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Mapping and Assessment of Land Use/Land Cover Using Remote Sensing and GIS in North Kordofan State, Sudan

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This thesis is submitted to fulfil the partial requirements for degree of Doctor of Natural Science (Dr. rer. nat.)

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Dedication

To the departure soul of my lovely mother Eltaya bit Asha and
to my wife Misson,
I dedicate this work with a lot of love

Mohamed Salih

Declaration

I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person nor material which to a substantial extent has been accepted for the award of any other degree or diploma of the university or other institute of higher learning, except where due acknowledgement has been made in the text.
Necessary contacts with officials and private individuals and use of image processing facilities have been done as mentioned in this dissertation and with the agreement of the supervisors.

Mohamed Salih Dafalla
Dresden, Germany
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For coloured maps and photos please refer to the electronic version either at the Institute of Photogrammetry and Remote Sensing or the online service of SLUB.

LIST OF ACRONYMS

CA	Canonical Analysis.
CVA	Change Vector Analysis
DECARP	Sudan's Desert Encroachment Control and Rehabilitation Program.
DN	Digital Number.
DOS	Dark Object Subtraction.
DVI	Difference Vegetation Index.
ECe	Electrical Conductivity.
EROS	Earth Resource Observation System.
ETM+	Enhanced Thematic Mapper
ETP	Evapotranspiration.
FAO	World Food and Agriculture Organization.
FNC	Forestry National Corporation.
GCP	Ground Control Points.
GIS	Geographical Information System.
GLCF	Global Land Cover Facility.
GPS	Global Positioning System.
HC	Hydraulic Conductivity.
IDP	Internally Displaced Persons.
IFAD	The International Fund for Agricultural Development.
IR	Infiltration Rate.
LGP	Length of Growing Period.
LULCCS	Land Use/Land Cover Classification System.
MIR	Medium Infra-Red.
MSS	Multispectral Scanner.
NDVI	Normalized Difference Vegetation Index.
NIR	Near-Infrared.
NOAA -AVHRR	National Oceanic and Atmospheric Administration-Advanced Very High Resolution Radiometer.
OM	Organic Matter.
PCA	Principal Component Analysis.

PVI	Perpendicular Vegetation Index.
R	Red band
RGB	Red Green Blue.
RVI	Ratio Vegetation Index
SAR	Sodium Adsorption Ratio.
SAVI	Soil Adjusted Vegetation Index.
SP	Saturation Percentage.
SPSS	Statistical Package for Social Science.
SRAAD	Sudan Resource Assessment and Development.
TCA	Tasseled Cap Analysis.
UN	United Nation.
UNCCD	United Nation Convention to Combat Desertification.
UNCOD	United Nations Conference on Desertification.
UNSO	The United Nations Sudano-Sahelian Office.
USAID	United State Agency for International Aid.
USGS	United State Geological Survey.
UTM	Universal Transverse Mercator.

ABSTRACT

Sudan as a Sahelian country faced numerous drought periods resulting in famine and mass immigration. Spatial data on dynamics of land use and land cover is scarce and/or almost non-existent. The study area in the North Kordofan State is located in the centre of Sudan and falls in the Sahelian eco-climatic zone. The region generally yields reasonable harvests of rainfed crops and the grasslands supports plenty of livestock. But any attempts to develop medium- to long-term strategies of sustainable land management have been hampered by the impacts of drought and desertification over a long period of time.

This study aims to determine and analyse the dynamics of change of land use/land cover classes. The study attempts also to improve classification accuracy by using different data transformation methods like PCA, TCA and CA. In addition it tries to investigate the most reliable methods of pre-classification and/or post-classification change detection. The research also attempts to assess the desertification process using vegetation cover as an indicator. Preliminary mapping of major soil types is also an objective of this study.

Landsat data of MSS 187/51 acquired on 01.01.1973 and ETM+ 174/51 acquired on 16.01.2001 were used. Visual interpretation in addition to digital image processing was applied to process the imagery for determining land use/land cover classes for the recent and reference image. Pre- and post-classification change detection methods were used to detect changes in land use/land cover classes in the study area. Pre-classification methods include image differencing, PC and Change Vector Analysis. Georeferenced soil samples were analysed to measure physical and chemical parameters. The measured values of these soil properties were integrated with the results of land use/ land cover classification.

The major LULC classes present in the study area are forest, farm on sand, farm on clay, fallow on sand, fallow on clay, woodyland, mixed woodland, grassland, burnt/wetland and natural water bodies. Farming on sandy and clay soils constitute the major land use in the area, while mixed woodland constitutes the major land cover. Classification accuracy is improved by adopting data transformation by PCA, TCA and CA. Pre-classification change detection methods show indistinct and sketchy patterns of change but post-classification method shows obvious and detailed results. Vegetation cover changes were illustrated by use of NDVI. In addition

preliminary soil mapping by using mineral indices was done based on ETM+ imagery. Distinct patterns of clay, *gardud* and sand areas could be classified.

Remote sensing methods used in this study prove a high potential to classify land use/land cover as well as soil classes. Moreover the remote sensing methods used confirm efficiency for detecting changes in LULC classes and vegetation cover during the addressed period.

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CHAPTER ONE

INTRODUCTION

1.1 Desertification

The United Nations Conference on Desertification (UNCOD, 1977) defined the term desertification as "The diminution or destruction of the biological potential of land, which can lead ultimately to desert-like conditions. It is an aspect of the widespread deterioration of ecosystems and has diminished or destroyed the biological potential, i.e. plant and animal production, for multi-use purposes at a time when increased productivity is needed to support growing populations in quest of development". This definition was considered insufficient, particularly for those trying to engage in quantitative evaluation of desertification.

The latest definition on desertification, adopted by the United Nations in the beginning of 1990s, can be read as: "Land degradation in arid, semi-arid and dry sub-humid areas resulting from various factors, including climatic variations and human activities" (UNCCD, 1992).

1.2 Arid and Semi-Arid Lands

Arid and semi-arid areas are characterised by patterns of fluctuating annual rainfall. Thus these areas have been subjected to drought cycles during periods of low precipitation, which lead, in turn, to decrease in vegetation cover. However, the vegetation usually recovers during periods of normal precipitation.

Arid and semi-arid lands cover approximately 30 to 40 percent of the Earth's land surface. Therefore these lands play a major role in the energy balance and hydrologic, carbon and nutrient cycles. The activity of vegetation in these lands typically undergoes wide seasonal and inter-annual fluctuations, largely regulated by the availability of water, and may be readily affected by both climatic shifts and human activities such as grazing, wood cutting and urbanisation. Thus monitoring the vegetation vigor of these lands is of interest for both scientific and resource management applications. In past research, remote sensing has been successfully used to detect interannual variability such as the apparent expansion and contraction of Saharan desert (Hellden, 1978; Tucker *et al*, 1994). However, quantitative assessment of changes in green vegetation in these areas remains a challenge due to the relatively low spectral contribution by vegetation in image pixels, which is generally dominated by exposed rock, soil and litter.

1.3 Remote Sensing

Remote sensing is defined as the science of acquiring, processing and interpreting images and related data, obtained by sensing systems on aircraft and satellites, which record electromagnetic energy reflected/emitted by the earth's surface, thus representing the object-related interaction between matter and electromagnetic radiation (spectral signature). Remote sensing methods have been applied over a number of regions to monitor vegetation change (Lunetta, 1999). The multi-spectral and multi-temporal nature of satellite imageries facilitates the investigation of vegetation components, based on their typical minimum/maximum in spectral reflectance in the red (600-700 nm) and near-infrared (NIR) (700-1100 nm) bands of the electromagnetic spectrum (Tucker, 1979; Sellers, 1985).

1.4 Problem Statement and Justification

Sudan is the largest African country covering an area of approximately 2.6 million km^2 and inhabited by a population of about 40 millions (Fig. 1). The country extends over a variety of eco-climatic zones, ranging from desert in the north with nil annual rainfall to the wet monsoon zone in the south with up to 1200 mm annual rainfall (Danida, 1989). Being one of the Sahelian countries it faced numerous drought periods, especially during the 1960s, and 1980s. Severe famine and mass immigration occurred. Semi-arid regions of the Sudan are thus heavily attacked by desertification, which is driven by climatic changes as well as human activities (UNSO, 1992).

Sudan is considered one of the poorest countries in the world despite its unlimited natural resources. Besides, all kinds of data supply especially spatial data on dynamics of land use and land cover is poor and thus insufficient (Hielkema *et. al.*, 1986, Kassa, 1999, Larsson, 2002). Nevertheless, extended knowledge on state and changes of land use and land cover is needed in order to support the implementation of sustainable strategies of regional (re)development (Hielkema *et. al.*, 1986; IFAD, 2004).

Figure 1: Political map of the Sudan

Region of the study area

Source: United Nations (2005)

North Kordofan State is located in the centre of Sudan in the Sahelian eco-climatic zone (Fig. 1). The region generally provides reasonable harvests of rainfed crops such as sesame (*Sesamum orientale* L.), millet (*Pennisetum typhoideum* (Burm.)), karkade (*Hibiscus sabdariffa* var. *sabdariffa*), and Gum Arabic (*Acacia senegal*) and the grasslands allow for the raising of plenty of livestock such as sheep, goats, cattle and camels. Severe constraints for the development of medium- to long-term strategies of sustainable land management are raised by temporal variations of the impacts of drought and desertification during the last decennia (Hielkema *et. al.*, 1986).

1.5 Objectives of the Study

Land degradation is considered one of the major threats to the people in North Kordofan State. People of this State suffer from continuous decrease in productivity of the food crops, which leads to infrequent famines and food shortage. Therefore, this study aims to achieve the following objectives:

1. Determination of major dominant land use/land cover in the area using Landsat MSS and ETM+ satellite imagery of 1973 and 2001, and analysis of its relation to the process of desertification.

2. Assessment of desertification by detection of vegetation cover changes for the period 1973 and 2001.

3. Preliminary mapping of soils using Landsat ETM+ 2001 and field data by means of specific methods of data transformation by digital image analysis.

4. Improvement of classification by different data transformation methods such as Principal Components Analysis (PCA), Tasselled Cap Analysis (TCA) and Canonical Analysis (CA).

1.6 Hypotheses

Q1. Is the amount/degree of vegetation cover change large enough to state that desertification occurs in the study area?

Q2. Is the change in land use patterns due to human activities a major factor in causing desertification?

Q3. Is remote sensing a suitable tool for detection of vegetation cover change?

Q4. Are the different soil types in the study area related to different vegetation change patterns?

1.7 Structure of the Thesis

The thesis will consist of six chapters. Chapter one deals with the introduction, which covers the problem statement and the objectives of study. The second chapter gives a background of the study, including the application of remote sensing in assessment of vegetation cover change, and desertification in arid and semi-arid zones. The third chapter describes the study area which is the North Kordofan State, Sudan. In this chapter the location, climate, geology, soil, topography, vegetation and the main land uses practices are be discussed. The research methodology, image processing, image classification and accuracy assessment are outlined in chapter four. Presentation of results and discussion are included in chapter five. Conclusion and limitation of the study are presented in chapter six.

CHAPTER TWO

THEORETICAL BACKGROUND

2.1 Arid and Semi-Arid Lands

Arid and semi-arid lands are irregular low rainfall dry ecosystems. These habitats have a limited sustained economical potential. Over a quarter of the Earth's land surface is either arid or semi-arid (Adams *et al*., 1978). On basis of the ratio of average total annual rainfall and potential evapotranspiration (P/ETP), arid and semi-arid ecosystems show values of 0.05 to 0.65, respectively. This ratio provides only a crude measure of aridity or humidity of climate, and does not have a close relation with agricultural or grazing potential. However, a concept focusing on length of growing period (LGP) was developed and used in FAO studies on agro-ecological zones. This concept provides better information on the capability and suitability of land for different land uses and/or land covers. A reference "Growing Period" starts once rainfall exceeds half of the potential evapotranspiration (ETP) and ends after the date when rainfall drops below half of the ETP.

Areas with an LGP of less than 1 day are hyperarid (true desert), less than 75 days arid, 75 to less than 120 days (dry) semiarid, 120 to less than 180 day (moist) semiarid. These areas all together correspond closely to the areas denominated as drylands (FAO, 1993).
These arid and semi-arid ecosystems are very fragile and subjected to drought cycles during the period of precipitation deficit which accompanied with diminishing vegetation cover which simultaneously recover during periods of good precipitation.

Arid and semi-arid regions in the Sudan constitute the main areas of rainfed and irrigated crop production. Moreover, its open rangelands provide a good source for feeding a huge numbers of animals. Therefore, these areas are considered economically very important for the agro-pastoral sector in the Sudan.

