprouting of unplanned settlement as population of migrants continue to increase in the Municipal.

1.3 AIMS AND OBJECTIVES

1.3.1 Aim

This research aims at ascertaining the level of devastation of the forest cover using geospatial techniques to determine the impact of mining on land use change in Prestea Huni-Valley Municipality.

1.3.2 Objectives

Specifically, the study sought to;

I. determine the rates of change in the land use land cover in the Prestea Huni-Valley Municipal due to mining.

II. determine the intensity of land use transitions between the assessed land use classes.

III. forecast the future pattern of land use land cover change for the Municipal Assembly.

1.4 RESEARCH QUESTION

The following questions were answered:

i. What is the rate of land use land cover change in the study area?

ii. What is the trend of land use and land cover change? iii.

What will be the future land use pattern in the municipality?

CHAPTER TWO

LITERATURE REVIEW

2.1 Mining (Focus on Artisan small-scale mining)

The extraction of minerals from the earth has been in existence for a very long time. However, the types of extraction and medium of access to the minerals has been evolving. Globally, mining is a major resource for economic development (World Gold Council, 2017). In 2010, Zambia, and South Africa were the two countries in Africa that had mining contributing above 5% to their GDP at 31% and 9% respectively (International Council on Mining and Metals, 2014). Zambia was the leading country globally in 2010 that benefited from mining per percentage revenue generation. Ghana is also one of the African countries with an economy thriving on the mining industry especially gold (World Bank, 2013; GSS, 2014; World Gold Council, 2017). The location of the mineral in the earth determines the kind of method adopted for extraction. Due to the abundance of surface ore artisan smallscale mining is on the increase in Ghana especially in the Western, Central and Ashanti regions of the nation (Aragon and Rud, 2016).

Artisanal and small-scale mining (ASM) is globally accepted and because of its economic contribution to livelihoods and nations (IGF, 2018). Sub-Saharan Africa (SSA) is the world's largest location for ASM. Its definition is based on the level of machines involved in the operations, the number of labourers' or workers, the capital cost of operation and size of productivity (World Gold Council, 2017; IGF, 2018). According to IGF (2018) ASM has grown by about 575% between 1993 and 2017 globally. The increase is obviously due to the revenue it generates for those involved, communities and area although certification and appropriate payment of tax limit the benefit of the national government (Agyei, 2016). Nine out of the 13 countries with high operators of ASM that is between 200, 000 and 500, 000 are located in Africa (IGF, 2018). Moreover, all the 13 countries have vast coverage of vegetation which contribute significantly to the global energy budget in terms of climate change (Foley *et al*., 2005; MEA, 2005; Sonter *et al*., 2015).

In Ghana, about 1,100,000 people were reported to be actively involved in ASM supporting 4,400,000 dependents (Hilson, 2016). This is about 24% of the total population of Ghana from the 2010 population and housing census (GSS, 2013). The once less destructive smallscale mining has now exacerbated by the international interest with the introduction of heavy equipment that poses more threat to vegetation conservation or the possibility of reclamation after the extraction of the minerals (CONIWAS, 2011; Agyei, 2016; OwusuNimo *et al*., 2018). The increasing numbers of illegal ASM has worsened the situation as the drive for economic enrichment has less consideration for environmental impact and sustainability which could be traced largely to the high percentage of informal operators (Agyei, 2016; IGF, 2018). Large-scale mining companies also benefit from the sprouting illegal ASM as mineral feedstock are supplied to them for further processing. There is an increasing trend of abandoned lands after illegal mining in Ghana especially in the Western Region of the nation (Owusu-Nimo *et al*., 2018). This means that the lost vegetation might never be recovered for the benefit of both the immediate communities and the global environment as a whole.

2.2 Mining and Deforestation

The extraction method of mining companies especially the artisanal small-scale miners has a direct impact on vegetation as the vegetation cover is removed before operation commences (Agyei, 2016). Mining has been found to be a major driver of deforestation especially in the tropical rainforest zones of the world (Sonter *et al*., 2017). It further influences deforestation beyond its immediate environment as the location of large-scale mines attract artisan smallscale mining. The fight against deforestation cannot be won until this major component is sustainably resolved. The role of urbanization and agriculture expansion in deforestation are not neglected in this discussion because they also contribute significantly to forest loss. However, the rate at which mining drives deforestation directly and also indirectly through migration which results in urban expansion and increased food demand cannot be over emphasized (Bury, 2007; Sonter *et al*., 2017; Gough *et al*., 2018).

Deforestation was found to expand beyond 70 km of demarcated area of extraction and had resulted to the depletion of 11,670 km^2 of the Brazilian Amazon forest from 2005 to 2015 (Sonter *et al*., 2017). Illegal mining also contributed largely to the deforestation of the Venezuelan Amazon forest covering an area of 5, 266 km^2 (SciDev, 2019). This was more than 50% of the total deforestation in Venezuela from 2000 to 2015. An example of artisan small-scale mine effect is shown in Figure 2.1. Mining increased deforestation by 450 km^2 comparing involved and non-mining districts in India (Ranjan, 2018). In the Peruvian Amazon forest, artisan small-scale mining was 63% of the total 240% deforestation caused by mining from 2009 to 2017 (CINCIA, 2018).

Figure 2.1: Deforested area by small-scale mines in the Venezuelan Amazon forest

NB: Deforested area from 2011 – 2015 is about 2800 km^2.

(Source: SciDev, 2019, photo credit: Javier Mesa for SciDev.Net)

Deforestation rate of about 2% was reported for Ghana between 1990 and 2010 (CI, 2011). Major factors driving depletion of forest in Ghana are agriculture expansion, urbanization, mining and grazing (Agyarko, 2001; Asante, 2005; CI, 2014, Awotwi *et al*., 2017; 2018; Bessah *et al*., 2019a). These factors are also driving deforestation at the global scale. In the Pra River Basin, mining was assessed to have increased by about 300% between 2004 and 2016 with significant contribution to deforestation within this period (Awotwi *et al*., 2018). In the Wassa West District of Ghana, 58% of the deforestation between 1986 and 2002 was due to mining (Schueler *et al*., 2011). Mining operation besides its directly impact on vegetation clearing also results in displacement of rural communities, creation of new settlements by miners, land and water pollution and change in commodity supply chain (Schueler *et al*., 2011; Mwitwa *et al*., 2012; Edwards *et al*., 2014; Edwards and Laurance, 2015). The trend of mining expansion must be understood to plan a sustainable approach in curbing its effects on the environment (Sonter *et al*., 2014; Sonter *et al*., 2017). Artisan small-scale mining is synonymous with vegetation degradation and destroys rich biodiversity and cultural heritage with significant impact on water resources (Adu-Yeboah *et al*, 2008; Ocansey, 2013).

2.2.1 Deforestation and Climate Change

The Inter-Governmental Panel on Climate Change, IPCC (IPCC, 2007) duly recognize the role of vegetation lost in the dynamics of global warming via the emission of greenhouse gases (GHGs). Land use and land cover change contributes significantly to the role of both vegetation and soil acting as a sink or source of GHGs. Artisan small-scale mining popularly termed at the global level as "get-rich-quick" venture increase the demand for food, energy, space and other basic amenities as local population increase. The exposure of soils by mining (ASM) contributes significantly to soil organic carbon stock release into the atmosphere as bare lands increase from these mining activities (Bessah *et al*., 2016). The net CO_2 emission from land use change at the global scale was 11.11 and 10.30 $GtCO_2$/yr in the 1990s and 2000 – 2007 under forest regrowth periods respectively (Smith *et al*., 2014).

Deforestation was the major contributing factor emitting 2.97 $GtCO_2$/yr from 2000 – 2007 (Baccini *et al*., 2012). In Ghana, biomass for energy which is a direct cause of deforestation, accounted 50.54% of CO_2 emission of the energy consumption in 2012 (Bessah and Addo, 2013). It therefore implies that deforestation could be the highest contributor to CO_2 emission in Ghana since the highest source of energy is biomass and agriculture is becoming intense. The situation is being exacerbated by the current trend of using heavy equipment to clear vegetation for both legal and illegal small-scale mining (Agyei, 2016).

Sustainable land use and land cover changes mitigate climate change by reducing GHGs emission through, the conservation of carbon pools in vegetation and soils, sequestration of carbons from the atmosphere and by providing renewable energy resources to replace fossil fuels (Marland *et al*., 2004; Smith *et al*., 2014).

According to Sonter *et al*. (2015) deforestation for charcoal production in Brazil contributed to 79% of carbon emissions from 2000 to 2007. Modeling land use land cover change at the global scale showed that 5.2 grams of carbons are released when biomass is converted for the production of 1 calorie in crops for the simulated period between 2000 and 2015 (Nelson *et al*., 2010). Beside the depletion of forest by mining, exposure of the soils further contributes to carbon emissions (Houghton and Goodale, 2004). Soil organic carbon stocks decrease from land cover (forest, shrubs etc) to land use (especially bare areas) as temperature increases the rate of decomposition in the soils. In Ghana the dynamics of the trend of carbon storage from land cover to land use various from one agro-ecological zone to another (Adu-Bredu *et al*., 2010; Bessah *et al*., 2016) similar to most West African countries (Bationo *et al*., 2007).

2.3 Land Use Competition

Mining creates competition amongst sectors that produce from land like between farmers and miners, and also within the sector, that is, between large-scale miners and artisan smallscale miners (IGF, 2018). Land use competition varies from place to place and is driven by the economic sector or product of the area. For instance, land use competition in Northern Ghana was between agriculture and the energy sector (Addo *et al*., 2014). The competition for land now and in future always has agriculture and food security at the losing end of the game (Fargione *et al*., 2008; Searchinger *et al*., 2008). According to Hilson (2016), mining in Ghana is seasonal and has a strong connection with agriculture which is also seasonal because is mainly dependent on climate. That notwithstanding, agriculture continuously loses in the competition. According to Schueler *et al*. (2011), about 45% of agriculture land was lost between 1986 and 2002 to mines in the Wassa West district in Ghana.

The illegal operation of small-scale miners on land concessions from government to largescale mining companies has a long standing conflict between the two parties (Hilson, 2002a). This is as results of the inadequacies in policy and law to certify small-scale mines (Agyei, 2016). The problem poses a threat to foreign investment in the mining industry in Ghana. Unlike in agriculture where farms can be relocated for peace, competition for access to mineral ore can be bloody because of boundary trespassing (Hilson, 2002a; Schueler *et al*., 2011). The conflict has existed in the two main mining regions (Western and Ashanti) and the small-scale miners are often displaced from the land especially after the implementation of the IMF and World Bank-endorsed Economic Recovery Plan (ERP) in 1983 (Hilson, 2002b). Hilson (2002a) recommended that continuous research on field to be released by government to any large-scale mining company for operation could drastically reduce the competition thereby attracting more foreign investment into the mining industry in Ghana.

2.3.1 Mining Impact on Agriculture

Besides the usual conflict over land between farmers and miners, research has shown that agriculture close to mining areas are expensive compared to those far over (Mishra and Pujari, 2008). The land requires more inputs like fertilizer to boost crop yield. This is a negative consequence on soil fertility due to mining. Ocansey (2013) made the similar discovery in the

Eastern Region of Ghana. Mining also competes with agriculture for labour. Most of the free labour force available to farmers get involved in small-scale mining because it is lucrative compared with labour on farms (Doso Jnr *et al*., 2015). Unfortunately, mining companies compensate farmers who had their farms located in their concessions by start-up businesses in agriculture. It creates another kind of competition as small-scale mines are displaced and resort to the farms of the people to explore for gold. Productivity of farmers reduces by 40% when operating in mining locations (Aragon and Rud, 2015). The tendency of moving into forest to increase deforestation becomes high under such situations. Reclamation of degraded lands after mining especially illegal small-scale mines (*galamsey*) pushes farming far into the forest; an impact that might not be immediately realized (Mantey *et al*., 2016).

2.4 Impact of Mining on Urbanization

2.4.1 Migration

Mining has led to the migration of work force within and from outside the countries of operations. Mining increases economic activities in rural communities and changes the dynamics which affect the cultural structure of the communities (World Bank, 2015). In Vietnam, mining was reported to increase development with negative consequences of crimes as the population of the mining communities' increases (Nguyen *et al*., 2018). A similar situation is taking place in Ghana (Awumbila and Tsikata, 2007). Migrants are in search of employment opportunities and any one they come in contact with is suitable to go by.

The discovery of mineral ore and operation of mines comes with the development of settlement which could grow into a city on its own. Furthermore, the migration of employment seekers creates dispersed settlements around towns and increase the rate of constructing buildings to accommodate workers coming in from other locations because of the mines.

