KWAME NKRUMAH UNIVERSITY OF SCIENCE AND TECHNOLOGY

COLLEGE OF ENGINEERING

DEPARTMENT OF GEOMATIC ENGINEERING

ASSESSING LAND COVER CHANGE RESULTING FROM SURFACE MINING DEVELOPMENT (A CASE STUDY OF PRESTEA AND ITS ENVIRONS IN THE WESTERN REGION OF GHANA)

A THESIS SUBMITTED TO THE DEPARTMENT OF GEOMATIC ENGINEERING, PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE DEGREE OF

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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 materials previously published by another person nor material which has been accepted for the award of any other degree of the University, except where due acknowledgement has been made in the text.

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ABSTRACT

Land use and land cover change (LULCC); also known as land change is a general term for the human modification of Earth's terrestrial surface. LULCC are the direct and indirect consequence of human actions to secure essential resources. It has become necessary to analyse these land changes for the management of natural resources and maintenance of the environment.

The rate of urbanization and industrialization in Prestea is causing rapid change to LULC. Mining activities, especially surface mining in the area is creating pressure on the land cover, influencing other activities such as, deforestation, building of houses and industries, farming and other anthropogenic activities. In view of this problem of land cover change, this project was aimed at mapping, monitoring and analysing the spatio-temporal LULCC patterns using multi-temporal satellite images from 1990 - 2010 within the study area (Prestea and its environs).

Modelling and analysis of these multispectral images were performed using Erdas Imagine software and Idrisi selva. Seven LULC classes were identified including; high density forest, sparse forest, farmland, built-up, barren land, water and mine site. The results showed that during the period under review (1990-2010) there have been losses in high density forest and sparse forest, while farmland, built-up and mine site have seen some increase. Also the annual rate of change within this period was found to be 2.25%.

A LULC map for 2030 was generated for the study area using the 1990 to 2010 LULC map assuming that the transmission mechanisms stay the same, to project areas under risk of invasion in future. The results of the projection revealed an expansion of all land cover classes except high density forest and sparse forest, indicating an increase of 2.11%, 1.56% and 1.35% in farmland, built-up and mine site respectively.

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CHAPTER ONE : INTRODUCTION

1.1 Background

Land use and land cover change (LULCC); also known as land change is a general term for the human modification of Earth's terrestrial surface (Ellis and Pontius, 2007). Land has been modified by human activities to obtain food and other necessities for living and economic development. Human dependency on land has resulted in changes in land and other environmental processes worldwide. (Ellis, 2007). Changes made to land is of great environmental concern to human population, including water, soils, air (Ellis, 2010).

Changes in LULC has occurred far back in history. LULCC occur as a result of direct and indirect human activities, with the purpose of securing essential resources. Changes in the earth's surface occur naturally in a gradual way, but sometimes they may occur rapidly due to anthropogenic activities (Coppin et al., 2004). In order to manage and use resources effectively on the surface of the earth, the timely and accurate land cover change detection of the earth's surface features provides an understanding of the interactions between human and natural phenomena (Lu et al., 2004). In recent times, human population within urban areas has increased as a result of increased industrialization. This increase in urbanization has led to depopulation of rural areas. The effects of urbanization is observable around the world today.

LULC change dynamics can be investigated by the combined use of Remote Sensing, Geographical Information Systems (GIS) and Stochastic Modelling technologies. Remote sensing is an essential tool for land change science. As a tool, it facilitates observations across larger levels of Earth's surface than can be observed by ground-based observations. The use of GIS technology offers a flexible environment for storing, analysing, and displaying digital data necessary for change detection and database development (Demers, 2005).

In order to attain rapid economic development, many countries exploit their natural resources by various activities. Mining has been identified as one of such activities. Therefore, mining is an important economic activity which has the potential of contributing to the development of areas endowed with the resource. Ghana's colonial name, Gold Coast, gives an indication of the importance of mining to the economic development of Ghana (Akabzaa and Darimani, 2001).

Ghana has been successful as Africa's second largest gold producer. International investors has contributed to the success of gold mining in Ghana and has been a boost to the country's economy (Addy, 1998). As a country, Ghana, has to consider how the rush for gold has affected the livelihood and environment of citizens (Agbesinyale, 2003; Akabzaa and Darimani, 2001). Several studies made concerning Ghana's environment and economy indicates that Ghana stand the risk of facing problems as a result of improper management of resources available to the nation: as a result of lack of economic diversification and the rate of the nation's dependency on the export of mineral resources to grow its revenue (Adler and Berke, 2006; Aryee, 2001).

Gold mining in Ghana is carried out in two ways. One of these two ways is the small scale miners (also galamsey operators) are mostly operated in open pits. The other way gold is mined in Ghana is the large scale surface and underground mining. The difference in small scale mining and large scale mining is based on the social and environmental effects (Hilson, 2002). There has been indication by several researchers on the consequences of small-scale mining on the environment, such as the effects of chemicals , such as mercury used during the gold refining process, and the rivalry between large scale miners and small scale miners (Amankwah and Anim-Sackey, 2003; Hilson, 2002). As much as small scale mining searves as a means of employment to some Ghanaians, this economic development of individuals is achieved to the disadvantage of the environmental (Amankwah and Anim-Sackey, 2003).

There are some environmental issues that all of us must agree cannot be tolerated; such as Galamsey operations. As citizens of the state, we have an obligation towards the efficient and effective management of our environment for the sake of posterity. Galamsey operations contradict Article 257 clause 6, of the 1992 constitution, which states that ‘every mineral in its natural state - in, under or upon any land in Ghana’s rivers, streams, water course throughout Ghana, the exclusive economic zone and area covered by the territorial sea or continental shelf is the property of Ghana, and shall be vested in the President on behalf, and in trust for the people of Ghana’. Image classification is the most widely used method for obtaining information from remotely sensed data. From the time when Landsat - 1 multispectral scanner (MSS) data became available, research has been conducted in the aspect of land cover classification using multispectral remotely sensed data (Kumara and Minb, 2008). Classification techniques such as the parallelepiped, minimum distance to mean and maximum likelihood methods were developed. Classification in digital image processing has traditionally been concerned with the assignment of a specific and definite land-cover class to each pixel in the image. A decision rule is thus developed such that a hard, or crisp, assignment can be made for each pixel based on its spectral characteristics. It has always been understood that uncertainty surrounds this process, with the decision rule being designed to minimize the impact of such ambiguity. Recently, interest has focused on the nature of this uncertainty, with the explicit intention of extracting additional information based on its character. Soft classification is one approach that evaluates and utilizes this uncertainty.

Soft classification defers a hard decision in preference for some intermediate statement of class (set) membership. The reasons for doing so vary, including the explicit intention to assess classification uncertainty and the possibility of incorporating additional knowledge before a final hardening of the decision. The primary focus, however, has been its potential for subpixel classification; the determination of constituent classes that fall below the resolution of the pixel (Eastman and Lane, 2002).

1.2 Problem Statement

The rate of urbanization and industrialization in Prestea is causing rapid change to LULC. Mining activities, especially surface mining in the area is creating pressure on the land cover. This has also influenced other activities such as, deforestation, building of houses and industries, farming and other anthropogenic activities.

Some companies in Ghana have been permitted to operate open cast mining and as a result large portions of high density forests have been cleared for the purpose of mining. Although the mining companies make an effort in reclaiming the land by replanting, the natural ecosystem of the area is altered, and thus cause destruction to biodiversity. This condition is worsened by small scale miners who clear forest and dig large channels leaving them bare. The area that has been left is prone to erosion also serving as breeding grounds for mosquitoes as water stays in the channels that have been left by these miners (Wassa West District Assembly Medium Term Development Plan 2002- 2004). Kyei-Boateng, (2005), noted that,the nation's forest depleted annually at a rate of 1.7% between 1990 and 2000. This problem comes more to light by the cries of the people in Prestea during a demonstration staged by the Human Prestea stakeholders coalition in the Western region on 28th January, 2014, when some of the placards carried by the demonstrators read "surface mining will kill us", " we want underground mine and not surface mine"(Ghana news agency, 2014).

Authorities in charge of protecting the environment, do not seem to give a clear statement against the problems and changes caused by surface mining activities, especially registered mining companies. All what these authorities do is to try to solve conflict between these mining companies and the people in the community and also negotiate for compensations, which does not change the harm instigated to the environment as a result of their method of mining (surface mining). This is evident in a statement by Rolexi, 2008; The government of Ghana made one of its worst mistake by allowing surface mining of gold to be practised in the country This has led to the destruction of the natural environment.

It is therefore necessary for a study such as 'Assessing land cover change resulting from surface mining development' to be carried out, in other to analyse and quantify the amount of change and also do certain predictions in LULC changes to 2030, that will be useful to planners and decision makers in making strategic policies to curb problems that might result from these changes.

1.3 Research Questions

- How has open cast/ surface mining system in the study area affected LULCC.
- What are the trends, the rate of expansion or reduction, and the locations of LULCC that have occurred in the study area?
- What is the relation between mining activities; urbanisation and its resultant land use and land cover change?

1.4 Aims and Objectives

1.4.1 Aim

This project aims at mapping, monitoring and analysing the spatio-temporal LULC change patterns using multi-temporal satellite images from 1990 - 2010 within the study area (Prestea and its environs). Below are the specific objectives;

1.4.2 Objectives

1. Identify land cover types and their spatial distribution.
2. Identify the trend / key drivers of LULC change.
3. Project areas under risk of invasion in future.
4. Produce some form of information for local governments in their effort to sustain decision making and land use.

CHAPTER TWO: LITERATURE REVIEW

2.1 Land Change Science

Among the methods for management of natural resources and urban development including land, one of these processes is change detection. This is because it offers a means of recognising differences in the state of an object or phenomenon at different times (Singh, 1989). The earth surface is made up of a combination of cultural and natural landscapes. Each cover is made up of different landscapes which are interconnected, ranging from virgin natural ecosystems to human dominated urban and industrial areas. The surface of the earth has undergone changes as a result of fire, bad weather, glaciations, and other natural causes that have occurred.

Human existence on the earth has resulted in natural landscapes been affected by human activities, such as for settlement, cultivation and other economic activities. The range of changes in landscape is between local (conversion of a farm into a suburb) to regional (conversion of tall grass prairie ecosystems to agriculture) to global (climate change). Climate change is recognised to have the potential of transforming both ecological and cultural landscapes (USGA/climate_landuse, 2013).

Several researchers have expressed interest in studies in the area of landscape change, which has as a result led to the development of a new field of study; land change science. Scientist in the area of land change science, develop new concepts and approaches for better understanding of land resources. (Turner et al., 2007)

Land is an essential natural resource, both for the survival and prosperity of humanity, and for the preservation of all terrestrial ecosystems. Over a couple of years, people have become expert in developing land resources for their own welfares and developments. These resources are definite but there is unlimited demand on these resources by humans. The increase in demand on resources is evident as shown in the deprivation of land quality and quantity for crop production and other social activities, and competition for land. Land does not simply refer to the soils and surface topography, but also certain underlining superficial deposits, climate and water resources. Also, human activities, reflected by changes reflected by changes in vegetative cover or structures, are also regarded as features of the land. Changes in land use has potential impacts on factors such as flora and fauna, soils, climate, etc.

2.1.1 Land Cover and Land Use

The terms land cover and land use are the two main components of land change. Land cover is more easy to notice than land use. As the term land cover denotes the surface cover over the land. Land cover refers to the physical and biological cover over the surface of land, including vegetation, water and bare soil; some workers also include artificial structures as land cover. On the other hand, land use is more intricate as it is interpreted differently by different scientists. Natural scientists, refers to the term as the use of the land surface for human activities such as agriculture, forestry and building of structures, whilst the social scientists define land use as the manner in which the land is managed in terms of socioeconomic purposes (Ellis, 2009). According to Meyer and Turner, (1994), the concepts of land cover and land use are distinct but they are closely related in terms of their characteristics on the earth's surface. Land cover is easily observed directly, however, land use is different in that a single land cover type can be used in many ways. For instance, forest can be used for many purposes such as logging, hunting, firewood collection and recreation, to mention a few.

Changes in land cover result from land use; and changes in land cover affect land use. However, land cover may change if land use remains unaltered. Several environmental impacts such as biodiversity loss, soil erosion and degradation, water flow, water quality and climate change are considered to result from alteration in the physical state of the earth's surface. In return, these environmental changes have an impact on the land cover.

2.2 Gold mining in Ghana

Gold prices have been very attractive during the last decade, which caused a number of people to invest in the sector (Hammond et al., 2007). As the second largest gold producer in Africa, international investors in gold mining in Ghana, has been a success both to the economy of Ghana and the international investors (Addy, 1998). There is the need for Ghana as a nation to be on the lookout in facing a resource dilemma due to the total dependence on mineral resource export as a means of growing the nation's economy (Adler and Berke, 2006; Aryee, 2001).

The two ways of mining gold in Ghana are by; small scale miners (sometimes called 'galamsey'), mostly gold mined are sold in regional markets, whilst large scale surface mining and underground mining operators work with structured production chains and have direct links to international markets. The difference between the two ways in which gold is mined can be seen in their social and environmental implications (Hilson, 2002).

2.2.1 Surface Mining

Surface Mining, is a method of extracting mineral resources from the ground by their digging into pits or borrows. Its operation requires a large area of land (Wikipedia, 2008). This has resulted in conflict of interest between land to be used for mining and land for other uses, such as farming and housing. Surface mining causes several effects to the community and environment such as, loss of vegetation and soil cover, and interrupts ecosystem service flows. Also, poisonous waste substances that causes pollution in water and some health problems, may be attributed to surface mining in areas where surface mining is practised (Akabzaa and

Darimani, 2001; Habashi, 1996). Similarly, pollution from dust is caused as a result of vehicular traffic on dusty mining roads affecting neighbouring communities (Ayine, 2001).

Another common environmental effect caused is soil erosion around mines (Akabzaa and Darimani, 2001). In generally, sin the developing world, surface mining often wear away livelihood foundations, causing people to relocate and also farmers to develop alternative income strategies (Kumah, 2006). There has consequently been conflicts between people in mining communities and mining companies over the right to land use worldwide (Hilson, 2002) and this poses a risk to development and security of people in such communities (Maconachie and Binns, 2007).

2.3.2 Surface Mining in Prestea and its resulting impact on the Land Use and Land Cover of the area

Gold mining in Bogoso-Prestea area has been taken place for over a century. Following the technological development in mineral processing and the authorisation of the Ghana Mining and Mineral law 1986 (Anon, 1986 and Sraku Lartey, 1993), surface mining became popular in Ghana during the mid-eighties. Land use changes become noticeable with the development of surface mining (Edward et al., 2009). Most areas that has been for Gold surface mining concessions dominated by settlements and farmland, which has led to the rise in conflict among the locals in the community and the mining companies (Aidara, 2008; National Coalition on Mining, 2006). To better understand the effects of gold mining on local lifestyle and land use systems, Bogoso Prestea, Tarkwa, and Damang offer unique understanding, due to the region's extended (30 years) history in mining gold. Surface mining led to farmland loss, which is evident in the loss of about 5,000 ha of farmland (representing about 5% of the district's total farmland), affecting about 6.8% of the total agricultural labour force (Wassa West District Assembly, 2004). Prestea, a highly galamsey-prone area has always suffered serious flooding anytime it rained. This is as a result of the galamsey operations which has impeded the free flow of water through the drains. Bolaekyire, a suburb of Prestea, is one place that comes under severe attack from the floods.

2.4 Land Use/ Land Cover Change – The Role of Remote Sensing and Geographic Information Systems (GIS) Applications

In assessing the magnitude and environmental impacts of mining activities on landscapes, remote sensing serves as an adequate tool for that purpose. Correspondingly, deforestation and flooding can be measured by multi-date land cover change mapping (Akiwumi and Butler, 2008). Remote sensing has become one key technological means for checking land use changes (Turner et al., 2007). One study conducted in the Western region of Ghana, used remote sensing to indicate the rate of deforestation and urban expansion (Kusimi, 2008). In the study, rapidly changing land use types in the Wassa West District were identified to be farmland and built up/surface mines.

The rates and spatial patterns of land change can be mapped using remote sensing (Turneret al., 2007). In order to increase understanding in land use systems, carefully collected data gathered from participatory mapping and household surveys are useful. (Liu et al., 2003; Müller et al., 2009; Reenberg, 2001). There is no easy means of relating land cover information with socio-economic data, because socio-economic data does not possess spatial layers (Liverman et al., 1998; Veldkamp and Lambin, 2001). To overcome the problem of spatial layers, for instance, linking people and land by means of participatory approaches or comparing measures of land change and socioeconomic data (Castella and Verburg, 2007; Lambin, 2003).