2.2 Desertification

Desertification as a term became widely known after the environmental destruction and human suffering caused by the 1969-1973 drought in Sub-Saharan Sahel (Dregne, 1985). The United

Nation Convention to Combat Desertification (UNCCD, 1992) defined desertification as "land degradation in arid, semi-arid and dry sub-humid area resulting from various factors, including climatic variation and human activities".

Land degradation is defined as the reduction or the loss of the biological or economical production of irrigated and non-irrigated cropland, grassland, pastures, forests and woodland in arid, semi-arid and dry sub-humid zones as result of combination of factors including climatic variation and human impacts. Dry ecosystems are very vulnerable to overexploitation, inappropriate land uses and practices. Land degradation leads to unfertile soil, unavailable water, reduction in net primary production, and change of plant cover and biodiversity. The four desertification processes having the most intensive impact on the biological productivity of land are degradation of vegetative cover, soil erosion, salinisation, waterlogging, and soil compaction (UNCCD, 1992). Desertification is caused by overgrazing, excessive woodcutting, land abuse, improper soil and water management, and land disturbance. Its effect appears as reduced productivity of land, environmental degradation, impaired health and lowered standard of living for the local people (Dregne, 1985). Combating desertification requires several activities including technological, political, and social actions such as adoption of rehabilitation programmes and sustainable management practices. Solutions are theoretically possible but lack of finance and managerial ability are still the major constrains for implementation of these solutions. Desertification is measured with reference to status, rate, extent and hazard.

Desertification is different from desert creeping. It is evident that land degradation can and in fact does occur far from any climatic desert. The presence or absence of a nearby desert has no direct relation to desertification. It usually begins as a spot on the landscape where land misuse has become excessive. From that spot land degradation spreads outward if the misuse continues. Ultimately the spots may merge into a homogeneous area, but that is unusual on a large scale (Dregne, 1985).

The Sudan as a Sahelian country during the last decades was subjected to several occasions of drought especially during 1960s and 1980s, which resulted in a pronounced natural and human catastrophic destruction. People faced famines and large numbers of animals were lost as a result of shortage of food and fodder and water. People were displaced and had to immigrate to main cities and irrigated scheme in the area. The displaced people faced new socio-economics structures and they had to live in peripheries of cities "unplanned settlements" under very bad living conditions. This, in turn, resulted in uncontrolled destruction and removal of vegetation cover around the cities. Another negative outcome of the drift towards urban areas is an escalating deterioration of urban areas environment (ruralisation of cities).

The Sudan's Desert Encroachment Control and Rehabilitation Program (DECARP, 1976) concluded that "it appears that not one single factor causes desertification. Obviously, it is a combination of factors involving fragile ecosystem, harsh and fluctuating climate, and man's activities, some of which are increased in an irreversible magnitude by weather fluctuations, especially periodic droughts".

2.3 Remote Sensing

Remote sensing is a collective definition for several methods/technologies which study at distance the ground surface or the atmosphere based on measurement of spectral entities. Sensors installed on satellites or airplanes receive and/or emit radiation from/to the earth. The variation in amount versus wavelength of the reflected electromagnetic energy of investigated objects or phenomena gives the object its spectral signature and makes it possible to distinguish between different types of land use/land cover, vegetation, soils etc (Brogaard and Prieler, 1998). Remote sensing may be defined as the science of collection, processing and interpretation of images, and related data, obtained from aircraft and satellites, that record the interaction between matter and electromagnetic radiation (Sabins, 1997). On the other hand, remote sensing can also be defined as the variation of methods which employ electromagnetic energy such as light, heat and radio waves as the means of detecting and measuring target characteristics (Sabins, 1997).

2.3.1 Electromagnetic Energy

Electromagnetic energy refers to all energy which moves with the velocity of light in a harmonic wave pattern. Electromagnetic waves can be defined in terms of their velocity, wavelength, and frequency. All electromagnetic waves travel at the same velocity (C) which is $3 \times 10^8 m.sec^{-1}$. Velocity and wavelength change as electromagnetic energy passes through media of different densities, while frequency (v) remains constant and therefore, frequency is the fundamental property (Sabins, 1997).

Velocity (c), wavelength (λ) and frequency (v) are related by the equation (1):

$$c = \lambda v \qquad (1)$$

The electromagnetic spectrum is divided in wavelength regions (bands) ranging from the very short wavelengths of the gamma-ray region to the long wavelengths of the radio region (Fig. 1).

2.3.2 Interaction Processes

Electromagnetic energy encounters with matter is either absorbed, transmitted, reflected or emitted (Sabins, 1997). Levels of energy reflected, absorbed or transmitted depend on type and condition of the surface. These variations in spectral interaction are used to differentiate between different surface matters. Bare dry soil reflects electromagnetic energy in all wave lengths with the same proportion, while healthy vegetation shows low reflectance in the visible and high reflectance in the infrared range. Clear deep water is characterized by low reflectance in the whole spectrum thus absorbing energy of the visible, NIR and MIR spectrum (Fig. 2).

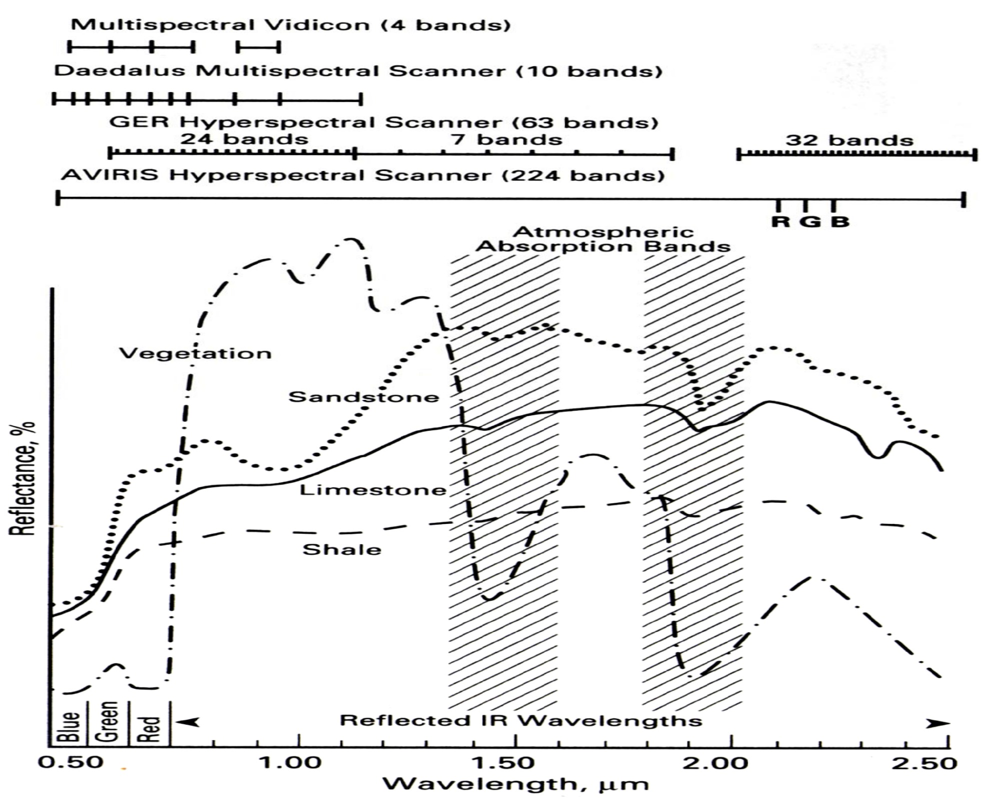


Figure 2: Reflectance of some surface types (Sabins, 1997)

2.4 Application of Remote Sensing in Land Use/Land Covers Classification

Land use defines how a parcel of land is used such as for agriculture, residence, or industry, whereas land cover describes the objects/matters present on the surface, such as vegetation, rocks or buildings. There are many systems for land use/land cover classification (LULCCS) such as US and Africover FAO classification systems. LULCC systems are hierarchical and multilevel categories. Generally LULCCS are priori classification systems in which the LULCs are determined before the conduction of classification. Developed LULCC system can support future comparison for change detection (Sabins, 1997).

Remote sensing methods are becoming increasingly important for mapping land use and land cover due to good characteristics of remotely sensed data such as large coverage, good spatial resolution, accessibility to harsh areas, faster interpretation, and objectivity and permanentability. However disadvantages like failing to distinguish some types of land use and lack of the horizontal perspective are also expected. Remote Sensing interpretation should be supplemented by sophisticated strategy of sampling good ground checks (Sabina, 1997).

Remote sensing has been used worldwide in vegetation change studies (Colwell, 1974, Tucker *et al.*, 1983; Tucker *et al.,* 1985; Justice and Hiernaux, 1986; Townshend and Justice, 1986; Tucker, 1986; Maselli *et al.*, 1993; Bastin *et al.,* 1995; Hobbs, 1995; Prince *et al.,* 1995, Schmidt and Karnieli, 2000, Kheiry, 2003, Suliman, 2003). Research proves that remote sensing can be considered a useful tool for studying arid and semi-arid ecosystems.

2.5 Application of Remote Sensing Methods in Soil Characterisation

Unlike for vegetation, application of remote sensing in soil studies is not straight forward, due to the masking affect of vegetation cover on the soil spectra and atmospheric interference with electromagnetic wave (Ben-Dor *et al.,* 1999). However, spectral libraries for pure soil types have been collected under controlled condition in laboratories while the soil under real condition is mixed; this also leads to difficulties in application of remote sensing in soil studies (Ben-Dor, 1999). Remote sensing is used to study soil physical condition such as hydrological condition of the soil using infrared and thermal bands (Curran, 1985, Thine, 2004). Hyperspectral imagery provides promising chances for soil mapping due to its narrow bandwidth which additionally derives significant information about physical and chemical conditions of a soil (Clark, 1999, Richter, *et al.,* 2005, Haubrock *et al*., 2005).

2.6 Remote Sensing Application in Sudan

In the Sudan use of remote sensing technology is a cost- and time-effective way for surveying natural resources. Many studies concerned with land degradation and land use/land cover classifications have been carried out in different ecological zones in Sudan with a focus on arid and semi-arid areas since they constitute the major areas for animal and crop production.

Starting from 1972 remote sensing has been used in natural resource survey at test areas that were chosen from Food and Agricultural Organization (FAO) for the possible utilisation of remote sensing for surveying, mapping, planning and development of natural resources.

Lampery (1975) studied vegetation change in the Sudan and concluded that the desert was moving southwards at the rate of 5-6 km per year. He attributed this desertification to misuse of land by people. However Hellden (1978) showed that there was no systematic desert encroachment and criticised the findings of Lampery (1975) as misinterpretation resulting from his application of the vegetation map compiled by Harrison and Jackson (1958), which depended mainly on the 100mm rainfall isohyets. Hellden (1978, 1988) stated that vegetation recovered during the rainy season. This finding coincides with finding of Olsson (1985) during his study that aimed to develop a methodology for integration remotely sensed data with ancillary data in raster as well as vector format in a geographical information system for studying desertification in a project region in semi-arid Sudan. The studies showed a severe decrease in agricultural crop yield and concluded that it was impossible to verify the traditional hypothesis that "degradation is continuous man-made process" as the main factors of degradation. But climatic conditions, as well, play a major role in controlling crop yield and growth of natural vegetation.

Olsson (1985) studied availability of fuel wood in North Kordofan using remote sensing. She stated that "no woody species seemed to have been eradicated from the areas, no ecological zones had shifted southwards, boundaries between different vegetation zones seemed to be the same as they were 80 years ago and no severe fuel wood supply problems were indicated". Ahlcorona (1988) concluded that the major impact on biological productivity of the land had been caused by climatic factors and not by man. The only observed indication of man-made land degradation was a qualitative deterioration of vegetation. It was also indicated that the very dry period, which began in 1966 might have constituted a medium-termed climatic change towards drier condition. Hielkema *et al.* (1986) used NOAA-AVHRR (Advanced Very High Resolution Radiometer) data to monitor vegetation and its relation to rainfall in Savanna zone. He concluded that NDVI values can be used to monitor effective rainfall in the Savanna zone of the Sudan.

The Sudan Resource Assessment and Development (SRAAD) project was established in 1987 to replace the Sudan Reforestation and Anti-desertification Project with the aim of forestry inventory and rehabilitation. This project was a co-project between Sudan Government and United State Agency for International Aid (USAID). This project used remotely sensed imageries, and produced vegetation maps for some areas in North Kordofan State such as Jebel El Dair and Kazgil (Hanfi and Hassan, 1992).