According to Gough *et al*. (2018) migrants for mining in Ghana acquire their own land and settle with indigenes by building and bringing in their family. Vegetation decline would continue as long as land use for the purpose of meeting the needs of humans are not strictly governed by policies and enforced. The dynamics of migration by mining is similar across the globe especially in developing countries (Bury, 2007).

2.5 Modeling Land Use and Land Cover Change

Varying land use models based on purposes, methodologies, geographic areas, assumptions and available data have emerged over the years. They integrate land use history with one or both of socio-economic factors and biophysical characteristics on remote sensing and Geographic Information Systems (GIS) platforms to forecast the possible changes in future (Lambin *et al*., 2001, 2003; Michetti and Zampieri, 2014). Some of the models developed and used for land cover analysis include ACCELERATE (Rounsevell *et al*., 2003), ELPENSystem (Wright *et al*., 1999), CLUE (Veldkamp and Fresco, 1996), Dyna-CLUE (Verburg and Overmars, 2009), EFISCEN (Schelhaas *et al*., 2007), SALU (Stéphenne and Lambin, 2001; 2004), MedAction (van Delden *et al*., 2007), KLUM (Ronneberg *et al*., 2005), ABM-Netlogo (Gilbert, 2008; Crooks and Heppenstall, 2012; O'Sullivan *et al*., 2012), LCM (Clark Labs, 2015) among others. Land change modeler (LCM) which forecast based on the Markov chain model has been successfully used in studies all over the globe (Mishra *et al*., 2014; Razavi, 2014; Huang *et al*., 2015).

Koranteng and Zawila-Niedzwiecki (2015) used the Markov chain model in LCM to forecast land use change of 2020 and 2030 for the southern part of Ashanti region in Ghana. Awotwi *et al*. (2018) also predicted land use change in the Pra River Basin for 2025 from the change between 2008 and 2016 using the Markov chain model in LCM. This study adopted the LCM in IDRISI since it has been tested in Ghana and the results were validated to be acceptable. Other models like Agent-Based Models are complex and difficult to build especially during a short research period such as this study. The LCM helps in quick scenario generation of future land use for decision making.

CHAPTER THREE

RESEARCH METHODOLOGY

3.0 INTRODUCTION

This chapter entails the research methodology used for the study.

3.1 STUDY AREA

3.1.1 Location and Size

This study was carried out in the Prestea-Huni Valley Municipal in Ghana. It is located between latitudes 5º 17' N and 5º 42' N and longitudes 1º 45' W and 2º 16' W and covers an area of about 1,809 km^2 (Figure 3.1). It shares boundary with Wassa Amenfi Central, Upper Denkyira East and Wassa Amenfi East to the north; Twifo Ati Morkwa and Wassa East to the

East; Wassa Amenfi West to the west; and Nzema East and Tarkwa Nsuaem to the South in the Western Region of Ghana (Figure 3.1). Bogoso is the capital town of the Municipal.

3.1.2 Relief and Drainage

The elevation of topography in the Municipal is between 240m and 300m above sea level. The Municipal is underplayed by Birimian Precambrian rocks within the physiographic regions of forest disserted plateau (DMTDP 2010-2013). This is the basis of the large expanse of mineral resources in the Municipal. Some of the notable rivers draining the area are Ankobra, Huni, Oppon, Bogo, Peme, Subri, Bonsa and Mansi. They are also used for both commercial and domestic purposes.

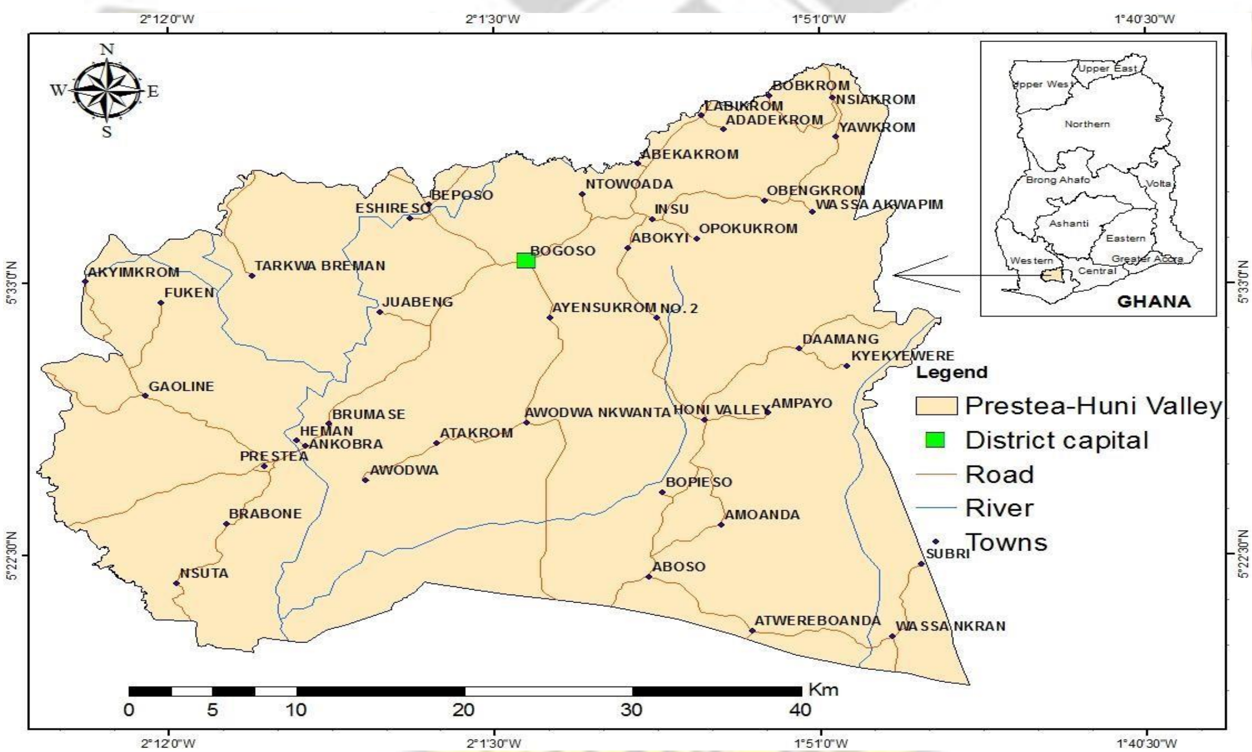

Figure 3.1:Map of study area

3.1.3 Climate

Prestea Huni-Valley Municipal experience a wet equatorial climate regulated by the former abundant forest and its location in the moist forest agro-ecological zone in Ghana. The Municipal benefits from bi-modal rainfall pattern with the major season starting in March and ending in July and the minor season from September to November with a mean annual rainfall of about 1870 mm. The annual mean temperature ranges between 26^{o}C and 30^{0}C with a relative humidity in the range of 75 – 80% and 70 – 80% for the wet and dry seasons respectively. High intensity rainfall has leached top soils reducing its acidity and nutrient content for agriculture productivity.

3.1.4 Vegetation

The Municipal benefit from a favourable climate that support high vegetation growth per its location in the tropical rainforest. Mean tree height are between 15 m and 40 m. The Bonsa Reserve is the main forest reserve in the Municipal covering an area of about 161 km^2. Huni-Valley is also a home to two other minor reserves; namely, Ben West and Nkontoben covering an area of about 26 km^2 and 50 km^2 respectively. Mahogany, wawa, odum, and sapele are the economic trees in the reserves. Farmers cultivate all kinds of food crops, due to the favourable climate.

3.2. DATASET USED IN THE STUDY

The study used the data presented in Table 3.1 for the land use assessment and prediction.

Table 3.1: Table showing the data required for the study

Data Used	Acquisition Date	Resolution	Sources
Landsat 5 TM	1986	30 m	USGS Glovis

Landsat 7 ETM	2002	30 m	USGS Glovis
Landsat 8 OLI TIRS	2016	30 m	USGS Glovis
Orthophoto (Reference data)	2010	30 cm	Forestry Research Institute (FRI)
Land Cover Map (Reference data)	2016	20 m	ESA CCI
Land Cover Map (Reference data)	2000	30 m	GlobeLand30
Google Earth Images	1986, 2002, 2016		Google Earth Pro
Data Used	Acquisition Date	Resolution	Sources
Population density			Department of Geological Survey, Ghana
Digital Elevation model (DEM)		30 m	NASA, Earthdata
Urban centers (shapefile)			Department of Geological Survey, Ghana
Roads (shapefile)			Department of Geological Survey, Ghana
River (shapefile)			Department of Geological Survey, Ghana

3.2.1. Landsat Images

Landsat satellite images of Prestea Huni-Valley Municipality were acquired for three Epochs; 1986, 2002 and 2016 from United States Geology Survey (USGS), Glovis (Global Visualization Viewer) platform with image scene of path 194 and row 56 at 30m spatial resolution. The images were acquired with high consideration of cloud cover (less than 10%), the seasonality and phenological effects (Kashaigili, 2006). To avoid seasonal differences in reflected radiation due to vegetation, Landsat images were selected based on similar season, that is, dry season from November to February.

Landsat images were used for the study because, their spatial and temporal data cover the intended period of study and its spatial resolution is good for land cover classification developed by the USGS (Markham *et al.*, 2018; Awotwi *et al.*, 2018, 2019; Bessah *et al.*, 2019a).

Table 3.2: Landsat Images used in the study

Data Type	Path and Row	Date	Sensor	No. of Bands
LANDSAT 5	WRS 196/056	1986	TM	7
LANDSAT 7	WRS 196/056	2002	ETM^+	8
LANDSAT 8	WRS 196/056	2016	OLI TIRS	11

3.2.2. Reference Data

Garmin GPS was also used to collect ground control points for the training and accuracy assessment of the current image (2016) while the historic images were classified with ALOS images, high resolution ortho photographs and a land cover map obtained from the European Satellite Association (ESA) Climate Change Initiative (CCI). Aerial photographs at high resolution of 30 cm for 2010 were also acquired from the Forestry Research Institute (FRI). A 30 m resolution land cover map from the Globeland30 project from the government of China for the year 2000 were also used. Google earth images and personal knowledge of the study area supported the classification process.

3.3 SOFTWARE APPLICATIONS FOR ANALYSIS

Both GIS and remote sensing software were used in achieving the objectives of this study. It employed QGIS for Image enhancement for temporal analysis (atmospheric and radiometric correction). Supervised classification (Random-Forest Algorithm) were carried out with QGIS and R software package. IDRISI 17.0 was used for the change detection analysis (Categorical and transitional changes). Both ArcGIS 10.1 and QGIS were used to generate the output maps.

3.4 METHODS

Image classification schemes was the main tool which was used for the analysis in this study. Radiometric and atmospheric corrections were done in QGIS to prepare the images for temporal analysis. The process followed the order presented in Figure 3.2.

3.4.1 Image Preprocessing

The Semi-Automatic Classification Plugin (SCP) of QGIS was used for the radiometric and atmospheric correction. Landsat images are already geometrically corrected. Band combination and site training were done in QGIS using the Raster processing tool. Random sampling from reference data were combined with ground truth points for the training. In order to have a clear view of mines for the classification, the band combination 5, 4, 3 and 6, 5, 4 were used for Landsat 5 & 7 and Landsat 8 respectively. The sub-setting of the study area was done using clip in QGIS before the classification.

3.4.2 Image Classification

Random-Forest Algorithmin R software packagewas used in classifying individual images into their respective classes. Post processing of the classified images were done using majority filter and sieve in QGIS. The majority filter was applied at square mode, radius 1 and threshold 0 percent. This was to filter the noise in the image. Sieve was applied at threshold 10 using the 8-connectedness box. This reduced all single standing classes below 10 located in other classes.

