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The Impact of Surface Gold Mining on Land Use/ Land Cover Types in the Birim North District

by

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MASTER OF SCIENCE

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DECLARATION

I hereby declare that this submission is my own work towards the MSc. and that, to the best of my knowledge, it contains no material previously published by another person nor material which has been accepted for the award of any other degree of the University, except where due acknowledgment has been made in the text.

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ABSTRACT

The method of surface mining has been the target of strong opposition in recent times in Ghana. LULC changes due to surface mining and their effects on the environment and local livelihoods, is on the ascendancy in Birim North District. The aim of this study was to map the LULC changes which have occurred in the Birim North District resulting from surface mining and to project the impact of surface gold mining on LULC types for the next ten years. Remote Sensing (RS) and Geographic Information System (GIS) based techniques and the Markov Chain Monte Carlo (MCMC) statistical methods were used in this study. Landsat satellite images of 2002, 2008 and 2015 were used to map LULC change types. Field interviews with farmers using designed questionnaire to understand the livelihood implications of surface gold mining-related LULC changes in the study area were conducted. The results showed that surface gold mining resulted in the loss of 18.5% of agricultural land and 8.4 % of forest cover in the 13 years period. Deforestation and land degradation were identified as the major environmental consequences of LULC change, owing to surface gold mining in the study area. Surface mining related LULC change affected local livelihoods especially the health and local economy of the study area. Analysis of the ten years LULC projection map of 2025 of the study area revealed a decrease of forest cover by 6.3% and agricultural land by 0.1%. This was attributed to population increase and built-up expansion due to the presence of mining activities in the study area. Government policies on mining should therefore be crafted with the intension to preventing the decrease in livelihood foundations of the rural areas in the district in mind.

DEDICATION

Dedicated to my lovely father and mother

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My soul gives thanks to the Lord and Bless his Holy Name for how far he has brought me.

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LIST OF ACRONYMS

ALPs…………………………………… Alternative Livelihood Programmes

ASM…………………………………… Artisanal Small-Scale Mining

BND…………………………………… Birim North District

BNDA ………………………………... Birim North District Assembly

DOS…………………………………... Dark Object Subtraction

DN……………………………………. Digital Number

ETM……………................................. Enhanced Thematic Mapper

FAO……………….............................. Food and Agricultural Organization

GIS ………………………………….. Geographic Information System

ILO………………………………….... International Labour Organization

IPCC…………………………….….…Intergovernmental Panel on Climate Change

LU…..…………………………………Land use

LC…………………………………….Land cover

LULC…………………………………Land use and Land cover

LULCC……………………………….Land use and Land cover Change
MCMC………………………………Markov chain Monte Carlo

NASA………………………………National Aeronautic and Space Administration

NDVI……………….………………Normalized Difference Vegetation Index

NGGL………………………………Newmont Ghana Gold Limited

NGOs……………………………….Non-Governmental Organizations

ODA………………………………. Overseas Development Administration

OICI………………………………...Opportunity Industry Centre Industrialization

PMMC………………………………Precious Minerals Marketing Corporation

PCC…………………………………Post-classification Comparison

PNDC……………………………… Provisional National Defense Council

RMSE………………......................Root-Mean-Square Error

RS…………………..………………… Remote Sensing

SPSS……………………………… Statistical Package for Social Scientist

STD……………………………….. Sexually Transmitted Diseases

UNEP………………………………United Nations Environment Programme

USEPA……………………………..United States Environmental Protection Agency

USGS………………………………United States Geological Survey

WACAM………………………….. Wassa Association of Communities Affected by Mining

WHO………………………………..World Health Organisation

WGS………………………………. World Geodetic System

CHAPTER ONE INTRODUCTION

1.1 BACKGROUND

Land has been an important asset for the use of humanity, and for the sustenance and interaction of all living things. For centuries, mankind has increasingly tapped terrestrial resources with the intension of improving their living standards. The ceilings on these assets are fixed whereas human requirements are not, increasing the stress on landed assets leading to a reduction in agriculture, land dilapidation and landed property struggles (FAO and UNEP, 1999).

A holistic understanding of Land use and Land cover (LULC) is significant as countries the world over strive to subdue the troubles of unplanned development, reduction in vegetation cover, size of fertile farmlands, contamination of water bodies, and aquatic and wildlife habitat destruction. LULC information is essential in the investigation of environmental operations and difficulties, and must be realized if circumstances in the lives of people are to be ameliorated or conserved (Anderson *et al.*, 1976). LULC constitute a major factor of the environmental system that has revealed a close match with anthropogenic actions and the ecosystem (Styers *et al.*, 2009; Otukei and Blascke, 2010)

Anthropogenic activities have already modified the earth's environment greatly, usually to feed the desires of the increasing world population (Ellis and Ramankutty, 2008; Foley *et al.*, 2005). Resources from the ecosystem are difficult to be extracted all together at the same time; as a result, land use decisions end up with some exchanges that occur as a compromise leading to appreciable state of opposition between persons, ideas or interests about the choice of use of land among decision makers. Many forms of developments have degraded ecosystems which sometimes result in struggles within terrestrial beneficiaries and stakeholders and surface mining is practically observed to be the utmost instance of an anthropogenic activity that can result in an extreme degree of disputes.

This phenomenon is mostly observed between mining communities and mining operators over the choice of use of landed properties; and is seriously gaining grounds in Ghana and the world over. This is a potential problem of national and global developmental insecurity. The difficulties that usually arise are the way the topical gold charge has resulted in detrimental ecological consequences and downgrading living standards. Current researchers have proposed prevalent terrestrial alterations and dilapidation as the outcome (Agbesinyale, 2003; Akabzaa and Darimani, 2001), even though surface gold mining is still in the ascendancy, particularly the illegal small scale mining activities.

The extraction of gold leave trails of harmful contents like mercury, making the ecological impacts of gold mining scourging, principally in delicate tropical ecologies (Akpalu and Parks, 2007; Kumah 2006; Sousa and Veiga, 2009). Fierce confrontations in negotiating for land uses have therefore accompanied majority of gold mining activities in developing countries (Müller, 2004). The mining trade is still the strength of character of numerous emerging economies in the world. The worldwide paradigm which stresses on private sector growth as the engine of economic growth in developing countries motivated the reappearance of mining sector in Ghana as at 1989. The historical importance of mining in the economic development of Ghana is evident in the country's colonial name, Gold Coast (Akabzaa and Darimani, 2001).

Proportionally, growth and wealth creation in developing countries has a direct link with gold mining; greatest in Papua New Guinea (15% of GDP), followed by Ghana with 8% of their GDP and Tanzania, 6% of GDP (Ogier *et al.*, 2013). In 2012, gold provided 36 per cent of all Tanzanian exports and 26 per cent of the exports of Ghana and Papua New Guinea (Ogier *et al.*, 2013).

Ghana accrued $2.5 billion through mineral exportations in 2007; approximately two hundred thousand people are engaged in large scale mining and five hundred thousand are employed in the small scale area. Approximately 7% of Ghana's entire corporate tax profits which has 41% of the entire exports, 12% of income generated by the Internal Revenue Service (IRS) and 5% of Gross Domestic Product is injected by the mining sector (Ghana Chamber of Mines 2008). The gold mining industry contributed more than US$78.4 billion into the economies of the top 15 countries noted for mining of which Ghana was a key player in 2012 (Ogier *et al.*, 2013).

Remote Sensing (RS) and Geographic information System (GIS) are powerful materials that are used together to investigate the association between LULC and the extent and impacts of surface mining activities on the environmental. The advantage of using RS and GIS is that, it is the major application of science for tracking LULC modifications (Turner *et al.*, 2007).

Through a research using RS fast reduction in forest cover and urban increase from 1986 - 2002 in Western Ghana was revealed (Kusimi, 2008). One way of assessing LULC change using RS and GIS is to apply change detection techniques. The technique refers to the recognition and position of alterations in the state of a geographic phenomenon or feature by examining the alterations in radiance values between sets of multi-temporal satellite images (Wang, 1993).

Geostatistics is a division of statistics that pertains to the nature of space and a collection of spatiotemporal datasets. The nature of spatial parameters differ in space and time, and a comprehension of their allocation pattern at any given position at a given time delivers a chance to foretell the proceedings of a specific neighborhood (Enkhtur, 2013).

This study sought to evaluate the LULC changes that have occurred due to surface mining in Birim North District using RS and GIS, and project these LULC changes using geostatistical modeling.

1.2 RESEARCH PROBLEM

Human activities like mining results in great change to landscapes, plants and animals by way of removal of the fertile upper soil of the earth to create space for surface mining (Fyles *et al.*, 1985). Surface mining activities have been the target of strong opposition in recent times in Ghana, especially the illegal Small-scale miners (galamsey) ultimately due to the ecological and social consequences they bring. Inept processes of regularization, anchored with a count of challenges in registration and licensing, contributes to an up swell in the galamsey population, approximated to be about two hundred thousand people and constitute the majority of the artisanal small scale mining (ASM) fraternity in Ghana (Appiah, 1998;

Hilson and Potter, 2003).

Different authors including Kumi-Boateng (2012) in the Tarkwa Mining Area of Ghana, have investigated the use of RS and GIS for evaluating the impact surface mining activities have on LULC in Ghana and have observed that the various LULC types especially vegetation, agricultural lands and water bodies continue to change downwards. Others including Schueler *et al.* (2011) in a research in the western region of Ghana, have gone further to determine and relate alterations to a number of ecological as well as socioeconomic factors significant to empathize the cost LULC changes bring to local livelihoods in the study area.

However, so far, less work has integrated RS and GIS techniques with statistical models to analyze spatial patterns of LULC changes and assessed the effects of surface mining related LULC changes on local livelihood over a given period and projected LULC changes in the Birim North District of Ghana. A research of that nature could render a deeper perceptivity into the environmental effects of surface mining, especially galamsey in the future, better interpret the impact of surface mining on LULC types in Ghana and elsewhere and provide a basis for future policy interventions in the District. The Markov Chain Monte Carlo (MCMC) statistics has been combined with RS and GIS techniques in this research project. This thesis would use MCMC in combination with RS and GIS to project LULC changes due to surface gold mining on LULC types from 2015-2025 in the study area.

1.3 RESEARCH OBJECTIVE

The objective of the project is to use RS, GIS and spatial statistical methods to map LULC changes resulting from surface mining and to project the impact of surface gold mining on LULC types for the next ten years in the study area.

1.4 SPECIFIC OBJECTIVES

1. To determine and map LULC changes from 2002-2015
2. To identify the environmental consequences of LULC changes emanating from surface gold mining in the study area
3. To analyze and project LULC changes in the study area to 2025
4. To determine whether surface mining related LULC changes in the study area affects local livelihood.

1.5 RESEARCH QUESTIONS

This research is interested in answering the following questions:

1. What are the LULC change types in the study area?
2. What are the impacts of these LULC changes on the environment?
3. What are the trajectories of LULC changes in the study area caused by mining?
4. How do gold mining-related LULC changes affect local livelihoods in the study area?

1.6 OUTLINE OF CHAPTERS

The thesis will be generally structured under five chapters.

- Chapter One will be the introduction. It will comprise the background to the study, research problem, research objectives, specific objectives, research questions and the outline of chapters.

- Chapter Two will be the literature review of previous works done on impact of surface mining on LULC in BND and Ghana as a whole and how RS and GIS with statistics has been used in the application.
- Chapter Three will outline the Study Area and the Materials and Methods in the thesis.
- The Chapter Four will discuss the results being the outcome of the materials and methods utilized in the research.
- The last chapter; Chapter Five will deal with the Conclusions and Recommendations of the thesis.

CHAPTER TWO LITERATURE REVIEW

2.1 LAND AND ITS USES

Landed assets are concerned with the defined surface of the earth's ecological system; this includes the properties of the biosphere directly above or below this surface. It also includes those of the sedimentary layers close to the surface and related geohydrological treasury, the flora and fauna, the built-up and observed effects of the past, current and future human interactions with natural phenomena (FAO and UNEP, 1997).

Industrial revolutions have resulted in different type of human activities leading to noticeable changes in LULC especially when land managers or stakeholders decide to change a land use type towards a desirable one. Such decisions are mostly affected by the land tenure system, the purpose of activities undertaken including the specific products and services that are sought, the geographic location and extent of the land under consideration (area, size, shape). Land can be used in different ways, including settlement, institutional, business, industrial, farming, parks and gardens (http://science.jrank.org/pages/3801/Land-Use-Uses-land.html, 20 July, 2015). Land for purposes of settlement for example, may be used by a single family, or collections of multiple-family habitations. Institutional land uses are usually connected with civic constructions including educational structures, hospitals and government offices. Land for purposes of industry is diverse and is dependent on the type of industry put to consideration. Urban-industrial land uses are mainly the locating of manufacturing plants or refineries, including utilities like electrical energy, water and waste management facilities.

Other specific land use classes include agriculture and forestry, but in this case the outcome is food or tree-fiber as inexhaustible products, other land uses involve the assignment of

peculiar areas as bionomic and natural parks (http://science.jrank.org/pages/3801/Land-Use-
Uses-land.html 20 July, 2015).

2.2 LAND USE AND LAND COVER

Land cover (LC) focuses on spatial depiction of the environment and the visual (bio) materialistic setting of the earth's terrestrial cover (Di Gregorio and Jansen, 1998). This definition makes way for varied eco-system classes to be differentiated as, classes of vegetation, bareland, built-up, rocky surfaces and water bodies. Similarly, Ellis *et al.* (2009) defined LC as a feature of land that is experimental, using the method of remote sensing.

LU is a sequence of activities on land, executed by humans, to attain resources and services. A series of activities like ploughing, planting, weeding, fertilising rearing and harvesting are typical examples of LU (Mücher *et al.*, 1993).

Unlike LC, LU is complex to "observe"; usually it is tricky to choose whether range lands are used for farming or not. Data received sometimes come from insufficient sources of experimentation and sometimes demand further knowledge (Meinel and Hennersdorf, 2002).

2.2.1 LULC Change

Identifying and understanding the major causes of LULC modification demands an apprehension of the way human resolution processes on LULC and how particular environmental and social factors intermingle. Essentially it is worth noting that conclusions on LU types are determined and affected by natural and anthropogenic factors over a broad array of spacial levels; from a family scale conclusion which alter local LU patterns, to major government policies and socio-economic drivers which influence LU regionally and even globally.

According to Lambin *et al.* (2001), the factors of LULC transformation is grouped into two: The immediate (direct) and supporting (indirect) factors. The immediate causes of LULC change explicates how and why local LC and land system processes are changed right away by humans, whiles the supporting causes elaborates the larger circumstance and underlying drivers assisting these local actions (Lambin *et al.*, 2001). Immediate causes generally operate at the local level such as individual farm lands, single households or simple communities while the underlying causes of LULC alteration begin at stages elevated than the local stage including districts, provinces, or country (regional) or even global stages, despite the fact that intricate exchanges occurring between these ranks of organizations are frequent.

2.3 GOLD MINING IN GHANA

Naturally occurring minerals are mostly located underneath the earth and thus demand digging and excavation of the earth. Agriculture is considered the world's most erstwhile and very significant sector, followed by mining (Down and Stocks, 1977). Mining is said to be ranked fifth in the class of industries and is essential economically in the world. International trade binds countries together and the trade of mineral commodities plays an essential part in this process (Madeley, 1999). Generally two major methods of mining are practiced in Ghana; surface and underground mining. Surface mining, is carried out if the ore is found to lie on or just beneath the earth surface. This method is generally requires fewer workers to produce the same quantity of ore than the underground mining does hence more costeffective. When the mineral deposit lies deep below the earth surface, underground mining is employed.

Gold is cherished by all and sundry, making it a principal target for colossal industrial mining operations designed to extract the mineral in the most economical way possible. Heavy machinery and chemical extraction techniques give miners access to the valuable metal, but they can have significant side effects. The gold mining industry produces a wide variety of environmental contamination, and if not handled well can cause extensive destruction to any region that is home to fertile lands of the adored mineral.

Gold mining is done mainly in two varied ways in Ghana; small-scale mining (galamsey) which involves mining in open pits by hand and selling of gold via regional markets, and large-scale mining companies on the other hand who function with industrialized output chains with direct links to the global consumer base. Small-scale and large-scale mining vary greatly in their environmental and socio-economic significance (Hilson, 2002a; Hilson, 2002b). In the case of Ghana though, there is substantial evidence, that gold mining is generally associated with high levels of pollution. Most studies including those of Amegbey and Adimado (2003) and WACAM (2010) focusing on gold mining areas in the Western Region like Tarkwa, Prestea and Wassa West district, have documented at least eleven incidence of cyanide pollution in mining areas.

2.3.1 Brief Gold Mining History of Ghana

The tenth century marks the time gold was first traded from West Africa to Europe; Ghana therefore has a long history of mining, especially for gold. The majority of the gold came by Sahara Caravans and the sources were the kingdoms of old Ghana, Mali, and Songhai. During the pre-colonial periods, more than a quarter of a million ounces of gold reached Europe from African gold reserves annually. Relying mostly on indigenous labour, many gold reserves were located around Nigeria, Guinea, Senegal, Ghana, Sierra Leone and other countries of Gold Coast in the final years of the nineteenth century (http://www.ghanamining.org/ghanaims/InvestorsGuide/tabid/194/Default.aspx, 15 January, 2016).

2.4 SURFACE GOLD MINING

According to Wood (1999); surface mining, is attempted when the ore is located just beneath the earth surface. This type of mining is more lucrative and necessitates less labour to produce the exact measure of ore that the underground operation does. Surface mining exposes the ore by depleting the vegetation cover. Large amounts of vegetation cover are destroyed, turned upside-down and put beneath the earth surface, transforming the originally vegetated land into bare, exanimate grounds (Greenwood and Edwards, 1979). Major sections of the vegetation cover in mined sites misplace their ability to function in any way (Charis, 1994).

The hydrological system of Ghana has been polluted, especially in town sections surrounded by gold mining (Davis *et al.*, 1994), gold mining is thus lacking general approval in current times and considered as a major origin of mercury (Hg), Lead (Pb) and other heavy metal pollution of water bodies (Paruchuri *et al.*, 2010). The primary ecological problems of smallscale mining activities are mercury contamination due to gold processing and land abasement

(World Bank, 1995) which primarily employs surface mining.

In 1994, Laing stated that all debris, be it harmful or otherwise, poses as high bother to neighbouring mining towns and is therefore consequentially detrimental to human health. It results in the overcrowding of plant pores and decreases plant photosynthesis (Laing, 1994). The United Nations Environmental Programme revealed that mining and mineral processing are accountable for approximately 10% of pollution in Ghana (ODA, 1992).

2.4.1 Surface Gold Mining Methods

Surface mining operations are generally classified into strip and open pit even though dredging and hydraulic mining methods are still practiced in a comparatively small scale worldwide. Strip mining is basically characterized by the removal of large overburden to expose the mineral for extraction. Open-pit mining is a type of strip mining in which the mineral sediment stretches just deeper below the earth surface, demanding the removal of multiple strata of waste before hitting the mineral (https://www.elaw.org/files/mining-eiaguidebook, 19 July, 2016).

Surface mining is typically employed in situations where the overburden is relatively thin, or

where underground mining would not be economically feasible (United States Environmental Protection Agency (USEPA), 2005). Surface mining is the principal operation in the world; it frequently demands a huge investment but normally leads to towering output, small in service expenditure and good safety environment. Nearly all metallic ores (98%), approximately 97% of the nonmetallic ores and 61% of the coal in the United States are mined by means of surface methods (Energy Information Administration, 2000).

2.4.2 Small Scale Gold Mining in Ghana

The small scale gold mining enterprise can be traced back to pre-colonial times in Ghana even though small scale gold mining went on secretly during colonial times. From almost the 19th century; Ghana has experienced three jungle gold booms. The first jungle boom targeted Wassa and Asante Gold, with both local and foreign investors founding mines in these areas just about 1874 (World Bank, 2004). The second jungle boom started in the later parts of 1930 and saw an incline in gold exportations from 6 million to 9 million ounce between 1946 and 1950. The second jungle boom was connected with the then colonial government forbidding native mining following 1933. This established the genesis of the large scale mining by the British and other foreign investors. The mining reserves that were once for the local people were totally reverted and the capture of aboriginal properties were amalgamated with laws (World Bank, 2004).

The legalization allowed for the rationalization of the licensing placement that provided small scale miners straight right of entry for capital and scientific support and an authorized selling and buying system. The Precious Minerals Marketing Corporation (PMMC), established in 1989, helped promote the marketing and purchasing of minerals, it also substituted the Diamond Marketing Corporation, which was in charge of the purchase and sale of only diamonds. (Minerals Commission of Ghana, 2004).

2.4.3 Gold potential in BND

Gold is one of the major minerals mined in the Birim North district in Ghana. Many gold prospecting projects have been carried out by mining companies and researchers alike. In 2014, Kwang *et al.* used RS and GIS techniques to map the gold potential of BND. The gold potential map demarcates 158 km^2 (32%) of the total of 497 km^2 as well-disposed for the occurrences of the gold ore in Birim North District, with a success rate of 88% and a prediction rate of 83%. The Newmont Gold Ghana Limited mine area was observed to be located in the sections with relatively higher posterior probabilities (Kwang *et al.*, 2014).

2.4.4 Small Scale Gold Mining in BND

Small Scale mining in Ghana refers to mining by any method not involving substantial expenditure by any individual or group of persons not more than nine in number or by a cooperative society made up of ten or more persons (Government of Ghana, 1989). In 2008, The Ghana Chamber of Mines estimated the number of galamsey operators in Ghana to be between 300,000 and 500,000 artisan small miners, constituting one of the biggest groupings of miners in Africa (Ghana Chamber of Mines Report, 2008), many function without license on concessions owned by large scale mining enterprises, or in restrained locations. The amalgamation technique is mostly used for small-scale mining (Akosa *et al.*, 2002); mercury is combined with gold concentrate to yield gold amalgam in this procedure, and is further fired up to extract the gold (Ntibery *et al.*, 2003).

Small scale mining is easily noticeable in the BND area, especially in the forest where illegal mining activities go unnoticed. In the light of this, stakeholders in the Eastern Region of Ghana have frequently set-out committees to investigate and report on small scale mining in the BND and other districts where the activity is severer (http://birimnorth.ghanadistricts.gov .gh/?arrow=nws&read=46072, 15 February, 2015).

The Ghana News Agency (2007) indicated that, the Minerals Commission was set to allocate 3,262.5 acres of land in the BND for distribution to 130 licensed ASM to enhance gold production in the area with the intention of regularising their activities. So severe is the level of forest destruction in this district that the organized groups are adding their voices: The National Coalition on Mining; a non- governmental organization (NGO) made up of 18 organizations, individuals and persons from communities affected by mining operations in the country have objected to surface mining in forest reserves in the BND (http://www. ghanaweb.com/GhanaHomePage/features/An-Assessment-Of-An Environmental-Problem-In-Ghana-294578, 15 February, 2015).

2.5 SOCIO-ECONOMIC EFFECTS OF GOLD MINING IN BND

The socio-economic life of Ghana has been improved greatly due to gold in the last hundred years (Akabzaa *et al.,* 2005). The presence of large scale mining companies like NGGL in the various mining communities within their proposed operational areas have served as an avenue for eligible unemployed youth of the area. The traditional authorities on the other hand use the opportunity to induce developmental projects into their communities. The BND assembly also gets revenue for development projects as well as jobs for the unemployed youth in the District.

The emergence of small scale mining has modified the LU patterns of the district: Traditionally farming is the predominant economic in the district; farming is the backbone of the economy of BND. About 73.5% of the active labour of the district engages in at least one of the varied agricultural activities (Ghana Statistical Service, 2014).

