COMPARISON OF LAND COVER IMAGE CLASSIFICATION METHODS

(Case Study: Ejisu–Juaben District)

By

Kingsley Nana Osei (BSc. Geomatic Engineering)

A Thesis submitted to the Department of Geomatic Engineering, Kwame Nkrumah University of Science and Technology in partial fulfilment of the requirements for the degree of

MASTER OF SCIENCE

Faculty of Civil and Geomatic Engineering, College of Engineering

January 2009

DECLARATION

I hereby declare that this submission is my own work towards the award of Master of Science in Geomatic Engineering and that, to the best of my knowledge; it contains no material previously published by another person or material which has been accepted for award of any other degree of the university, except where due acknowledgement has been made in the text.

____________	------------------	------------------
Student's Name	**Signature**	**Date**

Certified by:

____________	------------------	------------------
Supervisor's Name	**Signature**	**Date**

Certified by:

____________	------------------	------------------
Head of Dept. Name	**Signature**	**Date**

ABSTRACT

The use of remote sensing techniques for land cover classification have gain more and more importance and recent direction in research works indicates that image classification of satellite images for land cover information is the preferred choice. Various methods for image classification have been developed based on different theories or models. In this study, three of these methods Maximum Likelihood classification (MLC), Subpixel classification (SP) and Backpropagation Neural Network classification (BPNN) are used to classify a landsat etm+ image of the Ejisu-Juabeng district of Ghana into seven land cover classes and the results compared. MLC and BPNN are hard classification methods but SP is a soft classification. Hardening of soft classifications for accuracy determination leads to loss of information and the accuracy may not necessary represent the strength of class membership. Therefore in the comparison of the methods, the top 20% compositions per land cover class of the SP were used instead. Results from the classification, indicated that output from SP was generally poor although it perform well with land covers such as forest that are homogeneous in character. Of the two hard classifiers, BPNN gave a better output than MLC. Overall, BPNN gave the best results with an accuracy of 92.50%, whiles MLC gave an accuracy of 78.95%.

DEDICATION

I dedicate this work to my mum, Theresa Buadua Ampadu and my wife, Esther Ama Serwaa Osei

ACKNOWLEDGEMENT

“He who has begun a good work in us will bring it into completion in Christ Jesus”. I am very grateful to God who gave me life, strength and wisdom to go through this programme successfully. My sincere thanks go to my supervisor Dr. E. M. Osei Jnr. for his encouragement, support and the knowledge he imparted onto me. I am also grateful to Dr. Eric Forkuo and Mr. John Ayer for their advice and constructive criticisms.

My special gratitude also go to all lecturers of Geomatic Engineering department for their support and encouragement during my two and half years stay in school at K.N.U.S.T and also to my class mates for always being there for me and supporting me all the way through.

To my mum, God bless you for your spiritual and physical support and last but not the least to my loving wife for the wonderful support. I say thank you.

Finally, to all who in diverse ways have contributed to the success of this work, I say thank you. God richly bless everyone.

TABLE OF CONTENT

LIST OF FIGURES

LIST OF TABLES

CHAPTER ONE

INTRODUCTION

1.1 Background

It is an undeniable statement that 'land is an important asset and a means to sustain livelihood'. It is the key resource for most human activities including forestry, agriculture, industry, mining, etc. Land is therefore a fundamental factor of production closely linked with the economic growth of a nation and its people (Richards, 1990). However, as the population increases, demand for land for use in settlement, construction of infrastructure, farming (agriculture) and other human activities also increases.

As a result, land and its associated natural resources like forest, vegetation, etc are being subjected continually to changes and these changes in turns affect the ecosystem. Even water resources like rivers, streams and wetlands that may be found in areas where such activities occur are also affected. For example, when changes occur in vegetation; wildlife habitat, fire conditions; aesthetic and historical values and ambient air quality, are all affected.

As human and natural forces are transforming the landscape, resource agencies find it increasingly important to monitor and assess these alterations. Land use and land cover is therefore regarded as the single most important factor of environmental change such as deforestation, habitat fragmentation, urbanization, and wetland degradation (Turner et al., 1995; Lunetta et al., 2002). Land cover deals with the physical features or vegetation as evident on the land whereas land use is about what economic activity or use the land is put to.

Research in land use – land cover studies have generated so much interest locally and internationally due to concerns globally on land use – land cover changes and its consequences to the environment. It has therefore become one of the crucial elements in images classification for scientific research and real-life earth science applications (Campbell, 1996; Sellers et al., 1995).

One of the fundamentals required for such studies are maps. Various methods are used for the production of these maps, however, the application of remote sensing for map production is increasing become the relatively cheap and quick method of acquiring up-to-date information over a large geographical area. Conventional ground survey methods of mapping are labour intensive, time consuming and are done relatively infrequently. Especially in fast changing environments, maps produced using ground survey methods will soon become obsolete with passage of time.

1.2 Trends in Ghana

In Ghana, urbanization and high population growth are among the major factors or driving forces to land use – land cover changes. Studies have shown that from the year 1960 to the year 2000, the population of Ghana has grown over the period at an average annual rate of 2.6% (GSS 2003). According to the report by the Ghana Statistical Service, the population in 1960 was 6.7 million and by 2000 was 18.9 million. Currently, projections show that the population is about 20 million. Again, at the current rate of 2.6%, the population is expected to double within the next 27 years. This obviously puts pressure on land and other natural resources.

According to a National Report to the Third Session of the Conference of the Parties to the United Nations Convention to Combat Desertification, May 1999, Iddrisu & Telly raised concerns on issues of Deforestation and Land Degradation and the government's effort at dealing with the situation. Similar revelations about reduction in Forest Cover in the country have been made by other organizations (Friends of the Earth International, 1999) (FAO, 2001).

Kotey et al. (1998), Kufour (2000), Agyarko (2001), Lambin et al. (2001), Asubonteng (2007), Segedo (2007) and Tutu (2008) conducted works on land use – land cover in Ghana. They indicated that changes have taken place and enumerated the factors responsible for those changes. They attributed most of the changes to factors such as deforestation which begins with the gradual degradation of natural forests by excessive logging, mining and quarrying; slash-and-burn agriculture and government policies like the Structural Adjustment Program (SAP) embarked upon in the 1980s. This policy was prescribed by the World Bank to encourage the expansion of timber companies and increased timber exploitation to raise foreign exchange earnings to service Ghana's debt.

Yankson (1997), Konadu-Agyemang (1998), Kufuor (2000), and Otoo et al. (2006) also conducted studies on land use – land cover of Accra, focussing on urban growth, infrastructural development and housing. It is documented that many management efforts are hampered by lack of development of data inventories for sustainable management. Existing maps are usually old and out dated. They are therefore difficult to use as an effective information base for planning.

According to Otoo (2006), the inability of Planning Authorities to monitor and control urban growth is due largely to lack of reliable and up-to-date maps. Also much of these maps are available in analogue formats, which were difficult to integrate into digital (advance) systems that have been developed.

In view of the above developments, the need to manage resources such as forest, water bodies, etc. by Stakeholders, Policy Makers and Administrators have become vital and the contributions of land cover maps in spatial format to this effort, for that matter, cannot be overemphasized. Land cover maps, especially vegetation maps, are of increasing interest and use nowadays to resource agencies. This is because it provides so much information through visual impression that is quick and easy to understand. This enhances the processes of monitoring, decision-making and management on environmental issues, resources and policy formulation.

In the last decade, a number of institutions and firms (both governmental and private) are into the application of remote sensing and Geographic Information System (GIS) for the production of maps in digital formats. They include the Survey Department of

Ministry of Land & Forestry, Soil Research Center (CSIR), Forestry Department of Ministry of Land & Forestry, Centre for Remote Sensing & Geographical Information Systems (CERGIS), Rudan Engineering Works Ltd., and Grontmij Aerosat Surveys (CTK Aviation) Ltd. Generally, the use of satellite imageries for mapping purposes is rather low because most of these institutions and firms use mainly aerial photographs as source of data for their mapping works. CERGIS however, makes use of satellite image in their works.

The use of Geo Cover datasets that are geodetically accurate, have opened new opportunities for utilizing satellite data from extensive areas at relatively low cost. Aerial photographs are also good sources of data for extracting land cover information. However, for very large areas, the cost implication is also high. The extraction of information for land cover classes are done through a process called images classification.

Image classification is the organization of pixels in an image into groups (classes) based on their spectral properties. Generally, classification is of two forms; namely Pixel/Spectral-based classification which groups pixels into classes solely based on their spectral properties and Object-based classification which in addition to the spectral properties, uses information on the spatial relationship of neighbouring pixels in classifying pixels into classes. Depending on the training process employed by the analyst, the classification is termed supervised or unsupervised. It may also be considered parametric or non-parametric on the basis of theoretical models.

1.3 Research Problem

The availability of up-to-date land use land cover information is central to much resource management, planning and monitoring programmes. Maps are fundamental for the provision of such land use – land cover information and processes that enhances or leads to the production of such current maps in a cost effective manner is essential. Recent direction in research works indicates that classification of satellite images for land cover information is the preferred choice for producing such maps.

Out of the many methods for image classification, three were chosen for this project - Maximum Likelihood Classification, Sub-pixel Classification and Artificial Neural Network Classification. These methods were chosen because they provide a varied of options, good for comparison as;

- ❖ Maximum Likelihood is a supervised parametric hard classifier.
- ❖ Sub-pixel Classification is a supervised non-parametric soft classifier.
- ❖ Artificial Neural Network Classification is a supervised non-parametric hard classifier.

The focus of this project is to explore the capabilities of the selected methods (Maximum Likelihood Classification, Sub-pixel Classification and Neural Network Classification) to effectively represent land cover types.

1.4 Research Objectives

The objective of the study is

- To classify a Landsat images using three images classification methods - Maximum Likelihood Classification, Sub-pixel Classification and Neural Network Classification.
- To determine which of the three selected methods - Maximum Likelihood Classification, Sub-pixel Classification and Neural Network Classification well depicts or represent land cover types or information classes of interest by accessing their accuracies.

1.5 Research Questions

- What are the benefits and limitations of the classification methods being used?
- How do you assess the accuracy of each method?
- Do any of these methods reign supreme over the others?
- Are there marked differences or similarities between the various classification methods and how they are employed?
- Can any of these methods serve as an alternative to the other?

1.6 Structure of the Thesis

This research work is explained in six chapters. Chapter 1 dealt with introduction, background, trends in Ghana, research questions, objectives of this research and research questions. Chapter 2 gives a brief explanation of image classification, makes the survey of some literature related to this work and looks at the importance of land use - Land cover and the role of remote sensing. Chapter 3 shows the chosen study area. It also gives an explanation about the data used for this work. Chapter 4 illustrates in detail the methodologies used. Chapter 5 analyses and discusses the results. In the end, Chapter 6 concludes the research work with some recommendations for future line of work in this field.

CHAPTER TWO

LITERATURE REVIEW

2.1. The Role of Remote Sensing

Remote sensing is the acquisition of digital data in the reflective, thermal or microwave portion of the electromagnetic spectrum (EMS). Measurements of the EMS are made either from satellites, aircraft or ground-based systems, but characteristically at a distance from the target. Remotely sensed images are captured by sensors on board of the satellites and aircrafts. Depending on the design, purpose and use, these sensors are placed in different heights in space and sweep different areas of the ground (swath width). Images obtained from these can be manipulated by computers to highlight features of soils, vegetation, etc.

Remote sensing techniques make it possible to obtain and distribute information rapidly over large areas by means of sensors operating in several spectral bands, mounted on aircrafts or satellites. Although the use of remotely sensed data started in the 1930s (for aerial photography), they cover relatively large areas than single plot studies, and spatial patterns recognition are easier with photos than from the ground (Rango et al., 2002; Goslee et al., 2003).

Again, advancements in computer technology have aided the processing of observations made by sensors of satellites into digital formats, quick and relatively easier. Furthermore, the developments in Geographic Information System (GIS) and data integration, has greatly enhanced the use of maps in spatial format. Therefore methods of remote sensing are fast gaining significance in land cover classification analysis. As a result data from remote sensing form the primary source of data for most studies. Large collections of remote sensing imagery have provided a solid foundation for spatio-temporal analysis of the environment and the impact of human activities (Zhou *et al.*, 2004).

Gustafson (1993) used GIS for the analysis of lineament data derived from SPOT imagery for groundwater potential mapping. Minor et al., (1994) developed an integrated interpretation strategy to characterise ground water resources for identification of well locations in Ghana using GIS as the unifying element. Folly (1997) used remote sensing and GIS for erosion risk assessment in Northern Ghana. Twumasi et al. (2005) used the application of remotely sensing and GIS technologies in the biodiversity management of Digya National Park, Ghana.

Also developments in space technology and operations have led to the production of high resolution satellite images (SPOT 5 with ground sampling distances (GSD) of 10m; IKONOS, QuickBird and OrbView-3 with ground sampling distances (GSD) of 1m or better). This has improved the ability to address issues of image classification, effective monitoring of resources through change detections and early warning (forecasting) to name a few. Again the improvement in spatial resolutions of sensors has made the application of satellite images in such studies not only limited to the global and regional levels but also at the local level as well.

2.2. Land Cover / Land Use Mapping

Land cover designates the visible evidence of land use, to include both vegetative and non-vegetative features (Campbell, 1987). Land cover has also been defined as that which overlays or currently covers the ground, especially vegetation, permanent snow and ice fields, water bodies or structures (USDA Forest Service, 1989). In simple terms, it is the state of the land as describe by the physical features on it. Examples are cropland, forest, wetland, pasture, roads, urban areas among others

Land use on the other hand, may be defined as the use of land by people usually with emphasis upon the functional role of land in economic activities (Campbell, 1987). Therefore putting the land to use for activities such as mining, grazing, logging, urban development, and agriculture may be termed land use.

Land cover is easily recognised on the field than land use which is usually inferred from the cover. These two words are closely related that in mapping they are used together to avoid ambiguity (Lillesand and Kiefer, 1994). Meyer and Turner (1992), said land use and land cover share a common source of change in the form of human activities that directly alter the physical environment. According to Nagendra et al. (2004), the difficulty in splitting the two terms is due to the complex feedbacks loop that exists between them, making it difficult to distinguish effect from cause.

Land use, land cover and the environment are linked in dynamic and complex ways. Many studies have been conducted to understand this linkages and this has led to many findings.According to Meyer and Turner (1992), every parcel of land on the Earth's surface is unique in the cover it possesses. Land use and land cover are distinct yet closely linked characteristics of the Earth's surface. Topography, climate, vegetation and soil characteristics constrain land use but it also reflects the importance of land as a key and finite resource for most human activities. Land is therefore a fundamental factor of production closely linked with the economic growth of a nation and its people (Richards, 1990).

Generally and globally, the principal causes of land cover changes are by direct human activities or use. They range from the initial conversion of natural forest into cropland to on-going grassland management. (Hobbs, 1997). However, factors other than anthropogenic (human activities) such as climate fluctuations, flooding, weather, fire, and ecosystem dynamics may change the land cover.