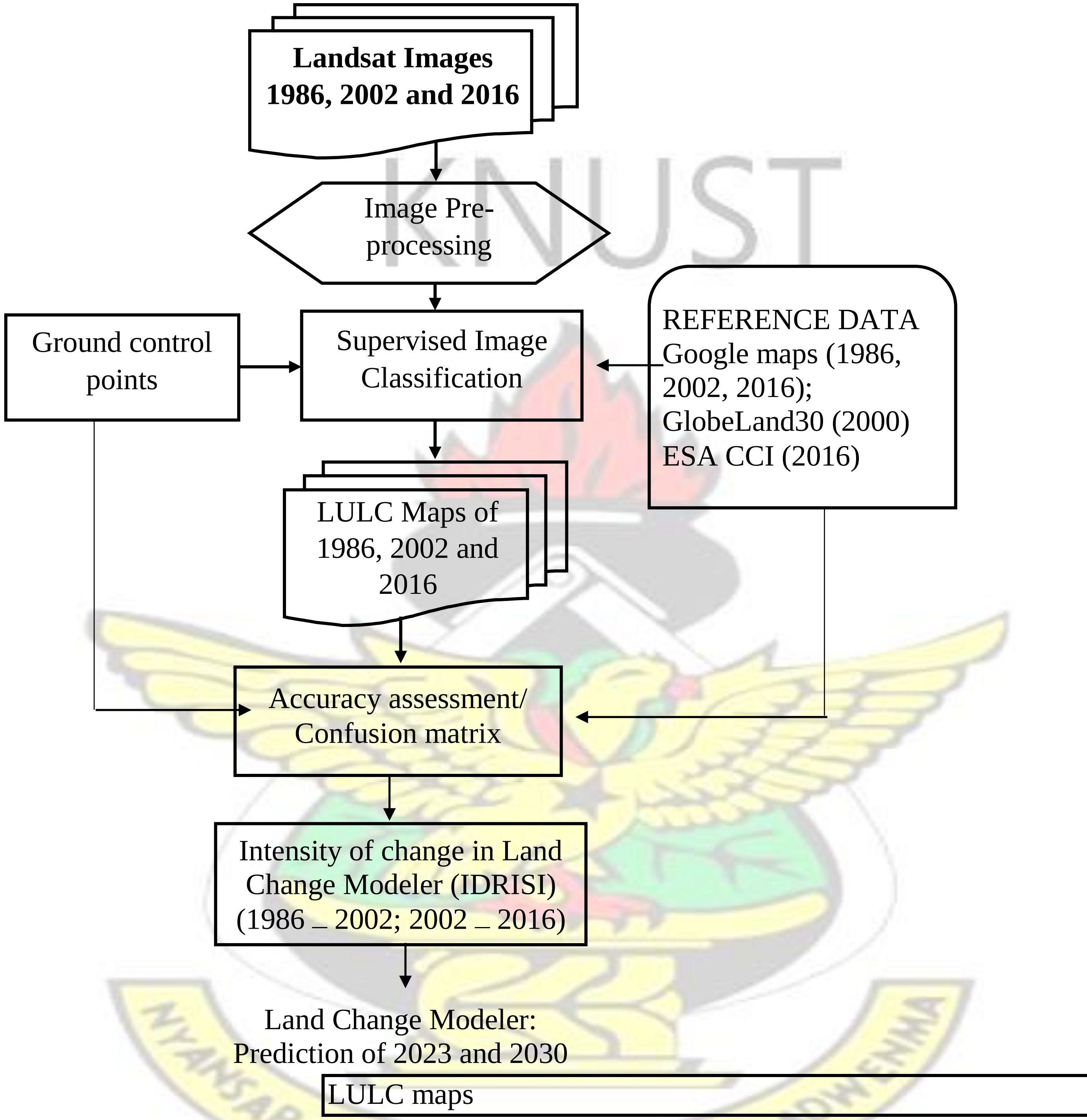

Figure 3.2:Image processing and analysis

Among other things, the objectives of the study, sought to identify the impact of mining in land use land cover changes in the Municipal. Therefore, the six LULC classes considered are presented in Table 3.3. Forest and open vegetation were the land cover types while builtup, cultivated, bare areas and mines were the land use (human induced changes to land cover). LULC classes were based on the Anderson classification scheme.

Table 3.3: Land use land cover classes used in this study

LAND USE/ COVER	DESCRIPTION
Forest	Areas where a tree-crown areal density (crown closure percentage) of 10 percent or more, are stocked with trees capable of producing timber or other wood products.
Built-up	Residential settlements, industrial buildings and compounds, transportation, and utilities.
Mines	All mining areas including both small-scale and large scale.
Bare areas	It covers, exposed soils, rock outcrop and even abandoned fields after mining.
Cultivated	It comprised of prepared fields for crop farming, already cultivated and harvested farms. All types of crops were considered under this class including tree plantations.
Open vegetation	Shrubs, grass land and sparse vegetation.

3.4.3 Accuracy Assessment

Accuracy assessment determines the confidence level in using the maps for other works and also for the interpretation of findings (Foody, 2002). In this study, all the checkpoints data were extracted from the Google Earth images of the assessed years, 2016 ESA CCI 20 m land cover map and GPS points of the area to perform accuracy assessment using the generated confusion matrix. A maximum of 100 random samples were collected for the accuracy assessment from the classification. The error matrix which compared the relationship between known reference data (e.g. ground truth) and the corresponding results of the classified images were used for the accuracy assessment (Lillesand and Kiefer, 2000).

Both pixel-based and area-based error matrix were determined as presented in Appendix I, II and III.

3.4.4 Post-Classification Change Detection

Two interval change detection were done between the three image years. This was to determine the trend of change for all classes. Classified images or LULC maps were exported in Geotiff extension into Idrisi Selva 17 environment for the post classification analysis. Land cover modeler (LCM) which works on automatic cross tabulation were carried out.

3.4.5 Cross-Tabulation

Cross-tabulation was used to compare change in intervals through confusion matrix. Two cross-tabulation maps and tables showing change from 1986 – 2002 and 2002 – 2016 were automatically generated through the LCM analysis.

3.4.6 Land Change Modeler (LCM)

The first three sub-sections of Land Change Modeler for ecological sustainability; namely, the change analysis, transition potentials and change prediction were used in this study. Two projects for first interval (1986 - 2002) and second interval (2002 – 2016) were created separately. Under the change analysis sub-section, change maps and intensity of change were determined. Transitional sub-models for the prediction of future land use maps were carried out under the transition potential sub-section. Evidence likelihood drivers were also generated at this section. Finally, transition maps were generated for the prediction of change to year 2030 under the last sub-section for this study.

The Land Cover Modeler was also used to predict land use change for 2030 based on the changes between 2002 and 2016 because of the predominance of illegal mining during that period. The prediction was down for 14 years at two intervals, that is, 2023 and 2030. The explanatory power of the drivers (Cramer's V) at 95% confidence level are presented in Table 3.4.

A total of seven divers namely; distance from rivers, distance from urban centers, distance from roads, elevation, population density and two evidence likelihood (created with land use change beyond 10 $km^2$and 30 km^2 for first and second intervals respectively) were used in projecting the future land use/cover change. Elevation was physical factor which determines the slope for suitable farming locations while distance from urban centers and roads could be classified under socio-economic factors of market accessibility (Meiyappana *et al*., 2014). Distance from rivers is a physical factor that determines suitable farming locations for accessibility to water for irrigation. Population density is a socio-economic factor for both market demand and urbanization land requirement. The evidence likelihood were the physical observed trends of change during the two intervals. The driver with the highest overall explanatory power was distance from urban centers at 0.1290 and distance from roads was the least at 0.0364. The transitions were grouped into anthropogenic and Natural also classified as persistence (see Table 3.5). The study utilized suitable maps from the evidence likelihoods which had been reported to be significant driving factors that reduces the risk of discrepancies in land use land cover modeling (Clarke *et al*., 1997; Zamyatin and Markov, 2005).

Table 3.4: Cramer's V explanatory power of land use/cover modeling drivers of anthropogenic transitions

Cover Class	**Evidence Likelihood from 1986 – 2002 change**	**Evidence Likelihood from 2002 – 2016 change**	**Elevation**	**Population density**	**Distance from Urban center**	**Distance from river**	**Distance from road**
Forest	0.1717	0.1917	0.1189	0.0465	0.1622	0.0235	0.2146
Built-up	0.0713	0.0942	0.0483	0.0536	0.1281	0.0323	0.0327
Mines	0.0202	0.0330	0.0709	0.0564	0.1144	0.0376	0.0649
Bare areas	0.0385	0.0485	0.1391	0.1396	0.1276	0.0411	0.0406
Cultivated	0.0327	0.0151	0.0947	0.1046	0.1021	0.0473	0.0442
Open Vegetation	0.1213	0.1542	0.1501	0.1253	0.1416	0.0262	0.1357
Overall	**0.0873**	**0.1030**	**0.1060**	**0.0938**	**0.1290**	**0.0364**	**0.1034**

The Multi-Layer Perceptron (MLP) neural network was the option of modeling algorithms used to predict the selected transition variables and validated. The default parameters were used in running the sub-model and transitions maps created at two intervals from 2016 to 2030 except the sample size that was changed to 2500 since it gave improved accuracy. The future maps were modeled and validated with the land use/cover map of 2016. The utilization of adequate suitable maps signifying the driving factors data on the degree of impact on the land cover types in upcoming modeling reduces the risk of discrepancies (Clarke *et al*., 1997; Zamyatin and Markov, 2005; Clark Labs, 2015).

Table 3.5: Transitional sub-models for land use prediction

Anthropogenic	**Natural**
Forest to Mines	Open vegetation to Forest
Forest to Cultivated	Forest to Cultivated

Open vegetation to Built-up	
Open vegetation to Mines	
Open vegetation to Bare areas	
Open vegetation to Cultivated	

CHAPTER FOUR

RESULTS AND DISCUSSION

The findings of the study are presented in the order of accuracy assessment of land use land cover maps, land use land cover changes and predicted changes in the future. Results are presented in Figures prepared in either QGIS, Idrisi Selva or ArcGIS and Tables from Microsoft Excel 2016.

4.1 ACCURACY ASSESSMENT OF MAPS

4.1.1 Land use Land cover map of 1986

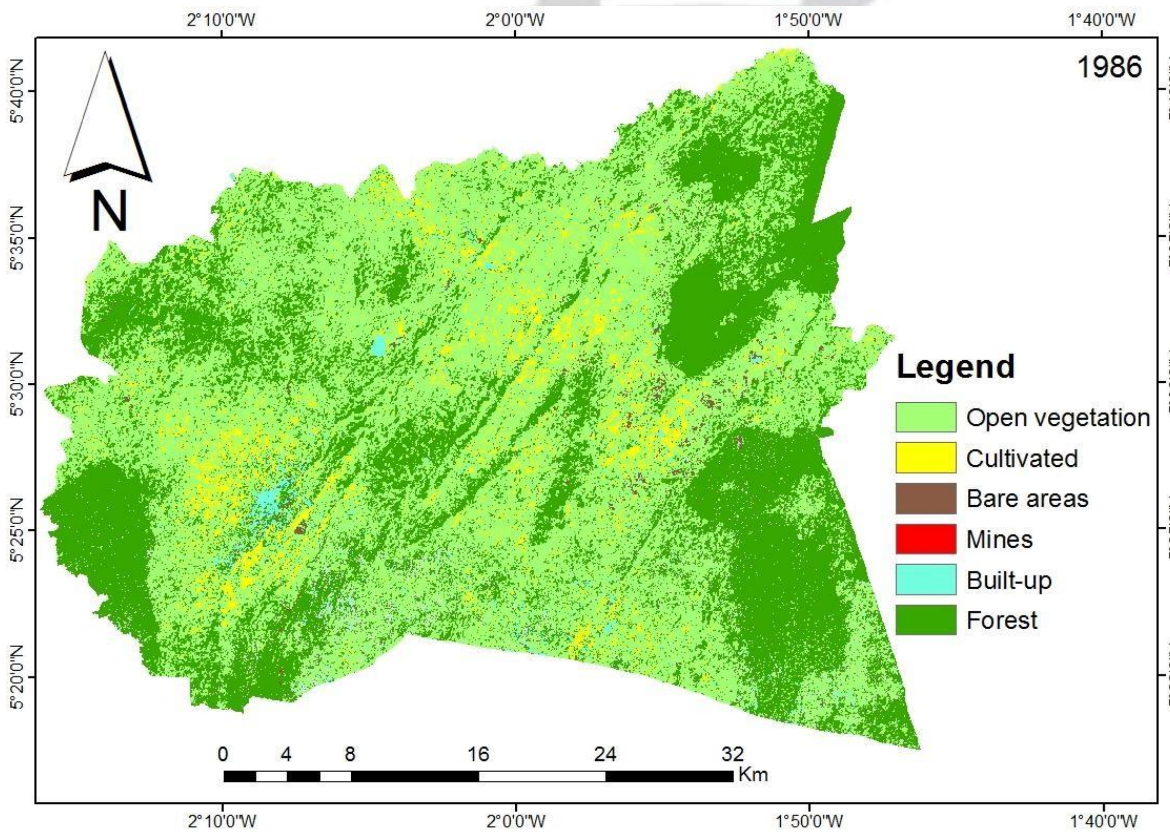

Figure 4.1: 1986 LULC map of study area

From the result of the classified image of 1986 in figure (4.1) which is presented in percentage, it was revealed that forest covered 38. 50%, built-up covered 2.72%, mines had

0.09%, bare lands 14.20%, cultivated area had 6.38% and open vegetation had 48.13%. Open vegetation had the highest percent and mines had the lowest percentage. This is an indication that in 1986, the study area was not prone to much human activities like gold mining and "galamsey". Most of the human activities that brought changes to the land cover was farming activities and this is seen table (4.1) with cultivated areas being the third highest after forest.