Ali (1996) assessed and mapped desertification in the western part of the Sudan using NDVI images created from AVHRR-NOAA sensor and also applied GIS. He stated that remotely sensed data provided good indicators of vegetation degradation throughout the period 1982-1994 in the form of the image maps. Yagoub *et.al.* (1994) assessed biomass and soil potential in northern Kordofan using the NDVI indices. They concluded that the land degradation and ecological imbalance in this region was associated with the combined adverse effects of rainfall and mismanagement of land.

One of the most efficient international efforts in Sudan was the Africover Project that was started in 1995. Africover developed a combined approach by using remote sensing and geographic information system technologies for the monitoring and promotion of sustainable use of natural resources as recommended by Agenda 21 and the last World Summit on Sustainable Development (WSSD). The innovations of land cover classification methodologies have been adopted by FOA and UNEP as the standard land cover classification system approach.
Kassa (1999) used NDVI based on NOAA-AVHRR and rainfall data to monitor drought risk for the Sudan and to produce drought risk map based on NDVI. This study concluded that NDVI-based map enables decision-makers to have a basic overview of areas at risk of drought in the Sudan.

Eklundh and Sjöström (2002) analysed vegetation changes in the Sahel using imagery of Landsat and NOAA. They showed that the NDVI values during the period 1982-2002 were increased, and areas of positive change showed a transition from barren or sparse vegetation to a denser vegetation cover. In addition they showed that as rainfall had increased over the course of time in several of these areas visual interpretation indicated an expansion of agricultural land.

Elmqvist (2004) studied land use change in northern Kordofan for the period 1969-2002 by using recent high resolution earth observation satellite data such as Corona and IKONOS. The study presented the state of land cover changes in the region of interest and concluded that the population increase was much higher than the increase in cropland areas during this period. Hinderson (2004) analysed environmental changes in semi-arid in Kordofan during 1982-1999 using NOAA-AVHRR and Landsat imagery. The research analysed the observed NDVI changes on local and regional scale by studying different processes and comparing areas with a positive trend in NDVI with areas with neutral trend in NDVI. It was found that there was no clear explanation of NDVI increase at regional level compared to dynamics at local level. Kheiry (2003) and Suliman (2003) used remote sensing methods to investigate land use/land cover changes in Khartoum State, and Darfour State, respectively. They stated that vegetation cover change could be significantly detected using remote sensing analysis methods. El Haja (2005) used remote sensing to study sand encroachment in North Kordofan State and concluded that remote sensing was efficient in determining areas affected by sand encroachment.

Dafalla and Csaplovics (2005) assessed the dominant land use/land cover types for the North Kordofan State by means of high resolution Landsat ETM+ imagery. The study revealed that remote sensing methods could be used with a satisfactory level of significance in land use/land cover classification.

Herrmann *et. al.* (2005) explored the relationship between rainfall and vegetation dynamics in the Sahel region using coarse resolution satellite data. They confirmed the general positive trend of NDVI and rainfall over the period 1982-2003. In addition they concluded that rainfall emerges as the dominant causative factor in the dynamics of vegetation greenness in the Sahel region, but they hypothesised that human impact might have been another causative factor due to presence of spatially coherent and significant long-term trends in the NDVI residuals.

2.7 Image Processing

Image processing is a collective name for the different methods of manipulating image raw data, including radiometric/geometric correction, enhancement, data transformation, classification and accuracy assessment.

2.7.1 Data Transformation

Data transformation is the production of new values for image pixels through application of a linear transformation matrix. Transformation generally reduces number of bands and improves the discrimination of different surface objects in the image. Different transformation methods, ranging from simple arithmetic ones such as vegetation indices to complicated linear ones such as tasselled cap analysis are used in remote sensing.

2.7.1.1 Vegetation Indices

The vegetation indices can be broadly divided into two basic categories: ratios and orthogonal indices. The ratio-based indices include the Ratio Vegetation Index (RVI) and the Normalized Difference Vegetation Index (NDVI). Orthogonal indices include Perpendicular Vegetation Index (PVI) and the Difference Vegetation Index (DVI). More recently a hybrid set of vegetation indices have emerged, such as Soil Adjusted Vegetation Index (SAVI).

Vegetation growth typically exhibits some type of annual cycle, with a period of low (or no) growth and a period of active growth and decline. This growth cycle is controlled by growth limiting factors, such as water availability, day length and temperature. Variations in these primary growth-affecting factors result in growth responses of vegetation that vary from year to year (Elvidge, *et al.,* 1999). Remote sensing is an accepted technique for resource assessment (Hess, *et al.,* 1996, Conese, *et al.,* 1993, Koslowsky, 1993, Treitz and Howarth, 1999). A specific requirement in the seasonally arid regions of Africa is the capability to evaluate and predict the response of vegetation to climate variability. In this context remote sensing can provide an indirect measure of vegetation growth through calculation of vegetation indices (Hess *et al.,* 1996, Kheiry, 2003, Suliman, 2003, Hermman *et al.,* 2005). The NDVI is one of the most generally used indices for vegetation monitoring. The NDVI is calculated as the normalised ratio between visible red reflectance and near-infrared reflectance. The main advantages of the use of the NDVI for monitoring vegetation are its simplicity of calculation and its high degree of correlation with a variety of vegetation parameters such leaf area index (Hess *et al.,* 1996).

2.7.1.2 Principal Component Analysis (PCA)

PCA is a powerful data transformation technique for information extractions for the analysis of multi-spectral or multidimensional data (Richard and Jia, 1999). PCA shows the patterns in data, and expresses the data in a way that highlights similarities and differences. PCA is used also as a data compressing tool without much loss of information (Smith, 2002). In addition PCA is used as change detection technique.

2.7.1.3 Tasseled Cap Analysis (TCA)

Tasseled cap analysis is a sensor-dependent linear transformation developed by Kauth and Thomas (1976) in order to describe the crop development in relation to soil background through its three components. Its three components are: brightness, greenness, and wetness. The component brightness highlights the higher brightness values from background soil, while the greenness refers to higher brightness from active vegetation and wetness defines the moisture status. TCA is used in classification and change detection with emphasis on greenness components (Lunetta, 1999).

2.7.1.4 Canonical Analysis (CA)

Canonical correlation analysis is a statistical method to identify and quantify the association between two sets of variables. It is a linear transformation that maximizes variance between different classes' means. Canonical correlation analysis focuses on the correlation between a linear combination of the variables in one set and a linear combination of the variables in another set (Lee *et al.,* 1999). While PCA may be optimal for image compression, it is not necessarily optimal for image classification and class separability.

2.7.2 Image Classification

Image classification or labelling in the remote sensing community is based on pixel-based labelling of spectrally unique and statistically similar pixels. There are two broad types of classification methods, namely unsupervised and supervised classifications. However hybrid approach that uses unsupervised and supervised together is also used.

2.7.2.1 Unsupervised Classification

Unsupervised classification (isodata analysis) is a technique in which an image is segmented into unknown classes depending on its statistical similarities by using a suitable clustering algorithm. In a second step the user has to label those classes to the relevant land use/land cover patterns by a posteriori analysis (Schowengerdt, 1997). This technique implies a grouping of pixels in multi-spectral space. Pixels belonging to a particular cluster are therefore spectrally similar. In order to quantify this relationship it is necessary to devise in part a similarity measure. Many similarity metrics have been proposed but those commonly used in clustering procedures are usually simple distance measures in the multi-spectral space. The most frequently encountered are Euclidean distance and L1 distance. If x_1 and x_2 are two pixels whose similarity is to be checked then the Euclidean Distance between them is calculated by the following equations.

$$d(x_1, x_2) = ||x_1 - x_2|| \quad (2)$$

$$= \{(x_1 - x_2)^t (x_1 - x_2)\}^{1/2} \quad (3)$$

$$= \left\{ \sum_{i=1}^{N} (x_1 - x_2)^2 \right\}^{\frac{1}{2}} \quad (4)$$

Where, N is the number of spectral components.

The L1 distance between the pixels is calculated by the equation (5)

$$d(x_1, x_2) = \sum_{i=1}^{N} |x_1 - x_2| \quad (5)$$

It is evident that the latter is computationally faster to determine. However, it is less accurate than the Euclidean distance measure (Richard and Jia, 1999).

After the completion of clustering, pixels within a given group are usually given a symbol to indicate that they belong to the same cluster. Then these clusters are labelled to their equivalent land use/land cover classes by means of maps, site visits or other forms of reference data. This method of image classification depends on unsupervised pixel assignment since the analyst plays only a minor role until the computational aspects are completed. Often unsupervised classification is used on its own, particularly if reliable training data for supervised classification cannot be obtained or are too expensive to be acquired. However, as noted earlier it is also of value to determine the spectral classes which should be considered in a subsequent supervised approach (Richard and Jia, 1999)

2.7.2.2 Supervised Classification Technique

Supervised classification is the procedure most often used for quantitative analysis of remotely sensed data. It depends upon using suitable algorithms to label the pixels in an image to particular ground cover types or classes. A variety of algorithms are available ranging from those based upon probability distribution for the classes of interest (maximum likelihood classifier, Mahalanobis) to those in which the multi-spectral space is portioned into class-specific regions using optimally located surfaces (minimum distance classifier, parallelepiped classifier). Recently, new methods like neural network and tree decision have been developed to maximise land cover classification accuracies (Friedl *et al.*, 1999). Irrespective of the method used, practical steps should be followed including determination of ground cover types, choose of representative training data to estimate the parameters of the particular classifier algorithm. Then pixels in the image will be labelled or classified into one of desired ground cover types. Tabular summaries or thematic (class) maps are the final outputs of the classification (Richard and Jia, 1999).

Maximum likelihood classification is the most commonly used supervised classification method of remotely sensed imagery. It uses the mean and covariance matrix of each class. Sufficient training samples for each spectral class must be available to allow reasonable estimates of the elements of the mean vector and the covariance matrix to be determined. For an N dimensional multi-spectral space at least N+1 samples are required to avoid the covariance matrix being singular. Maximum classifier algorithm computes these equations to classify the image based on training data for each pixel at specific location x:

$$p(x) = \sum_{i=1}^{M} p(x \mid w_i)\, p(w_i) \tag{6}$$

where:

p(x) = Probability of finding a pixel from any class at location **x**.
M = Total number of classes 1….M.
$p(x| w_i)$ = Probability that pixel at location x belong to class wi.
$p(w_i)$ = Probability that class wi occurs in the image.

The $p(w_i)$ are called a prior probabilities, since they are the probabilities with which class membership of a pixel could be guessed before classification. By comparison the $p(x|w_i)$ are posterior probabilities. Then the classification rule is:

$x \varepsilon w_i$ if $p(x|w_i)\, p(w_i) > p(x|w_j)\, p(w_j)$ for all $j \neq I$ (7)

2.7.2.3 Accuracy Assessment

Accuracy assessment is very important to measure the reliability of classification. Accuracy assessment requires determination of classes based on reference data which have been gathered by collecting ground truth derived from field work or the analysis of large scale maps or the visual interpretation of imagery. The reference classes are compared with the result of classification and the ratios of correctly versus wrongly classified pixels are calculated for each class. The most common types of errors in classification are confusion and omission. Confusion occurs if the classifier is labelling more pixels to a certain class although these pixels are not belonging to this class. Omission occurs when the classifier fails to label pixels to their reference class (Curran, 1985). Accuracy assessment measures producer, user and overall accuracy. This sort of accuracy assessment is simple compared to the calculation of the Kappa coefficient which determines the probability for each class. Accuracy assessment is affected by samples number for each class. As the samples number increases, the accuracy assessment becomes more reliable (Richard and Jia, 1999).

2.7.3 Change Detection

Change detection, as one of the most important applications of remote sensing, determines changes both quantitatively as well as qualitatively. It rests upon the assumption that under the same atmospheric conditions and sensor characteristic the major source for difference of a pixel's brightness is change of surface cover. However, this assumption is not always applicable before correcting imagery for atmospheric scattering, sun elevation and eventually also different sensor conditions (calibration). Despite these constraints change detection based on remote sensing is highly effective for studying dynamics of land use/land cover especially concerning vegetation and urban expansions. Analysis change detection is also very important for a better understanding of dynamics of ecosystem. There are two basic methods of change detection by mean of remote sensing, explicitly post-classification and pre-classification methods (Lunetta, 1999).