2.5 Image Classification Techniques

The land cover themes is extracted by classification, which plays a major role in this type of study. Lillesand and Kiefer (2008) described Image Classification as a means of sorting image pixels into their various land cover classes depending on the spectral response pattern within the data (Adu-Poku, 2010). The two main types of classification method are, supervised and unsupervised approach. These techniques can be combined to form what is termed as Hybrid classification which is performed to improve the accuracy or efficiency of the classification (Lillesand and Kiefer, 2008, pp. 484). Any of the two methods, either supervised or unsupervised approach may be used to perform either hard or soft classification. Hard classification allocates one class to each pixel which may not give the correct results for classification, especially for coarse spatial resolution images. On the other hand, soft classification is able to detect class proportion within a pixel and the results is a more accurate classification.

Classification systems are useful in representing land cover using remotely sensed imagery. The classes of interest are mostly perceived and so supervised image classification techniques are used by most researchers (Campbell, 1996). The supervised classification technique allocates each pixel to the land cover class which is similar to the training set created. For example, the maximum likelihood classification, which is commonly used assigns each pixel to the class which has the highest probability of membership. This type of classification assumes the membership of a class, which is a typical description of a ‘hard’ classifier. It is therefore suitable to use hard classification when the area represented has similar coverage. Hard classification might not be suitable for remotely sensed images (Campbell, 1996).

Pixels can have multiple or partial membership, this provides a means of solving the problem of mixed pixel in remotely sensed image (Smith et al., 1990; Wang, 1990).

Soft classifiers defer the decision about the class membership of a pixel in favour of an expression of the degree of membership it exhibits in each of the land-cover classes under consideration. The reasons for using a ‘soft’ classifier include the examination of classification uncertainty, but are most commonly directed to the potential of uncovering the proportional constituents of mixed pixels-a process called sub-pixel classification.

2.5.1 Sub-Pixel Image Classification

The basis for sub-pixel classification resides with the fact that a solid-state detector integrates the intercepted radiance within its instantaneous field of view (IFOV). Regardless of the effective resolution of a detector, it is inevitable that the IFOV will frequently intercept reflected energy from more than one land-cover class. Such cases will be uncertain, with the expectation that the pixel will exhibit spectral characteristics that are inter- mediate between those characteristics of each of the end-member (true constituent) classes. Thus, for example, a pixel equally occupied by conifers and open water should exhibit reflection characteristics that combine the characteristics of the two underlying classes in equal proportion. Given the integrating nature of the detector itself, one would expect the pixel to exhibit spectral characteristics that represent an area-weighted average of these constituent parts (Eastman and Lane, 2002).

The mixed pixel problem, which is a limitation of coarse resolution imagery is reduced /solved by subpixel classification techniques. The sub-pixel classification is most often appreciated by means of the linear mixture model or neural networks. Both the linear mixture model oror the neural networks can be useful either in high resolution or low resolution images (Kavzoglu and Mather, 2003; Lobell and Asner, 2004; Eerens and Dong, 2005).

Generally, algorithms used for classification are statistical in nature and each pixel is represented by a unique value. A pixel containing more than one class is referred to as a mixed pixel. As the remote sensing images become courser, the problems of mixed pixel increases, leading to erroneous classification. Information in a mixed pixel can be analysed by assessing the proportion of classes represented within each pixel.

The sub pixel classification algorithms can be characterised as statistical, fuzzy set theory and some neural network based. The Linear Mixture Model (LMM), can be implemented using data with equal dimensionality plus one.

Mostly, one or two soft classifiers are implemented in some of the commercial software. The Fuzzy C- Means is available in PCI Geomatica Software, Linear Mixture Model is available in ERDAS Imagine Software. The software gaining popularity in remote sensing analyst are not based on the SVM (Kumar et al., 2007). In this study, the IMAGINE Subpixel classifier in later software mentioned above is used.

IMAGINE Subpixel Classifier is designed to identify materials that are smaller than an image pixel, using multispectral imagery. It can also be used in detecting materials that are covered by a larger area but is mixed up with other materials that affect accuracy of the classification (IMAGINE Subpixel Classifier User's Guide, 2008). There are four required processing functions and three optional processing function used in the sub pixel classifier. The four required functions in this study were: Pre-processing, Environmental Correction, Signature Derivation, MOI Classification.

2.5.2 Pre-processing

In the pre-processing, a list of backgrounds are identified which are used in the MOI classification. It is necessary to remove all other materials leaving only the candidate MOI spectrum (IMAGINE Subpixel Classifier User's Guide 2008).

2.5.3 Environmental Correction

The automatic environmental correction is necessary to prepare the image for the signature derivation process. The correction factors obtained are necessary when performing scene to scene transfer. The final output for this process is a file containing environmental correction factors. (IMAGINE Subpixel Classifier User's Guide 2008).

2.5.4 Signature Derivation

This signature derivation function develops a signature which is used to classify an image. In developing a signature, training set can be defined by the AOI tool in the erdas imagine software from pixels in your source image. A signature can be derived from a training set in two ways: Manual and Automatic Signature Derivation. Manual Signature Derivation can be useful to develop a whole pixel signature from a whole pixel training set. It is a good practise to use Automatic Signature Derivation to derive a signature from a subpixel training set. A high quality signature is often derived testing and refining the signature. The automatic signature derivation simplifies the generating the material pixel fraction (IMAGINE Subpixel Classifier User's Guide 2008).

2.5.5 MOI Classification

The results for the classification are displayed using an ERDAS IMAGINE Viewer. The classification is performed by the MOI classifier module in the sub pixel classifier in the ERDAS IMAGINE software. A default tolerance value is one and the result is eight MOI classes between 0.20 to 1.0 with increments of 0.1 (IMAGINE Subpixel Classifier User's Guide 2008).

2.5.3 Linear Mixture Model

The Linear Mixture Model (LMM) approach considers the spectrum measured by a sensor as a linear combination of the spectra of all elements within the pixel (Roberts et al., 1998; Ustin et al., 1998). The mathematic model of LMM is be expressed as

$$R_i = \sum_{k=1}^{n} f_k \, R_{ik} + \varepsilon_i \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. \quad (1)$$

where:

i= 1, m (number of spectral bands); k=1, n (number of endmembers);

R_i is the spectral reflectance of band i of a pixel, which contains one or more endmembers; f_k is the proportion of endmember k within the pixel;

R_{ik} is known as the spectral reflectance of endmember k within the pixel on band i, and ε_i is the error for band i.

The RMS error was used to assess the fit of the model. The RMS was computed using

$$RMS = \sqrt{\left(\sum_{i=1}^{m} \varepsilon_i^2\right) / m}$$

Root Mean Square (RMS) error is computed for the individual image pixels. A greater RMS error, affects the fit of the model (Mather, 1999).

Different methods can be used to determine endmembers. Endmembers can be obtained from; a spectral library, as used in ERDAS IMAGINE and ENVI software packages and laboratory or field reflectance measurements (Quarmby et al., 1992; Settle and Drake, 1993). Image endmembers are easy to obtain and are therefore used for many applications of LMM (Roberts et al., 1998).

Endmembers varies in their number and types with precise applications (Ustin, Smith, and Adams, 1993). Generally, the number of endmembers can be determined by making account for most of the variation in data.

2.6 Accuracy Assessment

An error matrix is an array of numbers ordered in rows and columns which expresses the number of sample units (i.e. pixels and clusters of pixels) which will be assigned to a particular category relative to the actual category as shown by reference data (Congalton, 1996). The general acceptance of the error matrix as the standard descriptive reporting tool for accuracy assessment of remotely sensed data has significantly improved the use of such data.

Accuracy is obtained by averaging all accuracies for each class. The overall accuracy for a class is determined by the quantity of samples to be tested for that class (Yang, 2001). Kappa analysis is important because of the possibility to test for the quality of a LULC map compared to if the map had been generated by randomly assigning labels to areas (Congalton, 1996). The proportion of agreement achieved after removing the proportion of agreement that could be expected to occur by chance is represented by the kappa coefficient (Foody, 1992). This Kappa coefficient is represented on a scale between 0 (no reduction in error) and 1 (complete reduction of error). A coefficient of 1 shows complete agreement, and is mostly multiplied by 100 to give a percentage measure of the accuracy of the classification. A measure of agreement between model predictions and reliability can be determined by the kappa value, (Congalton, 1991) and also to determine if the values contained in an error matrix represent a result significantly better than random (Jensen, 1996). Kappa is computed as,

$$K = \frac{N\sum_{i=1}^{r} X_{ii} - \sum_{i=1}^{r}(x_{i+} \times x_{+i})}{N^2 - \sum_{i=1}^{r}(x_{i+} \times x_{+i})} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (1)$$

Where

N is the total number of sites in the matrix, r is the number of rows in the matrix, xii

is the number in row i and column i,

$x+i$ is the total for row i, and

$xi+$ is the total for column i (Jensen, 1996).

2.6 Normalized Difference Vegetation Index (NDVI)

Normalized Difference Vegetation Index (NDVI) is a numerical indicator which uses the visible and near-infrared bands of the electromagnetic spectrum. It is adopted in analysing remote sensing measurements and assess whether the target being observed contains live green vegetation or not. NDVI has been applied in many vegetative studies. It has been used in many areas of studies, such as; to estimate pasture performance, crop yields and rangeland carrying capacities and so on. Many time, it is directly related to other ground parameters such as percentage of ground cover, surface water, photosynthetic activity of the plant, leaf area index and the amount of biomass.

NDVI was first used by Rouse et al. in 1973 from the Remote Sensing Centre of Texas A&M University. Since the behaviour of plants across the electromagnetic spectrum is known, NDVI information can be derived by focusing on most sensitive satellite bands in response to vegetation information (near-infrared and red). Generally, healthy vegetation absorb most of the visible light that falls on it, and reflects a large portion of the near-infrared light. Unhealthy or scattered vegetation reflects more visible light and less near-infrared light. On the other hand, bare soils reflect reasonably in both the red and infrared portion of the electromagnetic spectrum (Holme et al 1987). The greater the difference between the near-infrared and the red reflectance, the more vegetation there has to be. The NDVI algorithm subtracts the red reflectance values from the near-infrared and divides it by the sum of near-infrared and red bands.

$$\boldsymbol{NDVI} = \frac{(\boldsymbol{NIR} - \boldsymbol{R})}{(\boldsymbol{NIR} + \boldsymbol{R})} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots..(\boldsymbol{2})$$

Where; NIR = the spectral reflectance measurements acquired in the near-infrared region(band) R = the spectral reflectance measurements acquired in the red region (band). In using the Landsat Thematic Mapper remote sensing data, the formula is

$$\boldsymbol{NDVI = \frac{(TM4 - TM3)}{(TM4 + TM3)} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(3)}$$

Where;

TM4 = near infrared band TM3 = red band

The NDVI produces a single-band dataset, mostly representing greenness, where any negative values are mainly generated from clouds, water, and snow, and values near zero are mainly generated from rock and bare soil. The outputs values between -1.0 and 1.0. Very low values of NDVI (0.1 and below) correspond to barren areas of rock, sand, or snow. Moderate values represent shrub and grassland (0.2 to 0.3), while high values indicate temperate and tropical rainforests (0.6 to 0.8) (http://earthobservatory.nasa.gov/Features/MeasuringVegetation).

2.7 Review of Previous Related Research Works

Many researchers have conducted studies to detect land use/land cover changes across sector such as forest cover, landscape, urban development, just to mention a few using multispectral remotely sensed data. Research has been conducted throughout the world in an attempt to understand major shifts in land use and land cover and to relate them to changing environmental conditions. According to Baulies and Szejwach (1998), during the next decades, land-use dynamics will play a major role in driving the changes of the global environment. Generally, agriculture is found to be the major driver of land cover change in tropical regions (Lambin et al., 2001; Daniels et al., 2008).

An analysis of land use and land cover changes using the combination of MSS Landsat and land use map of Indonesia (Dimyati, 1995) reveals that land use land cover change were evaluated by using remote sensing to calculate the index of changes which was done by the superimposition of land use land cover images of 1972, 1984 and land use maps of 1990. This was done to analyze the pattern of change in the area.

Kahsay, (2004) in his study to understand the dynamics of Land Use and Land Cover in and around Yerer Mountain and analyse implications of Land Use and Land Cover changes in terms of soil erosion and nutrition of both human and livestock. Landsat ETM + imagery and other remotely sensed data were used. In addition to the biophysical data, Kahsay also used socio-economic characteristics of households to interpret the biophysical feature occurring in the study area.

Matsa, and Muringaniza, (2011) used Geographic Information System and remote sensing techniques to establish the current status of land use and land cover changes for Shurugwi district as well as to determine the extent of these changes. Three satellite images for three different years (1991, 2000 and 2009) were used to come up with a land use/land cover map classification for Shurugwi district. Degraded land is mainly a result of agriculture and mining activities.

Rasim, (2004), in Assessing land cover change resulting from large surface mining development, a remote sensing based approach for quantifying primary and secondary impacts of surface mining is used. Affected areas were identified as the difference between land cover maps derived from LANDSAT data (30 m resolution) acquired in 1992 and 2001. Maps produced from remote sensing data provide information for subsequent impact assessments from surface mining development on land cover.

Wang and Paul (2009), used multitemporal subpixel analysis to identify cypress canopies from Landsat 7 ETM+ imagery during their study on the Detection of Cypress Canopies in the Florida Panhandle Using Subpixel Analysis and GIS. Their results indicated that multitemporal subpixel analysis greatly improved the classification accuracy and signatures developed from one scene could be used to the subpixel classification of another scene with caution. In conclusion, this project demonstrated the potential of subpixel analysis in specific materials such as detecting cypress trees.

Hussin et al. (2003), Classified Landsat image using maximum likelihood and sub-pixel classification in their research on identifying illegal logging and mapping tropical rain forest cover types in East Kalimantan, Indonesia. It was noted that more accurate detection of single tree felling can be achieved using the sub-pixel classifier and Landsat-7 ETM+ image. The sub-pixel classification had a higher than the maximum likelihood classification of the 30 m resolution image with an overall accuracy and kappa of 89% and 0.75 versus 79 % and 0.57 respectively.

Adu-Poku, (2010), in land-cover change monitoring in Obuasi, sought to identify and quantify the land cover changes that have taken place in the area and to project the likely land cover map in the future. An integration of Remote Sensing, Geographical Information System (GIS) and Stochastic Modelling was used to assess and map this land cover changes. PostClassification Change Detection was employed using three multi-spectral Landsat images of the years 1986, 2002 and 2008 to detect changes that have taken place within the past twentytwo year period. Subsequently, Markov Chain Analysis was used to predict the land cover distributions that are likely to occur by 2020.

Kumi-Boateng et al.(2010), used spatial information from remotely sensed data as a means of providing an effective solution to land use/ land cover change detection in Tarkwa municipality. Remote sensing technique was used for this change detection and to assess its implications for the management of future urban development.

There have also been researches that have been done in mining communities all around including Ghanaian communities such as, Obuasi, Prestea, Tarkwa etc. to identify and detect land cover changes caused by mining activities and other human activities on land.

Schueler et al. (2011), conducted a study to assess land cover change due to gold surface mining in Western Ghana. Satellite images were used to carry out a multi-temporal classification, in order to map mining related land cover changes. According to them, this approach resulted in a more vigorous and precise change maps than post-classification map evaluation. This study concluded that, land use systems in the Wassa West District of Ghana has been affected as a result of gold surface mining. It was shown from the analyses of landsat images that farmland loss and deforestation were the most evident mining related land cover changes.

In a similar study on Open Pit Mining and Land Use Changes: An Example From BogosuPrestea Area, Duncan et al. (2009), land use flows methods were used over a twenty year period (1986 – 2006) to estimate areas within the study area that have experienced land use change as a result of mining.

A look at these studies, it can be seen that most of the authors used traditional classification approaches to detect changes. Some few papers have been reviewed in this research where other authors used subpixel classification for different analysis.

CHAPTER THREE: STUDY AREA AND MATERIALS USED

This chapter describes the study area and data used for the study. A description of the study area is given to demonstrate the characteristics of the area in terms of geography, land cover and general narrative. It also illustrates the technical details of the various data used for the study.