Galamsey activities are performed illegally without statutory licensing and operate outside of regulatory and officially permitted procedures. That notwithstanding and with requisite license, ASM creates job opportunities to an essential sector of the labour market; it also acts significantly in production, income generation and provides necessary survival strategies. According to the International Labour Organization (ILO) (1999), about 13 million people are directly working in this sector worldwide. Additional, about 100 million people rely on it for survival and women who are mostly vulnerable to negative socio-economic impacts constitute about 50% of the ASM labour force in the world (ILO, 1999). Generally, the part played by mining and its associated activities to the socio-economic growth of the communities in which they are carried out is immense.

2.6 REMOTE SENSING AND GIS

Remote Sensing and GIS applications are often considered as cost effective procedures for the collection of data over large areas that would otherwise require a very large input of human and material resources. The collection of remotely sensed data facilitates the

synoptic analyses of Earth - system function, patterning, and change at local, regional and global scales over time; such data also provide an important link between intensive, localized ecological research and regional, national and international conservation and management of biological diversity (Wilkie and Finn, 1996). RS is the art, science and technology of observing an object scene or phenomenon by instrument based techniques (Tempfli *et al.*,
2009).

A GIS on the other hand is a special case of information systems where the database is made up of gathered data on spatially dispersed features, operations or events, which are determinable in space as points, lines, or areas. A geographic information system processes this data about these points, lines, and areas to retrieve data for ad hoc queries and analyses (Dueker, 1979). GIS may also be described as; a system designed to capture, store, manipulate, analyze and display diverse sets of spatial or geo-referenced data (Burrough and McDonnell, 1998).

2.6.1 Image Pre-Processing

Pre-processing of satellite images prior to actual change detection is essential and has as its unique goals as the establishment of a more direct linkage between the data and biophysical phenomena, the removal of data acquisition errors and image noise, and the masking of contaminated (e.g. clouds) scene fragments. The effects of the atmosphere upon remotelysensed data are not considered errors, since they are part of the signal received by the sensing device (Bernstein, 1983; Erdas, 1999). However, it is often important to remove atmospheric effects, especially for scene matching and change detection analysis purposes.

Many researches including those of Mahiny and Turner, 2007; Bruce and Hilbert, 2004; Furby and Campbell, 2001; Yang *et al.*, 2000 and Chavez, 1988, have all indicated the significance of removing errors in satellite images emanating from atmospheric effects. The essence of atmospheric correction in change detection analysis mostly corresponds to the method used. For instance Song *et al.* (2001) stated that in linear methods of change detection such as simple image differencing; the need to correct images is not mandatory if only the stable classes in the differenced image have a zero mean. It has been proven that atmospheric correction especially affects the results of ratio transformations such as Normalized Difference Vegetation Index (NDVI), and that image classification is the image experimental procedure least affected by correction. This is only possible when the image to be classified and the training data are at the same radiometric scale (Song *et al.*, 2001).

In many instances of change detection studies, it is adequate to convert raw digital number (DN) of the image dataset to be uniform with a reference haze-free image (Campbell *et al.*, 1994). So, a comparative atmospheric correction procedure such as pseudo-invariant features (PIF) or the radiometric control set (RCS) is usually approved. The alternative to these normalization procedures though is the cosine of the sun zenith angle (COST) absolute correction method which is regularly applied to translate raw Digital Numbers (DNs) of the images into true reflectance of geographic phenomena.

2.6.2 The Cosine of The Sun Zenith Angle Method

It is an image-based absolute correction method and applies just the cosine of sun zenith angle (**Cos TZ**) as an input factor for estimating the impacts of absorption of travelling earth bound electromagnetic rays by atmospheric gases and Rayleigh Scattering. In using the model, DNs of the images are first converted to radiance through the following formula (Chavez, 1988):

$$\boldsymbol{R_{sat}} = \frac{[\mathbf{R_{min}} + (\mathbf{R_{max}} - \mathbf{R_{min}})]}{(\mathbf{DN_{max}})} * \mathbf{DN} \text{------------------} \quad \textbf{Equation 2.1}$$

From Equation 2.1, R_{sat} is the spectral radiance at the sensor, $\mathbf{R_{min}}$ is the minimum spectral radiance for a given band, R_{max} is the maximum spectral radiance for a given band, and $\mathbf{DN_{max}}$ is the maximum $\mathbf{DN}$ of the image range. The parameters of $\mathbf{R_{min}}$ and $\mathbf{R_{max}}$ for each Landsat band are recommended by Markham and Barker (1986).

The radiance is then translated to reflectance of the objects at the Earth's surface using the Equation 2.2:

$$\boldsymbol{R_{ref}} = \frac{\boldsymbol{\pi}(\mathbf{R_{sat}} - \mathbf{R_{haze}})}{(\mathbf{E_0 Cos\ TZ})} \text{------------------} \quad \textbf{Equation 2.2}$$

$\boldsymbol{R_{ref}}$ is the reflectance at the Earth surface, $\boldsymbol{R_{sat}}$ is the spectral radiance at the sensor, $\mathbf{R_{haze}}$ is the path radiance, $\mathbf{E_0}$ is the mean solar exo-atmospheric irradiance, and $\mathbf{TZ}$, the average sun angle. The exo-atmospheric irradiance values for Landsat 5 are available from Markham and Barker (1987) and for Landsat 7 from the National Aeronautics and Space Administration (NASA's) Landsat 7 Science Data Users Handbook (2003).

The foremost step in computing the path radiance ($\mathbf{R_{haze}}$) is the extraction of the DN_{haze}. The DN_{haze} value is transformed to the source radiance for each band using Equation 2.2, which is about one percent (1%) of the whole image reflectance (Chavez, 1988), the radiance of an absolutely dark object when haze-free will be as in Equation 2.3:

$$\mathbf{DOS1\% = \frac{(0.01E0 \cos TZ)}{(\pi d^2)}} \text{------------------} \quad \textbf{Equation 2.3}$$

Where d^2 is the square of the distance between the sun and the Earth in astronomical units.

Hence, when the dark objects are hazy, the path radiance due to haze ($\mathbf{R_{haze}}$) can be calculated by subtracting $\mathbf{DOS1\%}$ from the at-satellite radiance of hazy objects (Dark Object Subtraction). $\mathbf{R_{haze}}$ is then substituted into Equation 2.2, and the images are corrected band by band for atmospheric and radiometric noise.

The COST method is comparatively simply executed and is built-in for many commercial image processing software (Mahiny and Turner, 2007), such as ERDAS Imagine. Imagebased pre-processing techniques like the '$\mathbf{DOS1\%}$' model can be applied using a modeling tool such as ERDAS Imagine's 'Spatial Modeler'.

2.6.3 Image Classification

Thematic files are usually created through image multispectral classification and entails spectral pattern recognition to identify groups of pixels that represent a common feature of the scene.

Supervised Training

Supervised training is closely controlled by the analyst such that one selects pixels that represent patterns or land cover features that are recognized, or identified with the help of aerial photos, ground truth data, or maps. There are several algorithms for performing supervised classification, but the most commonly used method is the Maximum Likelihood Classifier. This algorithm classifies images according to the variance and covariance of the spectral response patterns of pixels; the assumption of most Maximum Likelihood classifies is that the statistics of the clusters follow a normal (Gaussian) distribution (Tempfli *et al.*,

2009).

MLH supervised classification was used in this research because it is regarded as one of the most accurate classifiers, since it is founded on statistical analysis (Shalaby and Tateishi,

2007).

Unsupervised Training

Supervised classification requires knowledge at hand, however, this knowledge may not be readily available and the classes of interest not yet defined. In this case an unsupervised classification can be applied; this involves partitioning the feature space into a number of clusters using clustering algorithms. Unsupervised training is highly computer-automated; it helps in identifying some factors that the computer employs to reveal statistical patterns found in the datasets. These patterns do not essentially communicate to directly meaningful features of the scene, such as contiguous, easily recognized areas of a peculiar soil type or

LU or LC. They are just clusters of pixels with analogous spectral characteristics. It may be more significant to locate classes of pixels with analytical spectral characteristics in some cases than it is to group pixels into identifiable categories (Erdas, 1999). The most widely used algorithm for performing unsupervised classification is the Iterative Self-Organizing

Data Analysis Technique (ISODATA) and K- Means.

The Hybrid Classification

A hybrid classification also known as the directed clustering requires the amalgamation of both the unsupervised and the supervised classifications. An unsupervised classification is initially performed to identify spectral differences within the data and then a supervised classification is executed with areas of the unsupervised classification as training data in addition to ancillary ground-truth. Hybrid classifiers have been observed to be of particular value when making analysis in which there exist complex unevenness in the spectral response patterns of individual cover types, a condition that is quite common in vegetation mapping (Lillesand and Kiefer, 2000).

2.6.4. Accuracy assessment

The error matrix (confusion matrix) is generally accepted as the standard descriptive reporting tool for accuracy assessment of remotely sensed data. An error matrix is a square array of numbers arranged in rows and columns and indicates the number of sample points (i.e. pixels and clusters of pixels) assigned to a particular class relative to the actual class as verified by reference data (Congalton, 1996).

The average accuracy is the average of the accuracies for each class, whiles the overall accuracy is an average with the accuracy of each class weighted by the proportion of test samples for that class in the total training or verification sets. The overall accuracy is a more accurate estimate of the classification accuracy (Yang, 2001).

The Kappa coefficient corrects for any change acceptance (Rosenfield and Fitzpatrick-Lins, 1986), it constitutes the size of satisfaction obtained after eliminating the size of acceptance that could have been obtained by chance (Foody, 1992). Other quality parameters include; user's accuracy (error of commission), this refers to incorrectly classified samples, and the kappa statistics which is used to measure the agreement between the classified map and the reference data (Mather, 2004).

Kappa can be used as a measure of agreement between model predictions and reality (Congalton, 1991) or to verify if the values contained in an error matrix represent a result significantly better than random (Jensen, 1996). Kappa can be expressed mathematically as in Equation 2.4:

$$\mathbf{K} = \frac{[\mathbf{N} \sum_{i=1}^{r} \mathbf{x_{ii}} - \sum_{i=1}^{r} (\mathbf{x_{i+}} * \mathbf{x_{+i}})]}{[\mathbf{N_2} - \sum_{i=1}^{r} (\mathbf{x_{i+}} * \mathbf{x_{+i}})]} \text{ ------------------ } \quad \textbf{Equation 2.4}$$

Where;

N is the total number of sites in the matrix,

r is the number of rows in the matrix,

$\mathbf{x_{ii}}$ is the number in row **i** and column **i**

$\mathbf{x}_{+i}$ is the total for row $\mathbf{i}$ and

$\mathbf{x}_{i+}$ is the total for column $\mathbf{i}$ (Jensen 1996).

2.6.5 Application of RS and GIS in Change Detection

Five causes of LULC change have been listed by Lambin and Strahler (1994) as:

a) Long-term natural changes in climatic conditions,

b) Geomorphologic and ecological processes such as soil erosion and vegetation successions,

c) human-induced alterations of vegetation cover and landscapes including deforestation and land degradation,

d) Inter-annual climate variability and

e) The greenhouse effect caused by human activities.

LULC mapping is one of the very successful and widely used applications of satellite based RS, (Sexton *et al.*, 2013). Modern scientific applications like RS and GIS avail some of the most cost effective and accurate means of examining the extent and pattern of changes in LULC over a given study period (Miller *et al.,* 1998). These changing environmental problems reflect changing socio-economic conditions; and timely and accurate RS and GIS based information of LULC could contribute greatly to the effort of planners and policy makers in making resource management and LULC planning decisions especially when information is extracted from datasets of different times and analyzed.

The process of change detection forms an essential component of the process by which plans on the use of natural resources can be reviewed and up-dated. Change detection provides the basis for coordinated policies and an elaborate and systematic plan of action (Sarma, 2002). It may also uncover the spatial pattern of events in the area and judging whether it is positive or negative; it will enable planners to alter necessary schemes accordingly.

Additionally, change detection may locate areas of peculiar type of changes that should be encouraged or discouraged (Lambin *et al.*, 2001). Satellite data have become a major source of application in change detection because of the repetitive coverage of the satellites at short intervals (Mas, 1999), for example Damizadeh *et al.* (2000) used satellite images, as an effective tool to find out how changes in vegetation cover occurs.

Various researchers have applied change detection methods in their works including those of Townsend *et al.* (2009) who carried out a study on the precise determination of the amount of mining operation in Maryland and Pennsylvania, Central Appalachian region of West

Virginia; the aim was to assess the existence and effects of LULC changes on the ecosystem.

In Greece, Petropoulos *et al.* (2012) used RS and GIS to quantify land cover changes due to mining and reclamation at a watershed scale. The method was based on a Support Vector Machines (SVMs) classifier combined with multi-temporal change detection of Landsat TM imagery. The impact of mining activity on the study area was analysed for the time period from 1987–2010 through a post-classification change detection analysis (Petropoulos *et al.*, 2012).

Akinlotan (2012) also carried out a study on the analysis of LULC changes over three decades in the Akinyele Local Government Area of Oyo State, Nigeria that revealed a highly dynamic interchange of land use, driven by competition for land between built-up, farmland and forest (Akinlotan, 2012); this was made possible with RS and GIS techniques.

2.7 SPATIAL AND STATISTICAL ANALYSIS

Spatial analysis or spatial statistics includes any of the formal techniques which study entities using their topological, geometric, or geographic properties. Spatial data comes in many varieties and it is not easy to arrive at a system of classification that is simultaneously exclusive, exhaustive, imaginative, and satisfying (Upton and Fingelton, 1985)

Spatial statistical techniques have been significant tools in LULC research; it integrates spatial correlation in line with the way nearness of geographical phenomena is defined.

Geostatistics is the study of phenomena that vary in space and/or time (Deutsch, 2002). Geostatistics is used for modeling spatial data; it provides more reliable estimations of phenomena at locations where no measurements are available. It is intimately related to interpolation methods, but extends far beyond simple interpolation problems. Geostatistical techniques rely on statistical models that are based on random function (or random variable) theory to model the uncertainty associated with spatial estimation and simulation.

2.7.1 Application of Statistics in Mapping

Maps are an excellent means of presenting statistical information. Not only are they visually attractive, they also make it easier for users to relate data to location as well as help them to identify geographic trends in the data, in a way which would be difficult using a chart or a table. Statistics is a major field for the investigation and classification of sample data on geographic phenomena. It also avails a number of formats for interpolating surfaces from such data. Ordinary kriging in the form of Geostatistics is the most well-known of these. While the methods evolved from scientists working in the mining industry, a larger audience is now observed in scientific fields of study in which both data values and their spatial information are considered analytically essential (Eastman, 2012).

Maps are used to depict statistical data in fundamentally, two ways: qualitative and quantitative. Qualitative data differentiates between various types of entities. Quantitative data communicates a message of magnitude (Aileen, 2013). Understanding more about the nature of statistical data used for mapping purposes helps to better understand the methods that can be used to map it.

2.7.2 Markov Chain Monte Carlo (MCMC) and LULC Change Simulation

A Markov chain is a mathematical model for stochastic systems whose states, discrete or continuous, are governed by a transition probability; the current state in a Markov chain only depends on the most recent previous states (Zhu *et al.*, 2005)

The idea of MCMC sampling was first introduced by Metropolis *et al.* (1953) as a method for the efficient simulation of the energy levels of atoms in a crystalline structure and was subsequently adapted and generalized by Hastings (1970) to focus on statistical problems. A sequence of random variables:

A_0, A_1, A_2, A_3………..... with values in a countable set P is a Markov chain if at any

time n, the future states (or values) A_n+1, A_n+2, A_n+3, …………... depend on the history

$A_0, \ldots \ldots \ldots, A_n$ only through the present state A_n.

Markov chains are fundamental stochastic processes with many diverse applications. Markov chain Monte Carlo (MCMC) algorithms like the Metropolis-Hastings algorithm (Metropolis *et al.*, 1953; Hastings, 1970) and the Gibbs sampler (Gelfand and Smith, 1990) are very well known tools in statistics (Tierney, 1994). The 1990's in particular have witnessed a burst of activity in applying these Bayesian methods and most applications have used MCMC methods to simulate posterior distributions (Kass *et al.*, 1997).

The MCMC simulation method will be applied to estimate parameter values in the LULC change trajectory mapping. This technique relies on Bayesian inference is excellent for automatic model standardization and uncertainty analysis as previously applied in snow modeling by Kolberg and Gottschalk (2006) and He *et al.* (2011).

A fully Bayesian inference is based on the posterior distribution of the unknown parameters. In this approach, samples are drawn from the full conditionals of the unknown parameters given the data through MCMC simulations.

Mathematically, let $\boldsymbol{\beta}$ represent the unknown function to be evaluated.

i.e., $\boldsymbol{\beta} = (\boldsymbol{f}(\boldsymbol{h}))$ and $\boldsymbol{\tau}$ is the variance component.

The posterior distribution is then given as:

$$\boldsymbol{P}\ (\boldsymbol{\beta}, \boldsymbol{\tau}\ /\mathrm{y})\ \boldsymbol{\alpha}\ \boldsymbol{P}(\boldsymbol{y}/\ \boldsymbol{\beta})\ \boldsymbol{P}\ (\boldsymbol{\beta}\ /\boldsymbol{\tau})\ \boldsymbol{P}\ (\boldsymbol{\tau})$$

Where $\boldsymbol{P}(\boldsymbol{y}/\ \boldsymbol{\beta})$ is the likelihood function of the data given the parameters and $\boldsymbol{P}\ (\boldsymbol{\tau})$ represents the probability density function. Full conditional for the unknown function $\boldsymbol{f}$ $(\boldsymbol{h}(\boldsymbol{S}))$ is multivariate Gaussian and, as a result, a Gibbs sampler for MCMC simulation is employed. Cholesky decompositions for band matrices have been used to efficiently draw random samples from the full conditional. The model has been implemented in public domain software for Bayesian analysis, including IDRISI 17.0 (The Selva Edition) (Stefan and Andreas, 2004).

Saloranta (2014) used MCMC parameter estimation method in simulating more accurate snow maps for Norway, by revising the model code (especially the density and 20 snow melt algorithms), and estimated the parameters of the new model version 1.1.1 by using the Markov Chain Monte Carlo (MCMC) simulation method in combination with model sensitivity analysis. The MCMC simulation method is based on Bayesian inference, and is able to reveal all plausible parameter combinations that give a proper model fit with observations, taking also into account uncertainty in the model, input data and observations. Sohl *et al.* (2014) in a study on; Spatially explicit modeling of 1992–2100 land cover and forest stand age for the conterminous United States, developed four qualitative and quantitative scenarios of LULC change, with characteristics consistent with the Intergovernmental Panel on Climate Change (IPCC) Special Report on Emission Scenarios (SRES). The four quantified scenarios (A1, A2, B1, and B2) served as input to the forecasting scenarios of land-use change (FORE-SCE) model. Four spatially explicit data sets consistent with scenario storylines were produced for the conterminous United States, with annual LULC maps from 1992 - 2100. The future projections were characterized by a loss of natural land covers in most scenarios, with corresponding expansion of anthropogenic land uses (Sohl *et al.,* 2014).

CHAPTER THREE STUDY AREA, MATERIALS AND METHODS

3.1 STUDY AREA

The BND was originated from the former Birim District Council in 1987 as part of the Government of Ghana decentralisation programme to advance effective local governance and speed up the development of the area. The BND is one of the (21) Municipalities and Districts in the Eastern Region of Ghana. The Administrative Capital of the District is New Abirem (Figure 3.1). It is bordered to the south by Akyemansa District (newly carved out of the present Birim North District), to the north by Kwahu West Municipal, to the west by the Adansi South and Asante Akyem South Districts; both in the Ashanti Region, and to the east by Kwaebibirem and Atiwa Districts (Birim North District Assembly, 2006). The BND lies between latitude 6.15^{o}N - 6.35^{o}N and longitude 0.20^{o}W - 1.05^{o}W. The district is strategically located especially its capital New Abirem as it is posited among major commercial towns such as Nkawkaw, Oda and Kade. With improved road conditions linking the district to these commercial centres, the economy of the district stands a better chance of being improved. New Abirem can be described as a connecting or a confluence town as it is situated at the meeting point of the Nkawkaw- Oda-Kade roads (Birim North District Assembly, 2006). The district spans over an approximated total land area of 121,623.12 hectares which is approximately 6.47 percent of the total land area of the Eastern Region (Birim North District Assembly, 2006).

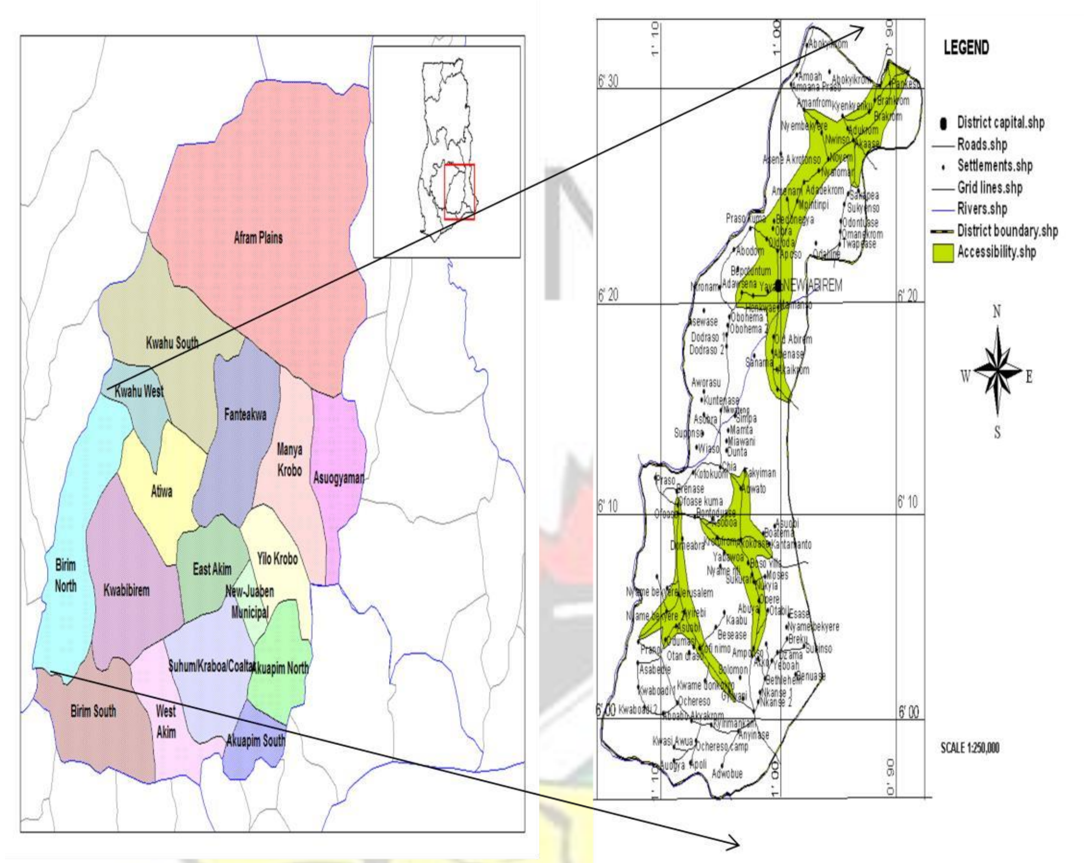
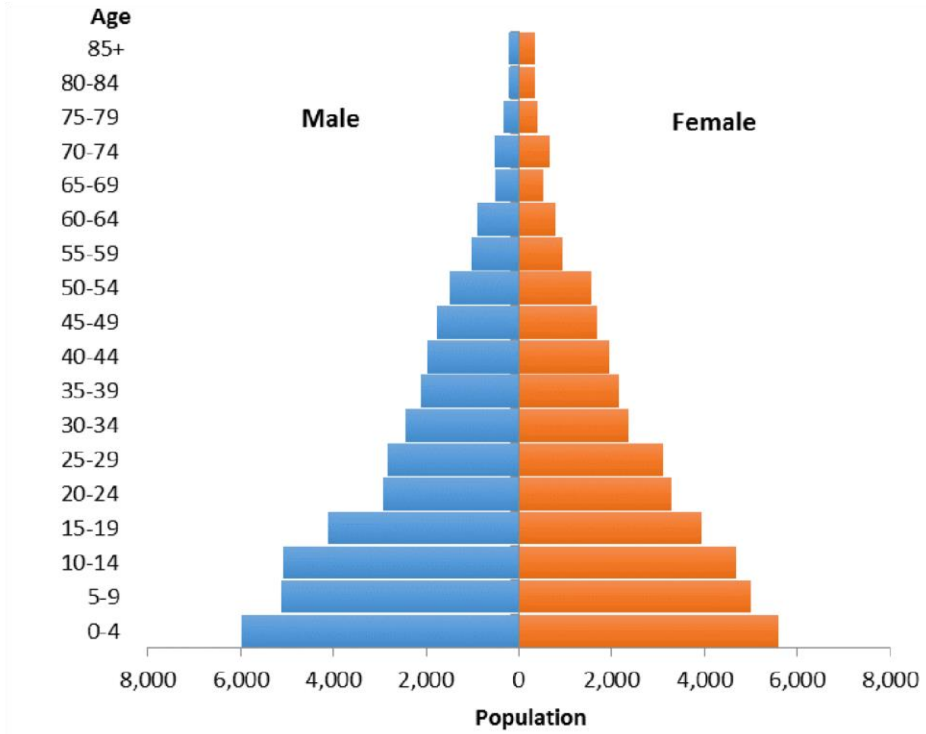


Figure 3.1: District map of Birim North.