Rapidly growing global population, increase in technological capacity and affluence; have led to the transformation of the Earth's land cover, especially, in developing countries. It is therefore one of the crucial elements in images classification for scientific research and real-life earth science applications (Sellers et al., 1995; Campbell, 1996).

Land cover and land use also affect climatic systems over the world through a number of processes such as energy exchange, biogeophysical and biogeochemical. The main processes involve the uptake and release of greenhouse gases (carbon dioxide being the main gas) through photosynthesis, evapotranspiration and respiration; variation in the exchange of sensible heat between the surface and the atmosphere due to land cover changes; variations in absorption and reflectance of radiation as land cover changes affect surface reflectance. (Turner et al., 1993)

For example, land-cover changes such as deforestation and forest fires alter ecosystems and release carbon dioxide, methane, carbon monoxide, and aerosols to the atmosphere. These consequently, change the reflectivity of the land surface which in turn determines how much of the sun's energy are absorbed and thus available as heat. Also, vegetation transpiration and surface hydrology determine how this energy is broken down into latent and sensible heat fluxes. At the same time, vegetation and urban structure determine surface roughness and thus air momentum and heat transport.

Gaining a better understanding of the ways that land cover and land use practises are evolving is a priority concern of the global changes research community (Karweger, 1993). Consequently, understanding the importance of land-cover changes for climate, biogeochemical, or ecological complexity is not possible, however, without information on land use. This is for the simply reason that land use affects land cover and changes in land cover affect land use.

Therefore accurate and up-to-date land use – land cover (mapping) information is necessary to understanding and assessing the environmental consequences of such changes (Giri et al., 2005). As Clawson and Stewart (1965) also put it: In this dynamic situation, accurate, meaningful, current data on land use are essential. If public agencies and private organizations are to know what is happening, and are to make sound plans for their own future action, then reliable information is critical.

At the national, regional and local levels, land use – land cover information are critical inputs in the formulation of policies regarding economic, demographic and environmental issues; decision making, monitoring and management practices as in water- resource inventory, flood control, water-supply planning, waste-water treatment, etc (Anderson et al., 1976; Campbell, 1987).

In land cover mapping, the aim is to represent the earth's surface as much as possible by delineating the different feature as they present in nature. Remote sensing plays an important role in providing information through satellite images and or aerial photograph by characterising spatial variation in land cover and monitoring temporal changes in land resources at various scales through classification procedures (Gholz et al., 1996). As a result of high cost in acquisition, processing and interpretation, aerial photography that have been the main source of land cover and use information, is giving way to multispectral satellite imagery which is cost effective, cover large areas and is available in digital formats.

Currently, one of the challenges in land use – land cover mapping is that there is no accepted global classification scheme, although many of such scheme have been proposed for some time now. The main reasons is that compiled classification systems/map legends (Kuchler and Zonneveld, 1988; Strong et al., 1990; Melillo et al., 1993) as well as land cover datasets (Oslon et al., 1985) are not the same but differ in definition, spatial resolution, purpose and outcome.

Anderson et al. (1976) developed a classification scheme for the United States Geological Survey. Under this scheme, Level I Classification for satellite data such as Landsat TM has 9 land cover classes and Level II Classification for high altitude photographs has 38 land cover classes. They added that although Level I Classification TM has only 9 land cover classes, many of the Level II category classification are still identifiable in the Landsat TM data. This classification scheme has been adopted and or modified by many for their works.

There is one also developed by the European Union under the CORINE (Coordinating Information on the Environment) land cover project, in which a land cover database for Europe is being developed. The land cover is mainly based on information from digital topographical maps interpretation and classification of Landsat TM images with 30 m resolution, resampled to a pixel size of 25 m. In most of Europe the CORINE land cover contains 44 classes.

Also there is another scheme under the DISCover project developed by IGBP (International Geosphere-Boisphere Programme), which has 17 landcover classes distinguished on the global scale. Under the project, 1 km spatial resolution AVHRR (Advanced Very High Resolution Radiometer) satellite images produced by the U.S. National Oceanographic and Atmospheric Administration (NOAA) (Belward et al., 1999) are used to produce the IGBP Global Land Cover Map. This is however not adequate for application at the Regional and Local levels where much detail is required and more classes are involved.

Many more have been developed or used in different works by researchers and scientist alike based on the purpose and interest area for their works. There are however, on-going efforts by researchers, and all stakeholders to see the possibilities of harmonising existing classifications and to develop a consistent and widely acceptable reference land cover classification (UNEP/FAO, 1994; De Bie et al., 1995; Turner et al., 1995) for application at the global, regional and local levels.

2.3. Image classification methods in use

2.3.1. The Concept of Image Classification

Image classification is the organization of pixels in an image into groups (classes) based on their spectral properties. These groups (classes) are obtained by identifying pixels that have similar spectral characteristics. Information on various features of the group can be used to determine the cover classes those groups represent.

Generally, classification is of two forms; namely Pixel/Spectral-based classification which groups pixels into classes solely based on their spectral properties and Object-based classification which in addition to the spectral properties, uses information on the spatial relationship of neighbouring pixels in classifying pixels into classes

In image classification, the aim is to classify each pixel into a class (i.e. crisp classification or hard classification) or associating the pixels with many classes (i.e. fuzzy classification or soft classification), thereby matching the spectral classes in the data to the information class of interest.

Depending on the training process employed by the analyst, the classification is termed supervised where the image analyst makes input that the image processing software (system) uses as guidelines to determine the classification of features or unsupervised where the processing of the image is virtually an automated one, in which the classification is based on search for natural groups of pixels present in the image (Campbell, 1987).

In the case of the unsupervised classification however, to determine the identity and information values of such spectral classes which are not known initially, there is the need for the analyst to compare the classified data to some form of reference data (such large scale imagery, maps, or site visits. (Lillesand and Kiefer, 1994; PCI, 1997). Coleman et al. (2004) used unsupervised classification technique to identify land cover features in their study of mangrove ecologies along the coast of Ghana. Classification may also be considered parametric or non-parametric on the basis of theoretical models.

2.3.2. Methods of Image Classification

Since the intent of classification is the categorization of pixels into classes, any method that seeks to identify and represent such classes based on the principle of correlation is applicable. As a result, various methods for image classification have been developed based on different theories or models.

Some of the common methods that are used in classification include K-Means, Isodata, Maximum Likelihood and Minimum Distance. Over time, scientists through great efforts have developed other advanced classification methods such as Extraction and Classification of Homogeneous Objects (ECHO) classifier (Kettig and Landgrebe, 1976), Neural network (Chen *et al.*, 1995; Paola and Schowengerdt, 1997; Augusteijn and Warrender, 1998; Tso and Mather, 2001), Fuzzy Set classification (Foody, 1996; Mannan *et al.*, 1998), Spectral Mixture Analysis (Roberts *et al.*, 1998; Mustard and Sunshine, 1999), Subpixel classifier (Huguenin *et al.*, 1997), and Per-field classification (Pedley and Curran, 1991; Aplin *et al.*, 1999a), etc.

Most traditional classifiers such as Isodata, Maximum Likelihood, and Linear Discriminant Analysis are parametric. Parametric models usually assume a spherical or Gaussian model for the shape of a class. They are based upon statistical assumptions, including the multivariate normal distribution within spectral classes. Parametric classifiers use class statistics such as mean vectors and covariance matrices in their computation. This assumption unfortunately, is not applicable to all situations and is also difficult to implement in complex landscapes with classes of high variance (Hansen et al., 1996).

An alternative is the development of non-parametric methods that are not limited by such assumptions. Such classifiers are known as non-parametric classifiers and it includes Support Vector Machines, K-Means, Artificial Neural Networks (ANN), Decision Tree and Classification and Regression Trees (CART).

Depending on the objective and or purpose of the research work, parametric classifiers (Guild et al., 2004; Pan et al., 2004), or non-parametric classifiers (Chen et al., 1995; Hansen et al., 1996; Paola and Schowengerdt, 1997; DeFries and Chan, 2000; Mannan and Ray, 2003; Kavzoglu and Mather, 2004), have been employed in land cover classification. Other works involved a combination of the both parametric classifiers and non-parametric classifiers, as with; (Warrender and Augusteihn, 1998) in which they used MLC and neural network and (Lu and Weng, 2004) used MLC and decision tree classifier.

Hussin et al. (1994) used the Area Productivity Model (APM) for forest change detection analysis and the algorithm used in the image classification was the Maximum Likelihood. Hedge (2003), used the fuzzy classification in modeling land cover changes. Roberts et al. (2002), in their work used Spectral Mixture Analysis and a Decision Tree classifier for land cover classification. Huang et al. (2002) used the Support Vehicle Machine (SVM), Maximum Likelihood, Neural Network and Decision Tree Classifier for their classification. Bhandari and Hussin (2006) used Sub-Pixel and Maximum Likelihood classification in detecting illegal logging in a tropical rain forest. Quin et al. (2007) used Normalised Difference Built-Up Index and Maximum Likelihood, which are pixel-based classifier and Object-Oriented classification in their research.

The methods employing remote sensing techniques for extraction of land cover information and subsequent analysis and modelling have evolved from the very basic visual interpretation into a complicated family.

From the 1980's, improvement of land cover classification and techniques so as to achieve higher accuracies have been the subjects of many researches (Kontoes et al., 1993; Foody, 1996; Stuckens et al., 2000; Pal and Mather, 2003). This is due to the increasing recognition by global, national and regional managers and planners of the need and significance of land cover information for a variety of developments. In most of these works, they seek to know how to better represent spectral classes as well derive maximum information from such classes

As a result, many of the works also involved comparison of result from two or more methods. Quin et al., 2007, used pixel-based (NDBI method, MLC) and object-oriented classification methods for Extracting Built-Up Areas and observed that the object-oriented classification produce the highest accuracy of the three method. Lu et al. (2003) did a comparison study of five classifiers – Minimum Distance Classifier (MDC), maximum likelihood classifier (MLC), Fisher Linear Discriminant (FLD), Extraction and Classification of Homogeneous Objects (ECHO), and Linear Spectral Mixture Analysis (LSMA) for the tropical land cover classification and recommended LSMA and ECHO classifiers as suitable since they gave a better accuracy compared with the other three.

It can be seen from the on-going literature that depending on the reason for the research, different methods can be used and the accuracies involved may differ from one method to the other.

2.4. Principles of Selected Classifiers

Three classifiers Maximum Likelihood, Sub-Pixel and Neural Network are used in the land cover classification. The principles of the classifiers are outlined as follows

2.4.1. Maximum Likelihood Classifier **(MLC)**

The source of the Maximum Likelihood Classifier (MLC) can be traced back to electrical engineering (Nilsson, 1965). Over time, it has become a standard classification approach applied in remote sensing (Richards and Jia, 1999).

With this method of classification, ‘training data’ are used in estimating means and variances of the classes, which are then used to estimate the probabilities for membership in each class. The training data are chosen representative or prototype pixel from each of the desired sets of classes (Richard and Jia, 1999). The probability for membership with the highest value is chosen as the correct class and the pixel is assign to that class (Lillesand and Kiefer, 2000).

Unique characteristic of the classifier to note is that the decision surfaces in MLC are quadratic. It is a parametric classifier that assumes that the data follows a normal (Guassian) distribution. Maximum Likelihood is one of the most commonly used supervised classifiers. It produces class maps with high classification accuracy, and is relatively efficient in its computational demands, given the speed of modern computers. There are several studies in which this supervised classification method has been utilised successfully, either directly or in combination with other methods (Lee et al., 2003; Wang et al., 2004;).

2.4.2. *Sub-Pixel Classifier (SP)*

Sub-Pixel classifier is a soft classifier, used in soft classification. With hard classifiers like MLC, classification (hard) is done by allocating a pixel on a 'one pixel per class' basis and the land-cover classes are mutually exclusive. However, in soft classification, the allocation of the pixel is not done on 'one pixel per class' basis. Rather, each pixel is expressed as in association with other classes within the neighbourhood of the pixel.

Due to the fact that land cover may vary more frequently than the sampling interval between pixels in the imagery (heterogeneity of landscapes) and limitation in spatial resolution of remote-sensing imagery, a single pixel may represent mixture of land cover classes. Such pixels are called mixed pixels or mixels. This is one of the major problems affecting the effective use of remotely sensed data in per-pixel classifications (Fisher, 1997; Cracknell, 1998).

Sub-Pixel classification approaches have therefore been developed to provide a more appropriate representation and accurate area estimation of land covers than per-pixel approaches, especially when coarse spatial resolution data are used (Foody and Cox, 1994; Binaghi et al., 1999; Woodcock and Gopal 2000).

Sub-Pixel can be useful in delineating forest boundaries, shorelines and other continuous classes. They can also bring out objects that cover small areas, which with conventional classifiers otherwise would have disappeared.

Different approaches including Fuzzy-set theory, Dempster–Shafer theory, Certainty factor (Bloch, 1996), Softening the output of a MLC (Schowengerdt, 1996), IMAGINE's Sub-pixel classifier (Huguenin et al., 1997) and Neural Networks (Foody, 1999; Mannan and Ray, 2003), have been used to derive a soft classifier.

2.4.3. Back Propagation Neural Network

Backpropagation Neural Network is one of the types of artificial neural network and like all artificial networks; it is a supervised – hard classifier. Based on biological theory of human brain, artificial neural networks (NN) are models that attempt to parallel and simulate the functionality and decision-making processes of the human brain.

In general, a neural network is referred to as mathematical models of theorized mind and brain activity. According to Kanellopoulos and Wilkinson (1997), neural networks are general-purpose, flexible, non-linear models consisting of a number of units organised into multiple layers.

Typically, artificial neural network consists of an input layer, a hidden layer and an output layer. The units in the input layer equal the number of variables used in the classification, whiles the output produces the network's results that denote the various land cover classes the hidden layer between the input and the output enables the network to model complex functions (Osei, 2003). The hidden layer is actually made up of a network of weights and bias and it is these that are applied to a set of input to produce an output. Selection of appropriate number of hidden layers and their units is, however, critical for the successful implementation of the neural network (Arora et al., 2000).

Artificial neural networks is also a non-parametric and like other non-parametric classifiers such as Classification and Regression Tree (CART) and Expert System have become prominent in recent works because it eliminates the restriction of parametric statistical assumptions (Chen et al., 1995; Hansen et al., 1996; Paola and Schowengerdt, 1997). There are other works that involved the use of neural networks (Bendiktsson et al., 1990; Kavzoglu and Mather, 2004; Verbeke et al., 2004). The allocation of the pixels by artificial neural network in land cover classification is done on one pixel to one land cover class basis. The resulting classification is therefore a crisp classification.

CHAPTER THREE

MATERIAL

3.1. Study Area

The research was conducted in the Ejisu-Juaben District in the Ashanti Region of Ghana. The study area is located in the northern part of the district. This area was chosen because it has experienced various changes in land use – land cover over the years due to increase in population as well as development pressures from more densely populated and expanding Kumasi Metropolis . It is therefore a suitable area for sampling various land cover types for image classification.