2.7.3.1 Pre-Classification Methods

Pre-classification method is considered simple and fast, and can be used on a massive number of images. Numerous methods exist such as image differencing, Change Vector Analysis (CVA), and composite analysis. Decisions are needed concerning which original input bands to use (e.g., DN, radiance reflectance, vegetation indices), what type of classification algorithm to apply (e.g., supervised, neural-net), and what strategy for error assessment to be chosen. Image differencing and CVA involve transformation of input bands into temporal change vectors, with the former being a band-by-band temporal subtraction, and the latter requiring derivation of magnitude and angle of spectral change. Composite analysis uses the input bands directly in classification (Lunetta, 1999).

Although difference and CVA images represent direct characterisations of spectral change over time, they contain no reference to location within the original input data space. In contrast, composite analysis uses input bands directly, and thus contains this reference information. Therefore, natural variability in original and final (i.e., T1 and T2, respectively) land cover classes are directly incorporated into the change classification procedure (Lunetta, 1999).
Radiometric normalisation of imagery data is not required (or makes a great problem) if the data were collected over a clear atmosphere for all dates and the solar illumination angles were virtually identical (Cohen and Fiorella, 1999).

2.7.3.2 Post-Classification Methods

Post-classification methods focus on the analysis of differences of land use/land cover classes of two independently classified images (Lunetta, 1999). This simple approach consists of a first step of classification which produces classified imagery, followed by a second step of comparison which identifies areas of change as pixel per pixel differences in class membership (Castelli, et al., 1999). Constraints of this approach include cost in term of money and execution time and errors propagated from classification of datasets (Castelli, 1999, Singh, 1999). On the other hand it has the advantage that data normalisation is not required because the two datasets are classified separately (Singh, 1999).

CHAPTER THREE

THE STUDY AREA

3.1 Sudan

Sudan is the largest country in Africa with Khartoum as its capital. The country has a population of about 40 millions of which almost half is below 15 years old. The country is one of the poorest countries in the world despite its almost unlimited natural resources. Sudan extends over different climatic zones, ranging from desert in the north through semi-desert, arid, semi-arid, dry monsoon to wet monsoon (equatorial) in the south. The vegetation coincides with climatic zones and ranges from desert vegetation in the north, semi-desert vegetation, mixed savannah in central Sudan and dense forest in the equatorial climatic zone (Fig. 3). During 19870s and 1980s the country was stricken by severe drought cycles that lead to corresponding incidences of famine. The country is rich in its natural resources such as oil, gold and chrome, but agriculture is the most important economical sector and employs nearly 80% of the workforce. Along the River Nile and Gezira scheme wheat and cotton are grown by irrigation, but traditional and mechanised rainfed agriculture compromises the biggest sector in the country and sorghum and sesame in addition to groundnut are the most commonly produced crops.

3.2 North Kordofan State

North Kordofan state, located in central Sudan, extends approximately from latitude 12° 40´ N to 14° 20´ N and longitude 28° 10´ E to 31° 40´ E. The capital is Elobeid (Fig. 3). North Kordofan is bordered by Northern State to the north, Khartoum State to the northeast, River Nile State to the east, North Darfur to the northwest, West Kordofan State to the west and South Kordofan State to the south. The state covers an area of 185,302km^2.

The state is unique in its natural resources. It is rich in agricultural products and rangeland resources which allow the raising of various kinds of livestock (sheep, camels, and cows). Animal husbandry is the backbone of the economy of the state and plays major source of income for the majority of the inhabitants.

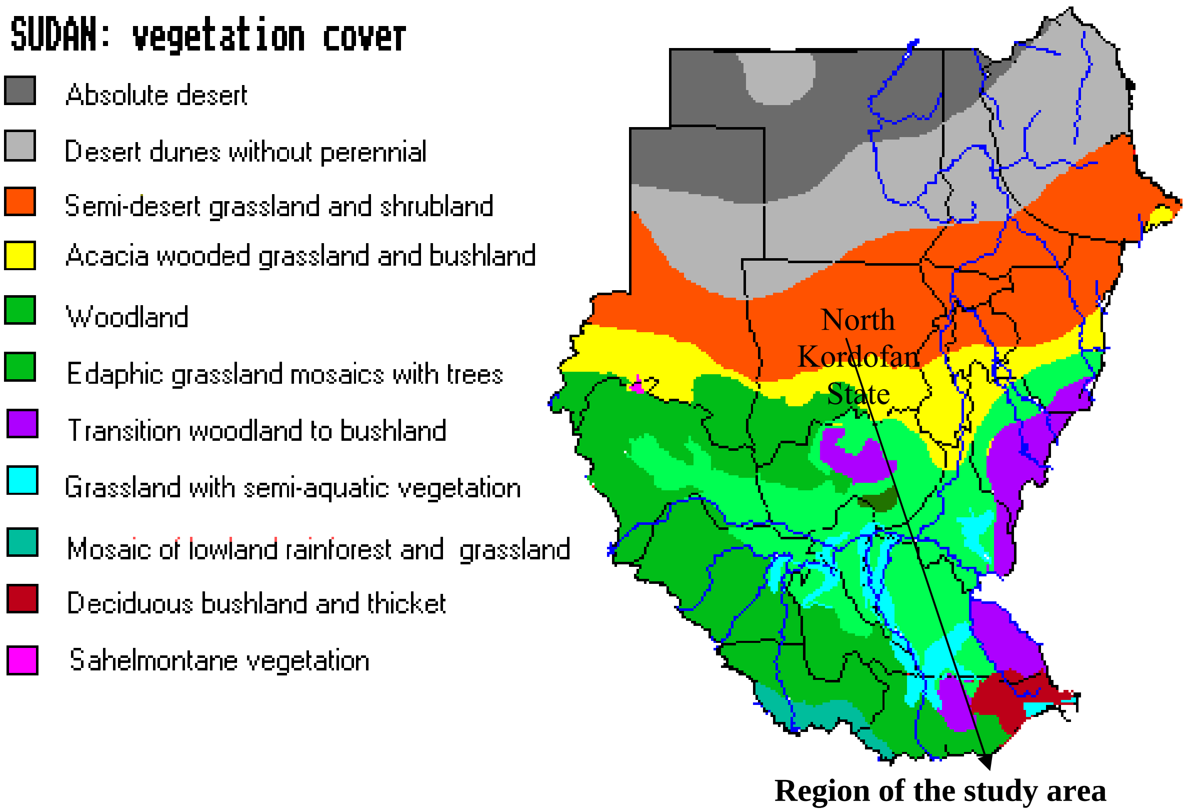


Figure 3: Sudan vegetation map

Source: FAO

3.2.1 Population

The total population of North Kordofan State was estimated as 1,554,000 in 2003 (67.08% rural), with a ratio of 92 males : 100 females. Between 1998 and 2003, the population grew at a rate of 1.55% annually, with crude birth and death rates of 40.1 and 12.2 per 1000 live births, respectively (UN, 2003).

The Bidairiya, Jawamma, Dar Hamid, Hamar and Nuba are the major ethnic groups in the state. Others include the Dayo, Bargo, Barno and Hausa.

North Kordofan State hosts internally displaced persons (IDP) from the war-affected areas of the Nuba Mountains and Southern Sudan. According to the latest IDP figures as edited by the Humanitarian Aid Commission (2003), there were an estimated 80,000 IDPs in the state in 2003.

3.2.2 Climate

The climate ranges from arid in north to semi-arid in south with a mean annual rainfall range of 225-400mm to 400-750mm for arid and semi-arid regions, respectively (Doka, 1980). The precipitation is confined to the summer months (June to September) with August as the wettest month (Fig. 4). Rainfall occurs in a few occasions with high intensity and it shows great variability both in time and space (Hulme, 2001). The length of the rainy season depends to a large degree on the latitude (Olsson, 1985). The mean annual temperature is about 20°C, but during summer the temperature can rise as high as 45°C during the daytime.

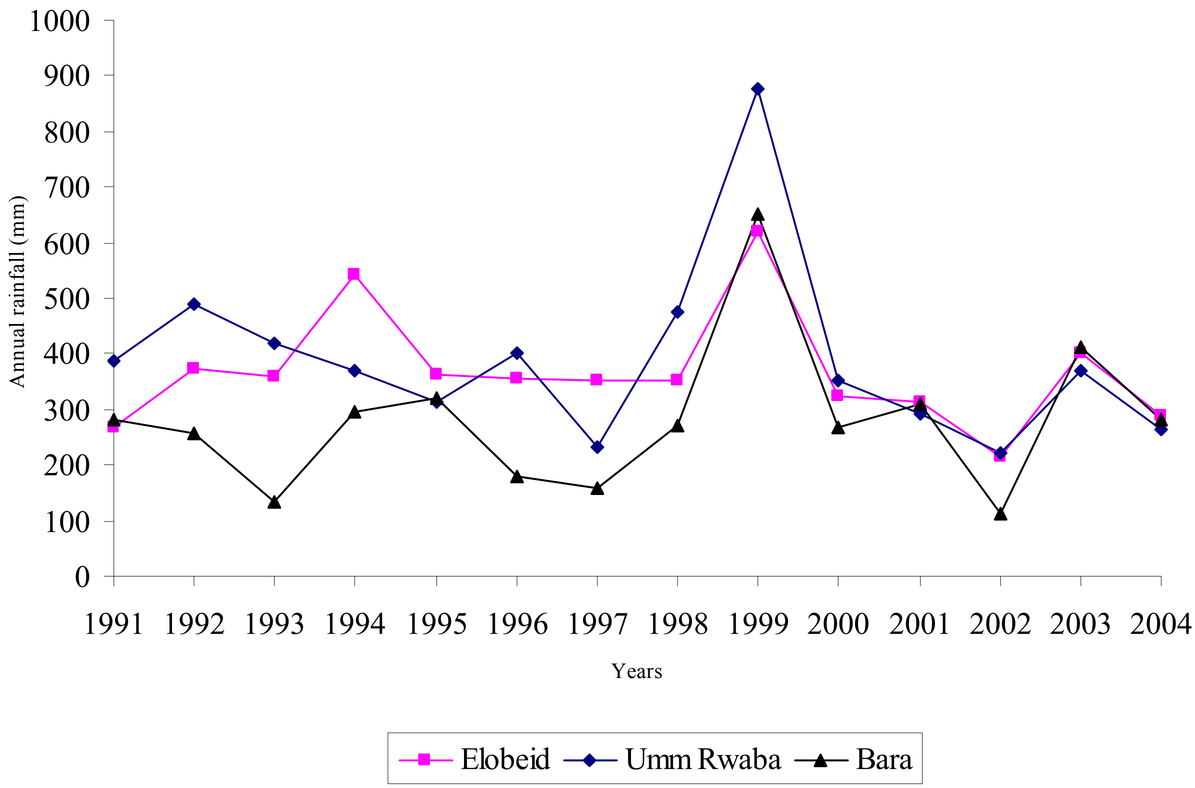


Figure 4: Annual rainfall distribution in North Kordofan State
Source: Ministry of Agriculture and Forestry, North Kordofan State, Sudan (2005)

3.2.3 Topography

The terrain of North Kordofan State is generally flat with some inselbergs in the north and in the south. It rises to the Nuba Mountains in the south. However, there are also longitudinal and transverse sand dunes. The heights of the longitudinal and transverse dunes might reach up to 140ft and 50ft, respectively (Shadul, 1980).