3.1.1 Population

The age and sex structure of BND is depicted in the population pyramid as in Figure 3.2. The pyramid displays a relatively large base; it reduces gradually upwards as the age groups increase. This indicates a relatively decrease in population in the older ages. The figure offers a significant lesson regarding the current and future fertility in the District. It also provides insight into the migration patterns which enhances policy formulation and infrastructure planning.

Figure 3.2: BND Population Pyramid



Source: Ghana Statistical Service, 2010 Population and Housing Census

3.1.2 Climate and Vegetation

The district has a two maxima rainfall pattern: Late March is when the first rainfall season starts and ends in the early parts of July. Mid August to the later parts of October is the start of the second season. The quantity of rainfall observed in the district falls within 150 cm and 200 cm throughout the dual maximum periods of May-June and September - October yearly. The temperatures span within 25.2 degree Celsius minimum and 27.9 degree Celsius maximum throughout the year (http://mofa.gov.gh/site/?page_id=1506, 17 February, 2014).

The high quantity of rainfall and optimum temperatures has resulted in maintaining good farming operations. The vegetation of the area comprises Semi-deciduous forest with rich undergrowth of climbers. Nine forest reserves can be located in the district; containing enormous species of trees with high economic value especially the wood industry (Birim North District Assembly, 2006).

3.1.3 Geology and Hydrogeology

The geology of the study area consists mainly of Proterozoic rocks of the Birimian (Upper and Lower Birimian) and Tarkwaian systems. Dixcove Granitoids Complex has intruded both the Birimian and Tarkwaian systems in many places in the district. The Upper Birimian rocks consist of black slates, sericite schist and phyllites, with subordinate grey, sandy phyllites and grewackes. The lower Birimian rocks are made of black phyllites, metasiltstones, metagreywackes, tuffaceous sediments, tuffs and hornstones. The Tarkwaian system is primarily sandstone, quartzite, phyllite, shale and conglomerate and is resting on and derived from the Birimian system (Kesse, 1985). The sandstone (a quartzite) consists of variable amounts of feldspar, sericite, chlorite, ferriferous carbonate, magnetite or hematite and epidote. The Tarkwa Phyllite consists of chloritoid and magnetite or hematite with sericite and chlorite (Kuma 2004). The conglomerates consist of silicified Birimian greenstone and hornstone with minor jasper, quartz, quartzporphyry, tourmaline-quartz rocks with Birimian phyllites and schists in a matrix with quartz, feldspar, chlorite, carbonate, epidote, magnetite, chert and gondite (Kuma, 2004).

Most of the towns/villages rely on groundwater with the exception of New Abirem and Afosu where surface water taken from the Pra and Afosu Rivers is treated and distributed.

The underground water reserve is rich, despite the scarcity and inadequacy of potable water in many communities.

The district is situated almost entirely in the primary mineral deposit of the region, a primary factor in the existence of prominent mineral prospecting and explorations by a chunk of companies into gold and diamond (Birim North District Assembly, 2006) and hence a target for surface mining especially galamsey by immigrants and natives alike.

3.1.4 Soil Types

The soils in the district can be group into five major classes. They include: SwedruNsaba/Ofin Compound Association; Atewa-Atukrom-Asikuma-Ansum Compound Association; Juaso-Manso-Debia Association; Bekwai-Oda Association; and BirimChichiwere Association (Birim North District 2006). The Swedru-Nsaba/Ofin Compound Association is the prevalent soil establishment and is developed over granite; they can be found around Prankese, Nkwateng, Otwereso and Abenase (http://mofa.gov.gh/site/?page_ id=1506, 17 February, 2015).

The Swedru-Nsaba series which is high in magnesia and potash, is a very good soil for tree and arable crops, and are particularly excellent for cocoa. The Ofin soils are unsuitable for tree crops and mostly used for growing dry season vegetables such as, sweet potatoes, sugarcane and rice (http://mofa.gov.gh/site/?page_id=1506, 17 February, 2015). The soil in the Atiwa-Atukrom-Asikuma-Ansum compound series is found around the Amuana Praso area and is restricted to a smaller part of the district. The Juaso-Manso-Adubea Associaiton is located all over Noyem, Prasokuma and Atobiaso whiles the Bekwai- Oda

Association is located all over New Abirem and Ntronang (http://mofa.gov.gh/site/?page_id=1506, 17 February, 2015).

The soil series suitable for mechanized irrigated rice farming is the Oda series; it occupies flat, averagely wide lands adjacent to rivers and streams. The Birim-Chichiwere Association is found around Edubia and is formulated across the River Birim banks. It is fairly drained, deep and easy to work with machines, take place on nearly gentle terrain where erosion is almost zero or least possible and good for a variety of arable flora (http://mofa.gov.gh/ site/?page_id =1506, 17 February, 2015).

3.1.5 Economy and Living Conditions

According to the Ghana Statistical Service (2014), agriculture is the backbone of the economy of BND. About 73.5% of the workforce in the district is engaged in one form of agriculture enterprise or the other, whiles 15.2% of the labour are engaged in commerce, 3.8% in service and 7.5% in industry as illustrated in Table 3.1. Fertile soils and a favourable climate are good for crop production; the presence of big companies into agriculture, especially for oil palm production and the Agricultural Research Institutions both within and outside the district suggests good opportunities for high crop outputs (http://mofa.gov.gh/ site/?page_id=1506, 17 February, 2015).

Table 3.1: Birim North District Economy

Division	**Labour (%)**
Industries	**7.5**
Services	**3.8**
Commerce	**15.2**
Agric	**73.5**

Source: Birim North District Assembly (BNDA), 2006

The total land area under crop growing in the district is about 91,037 hectares. Commercial farming is responsible for 77,546 hectares and an approximately 13,491 hectares is used for crop farming. The cash crops farmed include oil palm, cocoa and citrus and the prominent food crops grown in the district include plantain, maize, cocoyam, vegetables and cassava (BNDA, 2006). Farming is generally undertaken on subsistence basis except the ones involved in cash crop farming. The financial gain levels and poverty positions are affected by farm sizes in the district since their outputs depend on their farm holdings (BNDA, 2006). Farmers in the district employ the use of primitive farm implements like the hoe and cutlass which constitute one of the grounds for humble farm sizes. Farm implements used in farming is limited to hauling of farm produce (http://mofa.gov.gh/site/?page_id=1506, 17 February, 2015). Food production systems, which rely on elementary farm inputs like hoe, axe and cutlass requires major human workforce. The farm labour in the district is usually family and employed labour as elaborated in Table 3.2.

Table 3.2: Labour Types Employed

Type	Percentage
Family	37
Nnoboa	4.7
Hired Labour	51.3
More than one type	7

Source: BNDA 2006

The District has a number of sparsely located small-scale industries. They are grouped broadly as, service industries and agro-processing industries. It has economically large deposits of gold as well which is currently being exploited by companies such as Newmont Ghana Gold Limited, among others. Illegal miners popularly known as "galamsey" are also scattered all over the district (Ghana Statistical Service, 2014).

3.2 MATERIALS USED

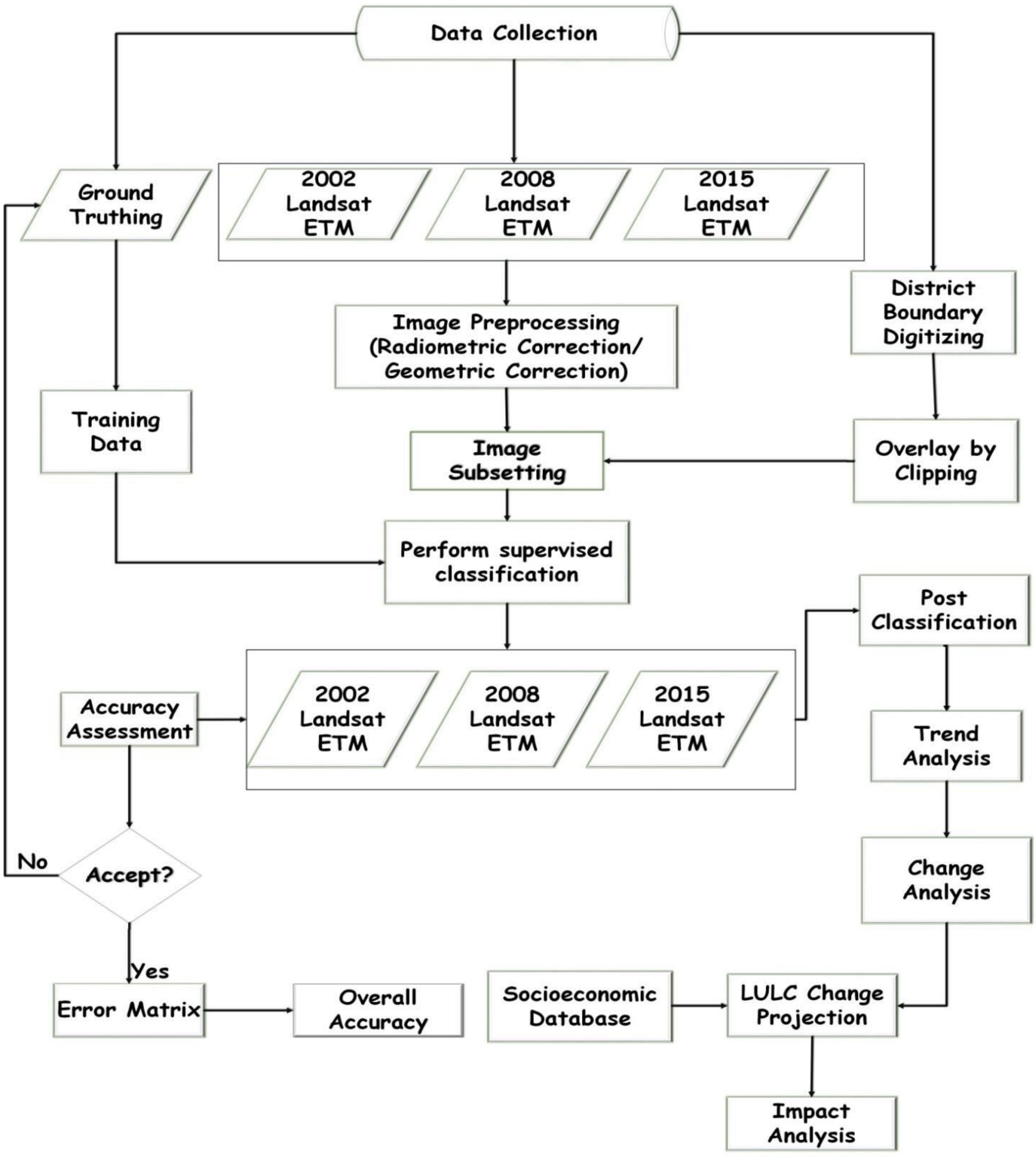
Three Landsat Enhanced Thematic Mapper Plus (ETM+) images; 15th January, 2002, 1st February, 2008 and 3rd January, 2015 (all path/row 194/56) from the U.S. Geological Survey (USGS) website: http://glovis.usgs.gov/ (17 March, 2015) were obtained. All images were obtained at Level 1T processing, meaning that they were orthorectified with systematic radiometric and geometric accuracies. All images were cloud-free and pixel sizes of 30 m. Also, all the bands apart from the thermal band (band 6) from each image were stacked, subsetted and used for this research (Appendix 1).

A digitized Boundary map of the district (Birim North District map (at a scale of 1:250,000) was used. A Garmin Etrex 10 Hand Held Global Positioning System (GPS) was used to obtain the spatial coordinates of LULC classes. The application software used for the study include: Erdas Imagine 2010, IDRISI 17.0 (The Selva Edition), Statistical Package for the Social Sciences (SPSS) and Microsoft Excel 2007.

3.3 METHODS

Following the data collection, a Supervised Image Classification was carried out. This was followed by multi-temporal change detection analysis in order to identify and quantify the LULC change due to mining excavation activities. Subsequently, a simulation algorithm was applied to the change maps and a projection made for the next ten years. The research framework and the methodology followed for this purpose is illustrated in Figure 3.3.

Figure 3.3: Flowchart depicting the overall methodology followed in the study



3.3.1 Image pre-processing

Pre-processing of satellite sensor images before performing change detection is necessary and has the distinctive aims of establishing straight linkage between the data and biophysical phenomena, the subtraction of data acquisition errors and image noise and the masking of contaminated (e.g. clouds) scene fragments (Coppin and Bauer, 1996).

It is essential to remove atmospheric effects, particularly for change detection experimentation. The variances in atmospheric conditions inherent in images were therefore extracted with a dark object subtraction (DOS) technique (Song *et al.*, 2001; Schueler *et al.*,

2011). A deep-water spectra from Lake Bosomtwe was used as a dark object in this research.

The DOS was then performed using the 'images Spatial Modeler' application in the Erdas Imagine 2010 software.

3.3.2 Assessment of Geometric Accuracy of Imagery

The first image processing step is geometric correction (pre-classification approach) which is carried out when the satellite image data are not geo-rectified (Liu and Mason, 2009). Geometric correction handles the errors in the relative locations of pixels. The images used in this study were acquired already systematically corrected for sensor geometry and terrain variations to Level 1T by the United States Geological Survey (USGS). Standard Terrain Correction (Level 1T) provides systematic radiometric and geometric accuracy by incorporating ground control points while employing a Digital Elevation Model (DEM) for topographic accuracy. Geodetic accuracy of the product depends on the accuracy of the ground control points and the resolution of the DEM used (http://landsathandbook.gsfc.nasa.gov/data_prod/prog_sect11_3.html, 20 July 2016). All images were registered in UTM zone 30N projection under a WGS84 ellipsoid.

To ensure that there were minimal errors, the positional accuracy of the images were tested. Fifteen (15) ground control points (GCPs) commonly identified on both the ground and images were picked from detectable points (e.g. road junctions) with a handheld GPS in UTM zone 30N projection under a WGS84 ellipsoid. Using the Erdas Imagine 2010 software a RMSE of 0.46 pixels was recorded (Appendix 2); this was less than half a pixel as commended by Osei and Zhou (2004) for geometric correction. It was therefore concluded that the correction undertaken by the USGS was acceptable and could be used for this research.

3.3.3 Ground Truth Data collection

In order to obtain the training and validation data samples of the image, a field survey from 25th - 30th June, 2015 was carried out. The survey was undertaken with the help of a Hand Held Global Positioning System (GPS) receiver according to four LULC classes; 'Mine/bareland', 'Built-Up', 'Forest' and 'Agricultural land'. In all 476 points as ground truth of the study area were obtained and divided into two categories of training (75%) and validation (25%) data sets as in Figure 3.4.

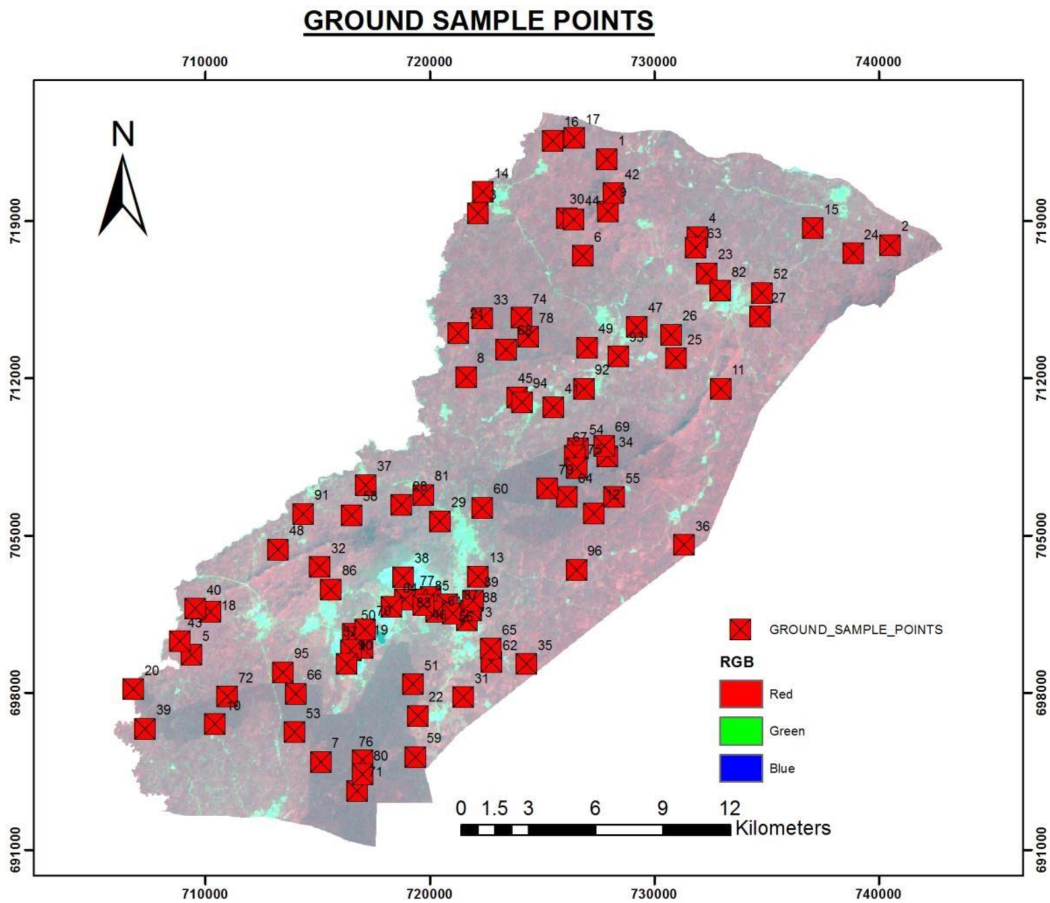


Figure 3.4: Spatial distribution of ground sample points

3.3.4 Image classification

After the pre-processing of the images, they were individually stacked and sub-setted and a supervised classification using the maximum-likelihood algorithm was performed using IDRISI selva. The individual images were classified into four different major LULC classes:

'Mine/bareland', 'Built-Up', 'Forest' and 'Agricultural land': These classes were recommended in line with the Anderson classification scheme (Anderson *et al.*, 1976).

Table 3.3: Description of the four LULC classes.

CLASS CODE	LULC CLASSES	DESCRIPTION
1	Mines/Bareland	Areas without vegetation cover (Bald soil patches), exposed rocks, landslides, earthen roads
2	Built-Up	Settlements, City/Town concentrations, metalled/paved roads and rural/urban residential sites
3	Forest	Thick vegetation stands and grooves of evergreen and deciduous trees forming a dense canopy
4	Agricultural Land	Sparsely distributed evergreen and deciduous trees and shrubs forming open canopy and farm trees/crops

Source: http://landcover.usgs.gov, 8 July, 2016

The salt-and-pepper effect usually observed due to spatial auto-correlation is not incorporated in the classification technique in pixel-based landscape classification (Ivits and Koch 2002). To eliminate this effect, the patches that were less than 4 pixels (0. 36 ha) were allotted to the nearest prevailing class (Schueler *et al.*, 2011)

The quality of image classification is checked by a sampling method such that a number of raster components of the resulting image are selected and both the classification result and the ground truth class are matched (Tempfli *et al.*, 2009). To validate the LULC maps, a random sample of 119 points were used, representing 25% of the ground truth datasets not used for training and a random sample of about thirty samples in each class was further done to create a good representation (Congalton, 1991). A statistical measure was computed from an error (contingency) matrix; which compares samples taken from the source to be evaluated with observations that are considered as correct (reference)(Tempfli *et al.*, 2009).

Plate 3.1: LULC mapping (galamsey operating site), near Nyafoman in the BND

3.3.5 LULC Change detection and Analysis

A Post-classification Comparison (PCC) technique was carried out to evaluate the level of modification in the various LULC types over the 13 year study period (2002-2015). In PCC, each date of rectified imagery is independently classified to fit a common type schema (equal number and type of LULC classes). This is recognized as the most accurate change detection technique, it detects LULC changes (LULCC) by comparing independently produced classifications of images from different dates (Singh, 1989; Yuan *et al.,* 1998). This technique also readily provides ''from-to'' transfers from one LULC type. Tian *et al.*

(2014) in their study on Examining Land Use and Land Cover Spatiotemporal Change and Driving Forces in Beijing from 1978 to 2010, Suresh and Jain (2013) in their study on Change Detection and Estimation of Illegal Mining using Satellite Images in India and Kumi-Boateng *et al.* (2012) who researched into a spatio-temporal approximation of changes in vegetation cover in the Tarkwa mining area of Ghana have all successfully used the PCC method.

In this study, change detection was carried out on an IDRISI Selva software environment. The process involved the insertion of multi-temporally classified pairs of images for each subset including the classified classes ('Mine/bareland', 'Built-Up', 'Forest' and 'Agricultural land'). The output consisted of new thematic image maps (2002-2008, 2008-

2015 and 2002-2015), a change matrix table and ''from-to'' combinations of class transitions. Change detection maps were visually inspected to determine the areas of LULC change that are caused by mining activities and maps depicting the changes were generated. LULC changes were quantified through statistical tables including changes in terms of area and percentage measures.

3.3.6 Questionnaire Administration

In order to understand the effect surface mining related LULC change has on local livelihoods, a questionnaire was structured and interviews conducted. The nature of the research permitted the use of purposive sampling in the selection of the communities and farmer representatives of the communities in the study area. The sampling technique was selected as against a complete census in order to save time and cost; for example some farmer representatives by the number of years they have farmed and the size of their farms were selected ahead of others. Some communities by their proximity to the Newmont Ghana Gold Limited (NGGL) concession and ASM sites were also selected; with the aim of assessing the livelihood effect of mining by NGGL on farmers who have their farms within the NGGL concession.