Table 4.1: Confusion matrix of LULC 1986 map

LULC	Forest	Built-up	Mines	Bare areas	Cultivated	Open vegetation	Class.error	Area (%)
Forest	112	1	0	1	0	8	0.081967	38.50
Built-up	0	97	2	0	0	2	0.039604	2.72
Mines	0	0	102	0	0	0	0	0.09
Bare areas	0	0	0	102	0	1	0.009709	14.20
Cultivated	0	2	0	0	93	11	0.122642	6.38
Open vegetation	16	3	0	3	18	67	0.373832	48.13
							Total	**100**

The confusion matrix is the sample that was automatically done in R software for the accuracy assessment of the map. The result of the class error, which is in ratio was transformed into percentage and used for analysis. From Table (4.1), 112 sample points were used to classify the forest areas and 8.1% of the points were mixed classified. Built-up used 97 sample points and 3.96% were wrongly mixed classified. Mines used 102 points and all points were rightly used to classify the mines. Bare areas used 103 sample points; with 0.97% point was wrongly classified. Cultivated lands used 93 points and had 12.26% points wrongly classified. Lastly, open vegetation had 37.38% wrongly classified out of a total of 67 sample points.

Table 4.2: Accuracy assessment analysis for 1986

	Pixel-based error matrix (%)	Area-based error matrix (%)
Overall accuracy	89.39	77.92

	User's Accuracy	Producer's Accuracy	User's Accuracy	Producer's Accuracy
Forest	91.80	87.50	91.80	83.08
Built-up	96.04	94.17	96.04	59.37
Mines	100.00	98.08	100.00	61.26
Bare areas	99.03	96.23	99.03	71.40
Cultivated	87.74	83.78	87.74	40.87
Open vegetation	62.62	75.28	62.62	90.18

The overall accuracy of the 1986 map was 89.39% and 77.92% for the pixel-based and areabased error matrix respectively (Table 4.2). Due to the band combination used, the mines class had the highest producer's accuracy under pixel and became last part-one under areabased due to the coverage of mines. However, user accuracy for mines was 100% for both error matrices used for the assessment (Table 4.2).

4.1.2 Land use Land cover map of 2002

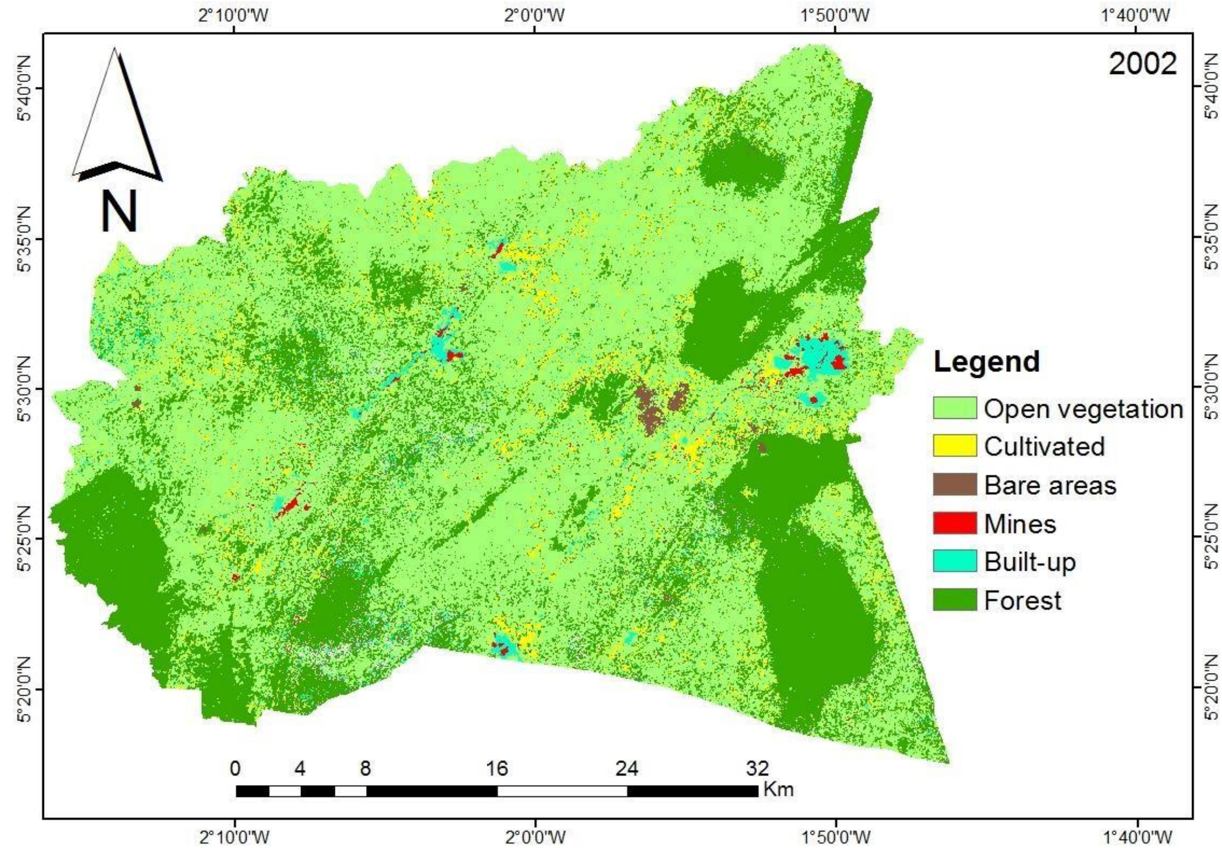

Figure 4.2: 2002 LULC map of study area

The result of 2002 classified image as shown in figure (4.1.2) in percentage revealed that forest covered 35. 09%, built-up covered 4.22%, mines had 0.09%, bare lands 1.72%, cultivated area had 9.04% and open vegetation had 49.02%. Still, open vegetation had the highest percentage of land cover and mines had the lowest percentage of land cover. Comparing the land cover in 1986 to 2002, there was decrease in forest (3.41%) increase in built-up (1.5%), increase in mines (0.09%), decrease in bare lands (12.48%), increase in cultivated land (2.66%) and increase of 0.89% in Open vegetation. The increase in mine areas which is the main focus of study is as a result of the decrease in the other land cover such as forest and bare lands. However, 2002 classified image showed that though there was an increase in mining activities, the increase in human activities which includes cultivated lands were not much.

Table 4.3: Confusion matrix of LULC 2002 map

	Forest	Built-up	Mines	Bare areas	Cultivated	Open vegetation	Class error	Area (%)
Forest	99	0	1	2	0	2	0.048077	35.09
Built-up	0	100	0	0	0	3	0.029126	4.22
Mines	0	0	109	0	0	0	0	0.90
Bare areas	0	0	0	98	0	5	0.048544	1.72
Cultivated	0	0	0	0	103	0	0	9.04
Open vegetation	4	2	1	5	8	84	0.192308	49.02
							Total	**100**

The confusion matrix is the sample that was automatically done in R software for the accuracy assessment of the map. The result of the class error, which is in ratio was transformed into percentage and used for analysis. From table (4.3), 99 sample points were used to classify the forest areas and 4.8% of the points were mixed classified. Built-up used 100 sample points and 2.91% were wrongly mixed classified. Mines used 109 points and all points were rightly used to classify the mines. Bare areas used 98 sample points, with 4.8% point was wrongly classified. Cultivated lands correctly used all of it 103 points and open vegetation had 19.23% wrongly classified out of a total of 84 sample points.

The overall accuracy of the 2002 map were 94.73% and 88.61% for the pixel-based and area-based error matrix respectively (Table 4.4). The increase in accuracy compared to the 1986 map could be due to the clarity of the 2002 satellite image and the details gained from the Google Earth Pro for the year 2002. Mines class had the highest producer's accuracy under pixel (98.20%) and became least under area-based (9.27%). This could be due to the spatial area distribution of the class in relation to its pixel. However, user accuracy for mines was 100% for both error matrices used for the assessment (Table 4.4).

Table 4.4: Accuracy assessment analysis for 2002

	Pixel-based error matrix (%)		Area-based error matrix (%)	
Overall Accuracy	94.73		88.61	
	User's Accuracy	Producer's Accuracy	User's Accuracy	Producer's Accuracy
Forest	95.19	96.12	95.19	95.19
Built-up	97.09	98.04	97.09	74.03
Mines	100.00	98.20	100.00	9.27
Bare areas	95.15	93.33	95.15	56.66
Cultivated	100.00	92.79	100.00	63.28
Open vegetation	80.77	89.36	80.77	97.44

4.1.3 Land use Land cover map of 2016

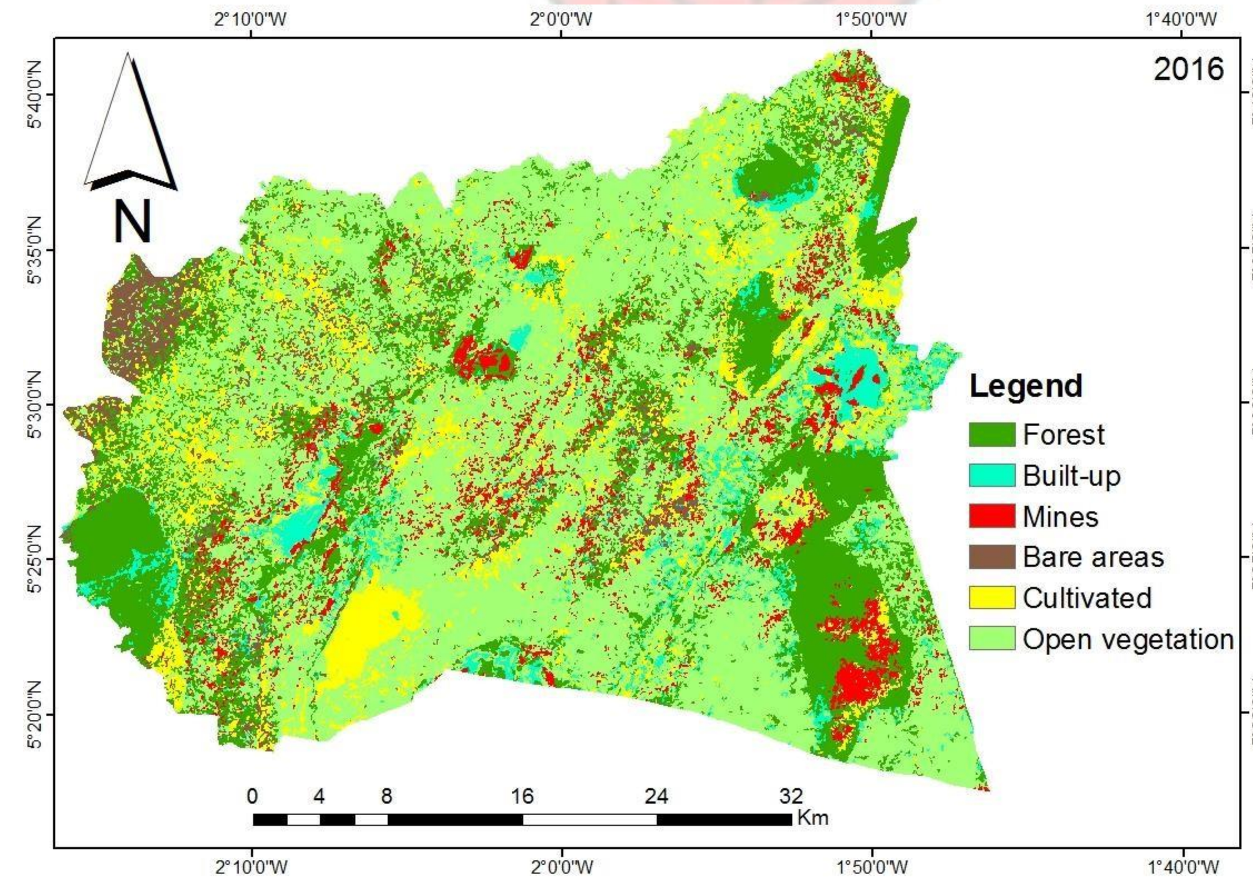

Figure 4.3: 2016 LULC map of study area

As shown in figure (4.3) in percentage, the 2016 classified image revealed that forest covered 23.91%, built-up covered 5.86%, mines had 7.44%, bare lands 5.84%, cultivated area had

12.69% and open vegetation had 44.26%. From the result, Open vegetation had the highest percentage of land cover and mines had the lowest percentage of land cover. Comparing the result of the various land cover in 2002 and 2016, there was decrease in forest (of 11.18%), increase in built-up (1.64%), increase in mines (7.35%), increase in bare lands (4.12%), increase in cultivated lands (3.65%) and decrease of (4.76%) in Open vegetation. The mine areas increased significantly from the decrease in the other land cover such as forest and open vegetation.

