ASSESSING LAND USE/COVER CHANGE AND LAND DEGRADATION RISKS USING MULTI- TEMPORAL LANDSAT IMAGES.

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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

Rapid land use/cover change and land degradation are occurring in Ghana as a result of demographic pressure, human-induce activities and environmental factors such as drought. This study analysed the dynamics of land use/cover and land degradation risk as revealed in the Kintampo Municipal district based on the multi-spectral Landsat imagery of 1986 TM and 2005 ETM+. A scheme of unsupervised and supervised classification approach was employed to generate land use/cover maps of 1986 and 2005 respectively. A total of six broad land use/cover classes were identified and mapped and these include built-up, grassland, shrub land, bare soil, agriculture land and water. Post-classification change detection was employed on 1986 and 2005 classified images to detect changes that have taken place within the past nineteen year period. Subsequently, Markov Chain Analysis was used to predict the land cover distributions that are likely to occur by 2024. Again, Tasseled Cap Transformation (TCT) was employed to the 1986TM and 2005ETM+ Landsat imagery to evaluate land degradation through TCT greenness index (measure vegetation cover), TCT brightness index (measure barren soil), and TCT wetness index (measure soil/vegetation moisture). In addition, the TCT brightness index was used to map land degradation risk regions of the study area.

The result of the change detection revealed that from 1986 to 2005, there have been losses in grassland and shrub land accounting to 5.56% and 14.31% respectively as a result of expansion of built-up, bare soil, agriculture land and water cover. The 2024 projected land use/cover predicts continuous expansion of built-up, bare soil, and agriculture land at the expense of grassland, shrub land and water cover. The TCT statistics indicate decrease in vegetation cover and soil moisture with increase in barren soil which support the land use/cover dynamics detected. This result of TCT also indicates that there was increase in land degradation in the region during the study period. The identified relationship between

land degradation risk and land use/cover revealed bare soil cover had the highest area in terms of susceptibility to land degradation followed by built-up, agriculture land, grassland and shrub land. Agriculture land however, increased in high susceptible area of land degradation with greatest rate per year of about 365.92 ha.

Finally, the results of the study conclude that land use/cover changes led to the degradation of large areas of land from 1986 to 2005. These changes were brought about by increasing population couple with human induced and socio-economic activities in the study area.

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LIST OF ABBREVIATION

AOI	Area of Interest
ASTER	Advanced Space Borne Thermal Emission & Reflection Radiometer
AVHRR	Advanced Very High Resolution Radiometer
BAR	Brong-Ahafo Region
DN	Digital Number
ERDAS	Earth Resources Data Analysis System
ETM+	Enhanced Thematic Mapper
FAO	Food and Agricultural Organization
GIS	Geographical Information System
Ha	Hectares
ISODATA	Iterative Self-Organizing Data Analysis Technique Algorithm
LULC	Land use and Land cover
MOARD	Ministry of Agriculture and Rural Development
MSS	Multispectral scanner
NDVI	Normalized Difference Vegetation Index
NOAA	National Oceanic and Atmospheric Administration
RS	Remote Sensing
SAM	Spectral Angle Mapper
SAR	Synthetic Aperture Radar
SBI	Soil Brightness Index
SRTM	Shuttle Radial Terrain mission
TCT	Tasseled Cap Transformation
TM	Thematic Mapper
UNCCD	United Nations Convention to Combat Desertification
UTM	Universal Transverse Mercator

CHAPTER ONE

INTRODUCTION

1.1 Background

Land is the terrestrial bio-productive system that comprises soil, vegetation, other biota, and the ecological and hydrological processes that operate within the system (UNCCD, 1996a). It is the basic natural resource, which provides space and raw materials for various developmental and other activities. Changes in land cover, hence land surfaces processes, are inherently dynamic and spatial and could impact the natural environment in a way that could, only, be paralleled to the effects of climate change (Aspinall and Hill, 2008; Foody, 2002).

Increase in population density, type and the use of land and climatic conditions of an area are few of the major driving forces to cause change in Land use/ cover. Transformations of land cover for agricultural, residential, industrial and urban development concomitant to the increasing population affects the functioning of environmental systems and processes in the long term. Several environmental impacts such as biodiversity loss, soil erosion and degradation, water flow, water quality and climate change are considered to result from changes in land use/cover.

As stated in Abate (1994), knowledge of the distribution and types of land use/cover are believed to be important indicators for resource base analysis with regard to land degradation and productivity, hence problems or possibilities for sustainable development. Inference could be possible by examining the changes in distribution and types of land use/cover in the past, and also those future predictions will be possible.

UNEP (1999), reports that land degradation has affected some 1900 million hectares of land word-wide. In Africa an estimated 500 million hectares of land have been affected by land degradation, including 65% of the region's agricultural land. The rate at which arable land is being lost is increasing and is currently 30-35 times the historical rate. And this is happening worldwide, not just in Africa or Asia (UNEP, 1999). Again, land degradation is growingly a severe problem in Sub-Saharan Africa and affects at least 485 million people in Africa (Reich et al., 2001). Up to two-thirds of Africa's arable land area is affected by land degradation and could effectively be non-productive by 2025 (UN, 2004).

Land degradation has long been recognised as a critical ecological and economic issue due to its impacts on food security and environmental conditions. It involves physical, chemical and biological processes. Physical processes include alterations in soil structure, environmental pollution and unsustainable use of natural resources; chemical processes include acidification, leaching, salinization, decrease in cation retention capacity and fertility depletion and biological processes include reduction of biomass and biodiversity (Eswaran et al., 2001).

Various literature reviewed provide similar definitions to land degradation; for example Eswaran et al. (2001) defines it as the loss of actual or potential productivity or utility as a result of natural or anthropic factors; that is, the decline in land quality or reduction in its productivity. Land degradation refers to the temporary or permanent reduction in the productive capacity of land ~~as a result~~ of human action (Barrow, 1990). Wiley-Interscience (2003) also defines land degradation as the loss of utility or potential utility through the reduction of change to physical, social, cultural, or economic feature and reduction of ecosystem diversity. Better still, it can simply be defined as the deterioration of soils, vegetation, water and landforms, with adverse consequences for people and ecosystems.

The continuous slow-steady spread of land degradation tends to make its existent observation, impacts measurement, and determination of the quantity of land at risk very complicated (Feddema and Freire 2001). When land is in a state of advanced degradation, restoration becomes difficult and requires a considerable investment for mitigation. The causes of land degradation are diverse and reflect complex interactions.

The primary causes of land degradation are population growth and improper land-use practices which is influenced by social, economic, political and technological factors. Land degradation is also caused by natural as well as anthropogenic or both factors. The natural causes include geology of the area, topography, tectonic structure, drought and major climatic change. Human factors include deforestation, overgrazing, intensive farming, road construction, urbanization. Population pressure on the resource and unmanaged land use resources results in land degradation (Gebeyehu, 2009). Dissimilar areas may exhibit different forms of land degradation, such as reduction of soil nutrients, salinization, agrochemical pollution, soil erosion and biodiversity loss (Scherr and Yadav, 2001). This makes monitoring and the evaluation of land degradation a difficult task because of the lack of effective methods and suitable criteria to quantitatively analyze the process.

Integrating remote sensing (RS), geographic information systems (GIS) and complemented with field ground truth; provide the best methodological toolset in accomplishing the task of inventory, mapping and monitoring of ecosystems health and degradation (Wolfgang, 2002). The traditional in-situ field survey is narrow in spatial and temporal scope, inefficient and costly, tedious and time consuming and difficult in large remote locations and difficult terrain. In addition, results obtained from traditional methods of assessment are often unreliable due to the difficulty in mapping contributing factors at a high level of accuracy (Feng et al., 2009). Remote sensing techniques are very effective in providing input data required in land degradation mapping. Visual and digital image interpretation can be used to derive input parameters such as land use/cover and to a less extent the conservation and erodible factors (Jaroslav et al., 1996). According to Veldkamp and Lambin (2001), land use change models are often used to assess the impact of land cover on biophysical processes, e.g. climate variability, land degradation, ecosystem stability and diversity. A vital prerequisite to the development of realistic models of land use change is the identification of the most important drivers of change, and how best to represent them in a model. GIS modeling does not only predict consequences of human actions on land degradation, on the contrary, it is also practicable in the conceptualization and interpretation of complex systems as it allows decision-makers to easily view different scenarios. Most of the data used in models i.e. vegetation, soil, relief, climatic, etc. can be processed in a GIS and used as first stage input to identify and map degraded lands (Shigeo et al., 1998; Wessels et al., 2001). RS and GIS offer tools to perform systematic inventory and diagnostic assessment of land resources, land degradation and ecosystems health over consistent space and time.

The strength of the study could, therefore, be justified in light of the GIS and Remote sensing capabilities and the advantage of integrating the system with other ancillary data to map and assess land use/cover and land degradation risks.

1.2 Problem Statement

About 65 percent of Africa's population is affected by land degradation and the loss in gross annual income estimated at nine billion dollars (Banguu-Ekekkah, 2010). However, land degradation in Ghana is increasingly being recognized as a key development issue because it impacts on the productive capacity of users. The need to provide adequate food for a rapidly expanding population has put enormous marginal land under cultivation. This has resulted in deforestation of the natural vegetation where the soil is exposed to erosion resulting in land degradation and eventual desertification (Girma, 2003).

Land use/ cover change is an ongoing process. As a result of land use / cover change, misuse of agricultural land, use of steep slopes and marginal lands for agriculture had led to land degradation (MOARD, 2007).

Rural households are the most affected because of their heavy dependence on natural resources for livelihood. Land degradation is also the cause of environmental degradation as a result of deforestation and erosion. The consequences of land degradation are dire and numerous. They include reduced land productivity, socio-economic problems among them uncertainty in food security, migration, limited development and damage to the ecosystem. This can undermine progress towards achieving the Millennium Development Goals of poverty reduction and environmental sustainability.

In this research, however, rate of deforestation and vegetation loss is quantified; to assess the extent and the rate of bare/degraded land which is more vulnerable to soil erosion is also analyzed and quantified with spectral characteristics of the Landsat images of 1986 and 2005 in the study area in general at a sample site in particular.

1.3 Significance of the Research

Mapping and monitoring land degradation has become an urgent task in Ghana, but such studies have not attracted sufficient attention yet. Land degradation in the study area (Kintampo Municipal) is mainly caused by deforestation and associated soil erosion; thus, a key to exploring land degradation risk relationships require good land use/cover types and an understanding of relationships between land use/cover and land degradation risks. Hence, this research explores an approach based on the Soil Brightness Index

(SBI) and Vegetation Index of Tasseled Cap Transformation to quickly evaluate and map land degradation risks areas.

1.4 Research Aim and Objectives

1.4.1 Aim

The main aim of this research is to asses land use/cover change and land degradation risk areas in kintampo municipal within 19 years (from 1986-2005) using Landsat TM/ETM+ images.

1.4.2 Objectives

This study, by using GIS and remote sensing, intended to:

a. Identify land cover types using image classification scheme.
b. Generate a land cover change map over a period of time
c. Predict future land use/cover patterns for the year 2024 using Markov and Cellular Automata model.
d. Map the coverage of land degradation risk area over time and space
e. Evaluate the relationship between land degradation risk areas and land use/cover types.

1.5 Methodology Framework

Figure 1.1 illustrates the framework for assessing land use/cover change and land degradation risks using multi-temporal Landsat TM/ETM+ images.

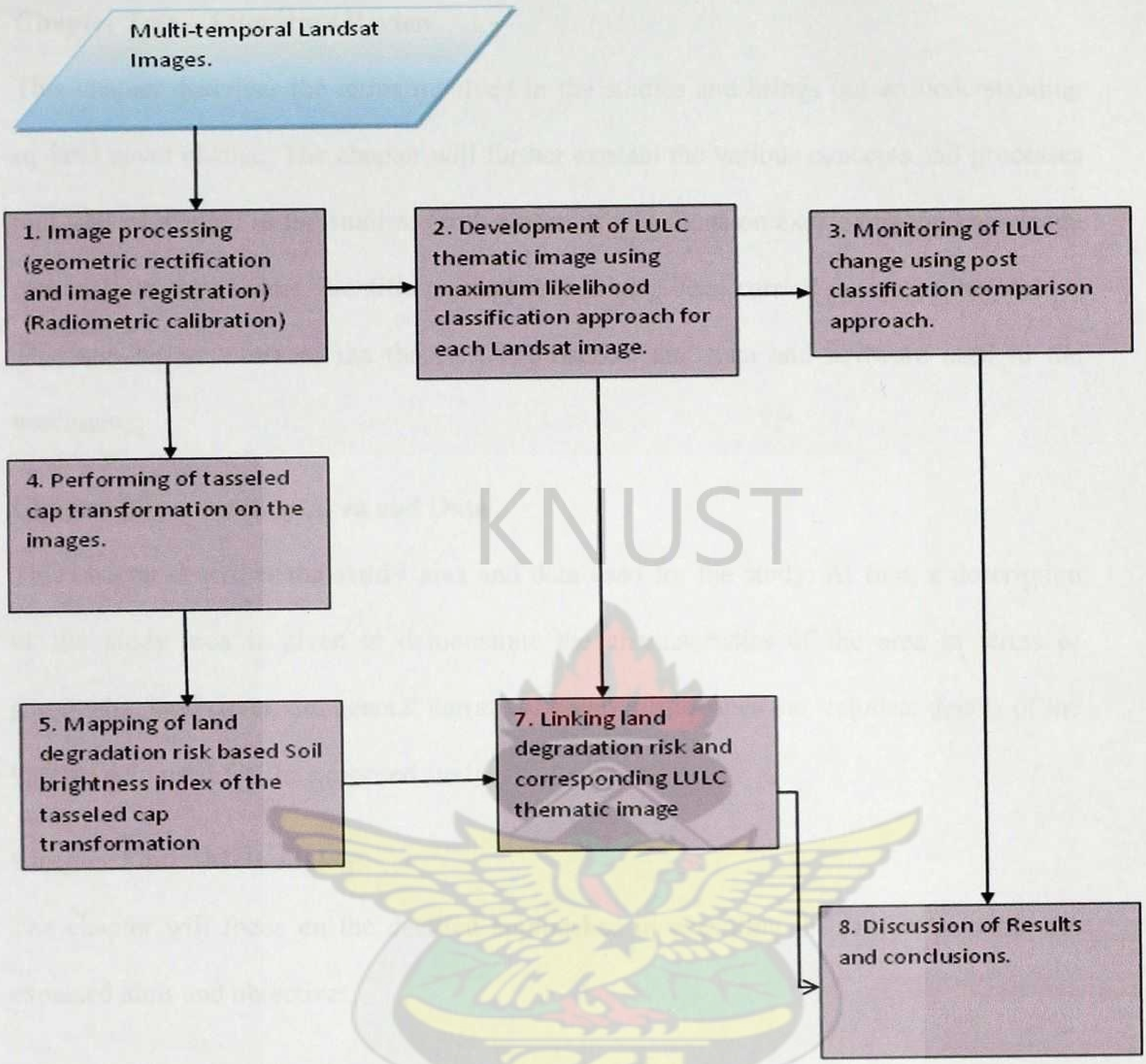

Figure 1. 1 Methodology Framework

1.6 Structure of the Report

The organisation of this report has been grouped into six chapters. Elaboration of the structure of this report is given below:

Chapter One – Introduction

This chapter is based on the proposal which describes the background information of study, highlights the aims and objectives of the project, and the justification of doing this project.

Chapter Two – Literature Review

This chapter describes the terms involved in the studies and brings out an understanding of land cover change. The chapter will further explain the various concepts and processes that will be applied in the studies. Furthermore, it will focus on expressing the knowledge gained from the various scientific researches that have been carried out about the project. This can be in terms of the theories, approaches, and data and software used in the processing.

Chapter Three – Study Area and Data

This chapter describes the study area and data used for the study. At first, a description of the study area is given to demonstrate the characteristics of the area in terms of geography, land cover and general narrative. Then, it illustrates the technical details of the various data used for the proposed study.

Chapter Four –Methodology

The chapter will focus on the detailed approaches in executing the project to attain the expected aims and objectives.

Chapter Five – Results and Discussions

The chapter seeks to present the findings of the project based on the specified aims and make analyses on these findings.

Chapter Six – Conclusions and Recommendations

This chapter will focus on the concluding statements from the project by looking at the findings and whether the specified aims were met or not. It will discuss recommendations for future studies and also will talk about the limitations of the project.

CHAPTER TWO

LITERETURE REVIEW

2.1 General Overview of Land Degradation

Land degradation is an extensive phenomenon influenced by natural and socioeconomic factors. As the problem is complex, the existing definitions of land degradation, the methods for its assessment and the related actions are varied and sometimes conflicting. Although soil represents one of the key ingredients of land, there is a clear distinction between land and soil degradation; this distinction should be considered by researchers, land managers, and stakeholders. Recognizing that the term land refers to more than just the soil, the United Nations Convention to Combat Desertification defines land as "the terrestrial bio-productive system that comprises soil, vegetation, other biota, and the ecological and hydrological processes that operate within the system"(UNCCD, 1996a).

According to Vlek et al (2008), the interaction of the land with its users is mainly what leads to any kind of land degradation, resulting in serious social problems, due to the change of the ensemble of the soil constituents, of the biotic components in and on it, and of its landscapes and climatic attributes. Because land use results in relevant services, such as food production and, more generally, support of livelihoods, land degradation directly affects social human benefits. Thus, interactions of natural processes, human activities, and social systems play a considerable role in land degradation (Safriel, 2007). Early definitions of land degradation refer to a decline in "the current and/or potential capability of soils to produce (quantitatively and/or qualitatively) goods and services" (FAO, 1979).

More recent definitions extend land degradation to spatial and time dimensions, as is reflected in the definition of the United Nations Convention to Combat Desertification

(UNCCD, 1996b), which defines land degradation in the context of its focus on dry lands: the "reduction or loss in arid, semiarid, and dry sub-humid areas, of the biological or economic productivity and complexity of rain fed cropland, irrigated cropland, or range, pasture, forest, and woodlands resulting from land uses or from a process or combination of processes, including processes arising from human activities and habitation patterns, such as:

1. Soil erosion caused by wind and water;
2. Deterioration of the physical, chemical, and biological or economic properties of soil; and
3. Long-term loss of natural vegetation.

Per definition, land degradation can be caused by both human activities and natural events (Mainguet and Da Silva, 1998). With the impact of global climate change becoming ever -more evident, it is important to separate human-induced land degradation from that caused by climate change, over which land users have little or no control (Vlek et al., 2010).

The dominant causes of degradation are mapped at a world scale in UNEP (1992). At this broad level, the relations are very much as would be expected. Agricultural activities are given as a cause of degradation throughout most of the agricultural lands of the world, in all continents. Deforestation appears as a joint cause with agriculture over large parts of the world, and as a cause ~~in its own~~ right over much of the remainder of the rain forest zone. A recent study (Kirschke et al., 1999) of 73 developing countries has shown that deforestation rates are relevant as a causative factor for both wind and water erosion (including degradation through loss of nutrients and organic matter) under both humid and arid climate conditions, except for the combination of wind erosion in dry countries, where the correlation is less clear.

Land degradation is therefore a social problem involving people at all stages not only as causative factors but also as victims (Blaikie and Brookfield, 1987; Spooner, 1987). Although, according to the UNCCD (1996b), land degradation is attributed to dry land ecosystems only, it is generally accepted that land degradation takes place in temperate climates as well (Akhtar – Schuster et al., 2010).