The Sample size for the study was 70 out of a population size of 46,342 farmers; interviews with representatives of towns/villages, clans, and households mainly in the agricultural sector were carried out. In the interaction process, local farmers outlined the nature of LULC around the village/surrounding in 2002 (before large scale mining/ASM started). This was done to link the observed changes in LULC in the satellite images to the changes in the local livelihood standards in the district.

Apart from the use of structured questionnaire to solicit for relevant information, informal interviews were also conducted alongside to seek other answers which were not originally planned for during the data collection exercise.

The results with reference to the questionnaire were analyzed using Microsoft Excel 2007 and SPSS computer software to provide descriptive statistics such as standard deviations, regression analysis, frequency tables and plotting of bar graphs.

3.4 LULC CHANGE TRAJECTORIES IN THE BND

A fully Bayesian inference is grounded on the posterior distribution of the unknown parameters, and in this approach, samples are drawn from the full conditionals of the unknown parameters given the data (2002, 2008 and 2015 images) and MCMC simulations modeled.

LULCC trajectories are the temporal sequence of LULC classes at the pixel level that are described through classified images assembled in a time series (Mena, 2008). The Markov Module is one of the six modules used in modeling future changes; it helps in analyzing qualitative LULC images of varying dates and produces a transition matrix, a transition area matrix, and a set of conditional probability images (Eastman, 2003).

The 'Markov' Module in IDRISI Selva was used to analyze the LULC images of 2002 and 2015 and a transition probability matrix, a transition area matrix, and a set of conditional probability images were generated. The 2015 LULC image was taken as the base LULC image and the transition probability matrix, transition area matrix, and set of conditional probability images fed into the Cellular Automata/ Markov Change Projection

(CA_MARKOV) module in IDRISI, Cellular Automata (CA) iterations were done for ten times to project the LULC for 2025.

A significant stage in the advancement of any projecting change model is validation (Eastman, 2012). In order to evaluate the model, the 2002 LULC image was taken as the base (earlier) image and all the suitability maps and transition area matrix developed for projecting 2025 land-use map was utilized as inputs in the CA_MARKOV module. CA iterations were done for ten times to project the LULC image for 2015. A comparison of similarity between the projected 2015 and actual 2015 LULC images was made to evaluate the suitability of the model used for this research to successfully project LULC change to 2025.

The 'VALIDATE' Module tool in IDRISI Selva was applied and the Kappa statistics (K) for similarity was assessed to determine the similarity in classification between the actual and projected LULC images of 2015 (Pontius, 2000). All K statistics (Kstandard, Kno, Klocation) should be above 80% (Viera and Garrett, 2005), for a CA-Markov model utilized for LULC change projection to be considered valid.

CHAPTER FOUR RESULTS AND DISCUSSIONS

4.1 RESULTS

4.1.1 Major LULC Classes of BND

LULC maps were obtained from the supervised classification of the satellite images (2002, 2008 and 2015). The 2002 image was categorized into four classes, i.e. 'Mine/bareland', 'Built-Up', 'Forest' and 'Agricultural land' as in Figure 4.1 . The classification results as in Table 4. 1 reveal that Mine/bareland, Built-Up, Forest and Agricultural land occupy 703.68, 682.63, 23919.23 and 96317.58 Hectares (ha) of area respectively. The 2008 and 2015 images were also categorized into the same number and type of classes as that of 2002 (Figure 4.2 and 4.4) so that PCC was made possible. The result obtained from the classification of the 2008 and 2015 imagery is as in Tables 4.1 and 4.2. Mine/bareland, BuiltUp, Forest and Agricultural land occupied 1027.12, 20882.7, 21525.39 and 78187.91 Ha of the study area in 2008 (Figure 4.3) and 1768.32, 32221.89, 73837.8, 13795.11ha of area in 2015 (Figure 4.4).

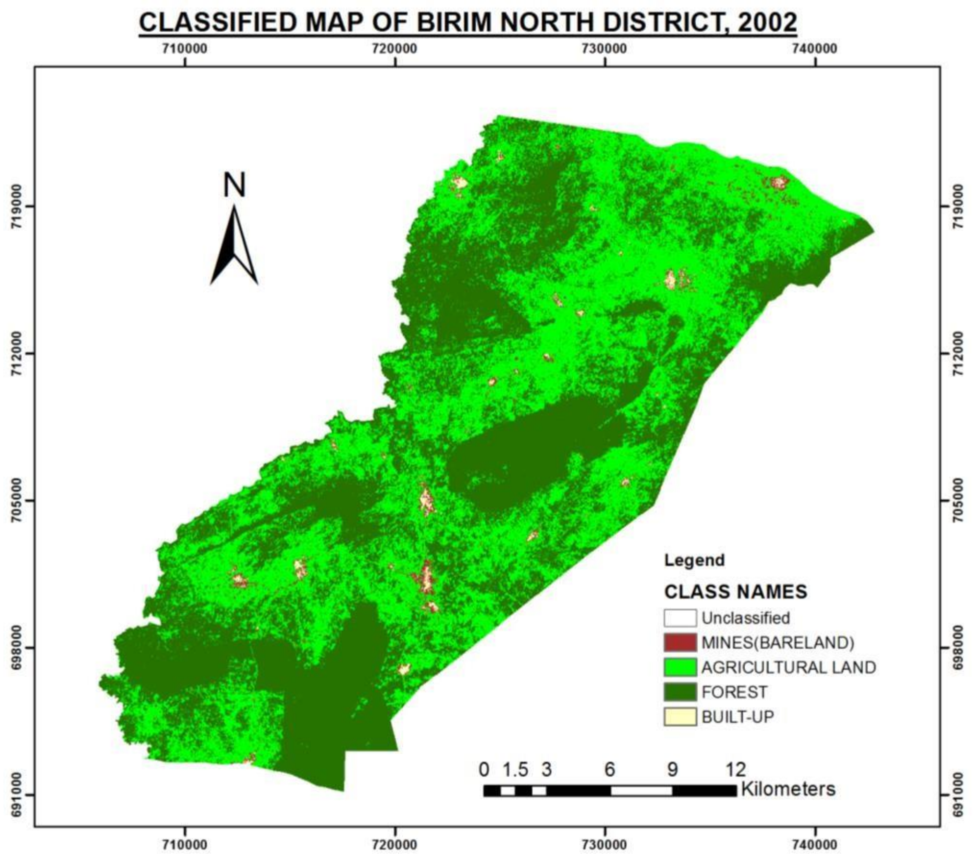


Figure 4.1: LULC map for the year 2002.

4.1.2 LULC Distributions in BND for 2002, 2008 and 2015

All Landsat ETM images yielded LULC maps after classification procedures with agricultural land occupying the largest areas of 96317.58 (79.19%) for 2002, 78187.91 (64.29%) for 2008 and 73837.8 (60.71%) for 2015. The class is distributed around the builtup environment and the forest class with a few patches around the mines/bareland classes

(Figure 4.1, 4.2 and 4.3) and (Table 4.1 and 4.3). Forest covers the second largest areas of 23919.23ha (19.67%) for 2002, 21525.39ha (17.7%) for 2008 and third largest area of

13795.11ha (11.34%) for 2015. It is mainly around the Western top portion, Eastern and Southern sections of the classified image and small patches in between the built-up and the agricultural land classes. Mines/bareland occupies the third largest area coverage as compared to the other LULC classes having 703.6 9ha (0.58%) for 2002, fourth largest area coverage of 1027.12 ha (0.84%) and 1768.32ha (1.45%) in 2008 and 2015 respectively. This is mostly centered around the South-Eastern part of the study area with patches within and around the Built-up classes. Built-up can be found mainly within the agricultural land and along the mines/bareland environment with the area of 682.63 ha (0.56%) for 2002 but 20882.7 ha (17.17%) in 2008 and 32221.89 ha (26.5%) in 2015.

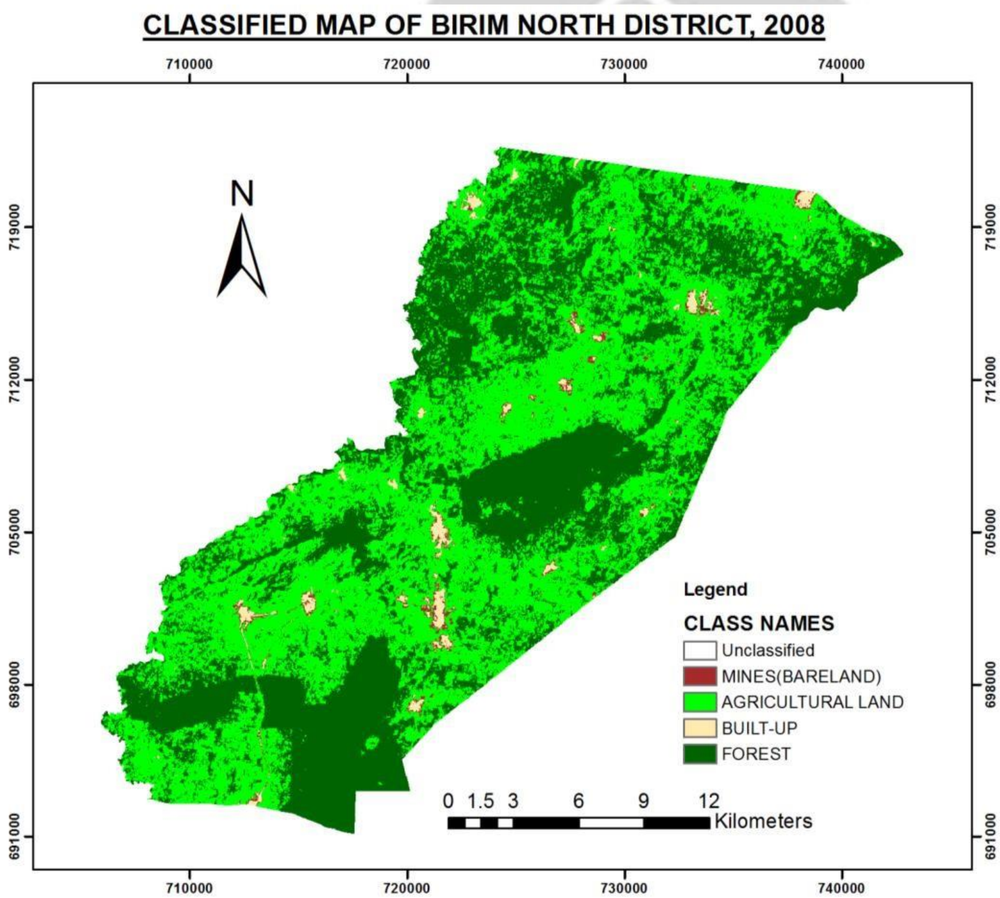
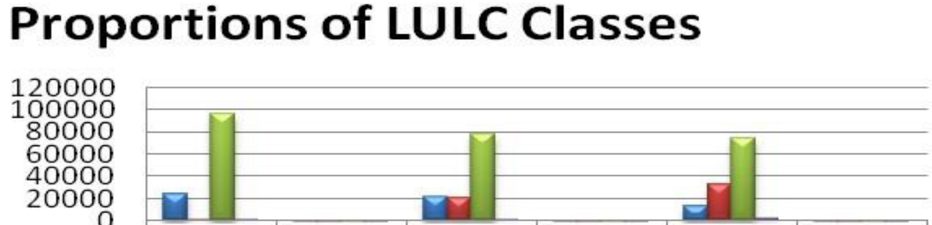


Figure 4.2: LULC map of BND, 2008.



	Area 2002 (Hectares)	Area (%)	Area 2008 (Hectares)	Area (%)	Area 2015 (Hectares)	Area (%)
FOREST	23919.23	19.67	21525.39	17.7	13795.11	11.34
BUILT-UP	682.63	0.56	20882.7	17.17	32221.89	26.5
AGRICULTURAL LAND	96317.58	79.19	78187.91	64.29	73837.8	60.71
MINES/BARELAND	703.68	0.58	1027.12	0.84	1768.32	1.45

Figure 4.3: Proportions of major LULC classes in BND from 2002 to 2015 in hectares.

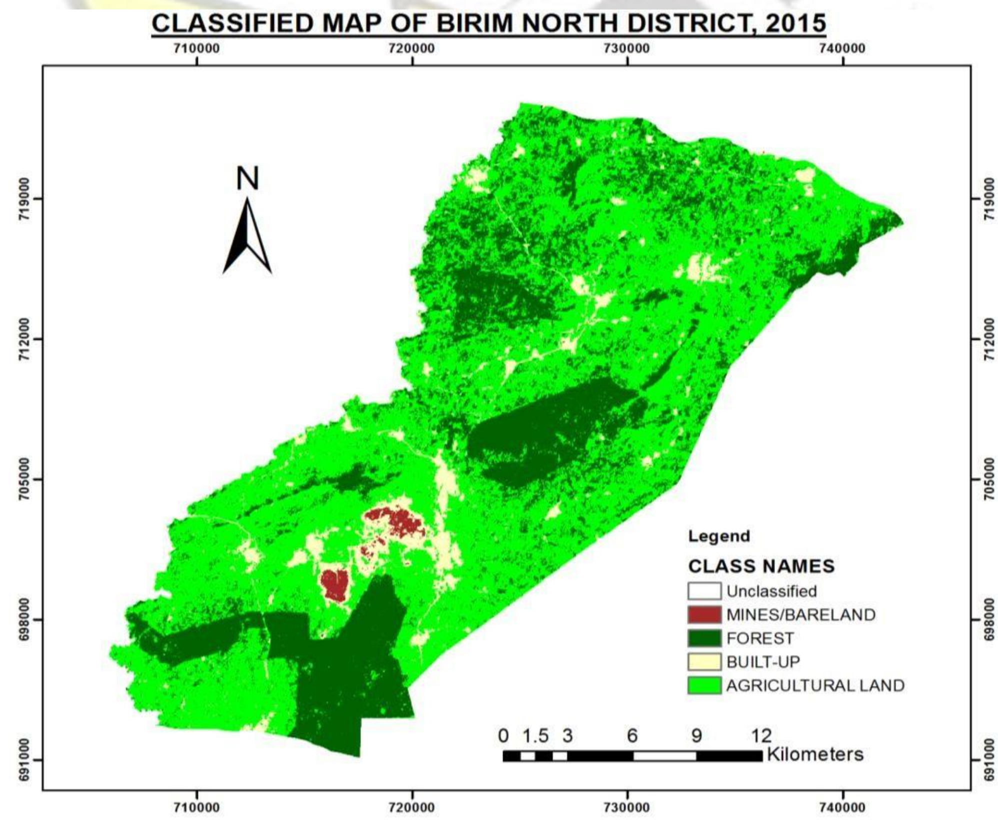


Figure 4.4: LULC map for the year 2015

Table 4.1: LULC comparison of 2002 and 2008

	2002		**2008**		**RELATIVE CHANGE**	
CLASS	**Area 2002 (Hectares)**	**Area (%)**	**Area 2008 (Hectares)**	**Area (%)**	**Area (Hectares)**	**Area (%)**
FOREST	23919.23	19.67	21525.39	17.7	-2393.84	-1.97 **Decrease**
BUILT-UP	682.63	0.56	20882.7	17.17	20200.07	16.62 **Increase**
AGRICULTURAL LAND	96317.58	79.19	78187.91	64.29	-18129.67	-14.90 **Decrease**
MINES/BARELAND	703.68	0.58	1027.12	0.84	323.44	0.26 **Increase**

Table 4.2: LULC comparison of 2008 and 2015.

	2008		2015		RELATIVE CHANGE	
CLASS	**Area 2008 (Hectares)**	**Area (%)**	**Area 2015 (Hectares)**	**Area (%)**	**Area (Hectares)**	**Area (%)**
FOREST	21525.39	17.7	13795.11	11.34	-7730.28	-6.38 **Decrease**
BUILT-UP	20882.7	17.17	32221.89	26.5	11339.19	9.34 **Increase**
AGRICULTURAL LAND	78187.91	64.29	73837.8	60.71	-1962.81	-1.63 **Decrease**
MINES/BARELAND	1027.12	0.84	1768.32	1.45	741.2	0.61 **Increase**

Table 4.3: LULC comparison of 2002 and 2015.

	2002		2015		RELATIVE CHANGE	
CLASS	**Area 2002 (Hectares)**	**Area (%)**	**Area 2015 (Hectares)**	**Area (%)**	**Area (Hectares)**	**Area (%)**
FOREST	23919.23	19.67	13795.11	11.34	-10124.12	-8.35 **Decrease**
BUILT-UP	682.63	0.56	32221.89	26.5	31539.26	25.94 **Increase**
AGRICULTURAL LAND	96317.58	79.19	73837.8	60.71	-22479.78	-18.49 **Decrease**
MINES/BARELAND	703.68	0.58	1768.32	1.45	1089.93	0.88 **Increase**

4.1.3 LULC Accuracy Assessment

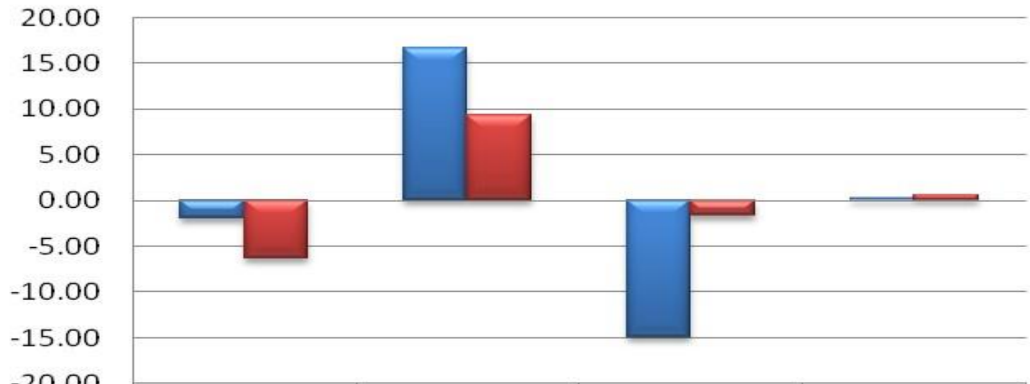
The quality of a LULC classification of a satellite image is determined by its accuracy, therefore the classification accuracies were accessed using error matrices. The producer's accuracy, user's accuracy, overall accuracy and kappa statistics were computed. Appendix 3 shows summaries for the three years: The overall accuracies for 2002, 2008 and 2015 were respectively, 88.24%, 87.50% and 92.44% which is in agreement with the classification accuracy of 85-90% for LULC mapping as recommended by Anderson *et al.* (1976). The Kappa statistics for 2002, 2008 and 2015 are respectively 0.843, 0.833 and 0.899 as in (Appendix 3).

4.1.4 Trends in LULC Distribution, 2002 to 2015

The trend analysis of the study area reveals a change in size of the four LULC over the 13 year period of the research (Table 4.4 and Figure 4.5). Built-up received the majority of positive and consistent changes while forest got the most consistently negative change. From 2002 to 2008, forest and agricultural land experienced negative changes in area while mines/bareland and built-up received a positive change. From 2008 to 2015, built-up and mines/bareland have their areas undergoing a positive change, whiles that of forest and agricultural land are undergoing negative changes.

Table 4.4: LULC change trend, 2002-2015

	CHANGE (Ha)		**% CHANGE**	
CLASS	**2002-2008**	**2008-2015**	**2002-2008**	**2008-2015**
FOREST	-2393.84	-7730.28	-1.97 **Decrease**	-6.38 **Decrease**
BUILT-UP	20200.07	11339.19	16.62 **Increase**	9.34 **Increase**
AGRICULTURAL LAND	-18129.67	1962.81	-14.90 **Decrease**	-1.63 **Decrease**
MINES/BARELAND	323.44	741.2	0.26 **Increase**	0.61 **Increase**



	FOREST	BUILT-UP	AGRICULTURAL LAND	MINES/BARE LAND
2002-2008 (%)	-1.97	16.62	-14.9	0.26
2008-2015 (%)	-6.38	9.34	-1.63	0.61

Figure 4.5: LULC change trend, from 2002 to 2015

4.1.5 Change Detection Results and LULC conversions

The LULC changes derived from comparison of the classified images of 2002, 2008 and 2015 are given in Figures 4.6 and 4.7. The classification results revealed that from 2002 to 2008, over a period of about 6 years, forest and agricultural land have decreased at the rate of -1.97 % and -14.90% respectively. On the other hand, Mines/bareland and Built-up have increased at the rate of 0.26 % and 16.62% respectively. Major losses are noticed in forest and agricultural land whereas mines/bareland and built-up made some gains (Tables 4.1 and 4.2). However, as forest continues to decrease by -6.38%, agricultural land by -1.63% between 2008 and 2015; built-up and mines/bareland made some gains within the same period at 9.34.62% and 0.61 % respectively. The two main dominant LULC modifications were the transitions of forest and agricultural land to mines/bareland as confirmed by the LULC change analyses (Figure 4.5, Table 4.4).

4.1.6 LULC conversions, from 2002 to 2008

Table 4.5 shows a summary of the major LULC conversions that have taken place from 2002 to 2008 in Birim North district, while Figure 4.6 shows its corresponding change map. From the table, agricultural land 520.98ha was converted to built-up representing 0.43% of the area whiles 7393.1ha of forest were changed to agricultural land, representing 6.08%. The conversion of agricultural land to forest and mines/bareland are 7117.75ha (5.85%) and

5261.59ha (4.33%) respectively.