Table 4.5: Confusion matrix of LULC 2016 map

	Forest	**Built-up**	**Mines**	**Bare areas**	**Cultivated**	**Open vegetation**	**Class error**	**Area (%)**
Forest	103	1	0	1	0	0	0.019048	23.91
Built-up	0	102	0	0	0	0	0	5.86
Mines	0	0	102	0	0	0	0	7.44
Bare areas	0	0	0	101	0	0	0	5.84
Cultivated	0	0	0	0	105	0	0	12.69
Open vegetation	2	1	0	0	0	99	0.029412	44.26
								100

The confusion matrix is the sample that was automatically done in R software for the accuracy assessment of the map. The result of the class error, which is in ratio was transformed into percentage and used for analysis. From table (4.5), 103 sample points were used to classify the forest areas and 1.9% of the points were mixed classified. Built-up,

Mines, Bares and Cultivated areas used 102, 102, 101 and 105 sample points respectfully with no point wrongly classified. Open vegetation had 2.94% wrongly classified out of a total of 99 sample points.

The 2016 classification had the highest accuracy at 99.19% and 97.85% for the pixel-based and area-based error matrix respectively (Table 4.6). The increase in accuracy compared to the 1986 map could be due to the clarity of the 2002 satellite image and the details gained from the Google Earth Pro for the year 2002. Mines class had the highest producer's accuracy under pixel (98.20%) and became least under area-based (9.27%). This could be due to the spatial area distribution of the class in relation to its pixel. However, user accuracy for mines was 100% for both error matrices used for the assessment (Table 4.4). Table 4.6: Accuracy assessment analysis for 2016

	Pixel-based error matrix (%)		**Area-based error matrix (%)**	
Overall Accuracy	99.19		97.85	
	User's Accuracy	Producer's Accuracy	User's Accuracy	Producer's Accuracy
Forest	98.10	98.10	98.10	97.56
Built-up	100.00	98.08	100.00	76.42
Mines	100.00	100.00	100.00	100.00
Bare areas	100.00	99.02	100.00	91.96
Cultivated	100.00	100.00	100.00	100.00
Open vegetation	97.06	100.00	97.06	100.00

4.2 LAND USE LAND COVER CHANGES IN THE DISTRICT

The interval changes of the three LULC maps (1986, 2002 and 2016) are presented in Table 4.7. The resultant land cover maps were shown in Figures 4.1, 4.2 and 4.3 respectively. The first and second intervals were 1986 – 2002 and 2002 – 2016 respectively.

Table 4.7: Land use land cover changes from 1986 to 2016 in the Prestea-Huni Valley district

LULC	**1986 (%)**	**2002 (%)**	**2016 (%)**	**1st interval change (2002-1986)**	**2nd interval change (2016-2002)**	**Total change (2016-1986)**	**Change per annum(20021986)**	**Change per annum (2016-2002)**
Forest	38.50	35.09	23.91	- 3.41	- 11.18	- 14.59	- 0.21	- 0.80
Built-up	2.72	4.22	5.86	1.50	1.64	3.14	0.09	0.12
Mines	0.09	0.90	7.44	0.82	6.54	7.36	0.05	0.47
Bare areas	14.20	1.72	5.84	- 2.47	4.11	1.64	- 0.15	0.29
Cultivated	6.38	9.04	12.69	2.66	3.65	6.31	0.17	0.26

Open vegetation	48.13	49.02	44.26	0.90	- 4.76	- 3.86	0.06	- 0.34
Total (%)	100	100	100					

In the first interval change, forest decreased by 3.41% and decreased by 11.18% in the second interval change. The total change of forest over the period was 14.59%. Built-up increased in the first interval by 1.50% and increased in the second interval by 1.64%, adding up to a total of 3.14%. Mines increased to 0.82% and 6.54% respectively in the first and second interval with a total of 7.36%. Bare areas decreased in the first interval with 2.47% and increased by 4.11% in the second interval. The total interval change of bare areas was 1.64%. Cultivated areas also saw positive change of 2.66% in the first interval and
3.65% in the second interval 6.31% was the total change of cultivated area from 1986 to 2016. Open vegetation increased in the first interval by 0.90% but decreased in the second interval by 4.76% which gave a total change of 0.06%
It was also realized that the impact of mining on land cover conversions (which is the main aim of the study) was high from 2002 to 2016 than from 1986 to 2002. This could be as a result of the increasing interest people have in mining activities as well as urbanization. The low influence of mines between 1986 and 2002 could be attributed to the fact that inhabitants were much interested in pure agricultural activities such as farming and lumbering.

4.2.1 Categorical Land Class Changes

The categorical change for the first interval is presented in Figure 4.4. The highest change took place in open vegetation at over 300 km^2 gains and loss in the first 16 years (1986 – 2002) of the assessed period. Forest was the second class to experience high change in both gains and loss (Figure 4.4). It shows that change was more adverse in land cover (forest and open vegetation) than land use; an evidence of human-induced change in the district. Cultivated and built-up classes gained more than they lost while the opposite occurred in bare areas. Mines gained only in the first interval. It implies that the mining fields were not remediated for any other use or the mines from the 1986 were not surface therefore, the holes dug could not be covered for any other use. Mining activities has been on the increase since it started in the district.

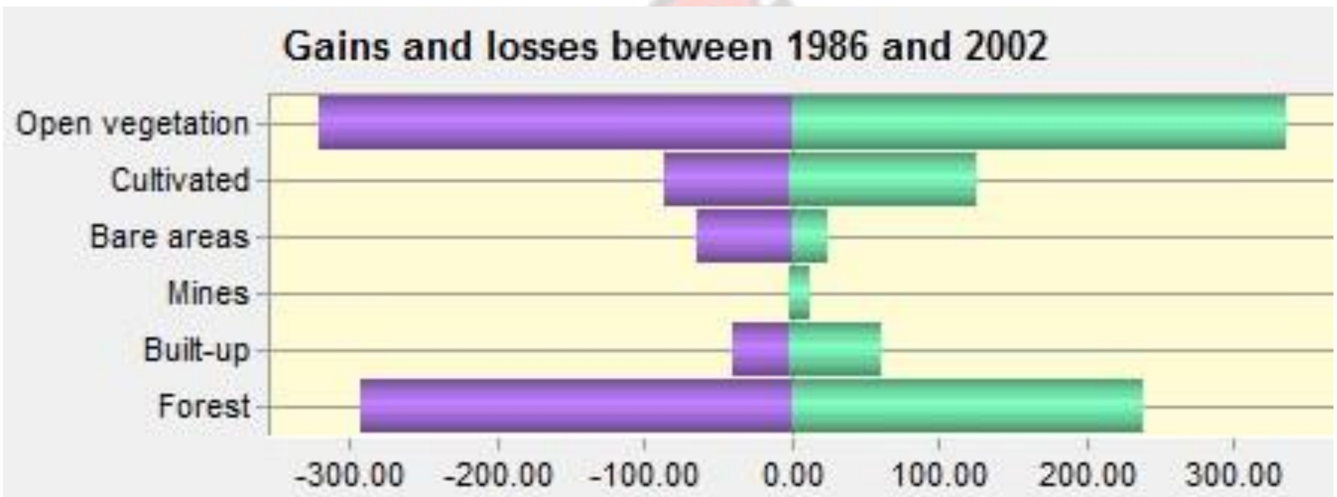

Figure 4.4: Categorical changes in Land classes between 1986 and 2002 (km^2)

Open vegetation experienced a greater change in the second interval compared to the first by losing about 380 km^2 and gaining 300 km^2 (Figure 4.5). Forest also lost more than it gained and more than the loss in the first interval. Forest lost about 360 km^2 and gained less than 200 km^2 in the second interval. This could result from the high gains in other land uses compared to their loss. Mines had the least loss (about 10 km^2) and gained more than 100 km^2 (Figure 4.5). Both mines and bare areas increased consistently in the second interval indicating the rate at which these land degradation of illegal and legal small-scale mining had expanded between 2002 and 2016. The increase in built-up indicate the increase in population probably migrants who relocated to the district to engage in the mining. The findings are similar to

Bessah *et al.* (2019a) for the Kintampo North Municipal where the major land use gaining from forest and open vegetation was agricultural land.

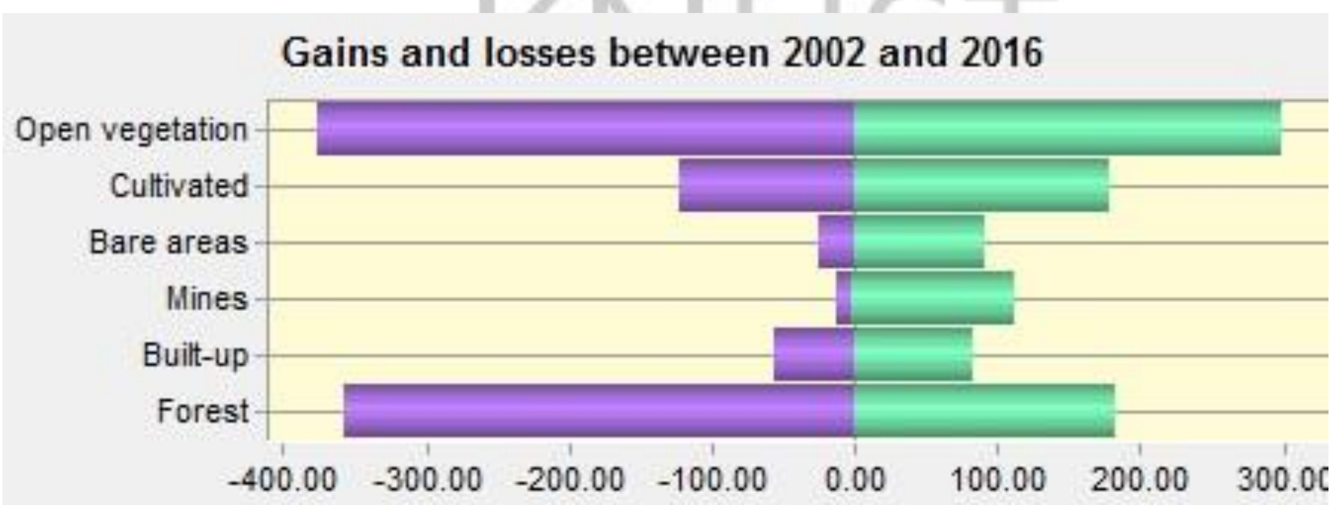

Figure 4.5: Categorical changes in Land classes between 2002 and 2016 (km^2)

4.2.2 Land Class Transitions

The overall contributions of mining or mine sites to other land use classes are losses as seen in figures 4.6 and 4.7 below. From 1986 – 2002 (16-year period), mines have contributed to about 10 km² each loss in forest, open vegetation and built-up. About 3 km² of area each of bare areas and cultivated lands were also lost to mining activities within the same period. It is worth noting that for the 16-year period, built-up made gains against all land use classes (i.e. open vegetation, cultivated land, bare lands and forest) except mines where built-up class lost some amount of area to mining activities. It shows that not even settlements are exempted when it comes to destroying a particular land class for mining activities to thrive.