3.1 Study Area

The Prestea-Huni-Valley District Assembly, with Bogoso as its capital, is one of the twentytwo (22) administrative authorities in the Western Region. The District was carved out of the erstwhile Wassa West District Assembly in 2008 as a result of the creation of more Districts and rising of some Districts to Municipal status. It was established under the Legislative Instrument 1844.

3.1.1 Location and Size

The District is located at about 33 Kilometres east of Tarkwa, in the Prestea-Huni-Valley District. It is a mining District which lies within the South Western Equatorial zone and covers an area of about 1376 sq/km. Bogoso/Prestea is located between Latitude 5°0'N and 5°40'N and Longitudes 1° 45'W and 2° 10'W. It shares boundaries on the North West with Wassa-Amenfi East District, on the West with Axim Municipal Assembly, on the south with Tarkwa-Nsuaem Municipal Assembly and the North by Wassa-Amenfi West District. It lies on the west bank of the Ankobra River (Oduro, 2011).

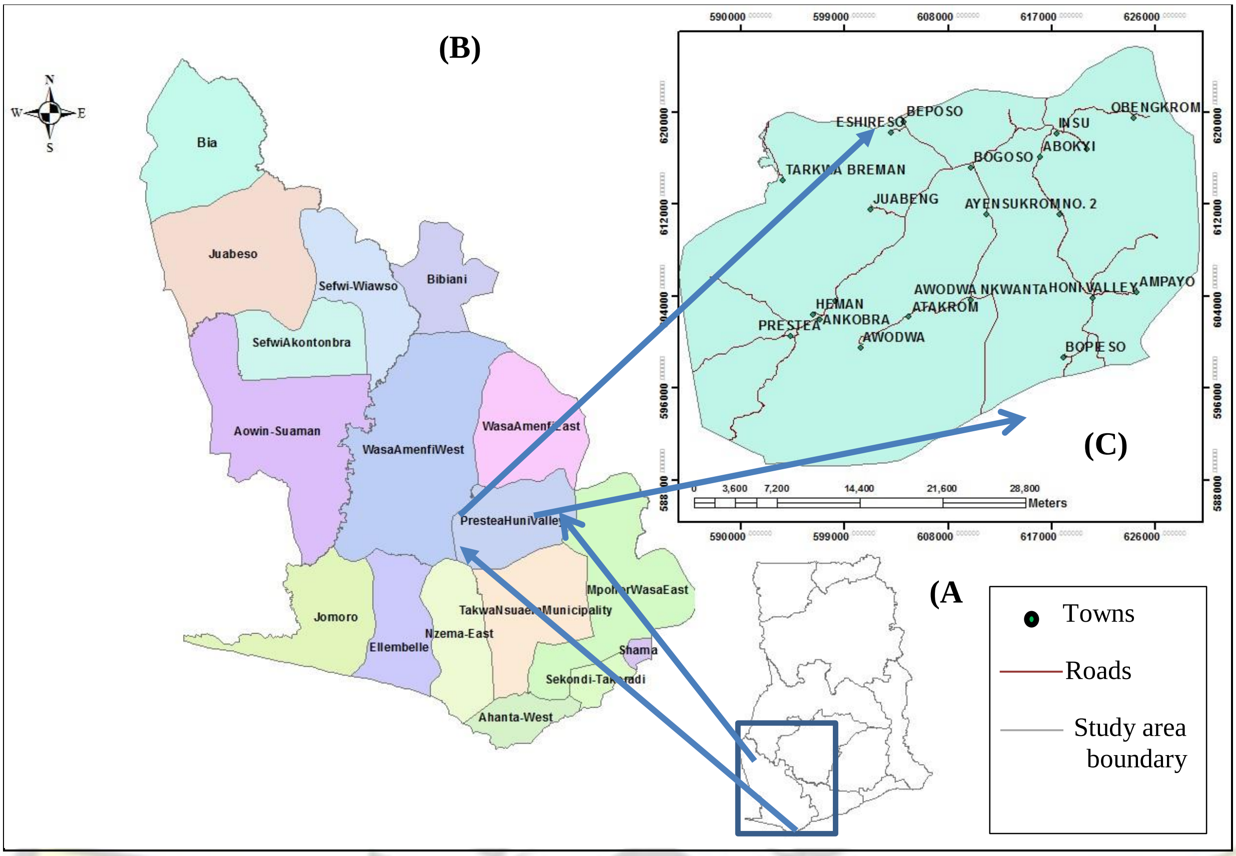


Figure 3.1: Map of study area- Map A: Ghana, Map B: Western Region and Map C: Prestea and environs

3.1.2 Population

Giving the 2010 Population and Housing Census, the total population of the Prestea Huni-Valley District was 159,304. The District's population comprise of 80,493 (50.5%) and 78,811(49.5%) of male and females respectively. The District is predominantly rural and has its rural population of 62.9% exceeding the regional average of 57.6%.

3.1.3 Climate and Vegetation

The District is located in the rain forest zone of Ghana and enjoys a wet equatorial climate. It has two rainfall patterns usually from March to July (major season) and from September to

November (minor season). The District experiences high rainfall with a mean annual rainfall of 187.83mm. The annual average temperatures range between 26°C and 30°C .

The vegetation of the District is tropical rainforest, with the height of trees ranging between 15-40 metres high. The forest is full of climbers and lianas, which are able to reach into the upper tree layer. Economic trees include mahogany, Wawa, odum, and sapele among others. Food crops like cassava, rice, maize and plantain are also grown. The District's major forest reserve is the Bonsa Reserve (Aboso) with 160.58 square kilometres. There are other two reserves; Ben West (Huni-Valley) with 26.00 square kilometres and Nkontoben (Hun-Valley) with 49.98 square kilometres.

Activities of illegal mining and other illegal logging are posing a threat to the natural vegetation. Cocoa, oil palm, coffee, rubber, coconut and citrus are some of the major cash crops grown (GSBPL EMP, 2008).

3.1.4 Geology and Soil

The District forms part of the Birimian and Tarkwain geological formations. The birimian rocks is an important rock due to its mineral potential. The area is covered by deep soils, acidic in many places. They are mainly forest oxysoils developed over a wide range of highly weathered parent materials including Tarkwaian and Birimian rocks. The acidic nature reduces amount of soil phosphorus, calcium and magnesium (GSBPL EMP, 2008).

3.2 Dataset used in the study

The study is based on several data types listed in the Table 3.1. These data types have been grouped into remote sensing (RS) and reference data. Time series satellite images were used in this study. Landsat images – Thematic Mapper™ and Enhanced Thematic Mapper Plus

(ETM+) as remote sensing data acquired in the years 1990 and 2000, and an Advanced Land Observing Satellite (ALOS) acquired in 2010. These satellite data were downloaded from the U.S. Geological Survey (USGS) database based on the availability and suitability due to cloud cover (which is problematic when it comes to detecting changes). One or more images between the years 1990 and 2000 would have aided a better understanding of the trends of land cover change. However, all the available 1990s images have cloud cover of more than the acceptable 10%.

Table 3.1: Table showing the data required for the study

Data Used	Acquisition Date	Resolution	Sources
Landsat TM	January, 1990	30m	USGS EROS Centre
Landsat ETM	April, 2000	30m	Forestry Department, Ghana
ALOS	January, 2010	10m	Forestry Department, Ghana
Orthophoto	2010	50cm	Town and Country Planning, Bogoso
Land Cover Map	2000, 2010		Forestry Department, Ghana
Google earth images	2011		

3.2.1 Landsat Imagery

Landsat imagery has been in existence since 1972, from six satellites in the Landsat series. These satellites have been a major component of NASA's Earth observation program, with three primary sensors evolving over thirty years: MSS (Multi-spectral Scanner), TM (Thematic Mapper), and ETM+ (Enhanced Thematic Mapper Plus). The goal of distributing appropriate range of imagery for land cover analysis is achieved through the GLCF.

The Landsat data covering the study area were downloaded from the USGS database with 194/56 as the path/row scene.

3.2.2 Advanced Land Observing Satellite (ALOS) Image

The Advanced Land Observing Satellite (ALOS) is developed by the Japan Aerospace Exploration Agency (JAXA). It was first launched in 2006. The satellite is made of three sensors i.e., two optical imagers (PRISM and AVNIR-2) and an L-band Synthetic Aperture (PALSAR). ALOS was developed cartographic purpose and other observations and monitoring. By its design, it has a short revisit capacities. ALOS has been designed to be able to capture images of the disaster area with AVNIR-2 or PALSAR within a few days (JAXA, 2007).

3.2.3 Reference Data

High resolution ortho photographs acquired in 2010 were obtained from the Department of Town and Country Planning, Bogoso in the Western region of Ghana at 50cm resolution. This was used to obtain ground truth to ascertain the accuracy of the image classification. In addition, a land cover map obtained from the Forestry Department of Ghana was used to aid in image classification. The 2011 Google earth image of the study area and personal knowledge about the study area helped in classifying the data.

3.3 Software Used

In this project the software used was based on the image processing procedures and the prediction of future land cover change. This project employed Erdas Imagine 2010 to perform image processing which includes pre-processing, image classification, accuracy assessment, and production of a change map. IDRISI Selva was used to handle the modelling and prediction aspect of this study. Arcgis 10.1 was used to generate the output maps.

CHAPTER FOUR - METHODOLOGY

4.0 Methods

The main tool for the analysis of this study is to use image classification schemes to obtain an idea of the impact of surface mining on the land use land cover dynamics of the study area. In this study, post classification comparison upon subpixel classification, is used as a quantitative technique of analysis.

In view of the above, this section divides the methodology into four steps which include Image Pre-processing, Image Classification, Change Detection Method and Modelling and Prediction of land cover change. The methodology adopted in this study is summarised in the flow chart (Figure 4.1).

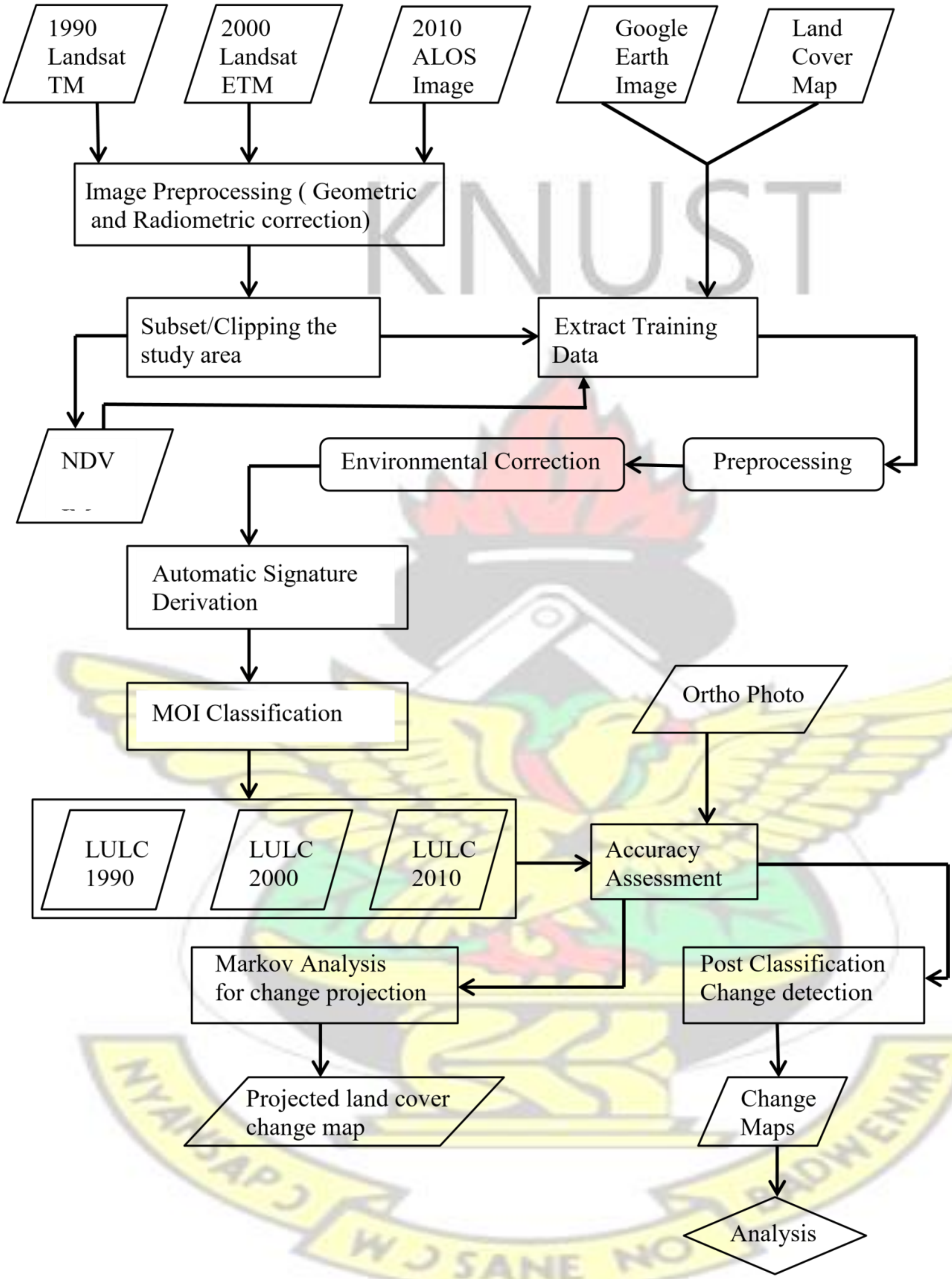


Figure 4.1: Flow chart showing the methodology of this study

4.1 Image Preprocessing

Preprocessing of satellite images is an essential step prior to image classification and change detection. In this study, preprocessing operations carried out include: atmospheric correction, geometric corrections, radiometric corrections, stacking of image bands.

The landsat images obtained for the study area were recorded in bands ranging from 1 to 8. A single band do not have colour (ie Panchromatic) that will help in analysing the data, visually. Individual bands were therefore combined to form multispectral images which can therefore be viewed in different colour combination (RGB combination). Upon careful examinations, band combination 5, 3, 2 was used as it revealed clearly all the land cover classes distinguishable on the images.

In order to subset the study area from each of the individual images, a vector polygon shape file as area of interest (AOI) was used for subsetting the study area.

4.2 Subpixel Image Classification

IMAGINE Subpixel Classifier was used in classifying individual images into their respective classes. The three multi spectral images; 1990 Landsat TM, 2000 Landsat ETM and 2010 ALOS images were subjected to subpixel classification using Imagine Sub-Pixel module in Erdas Imagine 2010. Environmental correction was applied for the image using the Environmental correction tool in Imagine Sub-Pixel package. Sub-pixel classification reports the fraction of Material of Interest(MOI) present at pixel level, as percentage of impervious surface present. Signatures were developed for the class impervious surface as containing different percentage of material of interest from 20 to 80 percentages as different Area of Interest (AOI) file. The output continuous map consisted of eight classes as having impervious surfaces from less than 20 percentages to greater than 80 percentages with 80 percentage confidence.

In line with the objectives of the study, to identify land cover types and their spatial distribution using the subpixel classifier, seven classes were identified. Due to inefficiency in the use of the signature combiner, each image representing a land cover type produced seven MOI classified images. With each image, the sixth, seventh and eighth classes with MOI fraction 0.7-0.8, 0.8-0.9 and 0.9-1.0 were identified as true representation of the particular land cover type.

The resultant image for each land cover type was combined using the overlay function, to produce a final image with seven land cover classes for each years' image of the study area. For visualization purpose sub-pixel classification image was overlaid with the supervised MLC classified map. LULC classes were based on the Anderson classification scheme (Anderson et al., 1976) and the descriptions shown in Table 4.1.

Table 4.1: Description of the Land use/Landover classification scheme

LAND USE/COVER	DESCRIPTION
Built-up	Comprised of areas of intensive use with much of the land covered by structures. Included in this category are, residential, industrial, transportation, utilities.
Farmland	Land used primarily for production of food and fibre, Cropland, pasture and other commercial and horticultural crops.
Mine site	Areas where both small scale and large scale mining activities are taken place. Extractive mining activities that have significant surface expression.
Sparse Forest	These are sparsely scattered of trees of all ages, plants, and underbrush covering the large area within the study area.
High Density Forest	Areas where a tree-crown areal density (crown closure percentage) of 10 percent or more, are stocked with trees capable of producing timber or other wood products
Barren land	This comprises of bare rock surface and land area of exposed soil surface resulting from human activities or natural causes
Water	This includes the main river in the study area and other ponds created as a result of abandoned mine pits.