3.2.4 Soils

The soil and landscape of North Kordofan State between latitudes 13° 00´ N and 12° 30´ N consists mainly of sand sheets and sand dunes which are stabilized by vegetation. These soils (classified as Cambric Arenosols according to FAO system of soil classification) are locally named *Qoz*. They are coarse textured soils of aeolian origin. They have high infiltration rates and inherent low fertility. South of the latitude 12° 30´ N, the soils are alluvial in origin with a silty clay texture. They are non-cracking clay soils mixed with aeolian sand (FAO, 1997) and locally named *Gardud.*

3.2.5 Geology

The North Kordofan State is covered by three main types of rocks: the basement complex of pre-Cambrian age, the cretaceous Nubian sandstone, and the Umm Rwaba sediments of the Tertiary age. The basement complex is the oldest rock form in the area and consists of schists, granite, gneisses and younger granite intrusive. The cretaceous Nubian sandstones are located unconformable on the basement complex rocks. The Nubian sandstones consist of two formations: the lower basal conglomerate and the upper sandstone. Umm Rwaba sediments are flat-lying, unconsolidated sands, silts and clays with some gravel. They are younger than the Nubian sandstones and older than the aeolian sands (Shadul, 1980)

3.2.6 Vegetation

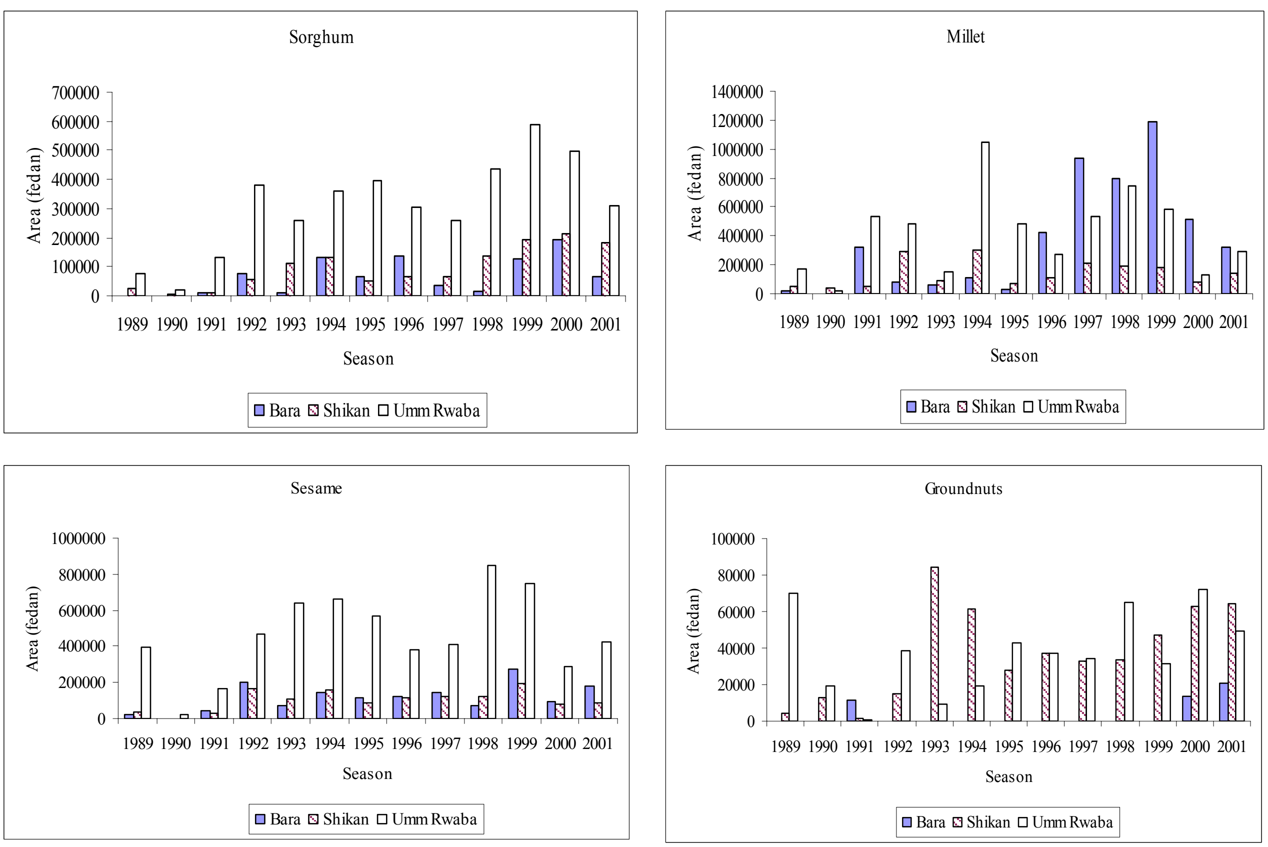
North Kordofan State is sparsely vegetated as a result of the low amount of rainfall. The vegetation is exposed to extreme conditions and must survive drought which can stretch over several years with little or no rain at all. In the semi-arid ecosystems with a single rainy season there is usually a short growth period followed by a long dry season with a great reduction in the amount of green plant material (Shmidt and Karnieli, 2000).

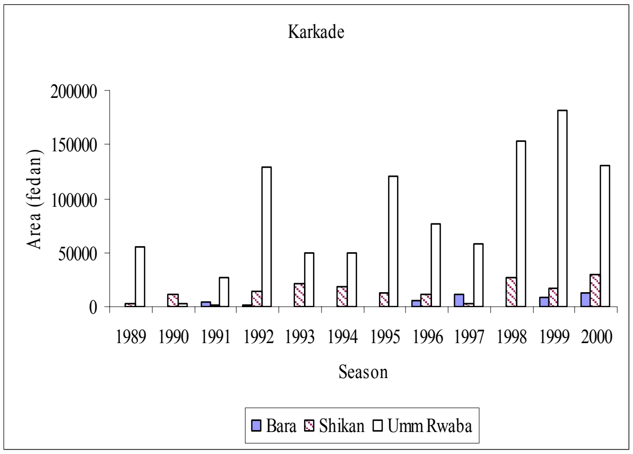
In the northern part of the area the *Merikh* (*Leptadaenia pyrotechniquea*) is very common (Photo 1). The under story consist mostly of *Tomam* grass (*Panicum turgidum*). The *Wadis* in this area support trees such as *Kitir* (*Acacia millifera*), *Seyal* (*Acacia tortilis* var spirocarpa), and *Higlig* (*Balanites aegyptica*) (Photo 2).

To the south the vegetation cover becomes taller and denser. Common trees and shrubs are *Tabeldi* (*Adansonia digitata*), *Hashab* (*Acacia Senegal*), *Kitir* (*Acacia millifera*), *Ushr* (*Calotropis procera*), and *Dahasir* (*Indigofera pancifolia*) (Photo 3). Trees and shrubs alternate with areas of open grassland.

3.2.7 Crops Production

The climate allows the cultivation of sorghum (*Sorghum vulgare Pers*), millet (*Pennisetum typhodieum*), watermelon (*Citrulus lanatus*) and sesame (*Sesamum orientale* L.) by shifting cultivation (Fig. 5, Photo 4). However, in the south area of the study area mechanised rainfed agriculture is practiced in which sorghum is the major crop. Recurrent drought has resulted in continuous cropping of millet without crop rotation leading to poor soil fertility (Care, 2002).





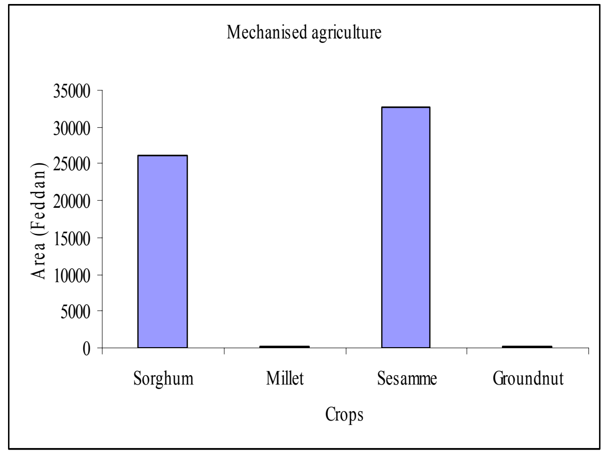


Figure 5: Crop production at different administrative units, and mechanised sector
Source: Ministry of Agriculture and Forestry, North Kordofan State, Sudan (2005)

3.2.8 Livestock

North Kordofan State is an area rich in livestock, especially camels, sheep and cattle (Table 1, Fig. 5). The open rangelands support rearing of large numbers of animals. However, water deficiency is the major constrain for this activity and the people migrate to the southern area where water is sufficient.

Table 1: Livestock statistics in different administrative sector in North Kordofan State

Animal type	Average /household	Total number	Birth rate (%)	Purchase rate (%)	Mortality rate (%)	Growth rate of the herd (%)
Shikan						
Goat	2.03	57953	30.3	18.8	6.2	5.3
Sheep	2.4	74142	38.5	4.7	14.9	18.9
Cattle	1.2	15427	26.5	3.3	12.1	25.3
Camel	0.07	2030	3.7	3.7	3.7	-3.7
Bara						
Goat	4.6	215906	27	50	30	-53
Sheep	6.8	319165	19	64	10	-55
Cattle	*	*	*	*	*	*
Camel	0.03	1603	14	14	0	0
Umm Rwaba						
Goat	2.29	178599	33	10	3	20
Sheep	2.69	209795	41	5	2	34
Cattle	0.2	15598	25	5	17	13
Camel	0.013	1013	5	0	0	5

Source: Ministry of Agriculture and Forestry, North Kordofan State, Sudan (2005)

3.2.9 Land Use and Human Impact

The economy of North Kordofan State is predominantly agro-pastoral. Crop production is mainly traditional (Mohamed *et al.,* 1996). Cereal and cash crops, cultivated in the fertile soils and/or stabilised sand during wet rainy years, include millet as the dominant crop, sorghum and sesame. Millet occupies the largest area accounting for more than 50% of the cultivated land. In areas around Umm Rwaba, Errahad and Tendalti sesame occupies substantial areas. In recent years natural fallow periods became less, giving only limited chance to woody herbaceous vegetation to recover. *Acacia senegal* plantations are another important type of land use. Because of its economic benefits for Gum Arabic collection, it is the only tree which is planted and protected by the farmers.

Livestock production is primarily based on systems of location and utilisation of rangeland. There are two types of livestock management: sedentary livestock and nomadic pastoralism. Settled villagers keep goats, sheep and few cattle, while nomads are mainly camel owners who traditionally move with their livestock in a north-south axis. Forestry activities are locally practiced mainly to secure fuel wood and construction material for local and commercial purposes.

Crop production declined during the years of drought. To compensate for the food shortage, the cultivated areas were increased. This might have lead to land degradation. However, good rainy seasons allow for the reestablishment of vegetation cover in comparison with dry seasons. The considerably rapid recovery and improved ecological conditions may be attributed to the following factors:

1. Throughout the prolonged Sahelian drought large-scale of the region immigration of the inhabitants and their livestock gave a resting period for degraded plants to recover.
2. The flora and fauna of North Kordofan are ecologically resilient and in case of good conditions, mainly during good rainy seasons, the recovery is rapid and almost guaranteed.
3. Successive years of drought induced suffering of people and raised their awareness. The inhabitants developed a reasonable degree of awareness of irrational practices in such fragile ecosystems and hence became more concerned with careful management of their land and water resources.

Photo 1: Merikh *(Leptadaenia pyrotechniquea)* vegetation around Bara

Photo 2: Acacia spp. on Wadies (near Jebel Koon, north of Umm Rwaba*)*

Photo 3: Dense kitir (*Acacia millifera*) on the southern part (south of Errahad near Jebel Eddair)

Photo 4: Traditional rainfed agriculture (millet + *Acacia seyal*, near Elzariba north of Umm Rwaba)

Photo 5: Livestock in the study area (Kazgil south of Elbeid city)

CHAPTER FOUR

RESEARCH METHODOLOGY

4.1 Satellite Imageries

Data analysis was done by personal computer equipped with Erdas 8.5 and Statistical Package for Social Science software (SPSS), supported by field measurement provided by a Geko 101 global positioning receiver.

The Landsat1 MSS Scene 187/51 acquired on 01.01.1973, which is considered as the driest year recorded ever in the Sahel (Hulme, 2001), was used as the reference dataset. This dataset was downloaded free of cost from the Global Land Cover Facility (GLCF) archive of Maryland University, USA. The MSS dataset had a line dropout problem with Band 4 and Band 6. This problem was solved by use of a median filter.

The Landsat ETM+ Scene 174/51, acquisition date 16.01.2001, was used as recent dataset. The ETM+ scene was acquired from EROS Data Centre as a recent image. The dataset of ETM+ of 2001 was used, since the ETM+ scenes acquired after this date were subjected to a serious defect. Products after this date are corrected by filling the bad lines with new values derived from old images of the same area. This would cause a serious decrease in the reliability of these images, for the use of detection of land use/land cover change.