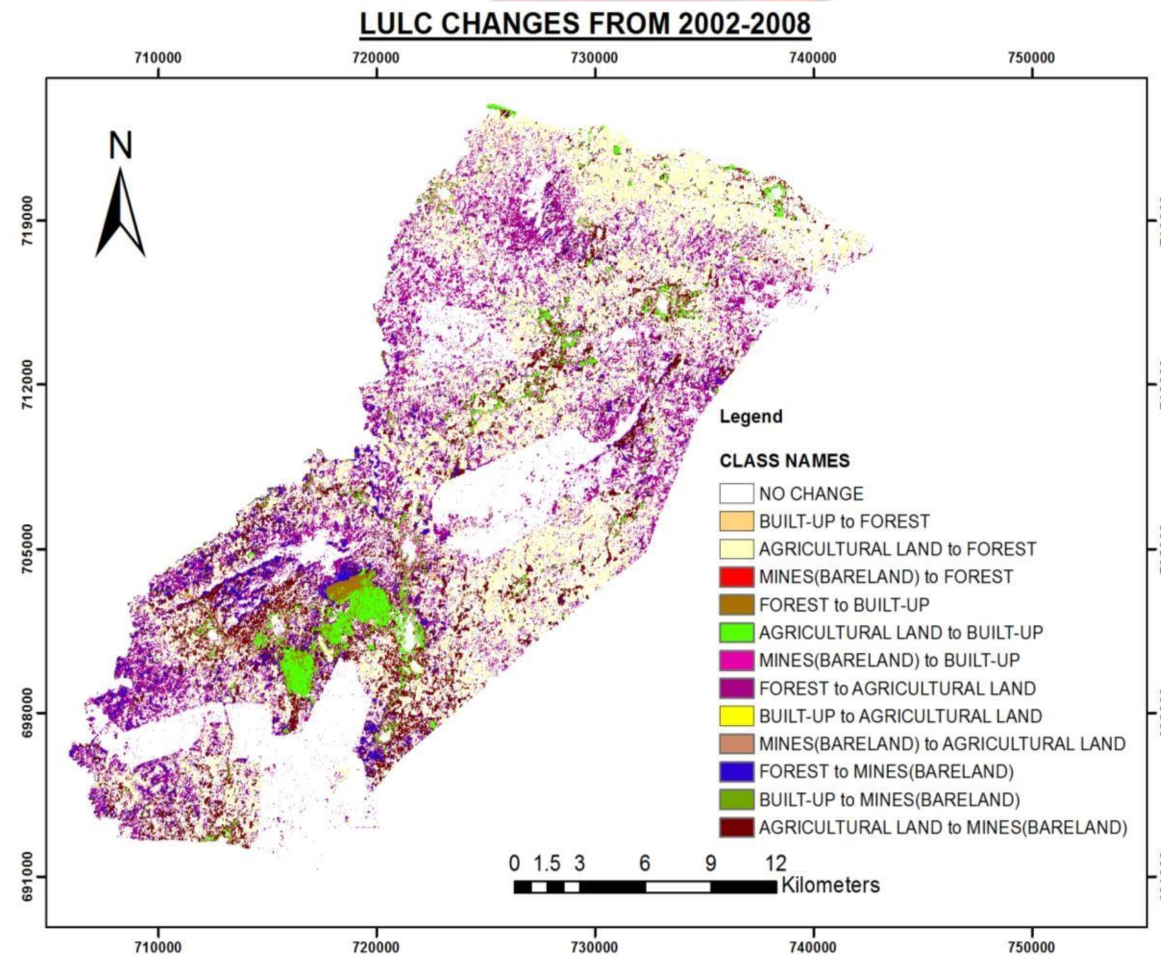


Figure 4.6: Major LULC conversions in Birim North District, 2002 to 2008

Table 4.5: LULC conversions in Birim North District, 2002 to 2008

CLASS ID	MAJOR "FROM-TO" CHANGES	AREA (Ha)
1	Built-Up to Forest	11.94
2	Agricultural Land to Forest	7117.75
3	Mines/Bareland to Forest	81.71
4	Forest to Built-Up	382.65
5	Agricultural Land to Built-Up	520.98
6	Mines/Bareland to Built-Up	217.11
7	Forest to Agricultural Land	7393.1
8	Built-Up to Agricultural Land	51.25
9	Mines/Bareland to Agricultural Land	207.69
10	Forest to Mines/Bareland	1836.42
11	Built-Up to Mines/Bareland	73.18
12	Agricultural Land to Mines/Bareland	5261.59

4.1.7 LULC conversions, from 2008 to 2015

Table 4.6 shows a summary of the major LULC conversions that have taken place from 2008 to 2015 in Birim North district, while Figure 4. 7 shows its corresponding change map. From the table, forest made the highest conversion of 8076.61ha to agricultural land representing

6.65% of the area. 1531.82ha of mines/bareland were changed to built-up, representing 1.26%. The conversion of agricultural land to forest, built-up and mines/bareland are 409.29ha (0.34%), 648.96ha (0.53%) and 379.91ha (0.31%) respectively.

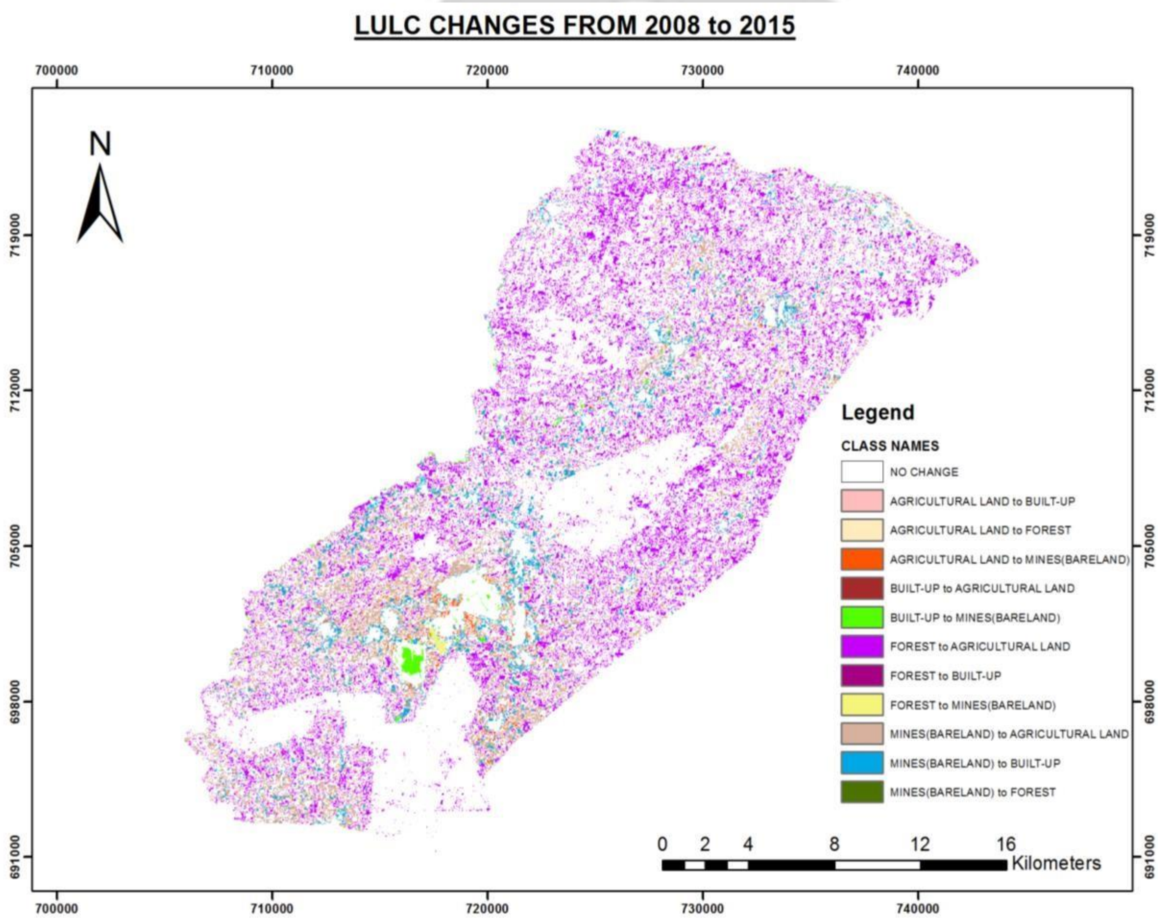


Figure 4.7: Major LULC conversions in Birim North District, 2008 to 2015

Table 4.6: LULC conversions in Birim North District, 2008 to 2015

CLASS ID	MAJOR "FROM-TO" CHANGES	AREA (Ha)
1	Agricultural Land to Forest	409.3
2	Mines/Bareland to Forest	1.06
3	Forest to Built-Up	1.06
4	Agricultural Land to Built-Up	618.37
5	Mines/Bareland to Built-Up	1531.82
6	Forest to Agricultural Land	8076.61
7	Built-Up to Agricultural Land	0.41
8	Mines/Bareland to Agricultural Land	4645.91
9	Forest to Mines/Bareland	60.68
10	Built-Up to Mines/Bareland	183.65
11	Agricultural Land to Mines/Bareland	359.91

4.1.8 LULC conversions, from 2002 to 2015

Table 4.7 shows a summary of the major LULC conversions that have taken place from 2002 to 2015 in Birim North district, while Figure 4.8 shows its corresponding change map. From the table, 1297.89ha agricultural land was converted to mines/bareland representing 1.07% of the area. 11970.78ha of forest were changed to agricultural land, representing 9.85%. The conversion of agricultural land to forest and mines/bareland are 2969.67ha (2.44%) and

1297.89ha (1.07%) respectively.

Table 4.7: LULC conversions in Birim North District, 2002 to 2015

CLASS ID	MAJOR "FROM-TO" CHANGES	AREA (Ha)
1	Built-Up to Forest	5.04
2	Agricultural Land to Forest	2969.67
3	Mines/Bareland to Forest	36.23
4	Forest to Built-Up	742.4
5	Agricultural Land to Built-Up	585.23
6	Mines/Bareland to Built-Up	320.19
7	Forest to Agricultural Land	11970.78
8	Built-Up to Agricultural Land	54.42
9	Mines/Bareland to Agricultural Land	290.54
10	Forest to Mines/Bareland	426.51
11	Built-Up to Mines/Bareland	12.67

12	Agricultural Land to Mines/Bareland	1297.89

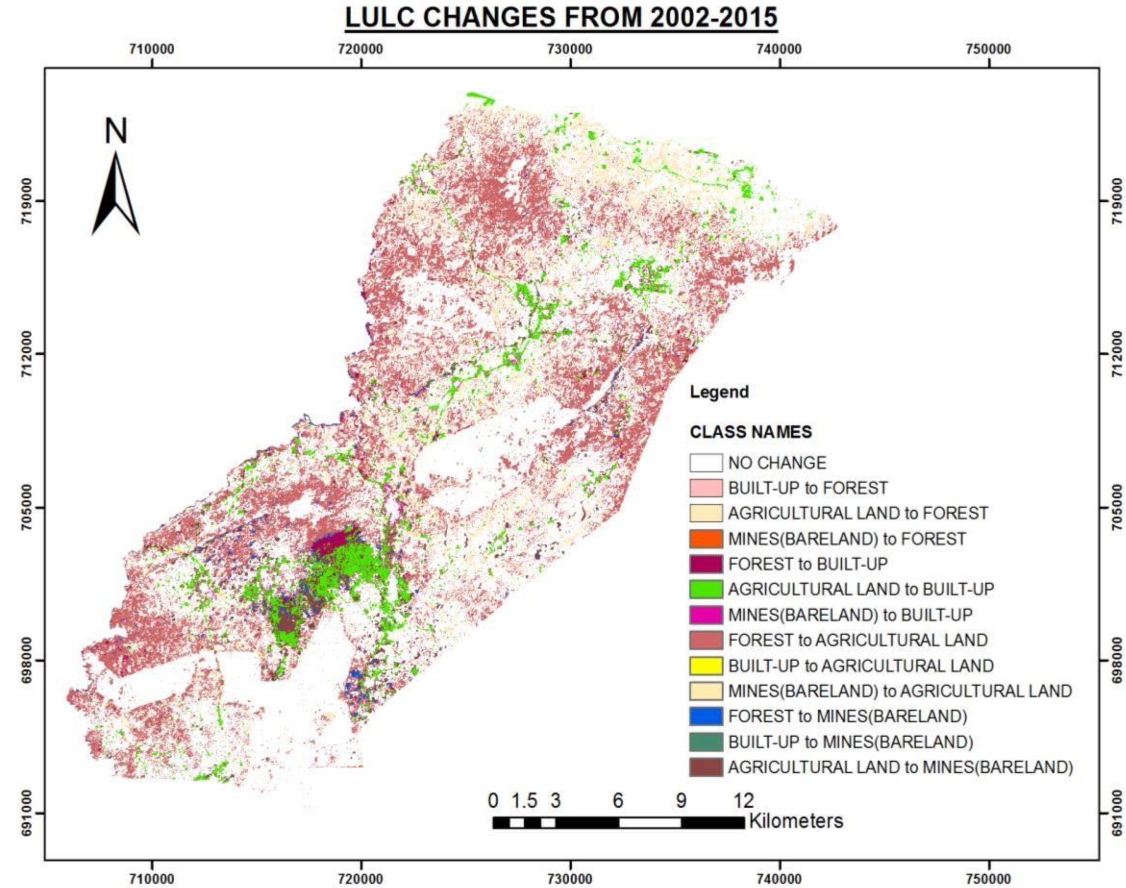


Figure 4.8: Major LULC conversions in Birim North District, 2008 to 2015

4.1.9 Persistence of LULC from 2002 to 2008

Figure 4.9 depicts the resulting persistence map whiles Table 4.8 shows the size of persistence of each class for the study period. The forest class got the highest persistence of 14307.05ha followed by agricultural land with 13231.88ha; the built-up class got 520.98ha and mines/bareland, 171.87ha.

Table 4.8: Class persistence for 2002-2008.

CLASS ID	CLASS	AREA (Ha)
0	No Persistence	93340.76
1	Forest	14307.05
2	Built-Up	520.98
3	Agricultural Land	13231.88
4	Mines/Bareland	171.87

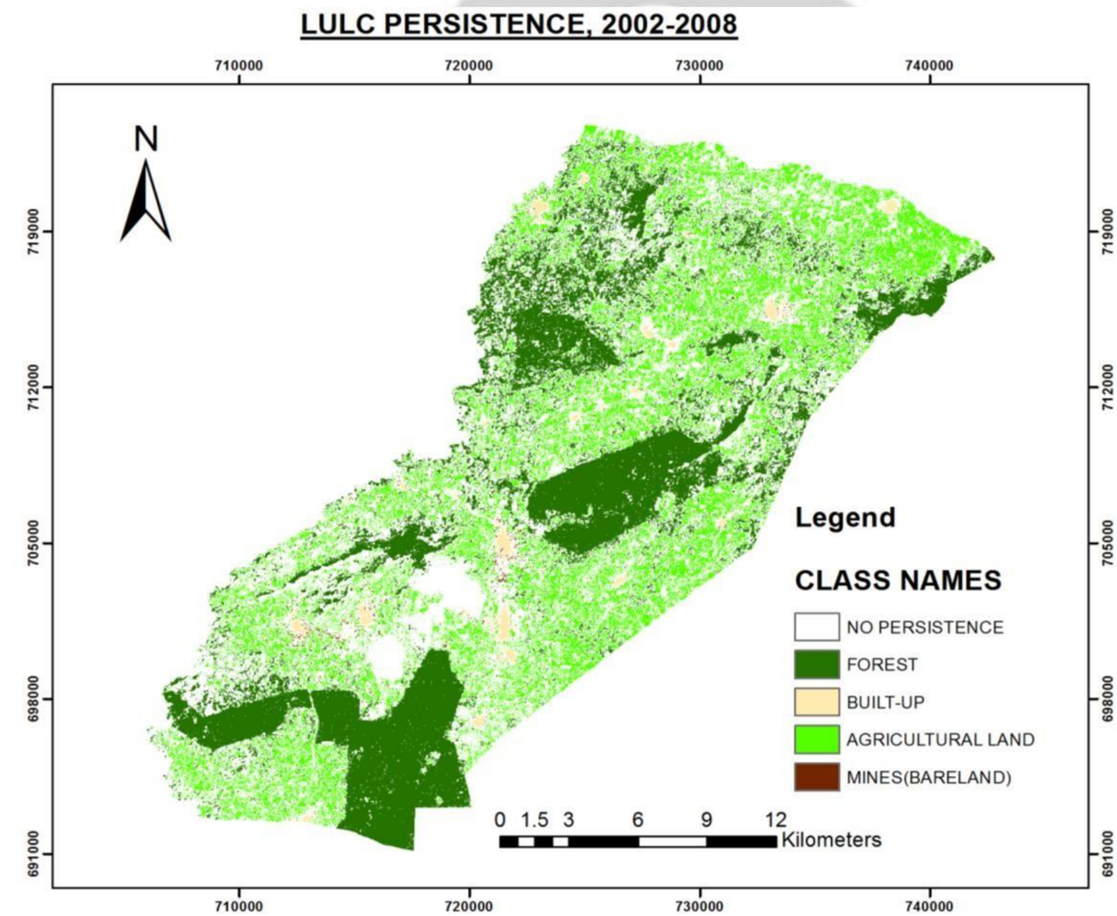


Figure 4.9: LULC persistence from 2002 to 2008

4.1.10 Persistence of LULC from 2008 to 2015

Figure 4.10 depicts the resulting persistence map whiles Table 4.9 shows the size of persistence of each class for the study period. The built-up class got the highest persistence of 71643.05ha followed by agricultural land with 19496.36ha; the forest class got 13380.11ha and mines/bareland, 1164.28ha.

Table 4.9: Class persistence for 2008-2015.

CLASS ID	CLASS	AREA (Ha)
0	No Persistence	15888.75
1	Forest	13380.11
2	Built-Up	71643.05
3	Agricultural Land	19496.36
4	Mines/Bareland	1164.28

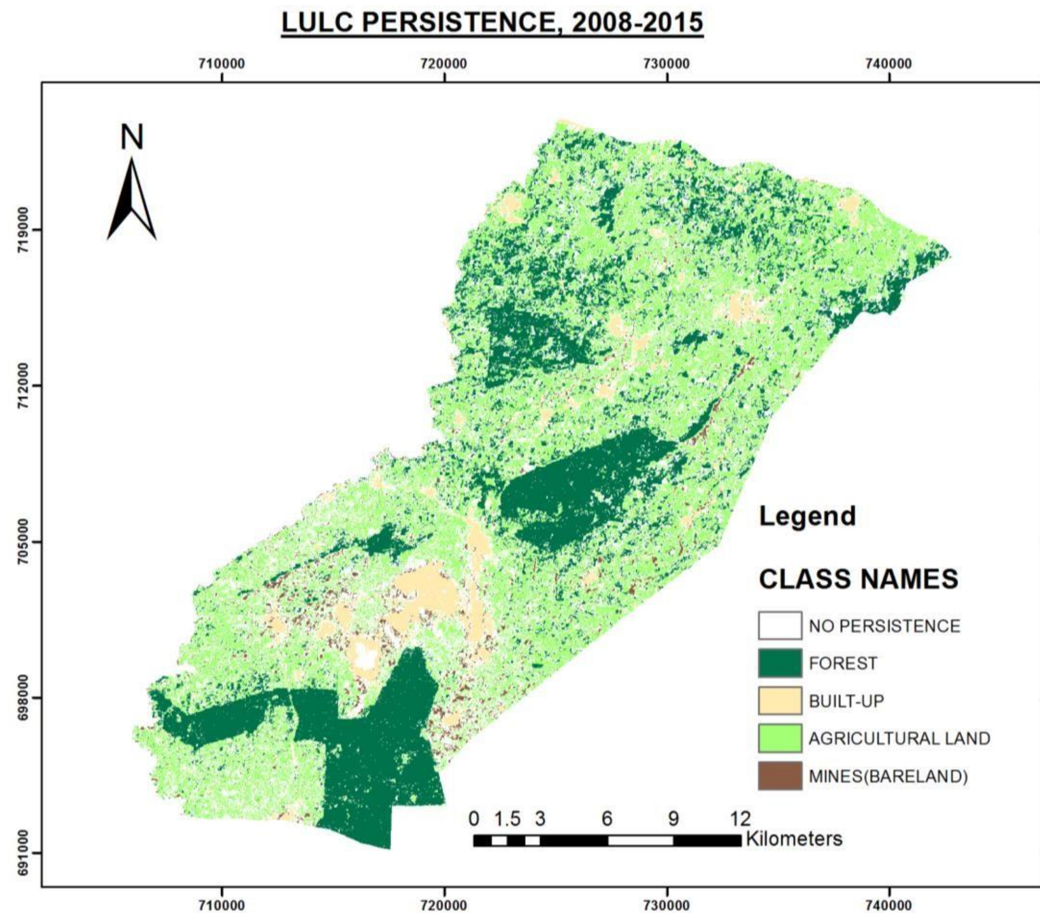


Figure 4.10: LULC persistence from 2008 to 2015

4.1.11 Persistence of LULC from 2002 to 2015

Figure 4.11 depicts the resulting persistence map whiles Table 4.10 shows the size of persistence of each class for the study period. The agricultural land class got the highest persistence of 19903.54ha followed by forest with 10779.53ha; the built-up class got 585.23ha and mines/bareland, 31.43ha.

Table 4.10: Class persistence for 2002-2015.

CLASS ID	CLASS	AREA (Ha)
0	No Persistence	90272.82
1	Forest	10779.53
2	Built-Up	585.23
3	Agricultural Land	19903.54
4	Mines/Bareland	31.43

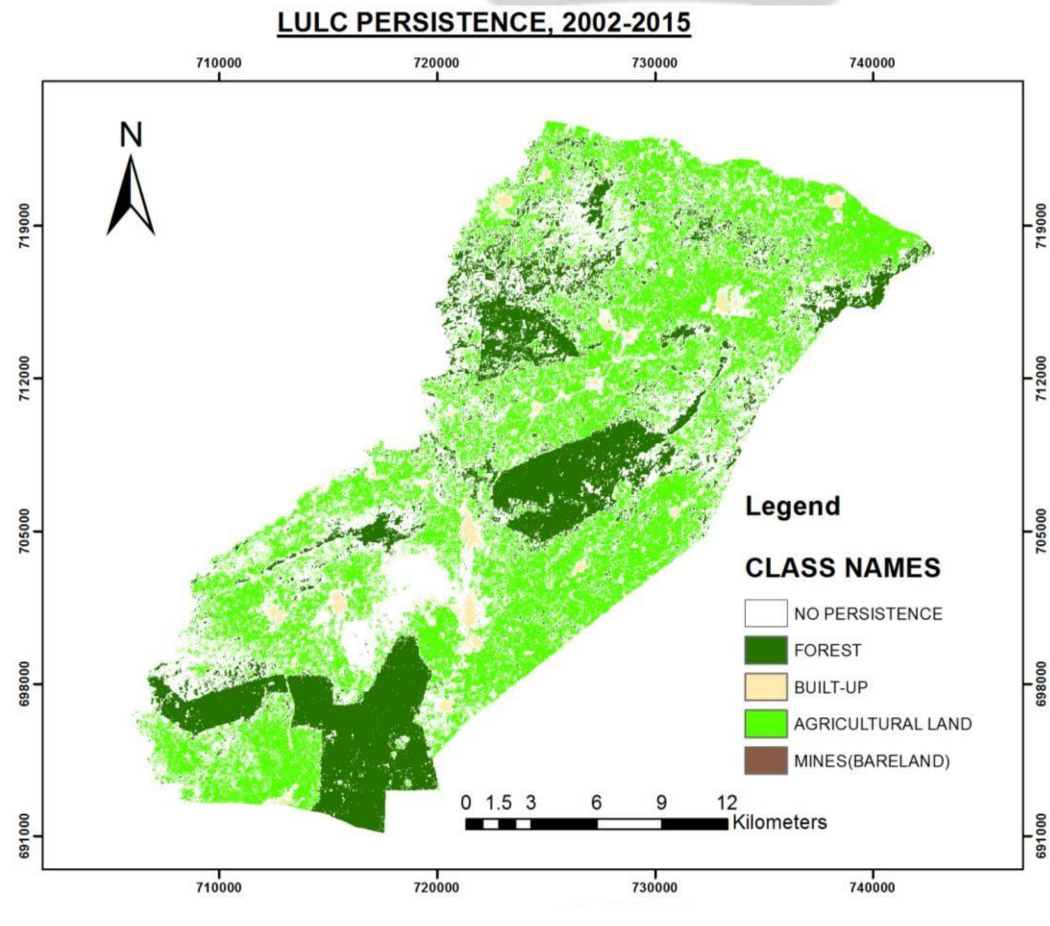


Figure 4.11: LULC persistence from 2002 to 2015

Changes from LULC class to another occurred in the study area and in different degrees within the study period. The results of gains and losses for the different classes of the study area between 2002-2008 (Figure 4. 12), 2008-2015 (Figure 4. 13) and 2002-2015 (Figure 4.

14) are given in (Figures on the x-axis are expressed in hectares).