<u>MAP OF AREA OF STUDY</u>

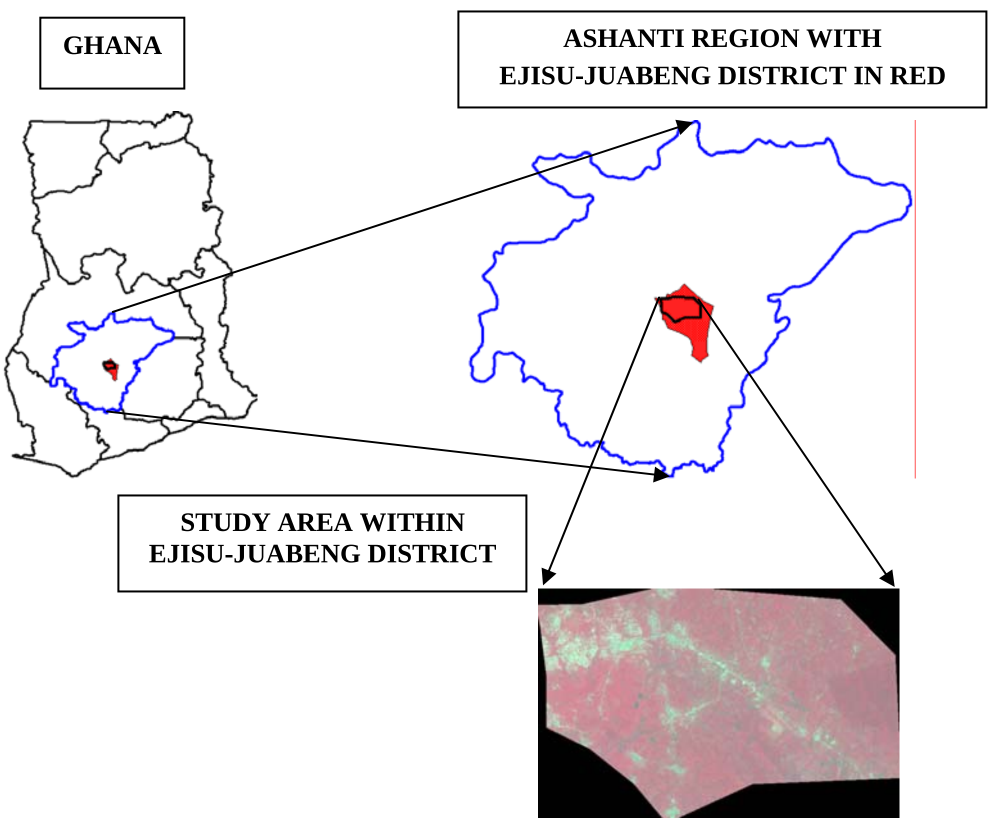


Fig. 3.1: Location Map of Study Area

3.1.3 Location & Size

Ejisu-Juaben District is located in the central part of the Ashanti Region. It shares boundaries with the Kumasi Metropolitan Area and Kwabre District to the east, Sekyere East and Asante Akim North Districts to the west and the Bosomtwe-Atwima-Kwanwoma and Asante Akim South Districts to the south. The entire district falls within the moist semi-deciduous forest region where different species of tropical wood with high economic value are found. It is also known globally for its rich cultural heritage and tourists attractions notably the booming kente weaving industry.

The District stretches over an area of 637.2 sq. km constituting about 10% of the entire Ashanti Region and with Ejisu as its capital. The District provides enormous opportunity for creating an inland port for Ghana to serve northern section of the country. It lies within Latitude 1° 15’ N and 1 ° 45’ N and Longitude 6° 15’W and 7° 00’W.

3.1.4 Topography and Drainage

The District falls within the forest dissected plateau terrain region and is underlain by the pre-cambrian rocks of the Birimian and Tarkwaian formations. It rises from about 240 to 300 metres above sea level. The area is generally undulating and is drained by a number of rivers; notable among them are Oda, Anum, Bankro, Hwere and Baffoe. In the rainy season, occasional flooding is experienced in the inland valleys along the river basins (Ejisu-Juaben District Assembly, 2002).

3.1.5 Climate

The rainfall pattern in the district is bimodal in nature with wet semi-equatorial climate. It is characterised by double maxima rainfall lasting from March to July and from September to late November. Mean annual rainfall recorded stands at 1200 mm. Relative humidity is usually fairly moderate but high during the rainy season and early mornings. Lying entirely within the tropical high forest zone of southern Ghana; it experiences annual temperatures ranging from 20°C in August and 32°C in March. (Ejisu-Juaben District Assembly, 2002).

3.1.6 Vegetation and Soil

The Ejisu-Juaben District lies in the moist semi-deciduous forest vegetation zone as categorised by (Hall and Swaine, 1976). Bobiri Forest Reserve is found in the district and has a total area of 54.6 km^2 serving production, tourism, research and conservation functions. It is one of the richest in terms of biodiversity in the country. The reserve is floristically diverse and endowed with large quantities of economic timber species which include *Triplochiton screloxylon, Terminalia superba, Nesogodonia papaverifera, Aningeria robusta, Chrysophyllum albidum* and various species of *Entandrophragma* (Bureau of Integrated Rural Development, 2001).

The off-reserve areas mainly consist of annual crops, cash crops, fallow lands, forest patches and riparian vegetation along rivers and streams and grass in abandoned areas. It is important to note that forests outside the reserves are unsustainably logged by illegal and legal loggers. The most predominant plant in the off-reserve is mainly *Chromolena ordorata*. (Bureau of Integrated Rural Development, 2001).

There are eight soil types in the district namely granite based Kumasi-Offin Compound, Bomso-Offin Compound and Swedru-Nsaba Simple Associations; Birrimian rock based Bekwai-Oda Compound, Kobeda-Eschiem-Sobenso-Oda Complex and Atunkrom-Asikuma Association; Tarkwaian based Juaso-Mawso association and lastly the superficial deposits based Boamang-Suko Simple Association (Gaespenu and Associates, 1996). All these soil types can support some form of agriculture ranging from annual crops to cash crops.

3.1.7 Demographic and Characteristics

The population of the district stood at 124,176 as of the year 2000 (Ghana Statistical Service, 2003) and estimated at 144,272 in 2006. Population of the district continues to increase at a growth rate of 2.5%. Population growth is attributed to the considerable expansion in peri-urban towns in the district. Currently, the district has three sub-urban settlements namely, Ejisu, Juaben, and Besease. These three towns account for 30.2% of the total population in the district with the district capital having 9.2%. The rural settlements are those with their population less than 5,000 and basically their economic activities are agricultural and account for 69.8%.The population growth rate of 2.5% will put pressure on the available natural resources and leading to conversion of agricultural lands into residential uses especially at the peri-urban areas. (Ejisu-Juaben District Assembly, 2002).

3.1.8 Agriculture

The major farming practice in the District is mixed farming (90.1% of the farmers). This implies that, whiles the farmers cultivate the food and tree crops, livestock and poultry are also kept in the backyard as a supplementary source of food and income. The remaining 9.9% of the farmers practice mono cropping. Considering the farming systems, bush fallowing, which is a system whereby a land is left for a period of time to regain its fertility. This is being practice by 48.5% of the farmers. (Ejisu-Juaben District Assembly, 2002).

The length of fallow period has been drastically reduced due to the growing population and the increasing demand for lands for uses other than agriculture. Continuous cropping is practiced by about 45.5% of the farmers. This can result in the lose of soil fertility and adversely affect output levels if measures are not put in place to retain the soil fertility in the course of continuous cropping. (Ejisu-Juaben District Assembly, 2002).

3.1.9 Economic Situation

Agriculture is the leading employer of the working population employing 68.2% of the people whilst the industrial sector is the least employer of the working population employing 8% of the populace in the district. The service sector also employs 23.8% of the population. The service sector that contributes most to the income (GH ¢56.5 per month) in the district, whiles the agricultural sector is the least (¢45.6 per month) contributor to the economy (Ghana Statistical Service, 2003). Even though most of the people within the district are engaged in agriculture, its contribution to income is very low thus contributing to the low living standards of the people (Ejisu-Juaben District Assembly, 2002).

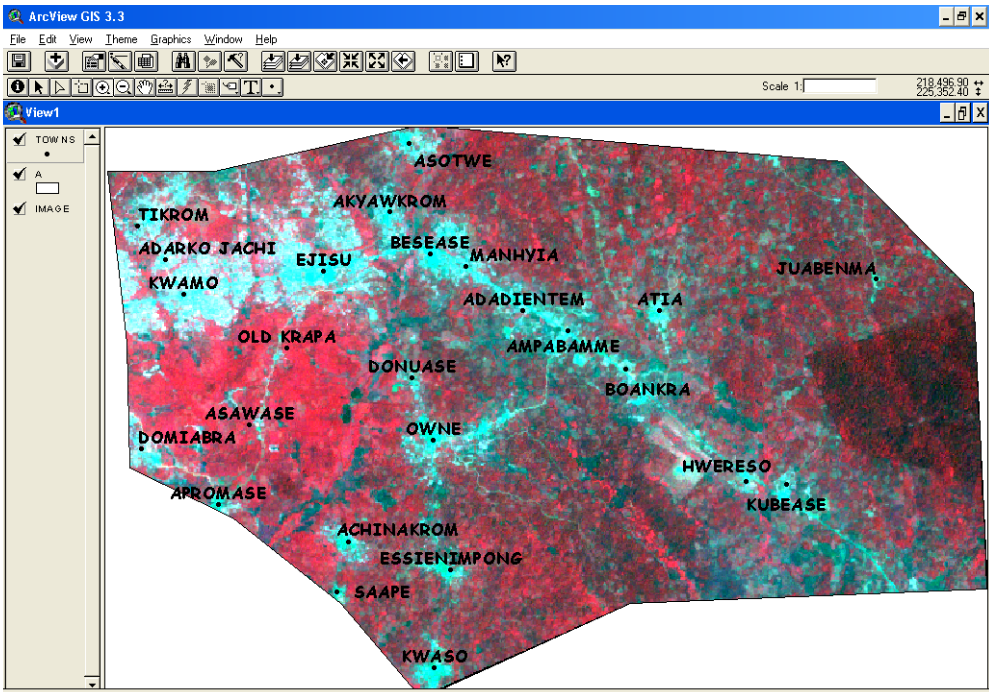


Fig.3.2: Display of image of study area with towns

3.2. Data

A Landsat Enhanced Thematic Mapper plus (ETM+) satellite imagery acquired on 16th February, 2007 (February, Level 1 B with path/row 194/55) was used for this study. It had no clouds over the study area and the day was relatively clear. The image was selected from the ITC database based on availability and suitability in terms of seasonal compatibility. The image was used for the land cover classification.

The Landsat (ETM+) has eight spectral bands – Band 1, Band 2, Band 3, Band 4, Band 5, Band 6, Band 7 and Band 8. Band 1 – 5 and Band 7 have a spatial resolution of 30m x 30m each. Band 6, for recording thermal energy has a spatial resolution 60m x 60m, whiles band 8, for panchromatic is 15m x 15m. Band 6 and band 8 are usually not used for land cover classification. The table below describes some properties of Landsat (ETM+)

SPECTRAL BAND	**WAVELENGTH (μm)**	**WAVELENGTH DEFINITION**	**IFOV (m)**
1	0.45 - 0.52	blue	30 x 30
2	0.52 - 0.60	green	30 x 30
3	0.63 - 0.69	red	30 x 30
4	0.76 - 0.90	near IR	30 x 30
5	1.55 - 1.75	mid IR	30 x 30
6	10.4 - 12.5	thermal	60 x 60
7	2.08 -2.35	mid IR	30 x 30
8	0.52 - 0.90	panchromatic	15 x 15

Tab. 3.1: Spectral Information of Landsat (ETM+).

Adopted and modified, from Richards and Jia, (1999).

3.3. Software

ERDAS imagine 8.7; IDRISI (Kilimanjaro Edition), ESRI ArcView 3.2, PC ArcInfo 3.5.2 and Garmin 72 GPS were the software used in this study.

CHAPTER FOUR

METHODOLODY

4.1. The Flowchart

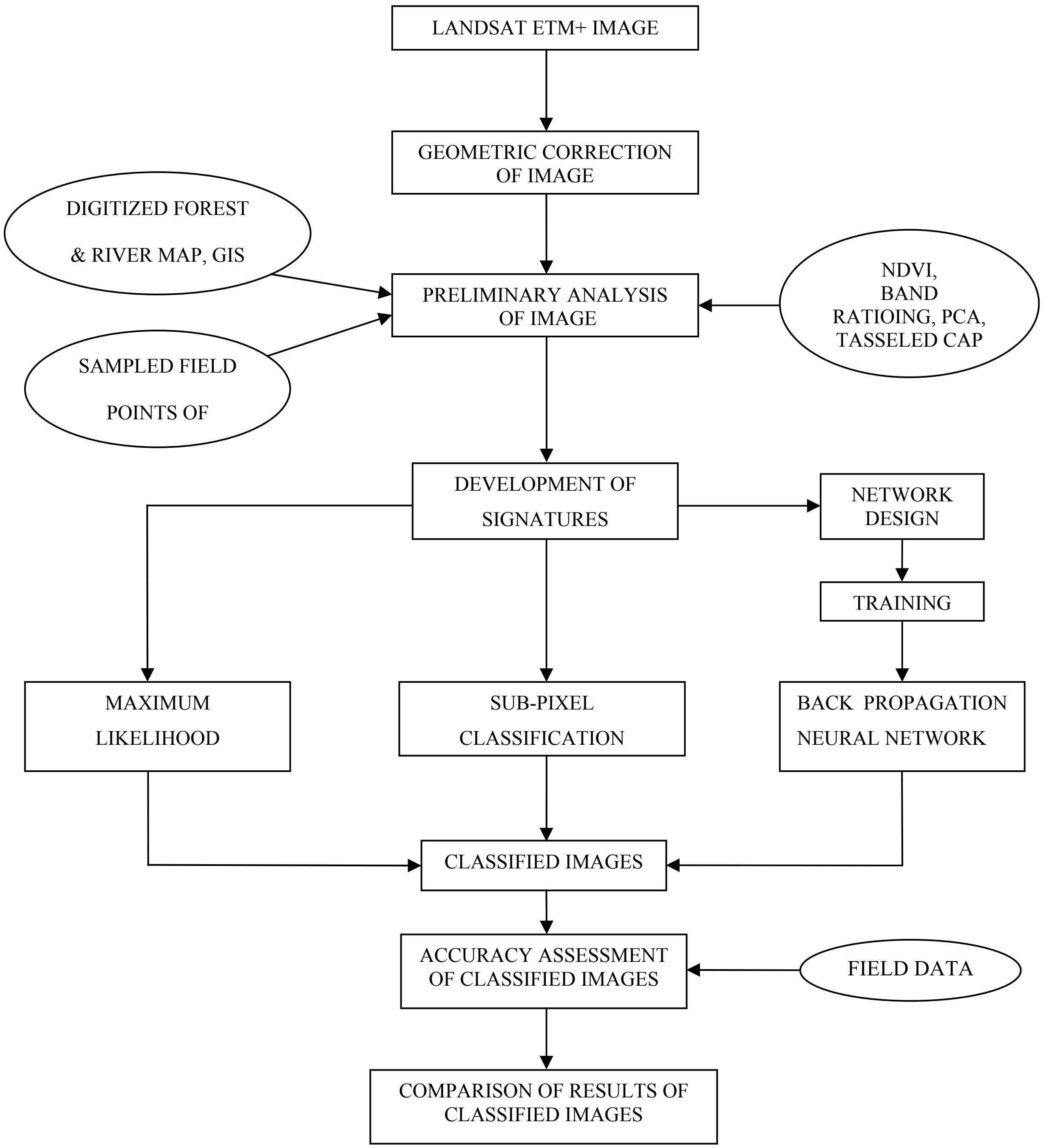


Fig. 4.1 : The Flowchart of Method Used

4.2. Image Pre-Processing

Image pre-processing are actions or processes undertaken prior to the main data analysis and extraction of information. They are of two main forms – radiometric correction or geometric correction. Radiometric corrections are needed to correct the data for sensor irregularities and unwanted sensor or atmospheric noise, and converting the data so they accurately represent the reflected or emitted radiation measured by the sensor.