4.2 Methods

Imageries and ancillary data were processed to determine the land use/land cover classes for the recent and reference image, and pre- and post-classification methods were used to detect changes in land use/land cover classes in the area (Fig. 6)

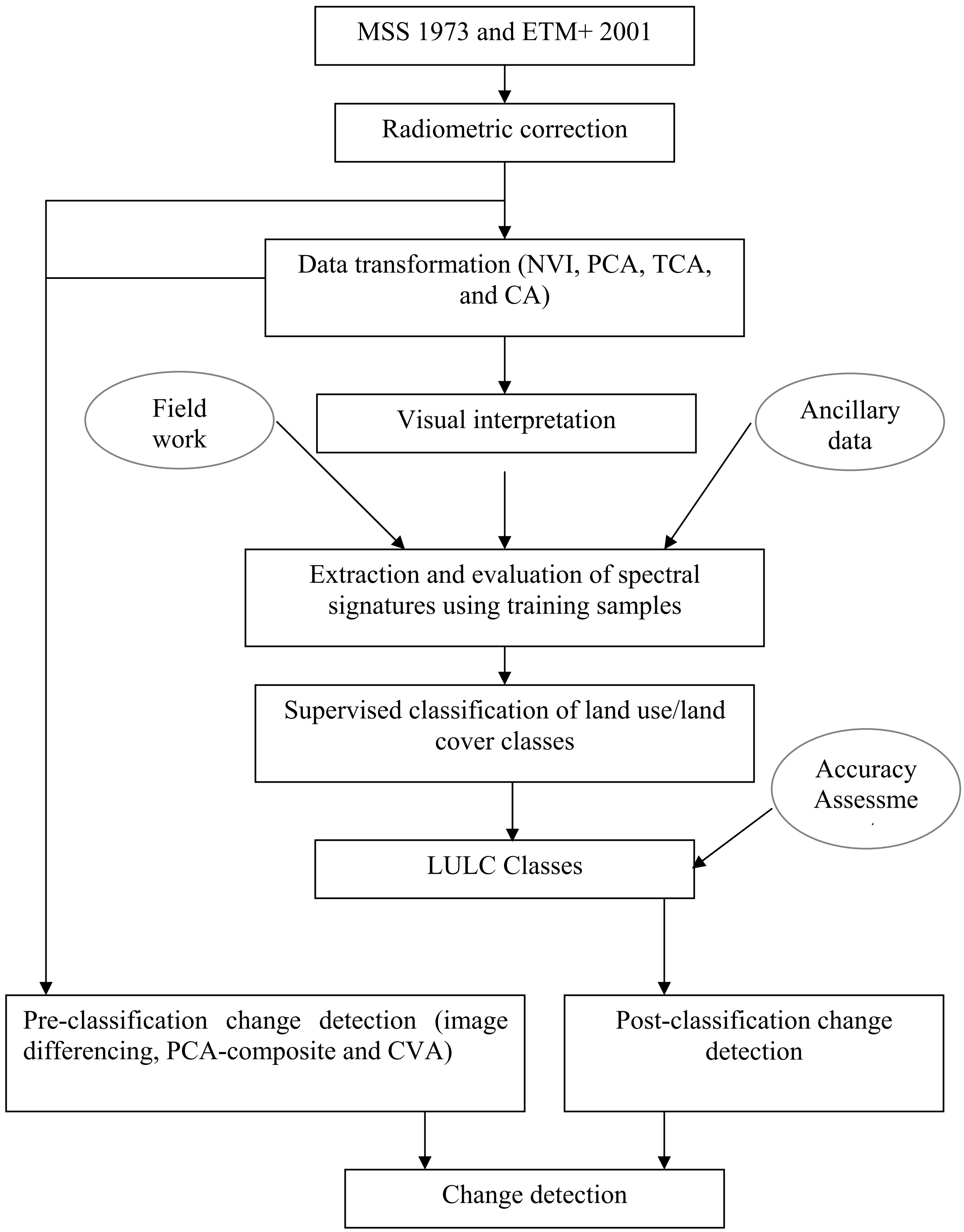


Figure 6: Methodological image processing for determination of land use/land cover classes

4.2.1 Geometric and Radiometric Corrections

4.2.1.1 Geometric Correction

Raw digital images usually need to be corrected for geometric deformation due to variation in altitude, velocity of the sensor platform, variation in scan speed, in the swath of the sensor's field of view, earth curvature, relief displacement etc. Systematic errors are normally corrected by the distributor. Random distortion of data was corrected by the analyst by the selection of a sufficient number of ground control points (GCP) with reference coordinates, usually from maps or by ground control points (GCP) measured in the field by use of Global Positioning System (GPS). GCPs were localised in the satellite image and thus image coordinates were corrected.

The geocoded data were not further geometrically corrected since it had been rectified to the same map projection, which is UTM, Zone 36, and lack of clear and well distributed features especially man-made ones, which were used as GCP. Geocoded data should be rectified only if they must conform to a different projection system or be registered to other rectified data (Erdas, 2003).

4.2.1.2 Radiometric Correction

Radiometric correction can be achieved through many methods such as detailed correction of atmospheric effects, calibration to surface reflectance, and bulk correction of atmospheric effect (dark object subtraction). Detailed correction of atmospheric effects requires detailed atmospheric information such as humidity and temperature at time of image acquisition, which is not easily available. Calibration to surface reflectance requires a spectral library of the darkest and brightest object in the image. Unfortunately no spectral library and no field spectrometer data have been available. According to these very limited options, dark object subtraction (DOS) was carried out after visual interpretation of histograms of each band for datasets 1973 and 2001.

4.2.1.3 Conversion of DN to At-Satellite Reflectance

The relative radiometric calibration was done to compensate for detector-detector, band-band, and time-time variation and should therefore be done priori to multi-temporal image analysis (Markham and Baker, 1986). These conversions provided better bases for comparison of data between images taken in different acquisition dates and/or by different sensors (Chander and

Markham, 2003). The relative radiometric calibration included the conversion of digital numbers to spectral radiance, which required post-calibration coefficients which are specific for the receiving station (Equation 8 and Table 2).

$$L\lambda = Gain * DN\lambda + Bia\ \lambda \tag{8}$$

This also can be expressed as in equation 9:

$$L\lambda = L\lambda \min + \frac{(L\lambda \max - L\lambda \min)}{DN \max} \times DN \tag{9}$$

where:

Lλ	= Spectral radiance
Gain	= Rescaled gain
DNλ	= Digital number
Biasλ	= Rescaled bias
DN max	= Maximum digital number
Lλ min	= Minimum spectral radiance
Lλ max	= Maximum spectral radiance

The next step in the correction procedure was to compensate for sun angle and irradiance effects to calculate the at-satellite reflectance (Equation 10).

$$\rho p \lambda = \frac{\pi . L \lambda . d^2}{Esun\ \ \lambda . \cos\ \theta s} \tag{10}$$

where:

ppλ	= Unitless effective at-satellite reflectance
Lλ	= Spectral radiance
d	= Earth-sun distance in astronomical units
E sunλ	= Mean solar exoatmospheric spectral irradiance (band specific)
θs	= Solar zenith angle in degrees

Table 2: Calibration coefficients

Platform	Band	Lminλ	Lmaxλ	Esun	DN max	d	θs
Landsat1	1	1.0	21.00	185.6	127	1.01524	42.35
	2	0.7	15.60	155.9	127	-	-
	3	0.7	14.00	126.9	127	-	-
	4	0.5	13.80	90.6	63	-	-
ETM+	1	-6.200	293.70	1969	255	1.01524	45.15
	2	-6.400	300.90	1840	255	-	-
	3	-5.000	234.40	1551	255	-	-
	4	-5.100	241.10	1044	255	-	-
	5	-1.000	47.57	225.7	255	-	-
	6 1	0.000	17.04	-		-	-
	6 2	3.200	12.65	-		-	-
	7	-0.350	16.54	82.7	255	-	-
	8	-4.700	243.10	1368	255	-	-

Source: USGS (2001)

4.2.2 Visual Interpretation

Visual interpretation of various band combinations as a preparation for field work was done to learn about the separability of apparent land use/land cover classes. Different band combinations were tested, but for MSS 7, 5, 4 (RGB), and 7, 6, 5 (RGB) band combinations, very clear delineation of most determined land use/land cover classes was possible. On the other hand, ETM+ 4, 2, 1 (RGB), 7, 4, 1 (RGB), 5, 4, 1 (RGB) band combinations showed best quality for separating the available land use/land cover classes.

4.2.3 Field work

4.2.3.1 Ground Control Points

A. Sampling Technique

During June to December 2004 corresponding to late and mid dry periods in the study area respectively, the field trips were made. The first trip (in June) was allotted to preparatory field work, while the second trip (in December) was the major one. Although the area is very large and hardly accessible, stratified and road sampling methods were used to collect observation so as to intensify the inventory for the purpose of improving the classification.

B. Measurements

By using Geko 101 global positioning receiver, approximately 110 GCPs in June and 160 GCPs in December were collected. In a plot of 30x30m, dominant trees, number of trees, dominant weed species and the apparent land use/land cover were recorded. Although dates of field works did not coincide with the dates of images acquisition (the field work was conducted in June and December 2004 and the images were acquired in January 1973 and 2001), the collected data was used to determine the major land use/land cover for the area and to classify the images.

C. Socio-Economic Data

Socio-economic data was collected by group discussions and interviews with local people and formal persons. The collected information was used as a supplementary data source. Through direct interviews with inhabitants information was collected on: past history of vegetation cover, newly introduced plant species, species that disappeared, distribution and extent of the past and present rangeland. All this information was used for a better understanding of the present and past land use/land cover and the related dynamics in the study area.

D. Secondary Data

1. Rainfall Data

Monthly rainfall records for the growing season (April-October) of 14 meteorological stations in the study area for the period 1991 - 2004 were obtained from the Ministry of Agriculture and Forestry, North Kordofan State (Appendix 1). This data was analysed to investigate the rainfall trend in the study area.

2. Agricultural Statistics

Agricultural statistics for the period 1989-2002 were obtained from the Ministry of Agriculture and Forestry, North Kordofan State (Appendix 2). This data showed the cultivated area, production (tons), productivity (ton/fed) for sorghum, millet, sesame, groundnut and karkade, plus data of average number of animal (heads/household), total number of animals, and growth and mortality rate of animals. These records were statistically analysed to investigate the human impact on the land use/land cover in the area.

4.2.4 Image Processing

4.2.4.1 Data Transformation

A. NDVI

Normalized Difference Vegetation Index (NDVI) is a data transformation which reduces data dimensionality. NDVI is the most widely used of all vegetation indices because it requires data from only the red and near-infrared portions of the electromagnetic spectrum, and it can be applied to virtually all remotely sensed multi-spectral data types (Lunetta, 1999). NDVI is derived through the equation (11):

$$NDVI = \frac{NIR - R}{NIR + R} \qquad (11)$$

where:
NIR= Near-infrared band.
R = Red band

NDVI is not always suitable especially in semi-arid areas where the vegetation cover is very sparse and soil background in reflectance values is very high (mixed pixels). Vegetation indices are likely to underestimate live biomass in deserts, they are insensitive to nonphotosynthetic vegetation, and are sensitive to soil color (Okin and Roberts, 2004)

B. PCA

Principal component analysis (PCA) is a powerful data transformation technique for information extraction in remotely sensed imagery in order to analyse multi-spectral and/or multidimensional data. The PCA transformation is a technique for reducing redundancy which leads to the description of multidimensional data in a spaced coordinate system with uncorrelated axis variables. The first variable or component (PC1) contains most variance and succeeding components contain decreasing proportions of data scatter variances. The monitoring of land cover change with multi-temporal Landsat MSS data using PCA analysis was first reported by Byrne *et.al* (1980). Due to its decorrelation nature, it has been shown to be of value in enhancing regions of localized change in Landsat multi-temporal data (Richard, 1984). PCA transformations have been applied to reduce multi-temporal data to fewer dimensions, with as much as 99% of the original information preserved along the first four axes (Lo *et al*., 1986). Experiments have shown that PC1 and PC2 tend to represent the unchanged land cover, whereas the PC3 and later PCs contain the changes in land cover (Byrne et al, 1980; Richard and Jia, 1999). These higher-order principal components are related to changes in brightness and greenness when analysis is performed using multi-temporal Landsat MSS data. PCA is thus also used as feature reduction technique since PCA transformation produces a new uncorrelated co-ordinated system or vector space. Variances of data are decreasing with increasing number of axis. The later principal components of higher order show little variance and can thus be ignored in the separability analysis. The essential dimensionality of the classification space is reduced and classification speed improved. Principal components for image 1973 and 2001 were produced and used for further image classification and change detection.

C. TCA

Tasseled Cap Analysis (TCA) has been developed by Kauth and Thomas (1976) as a means for highlighting the most important (spectrally observable) phenomena of crop development allowing for discrimination of specific crops, and separation of crops from other vegetation cover in Landsat multi-temporal imagery (Richard and Jia, 1999). TCA for images 1973 and 2001 were produced and used for image classification and change detection.