4.2.2 Accuracy Assessment

It is important to test the result, before using the outcome of the classification from satellite images for change detection. Accurate classifications are imperative to ensure precise changedetection results (Foody, 2002).

This process evaluates the accuracy of a derived thematic map. In this study all the checkpoints data were extracted from the 2010 ortho-photographs and GPS points of the area to perform Accuracy Assessment using the Classifier toolbar of Erdas Imagine. In all, sixty five random reference points were extracted from the orthophotographs, and were used to assess the accuracy of the classified images of 2000 and 2010. The error matrix compares the relationship between known reference data (ground truth) and the corresponding results of an automated classification (Lillesand and Kiefer, 2000).

4.3 Post-Classification Change Detection

Change detection have different meaning to different users (Singh, 1989; J. R. Jenson, 1996; Lu et al., 2004). Change detection in general is defined as a process to detect differences in the state of an object or phenomenon by observing it at different dates. The most common understanding of the Change Detection application is its ability to provide information on changes in terms of the location, extent, trend and spatial distribution of change. A PostClassification approach to Change Detection was employed in this project. As the main aim of this study was to map out, monitor and analyse the spatio-temporal LULC change and also to project areas under risk of invasion in future, Idrisi package was used to make these analysis of land cover changes. All the three classified images in Erdas format (.img) were exported to raster format (.rst) which is recognized by the Idrisi software. The following processes below were performed.

4.3.1 Land Cover Modeler (LCM)

LCM is a vertical application (a vertical application is directed towards a specific application) that sits within IDRISI. Land Cover Modeler (LCM) was used in analysing the land cover changes that have occurred between the various land cover classes in the periods 1990 – 2000, 2000 – 2010 and 1990 - 2010. Through the LCM, graphs of gains and losses, net change, contributors to the net change by each land cover category were generated from two thematic maps of the same dimensions. In addition to these results, it generated a change map to address the spatial distribution of change patterns within the given time interval (Eastman, 2006). Using the 1990 – 2000, 2000 – 2010 and 1990 – 2010 thematic maps as inputs in LCM modeler, all the above-mentioned outputs were generated. Subsequently, calculation of area in hectares (ha) was performed to ascertain the amount of land cover change.

4.3.2 Cross-tabulation

CROSSTAB module embedded in Idrisi performs a cross-tabulation analysis that compares images containing categorical variables of two types. Cross Tabulation provides the information on the frequencies with which each land cover classes remained either unchanged or has changed to one of the other classes, using two thematic maps of different dates. Three cross-tabulation Tables were generated from thematic maps 1990 – 2000, 2000 – 2010 and 1990 – 2010 using the CROSSTAB module. In the contingency matrix, elements in the diagonal represent the land cover classes that remain unchanged and those in the off-diagonal are the changed land cover classes. The column element *j* represents land cover class in the earlier date and the row element *i* represents land cover class in the later date.

4.4 Change Projection

The Change Prediction module in Idrisi provides the controls for a dynamic land cover change prediction process. This study adopted Markov Chain analysis and Cellular Automata (CA) as modelling techniques in predicting land cover change in the future. A Markov chain analysis (MARKOV) is used to estimate the transition matrix between the two past and documented dates (date 1 and date 2) and to estimate probabilities of change for the third date (date 3) to be predicted. A Cellular automata predicting model (CA_MARKOV) estimates the spatial distribution of land cover at a later date (date 3). (Eastman 2008).

Markov Chain analysis was implemented using the Markov module embedded in Idrisi. The use of the Markov module produced a transition matrix and a set of conditional probability images between two dates of thematic maps. The transition matrix and the suitable images generated from Markov module were later loaded in the CA_Markov module in the software and a contiguity filter of 5x5 was applied to generate the predicted map. This contiguity filter serves as a transition rule on which the prediction is based. For this study, the two land cover maps 1990 – 2000 were first used to generate a predicted land cover map of 2010. Afterward, the predicted land cover map was compared with actual land cover map of 2010 for validation. Once the validation was done, the 1990 – 2010 land cover maps were used to predict that of 2030.

CHAPTER FIVE – RESULTS AND DISCUSSIONS

5.1 Results

This chapter seeks to present the findings of the project and make analyses on these findings.

5.1.2 Classification and Accuracy Assessment Results

Three land cover maps were obtained through the analysis of the three multi-temporal images (1990, 2000 and 2010) of the study area, using Imagine subpixel classification approach in Erdas. For the purpose of visualisation, the imagine sub pixel classification was overlaid on the maximum likelihood classified image. Table 4.1 in chapter 4 depicts land use/cover of the study area in seven categories. The resultant land cover maps are shown in Figures 5.1, 5.2 and 5.3 respectively.

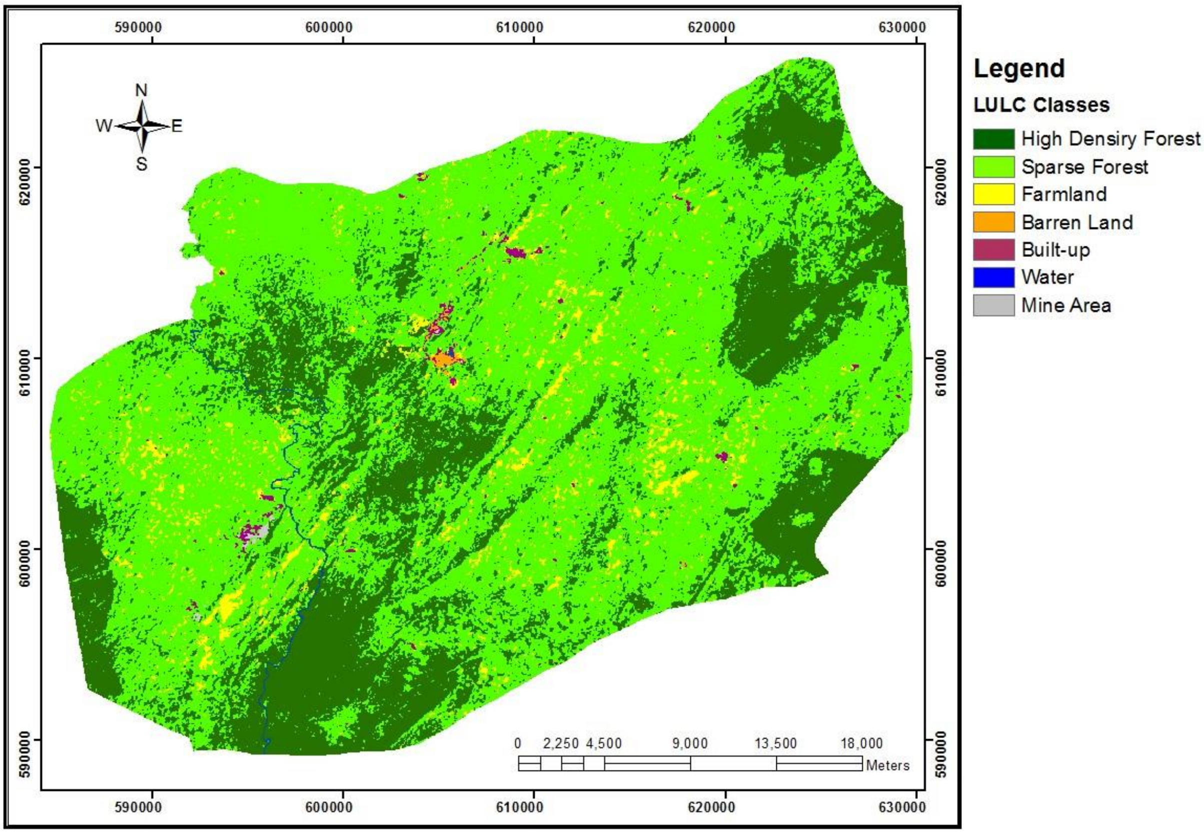


Figure 5.1: 1990 LULC map of study area

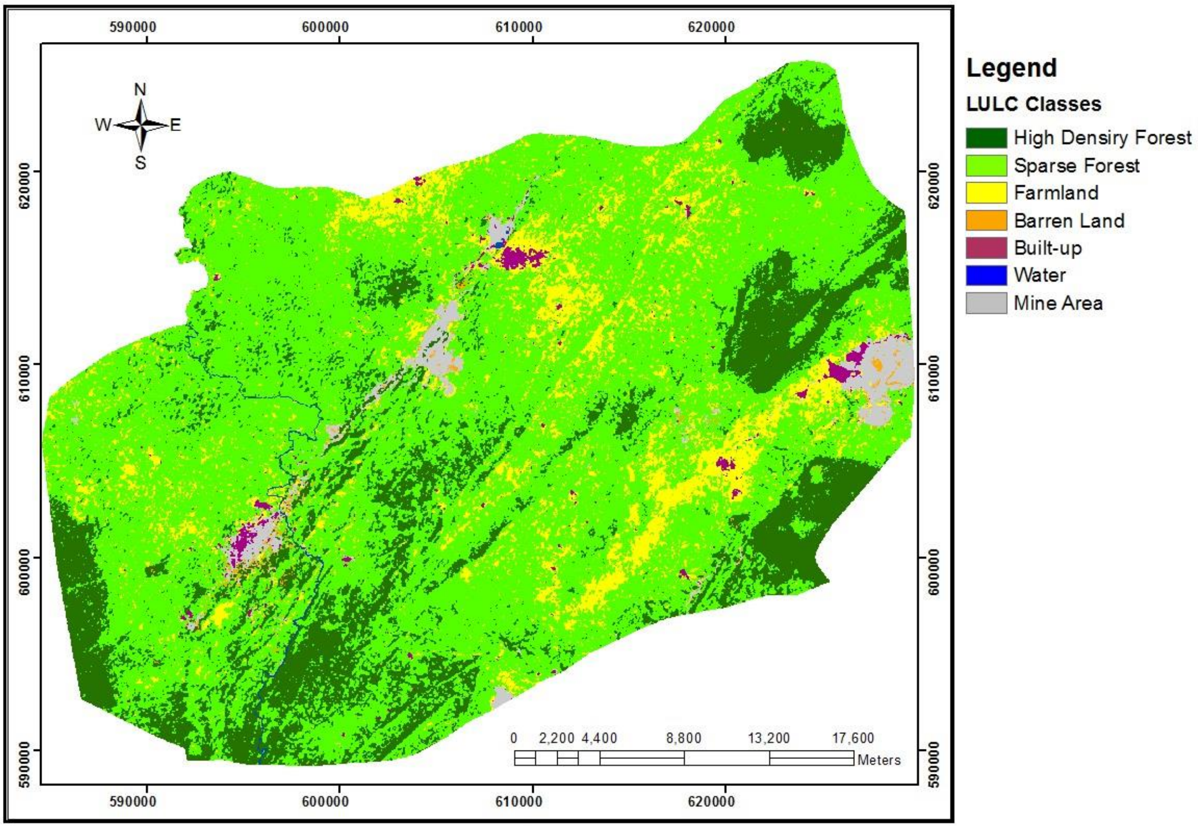


Figure 5.2: 2000 LULC map of study area

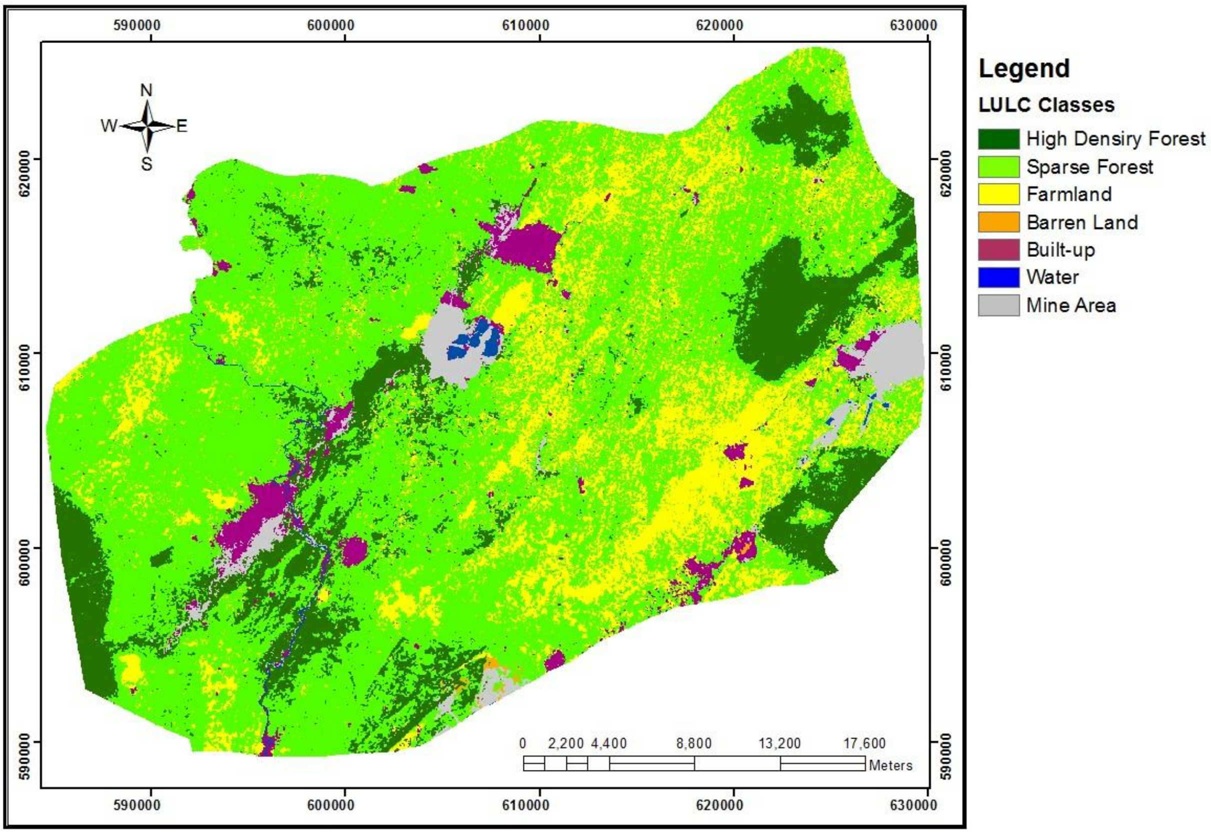


Figure 5.3: 2010 LULC map of study area

An account of the results of the land use/cover maps obtained from the sub pixel classification is discussed below. Critical examination of these three land use/ cover maps revealed the four main forest reserves covered by the forestry commission. Two of these forest reserves are found at the North-eastern side, one at the south- eastern side and another one at the south- western side of the study area. These constitute the highest portion of the high density forest. The rest of the high density forest are found around the southern part of the area with a few patches scattered around the north. The sparse forest is seen as the dominant land cover scattered all over the study area. Farmland is seen to have increased along the north- eastern and south- eastern part of the study area during the period under review. The other land cover classes: mine site, built-up, ponds and barren lands are seen to be interrelated. The pond which is a category under the land cover ‘water’, are always found to be part of the mine site.

The Table 5.1 shows the extent of the area of the individual land cover categories in hectares (ha) and the percentage they occupied and Figure 5.4 is the graph depicting the trends of land cover changes in the three years 1990, 2000 and 2010.