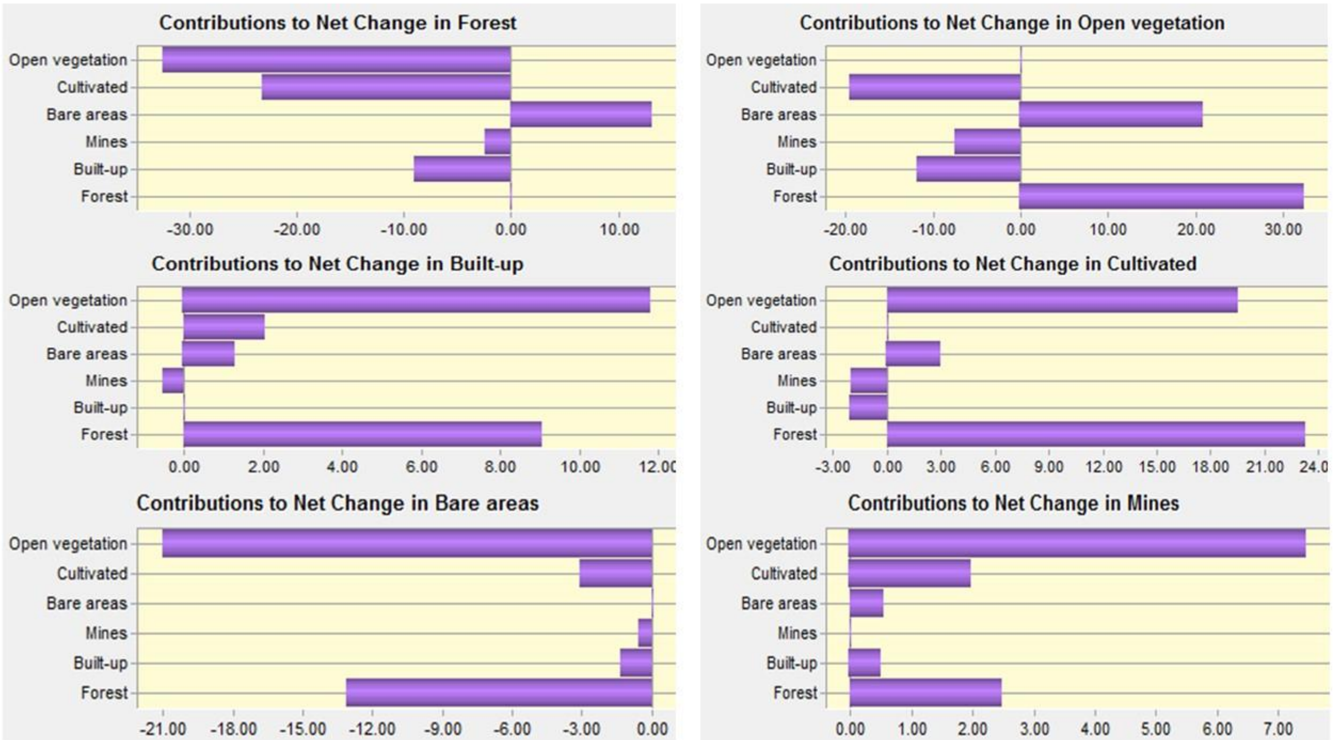

Figure 4.6: Net contribution (1986 -2002) of land classes to changes in each single class (km^2)

The contributions of mines to loss of forest cover from 2002 to 2016 were much greater than from 1986 to 2002. This is because over 40 km² of forest land was lost to mining activities within the 14-year period. It shows that mining is becoming a lucrative venture for most inhabitants. Pragmatic efforts must therefore be made to save the forest as a result of the land use conversions. About 2 km² of built-up area was also converted for mining purposes with an increasing trend from the previous data. Mines again contributed the largest of land use lost in open vegetation within the same period. It contributed over 40km² of open vegetation conversion from 2002 to 2016. Similarly, bare land gained appreciably against all other land use classes from 2002 to 2016 whilst it lost about 10 km² of land area to mines. Cultivated land also lost a greater percentage of land area to mines as shown in figure 4.7 below. With the trends analyzed so far, mines are likely to be the main contributor of various land use conversions in the near future if the activities of mining are not curtailed.

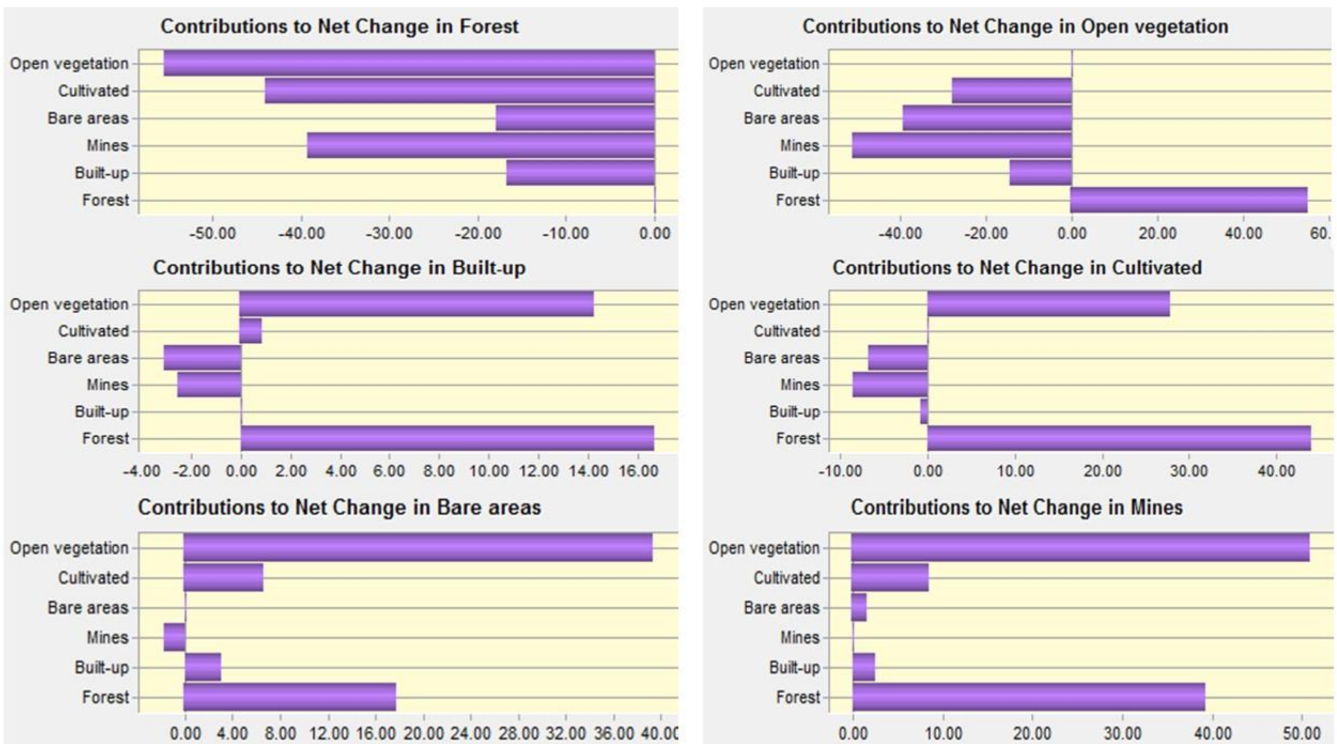

Figure 4.7: Net contribution (2002 -2016) of land classes to changes in each single class (km^2)

4.2.3 Changes in both intervals with persistence locations

The spatial distribution of LULC class transitions are presented in Figure 4.8. The dominant change was from forest to open vegetation followed by open vegetation to forest. It shows the high interactions between these two land classes. As forests were converted, open and sparse vegetation were allowed to grow to replace some of the lost forest, although the rate of deforestation was higher than re/afforestation in the district (Figure 4.8). This is clearly shown in the persistence, gains and loss of forest and open vegetation in Figure 4.9.

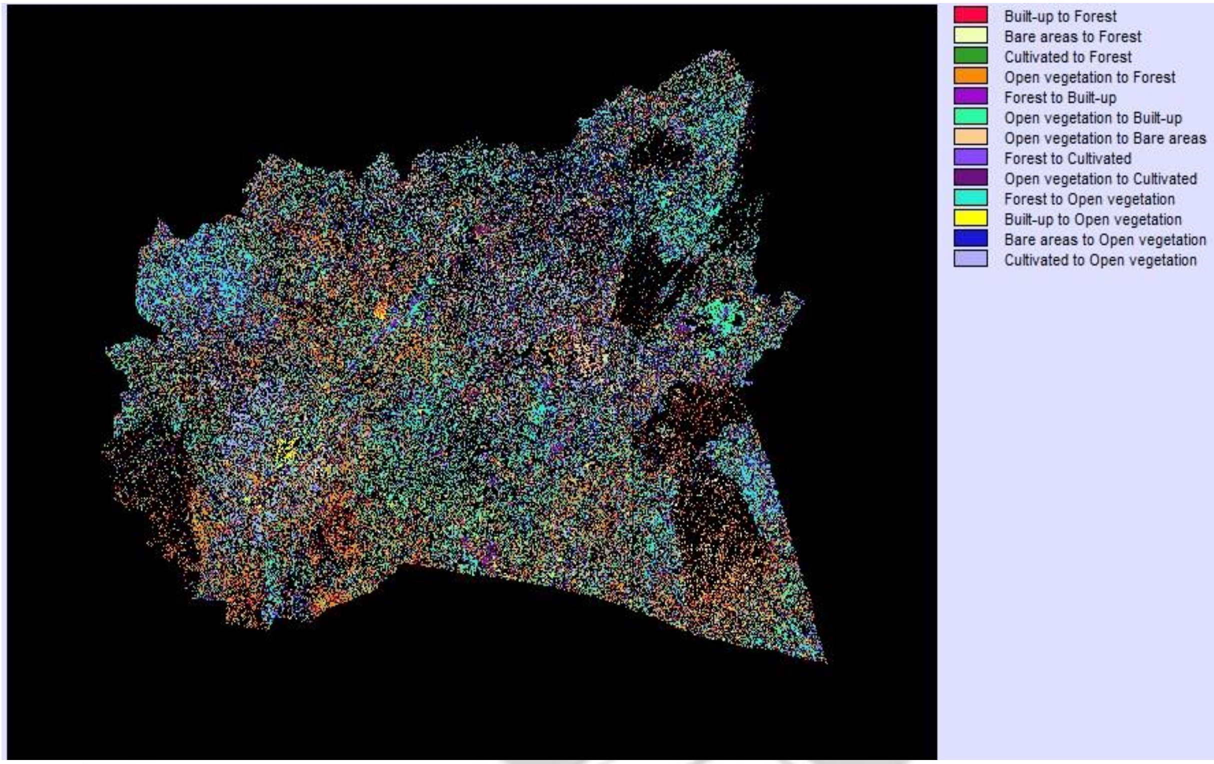

Figure 4.8: Distribution of LULC changes from 1986 to 2002

The major land use conversion that took place almost all over the district were forest to built-up and forest to cultivated fields. The rate of loss of bare areas indicate a recovery of most of the dry lands that resulted from the 1983 drought in the nation as rainfall increased generally since then in many part of Ghana (Greene *et al.*,2009; Bessah *et al.*, 2019b). Builtup class was persistent in the main towns like Bogoso (Centre North), Aboso (South) and Nsuta (South West) among others (Figure 4.9). Mines expanded around major towns with significant growth at Huni Valley, Ampayo, Kyekyewere and Damang area at the east-end of the basin (Figure 4.9). The loss of built-up were taken by mines from the spatial distribution. It implies that small-scale mining was close to the towns. The results showed that built-up also expanded significantly around major mining fields.

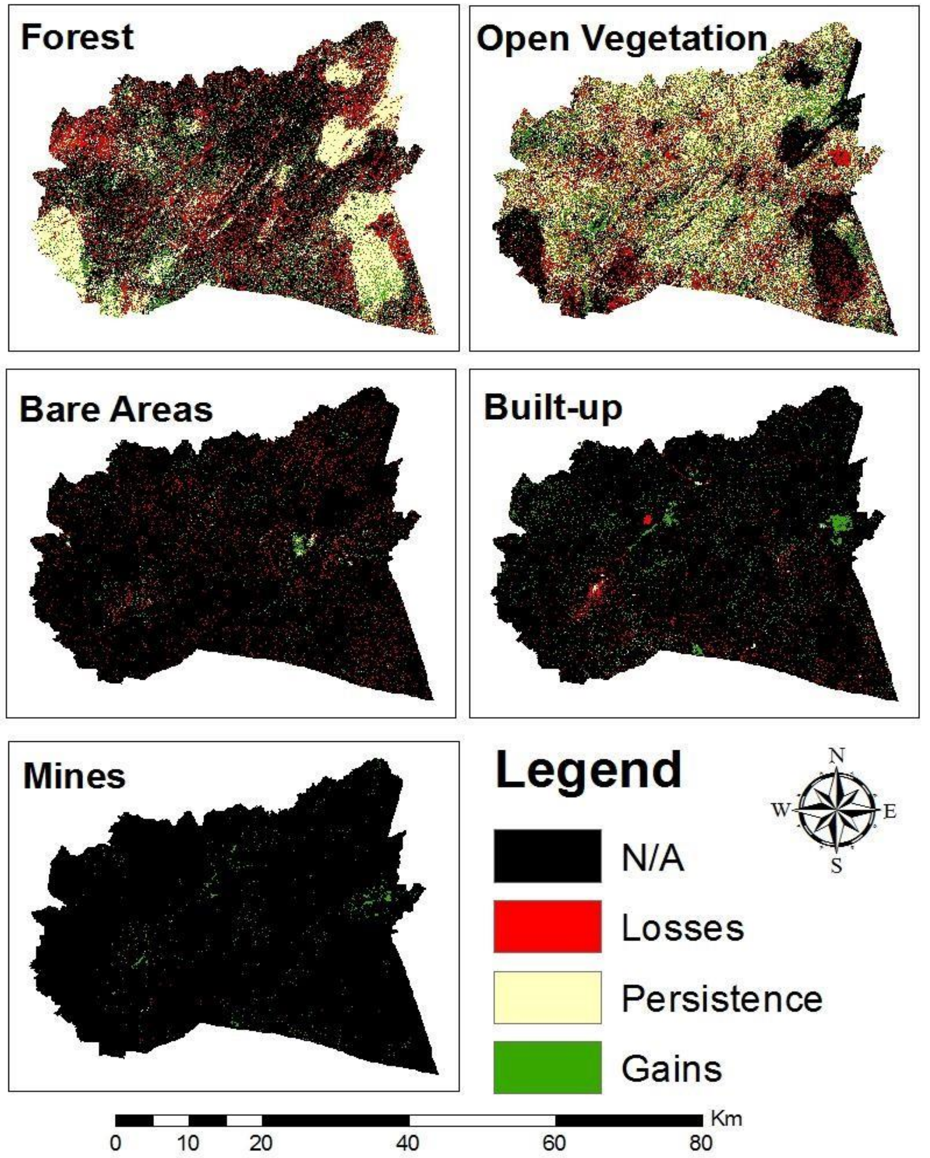

Figure 4.9: Gains, losses and persistent LULC locations from 1986 to 2002

The LULC changes in their spatial distributions from 2002 to 2016 are presented in figure 4.10 below. Open vegetation to forest, forest to open vegetation, open vegetation to mines as well as forest to mines experienced the dominant changes within the 14-year period. It confirmed that as forest convert to open vegetation as a result of deforestation, open vegetation also converts to mines due to the activities of surface mining by the inhabitants.