D. CA

The principal components transformation is based upon the global covariance matrix of the full set of image data and is thus not explicitly sensitive to class structure in the data. The reason of its reliability in remote sensing concerning feature reduction comes out of the fact that classes are frequently distributed in the direction of maximum data scatter. This is particularly so for soils and spectrally similar cover types. Canonical transformation is a rigorous method to increase the variance between targeted classes and to minimize the variance within classes by using means and variances of classes. The following result of equation (12) to be as high as possible:

$$\frac{\delta_A{}^2}{\delta_w{}^2} \qquad (12)$$

where:

δ_a = among classes variance

δ_w = within classes variance

Canonical discrimination of eigenvalues and eigenvectors was derived via statistical analysis of subset images for land use/land cover types as follows:

1. Subset for each land use/land cover type was created.
2. Subset image was converted to pixel values.
3. Pixel values for all subsets were combined together and then statistically processed using SPSS to calculate the eigenvalues and eigenvectors for canonical transformation.
4. Subset data was transformed according to the determined eigenvectors.

4.2.4.2 Classification

Supervised classification was carried out for each dataset separately. Training samples, for extracting spectral classes (signatures), were randomly selected from the visual display (Larsson, 2002). Spectral classes were tested and evaluated by visual on-screen verification, statistics and scatter plots. The Maximum Likelihood Classifier was used for classification of the images. A post-classification filter was used with the classified images in order to remove the heterogeneity.

A. Classification of Image 1973

Image classification was carried out on pixel DN values of the image of 1973, since it is considered only as a reference image. Training samples for farm on sand, fallow on sand, active sand dunes, grassland, mixed woodland, woodyland, forest, burnt/wetland and natural water bodies were selected with a sufficient number of pixels. Training samples were tested with use of scatter plot, mean plots, and contingency. Area and percentage for each land cover/land use class were determined.

B. Classification of Image 2001

2001 Image classification was carried out on pixel DNs and transformed PCA, TCA and CA images. Training samples for farm on sand, fallow sand, active sand dunes, grassland, mixed woodland, forest, burnt/wetland, natural water bodies, farm on clay, and fallow on clay were used. Training samples were also tested with use of scatter plot, mean plots, and contingency. Area and percentage of each land use/land cover class were determined.

4.2.4.3 Accuracy Evaluation

Accuracy assessment was done by visual interpretation of images supported by reference GCPs measurements derived during field work (Cohen *et al.*, 1998, Larson, 2002). User accuracy, producer accuracy, overall accuracy and Kappa coefficient were determined.

4.2.4.4 Land Use/Land Cover Change Detection

Change detection is the process of identifying differences in the state of an object or phenomenon by observing it at different times. The two main types of change detection analysis (post-classification change and pre-classification spectral change) were used in this study as follows:

A. Pre-Classification Method

The pre-classification method which is a pixel-based technique was used to compare the temporal variations of pixel vectors; its use included various methods like image differencing, composite analysis and change vector analysis.

1. Image Differencing

Image differencing was performed by first calculating a subtraction product for two complementary digital datasets, followed by the application of a threshold to distinguish significant spectral differences due to land cover change. The advantages of image differencing are low costs and potential for massive data processing volume; while disadvantages include required optimisation of change/no change threshold level and subsequent interpretation of image difference products (Lunetta, 1999). In this study ETM+ Band 4 and MSS Band 7 were subtracted to produce a change image, which was categorised as: negative change, no change, and positive change. Interpretation of change in imagery was numerous since differences might have been caused by a variety of factors. The normalised difference vegetation indices of images 1973 and 2001 were subtracted from each other to produce a NDVI change image. With the use of a threshold, changes in areas were determined.

2. PCA

Due to the nature of PC, higher order PCs can show changed areas (Byrne *et. al,* 1980; Richard and Jia, 1999). PCs for 10 layers of the two datasets were obtained, and the higher components PC3, PC4 were used to show the changed areas. This method is considered as a composite method. Then the PCs image was classified by an unsupervised approach into different change classes.

3. CVA

Tasseled cap analysis for each dataset was carried out and multi-temporal change vector analysis of the brightness and greenness components for both datasets was conducted to produce multidimensional change vector, in which the change in directions and magnitudes were determined as follows:

$$Magnitude = ((B_{T2} - B_{T1})^2 + (G_{T2} - G_{T1})^2)^{½} \quad (13)$$

$$Direction = (G_{T2} - G_{T1})/ ((B_{T2} - B_{T1})^2 + (G_{T2} - G_{T1})^2)^{½} \quad (14)$$

where:

B = brightness component.

G = greenness component.

$_{T1}$ = date one.

$_{T2}$ = date two.

B. Post-Classification Method

The post-classification approach involved the analysis of differences between two more or less independently classified images. A comparison of the categorizations was performed using GIS-based vector or raster analysis. An important advantage of post-classification method is that data normalisation is not required because the two dates are classified separately (Singh, 1989). Factors that limit the application of post-classification change detection technique can include cost, consistency and error propagation (Lunetta, 1999). The post-classification method was carried out and a change matrix was calculated.

4.2.5 Soil Mapping and Analysis

ETM+ imagery acquired on 16.01.2001 was used to map the soil types in the study area. Mapping of soil types was carried out by using mineral composition indices of clay mineral (B5/B7), iron oxide (B3/B1) and ferrous minerals (B5/B4) and secondary data derived from the literature.

42 soil samples were collected and georeferenced during the field work. The following analyses were carried out in these samples: (1) physical parameters such as hydraulic conductivity (HC), infiltration rate (IR), saturation percentage (SP) and soil texture, (2) chemical parameters such as soil reaction (pH), electrical conductivity (ECe), soluble cations including calcium (Ca^{++}), magnesium (Mg^{++}), and sodium (Na^{+}), sodium adsorption ration (SAR) and organic matter (OM). The measured values of these soil properties were integrated with the results of land use/ land cover classification of imagery.

CHAPTER FIVE

RESULTS AND DISCUSSION

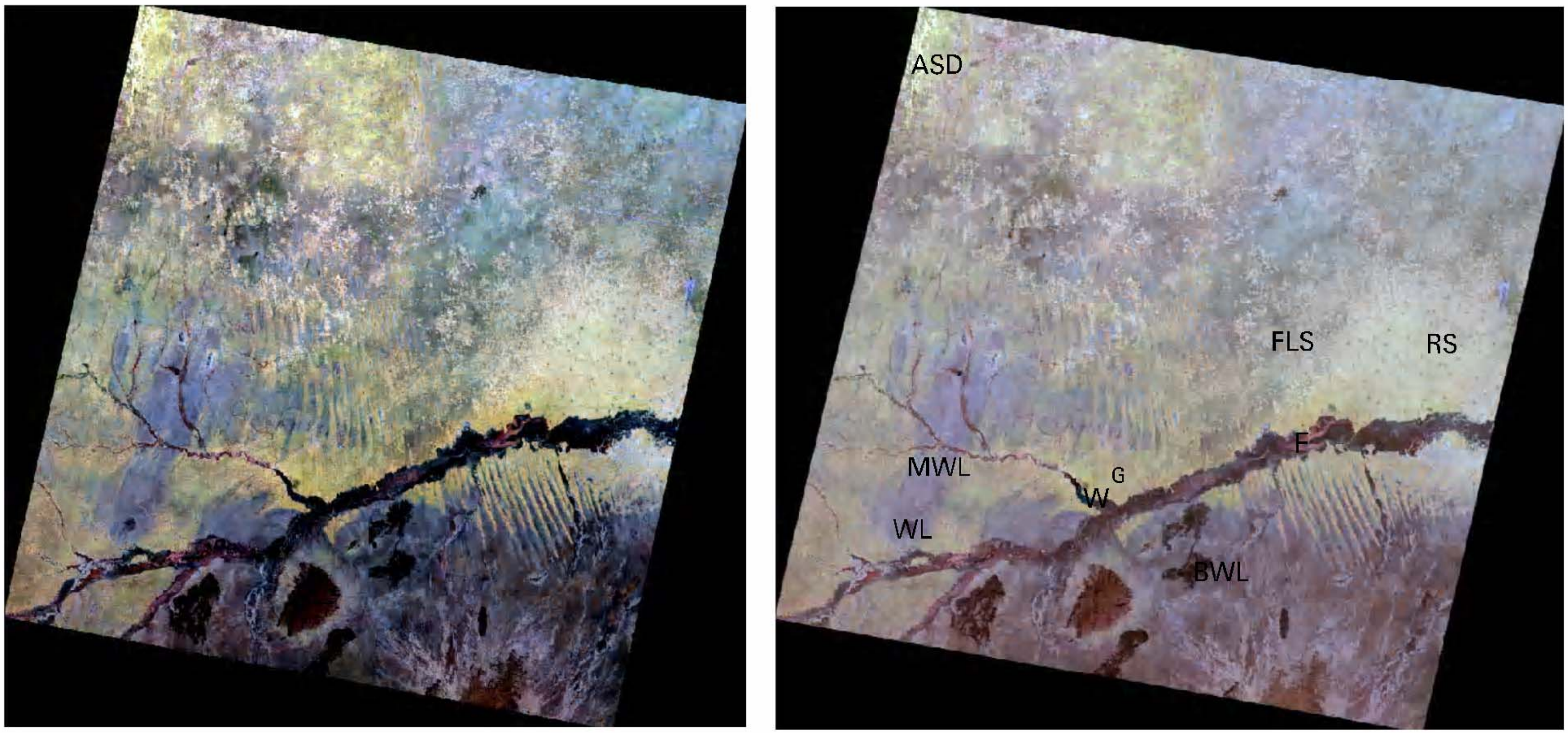
5.1 Radiometric Correction

Relative radiometric correction for reference and recent images with use of dark object subtraction spectrally enhances the imageries (Fig. 7 and 8).

5.2 Visual Interpretation

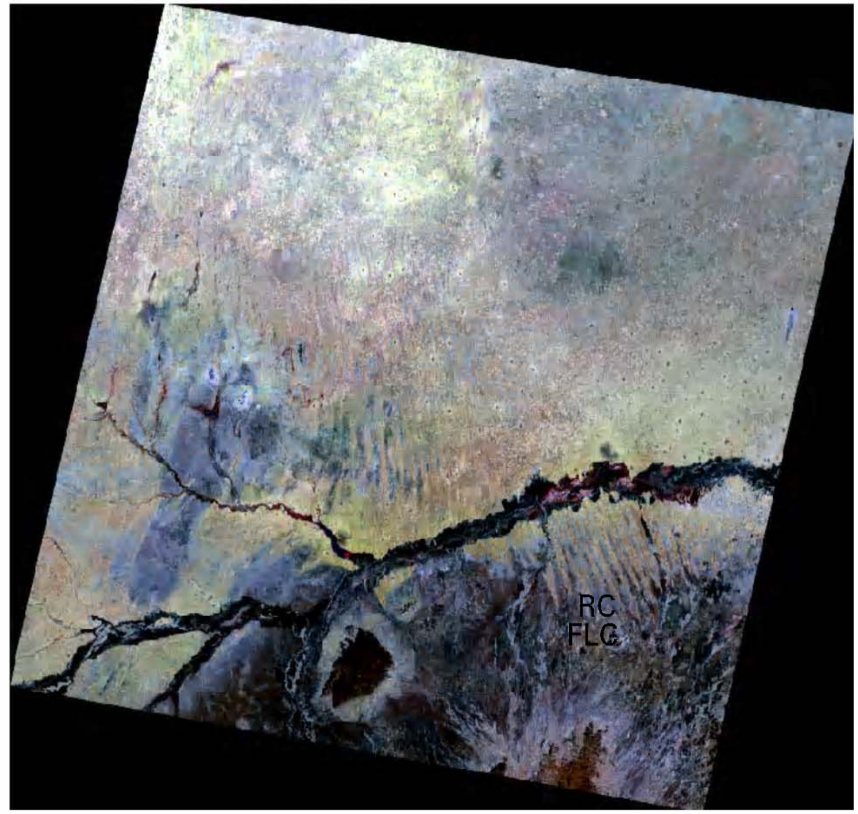
With use of information collected during field work, the major dominant land use/land cover classes in 1973 and 2001 were found to be as follows: farm on sand, farm on clay, fallow on sand, fallow on clay, woodyland, mixed woodland, natural water bodies, grassland, forest, active sand dunes, and burnt/wetland. However, all of the above mentioned land uses/land covers did not exist in both datasets. Some of them were present in images of 1973 and 2001 and *vise versa*.