Table 5.1: Table of area covered by land use / cover categories

Land use / cover class	1990		2000		2010	
	Area(ha)	Area(%)	Area(ha)	Area(%)	Area(ha)	Area(%)
High Density Forest	33119.8	29.25	21390.1	18.89	16417.4	14.50
Sparse Forest	74438.8	65.74	75268.7	66.48	66728.4	58.93
Farmland	4656.78	4.11	12080.4	10.67	22297.3	19.69
Barren land	120.96	0.11	522.36	0.46	129.51	0.11
Built-up	521.73	0.46	909.45	0.80	3463.83	3.06
Water	276.66	0.24	255.69	0.23	516.69	0.46
Mine area	90.27	0.08	2798.73	2.47	3671.28	3.24
Total Area	113225	100	113225	100	113225	100

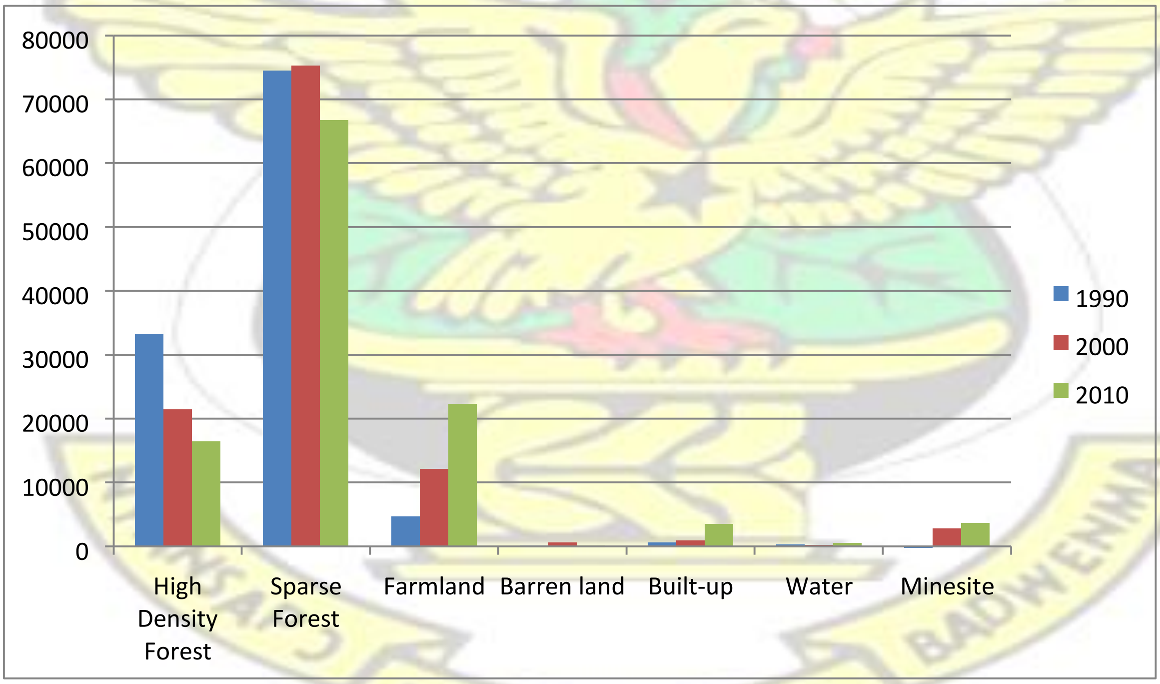


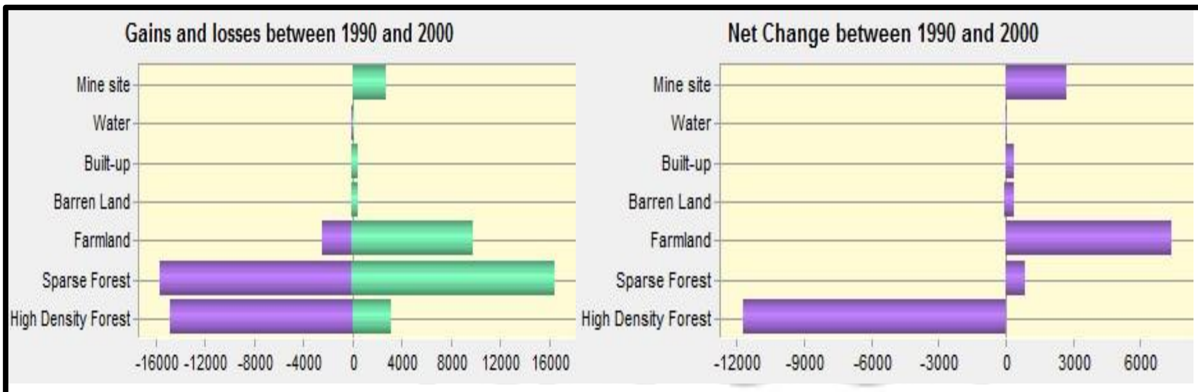
Figure 5.4: Graph showing the extent of area occupied by land cover categories in the years 1990, 2000, 2010.

5.1.3 LCM Modeler Results

The LCM model generated from 1990 – 2000 land cover map is shown in Figure 5.4. Graph A in Figure 5.5 revealed the degree of changes (Gains + and Losses -) in the study area resulting from the land cover conversions, with water experiencing very minimal change compared to other classes. It can be seen that all the land cover classes experienced some form of transition either gain or loss.

Graph B in the figure explained the net change under the period of review. It can be deduced that with the exception of High Density Forest which suffered a very high loss of 11740ha (7.08%) of land cover area and water also losing a very minimal of 21ha (0.01) within the period of review to other classes, all the other land classes experienced gains, with mine area having the second highest gain of 2708ha. Figure 5.5 is summarised in Table 5.2.

Since we would like to understand the correlation between the land cover classes and also to access the impact of mining activity on land cove changes, Figure 5.5 revealed how all the other classes have contributed to change in high density forest, farmland, built-up and mine area during the period under review. This also gives an idea as to how other classes are changing dues to changes in the mine site. The correlation between mine area and other classes can also be understood. It is evident that within the period under review, these classes, high density forest, farmland and built-up have all lost to mine area, losing 205ha, 102ha and 117ha, respectively. We can also see that mine site is gaining from all the other classes.



Graph A Graph B

Figure 5.5: LCM of 1990-2000 (Area units are in hectares).

Table 5.2: Table showing the net change of land cover transitions from 1990-2000

LAND COVER CLASS	GAIN (+)		LOSS(-)		NET CHANGE		ANNUAL RATE OF CHANGE
	Area(ha)	Area(%)	Area(ha)	Area(%)	Area(ha)	Area(%)	
High Density Forest	3141	1.89	14882	8.98	-11740	-7.08	-0.708
Sparse Forest	16568	9.99	15721	9.48	847	0.51	0.051
Farmland	9851	5.94	2434	1.47	7417	4.48	0.448
Barren land	508	0.31	107	0.06	401	0.24	0.024
Built-up	523	0.32	135	0.08	388	0.23	0.023
Water	48	0.03	69	0.04	-21	-0.01	-0.001
Mine area	2728	1.65	20	0.01	2708	1.63	0.163
Total change	33367	20.13	33367	20.12	0	0	

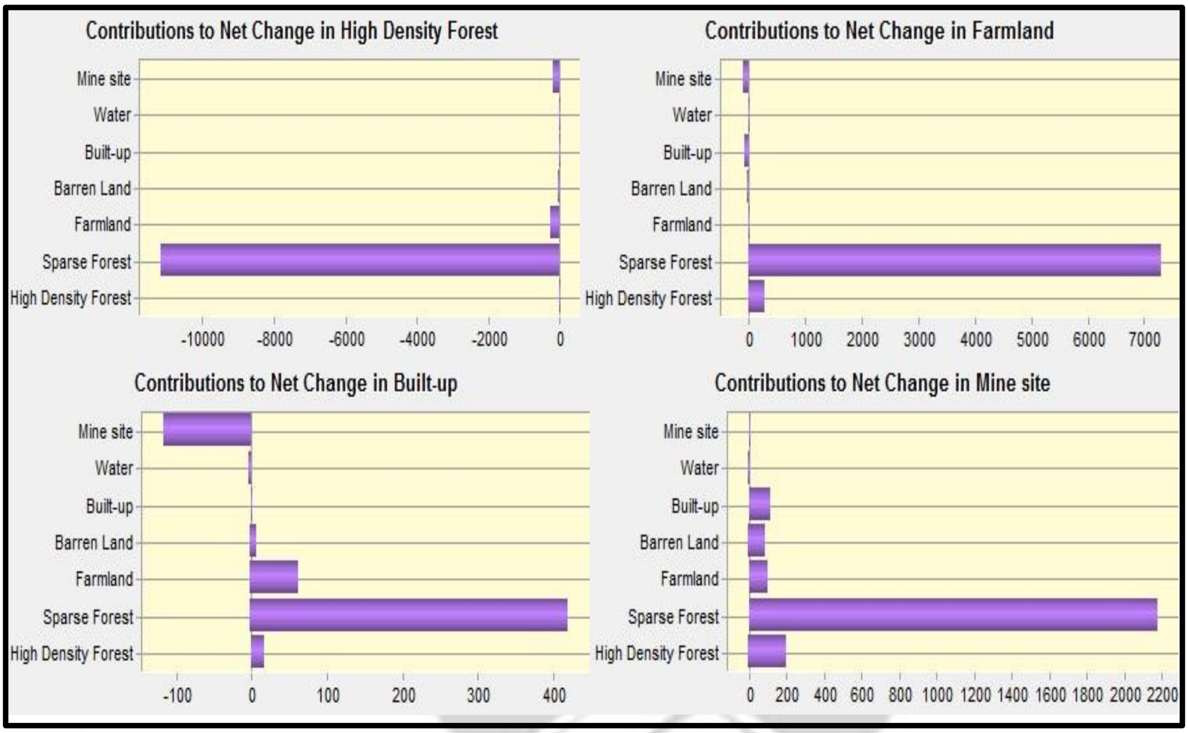


Figure 5.6: Contribution to net change of the selected land cover between 1990 and 2000. (Area units are in hectares)

The LCM model for 2000 – 2010 is shown in the Figure 5.7 indicating the overall changes in the various land cover classes during the eight year period. Within this period, it can be noticed that all the land cover classes experienced both types of changes in the study area, either gains or losses. Graph B in the Figure 5.7 revealed that mine site, water, built-up, and farmland did appreciate in the context of net change during the period under review. Table 5.3 is used to summarise the figure below. It can be inferred from the Table that land use / cover experienced equal amount of change during this period.

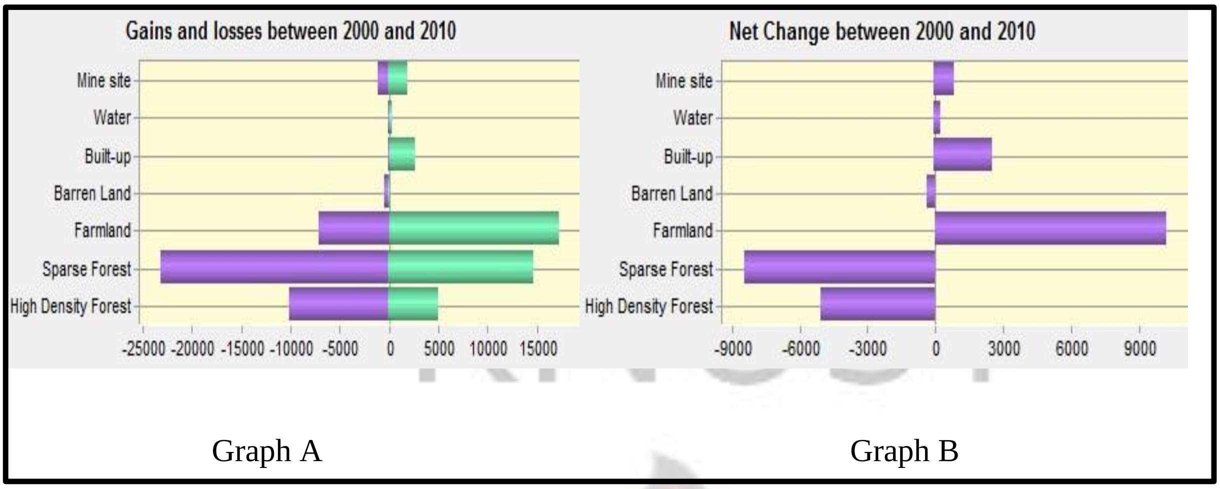


Figure 5.7: LCM of 2000-2010(Area units in hectares)

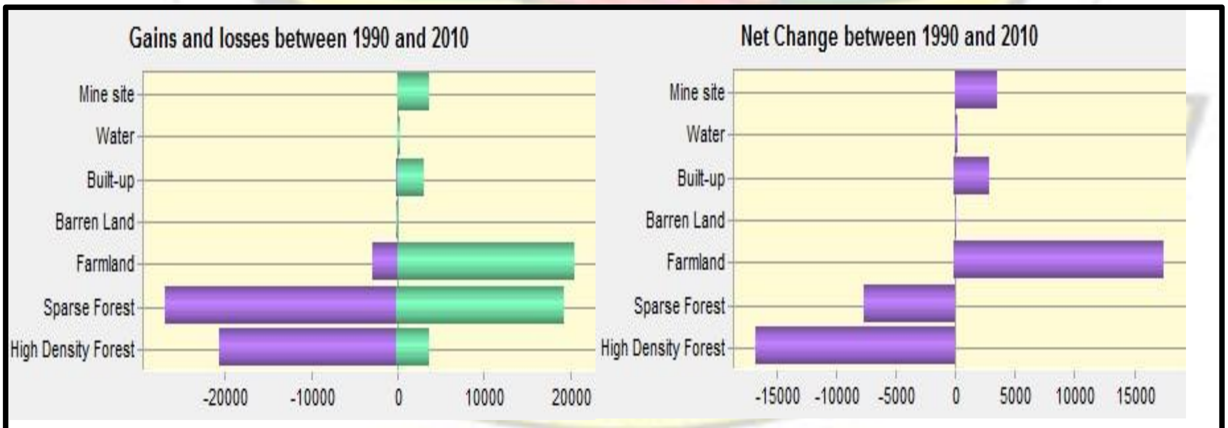
Table 5.3: Table showing the net change of the selected land cover between 2000 and 2010. (Area units are in hectares)

LAND COVER CLASS	GAIN (+)		LOSS(-)		NET CHANGE		ANNUAL RATE OF CHANGE
	Area(ha)	**Area(%)**	**Area(ha)**	**Area(%)**	**Area(ha)**	**Area(%)**	
High Density Forest	5059	3.05	-10119	-6.10	-5060	-3.05	-0.31
Sparse Forest	14764	8.90	-23226	-14.01	-8463	-5.10	-0.51
Farmland	17306	10.44	-7082	-4.27	10224	6.18	0.62
Barren land	129	0.08	-522	-0.31	-393	-0.24	-0.02
Built-up	2587	1.56	-33	-0.02	2554	1.54	0.15
Water	313	0.19	-52	-0.03	261	0.16	0.02
Mine area	2006	1.21	-1129	-0.68	877	0.53	0.05
Total change	42164	25.43	42164	25.43	0	0	

In order to further understand the trends of changes, figure 5.8 revealed the contributions to these net changes of mine site and the other land cover classes between 2000 and 2010.

Figure 5.8: Contribution to net change of the selected land cover between 2000 and 2010. (Area units are in hectares)

Taking a critical look at the two models (1990-2000 and 2000-2010) it can be seen that the land cover changes do not follow a regular pattern. It was therefore necessary to quantify and observe the changes that have taken place by the various land cover classes within the twenty year period, the period between 1990-2010.



Graph A

Graph B

Figure5.9: LCM of 1990-2010 (Area units are in hectares)

From graph A in figure 5.9 it can be deduced that all the land cover classes had experienced some changes either gains or losses. Graph B revealed the net change of individual classes and it can be inferred from it that farmland, mine site and built-up land cover classes had experienced expansion within the period of review. Even though minimal, it must be noted that water and barren land experienced little expansion. High Density Forest and sparse forest are seen to have experienced losses at the expense of other land cover class as summarised Table 5.4.

Table 5.4: Table showing the net change of the selected land cover between 1990 and 2010. (Area units are in hectares)

LAND COVER CLASS	GAIN (+)		LOSS(-)		NET CHANGE		ANNUAL RATE OF CHANGE
	Area(ha)	Area(%)	Area(ha)	Area(%)	Area(ha)	Area(%)	
High Density Forest	3879	2.34	-20662	-12.46	-16783	-10.12	-1.01
Sparse Forest	19379	11.69	-27005	-16.29	-7626	-4.60	-0.46
Farmland	20561	12.39	-2924	-1.76	17638	10.64	1.06
Barren land	130	0.08	-121	-0.07	9	0.01	0.01
Built-up	3058	1.84	-116	-0.07	2942	1.77	0.18
Water	312	0.19	-72	-0.04	239	0.14	0.01
Mine area	3611	2.18	-30	-0.02	3581	2.16	0.22
Total change	50932	30.71	50930	30.71	0	0	

Analysis on the contributions to the land cover changes is very important to this study, especially the contribution of mine site to other land cover classes. Figure5.10 shows the net contribution to land cover classes. Within the period under review, the figure reveals that high density forest and sparse forest has experienced high amount of losses as a result of expansions in farmland, mine site, and built-up. Sparse forest particularly is seen to have given way to farmland, built-up and mine site.