There is an increasing rate of forest and open vegetation losses to mining activities.

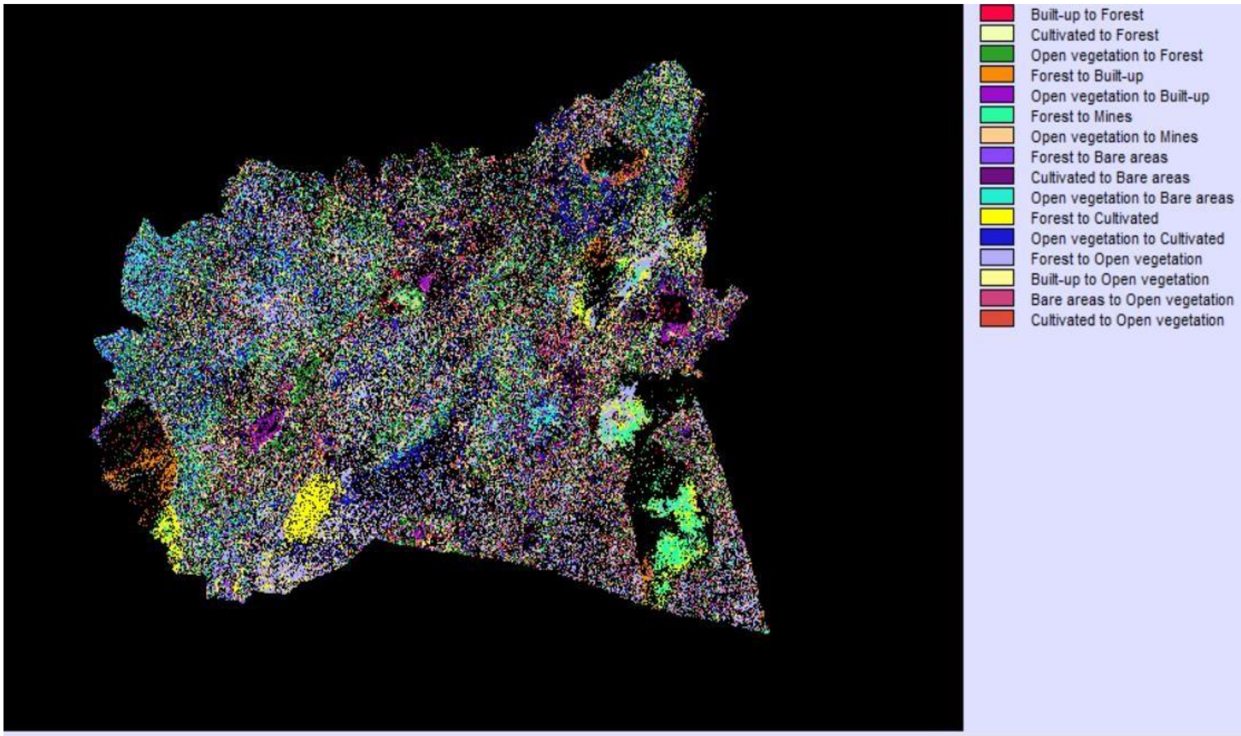

Figure 4.10: Distribution of LULC changes from 2002 to 2016

Figure 4.11 shows the major land use gains and losses from 2002 to 2016 in the study area. It was revealed that forest and open vegetation experienced more losses whilst bare areas, built-up and mines gained considerably. The rate of losses in the forest and open vegetation are indications of the persistent conversion of such land classes for other land uses especially mines. Built-up was also persistent in the main towns like Bogoso (Centre North), Aboso (South) and Nsuta (South West) among others. Mines expanded around major towns with significant growth at Huni Valley, Ampayo, Kyekyewere and Damang area at the eastend of the basin. The loss of built-up were taken by mines from the spatial distribution. It implies that small-scale mining was close to the towns. The results showed that built-up also expanded significantly around major mining fields.

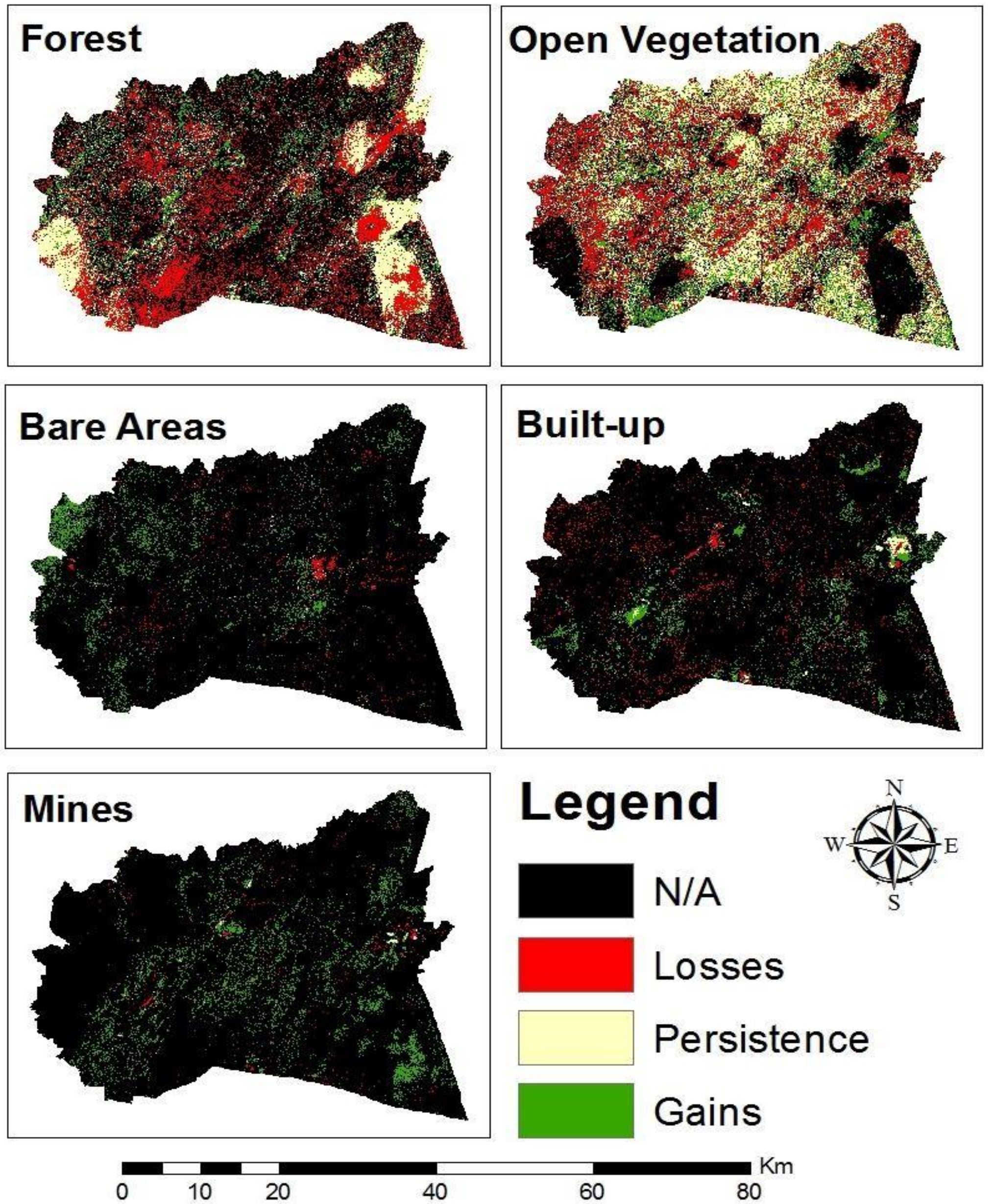

Figure 4.11: Gains, losses and persistent LULC locations from 2002 to 2016

4.3 FUTURE LAND USE LAND COVER CHANGES

The change in land use land cover for the future period assessed from the 2016 map are presented in Table 4.8. The first interval was from 2016 to 2023 and the second interval was 2023 to 2030. In the first interval change from 2016, forest was predicted to decrease by 2.69% and by 2.76% in the second interval change. The total change in forest was predicted at -5.45%

between 2016 and 2030 (Table 4.8). Open vegetation also decreased in the first and second interval by3.79% and 3.68% respectively showing a total change of -7.47% from 2016 – 2030.

Table 4.8: Predicted Land use land cover changes from 2016 to 2030 in the Prestea-Huni Valley district

	Forest	**Built-up**	**Mines**	**Bare areas**	**Cultivated**	**Open vegetation**	**Total (%)**
2016	23.91	5.86	7.44	5.84	12.69	44.26	100
2023	21.22	7.00	10.02	7.36	13.92	40.47	100
2030	18.46	8.15	12.54	8.83	15.23	36.79	100
2023-2016	-2.69	1.14	2.58	1.53	1.23	-3.79	
2030-2023	-2.76	1.14	2.52	1.46	1.31	-3.68	
2030-2016	-5.45	2.29	5.10	2.99	2.54	-7.47	
change per annum (20232016)	-0.38	0.16	0.37	0.22	0.18	-0.54	
Change per annum (20302023)	-0.39	0.16	0.36	0.21	0.19	-0.53	
Change per annum (20302016)	-0.39	0.16	0.36	0.21	0.18	-0.53	

Built-up land was predicted to increase in both intervals by 1.14%, with a total change of 2.29% increase in the 14 years predicted period. Mines, bare areas and cultivated areas were predicted to increase by 2.58%, 1.53% and 1.23% respectively in the first and by 2.52%, 1.46% and 1.31% in the second interval respectively (Table 4.8). Land use (mines, cultivated and bare areas) showed a continuous uneven distribution in the future period (Figure 4.12). In 2030, mines and cultivated areas contributed to the deforestation at the south-east end and east of the district. Mines also increased massively close to the west end in 2030 (Figure 4.12).