2.2 Importance on the Availability of Land Degradation Information

Knowledge on the spatial distribution of land degradation is as relevant as knowing the availability of a resource base. Sujatha et al. (2000) claimed that the information on the nature, extent, severity and geographic distribution of degraded lands is of paramount importance for planning reclamation strategies and setting up preventive measures for sustainable agriculture development. As such, they become a significant basis for planners in drafting and implementing development plans for sustainable use of land resources (Hill et al., 1995a) as well as for resource restoration and quality enhancement (Lal, 1998b). Particularly, reliable information on the nature, extent and magnitude of soil erosion is required in planning and implementation of soil conservation and management programs (Dwivedi et al., 1997a).

Satisfactory information on degradation changes provides satisfactory strategies for the prevention and mitigation of land degradation (Barrow, 1994). Degradation changes being monitored give a considerable attention to the planners. According to Eswaran et al. (2001) ~~information which~~ gives a warning indicator to degradation problems can gain a collective effort to determine mitigation measures

2.3 Land Degradation in Ghana

Many factors are driving long-term soil and vegetation degradation in Ghana, including population pressure, increased urbanization, and climatic changes. These long term driving factors are reflected in agricultural, mining and other production practices that have led to soil erosion, soil nutrient depletion, overgrazing, pollution, river and groundwater depletion, and desertification arising from deforestation. The short-term causes of land degradation are mainly natural factors and human activities. Natural factors include the physical and other characteristics of the soil, which affect the eroding of the soil and its capacity to retain and drain water and to hold nutrients; topography; and climatic conditions.

Climatic conditions are important for soil erosion as prolonged periods of heavy rain separated by prolonged dry periods contribute to the reduction of vegetative cover, thereby increasing the risk of soil erosion. Such climate patterns are more prevalent in the Guinea and Sudan Savannah zones, as these areas have soil/vegetation types that are particularly susceptible to such type of climate pattern. In addition to the seasonal variability in rainfall, wide fluctuations in spatial distribution and amount of rainfall, as well as number of rainy days that occur over years and decades, lead to frequent droughts. The major droughts of 1968–73, 1982–85, and 1990–92 in Ghana caused serious hydrological imbalances that negatively affected land resources, particularly soil quality and fresh water supplies (EPA, 2002). Climate change may also contribute to accelerated coastal erosion, to which Ghana is particularly vulnerable (ISSER/DFID/WB, 2005).

The human-associated factors driving long-term soil and vegetation degradation in Ghana are reflected in unsustainable farming practices, removal of vegetation cover (including deforestation and overgrazing), mining activities, and urbanization and industrial activities caused by increased population growth pressures. The agricultural farming systems used in Ghana can be categorized as rotational bush fallow, permanent tree crop, compound farming, mixed farming, and special horticultural farming systems. These farming systems have peculiar characteristics that have different effects on the soil. The rotational bush fallow system which is characterized by clearing and burning of the vegetative cover is the dominant farming system throughout Ghana. The clearing and burning normally destroys the vegetative cover and makes the soil susceptible to erosion and leaching to soil infertility (Diao et al., 2007).

2.4 The role of Remote Sensing and GIS in Land Degradation Detection and Monitoring

The most accurate method for detection of land degradation is the direct measurement and observation at individual sites. This demands many observations as the area of mapping coverage becomes large. Consequently, stratification is done and examination of representative sites are employed which lead to subjective and non-rigorous selection (Pickup, 1989). In most cases, such a technique fail to produce detailed mapping outputs due to budget constraints, inaccessible areas, insufficient standardization and repeatability (Hill et al., 1995a). As mentioned in Sujatha et al (2000), impracticalities of the conventional survey are reasonably due to rugged areas and inaccessible terrain. With such a constraint, remote sensing becomes an alternative to map land degradation (King and Delpont, 1993; De Jong, 1994).

Pickup (1989) also stressed the importance of the spectral temporal model of analysis in assessing land degradation. It is because of the differences of soil and vegetation reflectance at the different wavelengths and the temporal components giving a trend idea on the pattern at which ~~land~~ degradation occurs. Hill et al (1995b) pointed out the importance of monitoring soil conditions including vegetation regime and recovery over time in understanding the process of land degradation from their spatial context. The study identified that the incorporation of terrain parameters improved the classification not only for the current degradation but also for erosion risk analysis. Temporal variation of eroded lands was investigated by Dwivedi et al. (1997b) using Landsat MSS and Landsat TM and reported the increase in land degradation units both in spatial context and severity.

Remote sensing provides a convenient source of information but the data collected by these instruments do not directly correspond to the information we need (Hill et al., 1995b). The study emphasized that changes in albedo and/or reflectance do not necessarily mean changes or worsening of degradation problems. This could be attributed to other changes in land surface characteristics such as clearing of woodlands, maturing cereals and dry vegetation. In a temporal aspect of analysis, Hill et al. (1995a) stressed that change detection should also be given extra care due to the radiometric effects that would mislead the analysis at different times of acquisition such as state of the atmosphere, illumination and drifts in sensor calibration. Singh (1989) on the other hand considers soil moisture as an important factor affecting land degradation change detection analysis and thus proposes to be taken into account.

Remote Sensing has high potential for land degradation data collection due to large area coverage, regular time interval, spatial and spectral resolution and which facilitates detection of degraded areas (De Jong, 1994). For degradation mapping, features whether they are directly or indirectly visible on the ground should be considered. For this reason, signs of degradation features should be well considered (Metternicht and Zinck, 1997). Degradation features that must be checked in the field include 1) signs of degradation on bare ground, 2) signs of degradation provided by vegetation and land use, and 3) signs of degradation provided by the terrain morphology (King and Delpont, 1993).

Singh (1989) arrived at two basic approaches dealing with change detection; 1) the comparative analysis of independently produced classification for different dates, and 2) the simultaneous analysis of multi-temporal data. Different change detection techniques include univariate image differencing, vegetation index differencing, image regression, image ratioing, principal component analysis, post classification comparison, direct multi-date comparison, change vector analysis and background subtraction. Various researchers use multi-sensor data in monitoring salt affected soils, water-logged and eroded soils, and desertification (Tripathy et al., 1996; Dwivedi et al., 1997b; Sujatha et al., 2000). Though researchers devised best techniques to serve their purpose, these techniques seem to yield different levels of results for different environmental features and applications (Pohl and Van Genderen, 1998).

2.5 Land Use/Cover

FAO (2000), define Land cover as the observed (bio) physical cover of the earth's surface and also define Land use as the arrangements, activities and input that people undertake on a certain land cover type. From these definitions, it can be deduced that Land cover is more obvious to notice than land use as the term 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 complicated as it has different meanings to different scientists. According to natural scientists, the term refers to the application of the land surface to human activities ~~such~~ as agriculture, forestry and building of structures, whilst the social scientists define land use as how the land is managed in terms of socio-economic purposes (Ellis, 2009). Therefore, 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 (Meyer and Turner II, 1994). For instance, forest can be used for many purposes such as logging, hunting, firewood collection and recreation, to mention a few.

2.6 Land Use/Cover Change

Land use change is defined to be any physical, biological or chemical change attributable to management, which may include conversion of grazing to cropping, change in fertilizer use, drainage improvements, installation and use of irrigation, plantations, building farm dams, pollution and land degradation, vegetation removal, changed fire regime, spread of weeds and exotic species, and conversion to non-agricultural uses (Quentin et al., 2006).

In order to understand land cover change, careful investigation should be carried out since studies in land cover change involve complex procedures. According to FAO (2000), land cover change can be of two types:

- Conversion from one land cover category to another, e.g. from forest to grassland; and
- Modifying within one category, for example from dense forest to open forest.

Changes in land cover results 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 changes in land cover due to alteration in the physical state of the earth's surface. In return, these environmental changes have an impact on the land cover.

2.7 Digital Change Detection

Lu et al (2004) categorized change detection procedures into three steps namely image pre- processing, selection of suitable techniques and accuracy assessment. The study further expressed that research in change detection should be able to provide information on (1) area of change and change rate; (2) spatial distribution of changed types; (3) change trajectories of land use/cover types; and (4) accuracy assessment of change detection results. For change detection procedures to be effective, the multi-temporal images used should be recorded in the same spatial resolution and in the same season of the year and most importantly, spatially registered accurately (Lillesand and Kiefer, 2008). This is because various factors such as the sensor system, the image processing methods and environmental factors strongly affect the reliability of change detection.

Since the launch of remote sensing satellites in 1972, there have been several attempts to detect land cover changes based on remote sensing data. Many methods of change detection techniques have been developed by several researchers (Lambin & Ehrlich, 1997; Mas, 1999; Singh, 1989), but in spite of the numerous evaluations of these techniques, there has been no concrete conclusion on which ones to be adopted as the the most effective (Macleod and Congalton 1998; Lu et al., 2004). These methods have been broadly categorised into two approaches, which are pre-classification and post-classification methods (Lunetta, 1999; Nelson 1983; Pilon and Howarth, 1988; Singh, 1989).

Pre-classification change detection includes techniques such as image differencing, image ratio, image regression, vegetation index differences, change vector analysis and principal component analysis. This technique is based on pixel-wise operation in that it uses the raw digital numbers (DNs) to discriminate temporal difference between multi-spectral images. The results of this change detection technique are pixel values providing meaningful information on “change and no -change” within the data. The limitations of this technique are that it requires application of a suitable threshold to differentiate change from no-change areas and since it is dependent on raw DNs values, the image data should usually be corrected for illumination and atmospheric effects (Lillesand and Kiefer, 2008).

The second approach, post-classification change detection requires independent classification of two satellite images to detect change in land cover type. It operates with two independent classified images as inputs and produces information on change matrix and change map which provide transitional (“from-to”) change information on the two dates of imagery (Bauer et al., 2004). The principal advantage of this technique lies in the facts that the two dates of imagery are separately classified; thereby minimizing the problem of radiometric calibration between dates (Singh, 1989). However, the accuracy of the change information depends on the accuracy of the classification of the individual images (Mertens and Lambin, 2000).

2.8 Markov and Cellular Automata

Markov chain analysis has been used as an effective tool in modelling and predicting land use/cover change. A Markov chain is a discrete random process with the property that the future state of system at time t_2 can be modelled solely on the basis of the current state at time t_1 (Eastman, 2006). Thus, knowing the current state of system provides much information on the future state and does not depend on the history before the current state at time t_1.

The Markov chain process takes two classified images to generate a transition probability matrix which represents the conditional probability for a transition from one class at time t_1 to another at time t_2. The accuracy of the predicted land cover map is based on the accuracy of the individual classified images. Harbaugh and Bonham-Carter (1970) explained that the transition matrix is a powerful analytical tool for describing a succession of events in space or time. Cellular automata are discrete spatio-dynamic systems which were first, developed by Ulam in the 1940s and used to investigate the logical nature of self-reproducible systems (White and Engelen, 1993). A Cellular Automaton system comprises of a regular grid of cells which is updated synchronously in discrete time steps according to a local, identical interactive rule. The state of a cell is determined based on its previous state, its surrounding neighbourhood cells and according to specific rules.

Eastman (2006) compares Cellular Automata to Markov process and considers them to be similar except that the transition rule is not only based on the previous state but also the state of neighbouring cells. In addition to this difference, Cellular Automata incorporate a spatial component to address the dynamism of change with the advantage of increasing the computational efficiency. Based on these advantages, a Cellular Automata have become favourites to many modellers (White and Engelen, 1997).

2.9 Tasseled Cap Transformation (TCT)

Tasseled Cap Transformation (TCT), also known as Kauth–Thomas tasselled cap (TC), was initially developed for crop-development surveys (Kauth and Thomas, 1976). The name "tasseled cap" comes from the fact that when the greenness and brightness of a typical scene are plotted perpendicular to one another on a graph, the resulting plot usually looks like a cap (Jensen, 1996). It is basically a guided and scaled principal-components analysis (PCA) that transforms the six Landsat ETM/TM bands into three orthogonal planes or components of known characteristics (Fung 1990, Collins and Woodcock 199; Huang et al. 2002). Research has produced three data structure axes that define the vegetation and soil information content (Crist et al, 1986; Crist and Kauth, 1986):

- Brightness—a weighted sum of all bands, defined in the direction of the principal variation in soil reflectance.

- Greenness—orthogonal to brightness, a contrast between the near infrared and visible bands. It is strongly related to the amount of green vegetation in the scene.
- Wetness—relates to canopy and soil moisture (Lillesand and Kiefer, 1987). It contrasts the sum of the visible and NIR bands with the longer infrared bands to determine the amount of moisture being held by the vegetation or soil (Crist and Cicone 1984; Cohen et al. 1998).

2.10 Previous Works

There are numerous examples of traditional and expert based image classification systems for detection, monitoring and mapping of land use/cover change and land degradation using remote sensing data.

Tasseled Cap Transformation and Normalized Difference Vegetation Index (NDVI) are very useful techniques to identify and delineate land degradation from vegetation coverage. Hu et al (2004) used NDVI and Tasseled Cap Transformation for negative and positive change of land degradation over time in the northwestern part of China. They found that the area of vegetation cover and soil wetness increased in this part from 1987 to 1996.

Breunig et al (2008) used reflectance and emissivity information from ASTER imagery to identify exposed soils as well as produce topsoil texture image in an agricultural area of central Brazil. They used band combination by band 5, 6 and band 10, 14 to discriminate dark-red clay soils and bright sandy soils, respectively. From this study, highest sandy surface at lower elevation and clay surface at higher elevation were observed. The highest sandy surfaces were coincident with land degradation process in the area.

A helicopter view of Land degradation using multi-sensor image fusion and post classification procedure was given by Torrion (2002). The study used Landsat TM, ASTER, ERS-2, SAR, and DEM. Severe soil degraded areas were discovered in the South-Western part of the Nakuru district, Kenya. Vegetation cover, rainfall, surface run-off and soil erosion have an important role in the prediction of land degradation.

Shareful (2009) used Landsat TM and ETM+ to identify land degradation and to assess land use change over 12 years in he North-Western part of Bangladesh. Spectral Angle Mapper (SAM) classifier of supervised classification technique was used to classify land use. The brightness image of a Tasseled Cap Transform (TCT) was used to extract dry soil in this study. Degraded soils have increased from 1989 (3% of total lands) to 2001 (6% of total lands) while forest and winter agriculture changed to irrigated agriculture and settlements.

Symeonakis and Drake (2004) have used these factors over Sub-Saharan Africa. They estimated vegetation cover from digital satellite imagery using NDVI, surface run-off from Meteosat and soil erosion data from soil conservation service. Consequently, these factors were combined to highlight severe susceptibility of land degradation. They proposed this methodology for near real-time monitoring of land degradation as well.

To identify the characteristics of the arid rangelands of Australia, Graetz (1987) used the nature of soil and vegetation, spectral modeling and the indices of soil and vegetation from Landsat and NOAA to assess regular monitoring, mapping and management of land degradation in Australian rangeland. In this study, the arid and semi-arid lands were extended from the central area of Australia to the Western and Southern coasts. The study suggested that future studies of Australian rangeland will most likely use high frequency/low resolution spatial data (NOAA AVHRR) with low frequency/high resolution spatial data (SPOT, MSS/TM/ETM).

Zurayk et al. (2001) assessed land degradation in Aarsal, Lebanon using thematic map of drainage density, drainage texture, grazing, slope, and land use information. They used spatial overlay technique to create factorial soil degradation risk map in their study. From the resulting map they found over 90% of the areas are in low and very low soil degradation categories. The Nam Cham sub-watershed in Thailand was covered by dense forest about 35 years before. To neutralize communist activities, the government cut down a lot of trees and afterward those cut down forest areas were replaced by cultivation which has led to land degradation in the area. Patanakanog and Shrestha (2004) used Landsat TM and analogue aerial photographs to asses land use/cover and land degradation in the sub-watershed area. Aerial photos were used to classify land use/cover while Landsat TM was used for vegetation mapping (NDVI). In this study, highest land degradation was found in cropped areas while lowest in forest and grass areas.

Kiage et al. (2007) used Landsat TM and ETM+ to identify land degradation with land use change in Lake Baringo catchment in Kenya. In the study, NDVI and post classification comparison depicted the hotspots of land degradation and land use change. Most of the bare ground which was degraded significantly where found to have lower NDVI values.

Rao and Chen (2008) used brightness, greenness and wetness from the Kauth-Thomas Transforms (KT), NDVI to identify land degradation in the northwest China using Landsat TM and ETM+ data. Post-classification changed detection was followed to identify change. Their overall classification accuracy was over 80%. Most of the degraded grassland was found around the salt-affected soil in the study area.

Standard image enhancements and supervised image classification techniques were used by Ernani and Gabriels (2006) to identify land use and land degradation in the Yazd-Ardaka basin, Iran. To detect the changes of land use, they used the post classification comparison method. From the study, it was concluded that the condition of range land is improving, but an increase in irrigated agriculture lands has led to a decrease in ground water levels and an increase in salinity. Hellden and Stern (1980) carried out research on land degradation using Landsat imagery and social indicators in Southern Tunisia. They implemented two procedures during their study: (i) digital image classification by software and (ii) ground truth sampling of social and physical parameters, e.g., slope, gully erosion, vegetation cover, population density, dunes, deflation patches and so on. Finally, they combined all parameters in a weighted overlay table and identified degraded areas. In this research, population density and gully erosion were identified as the key factors for land degradation. They found high land degradation in the settlement and agricultural areas.

Combined applications of points-measurements of physical properties, soil spectral reflectance with Landsat TM and ETM+ data were used to identify physical degradation of soil by Omuto and Shrestha (2007) in the upper Athi river basin in eastern Kenya. In addition, NDVI and land surface temperature (LST) were used to recognize long term vegetation as well as thermal condition in the study area. They found 80% of classification accuracy with respect to ground data.

CHAPTER THREE

STUDY AREA AND DATA

3.1 STUDY AREA

The then Kintampo District was established in 1988 under LI 1480. However, in 2004 the Kintampo South District was carved out from it, and it was renamed the Kintampo Municipal by the Local government Act (Act 462, LI 1762). The Kintampo Municipal as illustrated in Figure 3.1 is one of the Seven (7) Municipals and among the Twenty-two (22) Municipal/Districts in the Brong-Ahafo region (BAR) of Ghana. It is located between latitudes 8°50'N and 7°58'N and Longitudes 1°58'W and 1°05'W and shares boundaries with five districts in the Country:, namely; Central Gonja District to the North; Bole District to the West; East Gonja District to the North-East (all in the Northern Region); Kintampo South District to the South; and Pru District to the South- East (all in the BAR).