Geometric on the other hand is important to correct for distortions due to sensor-Earth geometry variations such as movements of sensor platforms, terrain relief, rotation of the earth, etc. and the need to convert the data to real world coordinates (e.g. latitude and longitude) on the Earth's surface (Lillesand and Kiefer, 1994)

4.2.1. Radiometric Correction

As has been identified above, radiometric corrections are important and mandatory when using multi-date images datasets (Richter, 1990; Mas, 1999). This must be done so that images obtained by sensors at different times are made comparable in terms of radiometric characteristics. Techniques like image enhancement, normalization, calibration etc have been applied to multi-date satellite images to increase the amount of information for improve interpretability (Bektas et. al., 2003). In this study however, no atmospheric correction was applied because data on atmospheric characteristics was not available. Secondly only a single-date image is being used for the classification and therefore atmospheric correction can be ignored (Song et al. 2001).

4.2.2. Geometric Correction

The objective of geometric correction is used to register each pixel to real world coordinates (Jensen, 1996). The Landsat image was geometrically corrected to the local coordinate system –Traverse Mercator projection with War Office ellipsoid using a 1:50000 scale digital line map (Osei et al., 2004; Nangendo et al., 2006) of forest reserves, rivers and roads and ERDAS Imagine 8.7 software. The digital line map was obtained from the Survey Department of Ghana.

The image was georeferenced with thirty-five (35) pairs of well and carefully selected control points. Musaoglu et al. (2002), Attua et al., (2001) and Yuan et al., (2005) in their study used 25, 30 and 35 ground control points respectively to geo-reference their images. The Landsat image was then transformed using 1st order polynomial transformation and resampled to 30m x 30m pixel size using the nearest neighbour resampling method to preserve the radiometric integrity of the data. The nearest neighbour resampling method assigns the DN value of the closest original pixel to the new pixel thereby retaining all spectral information and therefore an efficient method to apply to images that will be in classification (Kerle et al., 2004).

The root mean square (RMS) error for the ground control points (GCPs) was approximately 0.22 pixels on the average of a pixel, corresponding to a spatial accuracy of about 6.6m on the ground. Osei *et al.* (2004), Yuan *et al.* (2005), Nangendo et al. (2006), and Shalaby *et al.* (2007) all conducted research works with acceptable RMS value of up to 0.5. Root Mean Square error is the distance between the desired output coordinates for GCPs and the actual output coordinates for the same points, when the points are transformed with the geometric transformation. The amount of RMS error can be thought of as a window of tolerance around the source coordinates, inside which a retransformed coordinate is considered to be correct that is, close enough to use (Smith and Brown, 1997). The image was further subsetted to fit the study area.

4.3. Image Processing

In remote sensing, images are historically processed digitally because of two important principal areas of application namely; the improvement of the spectral information to enhance the process of visual interpretation and the processing of image data for computer assisted classification. The aim of both processes is to increase spectral separability of the object features in the image.

Commonly used image enhancement techniques include image reduction, image magnification; transect extraction, contrast adjustments (linear and non-linear), band ratioing, spatial filtering, Fourier transformations, principal components analysis, and texture transformation (Jensen, 1996). Two of these techniques; Vegetation Indices developed under the band ratioing technique and Principal Components Analysis will be considered briefly as they were used in the this study.

4.3.1. Relationship between spectral bands of a Landsat ETM+ image

When electromagnetic radiation (EMR) is incident on a target, object or material; the energy may be reflected, transmitted or absorbed. In many cases however, the materials under observation are sufficiently thick that no energy is transmitted right through it and therefore transmission does not occur.

Different materials interact differently with this energy and the characteristics of the interaction are consistent with the material types. This phenomenon is used in remote sensing to identify various materials. Bands 1, 2, 3, 4, 5, 7 were used in the image classification and the importance of these bands are briefly described.

The first three bands (bands 1, 2, 3) of Landsat ETM+ represent the visible portion of the electromagnetic spectrum. Energy in the band 1 illuminate material in shadows, penetrates very clear water, and is absorbed by chlorophyll. Energy from band 2 penetrates water but not as deep as that of band 1. It provides a contrast between clear and turbid water, discriminates oil on water, and is reflected by vegetation. Energy in band 3 is strongly absorbed by chlorophyll but has strong reflectance for most soils. It is therefore good for vegetation discrimination, soils discrimination, and urban features analysis.

The reflectance of radiation from Band 4 (band for near infrared) is strongly affected by the cellular structure of leaf tissue and is used for vegetation analysis. Also since it is strongly absorbed by water, it can be used to delineate water bodies (lakes and sinkholes), distinguished between dry and moist soils (barren land and croplands) and shoreline mapping.

Band 5 and band 7 representing the short wave infrared (SWIR) portion of the electromagnetic spectrum is used for discriminates oil on water, detects moisture of soil and vegetation, and provides contrast between vegetation types. It is also useful for discriminating snow from clouds.

4.3.2. Vegetation Indices

Indices are used to create output images by mathematically combining the digital number (DN) values of different bands. In many instances, these indices are ratios of band DN values (band ratioing). In simple term, band ratioing is a measure of the difference in reflectance of the same surface for two separate portions (bands) of the electromagnetic. Band ratioing is very useful in vegetation identification because of the high spectral absorption in the visible red and high reflection in the near-infrared region.

Vegetation indices are therefore empirical formulae designed to emphasize the spectral contrast between the red and near-infrared. According to Campbell (1996), it is an attempt to measure biomass and vegetation health. The higher the value of the index, the greater is the amount of healthy vegetation expected at the ground.

Many vegetation indices such as Ratio Vegetation Index (RVI), Perpendicular Vegetation Index (PVI), Normalised Difference Vegetation Index (NDVI), Difference Vegetation Index (DVI), Weighted Difference Vegetation Index (WDVI, and Enhanced Vegetation Index (EVI), Soil-Adjusted Vegetation Index (SAVI), Modified Soil-

Adjusted Vegetation Index (MSAVI), Global Environment Monitoring Index (GEMI) have all been developed to determine the strength of vegetation of an area.

Normalized Difference Vegetation Index (NDVI) is one of the most widely used vegetation indices and it was also applied in this study. It is an index or measure that is related to the proportion of photosynthetically absorbed radiation. Chlorophyll in green leaves absorbs strongly red light while near-infrared light either passes through or is reflected by life leaf tissues, regardless of their color.

In general, higher values of NDVI indicate greater vigour and amount of vegetation. NDVI values ranges from -1 to 1, where vegetated areas will typically have values greater than zero and negative values indicate non-vegetated surface features such as water, barren, ice, snow, or clouds. Most vegetated areas have values of between 0 and 0.7. It can sufficiently be used to discriminate between vegetated areas and non-vegetated areas. Areas of vegetation appear in bright tones whiles non-vegetated areas appear in dark tones.

For Landsat ETM+, NDVI from equation (1) can be written as

$$\text{NDVI} = \frac{\lambda_{\text{Band 4}} - \lambda_{\text{Band 3}}}{\lambda_{\text{Band 4}} + \lambda_{\text{Band 3}}}$$

where, $\lambda_{\text{Band 4}}$ = reflectance (DN value) in band 4

(Band for near-infrared [NIR] light)

$\lambda_{Band\ 3}$ = reflectance (DN value) in band 3

(Band for red light)

The main advantage of the NDVI like other band ratio techniques is that, it corrects for eventual errors due to topography and shade and compensating for variation in illumination due to terrain (Lillesand and Kiefer 2000)**.**

To maximize the range of values and provide numbers appropriate for display in an 8 bit image, the NDVI value may be scaled. In this study, the NDVI values were scaled according to the following equation:

$$\text{Scaled NDVI} = 100(\text{NDVI} + 1) \quad (1)$$

Thus, using this equation, a pixel with an NDVI value of 0.43 becomes 143 on the grey scale. Using this technique, the NDVI computed value is scaled to the range of 0 to 200, for -1.0 to 1.0.

As a result, NDVI values below 100 now represent clouds, snow, water, and other non-vegetative surfaces, and values equal or above 100 represent vegetative surfaces. The resulting scaled values can be displayed on a grey tone display or converted to a colour image.

4.3.3. Tasseled Cap

The Tasseled Cap transformation is a spectral enhancement technique that is used to optimize data viewing for vegetation studies (Crist et al, 1986, Crist and Kauth, 1986). The pixel (DN) distribution in a remotely sensed image is determined by the absorption and or reflection spectra of the imaged material and the clustering of the pixels is known as the data structure. The transformation produces three data structure axes that define the vegetation information content and are more directly related to the absorption spectra (Crist and Kauth, 1986).

These data structure axes are defined as (Lillesand and Kiefer, 1994):

- 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. Strongly related to the amount of green vegetation in the scene.
- Wetness—relates to canopy and soil moisture.

4.3.4. Principal Component Analysis (PCA)

Data from bands of remotely sensed images are usually highly correlated because it is the same area that is captured by bands of different wavelengths. Principal component analysis (PCA) is a spectral enhancement technique applied in remote sensing for the production of images where the correlation between bands is zero. The objective of this transformation is to reduce the dimensionality (i.e. the number of bands) in the data, and compress as much of the information in the original bands into fewer bands (Smith and Brown, 1997).

According to Diamantaras and Kung (1996), it represents a classical statistical technique for analysing the covariance structure of multivariate statistical observations and can be considered as a feature extractor as well as data compression techniques.

The ability of PCA to compress data has immensely been employed in neural network applications. According to Subramanian et al. (1997), in neural network classification using hyperspectral image of sensors such as AVIRIS (224 bands), PCA technique can significantly decrease the training time by reducing the problem of dimension (by factor of 20 to 50). In this study however, the PCA technique is used as an aid for the extraction of features.

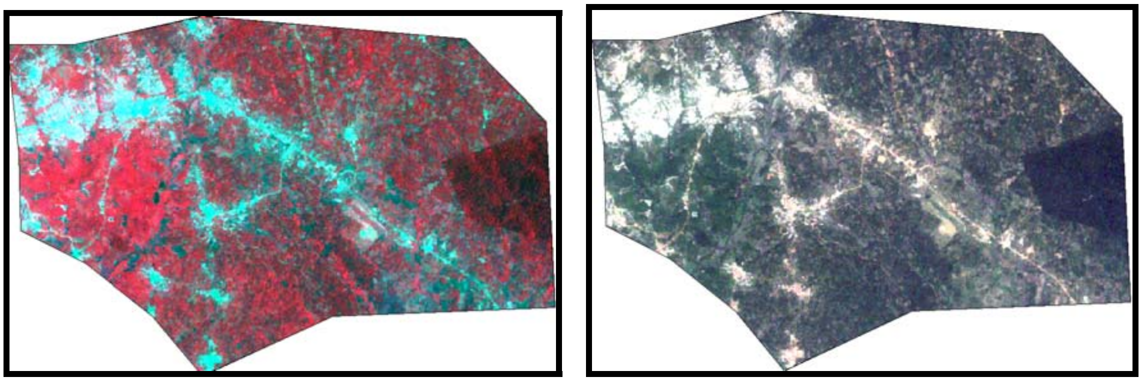
4.4. The Classification

Lu and Weng (2007) in their review outlined the major steps of image classification to include, the determination of a suitable classification system, which involves:

- Image pre-processing
- Feature extraction
- Selection of training samples
- Selection of suitable classification approaches
- Accuracy assessment

Issues of image pre-processing in this study have been dealt with under section 4.1 above. As a preliminary to the extraction of features for the classification of the image, the image is first displayed in 4-3-2 bands combination (i.e. RGB format – band 4 for red, band 3 for green and band 2 for blue) and 3-2-1 bands combination, for visual analysis using ERDAS imagine 8.7.

The display of 4-3-2 bands combination showed that a greater part of the area under the study is in shades of red, which is an indication of vegetation. The next pronounced colour is the light blue colour, which are urbanised areas. For the 3-2-1 bands combination (natural colour), greater part of the area is dark green; an indication of dense vegetation whiles urbanised area is in white and off-white.



(a) (b)

Fig. 4.2: Image display in different bands combinations; (a) 4-3-2 and (b) 3-2-1.

Other processes such as Vegetation Index (NDVI), Tasseled Cap and PCA transformations were also applied to the image to access information on vegetation, level of canopy or soil moisture as well as suitable areas for sampling data through field observations.

Based on the spectral information gathered, seven land cover classes were selected. Adopting and modifying the classification scheme (level I) developed by Anderson and others (1976), these seven classes were identified as forest, forested wetland, open woodland, water, non-forested wetland, grassland and urban. Table 4.1 below is the scheme used in this study for the image classification.