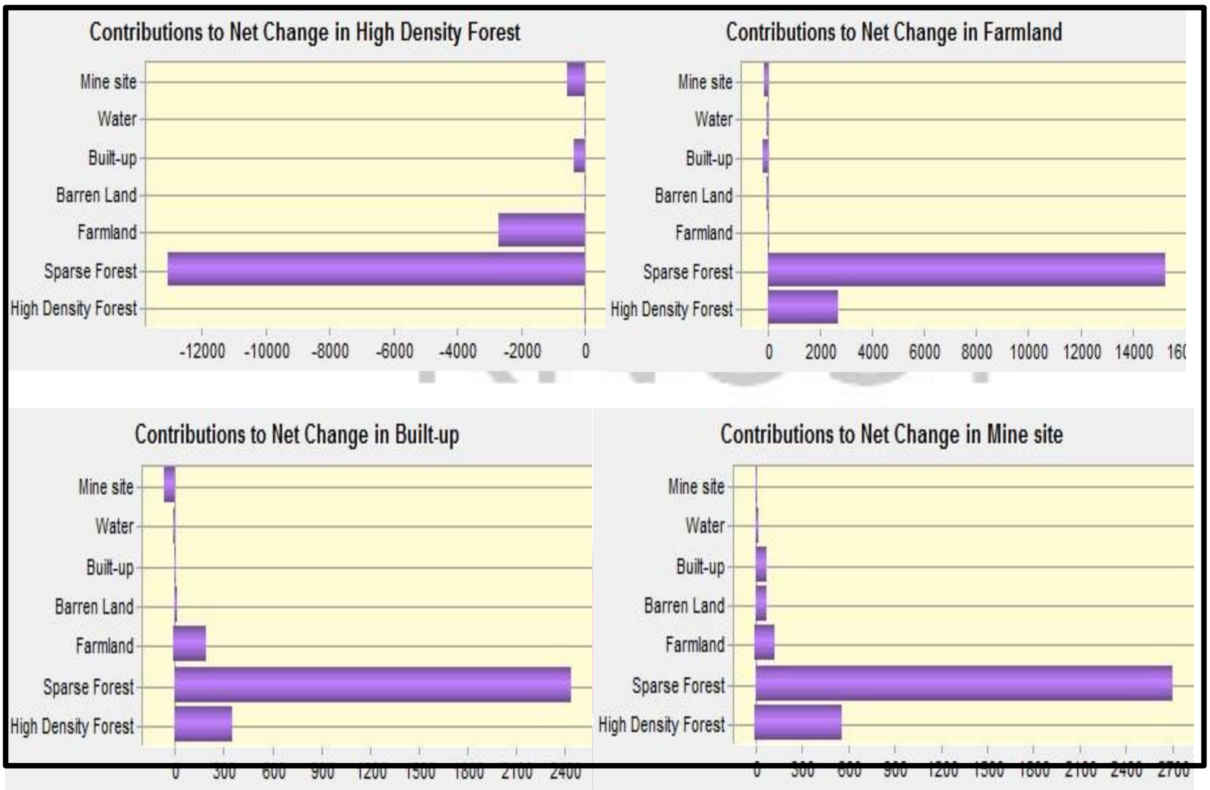


Figure5.10: Contribution to net change of the selected land cover between 1990 and 2010. (Area units are in hectares)

To understand the land cover changes in terms of the amount of change, rate of change, the location of change and whether the changes follow specified trends within the period of review, the CROSSTAB module embedded in Idrisi was used to generate transition matrices and change maps between periods 1990 – 2000, 2000 – 2010 and 1990 – 2010; which explain the cross correlation between the land cover transitions. It can be noted from Tables 5.5, 5.6 and 5.7 that the columns represent the land cover classes of the earlier date and the rows represent that of the later date.

Table 5.5, 5.6 and 5.7 show the transition area matrix produced by running CROSSTAB module for the periods 1990 – 2000, 2000 – 2010 and 1990 – 2010 respectively. The off diagonal elements indicate the number of cells that have changed from existing land cover class in earlier date to other new class in later date. However, the diagonal elements of the matrix represent the unchanged cover class.

It was revealed from the tables that 79864.62ha, 71037.83ha and 62270.68ha of land cover area remained unchanged within periods 1990 – 2000, 2000 – 2010 and 1990 – 2010 respectively. It can therefore be deduced that the amount of change for the three periods were 29.46%, 37.26% and 45.00% within the study area respectively.

Table 5.5: Transition matrix of 1990 – 2000 (Area units in hectares)

	1990								
	Class	**High Density Forest**	**Sparse Forest**	**Farmland**	**Barren land**	**Builtup**	**Water**	**Mine site**	**Total**
2000	**High Density Forest**	18350.43	3113.26	7.47	0	0	26.91	1.8	21499.87
	Sparse Forest	14283.47	58614.12	2246.4	3.15	0	26.19	3.15	75176.48
	Farmland	288.81	9553.59	2221.56	1.89	0	2.16	0	12067.74
	Barren land	59.04	435.33	12.24	14.31	0	0.54	0.81	522.27
	Built-up	16.2	421.38	63.45	8.55	386.37	0	13.5	909.45
	Water	23.4	18.72	0.45	0.54	4.5	207.27	0.45	255.33
	Mine area	206.55	2177.28	102.33	92.52	130.86	13.5	70.56	2793.6
	Total	33227.9	74333.68	4653.9	120.96	521.73	276.57	90.27	113225

Table 5.6: Transition matrix of 2000 – 2010 (Area units in hectares).

	2000								
	Class	**High Density Forest**	**Sparse Forest**	**Farmland**	**Barren land**	**Builtup**	**Water**	**Mine site**	**Total**
2010	**High density forest**	11370.71	4490.12	156.15	159.57	0.72	4.95	258.75	16440.97
	Sparse Forest	8446.43	51933.51	6019.2	69.48	4.05	9.36	231.66	66713.69
	Farmland	1141.02	16043.94	4988.34	31.32	0	0.81	85.41	22290.84
	Barren land	7.74	94.14	19.26	0.72	0	0	7.65	129.51
	Built-up	235.26	1217.52	584.82	57.24	876.15	15.48	476.64	3463.11
	Water	33.39	180.9	15.21	12.69	1.98	203.4	68.49	516.06
	Mine area	274.32	1207.35	285.03	191.25	26.55	21.33	1665	3670.83
	Total	21508.87	75167.48	12068.01	522.27	909.45	255.33	2793.6	113225

Table 5.7: Transition matrix of 1990 – 2010 (Area units in hectares).

	1990								
	Class	**High Density Forest**	**Sparse Forest**	**Farmland**	**Barren land**	**Builtup**	**Water**	**Mine area**	**Total**
2010	**High Density Forest**	12544.87	3793.05	84.6	1.8	0.27	6.84	1.44	16432.87
	Sparse Forest	16886.31	47326.14	2479.14	0.27	3.51	22.05	2.43	66719.85
	Farmland	2799.27	17761.59	1729.62	0	0	1.35	0.36	22292.19
	Barren land	30.69	91.98	6.84	0	0	0	0	129.51
	Built-up	351.18	2447.46	200.52	11.97	405.72	20.97	25.65	3463.45
	Water	35.91	212.94	16.11	31.32	14.85	204.48	0.54	516.15
	Mine area	573.57	2706.75	137.16	75.6	97.38	20.97	59.85	3671.28
	Total	33221.8	74339.91	4653.99	120.96	521.73	276.66	90.27	113225

Figures 5.11, 5.12 and 5.13 show the spatial distribution (location) of land cover change that have taken place between the individual cover types.

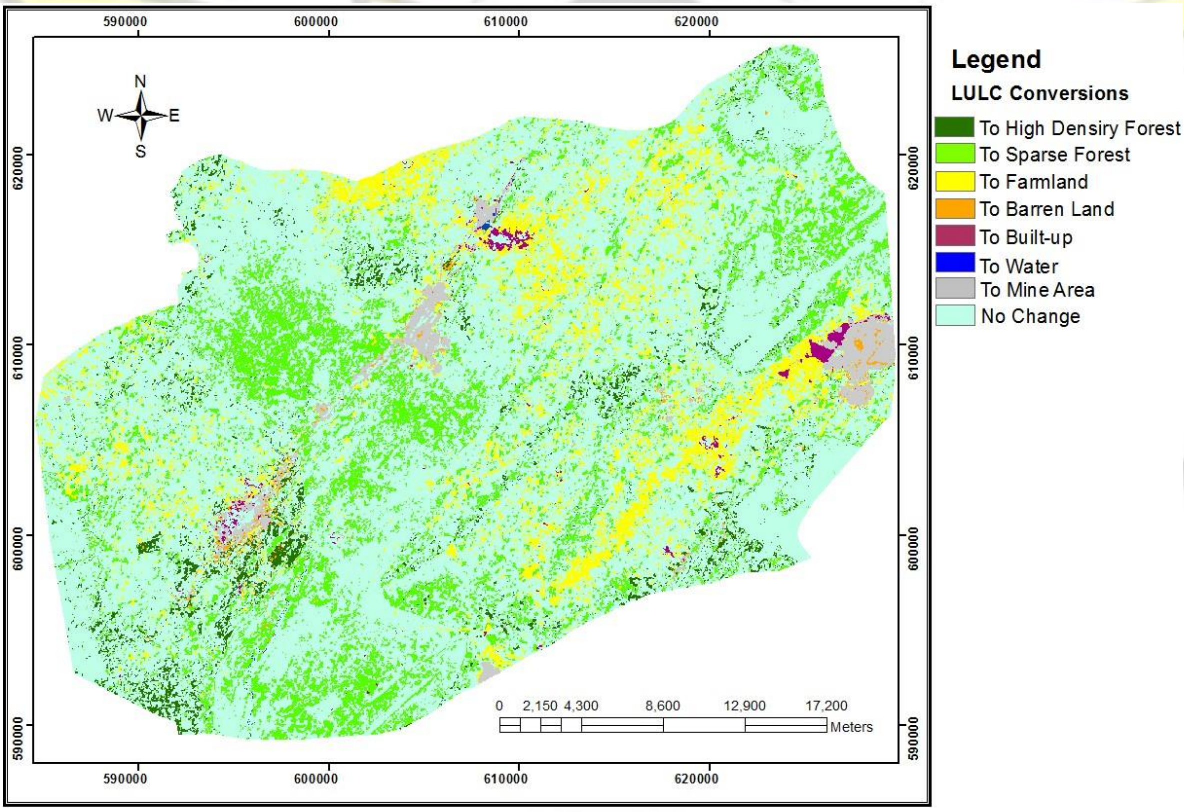


Figure 5.11: 1990 - 2000 Change map showing land cover transition types

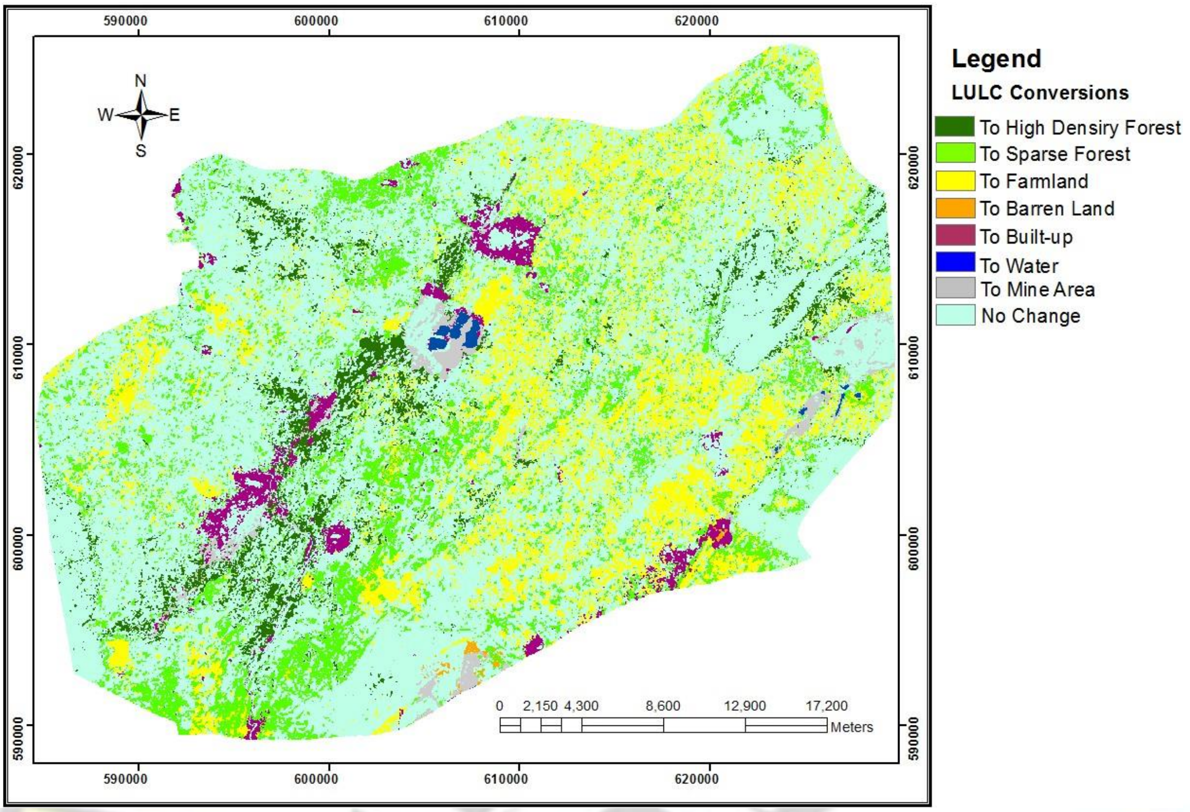


Figure 5.12: 2000 - 2010 Change map showing land cover transition types

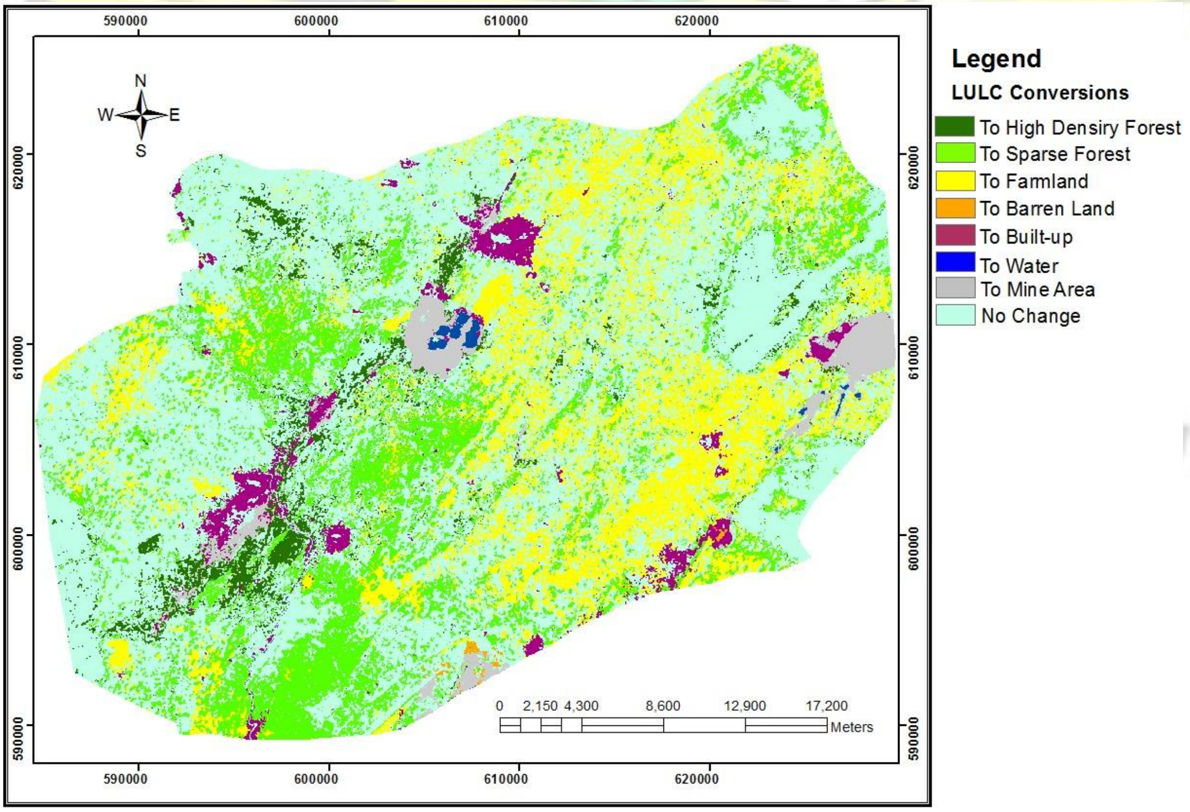


Figure 5.13: 1990 - 2010 Change map showing land cover transition types

5.1.1 Normalized Difference Vegetation Index

Normalized Difference Vegetation Index Using the equation given in section 2.6, NDVI images of the study area were generated from the 1990 Landsat TM, 2000 Landsat ETM and 2010 ALOS imagery , shown in Figure 5.14.