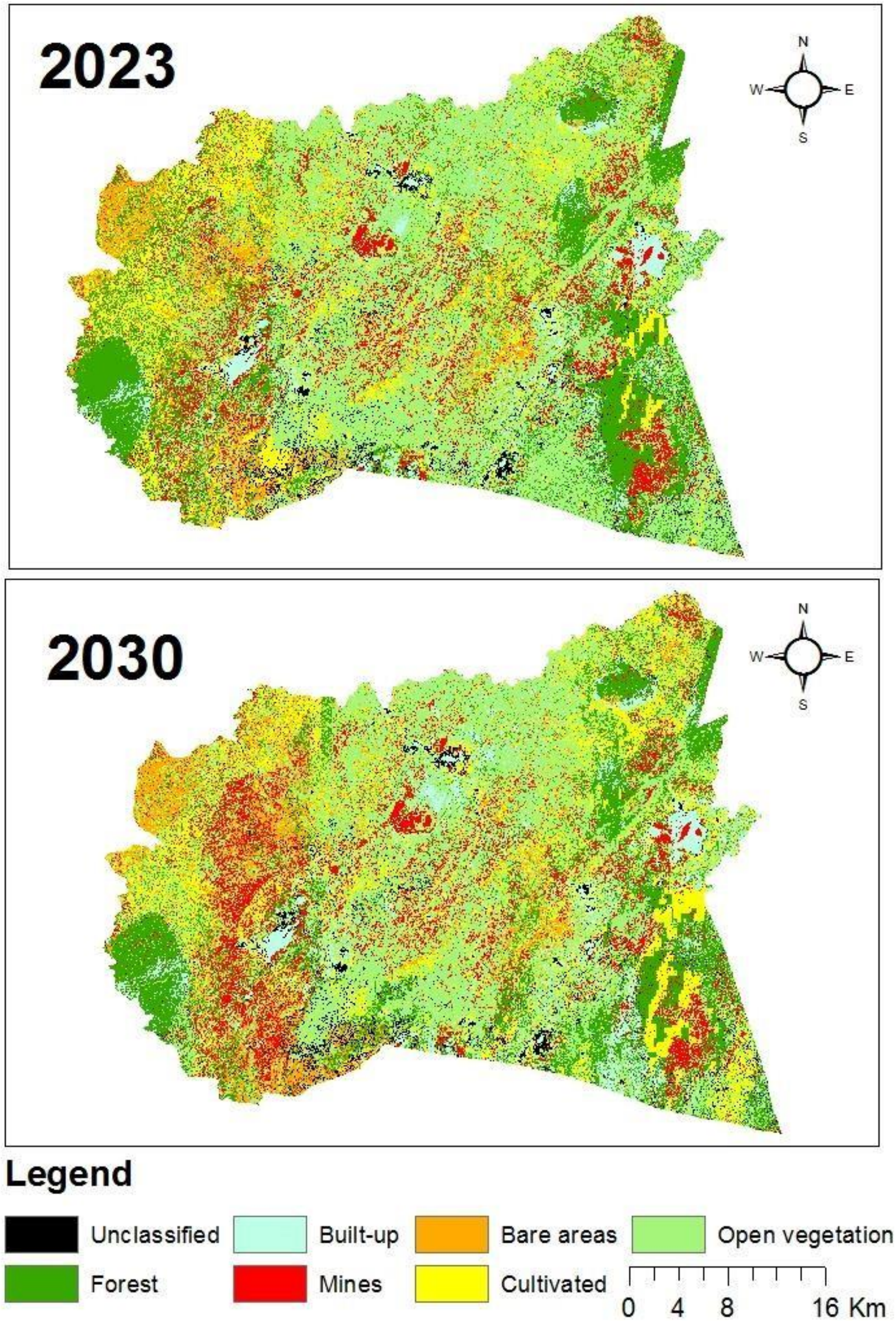

Figure 4.12: Predicted land use land cover maps for 2023 and 2030

CHAPTER FIVE

CONCLUSIONS AND RECOMMENDATIONS

5.1 CONCLUSIONS

The following conclusion can be made based on the objectives and findings of the work.

- Land cover (forest and open vegetation) has significantly declined during the assessed period in the Municipal due to agriculture expansion, urbanization and mining. However, the change was intense in the second interval between 2002 and 2016 when the interest of both indigenes and migrants shifted to mining (mostly small-scale illegal mining).
- The most intense transition took place in forest and open vegetation. Mining gained more with no loss or least loss compared to agriculture expansion and urbanization. The highest gains and losses were between forest and open vegetation indicating the practice of fallow in the study area for the natural restoration of forest in part from open vegetation. Generally, transitions were more intense between 2002 and 2016 which may be traced to the rapid expansion of small-scale mining (both legal and illegal) in the study area.
- Forest and open vegetation would continue to decrease in the next 14 years from 2016 at a rate of about 5 % and 7 % respectively as migrants increase in the Municipal with demands on agriculture (+3%) and accommodation (+2%) due to the projected increase in mining.

5.2 RECOMMENDATIONS

Some measures that can help change the narrative of mines or mining activities impacting negatively on land cover changes in the study area include;

- ✓ A lot of sensitization or education on the effects of mining on the environment such as deforestation, pollution of air and water bodies among others should be carried out by relevant authorities (Assembly Members, NGOs, and Government Agencies) to help avert the situation in the near future.
- ✓ The enforcement of environmental protection laws should be made effective. This will assist in bringing defaulters to face the law and that would serve as deterrent to those yet to commit to such activities (mines).

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APPENDICES

APPENDIX I: Accuracy assessment spreadsheet for 1986

Pixel-based Error Matrix									
CLASSIFIED	**Forest**	**Built-up**	**Mines**	**Bare areas**	**Cultivated**	**Open vegetation**	**Total Reference points**	**Total Area (pixels)**	**Total Area (hectares)**	**Stratum Weight (Wi)**
Forest	112	1	0	1	0	8	122	680689	61262.01	0.38497591
Built-up	0	97	2	0	0	2	101	48035	4323.15	0.02716706
Mines	0	0	102	0	0	0	102	1504	135.36	0.00085061
Bare areas	0	0	0	102	0	1	103	74196	6677.64	0.04196288
Cultivated	0	2	0	0	93	11	106	112789	10151.01	0.06378985
Open vegetation	16	3	0	3	18	67	107	850921	76582.89	0.48125368
Total Classified points	128	103	104	106	111	89	**641**	1768134	159132	1
			Total Correct Reference Points	573						
			Total True reference points	641						
			Overall Accuracy (%)	**89.39**						
	User's Accuracy	**Producer's Accuracy**								
Forest	91.80	87.50								
Built-up	96.04	94.17								
Mines	100.00	98.08								
Bare areas	99.03	96.23								
Cultivated	87.74	83.78								
Open vegetation	62.62	75.28								

Area-based Error Matrix										
CLASSIFIED	**Forest**	**Built-up**	**Mines**	**Bare areas**	**Cultivated**	**Open vegetation**	**Total Reference points**	**Total Area (pixels)**	**Total Area (hectares)**	**% of Total**
Forest	0.353421	0.003156	0.000000	0.003156	0.000000	0.025244	0.384976	680689.00	61262.01	38.50
Built-up	0.000000	0.026091	0.000538	0.000000	0.000000	0.000538	0.027167	48035.00	4323.15	2.72
Mines	0.000000	0.000000	0.000851	0.000000	0.000000	0.000000	0.000851	1504.00	135.36	0.09
Bare areas	0.000000	0.000000	0.000000	0.041555	0.000000	0.000407	0.041963	74196.00	6677.64	4.20
Cultivated	0.000000	0.001204	0.000000	0.000000	0.055967	0.006620	0.063790	112789.00	10151.01	6.38
Open vegetation	0.071963	0.013493	0.000000	0.013493	0.080959	0.301346	0.481254	850921.00	76582.89	48.13
Total Classified Area	0.425384	0.043943	0.001389	0.058204	0.136925	0.334155	1.000000	1768134.00	159132.06	100.00
	Overall Percent Accuracy		**77.92**							
	User's Accuracy	**Producer's Accuracy**								
Forest	91.80	83.08								
Built-up	96.04	59.37								
Mines	100.00	61.26								
Bare areas	99.03	71.40								
Cultivated	87.74	40.87								
Open vegetation	62.62	90.18								

APPENDIX II: Accuracy assessment spreadsheet for 2002

Pixel-based Error Matrix

CLASSIFIED	Forest	Built-up	Mines	Bare areas	Cultivated	Open vegetation	Total Reference points	Total Area (pixels)	Total Area (hectares)	Stratum Weight (Wi)
Forest	99	0	1	2	0	2	104	680689	61262.01	0.384975912
Built-up	0	100	0	0	0	3	103	48035	4323.15	0.027167059
Mines	0	0	109	0	0	0	109	1504	135.36	0.000850614
Bare areas	0	0	0	98	0	5	103	74196	6677.64	0.041962883
Cultivated	0	0	0	0	103	0	103	112789	10151.01	0.063789849
Open vegetation	4	2	1	5	8	84	104	850921	76582.89	0.481253683
Total Classified points	103	102	111	105	111	94	**626**	1768134	159132	1
Total Correct Reference Points			593							
Total True reference points			626							
Overall Accuracy (%)			**94.73**							
	User's Accuracy	**Producer's Accuracy**								
Forest	95.19	96.12								
Built-up	97.09	98.04								
Mines	100.00	98.20								

Bare areas	95.15	93.33								
Cultivated	100.00	92.79								
Open vegetation	80.77	89.36								
					Area-based Error Matrix					
CLASSIFIED	**Forest**	**Built-up**	**Mines**	**Bare areas**	**Cultivated**	**Open vegetation**	**Total Reference points**	**Total Area (pixels)**	**Total Area (hectares)**	**% of Total**
Forest	0.366467	0.000000	0.003702	0.007403	0.000000	0.007403	0.384976	680689.00	61262.01	38.50
Built-up	0.000000	0.026376	0.000000	0.000000	0.000000	0.000791	0.027167	48035.00	4323.15	2.72
Mines	0.000000	0.000000	0.000851	0.000000	0.000000	0.000000	0.000851	1504.00	135.36	0.09
Bare areas	0.000000	0.000000	0.000000	0.039926	0.000000	0.002037	0.041963	74196.00	6677.64	4.20
Cultivated	0.000000	0.000000	0.000000	0.000000	0.063790	0.000000	0.063790	112789.00	10151.01	6.38
Open vegetation	0.018510	0.009255	0.004627	0.023137	0.037020	0.388705	0.481254	850921.00	76582.89	48.13
Total Classified Area	0.384977	0.035631	0.009180	0.070466	0.100809	0.398937	1.000000	1768134.00	159132.06	100.00
		Overall Percent Accuracy	**88.61**							
	User's Accuracy	**Producer's Accuracy**								
Forest	95.19	95.19								
Built-up	97.09	74.03								
Mines	100.00	9.27								
Bare areas	95.15	56.66								
Cultivated	100.00	63.28								
Open vegetation	80.77	97.44								

APPENDIX III: Accuracy assessment spreadsheet for 2016

Pixel-based Error Matrix										
CLASSIFIED	**Forest**	**Built-up**	**Mines**	**Bare areas**	**Cultivated**	**Open vegetation**	**Total Reference points**	**Total Area (pixels)**	**Total Area (hectares)**	**Stratum Weight (Wi)**
Forest	103	1	0	1	0	0	105	680689	61262.01	0.38497591
Built-up	0	102	0	0	0	0	102	48035	4323.15	0.02716706
Mines	0	0	102	0	0	0	102	1504	135.36	0.00085061
Bare areas	0	0	0	101	0	0	101	74196	6677.64	0.04196288
Cultivated	0	0	0	0	105	0	105	112789	10151.01	0.06378985
Open vegetation	2	1	0	0	0	99	102	850921	76582.89	0.48125368
Total Classified points	105	104	102	102	105	99	**617**	1768134	159132	1
Total Correct Reference Points			612							
Total True reference points			617							
Overall Accuracy (%)			**99.19**							
	User's accuracy	**Producer's accuracy**								
Forest	98.10	98.10								
Built-up	100.00	98.08								

Mines	100.00	100.00								
Bare areas	100.00	99.02								
Cultivated	100.00	100.00								
Open vegetation	97.06	100.00								
Area-based Error Matrix										
CLASSIFIED	**Forest**	**Built-up**	**Mines**	**Bare areas**	**Cultivated**	**Open vegetation**	**Total Reference points**	**Total Area (pixels)**	**Total Area (hectares)**	**% of Total**
Forest	0.377643	0.003666	0.000000	0.003666	0.000000	0.000000	0.384976	680689.00	61262.01	38.50
Built-up	0.000000	0.027167	0.000000	0.000000	0.000000	0.000000	0.027167	48035.00	4323.15	2.72
Mines	0.000000	0.000000	0.000851	0.000000	0.000000	0.000000	0.000851	1504.00	135.36	0.09
Bare areas	0.000000	0.000000	0.000000	0.041963	0.000000	0.000000	0.041963	74196.00	6677.64	4.20
Cultivated	0.000000	0.000000	0.000000	0.000000	0.063790	0.000000	0.063790	112789.00	10151.01	6.38
Open vegetation	0.009436	0.004718	0.000000	0.000000	0.000000	0.467099	0.481254	850921.00	76582.89	48.13
Total Classified Area	0.387079	0.035552	0.000851	0.045629	0.063790	0.467099	1.000000	1768134.00	159132.06	100.00
Overall Percent Accuracy		**97.85**								
	User's accuracy	**Producer's accuracy**								
Forest	98.10	97.56								
Built-up	100.00	76.42								
Mines	100.00	100.00								
Bare areas	100.00	91.96								
Cultivated	100.00	100.00								
Open vegetation	97.06	100.00								