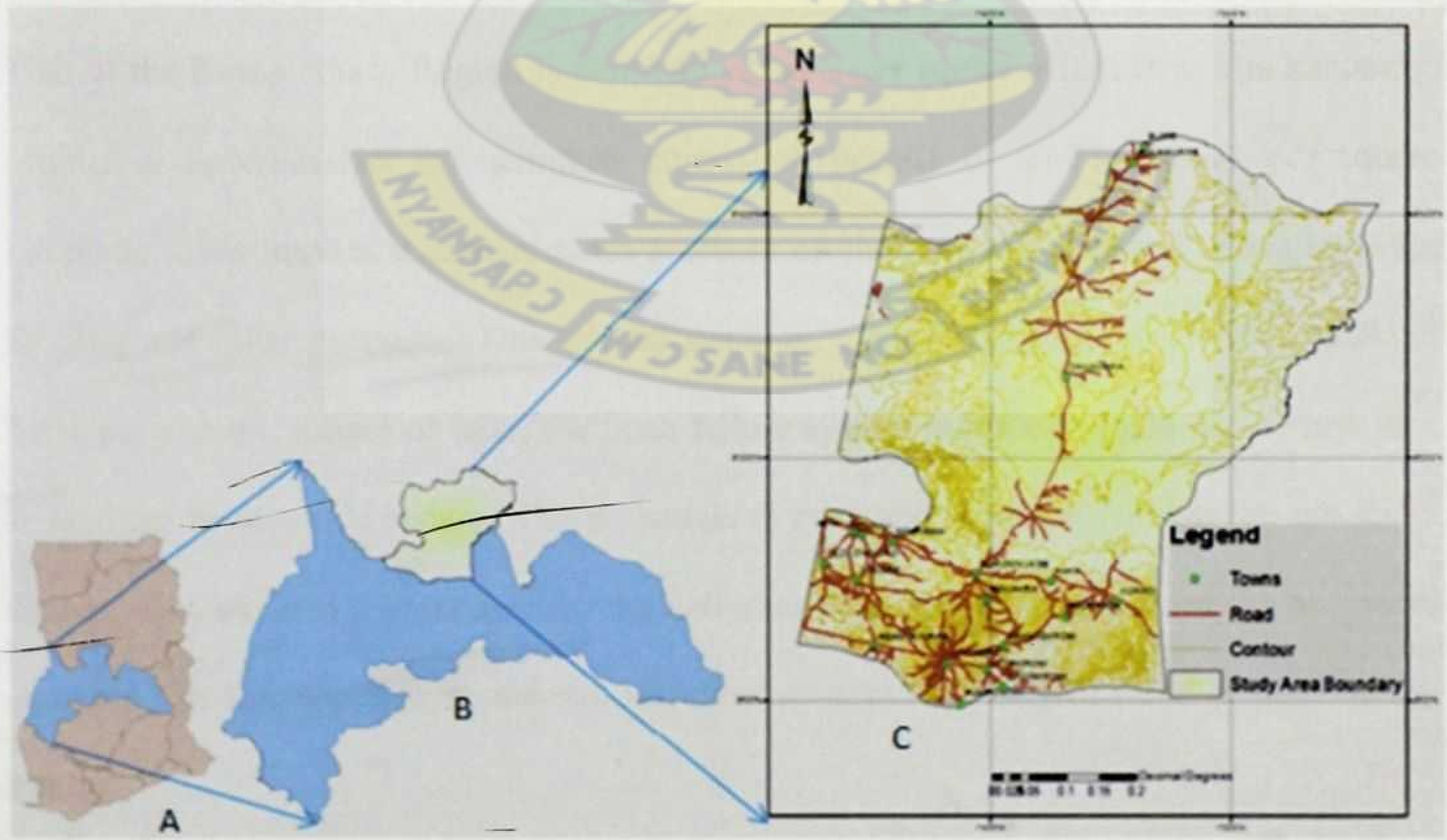

Figure 3. 1 Shows: A-map of Ghana, B-map of BAR and Kintampo Municipal , C-map of the Study Area (which is a subset of kintampo municipal)

The Municipal Capital, Kintampo, is about 130KM away by road from the regional capital and lies east of the BAR Capital, Sunyani. The Municipal has a surface area of about 5,108km^2, thus occupying a land area of about 12.9% of the total land area of BAR (39,557km^2) whereas the area of interest for this study covers a surface area of 4551.4 Km^2 of the municipal. In terms of location and size, the municipal is strategically located at the centre of Ghana and serves as a transit point between the northern and southern sectors of the country (Ministry of Local Government Rural Development & Environment, 2006).

3.1.1 Demographic (Population Size and Growth Rates)

Kintampo Municipal has an estimated population of 111,122 comprising 49.1% male and 50.9% female, with a growth rate of 2.6% (2000 population census). Because of the fertile nature of the land, migrant farmers from the north move to settle on arable lands where they can get enough farm produce consequently the area has a potential of population explosion. Table 3.1 shows population distribution in the study area.

The population density for the entire nation is about 79.3 persons per square Kilometre. That of the Brong Ahafo Region is about 44 persons per square Kilometre. The Kintampo Municipal however has an estimated population density of 21.75 persons per square kilometre. This implies that there is no pressure on the land and the land is available for farming and other purposes. This notwithstanding, with population growth rate of about 2.6% per annum, sooner or later, the bush fallow system practiced would not be possible, as land per head would reduce. The potentials in crop and livestock farming are not just a district asset but also a great asset to the nation at large and when accorded the necessary attention can enhance district and national development (Ministry of Food & Agriculture, 2011).

Table 3. 1 Distribution of Population (Source: Ministry **of Food & Agriculture, 2011)**

AREA/COMMUNITY	SEX		
	MALE	FEMALE	TOTAL
Kintampo	17,240	19,431	36,671
Babatokuma	3,823	3,818	7,641
Busuama	1,162	1,205	2,367
Dawadawa No.1 AND 2	4,266	4,422	8,688
Gulumpe	10,760	11,154	21,914
Kadelso	4,408	4,570	8,978
Kunsu	5,973	6,191	12,164
New Longoro	2,133	2,211	4,344
Portor	2,042	2,117	4,159
Others	2,060	2,136	4,196
TOTAL	54,561	56,561	111,122

The population figures given in Table 3.1 however include other smaller settlements around these major settlements. Thus, though, from the table Kintampo, Babatorkuma, Gulumpe and Kunsu are of urban status, only Kintampo is urban with the other communities more rural than urban settlements.

Table 3. 2 Estimated Age/Sex Structure (2010) (Source: Ministry of Food & Agriculture, 2011)

Age group	SEX					
	MALE	%	FEMALE	%	TOTAL	%
0-14	16,641	30.5	16,120	28.5	32,781	29.5
15-64	34,046	62.4	37,104	65.6	71,118	64.0
65+	3,874	7.1	3,337	5.9	7,223	6.5
TOTAL	**54,561**	100	**56,561**	100	**111,122**	100

From Table 3.2, it can be concluded that the Municipal has a matured population. This is manifested in the economically active population of 64.0% falling within the age group 15-64. This implies that the Municipality has the potential to produce more for the dependent group who fall within age groups 0.14 and 65 and above.

The Labour force (active population) made up of people between the age groups of 15-64 is estimated to be 64%. This is the population that works to earn a living or contribute meaningfully to the Municipal development. The remaining 36.0% (made up of 29.5% children aged 0-14 and 6.5% aged 65+) constitute the dependence load (Ministry of Food & Agriculture, 2011). Table 3.3 reveals that Agriculture has the highest occupational distribution with 71.1% followed by commerce with 13.7% at the study area.

Table 3. 3 Occupational Distribution (Source: Ministry of Food & Agriculture, 2011)

OCCUPATION	FREQUENCY	%
Agric	50,565	71.1
Commerce	9,743	13.7
Industry	2,916	4.1
Service	7,894	11.1
TOTAL	71,118	100

3.1.2 Migration

Migration here refers to the movement of people to and from Kintampo. The Municipality is a net receiver of immigrants mainly from the northern part of the country as settler farmers and a sizeable number of Nomadic herdsmen. They settled along the trunk road that runs through Kintampo to Tamale but others are scattered over the Municipality. Out-migrant is mainly of the youth who move out for greener pastures especially to Techiman, Kumasi and other towns (Ministry of Food & Agriculture, 2011).

3.1.3 Geology

The rock formation and type forms the geology of an area. The rocks underlying the Kintampo North Municipal form part of the "Voltarian formation" which covers about two – fifths (2/5) of the surface area of Ghana and about 80% of the District's land surface. Rocks belonging to this formation are mainly sedimentary and exhibit horizontal alignments.

Sand stone, shale, mudstone and limestone are the principal examples of these rocks. Oral reports revealed that the Voltarian formation was created soon after the Precambrian era when sagging of land occurred resulting in scarp slopes due to different levels of sagging. (Ministry of Local Government Rural Development & Environment, 2006)

The geology of the district is a potential resource for development. As already mentioned, deposits of clay, sand, limestone, stone/gravel and a few reported traces of gold at Kunsu, Sogboi, Bankamba and Dwere could be a stepping stone in the development of the entire district.

For instance, the abundant clay deposits at Benkrom, Bewele and Dwere could be used for glazed pottery and manufacture of burnt bricks and roofing tiles. However, large-scale exploitation of these resources has not taken place yet; neither is their economic viability established (Ministry of Local Government Rural Development & Environment, 2006).

3.1.4 Soils

Soils in the District belong to two main groups; the ground water lateral soils" which cover nearly three fifths of the district in particular and the interior wooded savannah zone in general Government Rural Development & Environment, 2006).. The other soil group, covering the rest of the two-fifths of the Municipality is the savannah ochrosols occurring in the south and south- western parts of the district.

These soils are formed mainly over Voltain shale and granites. The ground water lateral soils are generally poor in organic matter and in nutrients. However the savannah ochrosols are more supplied with organic matter and nutrients. Generally, these soils are good for the cultivation of tubers, cereals, tobacco, vegetable and legumes. Cashew and cotton production has been on a large scale in the Municipality (Ministry of Local Government Rural Development & Environment, 2006).

3.1.5 Climate

The Municipality experiences the Tropical Continental or interior Savannah type of climate, which is a modified form of the tropical continental or the Wet-semi equatorial type of climate. This is due largely to the fact that the district is in the transitional Zone between the two major climatic regions in Ghana.

The mean annual rainfall is between 1,400mm-1,800mm and occurs in two seasons; from May to July and from September to October with the minor season (May – July) sometimes being obscured (Ministry of Food & Agriculture, 2011). However, because of the transitional nature of the area, the distinction between the two peaks is often not so marked.

The mean monthly temperature ranging from 30°c in March to 24°c in August with mean annual temperatures between 26.5°c and 27.2°c. These conditions give rise to sunny conditions for most parts of the year. Relative humidity are light varying from 90%-95% in the rainy season to 75%-80% in the dry season. The climate of the district has the tendency to change and be inclined more to the drier tropical continental conditions or to the wet semi-equatorial conditions (Ministry of Local Government Rural Development & Environment, 2006).

3.1.6 Vegetation

The district comes under the interior wooded savannah or tree savannah. However, owing to its transitional nature, the area does not totally exhibit typical savannah conditions. Thus the savannah here is heavily wooded, though most of the trees are not as tall and gigantic as those in the most deciduous forest.

It is believed that the transitional Zone was once forested and that the savannah conditions currently prevailing have been the result of man's activities. This may be evidenced by the existence of "fringe forest" found along the banks of major rivers and streams and other areas where the impacts of man's activities are minimal.

Only trees such as the Mahogany, Wawa, Odum, Onyina, Boabab, Dawadawa, Acacia, and the Sheanut trees, which have adapted to this environment are found in the vegetation zone. They are few and scattered except along the margins of the moist deciduous forest where the trees often grow quite close together. Grass grows in tussocks and can reach a height of about 10 ft. (Ministry of Local Government Rural Development & Environment, 2006)

3.1.7 Topography and Drainage

The Kintampo North Municipal which falls within the Voltain Basin and the Southern Plateau physiographic regions is a plain with rolling and undulating land surface with a general elevation between 60-150m above sea level. The southern Voltain plateau occupying the southern part of the district is characterized by series of escarpments.

The municipal which falls within the Voltain basin is endowed with a lot of water resources. The major water bodies include the Fra, Urukwain, and the Nyamba rivers. Others are rivers Oyoko, Nante, Pumpum and Tanfi. These water bodies flow through the west of the district and join the Black Volta at Buipe. The slopes through which the rivers flow have given rise to waterfalls. The major ones include the Fular Falls on the Oyoko River and the Kintampo water falls on the Pumpum River. Most of these rivers are intermittent and the large ones like Urukwain and Pumpum fluctuate in volume. This makes them unreliable for irrigation purpose.

In terms of relief and drainage, the vast expanse of flat land especially the northern part makes it suitable for large scale mechanized farming. Road construction and other activities are also relatively cheap. The vast water resources in the western part of the district could be harnessed for irrigation purposes especially rice cultivation and dry season gardening as well as domestic supply of potable water. Fishing which is already an important activity on the Black Volta can be promoted if measures are put in place to ensure sustainable operations by the fishermen. (Ministry of Local Government Rural Development & Environment, 2006)

3.2 DATA

The study is based on several data types listed in the Table 3.4. These data types have been grouped into remote sensing (RS) and reference data. The study is based on the use of a time series satellite Landsat images – Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM+) as remote sensing data acquired in the years 1986 and 2005. These satellite data were downloaded from the Global Cover Land Facility (GCLF) database (with path 194 and row 054) based on the availability and suitability due to cloud cover (which is a problematic when it comes to detecting changes). One or more images between the years 1986 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%. Landsat images with a 30m x 30 m resolution were selected because they are free of charge, with high monitoring frequency and cover areas appropriate for monitoring the environment in a large geographic zone. Among the reference data are Google image, and land cover map of Ghana and digitized topographical maps of the study area.

Table 3. 4 Remote Sensing Data

RS Data	**Acquisition Date**	**Resolution**	**Sources**
Landsat TM	November, 1986	30m	GLCF WEBSITE
Landsat ETM+	November, 2005	30m	GLCF WEBSITE
Reference Data	**Acquisition Date**	**Scale**	**Sources**
Digital Ortho-Photo	2008		Survey and Mapping division, Lands Commission
land cover map	2005		GIS unit of CSIR-Soil division, Kumasi.
land cover map	2000		GLC 2000 database
digitised topographical map	2002	1:50000	Geomatic Eng. Dept. KNUST

3.2.1 Landsat Imagery

Since 1972, the Landsat satellites have provided repetitive, synoptic, global coverage of high-resolution multispectral imagery. Their long history and reliability have made them a popular source for documenting changes in land cover and use over time (Turner et al., 2003). Since the first launch, five other satellites have been successfully launched with the recent one being Landsat 7 which carries the Enhanced Thematic Mapper sensor on-board (U.S. Geological Survey, 2010). Table 3.5 show the technical summary information of Landsat imagery.

Table 3.5 Spectral property of various versions of Landsat images (source: Engineering manual, 2003)

Serial no	Name of Satellite	Sensor	Band number	Band wavelengths (μm)	size of Pixels (m)
2	Landsat 4-5	MSS	1	0.5 to 0.6	82
			2	0.6 to 0.7	82
			3	0.7 to 0.8	82
			4	0.8 to 1.1	82
		TM	1	0.45 to 0.52	30
			2	0.52 to 0.6	30
			3	0.63 to 0.69	30
			4	0.76 to 0.9	30
			5	1.55 to 1.75	30
			6	10.4 to 12.5	120
			7	2.08 to 2.35	30
3	Landsat 7	ETM	1	0.45 to 0.52	30
			2	0.52 to 0.6	30
			3	0.63 to 0.69	30
			4	0.76 to 0.9	30
			5	1.55 to 1.75	30
			6	10.4 to 12.5	120
			7	2.08 to 2.35	30
		PAN	4	0.5 to 0.9	15

The Landsat imagery used in this study is a Standard Terrain Correction (Level 1T) product. Level 1T - provides systematic radiometric and geometric accuracy by incorporating ~~ground control points~~ while employing a Digital Elevation Model (DEM) for topographic accuracy and to attain absolute geodetic accuracy. The WGS84 ellipsoid is employed as the Earth model for the Universal Transverse Mercator (UTM) coordinate transformation. Associated with the UTM projection is a unique set of projection parameters that flow from the USGS General Cartographic Transformation Package. The end result is a geometrically rectified product free from distortions related to the sensor (e.g. jitter, view angle effects), satellite (e.g. attitude deviations from nominal), and Earth (e.g. rotation, curvature, relief). Geodetic accuracy of the L1T product depends on the accuracy of the GCPs and the resolution of the DEM used. The 2000 and 2005 Global Land Survey is used as the source for GCPs while the primary terrain data is the Shuttle Radar Topographic Mission DEM.

3.2.2 GIS Data

An existing vector map of the study area was obtained from Geomatic engineering GIS centre. This map was used to clip or resize the Landsat imagery. The projection system of the vector map has been converted to the satellite data projection system, UTM zone 30N.

3.2.3 Referenced Data

In order to develop training data for the image classification and the accuracy assessment, combination of high resolution ortho-photograph, Google map and previously published maps as well as personal field experience were used in this study.

3.2.4 Selection of Software

The choice of Software used in this study was based on the image processing procedures, the prediction of future land cover change and generation of output map. 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 Kilimanjaro 15 was used to handle the modelling and prediction aspect of this study. ArcGIS 10 was used to generate the output maps.

CHAPTER FOUR

METHODOLOGY

This chapter describes the methods that were applied in the collection, processing, analysis and presentation of data with a view to fulfilling the set objectives. The methodology adopted in this study is summarised in the flow chart shown in Figure 4.1 below.

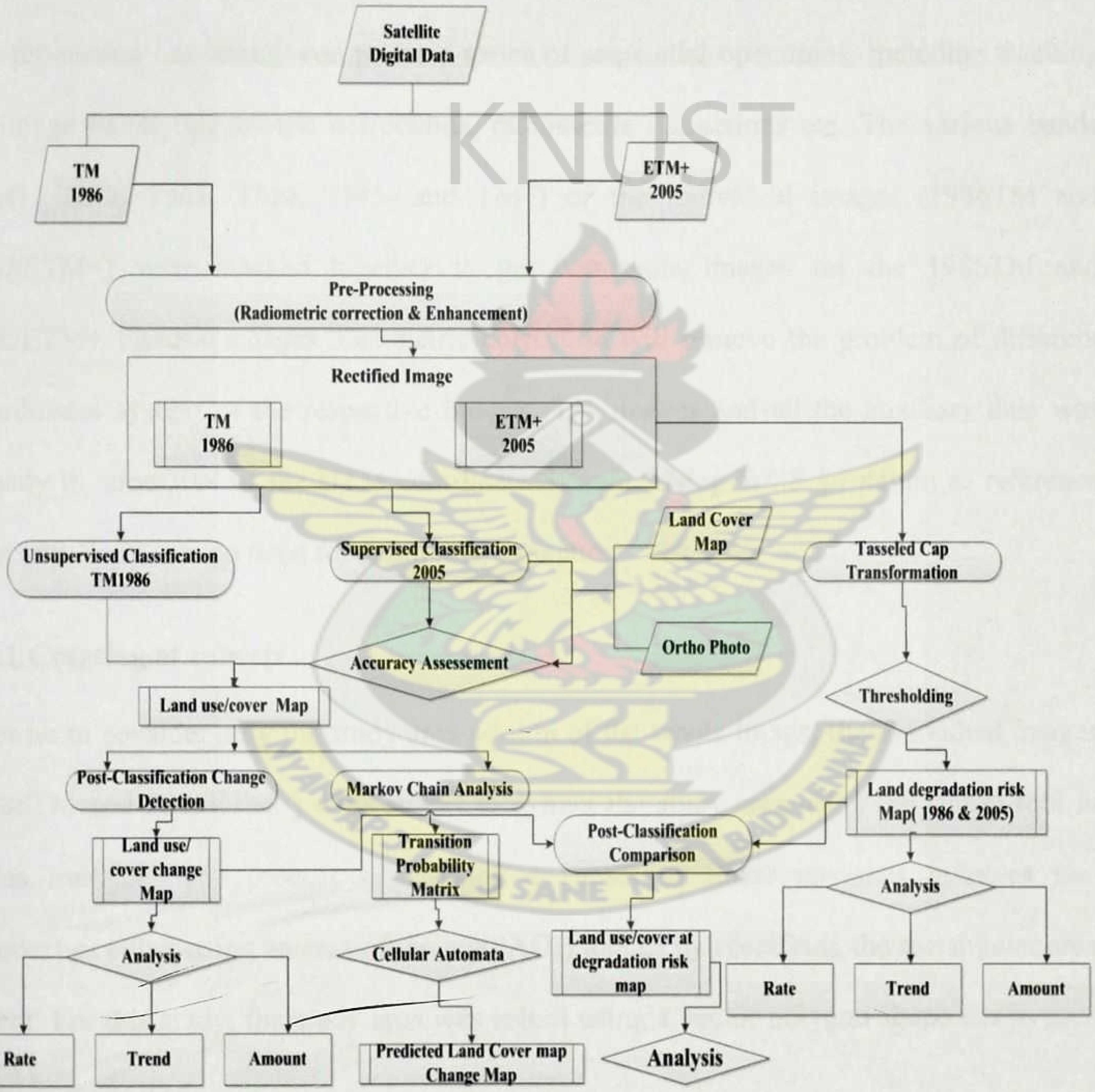

Figure 4. 1 Flow chart of methodology

4.1 IMAGE PRE-PROCESSING

Pre-processing of satellite images prior to image classification, change detection and tasselled cap transformation is essential. Due to spatial, spectral and temporal radiometric resolution constraints, the complexity of physical environment cannot be accurately recorded by normal remote sensing sensors. As a result, it is necessary to pre-process the remotely sensed data before the analysis.