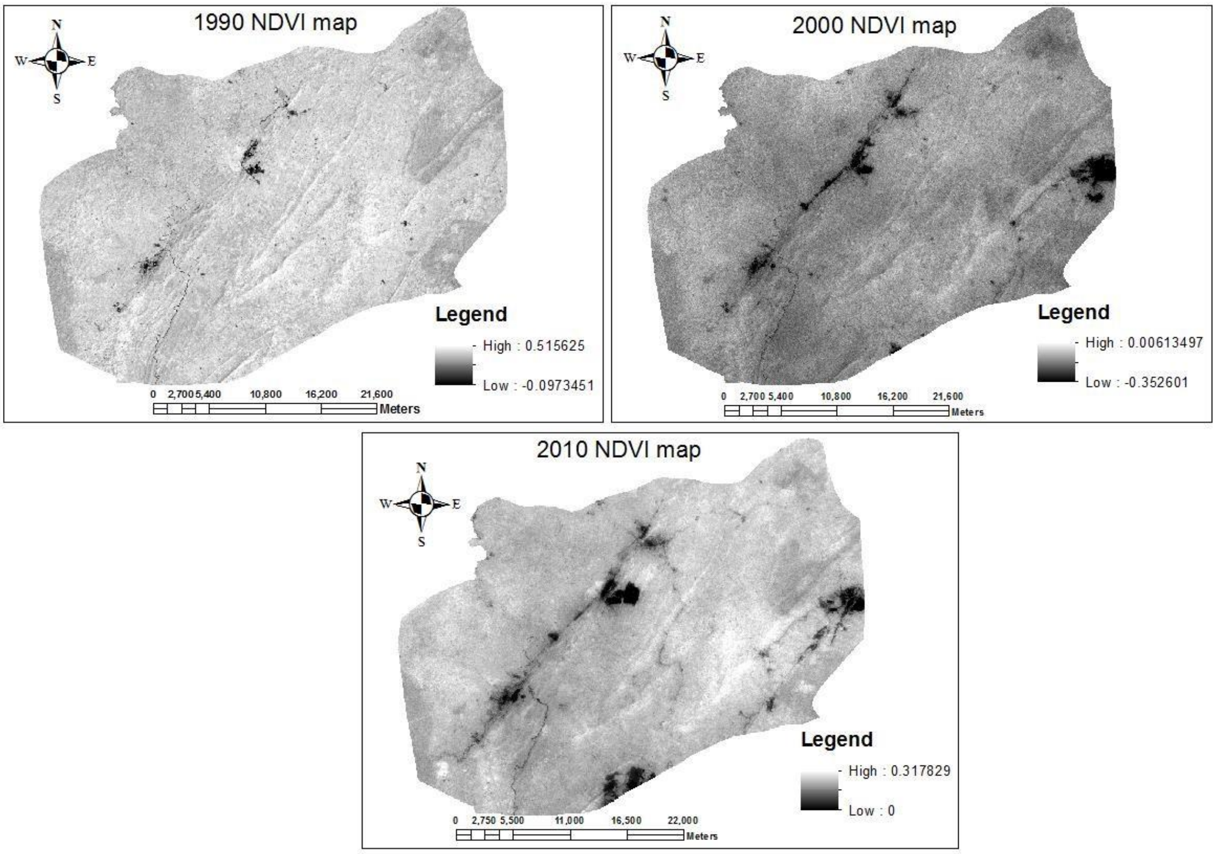


Figure 5.14: NDVI maps showing vegetative and non-vegetative cover

According to section 2.6, this index outputs values between -1.0 and 1.0. Very low values of NDVI (0.1 and below) correspond to barren areas of rock, sand, or snow. Moderate values represent shrub and grassland (0.2 to 0.3), while high values indicate temperate and tropical rainforests (0.6 to 0.8).

The NDVI gave good results in identifying forest areas for subsequent field validation. Also, the results of the NDVI gives a reflection of the subpixel classification as differentiating portions of the study area covered by vegetation or no vegetation cover.

5.1.4 Projecting the Change

To be able to achieve the objectives 4 and 5, project areas under risk of invasion in future, and produce some form of useful references for the local governments in their sustainable land use planning and decision making, as stated in section 1.4.2, it was necessary to perform change prediction. Markov Chain Analysis was used to predict the future land use / cover map within a specified period. First the LULC maps of the years 1990 – 2000, were used to predict the future land cover map of 2010. The LULC map for 2010 produced was used as a reference with which the predicted map of 2010 was compared for validation, before proceeding to use this module to predict further into the future, see Figure 5.15.

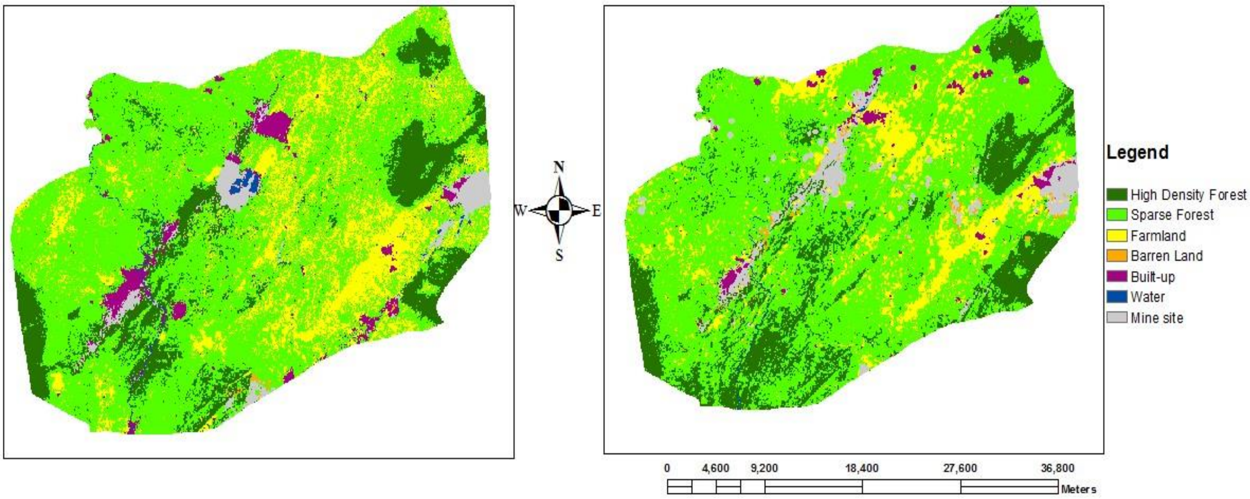


Figure 5.15: A figure of reference (left) and predicted (right) land use / cover map of 2010

The validation was evaluated by the use of kappa statistic generated from VALIDATE module in Idrisi. The Kno which indicates the overall accuracy of prediction was calculated to be 70%. Other kappa statistics like Klocation and Klocation Strata were computed to be 68%

each (Appendix B). Even though these values does not fall within the standard values suggested by Monserud and Leamans (1992) that a value of kappa of 75% or greater show a very good to excellent classifier performance, while a value less than 40% is poor, according to Bell (1974), if the Markov process is found not to be stationary, it does not necessarily mean the model has lost all its predictive or descriptive power. The discrepancies between the predicted and reference land cover maps of 2010 can be as a result of the fact that the land cover changes do not follow a regular pattern as already stated. This model can therefore be considered to be good for any future predictions based on these suggestions.

The land cover map for 2030 was projected using the 1990 and 2010 land cover maps in the same way assuming that the transmission mechanisms stay the same. The transition probability matrix generated is shown in Table 5.8 and resulting 2030 predicted land cover map shown in Figure 5.16.

Table 5.8: Transition probability matrix between 2010 and 2030

	2010							
2030	**Land use / cover class**	**High Density Forest**	**Sparse Forest**	**Farmland**	**Barren land**	**Built-up**	**Water**	**Mine area**
	High Density Forest	0.3050	0.5064	0.1342	0.0008	0.0276	0.0034	0.0225
	Sparse Forest	0.0774	0.6090	0.2395	0.0013	0.0408	0.0044	0.0276
	Farmland	0.0446	0.5584	0.2788	0.0014	0.0792	0.0035	0.0341
	Barren land	0.2052	0.2737	0.0808	0.0014	0.1781	0.0295	0.2314
	Built-up	0.0042	0.0102	0.0019	0.0001	0.9333	0.0046	0.0458
	Water	0.0357	0.0709	0.0152	0.0003	0.1219	0.6370	0.1190
	Mine area	0.1110	0.1603	0.0537	0.0018	0.2717	0.0350	0.3665

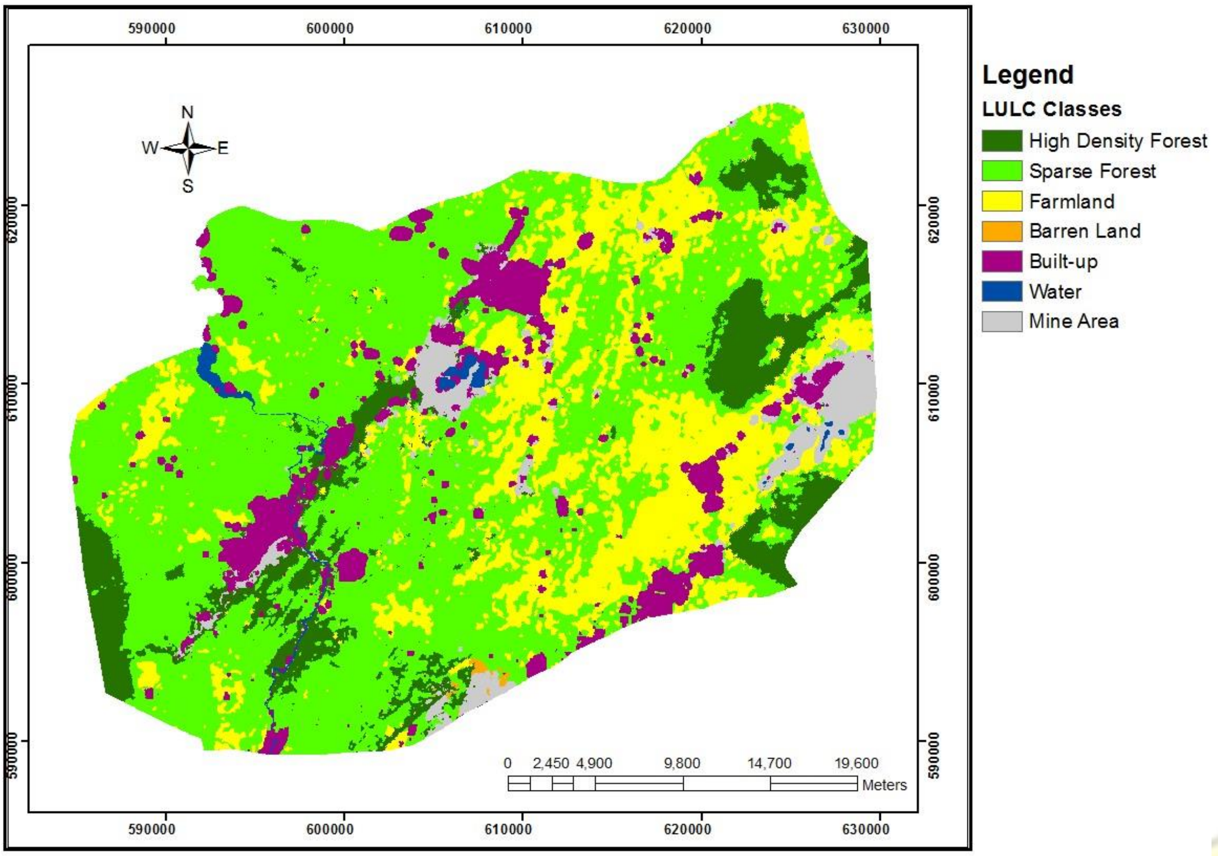


Figure 5.16: 2030 Predicted land use / cover map

Table 5.9: Table showing the change analysis between 2010 and predicted 2030

Land use / cover class	2010		2030		Net Change	Annual Rate of Change
	Area(ha)	Area(%)	Area(ha)	Area(%)		
High Density Forest	16417.4	14.50	15009.32	13.26	-1.24%	-0.12%
Sparse Forest	66728.4	58.93	62362.23	55.08	-3.85%	-0.39%
Farmland	22297.3	19.69	24692.50	21.80	2.11%	0.21%
Barren land	129.51	0.11	170.73	0.15	0.04%	0.00%
Built-up	3463.83	3.06	5232.42	4.62	1.56%	0.16%
Water	516.69	0.46	559.62	0.49	0.03%	0.00%
Minesite	3671.28	3.24	5198.58	4.59	1.35%	0.14%
Total	113225	100	113225	100		

The spatial trend of change in the LCM was used to facilitate interpretation of the complex land change patterns by providing a means of generalization about transition trends between selected categories. Three spatial trend maps (Figures 5.17, 5.18 and 5.19) were created showing the transitions from 1990 to 2010 between categories of interest: high density forest to sparse forest, high density forest to mine site, and farmland to mine site. The numeric values do not have any special significance (in and of themselves), other than to provide an indication of where the change was more intense (higher numbers, redder colours) or less intense (lower numbers, darker green to blue colours). The resulting maps depict a simulated surface that denotes the generalized locations of transition between these categories, from areas with no change to areas with marked change.

The general trend of transition from high density forest to sparse forest was located in the south western and a small portion in the far end of north eastern part of the study area. The general location of mine site occurring in high density forest areas was identified around the western through the central to the eastern parts of the study area. The major transition from farmland to mine site was detected in the central and eastern portions of the area.

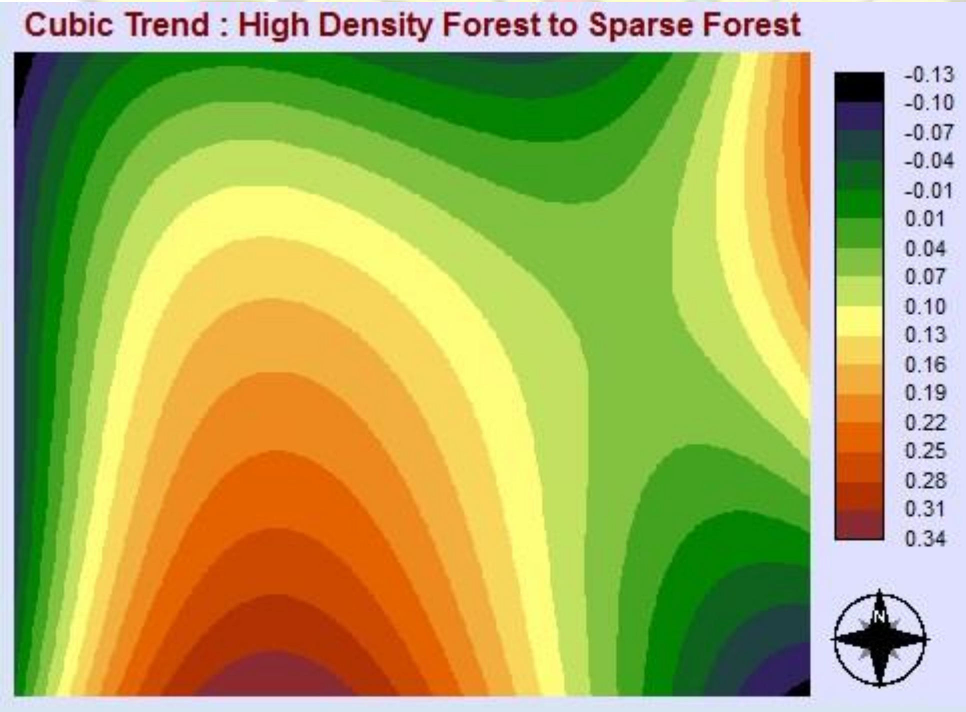


Figure 5.17: Map showing spatial trend of change from high density forest to sparse forest