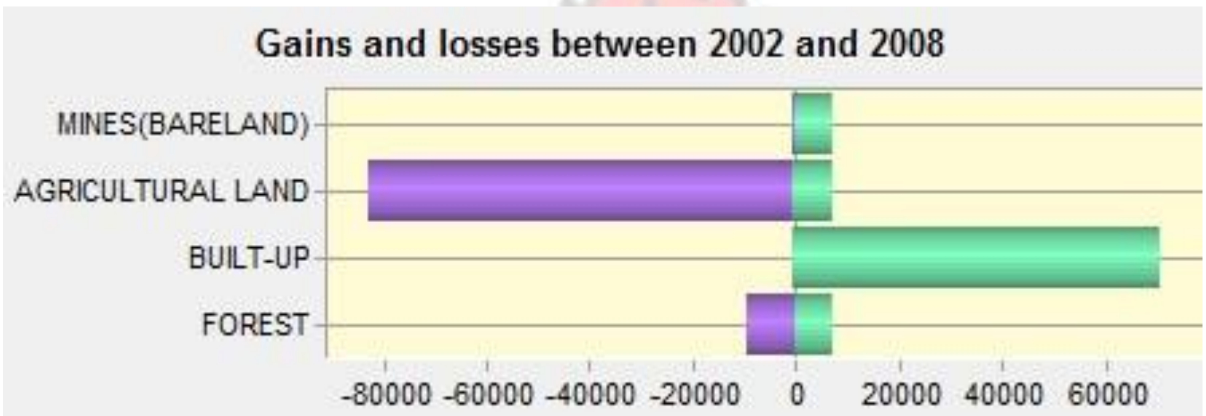


Figure 4.12: Gains and losses of LULC classes (Ha)

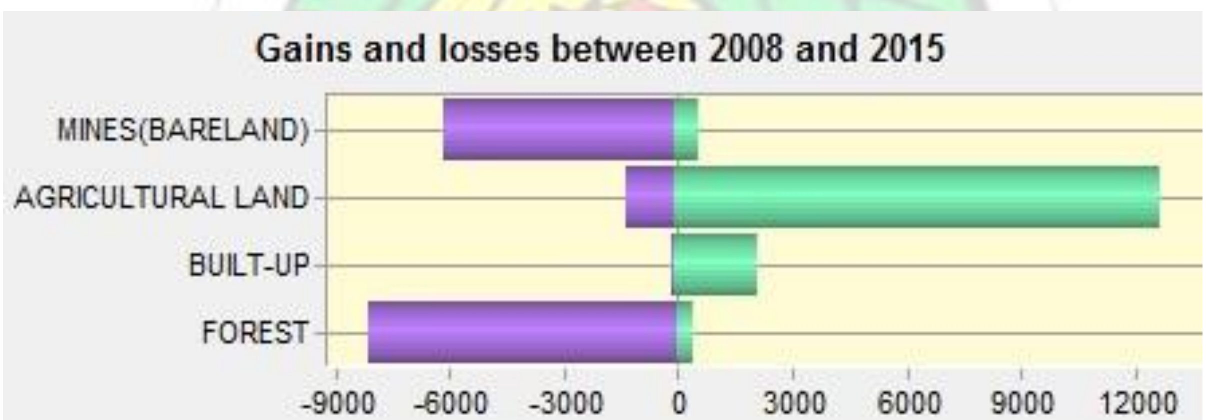


Figure 4.13: Gains and losses of LULC classes (Ha)

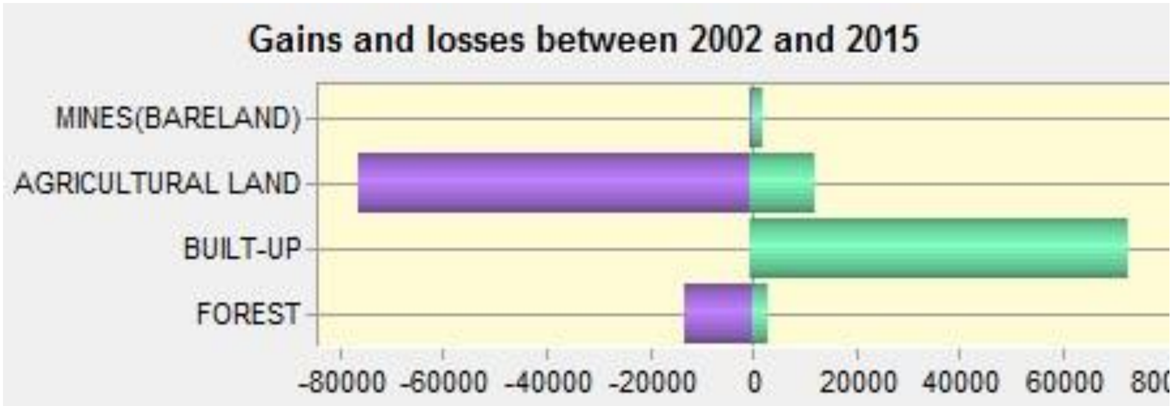


Figure 4.14: Gains and losses of LULC classes (Ha)

The effect of the forest, agricultural land and built-up on the mines/bareland class and the contributions to the net gain in mines/bareland over the 13 year period is depicted in Figure 4.15.

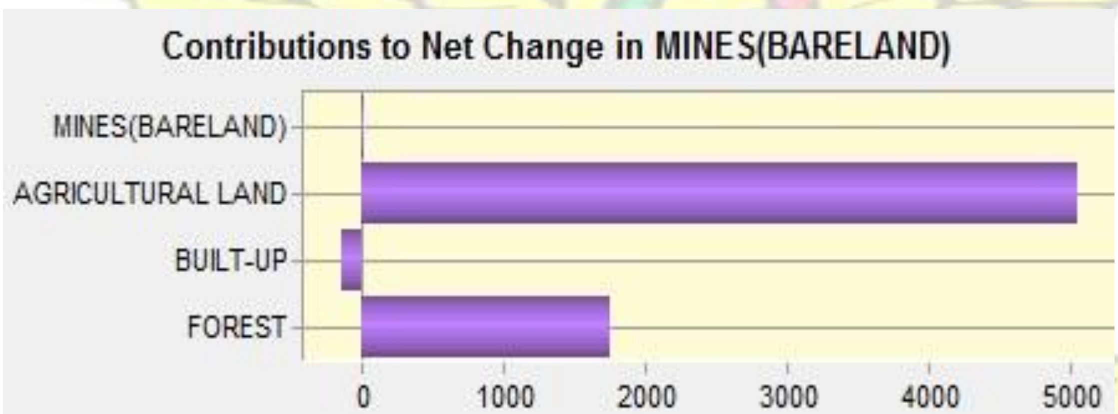


Figure 4.15: Contributions to net change in mines/bareland areas (Ha)

4.2 LULCC TRAJECTORIES

4.2.1 Evaluation of LULC Projection Model

This research work was to analyze and map LULC trajectories in the BND using statistical methods as of the objectives; this was made possible with the application of IDRISI Selva software. The predicted map created in such instances highlights areas of high probability to change.

Before the projection to 2025, the model was first tested; a similarity comparison between the projected map and the actual LULC maps of 2015 was conducted (Appendix 11) and the kappa statistics obtained were, Kstandard = 83.53 %, Kno = 80.39% and Klocation = 88.88%. All the Kappa statistics obtained were above 80%, and as recommended by Viera and Garrett (2005), the CA-Markov model was considered suitable for the LULC change projection of Birim North District to 2025 (Appendix 12).

4.2.2 LULC Projection of Birim North District to 2025

Application of the IDRISI Selva software procedures yielded a projected LULC map for 2025; the system underwent iterations until the projected LULC map was obtained. Projected LULC classes (Figure 4.16) and their corresponding areas were generated (Figure 4.17). Agricultural land occupied the highest area coverage of 73791.73ha representing 60.67% of the study area. The spatial extent of the remaining LULC classes are mines/bareland, 5774.67ha representing 4.75%, built-up, 35923.83ha representing 29.54% and forest, 6132.89ha representing 5.04%.

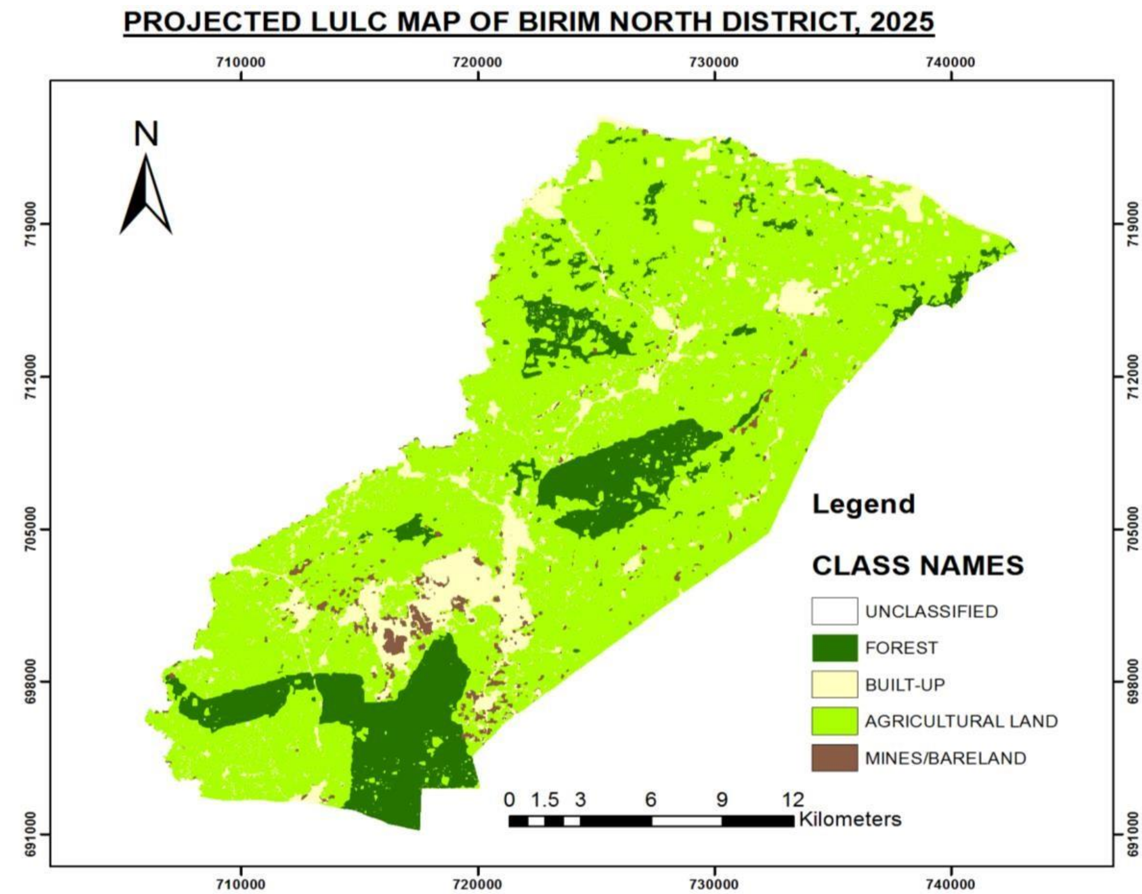


Figure 4.16: LULC projection map of Birim North District, 2025

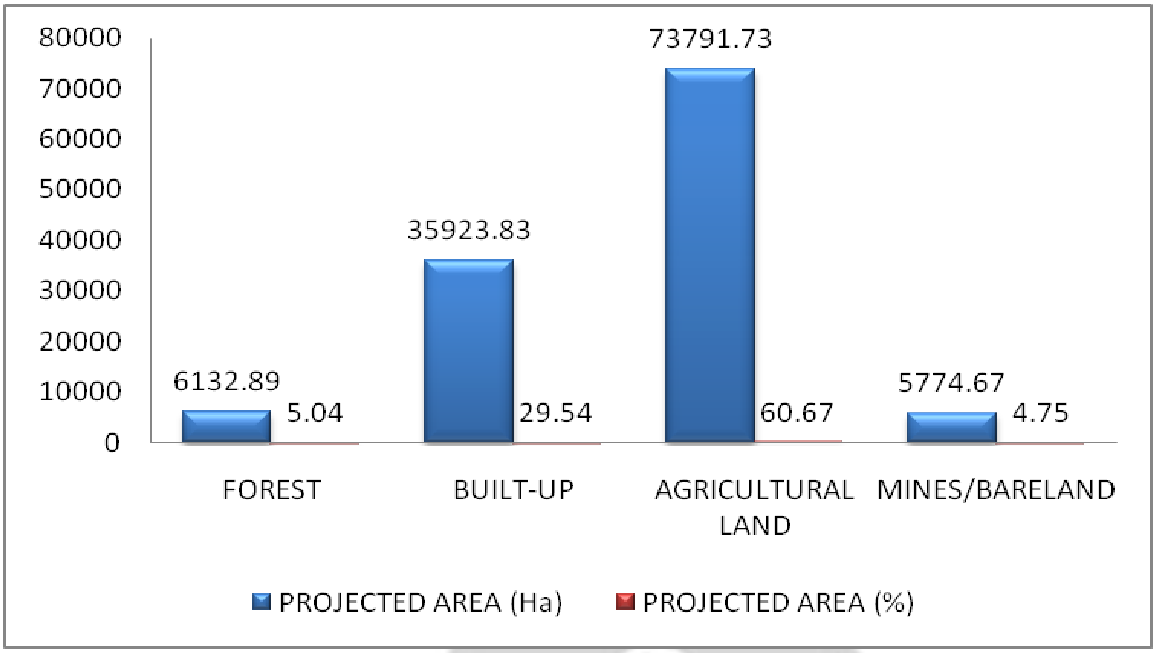


Figure 4.17: Areas (ha) of Projected LULC classes in 2025.

4.3 LOCAL LIVELIHOOD IN BND

4.3.1 Socio-Economic Characteristics of Respondents in BND

Fundamental data was sampled from a sum of 70 respondents in a one-on-one questionnaire administration. Majority (61 percent) of the interviewees were of the male sex, whiles female interviewees accounted for the last 39 percent. Within the 61 percent of males interviewed, 98 percent were household heads, and are traditionally responsible for making decisions regarding resource utilization and management (Table 4.11, Figure 4.18). The majority of the interviewees fell between 31 and 60 years of age as in (Table 4.11, Figure 4.18). Essentially, it is necessary in situations in which respondents are expected to deliver a past description of LULC changes which might have taken place in and around their communities over time, to link these changes to the LULC maps (Figure 4.1, 4.2, 4.4).

Table 4.11: Age and Gender Structure of respondents

		Gender of respondents		Total
		Male	Female	
Age of respondents	16-30	10	1	11
	31-60	26	21	47
	>60	7	5	12
Total		43	27	70

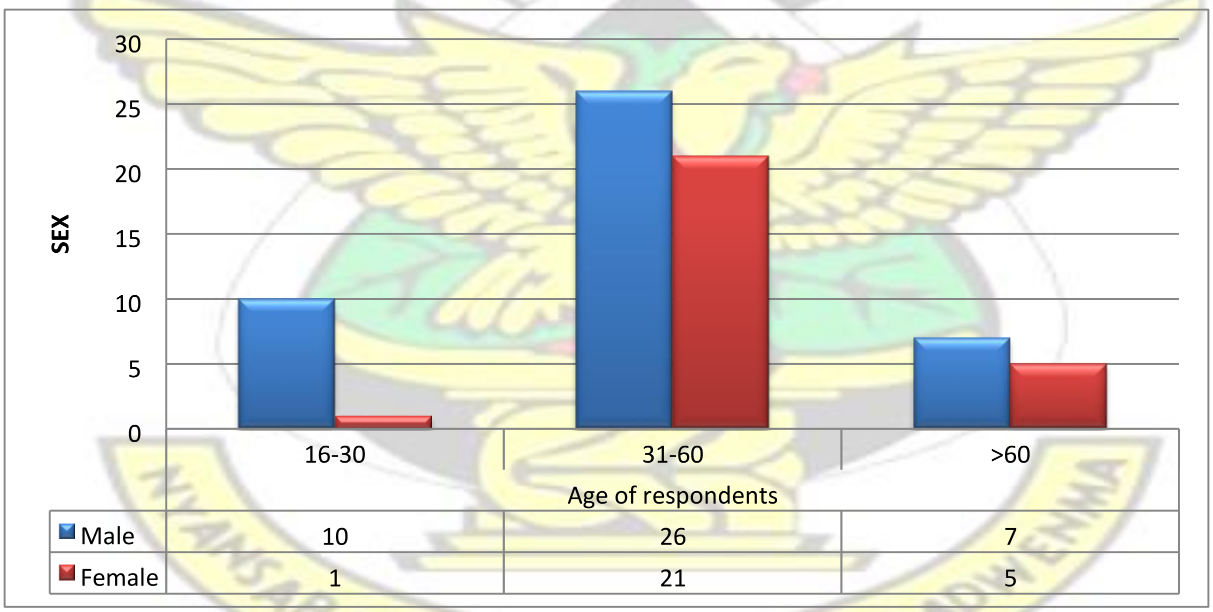


Figure 4.18: Age and Gender distribution of respondents

The age distribution as illustrated in Figure 4.18 is statistically significant in explaining the age distribution and formation of the populace in the District. The 31-60 years age group is the dominant age group with a representation of 67.1 percent and majority of the respondents (78.6 percent) in this age bracket were married whiles 5.7 percent were single. The remaining 15.7 percent were either widowed or divorced.

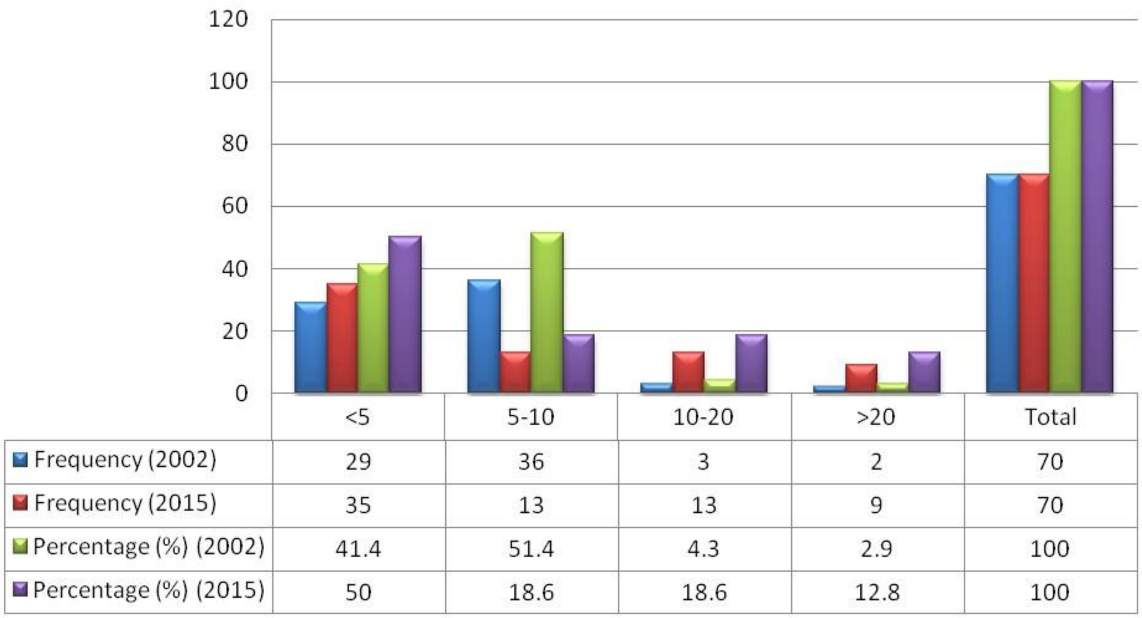
Out of the 70 respondents interviewed, about 36 respondents representing 51.4 percent had farm sizes between 5-10 acres as at 2002; whiles 29 respondents (41.4 percent) had less than

5 acres. 5 respondents (7.1 percent) had farm sizes of 10 acres and above as depicted in Table 4.12 and Figure 4.19. About 35 respondents representing 50 percent had farm sizes of

5 acres or less as at 2015; whiles 13 respondents (18.6 percent) had farm sizes between 1020 acres, 13 (18.6 percent) respondents had 5-10 acres and 9 (12.9 percent) respondents had more than 20 acres.

Table 4.12: Farm Size Distribution, (2002-2015)

Size of Farm	Frequency (2002)	Frequency (2015)	Percentage (%) (2002)	Percentage (%) (2015)
<5	29	35	41.4	50
5 - 10	36	13	51.4	18.6
10 - 20	3	13	4.3	18.6
>20	2	9	2.9	12.8
Total	70	70	100	100



	<5	5-10	10-20	>20	Total
Frequency (2002)	29	36	3	2	70
Frequency (2015)	35	13	13	9	70
Percentage (%) (2002)	41.4	51.4	4.3	2.9	100
Percentage (%) (2015)	50	18.6	18.6	12.8	100

Figure 4.19: Farm Size Distribution of Respondents (2002 and 2015)

From Figure 4.19, the farm size group owned by majority of the farmers was 5-10 acres in 2002 comprising 36 farmers whiles the farm size group owned by majority of the farmers was less than 5 acres in 2015 comprising 35 farmers. Farmers owning more than 20 acres had increased from 2 to 9 while farmers owning between 10-20 acres of farm land had increased from 3 to 13 in 2015. The number of farmers with 5-10 acres of farmland had however decreased from 36 to 13 between 2002 and 2015.

4.3.2 Effects of Mining

Table 4.13 illustrates the mining types operating in the BND; out of the 70 respondents, 15 (21.4 percent) farmers said they were not affected by any form of mining in any way. 20 (28.6 percent) said they were affected by large scale mining and 35 (50 percent) said they were affected by small scale mining. It is worth noting that all the farmers who said they were affected by large scale mining have their farmlands in the Newmont Ghana Gold Limited (NGGL) concession.

Table 4.13: Effects of the types of Surface Mining in BND

Mining Type	Frequency	Percentage (%)
None	**15**	**21.4**
Large Scale Mining	**20**	**28.6**
Small Scale Mining	**35**	**50**

The 50 percent of respondents who suffered from small scale mining were also of the view that small scale mining had existed in the District for close to 20 years, just that it wasn't patronized largely as it is done in recent times. Most of these people have lived in the district longer than 30 years and as such were in a better position to recollect events as they unfolded. A total of fifteen (15) communities within the study area were used for the study as in Appendix 6. A total number of 15 (21.4%) respondents out of the sample size were of the view that they were not affected by mining operations in any way whiles 55 (78.6%) thought otherwise. Majority of the respondents; 32(46%) considered Farmland Loss as the dominating effect of mining. A combination of farmland loss, water pollution, forest destruction, air pollution and settlement destruction were also said to have been experienced in some communities of which 13 (19%) alleged as a significant risk to their livelihoods.

4.3.3 Compensation Determination and Payments

The dominant contentious issue between the mining companies and the local communities mostly has to do with adequate compensation payments. Section 71(i) of the Minerals and mining law of Ghana, 1986 (PNDCL153) provides for compensation payments (Antwi, 2010). It states: "The owner or occupier of any land subject to a minerals right may apply to the holder of any disturbance of the rights of such owner and for any damage done to the surface of the land, buildings, works or improvements or to livestock crops or trees in the area of such mineral operations" (Government of Ghana, 1986).

From all indications rather, compensations usually cover just the current estimated value of the properties on the lands and not the source of livelihood of the farmers. The principle usually applied in Ghana the head-count technique of cultivated plants damaged, times a traditionally predetermined government price for a range of cultivated plants in an inflationary financial system like Ghana (Kasanga, 2002).

The effects of LULC changes due to surface mining on local livelihoods in BND is brought to bare by the interviews which points to a degradation of the districts farming pedestal with an extensive erosion of flora and fauna on which the communities rely. The effect of agricultural land loss and lack of adequate remuneration was collectively alleged to be a drawback and was directly linked to diminishing earnings and living standards. Hence, majority of the farmers who were interviewed defined their living conditions as worse after relocation, chiefly because of the loss of their conventional agricultural lands and insufficient reimbursement systems. Out of the respondents who said the mining operators sought their consent before operating on their lands, 25 (35.7%) received some form of compensation whiles 22 (31.4%) received none (Table 4.14, Figure 4.20). A total of 23 (32.9%) interviewees lamented that mining operators did not seek their consent before using their lands.