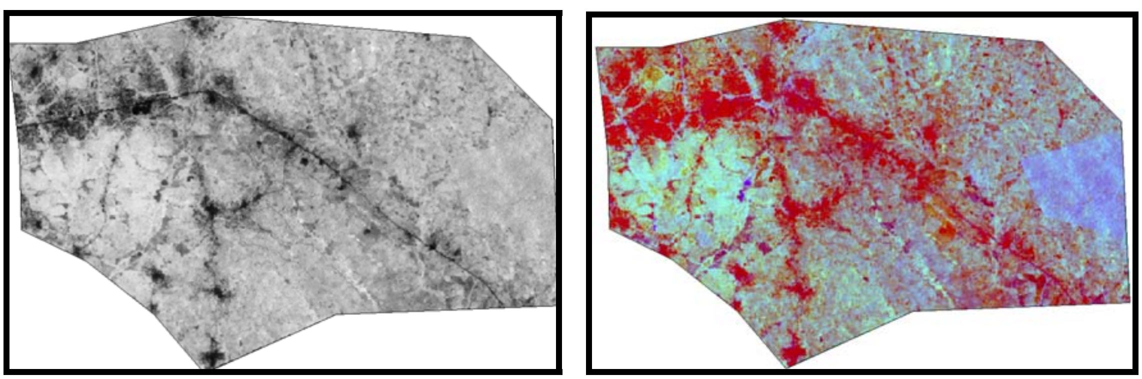
LAND COVER CLASS	ABBREVIATION	DESCRIPTION
Forest	**for**	These are areas with a tree-crown areal density (crown closure percentage) of 10 percent or more and canopy levels of more than 60 percent. They are stocked with trees capable of producing timber or other wood products, and exert an influence on the climate or water regime
Forested Wetland	**for_w**	Comprises of trees that usually grow along water bodies or courses, waterlogged or marshy areas and low-lying areas that are periodically flooded during raining season. They are predominantly Raffia-Palm mixture and *Bambusa vulgaris* (bamboo). Such areas harbour non-tree vegetation like ferns and water cocoyam.
Open Woodland	**open_w**	Sparsely distributed trees, interspersed with shrubs and grasses. Included in this category is Teak plantation. Here canopy level if any is small (less than 20 percent.
Water	**water**	These comprises of mainly shallow water bodies such as potholes and ponds. In them are other growths such as water lily, water grass.
Non-Forested Wetland	**nfor_w**	These are dominantly wetland herbaceous vegetation or are nonvegetated. These wetlands include freshwater meadows, wet grassland, open bogs and nonvegetated flats. The main features are grass with varying heights up to a maximum of about 4m.
Grassland	**grass**	Includes all forms of grasses, ranging from creeping species up to tall elephant grass with a height of about 3m.

Urban	**urban**	These are areas of intensive use with much of the land covered by structures. It Includes towns, villages, strip developments along highways, transportation, power, and communications facilities, and areas such as those occupied by mills, shopping centers, etc.

Tab. 4.1: The classification scheme (adopted and modified from Anderson et al., 1976)

Column two of the Table xx is abbreviations used for the land cover classes to facilitate easy entry of field observations.

Three classification methods - maximum likelihood, sub-pixel, and neural network were used to classify the image in this study.



(a) (b)

Fig. 4.3: Display of NDVI (a) and Tasseled Cap (b) transformed images

4.3.1. *Maximum Likelihood Classification (MLC)*

NDVI, Tasseled Cap and PCA transformations were applied to the pre-processed image to access information generally about vegetation, levels of canopy or soil moisture and the distribution of land cover classes. Various band ratio images produced from two of the six bands were also created and examined. Three of these images (band 3 / band 2, band 5 / band 2 and band 5 / band 7) were selected due to the contrast they produce between land cover classes and then stacked together to produce a composite (colour) image.

Training samples or data were collected from the composite image based solely on difference in colour. Training samples of the same geographic locations are also collected from Landsat image in 4-3-2 bands combination. Analysis of information from the spectral bands, the NDVI image and the Tasseled Cap transformed image were used to identify the seven land cover classes. Field observations of sample points, representative of the land cover classes, were also collected and used together with the above information in the development of the signatures that were used in the classification.

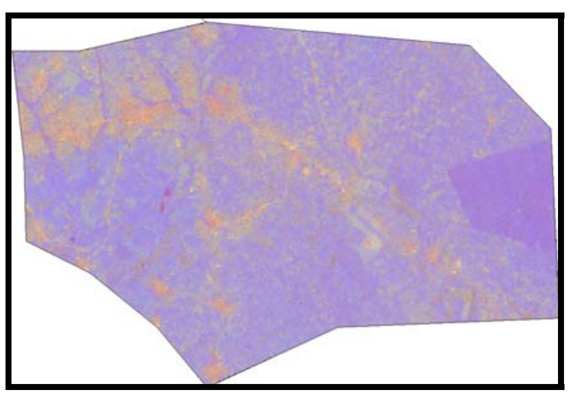


Fig. 4.4: Display of composite map of three band ratioing

4.3.2. Sub-Pixel Classification

The ERDAS Imagine Subpixel classifier 8.7 is used for the sub-pixel classification. It is an add-on module of the ERDAS Imagine software used in image exploitation to detect materials that are smaller than an image pixel as well as those that cover larger areas but are mixed with other materials. The Material of Interest (MOI) is the material the analyst seeks to extract from the image. The training samples or data developed under the maximum likelihood classification were employed in the sub-pixel classification.

The module required four major processes in the image classification, namely; Preprocessing, Environmental Correction, Signature Derivation, and MOI Classification. Preprocessing identifies potential backgrounds used during the signature extraction and MOI classification, Environmental Correction generates a set of environmental correction factors necessary for signature derivation and MOI classification of the image, Signature Derivation develops the signature that is used in classifying the image (this is where the training samples developed under the maximum likelihood classification were used as input) and MOI Classification uses the developed signature to generate an overlay image file.

4.3.3. Neural Network Classification

The IDRISI (Kilimanjaro Edition) software is used for the artificial neural network and the method employed is the Backpropagation with momentum. As was stated in chapter 2, artificial neural network consists of an input layer, a hidden layer and an output layer; with the hidden layer being a network of weights and bias.

Backpropagation was created by generalizing the Widrow-Hoff learning rule to multiple-layer networks and nonlinear differentiable transfer functions. Input vectors and the corresponding target vectors are used to train a network until it can approximate a function. Standard back propagation is a gradient descent algorithm, as is the Widrow-Hoff learning rule, in which the network weights are moved along the negative of the gradient of the performance function.

The Backpropagation method is a widely used method in artificial neural networks (Lippman, 1987; Gupta and Rao, 1994). Although it works well for many problems such as in classification or pattern recognition (Rumelhart et al., 1996; Cun, 1989; Alirezaie et al., 1995; Arisawa and Watata, 1994), it suffers two critical drawbacks from the use of gradient-descent method: one is the learning process often traps into local minimal and another is its slow learning speed. Momentum, Variable Learning Rate, Conjugate Gradient and Levenberg-Marquardt (LM) are variations (as well as an improvement) of the Backpropagation method that have been developed through research (Baba, 1989; Konig and Barmann, 1993).

Images of band 2, band 3, band 4 and band 5 are used as inputs into the network design that is made of five hidden layers. The five hidden layers for the design were chosen after running the classification process many times at increasing numbers of hidden layers comparing the output visually and also in terms of accuracy. The output is a classified thematic map of the seven land cover classes. A learning rate of 0.2, momentum factor of 0.5, acceptable RMS error and number of iterations are some of the *a prior* information fed into the classification system for the classification of the image.

4.3.4. Accuracy Assessment

A total of 285 carefully selected points of the study area are used in the accuracy assessment. Stratified Random Sampling and to some extent Clustering sampling were the sampling designs employed in the selection of the 285 points. This is mainly because the distribution of the land cover classes is not even but rather localized (i.e. confined to certain portions of the study area). Also, the areas covered by the land cover classes differ.

The field observations were made with Garmin 72 GPS. The locations of the sample points were recorded in the geographic coordinates of WGS 84. The observations were downloaded and then processes and converted to Transverse Mercator with War Office ellipsoid using Geo-Environs Geomatica developed by Ayer and Tienaah (2008).

In order to increase the accuracy of land-use/cover mapping of the image, ancillary data from visual image interpretation were integrated into the initial image classification results using GIS.

CHAPTER FIVE

RESULTS AND DISCUSSIONS

5.1. Classification of Land Cover Classes

The landsat etm+ image was classified into seven land-cover classes using three different methods: Maximum Likelihood classification, Sub-Pixel classification and Back Propagation Neural Network classification. A review of the classification by the three methods indicated that certain areas had similar results, whereas for other areas the results were different. In the following, the results of the classification of each method are considered in turns.

5.1.1. Classification of LANDSAT ETM+ Image Using Maximum Likelihood

The land cover thematic map (Figure 5.1) produced from the landsat etm+ shows that, forested wetlands are mainly found in western portion of the study area with forest predominantly in the eastern portion. Open woodland is found in the mid-portion of the study area and is generally spread in the north-south direction. Water occurs as patches across the landscape although a greater percentage is found in the central portion of the area and in association with the non-forested wetlands or forested wetlands. Grassland is scattered throughout the area. It is frequently associated with the urban areas. The urban areas are found along the main roads and are extensive in the western part of the study. Large areas of urban growth found in the west of the study, is due to the proximity of such areas to Kumasi, an expanding city.

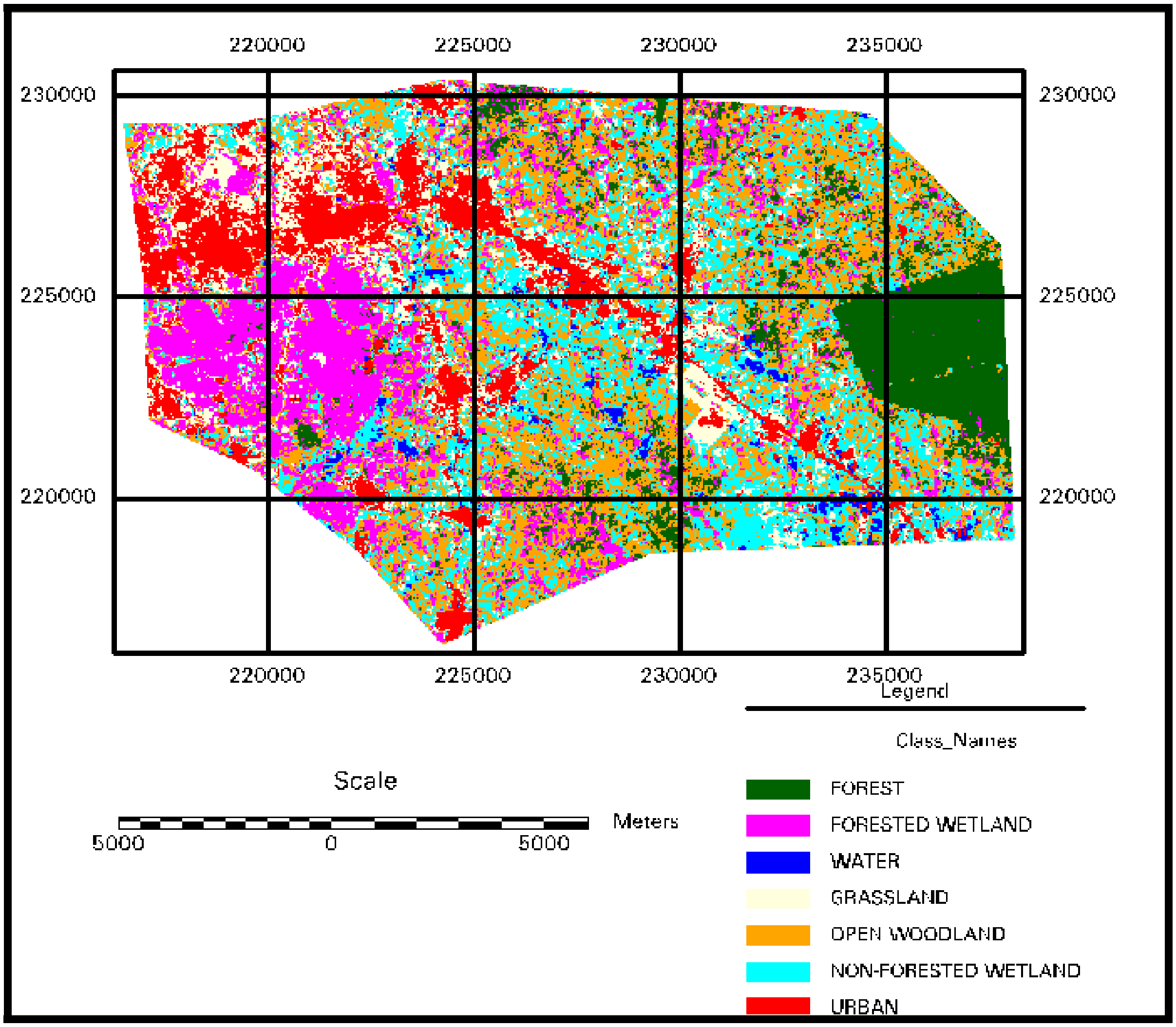


Fig. 5.1: Maximum Likelihood Classification of Landsat etm+ 2007

5.1.2. Classification of LANDSAT ETM+ Image Using Sub-Pixel

The result of the sub-pixel classification is seven images (one per class) showing the percentage composition (proportion) of the class per pixel. The images (Figure 5.2) below are a display of the top 20% composition per class for three land covers; namely forest, open woodland and urban . In general, the distribution of these classes is not so different from what was produced using the MLC.

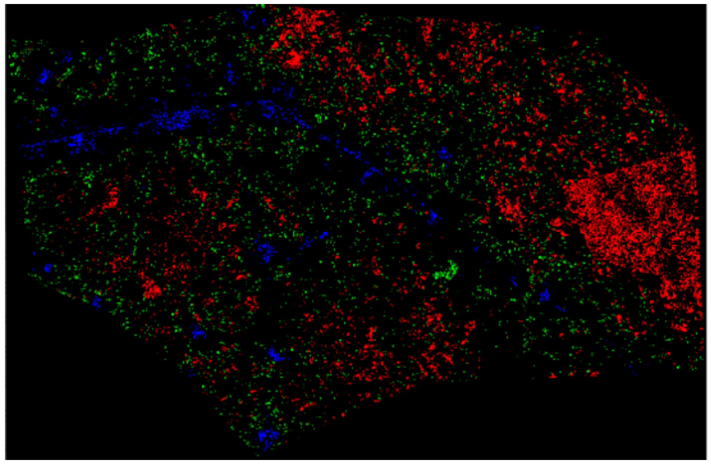


Fig. 5.2: Displays of Sub-pixel Classification for forest, open woodland and urban.

5.1.3. Classification of LANDSAT ETM+ Image Using Neural

The result of the Backpropagation neural network classification reveals that the distribution of land cover classes generally follows a similar pattern to that of MLC. However, more patches of water were detected. Below is a display of the classified image and corresponding look-up table for the legend.