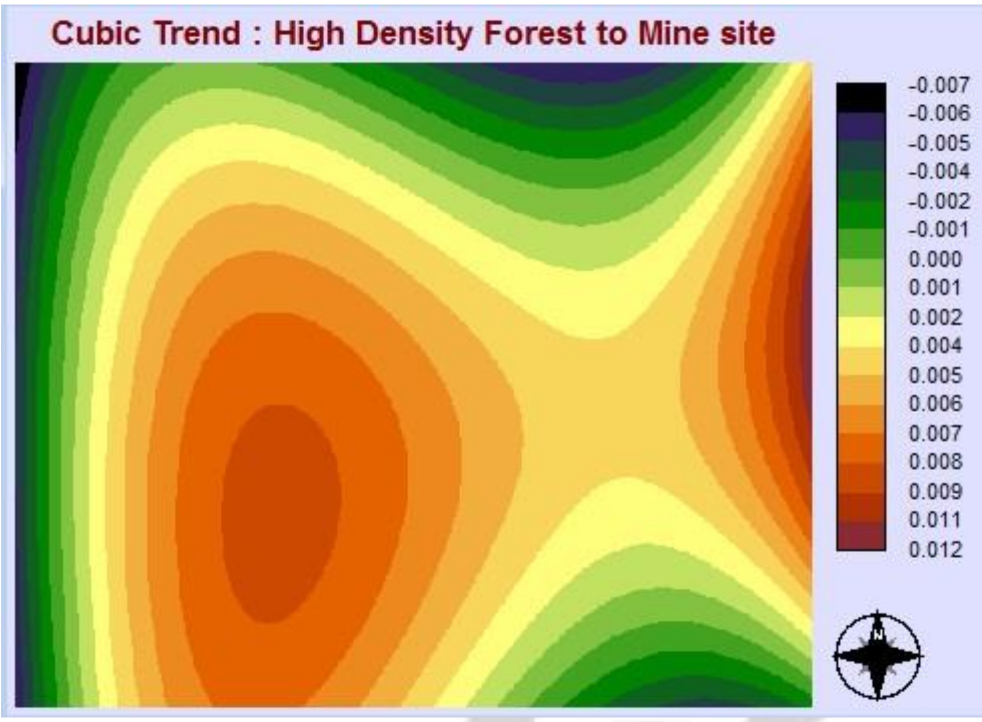


Figure 5.18: Map showing spatial trend of change from high density forest to mine site

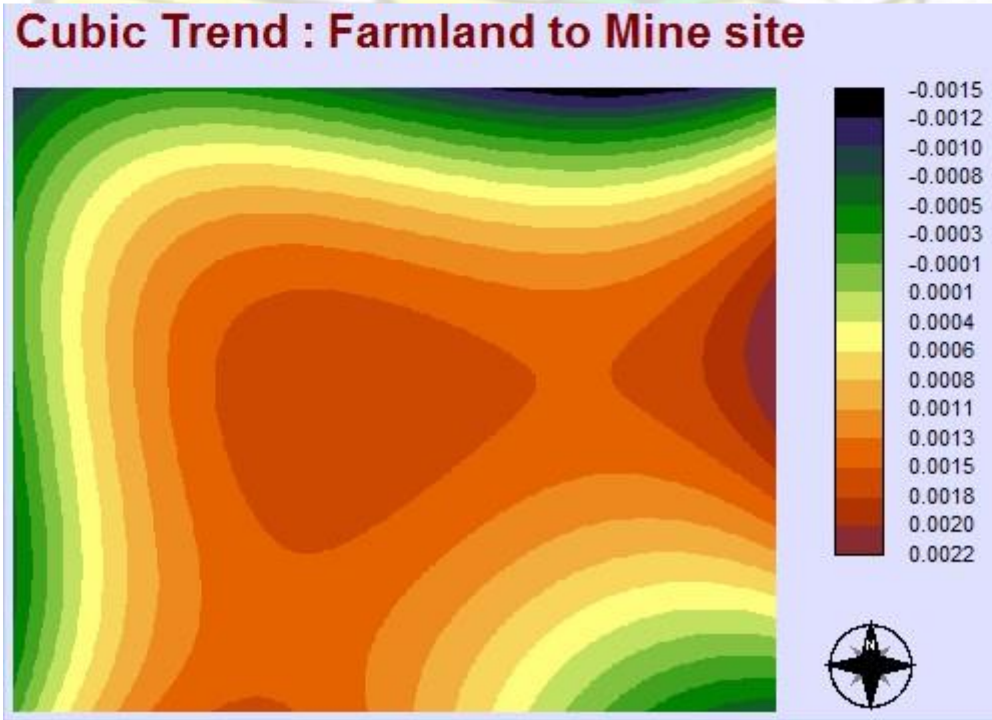


Figure 5.19: Map showing spatial trend of change from farmland to mine site

5.2 Discussions

5.2.1 Land Cover Change Analysis

The main advantage of using Post-Classification change detection is its ability to provide detail and comprehensive information on the exchanges of land cover classes, in the context of the amount, rate, location and the trends of change (Adu-Poku, 2010). Within the period under review (1990 – 2010), the study area has experienced divergent changes in the LULC as a result of human / artificial activities.

The land use / cover maps of 1990, 2000, and 2010 reveals that the most wide spread land cover change is from high density forest to sparse forest, and from sparse forest to farmland. Surface mining has also resulted in extensive land cover changes in the study area, mainly leading to the loss of forests and farmland. The land use / cover maps of the study area shows the intense change in land cover around the areas where even mining companies have concession. Even though some of these mining companies are now practising land reclamation, it is clear that the intense change from sparse forest to farmlands as a result of increase in urbanisation in the study area which has been caused by both legal and illegal mining activities in the area. A good look at the land use / cover maps reveals, a substantial social and environmental cost, example spill – over effects in together to with direct effects such as loss of the rich forest land and also pollution. A look at figures 5.2 and 5.3, reveals the pollution made to the main river in the study area, river ankobra. Mining activities and settlement have increased causing pollution to this river in the 2000 and 2010 land use / cover maps. As a result of this pollution, portions of the river along these areas gives different reflectance during classification. This is therefore a great loss of a source of water to the community.

It can be realised from Table 5.1 that sparse forest cover increased from 1990 to 2000 as a result of deforestation and farmlands which are abandoned when the land has been polluted as a result of spillage caused by illegal miners. Increase in the indiscriminate act of these illegal miners, resulted in a decline of sparse forest to 66728.4ha in 2010, representing 7.55% from the year 2000.

Subsequently, it was also revealed that farmland has increased through the past two decades. By 2010, farmland in the study area covered 19.69%. Subsidy and incentives given to cocoa farmers by the government since 2000 and also the establishment of fruit processing companies are the reasons why there was an increase in farmlands in the area.

High density forest is noticed as the next most dominant land category after farmland category. The area covered by high density forest declined through the past two decades. In 1990, high density forest covered 33119.8ha (29.25%), but it declined sharply by about 10% in 2000 and further to 16417.4ha (14.50%) in 2010. Even though there has been a rapid change in the high density forest cover in the area during the period under review, 1990 – 2010, it can be seen from the land cover maps(Figures 5.1, 5.2 and 5.3) that most portions of the main forest reserves in the study area are preserved. The decrease in high density forest could be attributed to booming in mining activities resulting in fast-paced population growth. The high density forest is depleted by people for their livelihoods such as farming, firewood collections, mining, construction of houses and roads.

For the minor land cover categories, built-up and mine site covered most of the remaining cover in the area. Barren land and water, mainly the ponds, covered a small portion of the area but the changes in these two cover was as a result change in area covered by mine site.

Examining the change maps, Figure 5.10 – 5.12 shows the distribution of exchanges in the land cover classes revealing the location of changes in the study area. It can be noticed from the figures that changes occurred all over the study area with most of the changes taken place close to built-up areas indicating the influences of human activities on the land cover.

From the transition matrices generated for the three time series (Tables 5.4 – 5.6) it can be deduced that 70.54% (79864.62 ha) of total land cover remained unchanged and the area experienced 2.95% annual rate of land cover change within the ten year period (1990 – 2000); 62.74% (71037.83ha) of the land cover remain unchanged within the next ten years (2000 – 2010) and the annual rate of land cover change in the area was 3.73%. Taking into account this two periods of time series (1990 – 2010), the results from Table 5.6 revealed that 55.00% (62270.68 ha) of the study area experienced no change at 4.50% annual rate of change. Comparison of these three rates revealed an increase change from the period 2000 – 2010. This can be attributed to the fast growing population resulting in activities such as farming, construction of houses and roads, firewood collection and mining.

Within the period between 1990 and 2010, mining activities, urbanisation and farming activities have been identified as the main driving forces causing alteration of land cover in the study area. This establish the idea that the Earth's land surface is affected rapidly by the presence of humans and their activities (Sherbinin, 2002). This is evident as there has been a massive increase of mine area, built-up and farmland in the study area, from 90.27ha in 1990 to 3671.28ha in 2010, 521.73ha in 1990 to 3463.83 in 2010 and 4656.78ha in 1990 to 22297.3ha in 2010 respectively, as shown in Table 5.1.

5.2.2 Land Cover Modelling Analysis

Figures 5.5 – 5.10, reveals the correlation between mine site to other land use / cover classes. It is evident that mine sites increase is directly related to built-up and farmland. This is so because in graph B of Figures 5.5, 5.7 and 5.9, these three classes, mine site, built- up and farmland are constantly gaining in net change computation.

Examining the figures showing contribution to net change of the land use / cover classes calls for much concern. From Figure 5.6, between 1990 – 2000, with the exception of high density forest that lost 11182ha of land to sparse forest, farmland, built-up and mine site has gained hundreds of hectares of land from sparse forest, with the gains of, 7310ha, 421ha and 2179ha respectively. Between 2000 – 2010, Figure 5.8 reveals a similar pattern of loss of sparse forest to other classes. The loss of forest (high density forest and sparse forest) can also be attributed to illegal logging as surface mining expands. Also farmers that are displaced by gold surface mining mostly re-established in close forest areas. This is because deforestation at its initial stage provides benefits from wood extraction. Previously fallow soils are more fertile than areas that have been degraded. It is hard to find a fertile farmland these days (Wassa West District office of the Ministry of Lands, Forestry, and Mines). It can be realised from the contributors to net change that, farmers are also losing their lands to surface miners, both legal and illegal and also to built-up.

The intention of the spatial trend of change module is to provide a means of generalising the pattern of change. The output from the spatial trend of change module is a smooth surface that represents gradual trends in the surface (the transition in land cover) over the area of interest. The spatial trend of change maps shown above explains the fact that as farmers loss their lands to surface miners they in turn move to clear the forests to re-establish their farms.

5.2.3 Change Projection

Although the model used in this study was found to be acceptable, it fails to attain a kappa value of 75% or more as proposed by Monserud and Leamans (1992) as a model with excellent prediction. The reasons could be attributed to inadequate suitability maps used during the modelling process and also the contiguity filter applied. In order to efficiently model land cover maps in the future; it is convenient to implement adequate suitable maps representing the driving factors information on the degree of impact on the land cover types (Clarke et al., 1997; Zamyantin and Markov, 2005).

These suitability maps and the contiguity filter applied act as a transition rule during the modelling process and have a great influence on the results of the model. Maps such as population data, meteorological data and even policy data were not included in this study. Markov chain analysis predicts the future land cover patterns based on known land cover patterns of the past (Eastman, 2006; Sun et. al., 2007). The inference that can be drawn from this is that Markov chain analysis used to predict 2010 land cover map based on 1990 – 2000 land cover maps fails to acknowledge the driving factors that took place between 2000 and 2010, and thus contributing to the discrepancies between the predicted and reference land cover maps of 2010.

From Figure 5.15 and Table 5.8, it is evident that all the land cover classes except high density forest and sparse forest will be expanding, with farmland and built-up areas experiencing a gain of about 2.11 % and 1.56% respectively. Table 5.7 reveals that in the next ten years, built-up and mine site will be increasing at the expense of each other. Built-up is expected to gain by 12.4% from mine site, and mine site on the other hand is expected to gain by 19.3% from built-up. Sparse forest is expected to increase by 4.6% at the expense of high density forest, while farmland will in turn gain by 50.7% from sparse forest. Within this period, barren land will be gaining from water and mine site by 28.3% and 70.9% respectively. This is alarming because the effect of mining activities on the land is revealed as most lands will be left barren due to mining activities in past years.

CHAPTER SIX - CONCLUSIONS

6.1 Conclusions

Based on the objectives of this study, the following conclusions can be made.

This study used the integration of Remote Sensing techniques to analyse and quantify the land cover changes (in terms of the amount, rate, trend and the location) that have occurred within the period of 1990 – 2010 in the study area. It can be seen that the study area has witnessed widespread land cover changes with the annual rate of change as 4.50%. It can be realised from the analysis made in this study that, the slightest increase in mine area has a corresponding increase with farmland and built-up (Graph B of figure 5.5, 5.7, 5.9).

Within the period between 1990 and 2010, mining activities and urbanisation has been identified as the main factors behind the alteration of land cover in the study area. This confirmed the idea that the Earth's land surface is rapidly affected by the presence of human being and their activities. This is evident as there has been a massive shot up of built-up, mine area and farmland in the study area. Also, the trend of land cover losses, mainly the loss of vegetation in the study area could be attributed to the LULC conversions to the main drivers of change. The rapid growth in mining activities has resulted in the fast-paced in urbanisation as the major sources of land cover changes in the area of study.

The application of sub-pixel classifier was successful, but it is important to point out some limitation of the sub pixel classifier; Sub pixel classifier shows low number of classified pixels, this is because sub pixel classifier is more suitable for extracting pure material specific in nature. For this reason, the classified image obtained from the sub pixel classification was over laid on a maximum likelihood classification image for a better visual representation. The NDVI classification gave a reflection of the subpixel classification as differentiating portions of the study area covered by vegetation or no vegetation cover.

Projecting areas under risk of invasion in the future was successful using the Markov Chain analysis. The projected LULC map of 2030 reveals that, high density forest and sparse forest are under risk of invasion in the future. It must be noted that, the Markov Chain analysis predicted the state of each land cover class based on the past history but fails to take into account the future trends.

6.2 Recommendations

Even though this study has been concluded, it is necessary to make some recommendations, since there still remain some unanswered questions due to the limitation of resources. These recommendations include;

- For an effective application of the subpixel classifier for surface mining studies where mining pits for most of the small scale miners is less than 30m*30m or 10m*10m,High resolution images such as IKONOS and QUICKBIRD with resolution of 1m or less will be suitable.
- With the projection of areas under risk of invasion in future for the study area already done, it may be helpful and useful to conduct further studies on how to protect the land cover types under risk of invasion in future.

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APPENDIX

Appendix 1: Error matrix generated from 2000 land cover map

ACCURACY TOTALS						
Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy	Kappa
Unclassified	0	0	0	---	---	0.0000
High Density Forest	6	5	5	83.33%	100.00%	1.0000
Sparse Forest	11	10	8	72.73%	80.00%	0.7593
Farmland	22	25	21	95.45%	84.00%	0.7581
Barren land	4	2	1	25.00%	50.00%	0.4672
Built-up	8	10	8	100.00%	80.00%	0.7719
Water	3	3	2	66.67%	66.67%	0.6505
Minesite	11	10	8	72.73%	80.00%	0.7593
Totals	65	65	53			
Overall Classification Accuracy = 81.54%						

Overall Kappa Statistics = 0.7656

Appendix 2: Error matrix generated from 2010 land cover map

ACCURACY TOTALS						
Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy	Kappa
Unclassified	0	0	0	---	---	
High Density Forest	5	5	4	80.00%	80.00%	0.7833
Sparse Forest	13	11	9	69.23%	81.82%	0.7727
Farmland	19	21	18	94.74%	85.71%	0.7981
Barren land	5	2	2	40.00%	100.00%	1.0000
Built-up	9	12	9	100.00%	75.00%	0.7098
Water	2	4	2	100.00%	50.00%	0.4841
Minesite	12	10	8	66.67%	80.00%	0.7547
Totals	65	65	52			
Overall Classification Accuracy = 80.00%						
Overall Kappa Statistics = 0.7523						

Appendix 3: Attribute table showing subpixel representation of Material of Interest (MOI)

farmland.img

Row	Histogram	Class_Names	Opacity	Color	Red	Green	Blue
0	0		0		0	0	0
1	30725	0.20 - 0.29	1		1	1	0
2	22383	0.30 - 0.39	1		1	0.85	0
3	16295	0.40 - 0.49	1		1	0.71	0
4	38999	0.50 - 0.59	1		1	0.57	0
5	67766	0.60 - 0.69	1		1	0.43	0
6	28479	0.70 - 0.79	1		1	0.28	0
7	1923	0.80 - 0.89	1		1	0.14	0
8	2	0.90 - 1.00	1		1	0	0

Appendix 4: Showing the kappa statistics for validation performed using the predicted and reference land cover maps of 2010.