Table 4.14: Land compensation status

	Large scale mining	Small scale mining	Frequency	Percentage
No Consent at all	**2**	**21**	**23**	**32.9**
Compensation	**24**	**1**	**25**	**35.7**
No Compensation	**2**	**20**	**22**	**31.4**
Total	**28**	**42**	**70**	**100**

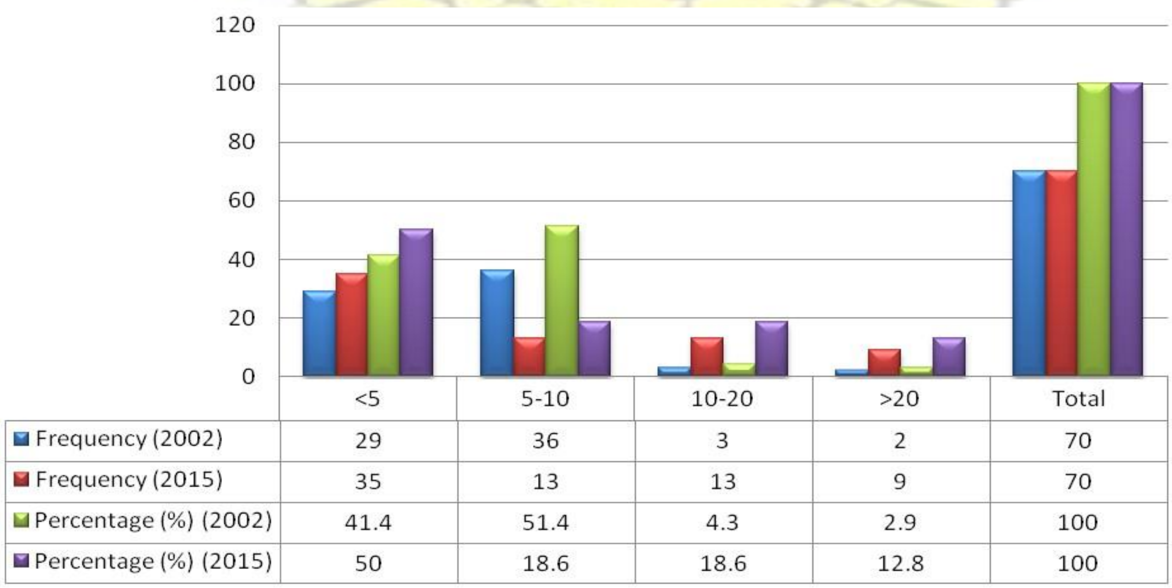


Figure 4.20: Land compensation status.

All 24 respondents who received compensation under large scale mining had their properties in the NGGL concession. They however complained of under valuation of properties and for that matter inadequate compensation. Twenty-one (30%) of the respondents have their lands taken over by small scale miners of which just one respondent received an insignificant amount for their land. All respondents who were either not consulted before using their lands or were denied compensation indicated that attempts to push for any form of compensation were followed with threats by the ASM operators.

4.3.4 Farm Size and Family Dependence

Information on family dependence was sought and matched against farm size; the farm size serves as a major factor in determining the income generation, revenue grade and scarcity positions in the study area as the incomes of the farmers depend on their farm holdings. Especially in a district in which not less than 73.5 % of the labour force cultivates at least one food crop or another (http://mofa.gov.gh/site/?page_id=1506, 17 February, 2015). Table 4.15 shows a cross tabulation of farm size against the number of family dependants a farmer has, out of the 70 respondents, 34 (48.6%) had a farm size less than 5 acres with at least one dependant. 14 (20.0%) had 5-10, 13(18.7%) had 11-20 acres with at least one dependant and 9 (12.9%) had a farm size greater than 20 acres with at least one dependant. A majority of 23 (32.8%) of the respondents had less than 5 acres of land but still had 5-10 dependants to cater for.

Table 4.15: Tabulation of farm size against family dependants

		Number of dependants			Total	Percentage (%)
		<5	5-10	>10		
Size of farm	<5	11	23	0	34	48.6
	5-10	4	9	1	14	20.0
	11-20	11	2	0	13	18.7
	>20	6	3	0	9	12.9
Total		32	37	1	70	100

4.4 DISCUSSIONS

4.4.1 LULC Dynamics from 2002 to 2015

The overlay of the classified images of 2002, 2008 and 2015 shows that both positive and negative changes had taken place over the past 13 years (Figure 4.5). Surface mining led to broad LULC modifications in the study area, particularly resulting in loss of thick vegetation cover and agricultural land

In 2002, agricultural land occupied the highest percentage of area having 79.23%, forest covered 19.67% while mines/bareland and built-up occupied 0.56% and 0.54% respectively. In the year 2008, the percentage of area occupied by agricultural land decreased to 59.11%, forest cover decreased to 17.7% while mines/bareland and built-up increased to 6.03% and

17.16% respectively. In the year 2015, forest further reduced to 11.32%, agricultural land increased slightly to 60.74%, mines/bareland decreased to 1.44% and built-up increased to 26.5%. (Table 4.4, Figure 4.5). These trends of general decrease in agricultural land and forest coverage coupled with subsequent increments of mines/bareland and built-up is attributed to population expansion, rapid urbanization of the district, the influx of ASM operators, the expansion of mining activities, especially in the forest, on farmlands and around New Abirem and the expansion of agricultural activities (the leading economic activity in the district) around the forests zones (Figure 4.8).

4.4.2 Persistence of LULC

Mines/bareland had the least persisted area within the landscape from 2002 to 2015 as in (Table 4.7 and 4.8) and therefore had the highest tendency to expand as a result of conversions of other classes to mines/bareland as depicted in the LULC change trend (Table 4.4). The agricultural land has the largest persisted area over the period and therefore had the highest tendency to convert or be converted to other LULC types and therefore lost the highest catchment area of 18.49% within the 13 year period. Forest made huge conversions to agricultural land but made relatively small conversions to built-up and mines/bareland LULC types (Table 4.7); it is the second most persisted class resulting in the loss of 8.35% of the catchment area.

4.4.3 LULC Analysis of Birim North District

Losing a considerable amount of both forest and agricultural land in the study area signifies an inability of the environment to persist in the forest and agriculture land cover sector.

This is linked to variables such as mining, construction of new settlement and roads (i.e. urbanisation), farming and fuel wood collection as the population of BND inclines. Mining operations have been recognized as one of the foremost driving forces causing rapid LULC changes in the study area.

Within the period of 2002 and 2008, build-up increased by 16.62% and 9.34% between 2008-2015**.** The visual inspection of the change maps for 2002, 2008 and 2015 revealed that build-up expansion is mainly directed towards the agricultural land class (Figure 4.8), which is the highest net contributor to the change in built-up coverage from 2002 to 2015 (Appendix 5). This is attributed to the fact that the nearest adjacent class to the built-up environment that can be exploited to expand the built-up class is the agricultural land class (Figure 4.1, 4.2, 4.4). This establishes urban growth as one of the repelling forces behind the modification of LULC in the BND, supporting the submission that population expansion is generally conceived as a key force behind environmental change. Population expansion, through its effects on the expansion of built-up, agricultural land and the harvesting of firewood for fuel, is a significant issue; contributing to forest cover loss (United Nations, 2001). There has been a population increase in BND since 2000; and hence in 2010, BND recorded a population of 144,869 as against 123,579 in 2000 (Antwi, 2010).

4.4.4 Effect of Mines/bareland Expansion on LULC change.

The catchment area of forest decreased from 2002-2015 by mainly converting to agricultural land (Table 4.6). This is attributed to the fact that the nearest class to the forest environment that can expand into the forest class is the agricultural land class; the forest class is the leading net contributor to agricultural land expansion. However, a net decrease of agricultural land, over the 13 year study period is observed and attributed to built-up and mines/bareland expansion (Appendix 5) of which agricultural land is the leading net contributor to the net change in both the built-up and mines/bareland classes (Figure 4.15). Surface gold mining (both Large Scale and Small Scale Mining) in Birim North District displaced farmers (Table 4.13), making majority of the respondents; 32(46%) consider farmland loss as the major effect of mining. This triggered farmers to seek new farmlands in the forest as confirmed by the LULC change maps (Figure 4.6, 4.7, 4. 8), thereby decreasing the forest cover.

The interviews conducted also suggested that farmland loss within and around Nyafoman, Noyem and Hweakwae was as a result of some farmers practicing galamsey activities on their own farmlands. A close encounter with some of them revealed that, it is more profitable to mine for gold dust at a price in their estimation, worth ten times their earnings in agriculture on the land for an entire year. They also suggested that it is better to mine their own lands than for the lands to be forcefully taken over by notorious ASM for just a little or no compensation at all.

The increase in the spatial extent of built-up in the study area (Table 4.4) resulted from the population enlargement in the area, of which ASM activities and the presence of NGGL in the New Abirem area are the major causes. The repair, construction and expansion of housing facilities to accommodate the growing population increased the demand for timber which is being met by the timber companies and chainsaw operators logging from the existing forest resources. Apart from the upsurge in urban concentration, rural families also tend to expand their accommodations in order to meet the needs of grownup family sizes.

Construction of road infrastructure to connect other parts of the district and to link mine sites also contributes substantially toward the destruction of LULC classes such as forest and agricultural land that are encountered on route. The general status of trunk roads in Ghana as at 2002 had 3,089.00km (26%) good, 3,244.00km (27%) fair and 5,639.00km (47%) poor
(Ghana Highway Authority (GHA), 2010). However, the general status of trunk roads in Ghana as at 2014 had 7,492.33km (52%) good, 5,643.59km (39%) fair and 1,262.80km (9%) poor (GHA, 2014). The total road network in BND in 2010 was 395.6km, made up of
101km trunk roads, 206km of feeder roads and 88.6km of earth surfaces (Ghana Statistical Service, 2014) whereas the total road network in BND in 2014 was 432.3km. This was made up of 121.5km trunk roads, 234km feeder roads and 76.8km earth surfaces (GHA, 2014). According to the figures provided by the Ghana Highway Authority (2014), the road network in the Eastern Region of Ghana has generally extended from 1436 km to 1537.9 km while other road networks have been upgraded (resulting in increase in length and width) between
2002 and 2015.

Apart from the reasons discussed above, some more generalized reasons which play essential roles in the degradation of vegetation cover were also observed. The increase in demand for fuel wood and timber on account of population growth; majority (86.4%) of households use wood and/or its products as their main source of cooking fuel (Ghana Statistical Service,

2010) which implies that more forest cover would have been depleted (Table 4.4).

The field visits and interviews conducted with the farmers revealed that 31-60 years age group was the dominant age group with a representation of 67.1 percent. This suggests that, majority of the farmers have stayed in the communities that were visited long enough to recollect major events as they unfolded. Their response confirmed to the results of the change map which indicates a general decrement in forest and agricultural land cover and a rather expansion in settlements put up by non natives of the visited communities.

4.5 ENVIRONMENTAL CONSEQUENCES OF LULC CHANGES IN BND

4.5.1 Land degradation

Surface gold mining in BND has led to land degradation by way of forest cover depletion and top soil removal; hence soil wearing away, resulting in predominantly loss of fertile lands and farms. Appendix 7 depicts illegal farm devastations as a result of the operations of illegal gold miners. This is confirmed by Akabzaa (2005) who concluded that the crowding of mining operations in an area leads to environmental degradation which rapidly diminishes its massive economic value annually. Generally, small scale gold mining is hitting global significance as a cause of environmental degradation (Barry, 1996; United Nations, 1996; Heemskerk, 2002).

A study by Nartey *et al*. (2011) was carried out to determine the degree of mercury pollution in rivers and streams around ASM areas of the Birim North District of Ghana. The Pra, Nwi, Suten, Nyanoma, Nkwasua and Tainsu rivers were chosen due to their considered locations in relation to the ASM operations and their impending effect on household water distribution in the area. Similarly, the outcome of a research on the estimation of mercury (Hg) levels in water, sediment, soil and human hair samples collected from the Pra river basin and its main tributary, River Offin in the south-western part of Ghana in July 2002 by Donkor *et al.* (2006) indicated a great deal of Hg contamination. Water samples obtained from areas around gold mining sites revealed high Hg concentrations of about 148 ng/L. Total Hg concentrations in water samples collected from mining impacted sites along the River Offin were in the range of 41.6–420 ng/L whereas in the upper and lower streams of River Pra, Hg concentrations range from 24–294 ng/L and 28.7–403 ng/L, respectively. These levels of Hg, exceeded values of safe limits of 1.0 ppb given by the World Health Organisation (1996) (Donkor *et al.*, 2006).

Elemental Hg is now known to be effective in spreading from sources through terrestrial or aquatic media. The Hg used by the miners is usually discharged in a scurrilous manner into ecosystems (Pfeiffer and Larceda, 1988; Meech *et al.,* 1998). Plate 3.1 shows indiscriminate disposal of waste water running into the Nwi river at a mine site in the study Area, whiles Appendix 8 depicts the resulting river water colour. It shows that debris and dust from crushed rocks and soils in the mining process all affect the health of water bodies.

Land degradation through indiscriminate surface mining led to fertile soil destruction, a decrease in the geo-spatial extent of the vegetation cover and an increase in mine/bareland coverage in the district as confirmed by the LULC change analysis.

4.5.2 Deforestation

Remote sensing analysis of the LULC change has demonstrated that there has been a major decrease in forest land area. This results from the fact that the vegetation cover will normally have to be removed with the top soil to make way for either underground mining or surface mining. Surface mining was the dominating type of mining observed and therefore resulted in the wide spread deforestation, even though increase in other adverse anthropogenic activities like logging, firewood gathering and expansion of settlements which resulted from a corresponding increase in population made contributions.

4.6 SCIO-ECONOMIC CONSEQUENCES OF LULC CHANGES IN BND

The socio-economic effects of mining in the Birim North District are varied. They include the lead and collateral consequences of mining activities on the health of humans and the local economy.

4.6.1 Effects of Mining on Human Health

The effects of mining on human health have been widely and extensively documented. Several of the diseases and health disorders associated with mining are caused through the various processes and stages involved in the mining operation (Antwi, 2010). The various stages of mineral processing including ore roasting (calcinations), mineral beneficiation, amalgamation etc, produce and release various toxic chemicals including cyanide, arsenic compounds, sulphur dioxide, mercury etc, into soils, water and air, with both situational and downstream effects, The potential of these chemicals to poison both human and livestock is overwhelming (Antwi, 2010).

Health authorities in the District have acknowledged the incline in the incidence of Sexually Transmitted Diseases (STDs) including Gonorrhea, Syphilis and HIV/AIDS. Infection cases of STDs including HIV/AIDS in the BND have been ascending steadily since the arrival of Newmont (Antwi, 2010). Twenty officially recorded HIV/AIDS cases were presented in 2003; however the District recorded about 150 cases in December 2007 (Antwi, 2010). This is closely tied to the high rate of immigrants on account of gold mining and a corresponding increase in urbanization of the communities in the District.

From the field study, many respondents added that malaria is the most prevalent disease of which majority claimed they suffer at least three major attacks, on the average, from the disease annually. The cause was attributed to frequent and excessive mosquito bites. However, the only comprehensive evidence, which links the very high incidence of malaria in the District to mining activities, is that; the District is a tropical wet region, with very heavy annual rainfall and natural climatic conditions (http://mofa.gov.gh/site/?page_id= 1506, 17 February, 2015), and when runoff or rain water from heavy rainfalls supposed to naturally soak away is left to pond, creates favourable grounds for the mass breeding of the malaria vector. These ponds are a result of the excavations, dug-outs and terraces (Appendix 9).

In view of this, NGGL has taken upon itself to educate community members about the need to use treated mosquito nets whiles undertaking regular mass spraying exercises of these areas. In addition, the company in collaboration with the security agencies has succeeded in driving away a good number of these illegal small-scale miners, who are the cause of this problem (Antwi, 2010).

4.6.1 Effects of Mining on the local economy

Loss of agricultural land in particular was believed to be the major menace to the livelihoods of respondents, with 64% suffering from a decrease in income due to farmland loss. Over the study period Surface mining resulted in the express net loss of about 22479.78 ha out of the

90,103ha of land used for farming (representing about 24.95% of the district's total farmland) (Birim North District Assembly, 2006). This affected an estimated 18.34% of the overall agricultural labor force (Birim North District Assembly, 2014). Based on the evidence above, the operations of the mining companies are affecting crop cultivation in the District there by affecting the majority who depend on crop cultivation for their livelihood and general well being.

Conflicts were observed to occur between the small-scale gold miners and local farmers in the district due to lack of land compensation. Thankfully NGGL seems to be handling and managing its conflicts with the residents satisfactorily in confirmation to Table 4.15: Out of the 25(35.7%) respondents who were compensated, 24 (34.3%) had their lands in the

NGGL concession. All respondents who received compensation packages believed it did commensurate the values of their landed properties; this may be due to the presence of mediators like Olives Ghana (a non-governmental organization) who intervene in the negotiation process for the betterment and protection of land owners especially the farmers.

Perhaps the presence of other non-governmental organizations (NGOs) like Opportunity Industrialization Centre for Industry (OICI) in the District to build the capacity of the affected communities towards Alternative Livelihood Programmes (ALPs) (Antwi, 2010) is a step in the right direction. The activities of NGGL have resulted in the payment of tax and royalties to the District Assembly and the Traditional Authorities respectively. This would serve as a dependable source of revenue with little dependence on government for carrying out developmental projects, thereby raising the livelihood standards of the District. The company has also employed about 78 percent of the youth in the District to provide labour for the mines (Antwi, 2010)

This is contrary to the approach taken by small scale miners who trespass on lands in an abusive manner. In areas like Nyafoman and Noyem in particular where many people depend on small scale mining, violent conflicts between security forces and the mining operators occur often. Any attempt to stop them according to victims of such violent acts especially in the Nyafoman and Noyem communities, is sometimes met with violent physical attacks. This confirms the reason why out of the 42 (60%) of respondents, one person received an unsatisfactory token for his farmland.

4.7 SPATIAL PROJECTION OF BND

The ten year spatial projection from 2015 to 2025 shows that the 2025 projected LULC map has a built-up area of 35923.83ha as against 32221.89ha in 2015; an increase of about 3.04%. (Figure 4.17, Appendix 4). The 2025 projected LULC map has a lot of agricultural land spatially observed scattered around the forest class (Figure 4.16) and decreasing by 0.04% from 2015-2025 after previously decreasing by 18.49% from 2002-2015 (Table 4.3). This is because; relocated farmers in a bid to satisfy the hunger of the growing population in the district would predictably expand their farms into nearby forests (Appendix 4) to feed the growing population in the district. Even though full scale mining may still be going on, but mine/bareland left unattended to for a period of time coupled with suitable atmospheric conditions would be converted to the agricultural land class. The removal of the top soil to give way for mining activities the years over would create favourable environment for shrubs with the ability to grow in the unpleasant edaphic environment as observed in a similar study conducted by Kumi-Boateng (2012) in the Tarkwa Mining Area. This is confirmed with a minimal decrease of 0.04% in agricultural land (Appendix 4). The mine pits would be expanded further for exploration within the ten year period with an expected increment of
3.3% (Appendix 4).

CHAPTER FIVE CONCLUSIONS AND RECOMMENDATIONS

5.1 CONCLUSIONS

In this research, a multi-temporal change detection scheme based on Landsat ETM+ imagery was used for identifying, quantifying and analyzing the spatio-temporal response of the landscape due to surface gold mining activities. The potential of the technique was explored using the Birim North District as a case study, a hotspot for surface gold mining activities.

Thematic maps of 2002, 2008 and 2015 depicting forest cover, agricultural land, mines/bareland and built-up LULC classes were distinguished through image classification.

Objective 1: To determine and map LULC changes from 2002-2015.

LULC conversions as well as trends were analyzed and this aided in LULC change detection and mapping in the study area. The forest and agricultural land cover reduced by 2.0 % and 14.9 % respectively, whereas built-up increased by 16.6 % and mines/bareland, 0.3 % between 2002 and 2008. The forest and agricultural land cover reduced further by 6.4 % and

1.6% between 2008 and 2015, whereas built-up increased by 9.3 % and mines/bareland, 0.6% within the same period. The forest and agricultural land cover generally reduced by 8.4% and 18.5 % respectively, whereas an increase in built-up and mines/bareland areas was observed; mines/bareland increased by 0.9 % and built-up, 25.9% within the 13 year study period (2002-2015). Conversions from forest to agriculture and agriculture to built-up or mines/bareland classes were the wide spread LULC changes in the study area. The forest class made the highest conversion of 11970.78(ha) (9.8%) to the agricultural land class. The conversion of agricultural land to forest and mines/bareland are 2969.67ha (2.4%) and

1297.89ha (1.1%) respectively.

Objective 2: To identify the environmental consequences of LULC change, emanating from surface gold mining in the study area.

Surface gold mining resulted in widespread deforestation, leading to a total destruction of 10,124.12 ha (8.4%) of the forest cover in the district of which 733 ha (0.6%) was lost to the built-up environment in the form of settlement and road expansion. Three hundred and ninety hectares (390 ha) (0.3%) of forest was lost to mines/bareland and 9001 ha (7.40%)

was lost to agricultural land because relocating farmers regularly clear forests for fresh grounds to till, revealing a noticeable overflow effect of mining on LULC types.

Surface gold mining in Birim North District also led to land degradation through top soil removal, resulting in predominantly loss of fertile lands and pollution of water bodies like the Nwin River.

Objective 3: To analyze and project LULC change in the study area to 2025.

The LULC changes were projected from 2015 to 2025 in the study area; the forest class is expected to decrease by 7662.22ha (6.3%) and agricultural land by 46.07ha (0.1%). The built-up class is expected to increase by 3701.94ha (3.1%), and mines/bareland to increase by 4006.35ha (3.3%).

Objective 4: To determine whether surface mining related LULC change in the study area affects local livelihood.

The interviews with the farmers that were conducted suggest that surface gold mining affects the farmers in the district. Fifty-five (55) of the farmers representing 78.6% considered surface mining has a negative effect: Majority of the respondents; thirty-two (32) (46%) considered farmland loss as the major effect of surface mining. The farm size group owned by majority of the farmers was 5-10 acres in 2002 comprising 36 farmers whiles the farm size group owned by majority of the farmers was less than 5 acres in 2015 comprising 35 farmers. This contributed to a 64% decrease in the income of farmers between 2002 and 2015.

While the gold boom in Birim North District has ensued considerable income in the district and national stage, the deprived farmers are revealed not to be benefitting from this boom, but rather going through difficult livelihood times through lost of farm lands and income opportunities.

5.2 RECOMMENDATIONS

The Landsat imageries employed in the research work had relatively low spatial resolutions of 30 m; this permitted classification of LULC into only broad classes. Such that geographic phenomena with area less than 30m X 30m (0.09 ha) could not be classified, hence the difficulty in distinguishing and classifying 'water'. In the light of this, there is the need to further this study with relatively higher spatial resolution imagery. This could better classify

LULC in the study area into more accurate thematic classes.

By taking more factors such as mercury and arsenic concentration in water bodies into consideration, the study could reach a higher accuracy for LULC change detection and the effect of LULC change on local livelihood in the district effectively evaluated and quantified.

The government of the day should endeavor to modify existing policies on agriculture to make the sector more attractive to discourage farmers from converting their own farms into mine pits and more importantly discourage further encroachment on the forests.

The spillover of surface mining effects on local livelihoods can lead to considerable deterioration of the district's LU systems in the future if ignored. To ameliorate this, and to discover collaborative development for the future, farmers, landlords and mining corporations must be integrated as part of LU systems in the district's rural areas.