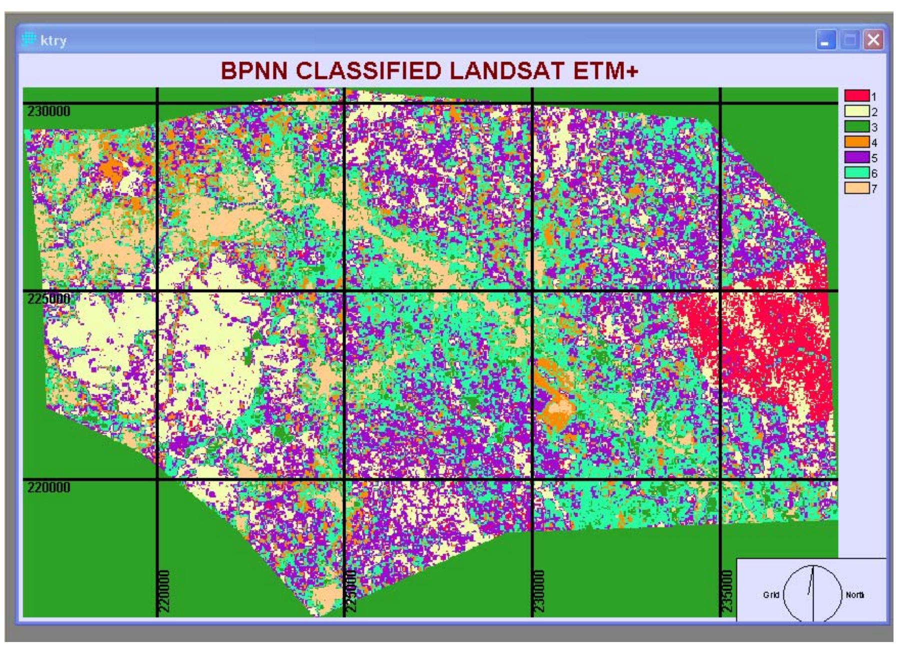


Fig. 5.3: Display of BPNN Classified Image

LEGEND NO.	LAND COVER CLASS
1	**For**
2	**For_w**
3	**Water**
4	**Grass**
5	**Open_w**
6	**Nfor_w**
7	**Urban**

Tab. 5.1: Look-Up for legend of map displayed in Fig. 5.3

5.2 Accuracy Assessment of Classified images

A total of 285 reference points were used for the accuracy assessment of the classified ETM+ 2007 image. The accuracy obtained from the Error Matrix is 78.95 % with a Kappa statistics of 0.74.

The accuracy assessment of the sub-pixel classification could not be determined. This is because the sampling strategy used is suitable only for a point to point analysis such as in the evaluation of accuracy using the error matrix.

In the neural classification, forty (40) pixels per sample for each land cover class were used in the training of the designed network and forty (40) pixels per sample for land cover class were used for the testing. The accuracy of the classified image after a thousand and nine-three (1093) iterations is 92.5 % with a Kappa statistics of 0.90.

5.3. Comparison of Methods

In order to assess the performance of the three classification methods used, the number of pixels classified, per land cover class from each classification were compared. For the sub-pixel classification, the top 20% were recoded into new images and used in the comparisons. Also image overlays of the classified images were used to determine the fitness of images to each other.

5.3.1. Representation of Land Cover Classes by Pixels

The table below is a matrix of the number of pixels that were classified per land cover class and corresponding area for each of the three methods. Consequently, figure 5.4 below is column chart display of the matrix in Tab. 5.2

	NUMBER OF PIXELS				**AREA (hectares)**		
LANDCOVER CLASS	**MLC**	**SP**	**BPNN**		**MLC**	**SP**	**BPNN**
FOR	**27468**	**19357**	**15604**		**2472.12**	**1742.13**	**1404.36**
FOR_W	**40282**	**19911**	**45649**		**3625.38**	**1791.99**	**4108.41**
WATER	**4244**	**1598**	**11576**		**381.96**	**143.82**	**1041.84**
GRASS	**27840**	**5850**	**20485**		**2505.6**	**526.5**	**1843.65**
OPEN_W	**66598**	**8466**	**69433**		**5993.82**	**761.94**	**6248.97**
NFOR_W	**53149**	**13815**	**69042**		**4783.41**	**1243.35**	**6213.78**
URBAN	**32581**	**2762**	**20373**		**2932.29**	**248.58**	**1833.57**

Tab. 5.2: Matrix of Classified Pixel and Corresponding Area

5.3.2. Similarities and Differences

The column chart (Fig. 5.4) below, shows that the comparison between MLC and BPNN is possible and that the results of the two classifiers follow a general trend. However, results from the sub-pixel classifier show rather low numbers of classified pixels. Also the trend from the sub-pixel classification cannot be followed through.

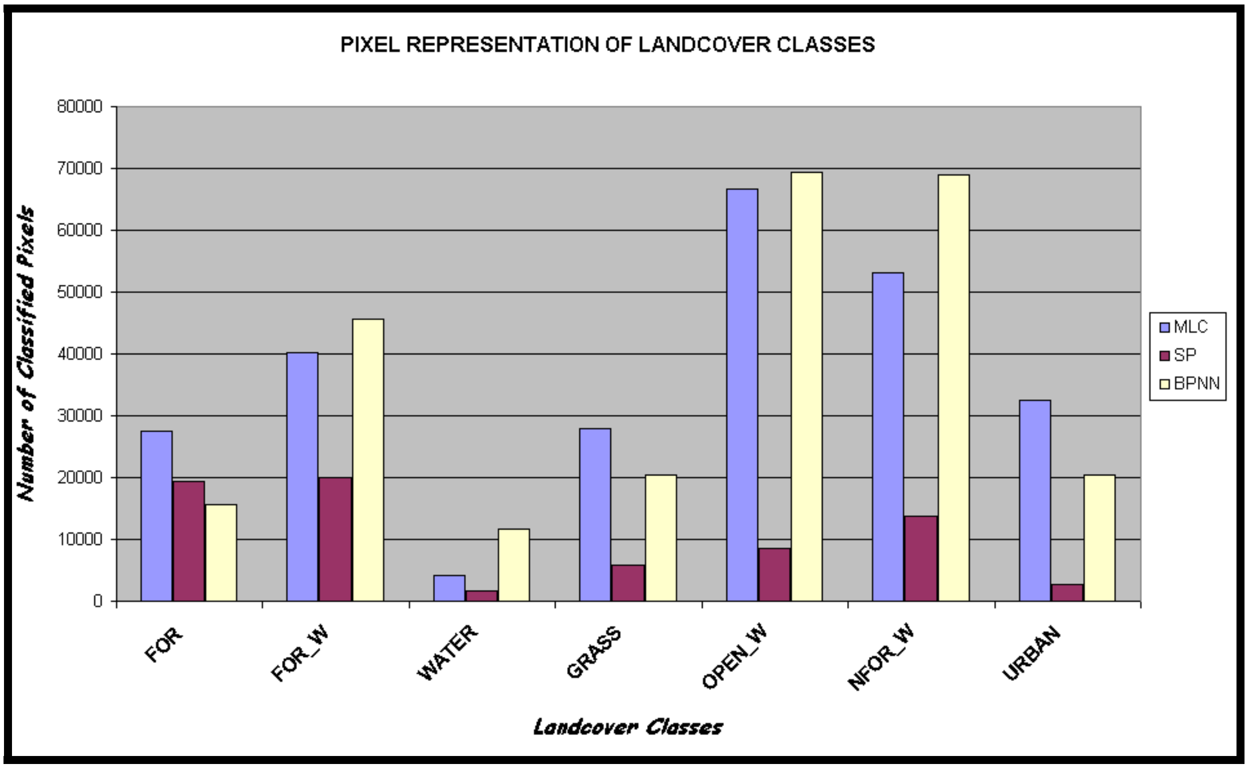


Fig. 5.4: Column Chart of Classified Pixels

A view of the column chart (Fig. 5.4) display indicates that dominant land covers within the study area are Open woodland and non-forested wetland. This is followed by the forested wetlands class. These results are clearly displayed by the two hard classifiers – MLC and BPNN. However, in all these cases, the BPNN classifier identified more pixels than the MLC classifier.

In the case of Open woodland, BPNN classified 69433 pixels (covering an area 6248.97 hectares), whereas for MLC, 66598 pixels (covering an area of 5993.82 hectares) were classified. For the Non-forested wetlands, BPNN classified 15893 pixels (covering an area of 1430.37 hectares) more than MLC 53149 pixels (covering an area of 4783.41 hectares). Again for the Forested wetland class, BPNN classified 45649 pixels (covering an area of 4108.41 hectares) as compared to 40282 classified pixels (covering an area of 3625.38 hectares) of MLC.

Another significant result to note is that of the water land cover class. The classified number of pixels from the BPNN classification is about three times that classified under the MLC classification. This is because water is the least dominant land cover class in the study area. Therefore for parametric classifiers such as MLC, least class such as water may be under estimated while dominant classes such as open woodland or non-forested may be over estimated.

As a result of similar phenomena, some pixels of forested wetland within the Bobiri Forest were classified as forest instead. Therefore fewer pixels were classified as forest by the BPNN classifier compared with that of MLC. Again in the urban land cover class, fewer pixels were classified by BPNN than that by MLC. However, the difference is due to the heterogonous characteristics or nature of urban land cover classes. Below is the percentage composition of pixels of land cover classes for MLC and BPNN.

Although the SP classifier performed poorly, it had quite a high representation of pixels for the forest and forested wetland classes. This is because the SP classifier is more suitable for extracting pure material specific in nature or for determining the percentage composition of the material in the pixel. The Forest and Forested wetland portions of the study area are generally homogeneous in nature. With the other classes such as grass or urban, where the homogeneity of sampled areas decreased, the performance of the SP classifier also decreased.

CHAPTER SIX

CONCLUSION AND RECOMMENDATION

6.1. Conclusion

From the results and discussion, the following conclusions have been drawn.

- That in comparison of the classification on landsat etm+ image, the back propagation neural network method produced a more accurate result than the maximum likelihood method. The overall accuracy in MLC method is 78.95 % and in BPNN method is 92.50%.

- The thematic map produced from the BPNN classification is more representative of the area of study than that derived from the MLC classification. This ascension was made after field visits and checks of selected sites within the study area.

- Sub-pixel classifiers is not suitable for classification of medium resolution satellite image such as Landsat etm+ (30m x 30m) due to problems of mixed pixels, the homogeneity of pixels being used as signatures and the distribution of corresponding land cover class within the area of interest.

- Of all the three methods – MLC, SP, and BPNN; BPNN is the best method for images classification of satellite images, although the design and training of network at the initial stage of the classification is time consuming.

6.2. *Recommendation*

The following are the recommendations arising from various factors that influence or contributed to the study.

- That MLC be used as classification method for extracting first hand information about an area since it is simple and fast. However, for better or improved results, BPNN should be used in addition to MLC for the classification.

- Although, backpropagation neural network classification is time consuming, its mathematical model is based on free assumption. Therefore if the training of the network is well done to achieve good acceptable error, the classification is more likely to give a better representation of the real world. The use of neural network in image classification should therefore be the preferred choice.

- Sub-pixel classifiers are more suitable for extracting pure material sample (i.e. specific material such as palm plantations, teak plantation, etc.) using signatures that are homogeneous in nature and the classification involves fewer numbers of land cover classes (maximum three). Also, because the extraction is specific in nature, it must be uniquely defined. As a result, satellite images of very high resolutions such IKONOS and QUICKBIRD with resolution of 1m or more are preferable.

- Agriculture is one of the leading economic activities undertaken in the Ejisu – Juabeng district. Unfortunately, agriculture as a land cover was not captured in the classification process due to factors such as small sizes of the farms involved, lack of crop calendar and low resolution (30m x 30m) of the satellite image that was used. It is therefore highly recommended that further studies of the area be conducted to investigate the possibility of mapping out plantations such as orange, plantain, cocoa and palm oil, using high-resolution images and Subpixel classifier.

7.0 REFERENCE

AGYARKO, T. (2001): *Country Report. In: G.M.A.L.A. Forestry (Editor)*

ALIREZAIE, J., JERNIGAN, M. E., and NAHMIAS, C., (1995): *Neural Network Based Segmentation of Magnetic Resonance Images of the Brain*. IEEE Nuclear Science Symposium and Medical Imaging Conference Record, Vol. 1, pp. 1397-1401,

ANDERSON, J. R., E. E. HARDY, J. T. ROACH, and D R. E. WITMER, (1976): *A Land Use and Land Cover Classification System for Use with Remote Sensor Data.* Washington, DC: US Geological Survey.

APLIN, P., ATKINSON, P.M. and CURRAN, P.J., (1999): *Per-Field Classification of Land Use Using the Forthcoming Very Fine Spatial Resolution Satellite Sensors: Problems and Potential Solutions*. In P.M. Atkinson and N.J. Tate (Eds), Advances in Remote Sensing and GIS Analysis, pp. 219–239 (New York: John Wiley and Sons).

ARISAWA, M. and WATATA, J., (1994): *Enhanced Back Propagation Learning and its Application to Business Evaluation*. IEEE International Conference on Neural Networks, Vol. 1, pp. 155-160.

ARORA, M, K., TIWARI, K. C., and MOHANTY, B., (2000): *Effect of Neural Network Variables on Image Classification*. Asian Pacific Remote Sensing and GIS Journal, 13, Pp. 1-11.

ASUBONTENG, O.K., (2007). *Identification of Land-use/cover Transfer Hotspots in Ejisu-Juaben District, Ghana*. International Institute for Geo-information Science and Earth Observation Enschede, Netherlands.

AUGUSTEIJN, M.F. and WARRENDER, C.E., (1998): *Wetland Classification Using Optical and Radar Data and Neural Network Classification*. International Journal of Remote Sensing 8:1545-1560

AYER, J. and TIENAAH, T., (2008): GEO-ENVIRONS GEOMATICA, version 1.0, Geo-Environs Consult, Accra, Ghana. (Unpublished).

BABA, N., (1989): *A New Approach for Finding the Global Minimum of Error Function of Neural Networks.* Neural Networks, Vol. 2, pp. 367-373.

BEKTAS, F., GOKSEL, C., (2003): *Remote Sensing and GIS Integration for Land Cover Analysis*, A case study: Gokceada Isaland. (Unpublished).

BELWARD, A.S. et al. (1999): *The IGBP-DIS Global 1-km Land-Cover Data Set DISCover: A Project Overview*. Photogrammetric Engineering & Remote Sensing 1999/9: pp. 1013-1020.

BENEDIKTSON, J.A., SWAIN, P.H., ESROY, O.K., (1990): *Neural Network Approaches versus Statistical Methods in Classification of Multisource Remote Sensing Data*. IEEE Transactions on Geoscience and Remote Sensing 28 (4), pp. 540–552.

BHANDARI, S.P., HUSSIN, Y.A., and SHARIFI, M.A., (2004): *Detection and Characterization of Selective Logging Using Remote Sensing and GIS in Tropical Forest Of East Kalimantan*. In: Asian Journal of Geoinformatics: A Quarterly Publication of ARSRIN, 4(2004)3, Pp. 57-70.

BINAGHI, E., BRIVIO, P.A., GHEZZI, P. and RAMPINI, A., (1999): *A Fuzzy Set Accuracy Assessment of Soft Classification.* Pattern Recognition Letters, 20, pp. 935–948.

BLOCH, I., (1996): *Information Combination Operators For Data Fusion: A Comparative- Review with Classification.* IEEE Transactions on Systems, Man, and Cybernetics, 26, pp. 52–67.