Pre-processing commonly comprises a series of sequential operations, including stacking of image bands, Geometric corrections, radiometric corrections etc. The various bands (TM1, TM2, TM3, TM4, TM5, and TM7) of the individual images (1986TM and 2005ETM+) were stacked together to get composite images for the 1986TM and 2005ETM+ Landsat images. Geometric correction will remove the problem of different coordinates system of the respective images. The images and all the auxiliary data was already in zone 30N of the UTM coordinate System. Using WGS 84 datum as reference ellipsoid, there was no need for geometric correction.

4.1.1 Creating of subsets

In order to consider only the study area portion of the whole image, the individual images (1986TM and 2005ETM+) were subset to extract the study area using the subset tool in Erdas imagine. The process of creating a subset in Erdas imagines involves two approaches either using an area of interest (AOI) tool or by specifying the rectangular area extent. For this study, the ~~study~~ area was subset using a vector polygon shape file as area of interest (AOI).

4.1.2 Radiometric correction

Radiometric correction is performed to remove or reduce the inconsistency between the pixels values recorded by sensors and the spectral reflectivity and spectral radiation brightness of the objects (Jianya et al., 2008). In this study, little radiometric correction was done because the datasets were already corrected to some extent; but the images appeared to be hazy and therefore were corrected for haze using the haze reduction module in Erdas Imagine.

4.1.3 Image Enhancement

The individual subset images underwent image enhancement to improve the visual interpretation of the images, which is essential during image classification. A wide range of techniques are available. However, this study employed Histogram Equalization to enhance the images. This approach is based on assigning image values to the display levels on the basis of their frequency of occurrence (Lillesand and Kiefer, 2008).

4.2 IMAGE CLASSIFICATION SCHEMES

This study is based on the application of Post-classification change detection to detect land changes that have taken place in the study area. Since this technique is dependent on two or more thematic maps of different dates to detect changes, Image Classification was used to extract thematic information from the images.

4.2.1 Unsupervised classification

Unsupervised classification was used to cluster pixels in a data set without any user - defined training classes. Although the method requires no user input to create the classified image, the output tends to require a great deal of post classification operations to make the results more meaningful. The Iterative Self-Organizing Data Analysis Technique (ISODATA) clustering algorithm was used. It uses the minimum spectral distance formula to form clusters. It begins with either arbitrary cluster means or means of an existing signature set, and each time the clustering repeats, the means of these clusters are shifted. The new cluster means are used for the next iteration. The ISODATA utility repeats the clustering of the image until either a maximum number of iterations have been performed, or a maximum percentage of unchanged pixels have been reached between two iterations. The ISODATA clustering algorithm (Tou & Gonzalez., 1974; ERDAS, 1997) compares the radiometric value of each pixel with predefined number of cluster attractors, aggregates pixels in cluster s and shifts the cluster mean values in a way that the majority of the former aggregated pixels belongs to a cluster.

The ISODATA algorithm has some further refinements by splitting and merging of clusters (Jensen, 1996). Clusters are merged if either the number of members (pixel) in a cluster is less than a certain threshold or if the centres of two clusters are closer than a certain threshold. Clusters are split into two different clusters if the cluster standard deviation exceeds a predefined value and the number of members (pixels) is twice the threshold for the minimum number of members. The ISODATA algorithm is similar to the k-means algorithm with the distinct difference that the ISODATA algorithm allows for different number of clusters while the k - means assumes that the number of clusters is known a priori. Performing an unsupervised classification is simpler than a supervised classification, because the signatures are automatically generated by the ISODATA algorithm.

4.2.2 Clustering to detect the land use/cover classes

In clustering, the pixels were grouped into classes based on similar spectral characteristics. This was achieved using ~~isoclust~~, the implementation of the ISODATA algorithm in ERDAS, to detect clusters of pixels that have similar spectral characteristics. The ISODATA method does not need any ground truth. It analyses the images and organizes the pixels into clusters with similar characteristics without consideration of what these pixels represent in reality. Here it is assumed that pixels with similar characteristics represent the same land -use. It is very likely that the same land-use type can be represented with several clusters.

4.2.3 Aggregation of clusters

The clustering procedure is just grouping of pixels of similar spectral characteristics. In order to get informational classes, the clusters were grouped. Vector files with ground-truth data were used to detect which land-use classes the different clusters that have been created by Isoclust belong to. The images were reclassified to six (6) classes to create a land use/cover map for 1986 as shown in Figure 5.1. These classes were chosen based on field observation and general historical information of the study area and the description shown in Table 4.1.

Table 4. 1 Description of land use/cover categories for classification of 1986 and 2005 image

LAND USE/COVER	DESCRIPTION
Built-up	This comprised of areas of intensive use with much of the land covered by structures. And this involves towns, cities, transportation networks, etc.
Bare soil	it comprises of land area of exposed soil surface resulting from human activities or natural cause.
Agriculture land	it may be defined as land primary use for production of food and fibre, and other commercial and horticultural crops
Grassland	Refers to land where the potential natural vegetation is ~~predominantly~~ grasses grass-like plants and forbs. Land areas with sparely distributed trees or shrubs are also included in this category. They are mainly serving as grazing for wildlife.
Shrub land	includes shrubs closely distributed coupled with some trees and few grasses under the shrubs and trees with a cover density reaching 15m
Water	it comprises of rivers, dams, stream, lakes, etc.

4.2.4 Supervised Classification

This is a procedure for identifying spectrally similar areas on an image by identifying 'training' sites of known targets and then extrapolating those spectral signatures to other areas of unknown target. In supervised classification, the identity and location of some of the land use/cover types are known prior through a combination of fieldwork, interpretation of aerial photography, map analysis and personal experience (Hodgson et al., 2003).

Training areas, usually small and discrete compared to the full image, are used to "train" the classification algorithm to recognize land cover classes based on their spectral signatures, as found in the image. The training areas for any one land cover class need to fully represent the variability of that class within the image. There are numerous factors that can affect the training signatures of the land cover classes. Environmental factors such as differences in soil type, varying soil moisture, and health of vegetation, can affect the signature and affect the accuracy of the final thematic map. It is really important to choose a desirable classification scheme and algorithm. The Maximum likelihood classifier algorithm was chosen for this study as it proved to give better results as compare to the other supervised techniques tried.

4.2.5 Training Sites Development

Training areas were determined from maps and ortho-photos, topographical maps and other ancillary information (~~e.g. land~~ use database). Training sites were free of anomalies and large enough to provide good statistical representation. Also, there were sufficient numbers of sites selected for each class to account for small local variations within the class. The objective of training data is to obtain a set of statistics that describe the spectral pattern for each land use/cover category to be classified. These sets of statistics are used to determine decision rules for the classification of each pixel in an image. The training site were representative of their respective classes, including the variation within the class itself and the training data should closely fit the distribution assumptions, on which the decision rules are based (Campbell, 2002). Sample pixels representing each of the land use/cover categories were selected through onscreen digitizing on individual images using the too create polygon AOI from AOI tools. Polygons (training sites) belonging to the same land cover category were given the same ID or name. In total, there were adequate sample of pixels for each cover type for statistical characterization.

4.2.6 Spectral Signature Development

Signature files which contain statistical information about the reflectance values of the pixels within the training sites for each class were created. The statistical analysis for the reflectance values of the trained areas selected was examined to avoid significant loss of recognition accuracy. Feature spaces were plotted to ascertain the distribution of the individual pixels in the images. Histogram plots for the class signatures were also examined. These signatures were used to assess the performance of the trained areas before classification. The training site polygons were defined as a vector file of polygons. The vector file was converted to a raster image during the development.

4.2.7 Maximum Likelihood Classifier

This is a statistical decision rule that examines the probability function of a pixel for each of the classes, and assigns the pixel to the class with the highest probability. The classifier assumes that the training statistics for each class have a normal or 'Gaussian' distribution. However, many are not radar statistics in particular. The classifier then uses the training statistics to compute a probability value of whether it belongs to a particular land cover category class. This allows for within-class spectral variance. Equal probabilities were assigned to each of the land use/cover classes to weigh the probability function. This classification technique usually provides the highest classification accuracies. Accordingly, it has a high computational requirement because of the large number of calculations needed to classify each pixel.

4.2.8 Accuracy Assessment

This defines the extent to which a manual or automatic processing system correctly identifies selected classes. This process evaluates the accurateness of a derived thematic map.

In this study all the checkpoints data were extracted from the 2007 ortho-photographs and 2008 topographical map to perform Accuracy Assessment using the Classifier toolbar of Erdas Imagine. In all, ninety random reference points were extracted from the ortho-photographs, and were used to assess the accuracy of the classified images of 2005. The error matrix compares the relationship between known reference data (ground truth) and the corresponding results of an automated classification (Lillesand and Kiefer 2000). The overall accuracy, producer and consumer accuracy are discussed in section 5.2. The accuracy of the 1986 classified image could not be assessed since there were no available reference data to be used to determine the accuracy of the classification of this image.

4.2.9 Post classification comparison change detection

To minimize phonological effects of remotely-sensed data, the post-classification comparison method was employed for image processing, as this method is less sensitive to radiometric variations between the scenes (Mas, 1999). However, 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. Digital change detection techniques aim to detect changes in images over a period of time. Change detection techniques rely upon differences in radiance values between two or more dates.

However, few quantitative comparative studies of change detection techniques are available. There is no universally 'optimal' change detection technique. The choice is dependent upon the application. The selection of an appropriate change detection algorithm is important. Most change-detection projects require that the 'from-to' information be readily available in the form of maps and tabular summaries. Post-classification change detection was chosen because:

- It produces a transition matrix. This matrix describes each pixel if it has changed and if it has, from which class to what. This change information is valuable for analyses and for planning purposes.
- It provides "from-to" change information.

4.2.10 Detecting 'from-to' change using Cross Classification and Tabulation

In order to have insight into which land cover category is converted into the other, both cross classification and tabulation operations were performed. The cross classification gives visual information about the transformation of each land cover category by clicking on the legend. With the cross-classification operation, it is possible to visualize the change of one cover category to the other within the two periods. There are 36 'from to' different categories for the 6 different classes. This matrix describes each pixel if it has changed and if it has, from which class to what. This change information is significant for analyses and for planning purposes. Some of the land cover classes have higher tendency of transforming ~~to~~ the other ~~and vice versa~~. For instance, vegetation have higher tendency to transform into built-up or barren soil areas but the probability for urban areas and water to change to other classes were considered to have less probability.

4.3 Markov Chain and Cellular Automata Analysis

Markov Chain analysis was implemented using the Markov module embedded in Idrisi. The two land use/cover images1986 and 2005 were analyzed to produce a transition probability matrix, a set of conditional probability images between the two dates of thematic maps.

A cellular automaton which is another component of Markov was used to produce that aspect of the result which is a land use/cover map of the year 2024. The transition area matrix and the conditional probability images generated from Markov module and the land use/cover map for 2005 were later loaded in the CA_Markov module in the software and a contiguity filter of 5x5 was applied to generate the predicted map for 2024. This contiguity filter serves as a transition rule on which the prediction is based.

4.4 Tasseled Cap Transformation

Tasseled Cap transformation is one of the available methods for enhancing spectral information content of Landsat TM/ETM+ data. The tasseled cap transformation model in the Erdas Imagine 2010 was used to perform the transformation on the 1986 TM and 2005 ETM+ images to convert the land use/cover information included in the six bands into three bands often used:

- Band 1 (Brightness, measure of soil).
- Band 2 (Greenness, measure of vegetation).
- Band 3 (Wetness, interrelationship of soil and canopy moisture)

The Tasseled Cap coefficients of TM (Landsat 5) and ETM+ (Landsat 7) which were used in the study as shown in Table 4. 2

Table 4. 2 The Tasseled Cap coefficients of TM and ETM+

Sensor	Index	Band 1	Band 2	Band 3	Band 4	Band 5	Band 7	Additive
L-5 TM	Brightness	0.2909	0.2493	0.4806	0.5568	0.4438	0.1706	10.3695
	Greenness	-0.2728	-0.2174	-0.5508	0.7221	0.0733	-0.1648	-0.731
	Wetness	0.1446	0.1761	0.3322	0.3396	-0.0492	-0.4186	-3.3828
	Haze	0.8461	-0.0731	-0.464	-0.0032	0.4162	0.0119	0.7879
	TC5	0.0549	-0.0232	0.0339	-0.1937	0.4162	-0.7823	-2.475
	TC6	0.1186	-0.8069	0.4094	0.0571	-0.0228	-0.022	-0.0336
L-7 ETM+	Brightness	0.3561	0.3972	0.3904	0.6966	0.2286	0.1596	
	Greenness	-0.3344	-0.3544	-0.4556	0.6966	-0.0242	-0.263	
	Wetness	0.2626	0.2141	0.0926	0.0656	-0.7629	-0.5388	
	Haze	0.0805	-0.0498	0.195	-0.1327	0.5752	-0.7775	
	TC5	-0.7252	-0.0202	0.6683	0.0631	-0.1494	-0.0274	
	TC6	0.4	-0.8172	0.3832	0.0602	-0.1095	0.0985	

4.5 Mapping Land Degradation risk Area

For the purpose of the study, the soil brightness index (SBI) which is the brightness component of the tasseled cap transformation was specifically used to map areas of the study susceptible to land degradation. The standard deviation threshold, thus Mean ± standard deviation of the brightness layers of 1986 and 2005 images resulted from the application of the tasseled cap transformation was used to mask out land degradation risk areas for the 1986 and 2005 images.

4.6 Linking Land Degradation Risk to Land Use/Cover

A linkage between the Land use/cover and the land degradation risk images is valuable for understanding how different land use/cover classes affect land degradation. The two images were compared pixel by pixel to generate a map and table indicating land degradation risk and associated land use/cover distribution.

CHAPTER FIVE

RESULTS AND DISSCUSTION

5.1 RESULTS

5.1.1 Land use/cover in 1986

The unsupervised classification produced land use/cover of TM1986 Landsat image of the study area. The classification categorized the area into six (6) main land use/cover types as elaborated in Table 4.1. The classified land use/cover map of the study area is shown in Figure.5.2. Table 5.1 and Figure 5.1 reveal the greatest share of land use/cover classes is Grassland which covers an area of 306110.25 ha (67.26 %). Bare Soil and Shrub land have covered areal size of 68888.43 ha (15.14%) and 48008.25 ha (10.55%), respectively. Agriculture land, Built-up and water have covered 20809.98 ha (4.57%), 9944.1 ha (2.18%) and 1377.27 ha (0.3%) from the total size of the study area respectively.

Table 5. 1 Area in hectares and percentage area coverage of land use/cover in 1986

	1986	
Land use/cover Class	Area (ha)	Area (%)
Shrub land	48008.25	10.55
Grassland	306110.25	67.26
Water	1377.27	0.3
Built-up	9944.1	2.18
Agriculture land	20809.98	4.57
Bare Soil	68888.34	15.14
Total Area	455138.19	100