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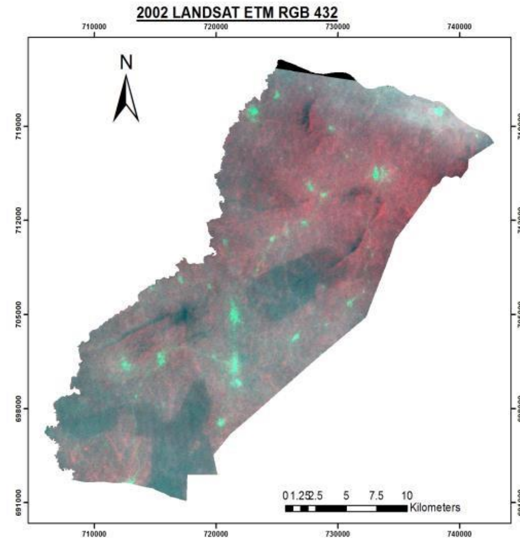
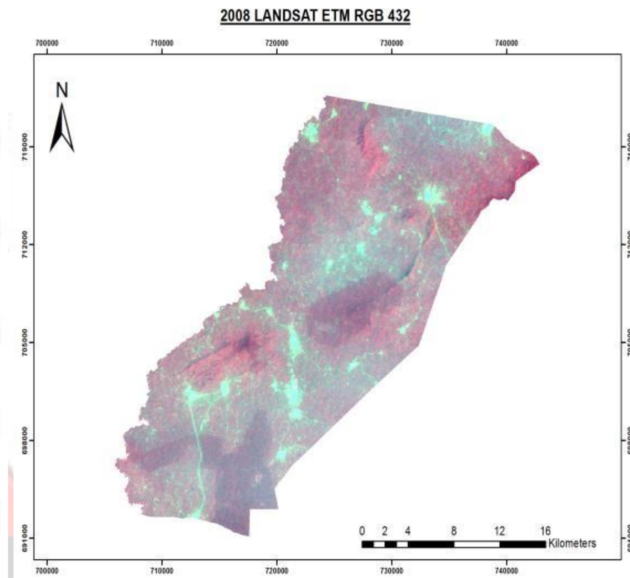
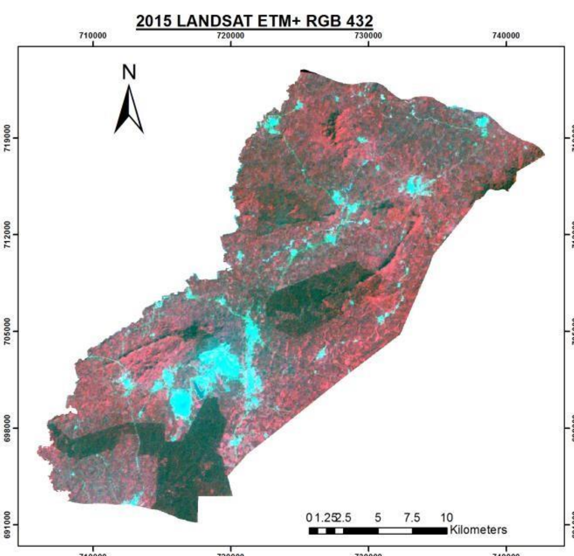
APPENDICES

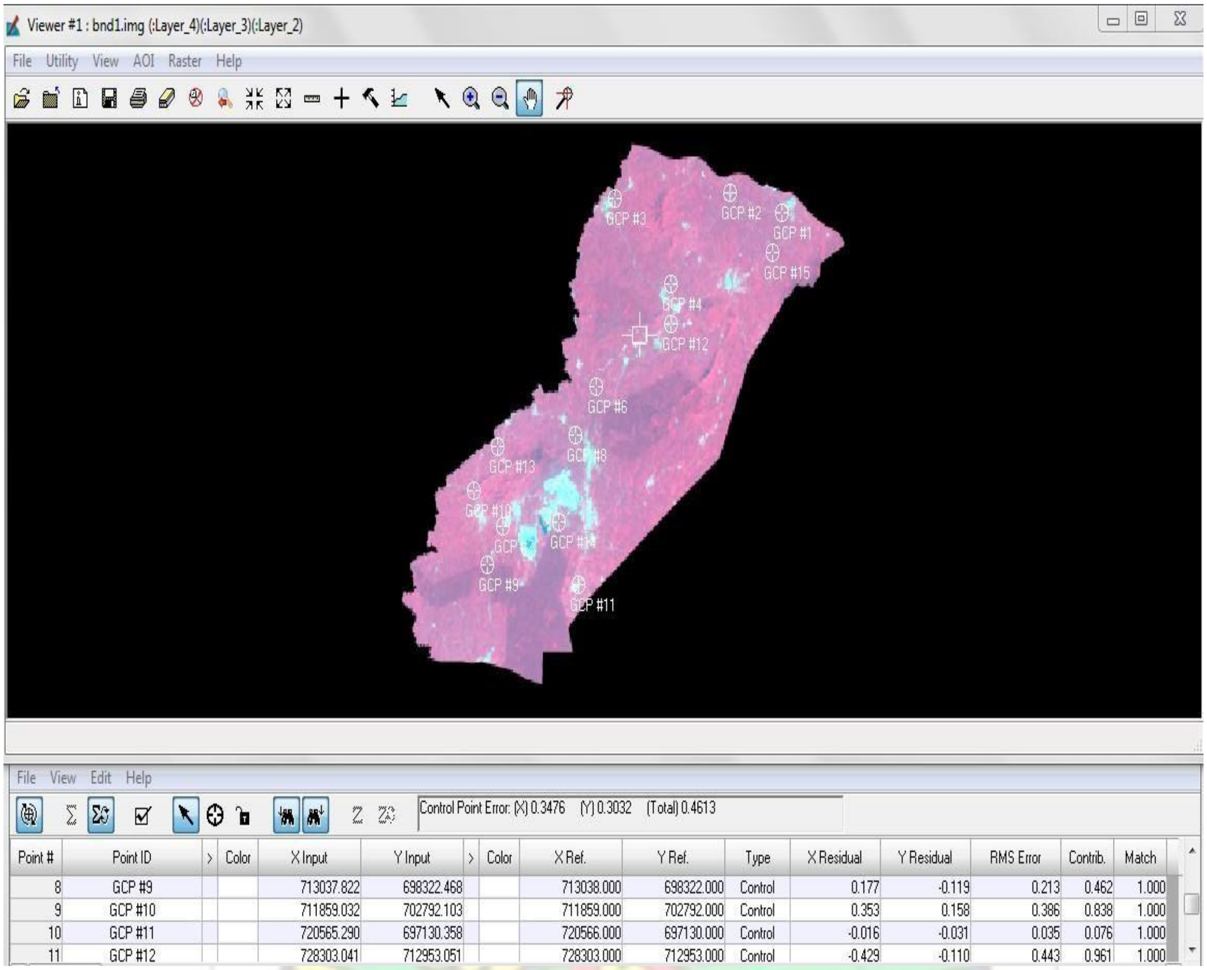
Appendix 1: Satellite Images of the study area







Appendix 2: Geometric Accuracy Assessment of Imagery



Appendix 3: Classification accuracy assessment

Table A3-1: Classification accuracy assessment for 2002

	REFERENCE DATA						
CLASSIFIED DATA	**FOREST**	**BUILT -UP**	**AGRIC LAND**	**MINES/BARE LAND**	**Total**	Producer's accuracy (%)	User's accuracy (%)
FOREST	**28**	2	0	0	30	93.33	90.23
BUILT-UP	3	**27**	0	0	30	90	93.1
AGRIC LAND	0	0	**24**	5	29	82.76	85.71
MINES/BARE LAND	0	0	4	**26**	30	86.67	83.87
Total	31	29	28	31	**119**		

Overall Classification Accuracy for the year 2002 = 88.24%, Kappa coefficient = 0.843

Table A3-2: Classification accuracy assessment for 2008

	REFERENCE DATA						
CLASSIFIED DATA	**FOREST**	**BUILT -UP**	**AGRI C LAND**	**MINES/BARE LAND**	**Total**	**Producer's accuracy (%)**	**User's accuracy (%)**

FOREST	**27**	0	3	0	30	93.32	84.85
BUILT-UP	0	**27**	0	3	30	90	87.1
AGRIC LAND	5	0	**24**	0	29	82.76	88.89
MINES/BARE LAND	0	4	0	**26**	30	86.67	89.66
Total	32	31	27	29	**119**		

Overall Classification Accuracy for the year 2008 = 87.50%, Kappa coefficient = 0.833

Table A3- 3: Classification accuracy assessment for 2015

	REFERENCE DATA						
CLASSIFIED DATA	**FOREST**	**BUILT -UP**	**AGRIC LAND**	**MINES/BAR ELAND**	**Total**	**Producer's accuracy (%)**	**User's accuracy (%)**
FOREST	**27**	1	2	0	30	90	93.1
BUILT-UP	0	**27**	0	2	29	93.1	90
AGRIC LAND	2	0	**28**	0	30	93.33	93.33

MINES/BARE LAND	0	2	0	**28**	30	93.33	93.33
Total	29	30	30	30	**119**		

Overall Classification Accuracy for the year 2015 = 92.44%, Kappa coefficient = 0.899

Appendix

4: LULC comparison of 2015 and 2025.

	2015		**2025**		**RELATIVE CHANGE**	
LULC CLASS	**Area 2015 (Ha)**	**Area 2015 (%)**	**AREA (Ha)**	**AREA (%)**	**Area (Ha)**	**Area (%)**
FOREST	13795.11	11.34	6132.89	5.04	-7662.22	6.3 **Decrease**
BUILT-UP	32221.89	26.5	35923.83	29.54	3701.94	3.04 **Increase**
AGRIC LAND	73837.8	60.71	73791.73	60.67	-46.07	0.04 **Decrease**
MINES/BARE LAND	1768.32	1.45	5774.67	4.75	4006.35	3.3 **Increase**

Appendix

5: Contributions to net change between 2002-2015

Contributions to net change in agricultural land between 2002-2015

LULC CLASS	AREA (Ha)
FOREST	9001 **gain**
BUILT-UP	-32064 **loss**
AGRICULTURAL LAND	0 **no change**
MINES/BARELAND	-1007 **loss**

Contributions to net change in forest between 2002-2015

LULC CLASS	AREA (Ha)
FOREST	0 **no change**
BUILT-UP	-733 **loss**
AGRICULTURAL LAND	-9001 **loss**
MINES/BARELAND	-390 **loss**

Contributions to net change in Built-up between 2002-2015

LULC CLASS	AREA (Ha)
FOREST	373 **gain**
BUILT-UP	0 **no change**

Appendix

AGRICULTURAL LAND	32064 **gain**
MINES/BARELAND	308 **gain**

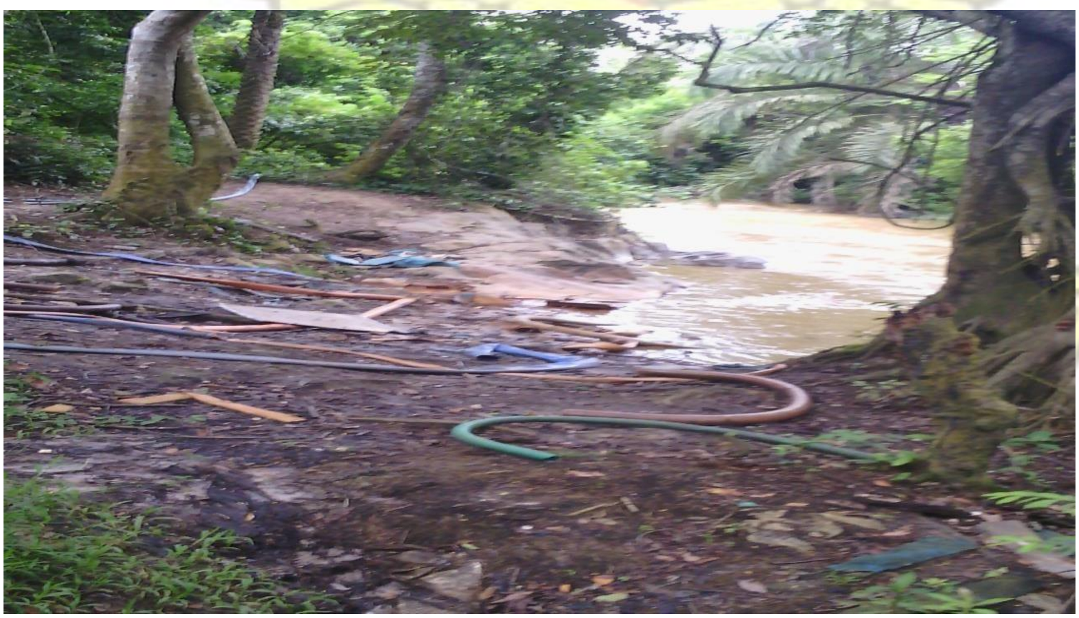
6: Relationship between Communities and Effects of Mining in the Study Area

Community	No effect	Farmland loss	Water pollution	Forest destruction	Air pollution (from dust particles)	Settlement destruction	All the above	Total
Adausena	0	0	0	0	0	0	1	**1**
Afosu	0	3	1	0	0	0	2	**6**
Amenam	2	1	0	0	0	0	0	**3**
Amuana Praso	0	3	1	1	0	0	1	**6**
Asenase	0	2	0	0	0	0	0	**2**
Hweakwae	0	5	0	0	0	1	0	**6**
Noyem	2	2	0	0	0	0	5	**9**
Ntronang	2	3	1	0	2	0	0	**8**
Nwinso	1	5	0	0	0	0	0	**6**
Nyafoman	0	2	2	0	1	0	1	**6**
Pankese	5	3	0	0	0	0	0	**8**
Praso kuma	0	0	0	0	0	0	1	**1**
Takosu	3	0	0	0	0	0	0	**3**
Yaayaaso	0	1	0	0	0	0	2	**3**
Yaw tano	0	2	0	0	0	0	0	**2**
Total	**15**	**32**	**5**	**1**	**3**	**1**	**13**	**70**

Appendix

Appendix 7: Farm destruction at a mine site near Nyafoman

Appendix 8: Water colour after waste water disposal into the Nwi river



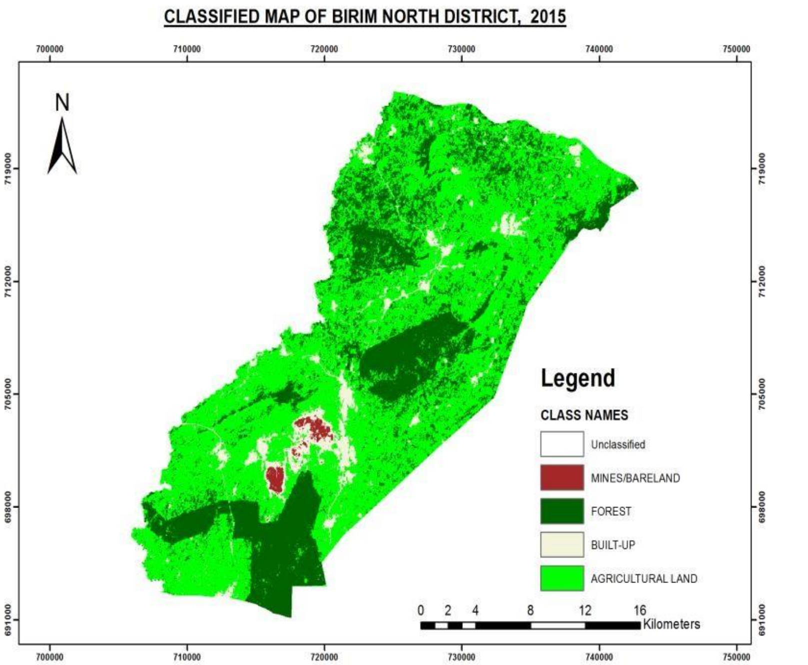
Appendix 9: Stagnant Water after galamsey, to serve as breeding grounds for mosquitoes

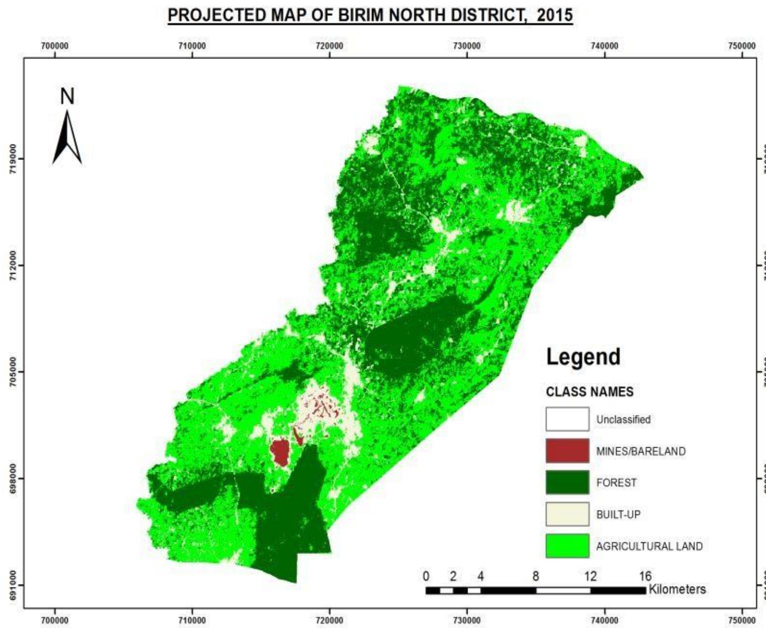
Appendix 10: Markov transition area matrix for 2015-2025, Birim North District

		Probability of changing to			
		Forest	**Built-Up**	**Agric Land**	**Mines/Bareland**
Given	**Forest**	0.23	0.4	0.35	0.02
	Built-Up	0.01	0.76	0.10	0.02
	Agric Land	0.03	0.83	0.13	0.02

	Mines/Bareland	0.04	0.76	0.18	0.02

Appendix 11: Actual and Projected LULC in Birim North District for 2015





Appendix 12: Validation of projected 2015 with actual 2015 LULC maps

Mumber of total runs : 1
Multi-resolution VALIDATE : Categorical Image Comparison
==
Comparison image file : 2015projected
Reference image file : 2015classified_map
Strata/Mask image file : N/A
Number of valid strata: 1; Number of valid categories: 6
//Beginning of run: 1
Resolution scale: 1 x 1
Classification agreement/disagreement
According to ability to specify accurately quantity and allocation

Information of Quantity

Information of Allocation No[n] Medium[m] Perfect[p]

Perfect[P(x)] P(n) = 0.5623 P(m) = 0.6154 P(p) = 1.0000
PerfectStratum[K(x)] K(n) = 0.5435 K(m) = 0.9615 K(p) = 1.0000
MediumGrid[M(x)] M(n) = 0.5355 M(m) = 0.8866 M(p) = 0.8638
MediumStratum[H(x)] H(n) = 0.1667 H(m) = 0.2562 H(p) = 0.3528
No[N(x)] N(n) = 0.1667 N(m) = 0.2562 N(p) = 0.3528
AgreementChance = 0.1667
AgreementQuantity = 0.1895
AgreementStrata = 0.0000
AgreementGridcell = 0.6034
DisagreeGridcell = 0.0898
DisagreeStrata = 0.0000
DisagreeQuantity = 0.2846
Kno = 0.8039
Klocation = 0.8888
KlocationStrata = 0.8888
Kstandard = 0.8353
//Ending of run: 1

Appendix 13: Sample questionnaire and survey instruments

KWAME NKRUMAH UNIVERSITY OF SCIENCE AND TECHNOLOGY

COLLEGE OF ENGINEERING

DEPARTMENT OF GEOMATIC ENGINEERING

A research questionnaire for determining the effects of surface mining related land use/land cover change on local livelihood in the Birim North District of Ghana.

Please indicate by stating or ticking [V] where applicable.

A) PERSONAL INFORMATION

1) How old are you?

a) 0-16 [ ]

b) 16-30 [ ]

c) 31-60 [ ]

d) >60 [ ]

2) Gender

a) Male [ ]

b) Female [ ]

3) Marital status

a) Married [ ]

b) Single [ ]

c) Divorced [ ]

d) Widow/Widower [ ]

4) Highest level of education reached

a) University [ ]

b) Training College [ ]

c) SHS [ ]

d) JHS/Primary [ ]

e) None [ ]

5) What is your main occupation?

……………………………………………………………………………………………………

……………………………………………………………………………………………………

……

B) **EFFECTS OF MINING**

1) Are you affected by mining operations in any way?

a) Yes [ ]

b) No [ ]

2) If yes, in which way?

a) Farmland Loss [ ]

b) Water pollution [ ]

c) Forest destruction [ ]

d) Air pollution (from dust particles) [ ]

e) Settlement destruction [ ]

f) All the above [ ]

g) Others (please state)……………………………………………………………………

3) If your answer to question 1) above is yes; which of these mining types affects you?

a) Large-scale mining [ ]

b) Small-scale mining (galamsey) [ ]

<u>EFFECTS OF SMALL SCALE GOLD MINING ON AGRICULTURE</u>

1) Do you have a farm?

a) Yes [ ]

b) No [ ]

2) If yes which year did you acquire your farm?

a) Before 2002 [ ]

b) In 2002 [ ]

c) After 2002 [ ]

3) What size was your farm in acres?

a) <5 [ ]

b) 5-10 [ ]

c) 11-20 [ ]

d) >20 [ ]

4) Have you observed small scale gold mining (galamsey) in any way in your farm? a) Yes [ ]

b) No [ ]

5) What is the size of your farm now?

a) <5 [ ]

b) 5-10 [ ]

c) 11-20 [ ]

d) >20 [ ]

6) In your view do you think small scale gold mining (galamsey) has affected the size of your farm?

a) Yes [ ]

b) No [ ]

7) If your answer to question 6 above is a), then has the farm loss affected your income

a) Yes[ ]

b) No [ ]

8) What major crops did you grow before mining started on your farm

………………………………………………………………………………………………

………………………………………………………………………………………………

………………………………………………………………………………………………

9) What major crops do you grow now

………………………………………………………………………………………………

………………………………………………………………………………………………

………………………………………………………………………………………………

10) If answers to questions 14 and 15 are different, please give reasons for the difference in your view

………………………………………………………………………………………………

………………………………………………………………………………………………

C) LAND COMPENSATION AND FAMILY DEPENDANTS

1) Did the mining operators seek your consent before operating on your land? a) Yes [ ]

b) No [ ]

2) Have you been paid any compensation?

a) Yes [ ]

b) No [ ]

3) If no, was the process of compensation and valuation of your land communicated to you?

a) Yes [ ]

b) No [ ]

4) If yes, how were the process of compensation and valuation of your land communicated to you?

a) Through a government institution [ ]

b) Through the traditional authorities [ ]

c) Through opinion leaders [ ]

d) Through the mining company [ ]

e) Through an NGO [ ]

5) Did you come to a common understanding with the other stakeholders before mining started on your farm?

a) Yes [ ]

b) No [ ]

6) How many dependants did you have before mining operations started on your land? a) None [ ]

b) <5 [ ]

c) 5-10 [ ]

d) >10 [ ]

7) How many dependants do you have now?

a) None[ ]

b) <5 [ ]

c) 5-10 [ ]

d) >10 [ ]

D) LIVELIHOOD CHANGES

1) Has your income generally changed since mining started in this community?

a) Yes [ ]

b) No [ ]

c) Don't know[ ] 2) If yes how?

a) Positively [ ]

b) Negatively [ ]

3) Please explain if your answer to question 2 above is a).

…………………………………………………………………………………………………

…………………………………………………………………………………………………

…………………………………………………………………………………………………