BUREAU OF INTEGRATED RURAL DEVELOPMENT, (2001): Tropenbos Ghana Programme Research Site Community Survey (Final Report), KNUST, Kumasi.

CAMPBELL JB, (1987): *Introduction to Remote Sensing*. New York: The Guilford Press

CAMPBELL, B.J. (1996): *Introduction to Remote Sensing (Second Edition).* Taylor and Francis, London.

CHEN, K.S., TZENG, Y.C., CHEN, C.F. and KAO, W.L., (1995): *Land-Cover Classification of Multispectral Imagery Using a Dynamic Learning Neural Network.* Photogrammetric Engineering and Remote Sensing, 61, pp. 403–408.

CLAWSON, M., and STEWART, C.L., (1965): *Land Use Information. A Critical Survey of U.S. Statistics Including Possibilities for Greater Uniformity*: Baltimore, Md., The Johns Hopkins Press for Resources for the Future, Inc., pp. 402.

COLEMAN, T. L., TWUMASI, Y. A. and MANU, A., (2004): *Spatio-Temporal Analysis of Migration Patterns in Ghana from 1970-2000 Using GIS*. In Proceedings of the 5th African Association of Remote Sensing of the Environment (AARSE) Conference. 18-21 October, 2004. Nairobi,Kenya.

CRACKNELL, A.P., (1998): *Synergy in Remote Sensing—what's in a Pixel?* International Journal of Remote Sensing, 19, pp. 2025–2047.

CRIST, E. P., LAURIN, R., and CICONE, R. C. (1986): *Vegetation and Soils Information Contained in Transformed Thematic Mapper Data*. Paper presented at International Geosciences and Remote Sensing Symposium (IGARSS)' 86 Symposium, ESA Publications Division, ESA SP-254.

CRIST, E. P., and KAUTH, R. J., (1986): *The Tasseled Cap De-Mystified*. P*hotogrammetric Engineering & Remote Sensing* 52 (1): pp. 81-86.

CUN, Y. L., (1989): *Back-Propagation Applied to Handwritten Code Recognition.* Neural Computing, Vol. 1, pp. 541-551.

DE BIE, K., LATHAM, J., LUXMOORE, R., SCHOMAKER, M., SIMS, D. and WYATT, B., (1995): *Background Note On-Going Activites Relating to Land Use and Land Cover Classification*. FAO/UNEP.

DEFRIES, R.S. and CHAN, J.C., (2000): *Multiple Criteria for Evaluating Machine Learning Algorithms for Land Cover Classification from Satellite Data*. Remote Sensing of Environment, 74, pp. 503–515.

DIAMANTARAS, K.I., and KUNG, S.Y., (1996): Principal Component Neural Networks: Theory and Applications, NY: Wiley.

EJISU-JUABEN DISTRICT ASSEMBLY, (2002): Ejisu-Juaben District, Ashanti. 2002. http://www.ejisujuaben.ghanadistricts.gov.gh/, accessed on 12/2/2008

FAO, (2001): *Global Forest Resource Assessment 2000, FAO, Rome.*

FISHER, P., (1997): *The Pixel: A Snare and a Delusion*. International Journal of Remote Sensing, 18, pp. 679–685.

FOLLY, A., (1997): *Land Use Planning to Minimize Soil Erosion – A Case Study from the Upper East Region in Ghana.* Geographica Hafniensia, A6. PhD Thesis, Publications, Institute of Geography, University of Copenhagen, Denmark

FOODY, G.M. and COX, D.P., (1994): *Sub-Pixel Land Cover Composition Estimation Using a Linear Mixture Model and Fuzzy Membership Functions*. International Journal of Remote Sensing, 15, pp. 619–631.

FOODY, G.M., (1996): *Approaches for the Production and Evaluation of Fuzzy Land Cover Classification from Remotely Sensed Data.* International Journal of Remote Sensing, 17, pp. 1317–1340

FOODY, G.M., (1999): *Image Classification with a Neural Network: From Completely-Crisp to Fully-Fuzzy Situation*. In P.M. Atkinson and N.J. Tate (Eds), Advances in Remote Sensing and GIS Analysis, pp. 17–37 (New York: John Wiley and Sons).

FRIENDS OF THE EARTH INTERNATIONAL, (1999): *Cut and Run: Illegal Logging and Timber Trade in the Tropics*. International Development Research Centre, Ottawa.

GAESPENU and ASSOCIATES, (1996): A Medium Term Development Plan for Ejisu-Juaben District (1996-2000).

GHANA STATISTICAL SERVICE, (2003): *2000 Population and Housing Census, Accra.*

GHOLZ, H. L., NAKANE, K. and SHIWODE (Editors), (1996): T*he use of Remote Sensing in Modelling of Forest Productivity. Detecting Structural and Growth Change in Woodland and Forest: The Challenge to Remote Sensing and Role of Geometric-Optical Modelling.* Kluwer Acad. Dordmoeh, Netherlands, pp 75-108.

GIRI, C., ZHU, Z., and REED, B., (2005): A Comparative Analysis of the Global Land Cover 2000 and MODIS Land Cover Data Sets. Remote Sensing of Environment, 94, 123–132.

GOSLEE SC, HAVSTAD KM, PETERS DPC, RANGO A, SCHLESINGER WH., (2003). *High-Resolution Images Reveal Rate and Pattern of Shrub Encroachment over Six Decades in New Mexico, U.S.A.* Journal of Arid Environments 54: pp. 755–767.

GUILD, L.S., COHEN, W.B., and KAUFFMAN, J.B., (2004): *Detection Of Deforestation and Land Conversion in Rondônia, Brazil Using Change Detection Techniques.* International Journal of Remote Sensing, 25(4): 731-750.

GUPTA, M. M. and RAO, D. H., (1994): *On the Principle of Fuzzy Neural Networks*. Fuzzy Sets and Systems, Vol. 61, pp. 1-18.

GUSTAFSON, P., (1993): *High-Resolution Satellite Imagery and GIS as a Dynamic Tool in Groundwater Exploration in a Semi-Arid Area*. In Proceedings of the IAHS Conference on Application of Geographic Information Systems in Hydrology and Water Resources Management held in Vienna, Austria, on 19-22 April, 1993, pp.93-100.

HANSEN, M., R. DUBAYAH, and R. DEFRIES, (1996): *Classification Trees: An Alternative to Traditional Land Cover Classifiers*. International Journal of Remote Sensing, 17(5): 1075-1081.

HEDGE, S., (2003): *Modelling Land Cover Change: A Fuzzy Approach.* M.Sc.Thesis, Publications, International Institute for Geoinformation Science and Earth Observation, (ITC), The Netherlands.

HOBBS, R. (1997): *Future landscapes and the Future of Landscape Ecology*. Landscape and Urban Planning, Vol. 37, Issues 1-2, pp. 1-9

HUANG, C., DAVIS, L. S. and TOWNSHEND, J. R. G., (2002): *An Assessment of Support Vector Machines for Land Cover Classification.* International Journal of Remote Sensing, 2002, vol. 23, no. 4, 725–749

HUGUENIN, R.L., KARASKA, M.A., BLARICOM, D.V. and JENSEN, J.R., (1997): *Subpixel Classification of Bald Cypress and Tupelo Gum Trees in Thematic Mapper Imagery*. Photogrammetric Engineering and Remote Sensing, 63, pp. 717–725.

HUSSIN, Y.A., A. De GIER and HARGYONO, (1994): *Forest Cover Change Detection Analysis Using Remote Sensing: A test for the Spatially Resolved Area Production Model*, 5TH European Conference and Exhibition on Geographic Information System, EGIS/MARI '94 Proceedings, Paris, France, March, 29-April 1, 1994, Vol 11, pp. 1825-1834.

IDDRISU, S. O. S. A. and TELLY, E. M., (1999): National Report: Republic of Ghana, to the Third Session of the Conference of The Parties to the United Nations Convention to Combat Desertification, May 1999.

JENSEN, R., (1996): *Introductory Digital Image Processing.* A Remote Sensing Perspective. Second Edition. New Jersey: Prentice Hall.

KANELLOPOULOS, I., and WILKINSON, G.G., (1997): *Strategies and Best Practice for Neural Network Image Classification*. International Journal of Remote Sensing, 18(4), pp. 711-725.

KARWEGER, A. (Ed.) (1993): *Globaler Wandel – Bestandsaufnahme einer Katastrophe. Der Einsatz von Satellitenbildern beim Umweltschutz und in Entwicklungsländern.* Munich.

KAVZOGLU, T. and MATHER, P.M., (2004): *The Use of Backpropagating Artificial Neural Networks in Land Cover Classification*. International Journal of Remote Sensing, 24, pp. 4907–4938.

KERLE, N., JANSSEN, L.L.F. and HUURNEMAN, G.C. (Editors), (2004): *Principles of Remote Sensing.* ITC Educational Textbook Series, 2. ITC, Enschede

KETTIG, R. L. and LANDGREBE, D. A., (1976): *Classification of Multispectral Image Data by Extraction and Classification of Homogeneous Objects*. IEEE Transactions, Geoscience Electronics. GE-14, pp. 19-26.

KONADU-AGYEMANG, K., (1998): *The Political Economy of Housing and Urban Development in Africa: Ghana's Experience from Colonial Times to 1998.*

KONIG, F.B. and BARMANN, F., (1993): *A Learning Algorithm for Muitilayered Neural Networks Based on Linear Least Squares Problems*. Neural Networks, Vol. 6, pp. 127-131.

KONTOES, C., WILKINSON, G.G., BURRILL, A., GOFFREDO, S. and MEGIER, J. (1993): *An Experimental System for the Integration of GIS Data in Knowledge-Based Image Analysis for Remote Sensing of Agriculture*. International Journal of Geographical Information Systems, 7, pp. 247–262.

KOTEY, N. A., FRANCOIS, J., OWUSU, J., YEBOAH, R., AMANOR, K. S. and ANTWI, L., (1998): *Falling into Place: Policy that Works for Forest and People*. 4th International Institute for Environment and Development, London, pp. 138.

KÜCHLER, A.W. and ZONNEVELD, I.S**.,** (1988): *Vegetation Mapping*. p. 623. Kluwer Publishers, Dordrecht, the Netherlands.

KUFUOR, K.O., (2000): *Forest Management in Ghana: Towards a Sustainable Approach*. Journal of African Law, 44(1): 52-64.

LAMBIN, E.F., TURNER, B.L., AGBOLA, S.B., ANGELSEN, A., (2001): *The Causes of Land-Use and Land-Cover Change; Moving Beyond The Myths*. Global Environmental Change, 11, pp. 261-269.

LEE, Y.-K., YANG, P., MISHCHENKO, M.I., BAUM, B.A, HU, Y.X., HUANG, H.-L., WISCOMBE, W.J., and BARAN, A.J., (2003): *Use of Circular Cylinders as Surrogates for Hexagonal Pristine Ice Crystals in Scattering Calculations at Infrared Wavelengths*. Appl. Opt., 42, pp. 2653-2664, doi:10.1364/AO.42.002653.

LILLESAND, T. M., and KIEFER, R. W., (1994): Remote Sensing and Image Interpretation (4th Ed.). New York: Wiley, pp. 750

LILLESAND, T.M. and KIEFER, R. W., (2000): Remote Sensing and Image Interpretation, Fourth Ed. John Wiley and Sons Inc., New York.

LIPPMANN, R. P., (1987): An *Introduction to Computing with Neural Net.* IEEE ASSP. MAG, pp. 4-22.

LU, D., MAUSEL, P., BATISTELLA, M., and MORAN, E., (2003): *Comparison of Land-Cover Classification Methods in the Brazilian Amazon Basin*. In Proceedings of ASPRS 2003 Annual Conference May 2003, Anchorage, Alaska

LU, D. and WEND, Q., (2007): *A Survey of Image Classification Methods and Techniques for Improving Classification Performance*. International Journal of Remote Sensing, 28(5), 823-870.

LUNETTA, R. S., EDIRIWICKREMA, J., JOHNSON, D. M., LYON, J. G., and MCKERROW, A., (2002): *Impacts of Vegetation Dynamics on the Identification of Land-Cover Change in a Biologically Complex Community in North Carolina, USA.* Remote Sensing of Environment, 82:258–270.

MANNAN, B. and ROY, J. AND RAY, A.K., (1998): *Fuzzy ARTMAP Supervised Classification of Multi-Spectral Remotely-Sensed Images*. International Journal of Remote Sensing, 4, pp. 767-774.

MANNAN, B. and RAY, A.K., (2003): *Crisp and Fuzzy Competitive Learning Networks for Supervised Classification of Multispectral IRS Scenes*. International Journal of Remote Sensing, 24, pp. 3491–3502.

MAS, J. F., (1999): *Monitoring Land-Cover Changes: A Comparison of Change Detection Techniques*. International Journal of Remote Sensing, vol. 20, No.1, pp. 139-152.

MEYER, W.B., TURNER II, B.L., (1992): *Human Population Growth and Global Land-Use/Cover Change*. Annual Review of Ecology and Systematics, 23: pp. 39-61.

MELILLO, J.M., McGUIRE, A.D., KICKLIGHTER, D.W., MOORE, B.I., VOROSMARTY, C.J. and SCHLOSS, A.L., (1993): *Global Climate Change and Terrestrial Net Primary Production*. Nature 363**:** 234-240.

MINOR, T., CARTER, J., CHARLEY, M., KNOWKS, B., and GUSTAFSON, P., (1994): The use of GIS and Remote Sensing in Groundwater Exploration for Developing Countries. In Proceedings of the 10th ERIM Thematic Conference on Geologic Remote Sensing held in San Antonio, USA on May 9-12 1994 pp.168-179.

MUSAOGLU, N., KAYA, S., SEKER, D. Z., and GOKSEL, C., (2002): *Spatial Information and Land Management: A Case Study of Using Remote Sensing Data and GIS for Land Management; Catalca Region.* Paper Presented at FIG XXII International Congress, Washington, D.C. USA, April 19-26 2002

MUSTARD, J.F., and SUNSHINE, J.M., (1999): *Spectral Analysis for Earth Science: Investigations Using Remote Sensing Data*. In A.N. Rencz (Ed.), Remote Sensing for the Earth Sciences: Manual of Remote Sensing, 3rd edn, Vol. 3, pp. 251–307 (New York: John Wiley & Sons).

NAGENDRA, H., MUNROE, D. K., and SOUHTWORTH, J., (2004): *From Pattern to Process: Landscape Fragmentation and the Analysis of Land Use / Land Cover Change*. Agriculture, Ecosystems and Environment, Vol. 110, pp. 111-115.

NANGENDO, G., SKIDMORE, A.K. and HENK VAN OOSTEN, (2006): *Mapping East African Tropical Forests and Woodlands — A Comparison of Classifiers.* ISPRS Journal of Photogrammetry & Remote Sensing 61 (2007) 393–404

NILSSON, J.N., 1965. *Learning Machines: Foundations of Trainable Pattern-Classifying Systems*. McGraw-Hill Series in Systems Science. McGraw-Hill Book Company, New York.