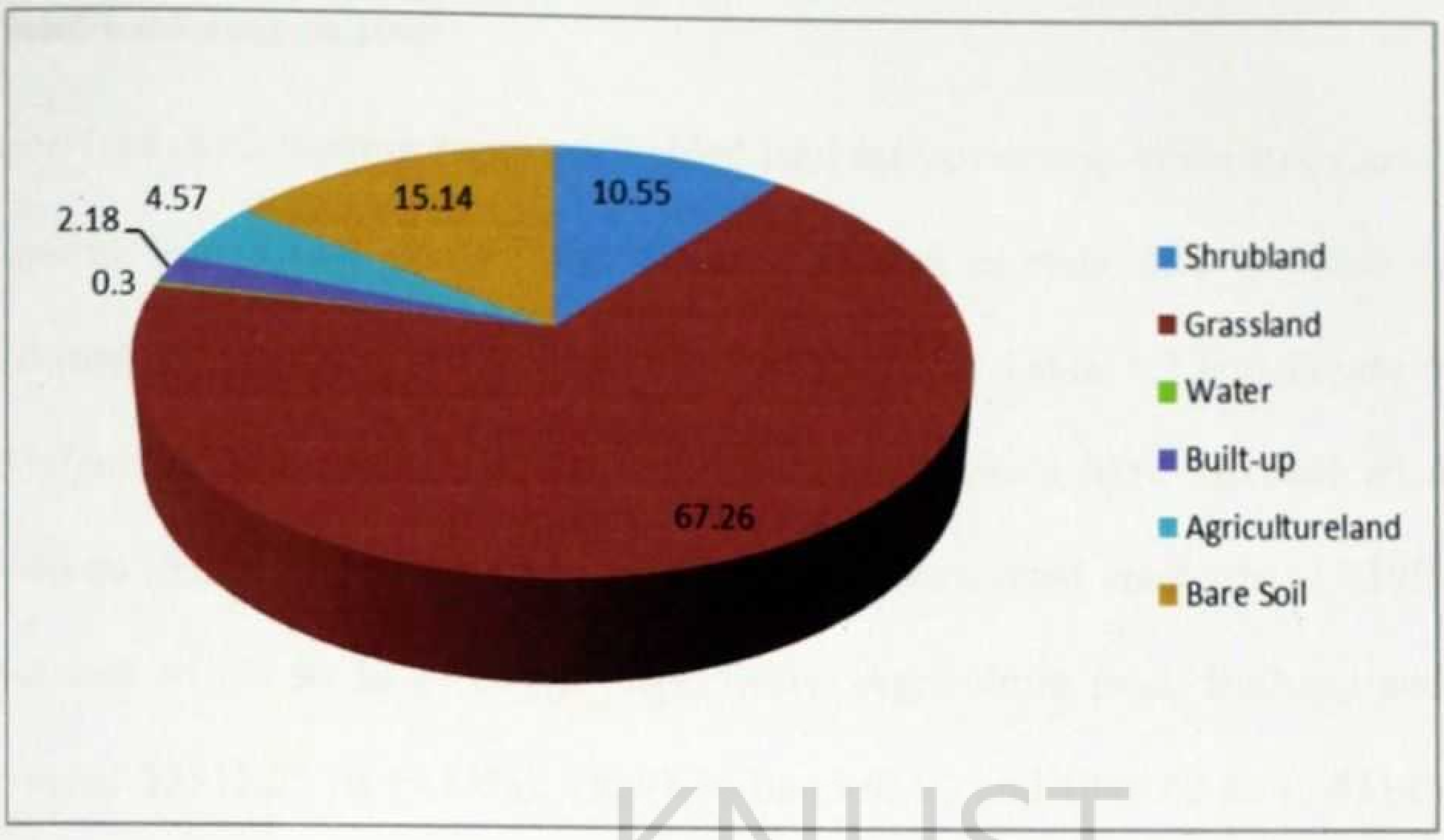

Figure 5. 1 Percentage coverage of land use/cover in 1986

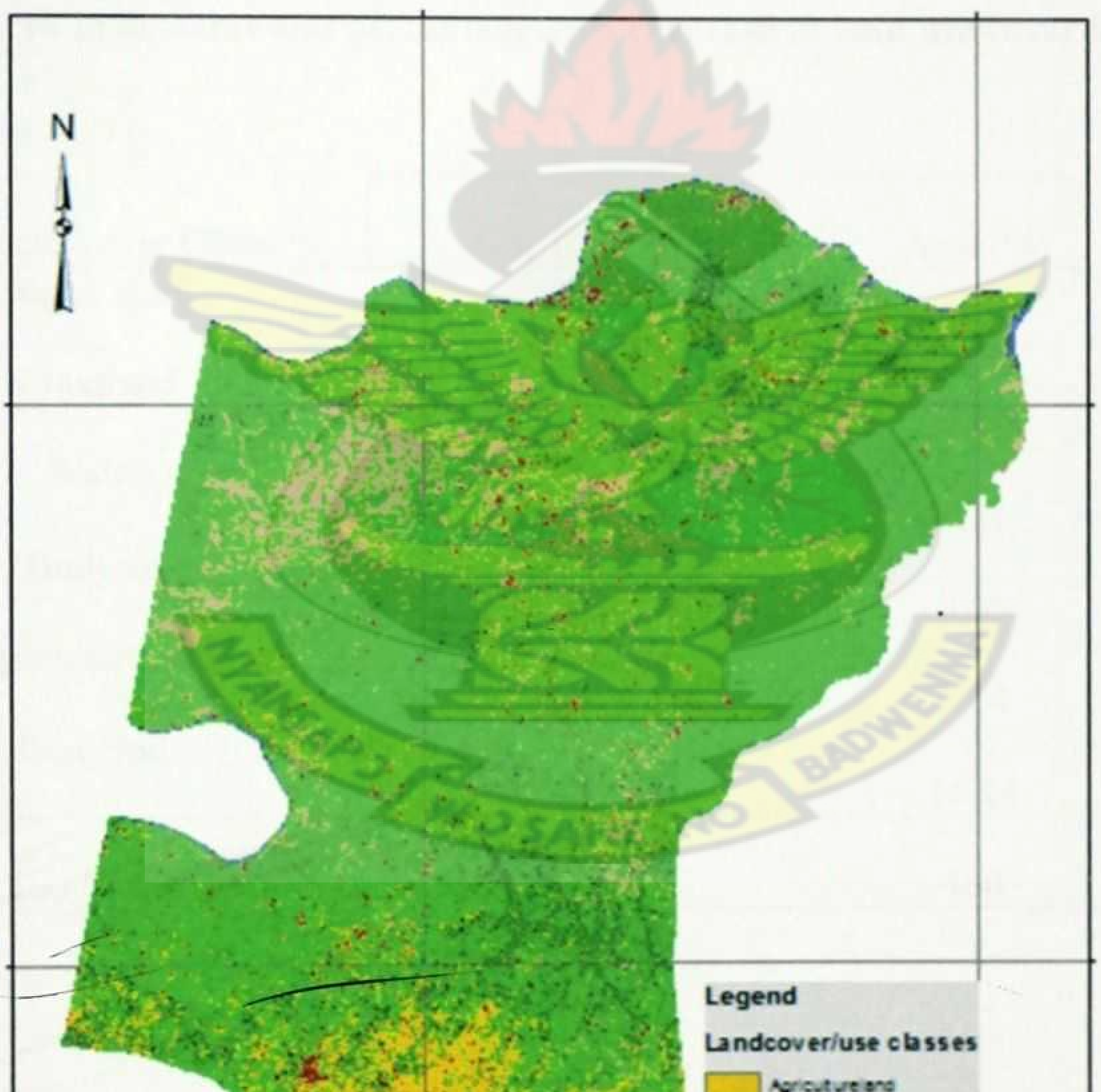

Figure 5. 2 land use/cover map of the study area in 1986

5.1.2 Land use/cover in 2005

The supervised classification approach yielded land use/cover map of the study area for the 2005 Landsat image with six (6) land use/cover classes as elaborated in Table 4.1. The thematic map is presented in Figure 5.4. As indicated in Table 5.2 and Figure 5.3: the greatest share of land use/cover classes is Grassland which have covered an area of 289086.66 ha (63.52 %). Bare Soil and Shrub land have covered areal size of 73952.73 ha (16.24%) and 41139.54 ha (9.04%), respectively. Agriculture land, Built-up and water have covered 32515.29 ha (7.14%), 16597.35 ha (3.65%) and 1846.62 ha (0.41) from the total size of the study area, respectively.

Table 5. 2 Area in hectares and percentage area coverage of land use/cover in 2005

	2005	
Land use/cover Class	Area (ha)	Area (%)
Shrub land	41139.54	9.04
Grassland	289086.66	63.52
Water	1846.62	0.41
Built-up	16597.35	3.65
Agriculture land	32515.29	7.14
Bare Soil	73952.73	16.24
Total Area	455138.19	100

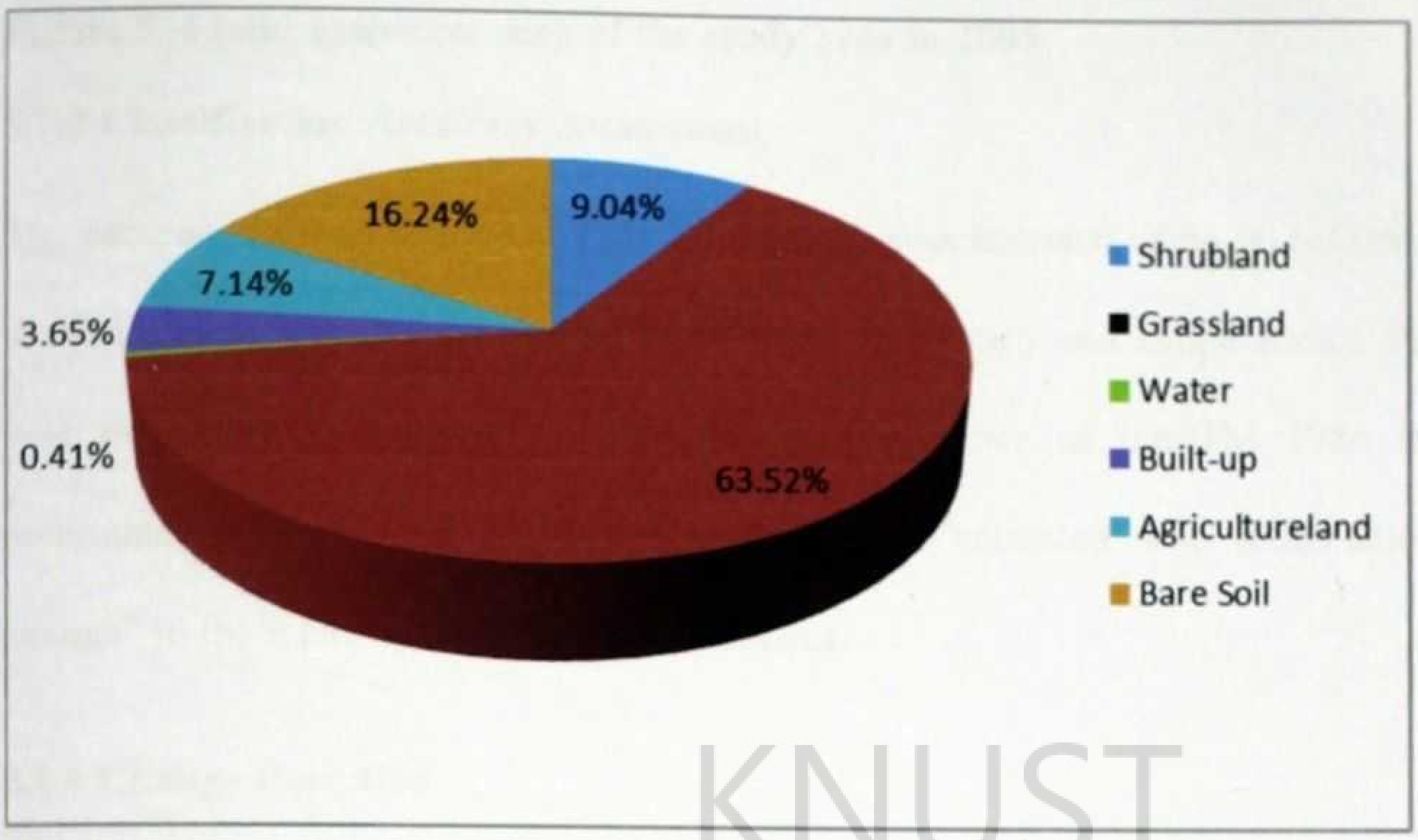

Figure 5. 3 Percentage coverage of land use/cover in 2005

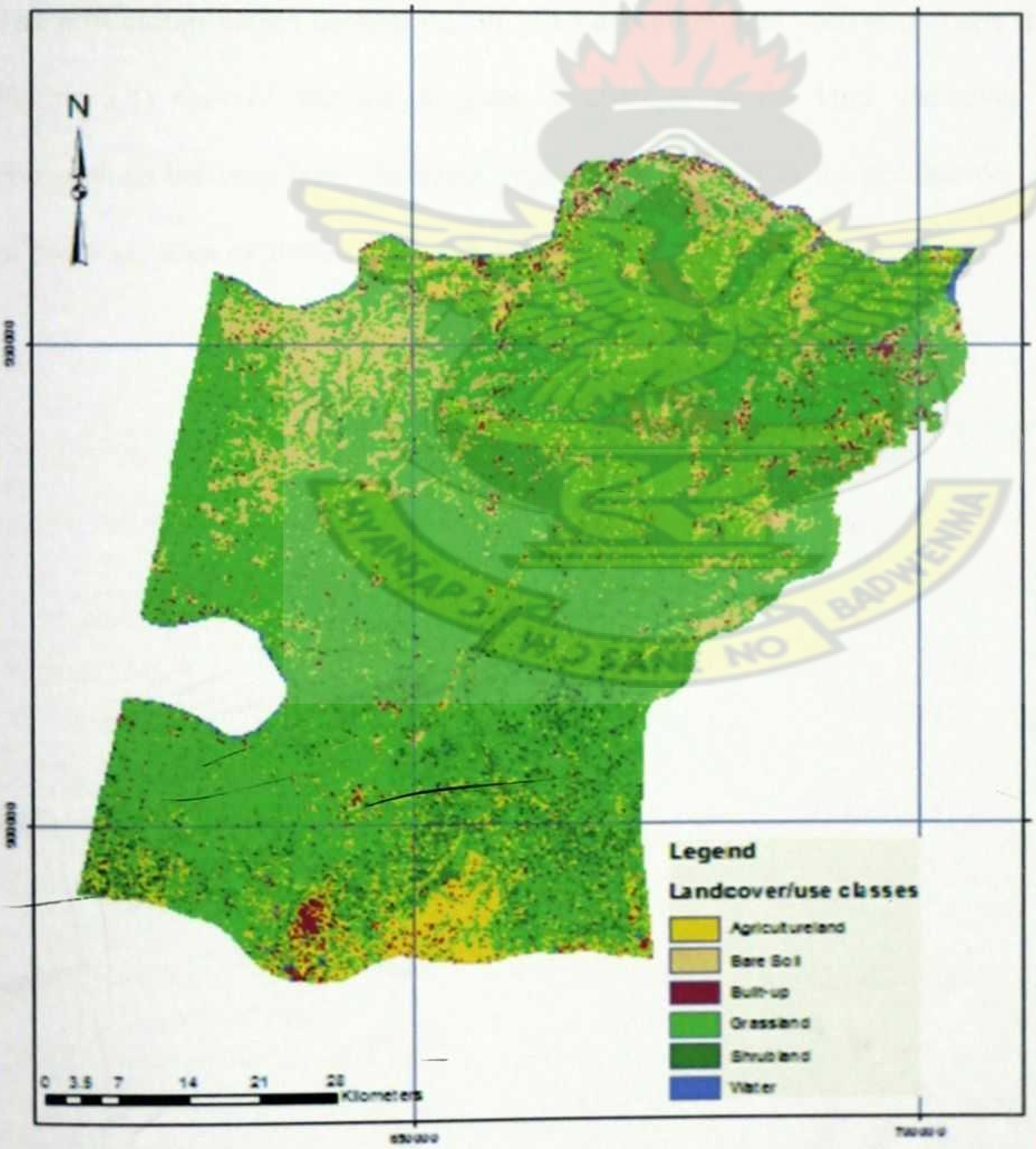

Figure 5. 4 land use/cover map of the study area in 2005

5.1.3 Classification Accuracy Assessment

The accuracy of the classified ETM+ 2005 image was assessed using 90 referenced points to obtain error matrix with overall classification accuracy and kappa statics 86.67% and 0.84 respectively (appendix 1). However, the accuracy of the TM 1986 image was ascertained with the use of local knowledge and validated with information on "no change" in the ETM 2005 and TM 1986 images.

5.1.4 Change Detection

5.1.4.1 Land use/cover Dynamics from 1986 to 2005

The post classification comparison of 1986 and 2005 land use/cover maps (Figure 5.2 and Figure 5.4) showed varying degrees of changes in the land use/cover types due to conversions between land use/cover types. This resulted in the production of change map of the study area as shown in Figure 5.5.

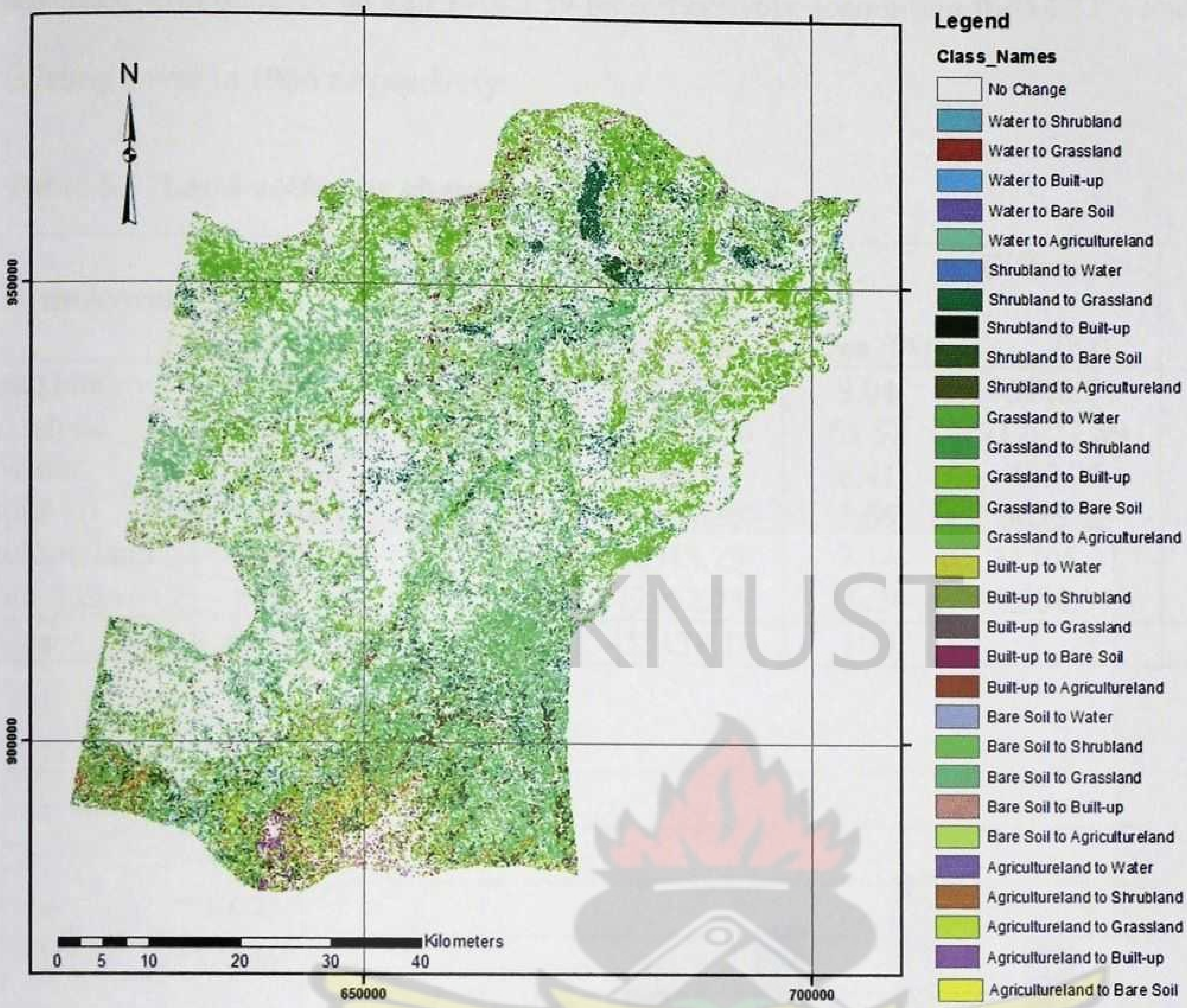

Figure 5. 5 Change map from 1986 to 2005

5.1.4.2 Land use/cover change trends from 1986 to 2005

Table 5.3 and Figure 5.6 show the extent of change trends among land use/cover types. Generally, all the six (6) land use/cover types experienced changes in areal coverage from 1986 to 2005. Agriculture land, built-up, bare soil and water have increased while shrub land and grassland have been decreased over areal coverage in this particular period of time. Agriculture land, built-up, bare soil and water have increased with 11705.31 ha, ~~which~~ is about 56.25% of the previous agriculture land extent, 6653.25 ha representing 66.91%, 5064.39 ha representing 7.35% and 469.35 ha representing 34.08% of existing land use/cover class in 1986 respectively. Shrub land and grassland have decreased in areal coverage with 6868.71 ha and 17023.59 ha respectively accounting for 14.31% and 5.56% existing cover in 1986 respectively.

Table 5. 3 Land use/cover change matrix

Land use/cover Class	1986		2005		Difference	change
	Area (ha)	Area (%)	Area (ha)	Area (%)	(ha)	(%)
Shrub land	48008.25	10.55	41139.54	9.04	-6868.71	-14.31
Grassland	306110.25	67.26	289086.66	63.52	-17023.59	-5.56
Water	1377.27	0.3	1846.62	0.41	469.35	34.08
Built-up	9944.1	2.18	16597.35	3.65	6653.25	66.91
Agriculture land	20809.98	4.57	32515.29	7.14	11705.31	56.25
Bare Soil	68888.34	15.14	73952.73	16.24	5064.39	7.35
Total Area	455138.19	100	455138.19	100		

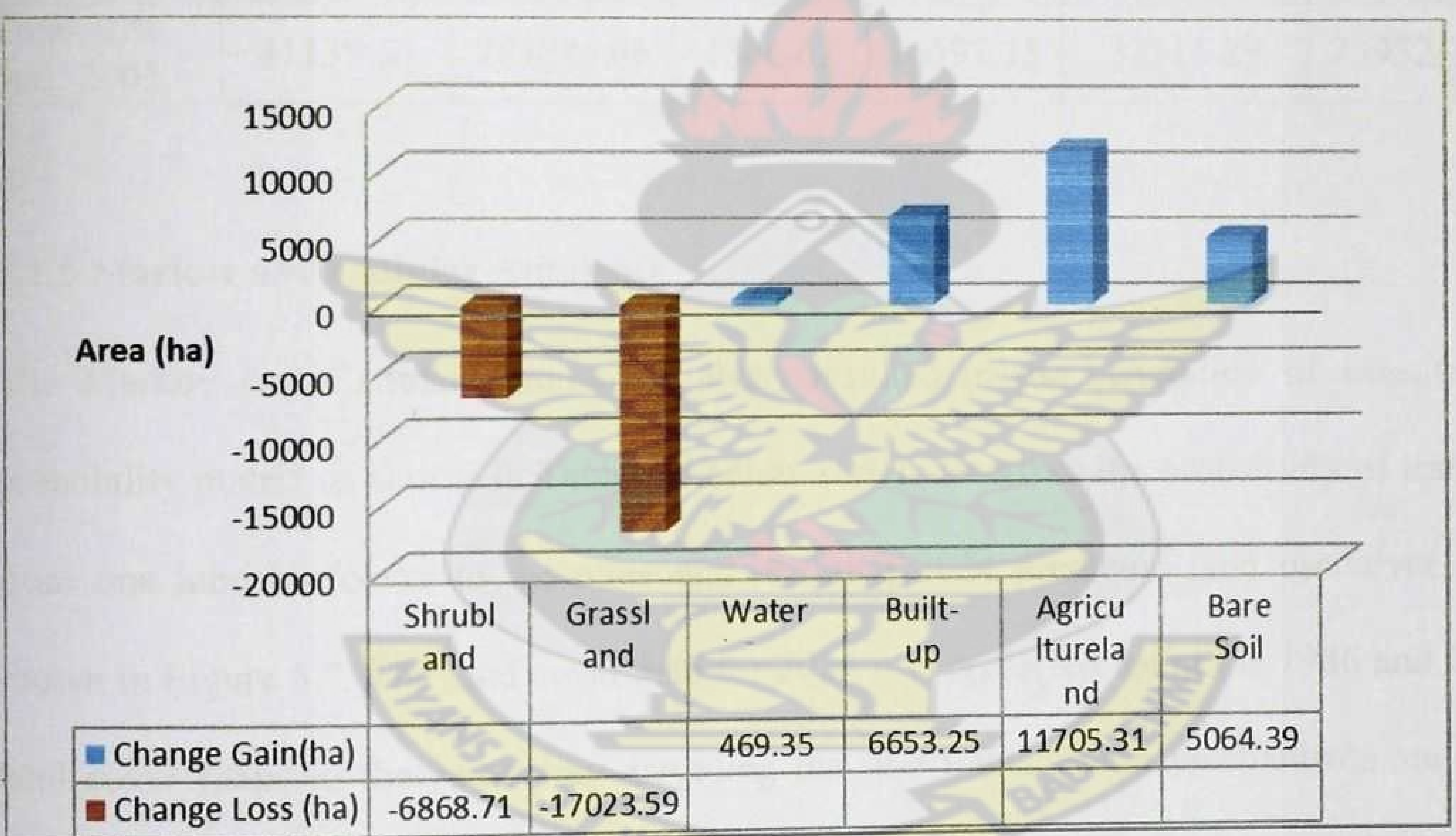

Figure 5. 6 Land use/cover change trend

5.1.4.3 Land use/cover transfers within the study area from 1986 to 2005

The diagonal of Table 5.4 depicts the proportion of the land use/cover classes that remained unchanged from 1986 to 2005 in the study area. A total of 24211.35 ha, 7502.4 ha and 1508.67 ha of shrub land was transferred to grassland, agriculture land and bare soil respectively. Grassland made a highest transfer of 42265.08 ha to bare soil, followed by shrub land with 19997.28ha, and then agriculture land with 10643.4 ha.

Table 5. 4 Land use/cover conversion matrix

		2005						
	Land use/cover	Shrub land	Grassland	Water	Built-up	Agriculture land	Bare Soil	Total area (ha), 1986
1986	Shrub land	**13634.55**	24211.35	289.89	861.39	7502.4	1508.67	48008.25
	Grassland	19997.28	**223732.53**	182.97	9288.99	10643.4	42265.08	306110.25
	Water	1.8	75.87	**1233.99**	54.18	8.46	2.97	1377.27
	Built-up	531.9	4663.08	39.24	**1602.36**	1279.98	1827.54	9944.1
	Agriculture land	3422.61	4192.11	54.18	1621.35	**10562.31**	957.42	20809.98
	Bare Soil	3551.4	32211.72	46.35	3169.08	2518.74	**27391.05**	68888.34
	Total area (ha), 2005	41139.54	289086.66	1846.62	16597.35	32515.29	73952.73	**455138.19**

5.1.5 Markov and Cellular Automata

The Markov and Cellular automata analysis resulted in the generation of transitional probability matrix as shown in Table 5.5 below which describes the probability of transfer from one land use/cover to the other and resulting 2024 predicted land use/cover map shown in Figure 5.7. The land cover map for 2024 was projected using the 1986 and 2005 land cover maps in the same way assuming that the transmission mechanisms stay the same. Table 5.6 indicates the amount and rate of land cover changes between 2005 and 2024.

Table 5. 5 Transition Probability matrix

		2024					
	Land use/cover Class	Shrub land	Grassland	Water	Built-up	Agriculture land	Bare Soil
2005	Shrub land	0.896	0.0013	0.0551	0.0393	0.0022	0.0061
	Grassland	0.006	0.284	0.5043	0.0179	0.0314	0.1563
	Water	0.0006	0.0653	0.7309	0.0303	0.1381	0.0348
	Built-up	0.0039	0.0535	0.4689	0.1611	0.1838	0.1287
	Agriculture land	0.0007	0.0516	0.4676	0.046	0.3976	0.0366
	Bare Soil	0.0026	0.1645	0.2014	0.0779	0.046	0.5076

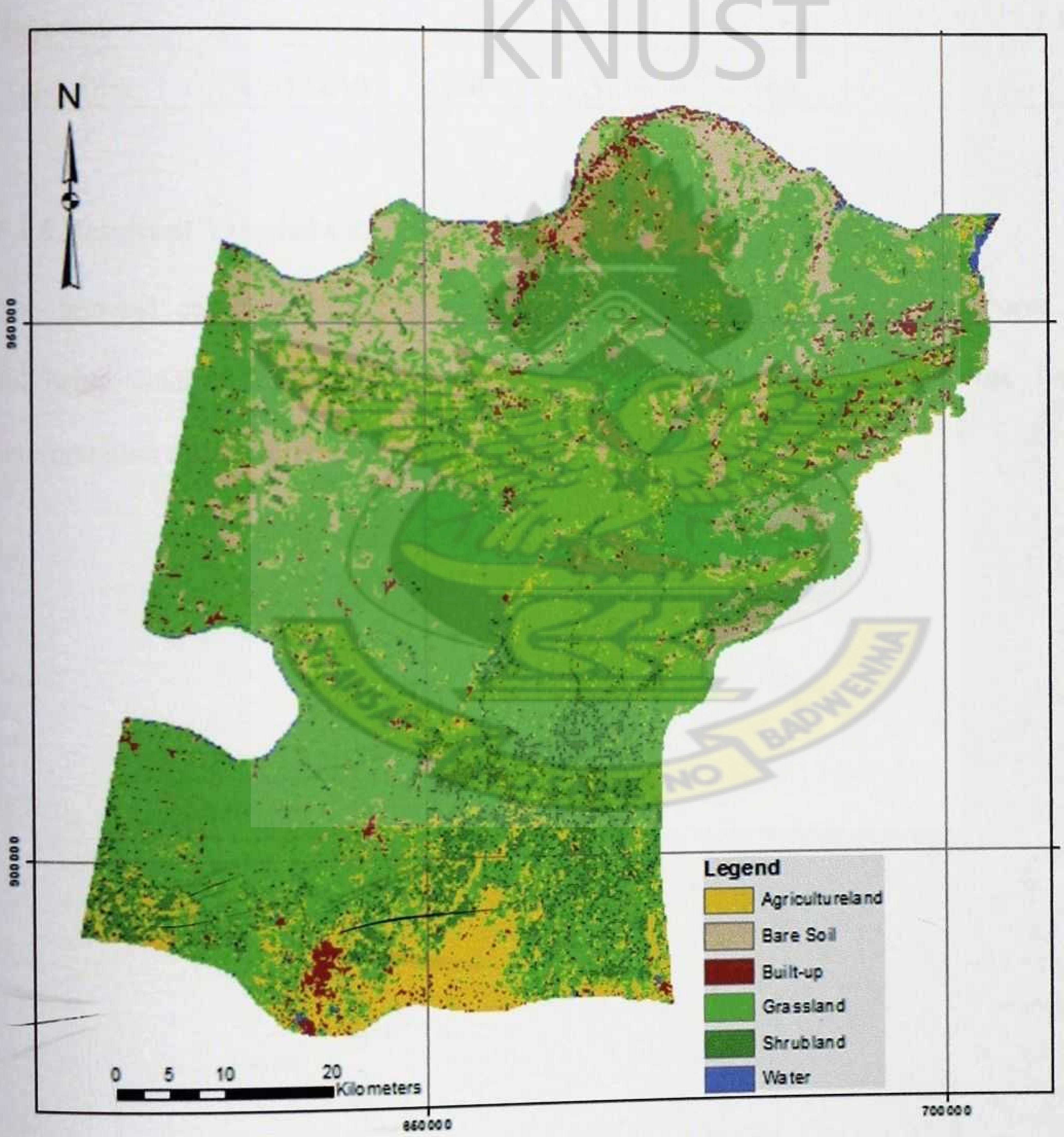

Figure 5. 7 Projected Land use/cover map for 2024

Table 5. 6 Land use/cover change matrix for 2005 and 2024

Land use/cover Class	2005 Area (ha)	2005 Area (%)	2024 Area (ha)	2024 Area (%)	Difference (ha)	change (%)
Shrub land	41139.54	9.04	40864.86	8.98	-274.68	-0.67
Grassland	289086.66	63.52	281127.06	61.77	-7959.6	-2.75
Water	1846.62	0.41	1832.4	0.40	-14.22	-0.77
Built-up	16597.35	3.65	18194.67	4.00	1597.32	9.62
Agriculture land	32515.29	7.14	37910.97	8.33	5395.68	16.59
Bare Soil	73952.73	16.24	75208.23	16.52	1255.5	1.70
Total Area	455138.19	100	455138.19	100		

5.1.6 Results of Tasseled Cap Transformation

The tasseled cap transformation applied on 1986TM and 2006 ETM produced the following images in Figure 5.8, 5.9.and its statistical analyses from the image interpretation of the Landsat imageries are shown in Table 5.7.

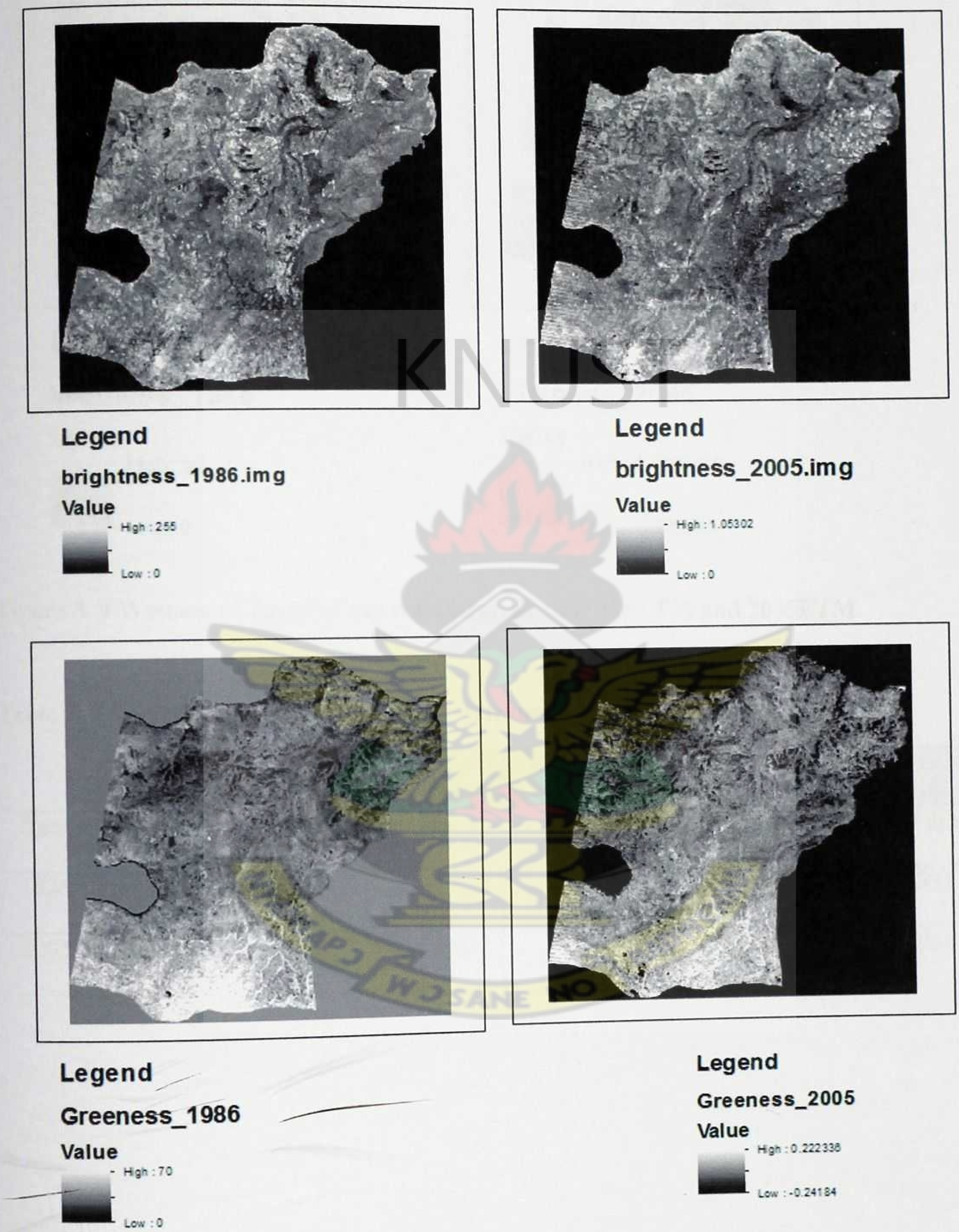

Figure 5. 8 Brightness and Greenness of Tasseled cap transformation for 1986 TM and 2005ETM

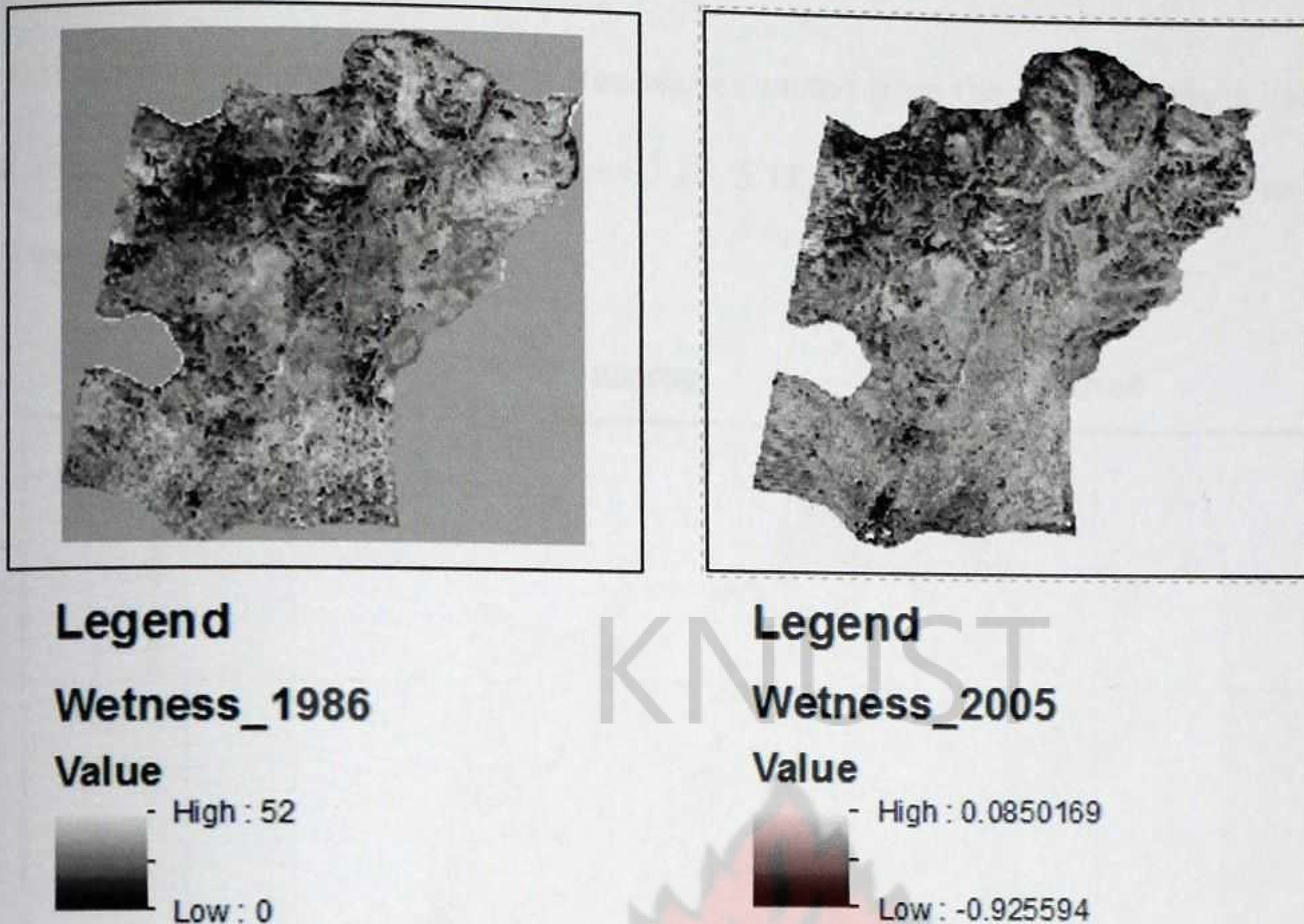

Figure 5. 9 Wetness of Tasseled cap transformation for 1986 TM and 2005ETM

Table 5. 7 Statistical analyses of tasseled cap transformation

	Brightness		Greenness		Wetness	
Year	mean	standard deviation	mean	standard deviation	mean	standard deviation
1986	0.046	0.21	1.398	3.71	0.49	1.931
2005	0.054	0.227	0.022	0.024	0.064	0.058

5.1.7 Mapping Land Degradation Risk Area

In this study, Land degradation risk area was extracted from the soil brightness image of the tasseled cap transformation. Figures 5.10, 5.11 show the land degradation risk map of 1986 and 2005 of the study area.