OSEI, E. M. JNR. and ZHOU, Y. X, (2004). *Land Cover Change detection in West Jilin using ETM+ images*. Journal of Geoscientific Research in N. E. Asia, Vol. 7(1), pp. 74-84.

OSEI, E. M. JNR. (2003): *Issues in Land Cover with Remote Sensing* Data. Journal of JilinUniversity. Vol. 33, pp. 96-104.

OSLON, J., WATTS, J. A. and ALLISON, L. J., (1985): *Major World Ecosystem Complexes Ranked by Carbon in Live Vegetation: A database Report*. Carbon Dioxide Information center.

OTOO, E. A., WHYATT, D. J., and ITE, U. E., (2006): *Quantifying Urban Growth in Accra Metropolitan Area (AMA), Ghana and Exploring Causal Mechanisms.* Paper Presented at Promoting Land Administration and Good Governance, 5th FIG Regional Conference, Accra, Ghana, March 8-11, 2006.

PAL M., and MATHER P.M., (2003): *An Assessment of the Effectiveness of Decision Tree Methods for Land Cover Classification*. Remote Sensing of Environment, 86: pp. 554-565.

PAN, W.K.Y., WALSH S.J., BILSBORROUR R.E., FRIZZELLE B.G., ERLIEN C.M, and BAQUERO F., (2004): *Farm-Level Models Of Spatial Patterns Of Land Cover Dynamics in the Equadorian Amazon*. Agriculture, Ecosystems, and Environment, 101: pp. 117-134.

PAOLA, J.D. and SCHOWENGERDT, R.A., (1997): *The Effect of Neural-Network Structure on a Multispectral Land-Use/Land-Cover Classification*. Photogrammetric Engineering and Remote Sensing, 63, pp. 535–544.

PCI Inc., (1997): EASI / PACE, version 6.1, PCI Inc., Richmond Hill, Ontario, Canada.

PEDLEY, M.I. and CURRAN, P., (1991): *Per-Field Classification: An Example Using SPOT HRV Imagery*. International Journal of Remote Sensing, 12 (11), pp. 2181-2192.

QIAN, J., ZHOU, Q., HOU, Q., (2007): *A Comparison of Pixel-Based and Object-Oriented Classification Methods for Extracting Built-Up Areas in Aridzone*. Paper presented at ISPRS Workshop on Up-Dating Geo-Spatial Databases with Imagery and the 5th ISPRS Workshop on DMGISs, 28-29 August 2007, Urumqi, China.

RANGO A, GOSLEE S, HERRICK JE, CHOPPING M, HAVSTAD KM, HUENNEKE LF, GIBBENS R, BECK R, and McNEELY R. (2002): *Remote Sensing Documentation of Historic Rangeland Remediation Treatments in Southern New Mexico*. Journal of Arid Environments 50: pp. 549–572.

RICHARDS, J. F., (1990). *Land Transformation*. Pages 341–353 in I. Turner, B. L. W. C. Clark, R. W. Kates, J. F. Richards, J. Mathews, and W. B. Meyer (eds.), *The Earth as Transformed by Human Action: Global And Regional Changes In The Biosphere Over The Past 300 Years*. Cambridge University Press, Cambridge.

RICHARDS, J. A. and JIA, X., (1999): *Remote Sensing and Digital Image Analysis: An Introduction.* 3rd ed., Springer-Verglag, New York, pp. 363

RICHTER, R. (1990): *A Fast Atmospheric Correction Algorithm Applied to Landsat TM Images*. International Journal of Remote Sensing 11 (1), pp. 159-166.

ROBERTS, D.A., GARDNER, M., CHURCH, R., USTIN S., SCHEER, G. and GREEN, R.O. (1998): *Mapping Chaparral in the Santa Monica Mountains Using Multiple Endmember Spectral Mixture Models*. Remote Sensing Of Environment, 65, pp. 267-279.

ROBERTS, D.A., I. NUMATA, K. HOLMES, G. BATISTA, T. KRUG, A. MONTEIRO, B. POWELL, AND O.A. CHADWICK, (2002): *Large Area Mapping Of Land-Cover Change in Rondônia using Multitemporal Spectral Mixture Analysis and Decision Tree Classifiers.* Journal of Geophysical Research-Atmospheres, 107(D20), 8073.

RUMELHART, D. E., HITON, G. E. and WILLIAMS, R. J. (1996) *Learning Internal Representation by Error Propagation.* Parallel Distributed Processing 1, pp. 318-362.

SEDEGO, C.A., (2007): *Assessing the Impact of Urban Expansion and Land-cover within the landscape of Kumasi Metropolitan Area.* Ghana International Institute for Geo-information Science and Earth Observation Enschede, 51 pp.

SELLERS, P. J., MEESON, B. W., HALL, F. G., ASRAR, G., MURPHY, R. E., SCHIFFER, R. A., BRETHERTON, F. P., e*t al.*, (1995): *Remote Sensing of the Land Surface for Studies of Global Change: Models—Algorithms—Experiments*. Remote Sensing of Environment, 51, pp. 3–26.

SCHOWENGERDT, R.A., (1996): *On the Estimation of Spatial-Spectral Mixing with Classifier Likelihood Functions*. Pattern Recognition Letters, 17, pp. 1379–1387.

SHALABY, ADEL, TATEISHI, RYUTARO, (2007). *Remote Sensing and GIS for Mapping and Monitoring Land cover and land-use changes in the Northwestern coastal zone of Egypt.* Applied Geography, 27, pp. 28–41.

SMITH, C., and BROWN, N., (1997): Erdas Field Guide. ERDAS, Inc, Atlanta, Georgia.

SONG, C., WOODCOCK, C.E., SETO, K.C., LENNEY, M.P. and MACoMBER, S.A., (2001): *Classification and Change Detection using Landsat TM Data: When and How to Correct Atmospheric Effect*. Remote Sensing of Environment, 75, pp. 230–244.

STRONG, W.L., OSWALD, E.T. and DOWNING, D.J., (1990): *The Canadian vegetation classification system. First Appoximation 1990*. Ecological Land Classification Series, No. 25, National Vegetation Working Group, Canada Committee on Ecological Land Classification; Sustainable Development Corpororate Policy Group.

STUCKENS, J., COPPIN, P.R. and BAUER, M.E., (2000): *Integrating Contextual Information with Per-Pixel Classification for Improved Land Cover Classification*. Remote Sensing of Environment, 71, pp. 282–296.

SUBRAMANIAN S., GAT N., SHEFFIELD M., BARHEN J., and TOOMARIAN N., (1997): *Methodology for Hyperspectral Image Classification Using Novel Neural Network.* Algorithms For Multispectral And Hyperspectral Imagery III, SPIE Vol. 3071-- Orlando, FL, April 1997

SWAINE, M.D., and HALL, J.B., (1976). *Classification and Ecology of Closed-Canopy Forest in Ghana.* The Journal of Ecology, 84(3); 419-428.

TSO, B. and MATHER, P.M., (2001): *Classification Methods for Remotely Sensed Data.* (New York: Taylor and Francis Inc).

TURNER, B. L., MOSS, R. H., and SKOLE, D. L., (1993): *Relating Land Use and Global Land-Cover Change: A Proposal for an IGBP-HDP Core Project. Report from the IGBP-HDP Working Group on Land-Use/Land-Cover Change*. Joint Publication of the International Geosphere-Biosphere Programme (Report No. 24) and the Human Dimensions of Global Environmental Change Programme (Report No. 5). Stockholm: Royal Swedish Academy of Sciences.

TURNER B. L., SKOLE D. L., SANDERSON S., FISCHER G., FRESCO L. and LEEMANS R., (1995): Land-Use and Land-Cover Change Science/Research Plan. Joint Publication of the International Geosphere-Biosphere Programme (Report No. 35) & the Human Dimensions of Global Environmental Change Programme _Report No. 7_. Royal Swedish Academy of Sciences, Stockholm, Sweden.

TUTU, B., D., (2008). *Assessing the Effects of Land-Use/Cover Change on Ecosystem Service in Ejisu-Juaben District, Ghana: The case study of Carbon Sequestration.* International Institute for Geo-information Science and Earth Observation Enschede, Netherlands and Kwame Nkrumah University of Science and Technology, Kumasi, Ghana

TWUMASI, Y.A., COLEMAN, T.L., and MANU, A., (2005): Biodiversity Management using Remotely Sensed Data and GIS Technologies: The Case of Digya National Park, Ghana. In Proceedings of the 31st International Symposium on Remote Sensing of Environment. June 20-21. Saint Petersburg, Russia Federation.

UNEP/FAO (1994): *Towards International Classification Systems for Land Use and Land Cover*. Proposal. UNEP/FAO.

USDA FOREST SERVICE, (1989): *Interim Resource Inventory Glossary.* Washington, DC.

VERBEKE, L.P.C., VABCOILLIE, F.M.B. and DE WULF, R.R., (2004): *Reusing Back-Propagating Artificial Neural Network for Land Cover Classification in Tropical Savannahs.* International Journal of Remote Sensing, 25, pp. 2747–2771.

WANG, L., SOUSA, W.P., GONG, P. and BIGING, G.S., (2004): *Comparison of IKONOS and QuickBird Images for Mapping Mangrove Species on the Caribbean Coast of Panama*. Remote Sensing of Environment, 91, pp. 432–440.

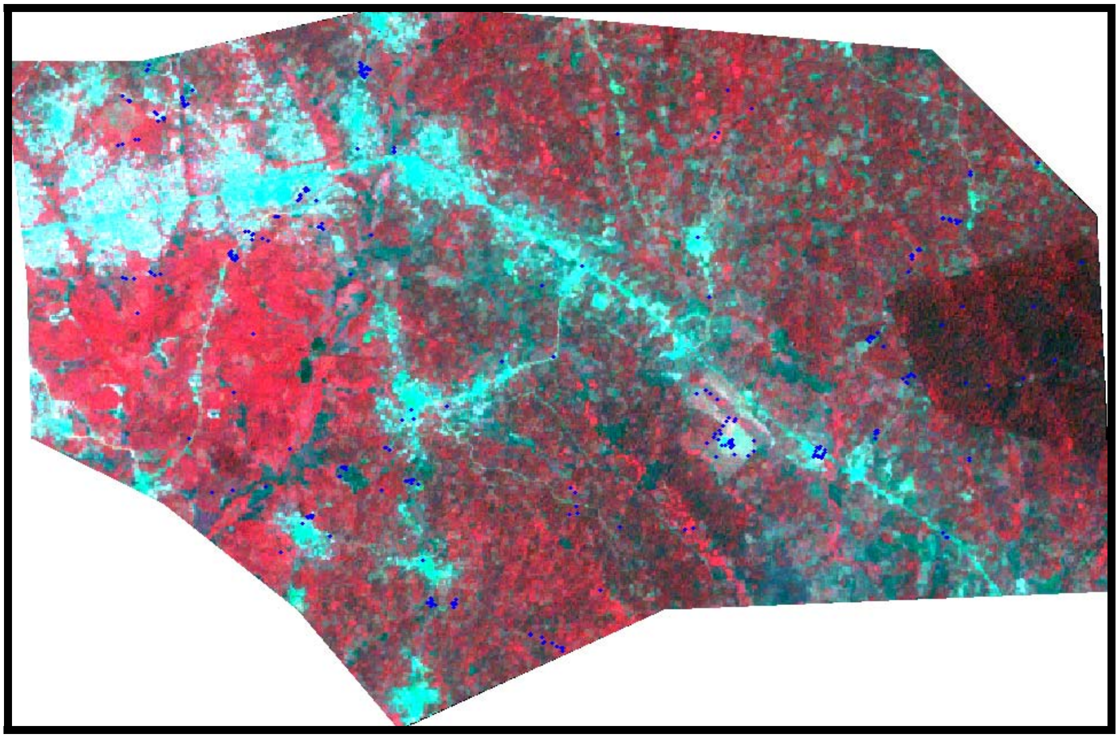
WOODCOCK, C.E. and GOPAL, S., (2000): *Fuzzy Set Theory and Thematic Maps: Accuracy Assessment and Area Estimation.* International Journal of Geographic Information Science, 14, pp. 153–172.

YANKSON P. (1997): *Land Markets in African Cities: The Case of Peri-Urban Accra, Ghana*. Urban Studies Vol. 37, (13) pp. 2485.

YUAN, F., KALI, E. and SAWAYA, (2005): Land Cover Classification and Change Analysis of the Twin Cities (Minnesota) Metropolitan Area by Multi-temporal Landsat Remote Sensing. Remote Sensing of Environment, 98, pp. 317-328.

ZHOU, Q., LI, B., and ZHOU, C., (2004): *Detecting and Modeling Dynamic Landuse Change Using Multitemporal and Multi-Sensor Imagery*. Paper presented at 20th ISPRS Congress, 12-23 July 2004, Istanbul, Turkey.

APPENDIX A



Sample Distribution of Points in the Study Area, used in the Accuracy Assessment of the MLC Classification.

APPENDIX B

	Archieve - KNUST TM - WAR OFFICE		Geo-Environs TM - WAR OFFICE				
POINT NAME	Eastings (meters)	Northings (meters)	Eastings (meters)	Northings (meters)	Diff. Eastings	Diff. Northings	Absolute Diff.
TP6	211813.40	221659.09	211817.96	221660.23	-4.56	-1.13	4.70
TP1	211787.52	221746.68	211792.58	221743.18	-5.06	3.50	6.15
KU6	211641.12	221740.90	211643.64	221740.28	-2.52	0.62	2.60
GE_1_78_134	210865.93	221706.32	210860.46	221702.80	5.47	3.52	6.51

Table of Comparison for Coordinates of Selected Controls.

APPENDIX C

ERROR MATRIX OF MLC CLASSIFICATION

Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy
FOR	9	11	8	88.89%	72.73%
FOR_W	46	46	40	86.96%	86.96%
WATER	9	5	5	55.56%	100.00%
GRASS	60	59	45	75.00%	76.27%
OPEN_W	58	46	40	68.97%	86.96%
NFOR_W	54	56	42	77.78%	75.00%
URBAN	49	62	45	91.84%	72.58%
Totals	285	285	225		

Overall Classification Accuracy = 78.95%

Overall Kappa Statistics = 0.7436

APPENDIX D

ERROR MATRIX OF BPNN CLASSIFICATION

	FOR	FOR_W	WATER	GRASS	OPEN_W	NFOR_W	URBAN	Total
FOR	381	0	0	0	0	0	0	381
FOR_W	45	212	0	0	0	0	0	257
WATER	0	0	74	0	0	8	0	82
GRASS	0	0	0	108	0	0	0	108
OPEN_W	19	6	0	0	58	0	0	83
NFOR_W	3	0	2	14	2	97	0	118
URBAN	0	0	1	0	0	0	256	257
Total	448	218	77	122	60	105	256	1286

Overall Classification Accuracy = 92.50%

Kappa Statistics = 0.9029