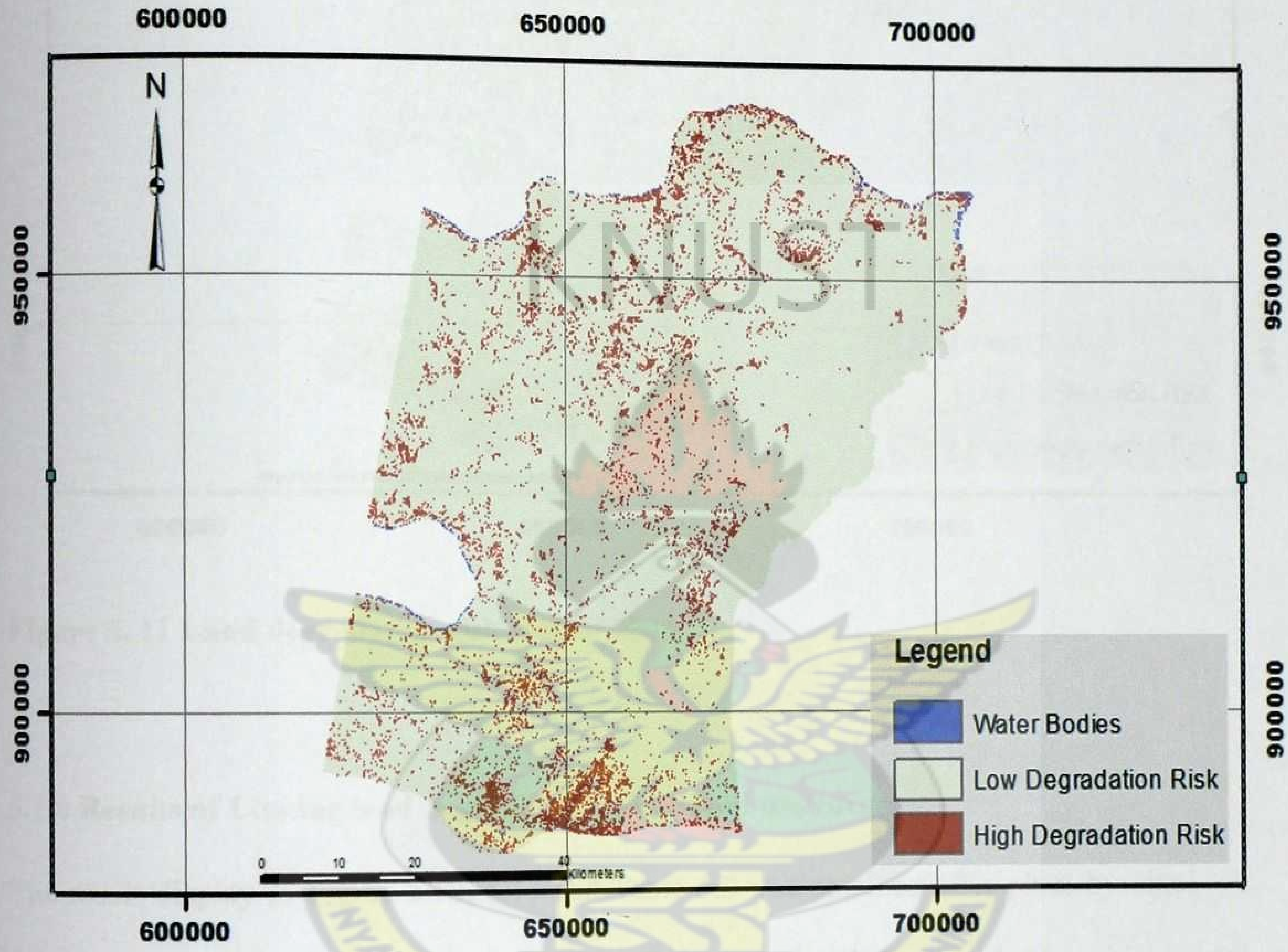

Figure 5.10 Land degradation risk map of 1986

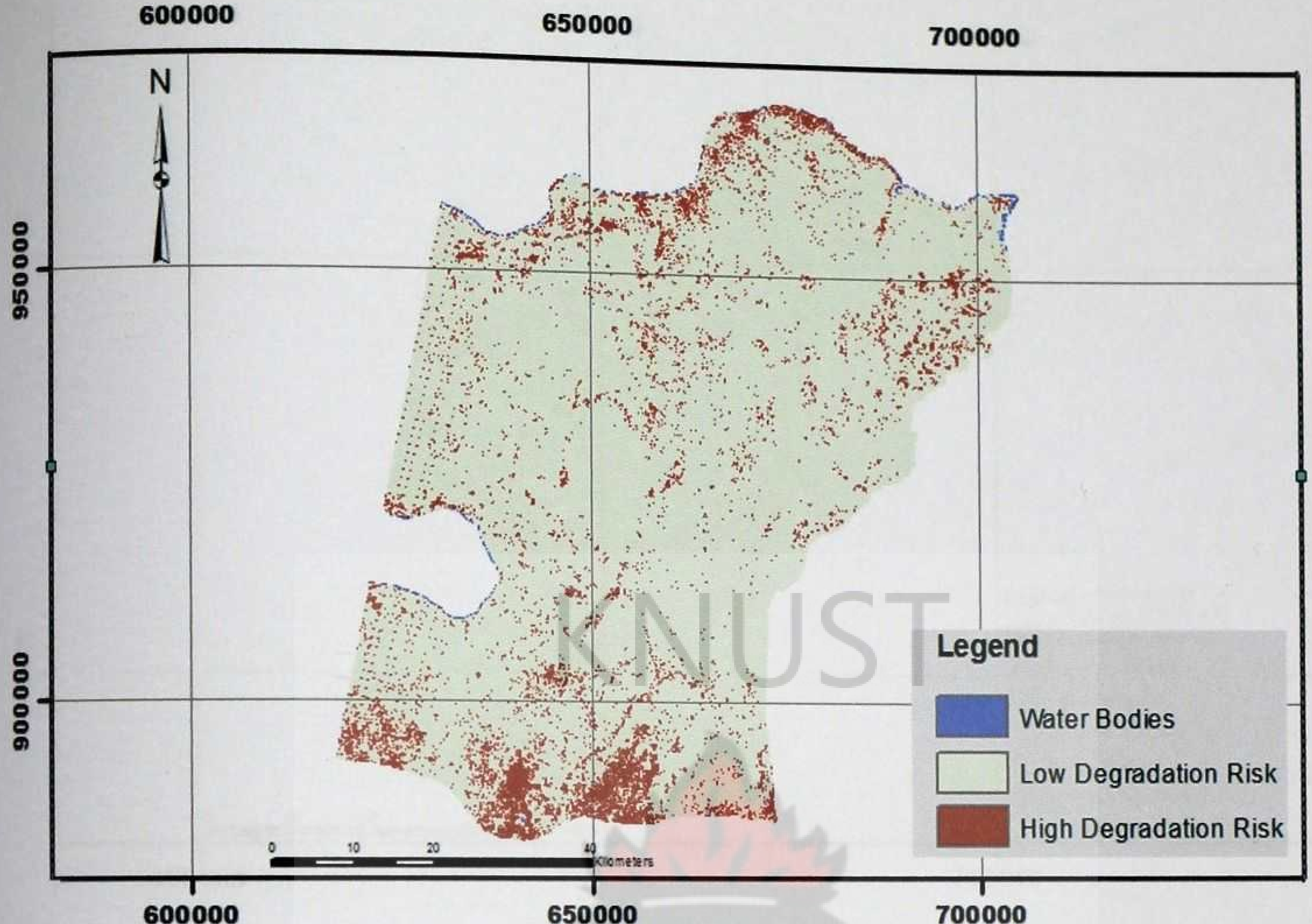

Figure 5. 11 Land degradation risk map of 2005

5.1.8 Results of Linking land degradation risk to land use/cover

The result display in Figure 5.12, 5.13 and Table 5.8 was obtained after pixel by pixel comparison of the land degradation risk images of 1986 and 2005 with its corresponding land use/cover images. Figure 5.14 illustrates the land use/cover at degradation risk trend from 1986 to 2005.

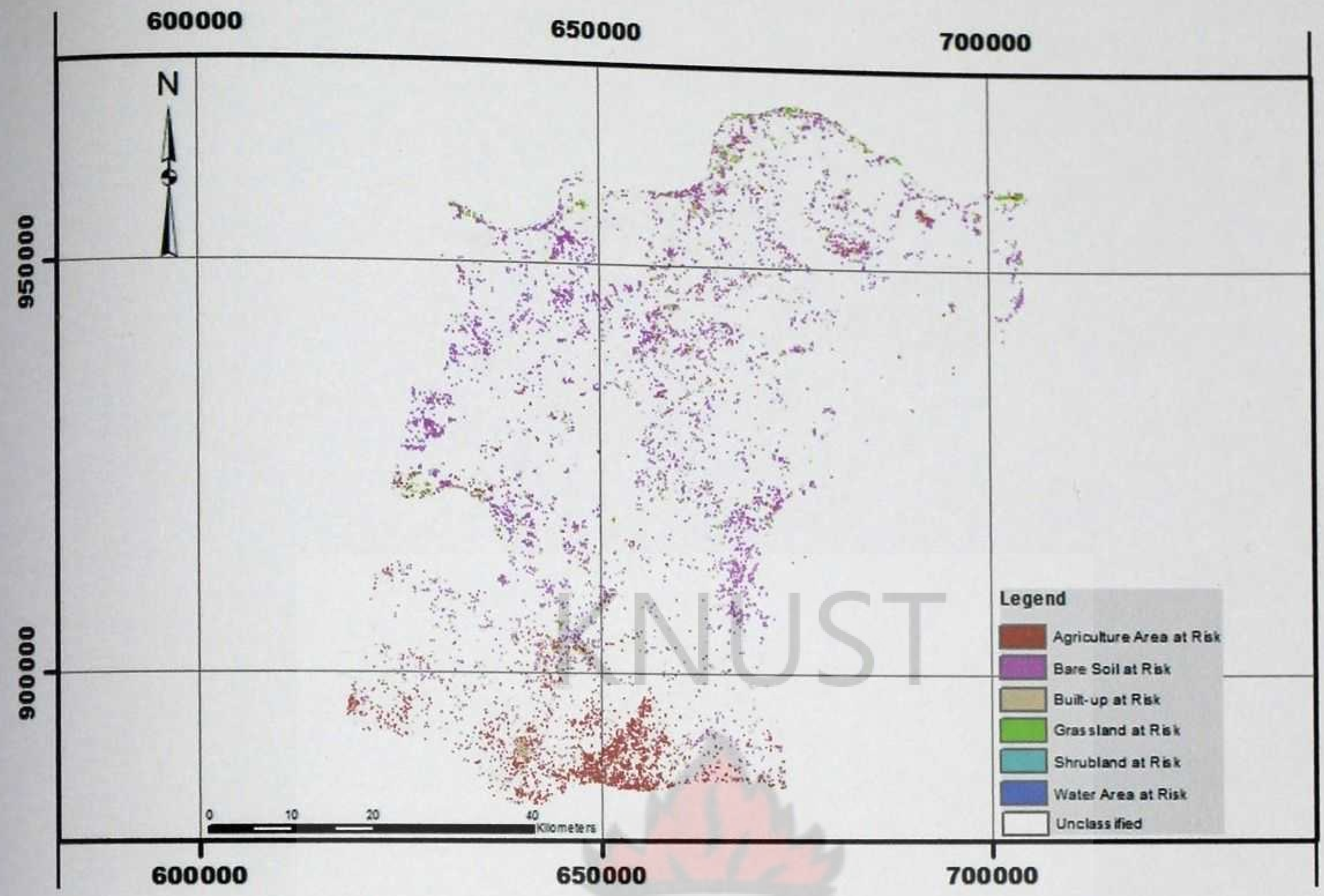

Figure 5. 12 Land use/cover at degradation risk map for 1986

Table 5. 8 Land use/cover at degradation risk area distribution for 1986 and 2005

	1986	2005		
	Area(ha)	Area(ha)	Difference (ha)	Rate of change per year(ha)
Water Area at Risk	0.09	19.35	19.26	1.01
Shrub land at Risk	2.79	717.57	714.78	37.62
Grassland at Risk	2091.69	2240.73	149.04	7.84
Built-up at Risk	8297.73	11616.6	3318.87	174.68
Bare Soil at Risk	13699	16728.3	3029.3	159.44
Agriculture Area at Risk	7231.95	14184.5	6952.55	365.92
Total	31323.25	45507.05		

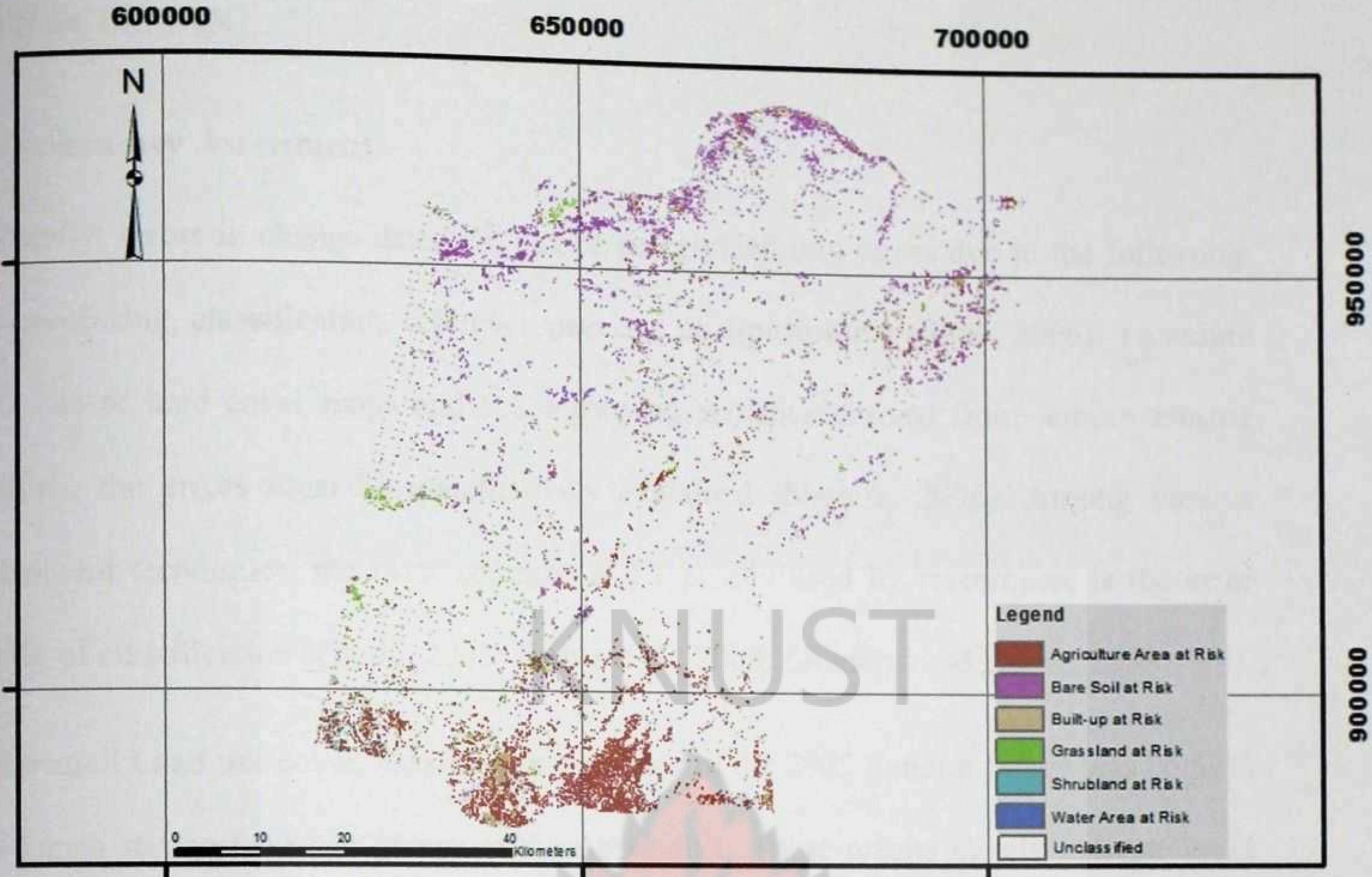

Figure 5. 13 Land use/cover at degradation risk map for 2005

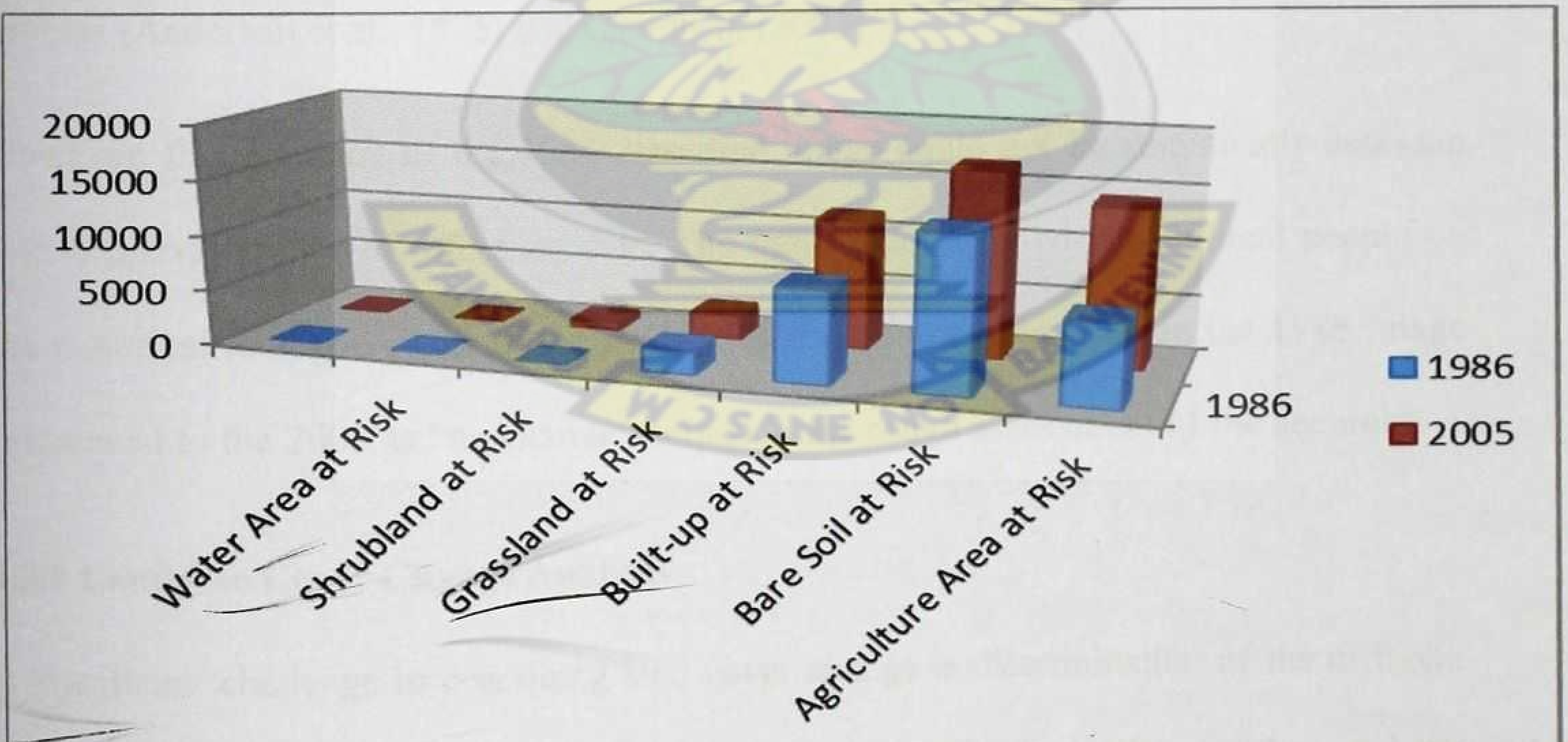

Figure 5. 14 Distribution of Land use/cover at degradation risk

5.2 DISCUSSION

5.2.1 Accuracy Assessment

Generally, errors in change detection can be categorized into errors due to the following: pre-processing, classification, reference data and post-processing (Shao, 2006). To assure wise use of land cover maps and accompanying statistics derived from remote sensing analysis, the errors must be quantitatively explained (Sherefa, 2006). Among various assessment techniques, the most common and typically used by researchers is the error matrix of classification (Foody, 2002; Jianya et al., 2008; Lillesand and Kiefer, 2008).

The overall Land use/cover classification accuracy of the 2005 Landsat image was 86.67% and kappa static of 0.84 as shown at the Appendix1. These results mostly indicate good compliance between the classification and the actual land use/cover categories with few misclassifications of pixels falling out across nearly all the categories. Clearly, the level of accuracy is within the minimum standards of 85% as stipulated by the USGS classification scheme (Anderson et al., 1976) and Campbell, (2002).

However, the accuracy of the 1986 classified image could not be statistically assessed due to unavailability of reference data. The information offered by the local people on the historical land use/cover of the study area and comparable areas in the 1986 image referenced to the 2005 as "no change" helped in the rough assessment of the accuracy.

5.2.2 Land Use/Cover Change Analysis

A significant challenge in describing land cover change is discrimination of the different dimensions of change (Aspinall and Hill, 2008). In this study, the land cover changes have been reported in terms of the areal change (losses or gains in areal extent), transformations (the patterns of transition from land cover to another), dynamics (the rates in areal extent) and geographic distribution. The land use/cover matrix (Table 5.4) indicates the direction and the Area extent of the change. Generally, all the six (6) land use/cover types experienced changes in areal coverage from 1986 to 2005. Agriculture land, built-up, bare soil and water have been increased while shrub land and grassland have been decreased over areal coverage in this particular period of time as a result of anthropogenic activities.

Agricultural land showed increasing pattern of change during the period comparison of 1986 to 2005. It increased from 20,809.98 ha (4.57%) to 32515.29 ha (7.14%) in 1986 and 2005 respectively. Horticultural development is the chief form of agricultural intensification in the tropical regions, which is propelled by underlying processes such as market availability, demographics and institutional regimes (Geist and Lambin, 2002). The increase of agricultural land from 20,809.98 ha in 1986 to 32515.29 ha in 2005 is purely population induced. The number of population has increased due to migration from northern part of the country that is the three (3) northern regions into the area. Patches of conversion to agriculture land are widespread around Kintampo the district capital and the towns or communities in the study area. This suggests that the nearness to a settlement and water bodies was an important factor affecting the spatial distribution of agriculture land. The amount of increase in agricultural land during the period of study was 11705.31 ha (2.57%), which was mainly at the expense of the grassland and shrub land.

The increment of this land use/cover shows the response of the residents to the mounting pressure for agricultural land. Some have resorted not only to clearing the shrub lands and grassland, but also the vegetation located on the banks of a river or stream. The shrub lands, known to have thrived as part of the outmoded shifting cultivation in most communities in the study area, are also disappearing and being replaced by agriculture lands. All these occurrences offer a plausible rationale for the increasing rates and magnitudes of agriculture land changes as the results indicate in Table 5.3 and the, subsequent, decline in the land cover types contributing to these increases. However, the gain achieved from 'built-up to agriculture' (1279.98ha) does not make sense in a logical point of view. It is unlikely that urban areas are removed for agricultural land use. This unreal change phenomenon is caused by a misclassification of the TM imagery due similar spectral signatures of built-up surfaces and agriculture land (i.e. arable-land) in the dry season.

Within the nineteen (19) year period under study, built-up areas are another land cover type that has maintained an upward trend in its rates and magnitude of change as shown in Tables 5.3. The rationale behind this could lie in the assumption that, as the population in an area increases so does the human habitation centres. The rapid increment in Built-up process was accompanied by the transfer of a large number of people from rural to urban areas, the rapid development of the real estate industry, and the extension of transportation network, green space in urban area, and other urban infrastructure. For instance, the rising population in Kintampo owing to the influx of labour force to the horticultural farms, tourism (Kintampo waterfalls and centre of Ghana) and industries has led to the emergence of residential settlements and small trading centres. Again, new developed areas consistently appeared near existing developed areas in the studied time intervals. In addition, due to the irregularity and emergence of existing developed areas, newly built areas expanded outward while constantly and gradually filling the vacant land areas adjacent to the existing developed area. This was revealed by the conversion matrix of Table 5.4 and Table 5.3 where built-up increased by 6653.25 ha at the expense of grassland which has the highest areal cover change to built-up followed by bare soil, agriculture land and others.

Bare soil showed increasing pattern of change during the period comparison of 1986 to 2005. Table 5.3 indicates that it increased from 68888.34 ha (15.14%) to 73952.73 ha (16.24%) in 1986 and 2005 respectively. The area of bare soil have increased by

5064.34ha and the land use/cover conversion matrix in Table 5.4 indicate that bare soil upward trend during the period of study was at the expense of grassland which has the highest areal coverage converted to bare soil followed by built-up, shrub land and agriculture land. Human induced and ecological processes are the driving force for such a change in the study area. The loss of vegetation due to bush fire, over cutting beyond silviculture permissible limit, improper crop rotation system, overgrazing, unsustainable fuel wood extraction are all human induced and ecological activities that mainly trigger soil erosion rendering the soil bare and contributing to land degradation in the study area. This confirmed the suggestion that the Earth's land surface is affected rapidly by the presence of human beings and their activities (De Sherbinin, 2002).

Shrub land and grassland saw a decreased trend in rate and magnitude of change during the 19 years period of study. Table 5.3.indecate that shrub land decrease from 48008.25 ha (10.5%) to 41139.54 ha (9.04%) in 1986 and 2005 respectively with a decrease by 6868.71ha. Based on land use/cover conversion matrix, most of the shrub land was converted into agriculture land followed by grassland, built-up and bare soil. Similarly, the total area of grassland that was covered in 1986 was 306110.25 ha (67.22%) while it amounts 289086.66 ha (63.52%) in 2005. Land use/cover classification, decrease by 17,023.59 ha. Most of the grassland was converted to bare soil, shrub land, built-up and agriculture land as indicated by the land use/cover conversion matrix (Table 5.4). The probable major cause for both changes could be ecological process and human induced. The decrease could have been precipitated by the increasing population and migration which has resorted to clearing areas of shrub land and grassland suitable for food production, grazing, highly fuel wood consumption, and residential infrastructure development.

The impact of decreasing shrub land and grassland have resulted in land degradation particularly soil erosion. Since these have the capacity to minimize the speed of runoff rain falls on the surface of the earth. The presence of these resources on the surface of the earth helps in rain water to percolate in the soil.

5.2.3 Land Use/Cover Change Prediction

Markov chain analysis predicts the future land cover patterns only on the basis of known land cover patterns of the past (Eastman, 2006; Sun et al., 2007). Analysis of the prediction map forecasts that by 2024 land-cover pattern of the study area will still be dominated by grassland with areal cover expected to be 61.77% of the total land cover of the study area. (Figure 5.7, Table 5.6). Bare soil land cover is expected to be 16.52% of the total land cover. Shrub land is expected to be only 8.98% of the total land cover. Agriculture land cover is expected to cover only 8.33% of the total land area. Built-up cover is expected to cover only 4.0% of the total land area and water will occupy the least with 0.4% of the total land area. The Markov transition probability table predicts shrub land followed by water and bare soil to have her probabilities of maintaining their land cover in the year of 2024.

The change matrix generated by the comparison of 2005 land use/cover with 2024 projected land use/cover revealed that Agriculture land, built-up and bare soil cover will have an increase trend of cover change whiles grassland, shrub land and water will experience decrease trend of ~~cover change~~. Built-up cover will continue to expand in the study area as the population increase. Increase in population in the study area may cause human induced and socio economic activities to increase which would be the main driving force contributing to conversion of land cover/use to the other and changes in the study area. Markov models are easy to build but their validation is difficult because it depends on prediction of system behaviour over time and may even be impossible (Adjapong, 2009).

5.2.4 Land Degradation by Tasseled Cap Transformation.

The tasseled Cap transformation (Crist and Cicone, 1984) on the TM images to convert the land cover information included in seven bands into three indicators: brightness, greenness and wetness, which respectively means the land bareness, vegetation vigour and soil moisture. Bai et al. (2008) define land degradation as the long-term loss of ecosystem function and productivity caused by disturbances from which the land cannot recover unaided. The soil brightness index of tasseled cap which measures land bareness was used to map area of land degradation risk. Barren land has higher propensity of being subjected to soil erosion hence rendering the land infertile and unproductive. Soil fertility decline (also described as soil productivity decline) is a deterioration of chemical, physical and biological soil properties. Soil erosion is usually caused by surface runoff in open fields with little vegetation cover. The main contribution processes, besides soil erosion, are; decline in organic matter and soil biological activity; degradation of soil structure and loss of other soil physical qualities' reduction in availability of major nutrients (N,P,K) and micro-nutrients and increase in toxicity due to acidification and salinization (FAO, 2001).

Figures 5.10 and 5.11 show the land degradation risk map of 1986 and 2005. In 1986, the land degradation risk area was 31323.25 hectares representing 6.88% of the total coverage of the study ~~area~~ which inc~~reased to~~ 45507.05 hectares in 2005 representing 10%. Land degradation risks have increase during the period of study by 14183.8 in 2005, which represent is 3.12% of the total land coverage of the study areas.

The greenness and wetness indicator that measure vegetation vigour and soil moisture respectively statistically experienced a decrease or reduction trend during the period of study as indicated in Table 5.7. The standard deviation and mean of both indicators had a lower statistical value in 2005 compared to that of 1986. This suggests that there is loss of vegetation vigour and soil moisture from 1986 to 2005 which are implications of land degradation in the study area. The impact of decreasing vegetation covers in the case of logging, fuel wood extraction/charcoal burning and grazing is indirectly accelerating soil erosion which is a form of land degradation. Again, soil moisture is crucial for the productivity of crops and the general well-being of vegetation. Land cover reduces evapotranspiration so that soil can retain their moisture for longer periods. Removal of vegetation as a result of land use/cover change will obviously lead to loss of soil moisture and hence less ability to support plant growth. Loss of flora will consequently lead to loss of habitat for animals and therefore lead to a degrade ecosystem which is a form of land degradation in the area.

5.2.5 Linking land degradation risk to land use/cover

A comparison between the land degradation risk and it's corresponding land use/cover for 1986 to 2005 yielded maps of land use/cover at degradation risk and its area distribution table in Figure 5.12, 5.13 and Table 5.8. The test under this topic estimated the areal coverage of land use/cover classes that have potential to soil erosion susceptibility which is a form of land degradation at the study area.

The result (Table 5.8) revealed that the areal of coverage of bare soil increased in land degradation ~~risk~~ area from ~~1986 to 2005~~ with 13699 ha to 16728.3 ha respectively in the study area. Built-up followed with susceptible area of land degradation increasing from 8297.73 ha to 11616.6 ha under the period of study. Agriculture land, grassland, and shrub land also experienced increasing trend of area susceptible to land degradation from 7231.95 ha to 14184.5 ha, 2091.69 ha to 2240.73 ha, and 2.79 ha to 717.57 ha respectively within the period of study.

However, agricultural land has increased in high susceptible area of land degradation with great rate per year of about 365.92 ha. The rapid population growths have resulted scarcity of agricultural land closer to home of resident so that they have forced to use marginal land. Again, improper agriculture practices are considered the reason for agricultural land expansion in the area of high potential to soil erosion which aggravates land degradation in the study area.

Land use/cover changes of the two periods as indicated before have shown bare soil increased pattern. However, in this particular topic, it is clearly indicated in Table 5.8 that the rate of bare soil changes is high in the area of high susceptible to soil erosion. This indicates that the soil brightness index result corresponds to the real world phenomena. In other words; the high potential site of soil erosion is highly affected to land degradation than the rest of the area of land cover. The rate of expansion in this area is higher than the rest. Therefore, to protect the land from land degradation, priority is to be given for the area of high potential to soil erosion.

CHAPTER SIX

CONCLUSIONS AND RECOMMENDATIONS

6.1. Conclusions

Remote sensing and GIS technology is a powerful tool for measuring, mapping, assessing and modelling of natural resources. In this study, land use/cover dynamics and land degradation risk was delineated and assessed using Landsat TM and ETM+ satellite imagery from 1986 to 2005.

Based on the analysis of the input data of land use/cover, about six land use/cover classes were identified for the years under study (1986-2005). These include shrub land, grassland, water, built-up, agriculture land and bare soil. Image analyses of the respective years indicate that the largest land use/cover class is grasslands which have covered 67.26 % in 1986, and 63.52 % in 2005. From this, it can be concluded that areal coverage of grasslands has decreased in the study area. Shrub land also experienced decrease in land cover from 10.55% in 1986 to 9.04% in 2005. The decrease in both land cover is due to increasing population and migration which has resorted to clearing areas of shrub land and grassland suitable for food production, grazing, highly fuel wood consumption, and residential infrastructure development. Decrease in these cover has also increased the propensity of land degradation risk in the study area. Again, bare soil which has the second highest share of land cover, agriculture land, built-up and water increased in areal coverage from 1986 to 2005. The increasing for bare soil which is vulnerable to soil erosion was as a result of human induced and ecological processes in the study area. Agriculture land increased mainly at the expense of the grassland and shrub land and the study also revealed that the nearness to a settlement and water bodies was an important factor affecting the spatial distribution of agriculture land in the study area. The increase for built-up cover was due to increase in population which results in increase in human habitation centres and infrastructure developments.

The Markov Chain and cellular automata used in this study demonstrates the effectiveness in predicting a likely land use/cover map for the year 2024. The prediction results revealed a continuous increased of bare soil, built-ups, and agriculture land at the expense of grassland and shrub land. Grassland, shrub land and water would also experience decreased in areal coverage as compared to 2005 land use/cover.

Land degradation assessment is a challenging task and has not obtained sufficient attention in Ghana. It is found that tasseled cap transformation have the potential to provide new insights for rapidly assessing land degradation risks in large areas. The soil brightness index of tasseled cap which measures land bareness was successful in mapping area of land degradation risk for 1986 and 2005 in the study area. The study revealed that areal coverage of land degradation risk has increased from 6.88% in 1986 to 10% in 2005 of the study area. The study again, revealed decrease in tasseled cap greenness indicator, tasseled cap wetness indicator from 1986 to 2005 which means that there was a decrease in the vegetation cover and soil moisture. In the same time showed an increase in the tasseled cap brightness indicator values, which points to increase in the soil bareness. In other words, there was an increase in the land degradation in the region during the study period.

The identified relationships between land degradation risks and land use/cover types and impacts of land use/cover change on land degradation risks is a first step in providing the foundation for better planning and managing land resources. The examination of the relationships between land degradation risks and land use/cover types conclude that bare soil cover stands the highest risk of being degraded in the study area; followed by built-up, agriculture land, grassland, and shrub land also experienced increment in area. This indicates that the results analogue to the real world phenomena. Agriculture land however, increased in high susceptible area of land degradation with greatest rate per year of about 365.92 ha. This is one of the main factors to land degradation in the study area. The use of marginal land for agriculture has resulted into bare lands and is more vulnerable to land degradation, particularly for soil erosion.

Finally, the results of the study conclude that land use/cover changes led to the degradation of large areas of land from 1986 to 2005.These changes were brought about by increasing population couple with human induced and socio-economic activities in the study area. In addition, the use Landsat imagery of Satellite Remote sensing and GIS, coupled with Markov modelling proved to be beneficial in assessing and analysing the land cover change and land degradation.

6.2 Recommendation

Based on the conclusions derived from the present research, the following recommendations are made:

- Land use land cover analysis with Landsat image results is a good indicator of the trend of dynamics. However, to use it for decision making, Spatial correlation between land use/cover pattern and intensive socio economic data should be used to increase its efficiency and accuracy.
- Ground truthing, which has not been done in the study, is recommended in future research as well.
- ~~The~~ predicted map produced in this study can be used by decision-makers to evaluate policies to curtail the impacts over fragile areas (shrub land and grassland) and help planning to manage the pressure over natural elements.

- To decrease the rate of population growth and its consequent effect on socio-economic activities and environment as whole, informal education for inhabitants about the impacts of population increase and misuse of natural resource is paramount advantage. Strong family planning and population control education is therefore a timely activity.
- Community based project of rehabilitation program should be conducted to increase vegetation cover in the study area by mobilizing the local people.

6.3 Limitations

Two limitations were identified in this study:

- 2008 ortho- photograph were used to perform Accuracy Assessment for the 2005 classified image. In addition, the accuracy of 1986 was not assessed due to lack of reference data.
- Could not use current or present day Landsat imagery for the study because of slc-off gaps on the images.

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APPENDIX

CLASSIFICATION ACCURACY ASSESSMENT REPORT

ERROR MATRIX

Reference Data

Classified Data	Unclassified	Water	Shrub land	Grassland
Unclassified	0	0	0	0
Water	0	14	1	0
Shrub land	0	0	12	3
Grassland	0	0	0	13
Built-up	0	0	0	0
Bare Soil	0	0	0	0
Agriculture land	0	0	0	2
Column Total	0	14	13	18

Reference Data

Classified Data	Built-up	Bare Soil	Agriculture	
Unclassified	0	0	0	0
Water	0	0	0	0
Shrub land	0	0	0	0
Grassland	0	0	2	0
Built-up	13	2	0	0
Bare Soil	2	13	0	0
Agriculture land	0	0	13	0
Column Total	15	15	15	0

----- End of Error Matrix -----

ACCURACY TOTALS

Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy
Unclassified	0	0	0	---	---
Water	14	15	14	100.00%	93.33%
Shrub land	13	15	12	92.31%	80.00%
Grassland	18	15	13	72.22%	86.67%
Built-up	15	15	13	86.67%	86.67%
Bare Soil	15	15	13	86.67%	86.67%
Agriculture land	15	15	13	86.67%	86.67%
Totals	90	90	78		

Overall Classification Accuracy = 86.67%

----- End of Accuracy Totals -----

KAPPA (K^) STATISTICS

Overall Kappa Statistics = 0.8400

Conditional Kappa for each Category.

Class Name	Kappa
Unclassified	0.0000
Water	0.9211
Shrub land	0.7662
Grassland	0.8333
Built-up	0.8400
Bare Soil	0.8400
Agriculture land	0.8400

--- End of Kappa Statistics -----