Figure (7) showed the result of the visual interpretation of Landsat MSS 1973 using band combination 7, 6, 5 (RGB). The figure showed rainfed farm on sand (RS) as clearly delineated regular white polygons with higher reflectance values similar to that of the active sand dunes (ASD). However, the regular shape of RS was used to differentiate between them. Mixed woodlands (MWL) had a distinct smooth texture and blue color. Woodyland (WL) was characterised by a rough texture and a dark reddish color. Forests (F) had red colors and their spatial distribution coincided with hilly (*Jebel*) areas and water courses of *Khor Abuhabil*. Fallow on sand (FLS) and grassland (G) looked similar with yellowish colors and smooth textures; but the differentiating factor between them was the regular shape of the fallow (similar to that of the farm) and irregular shape of grassland. Natural water bodies (W) were characterised by black colors such as the famous reservoirs *Turdat Errhad* and *Wad Elbagha*. Burnt/wet land (BWL) was clearly depicted in image 1973 and was characterised by black colors and rough textures. It was localised around *Jebel Eddair* mainly on clayey soils.



a: **b:**

Figure 7: Landsat MSS subset (1973), a: before, b: after correction



a: **b:**
Figure 8: ETM+ Landsat subset (2001), a: before, b: after correction

This might be due to the presence of tall grasses in this area and practices of burning related with shifting cultivation (*hareeg* cultivation). Villages visually looked like a network of small nodes, most of them present on sand plain or dunes, Umm Rwaba district hosts the biggest number of villages. This might be due to the availability of a good water supply and a relatively higher rainfall.

Landsat ETM+ 2001 (Fig. 8) showed also the above mentioned land use/land cover classes, but woodyland was not present in this image, as it was transformed into mixed woodland. Rainfed farming on clay (RC) and fallow on clay (FLC) were introduced. It is worth to mention also that planting of *Hashab* (*Acacia senegal*) for Gum Arabic production was also obvious in ETM+. This plantation was done to improve Gum Arabic production by clearing lands from their native woody shrub *Kitir* (*Acacia millefera*) in El Ain and Shikan forests. *Hashab* plantations were still stunted possibly due to unsuitable tree spacing and soil compaction (Taha, 2005). Visual interpretation of both images gave valuable information which was used in further digital image processing. It is worth to mention that visual interpretation gave superior information for certain details in comparison with digital classification due to the spectral similarity of some classes. For example *Hashab* plantation (*Acacia senegal*) and farm on clay were spectrally similar. The nature of visual interpretation implicitly integrates spatial dimensions while the pure multi-spectral digital classification is explicitly based on levels of spectral similarity (Richard and Jia, 1999).

5.3 Classification

Supervised classification was carried out by selecting training samples for each information class from visual interpretation of imagery supported by field measurement according to Cohen *et al.* (1998) and Hayes and Sader (2001). The spectral signatures of training samples were assessed by signature editor tools of Erdas as implemented in Imagine (2005) such as image alarm, statistics, mean plots and contingency. The supervised approach was followed instead of unsupervised classification which leads to many misclassification errors. Due to spectral similarities, many land use/land cover classes could not be fairly classified, such as plantation of *Hashab* and settlement areas (town/villages). Settlements were built from woody materials of the native vegetation (trees, shrub and grasses), thus it was difficult to separate them from their surroundings.

Classification accuracy assessment was conducted by collecting reference samples by stratified random sampling technique. Based on visual interpretation on-screen the land use/land cover types were assigned to these reference samples.

5.3.1 Reference Landsat MSS 1973 Imagery

Separability and contingency of spectral signatures of the information classes were tested prior to classification to reach appropriate training samples (Appendix 3). The classification results showed that the LULC classes were: farm on sand (22.28%), fallow on sand (29.88%), active sand dunes (0.11%), woodyland (9.73%), mixed woodland (9.49%), grassland (14.94%), forest (10.81%), burnt/wetland (2.73%) and natural water bodies (0.03%). The most dominant LULC were farm and fallow on sand, which collectively covered about 52.16% of the total area. This could be attributed to the fact that rainfed agriculture was the major land use in the area. Cultivated crops were millet (*Pennisetum typhodieum*), sorghum (*Sorghum vulgare*) for subsistence, in addition to other cash crops such as sesame (*Sesamum orientale* L.), groundnuts (*Arachis hypogaea*), karkade (*Hibiscus sabdariffa*) and watermelon (*Citrullus vulgaris*). Grassland, mixed woodland and woodyland (which are exploited for animal grazing) cover about 34.16% of the area. Livestock rearing included camels and sheep in the north and cattle in the south. Forest covered about 10% of the area and confined mainly to hilly slopes as well as seasonal water courses. However, natural water bodies covered only about 0.03% of the study area. This indicated that the area effectively suffered from water shortage especially during the dry season. This lead in turn to seasonal immigration towards the more wet areas to the south and irrigated and rainfed mechanised schemes to the east. Burnt/wetland (2.73%) was a very confused class, since these burnt lands were present in water courses and supposed to be wet. Therefore, in this study the class burnt/wetland was adopted as a mixture class to include both; although it is well known that large areas are subjected to fire prior to cultivation for crop production and after harvest to enhance grass regeneration (Zaroug, 2000, Ardö and Olsson, 2003) (Table 3 and Fig. 9).

Table 3: Area and percentage of the dominant land use/land cover in the study area (January, 1973)

Class Name	Area (Ha)	(%)
Natural water bodies	910.69	00.03
Burnt/wetland	73,853.67	02.73
Farm on sand	603,543.01	22.28
Fallow on sand	809,238.83	29.88
Woodyland	263,444.51	09.73
Active sand dunes	2,988.75	00.11
Forest	292,939.59	10.81
Mixed woodland	256,925.07	09.49
Grassland	404,628.51	14.94
Total	2,708,472.63	100.00

The overall classification accuracy of the classified image was 79.34% and the overall kappa statistics was 0.76 (Table 4 and appendix 4). The producer accuracy varied from 100% for water bodies and burnt/wetland to 61.11 for grassland. User accuracy showed high values ranging from 100% for water to 56.25 for farm on sand. The user and producer accuracy values were high for natural water, burnt/wetland, active sand dunes, forest and mixed woodland, intermediate for farm on sand, fallow on sand and woodyland and low for grassland. The spectral similarity was one source of misclassification. Classes like woodyland and mixed woodland as well as grassland and fallow on sand were very similar. The producer accuracy in general showed consistently higher values while the user accuracy was highly variable. For example farm on sand showed a very low value, while natural water, burnt/wetland and active sand dunes showed very high values.

Table 4a: Accuracy totals of classified image (January, 1973)

Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy
Natural water bodies	9	9	9	100.00%	100.00%
Burnt/wetland	8	10	8	100.00%	80.00%
Farm on sand	12	16	9	75.00%	56.25%
Fallow on sand	16	22	14	87.5%	76.36%
Woodyland	8	12	8	100.00%	66.67%
Active sand dunes	13	13	13	100.00%	100.00%
Forest	21	14	14	66.67%	100.00%
Mixed woodland	16	11	10	62.50%	90.91%
Grassland	18	14	11	61.11%	78.57%
Totals	121	121	96		

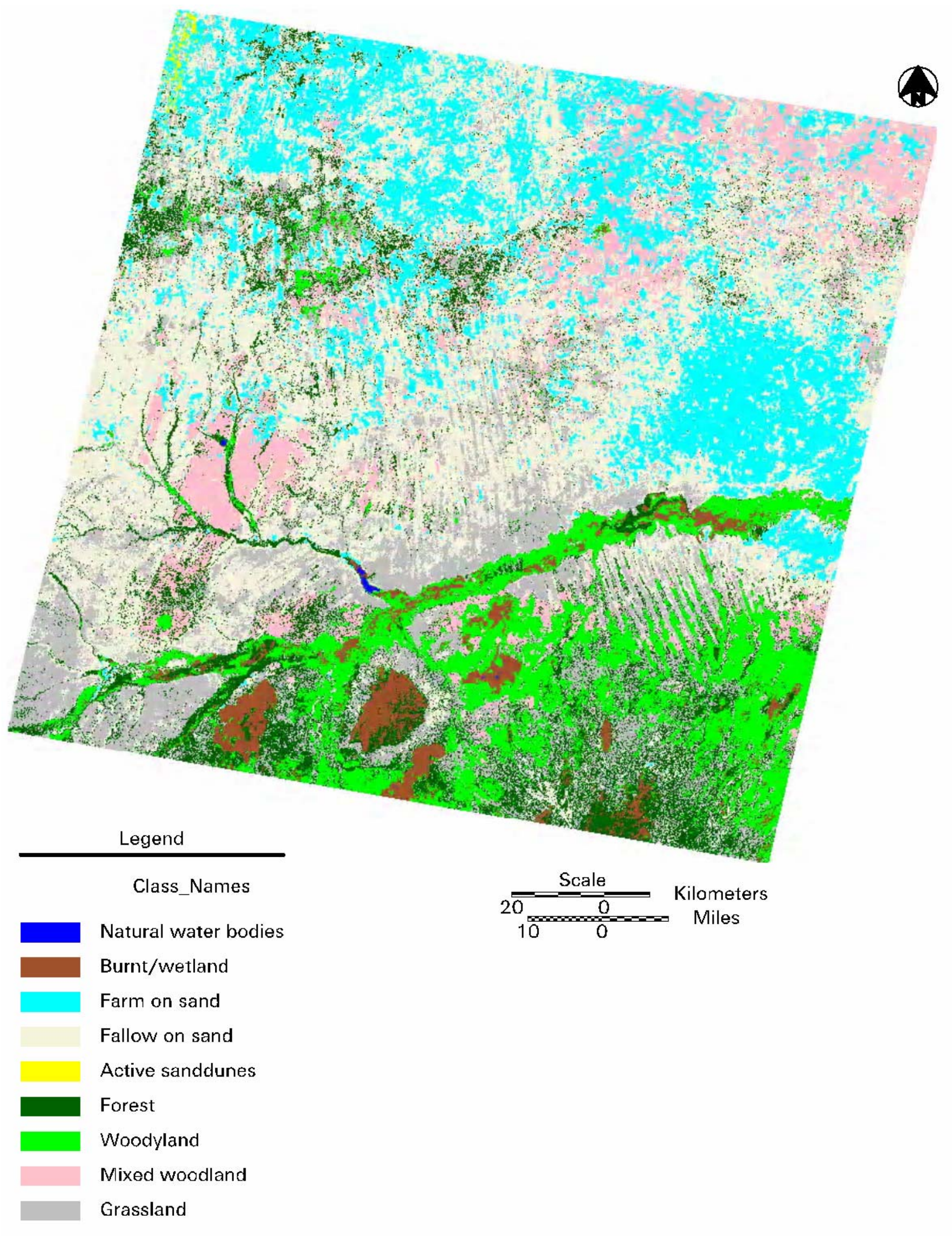


Figure 9: Dominant land use/land cover classes of classified image (January, 1973)

Table 4b: Conditional Kappa for each Category of classified image (January, 1973)

Class Name	Kappa
Natural Water Bodies	1.00
Burnt/wetland	0.78
Farm on Sand	0.51
Fallow on sand	0.58
Woodyland	0.64
Active sand dunes	1.00
Forest	1.00
Mixed woodland	0.89
Grassland	0.74

5.3.2 Recent Landsat ETM+ 2001 Imagery

Image 2001 was classified after various data transformations to increase the classification accuracy. Original pixel digital numbers (DN) and transformed images were classified into farm on sand, fallow on sand, active sand dunes, mixed woodland, grassland, forest, burnt/wetland, natural water bodies, farm on clay and fallow on clay.

5.3.2.1 Original Pixel DN Image

Spectral signatures for information classes were tested by using of contingency and mean plots (Appendix 5). Farm on sand (35.64%) and fallow on sand (27.3%) constituted the major classes (accounting for 61% of the area). Mixed woodland and burnt/wetland covered about 13.05% and 6.16% of the area, respectively. Farm on clay (5.95%) and fallow on clay (5.05%), the newly introduced classes, covered about 11% of the study area. This was possibly due to the food security policy adopted by the Ministry of Agriculture and Forestry, North Kordofan State, starting from 1990s to increase crop production in the State (Table 5, Fig. 10).

Table 5: Area and percentage of the dominant land use/land cover in the study area (January, 2001)

Class Name	Area (Ha)	%
Natural water bodies	1,384.47	0.05
Burnt/wetland	166,908.6	6.16
Farm on sand	965,053.89	35.64
Fallow on sand	739,089.36	27.30
Active sand dune	38,820.6	1.43
Forest	41,589.00	1.54
Mixed woodland	353,305.71	13.05
Grassland	104,238.45	3.85
Farm on clay	161,161.11	5.95
Fallow on clay	136,058.85	5.03
Total	2,707,610.04	100.00

Accuracy assessment of land use/land cover types of the classified image showed an overall classification accuracy of 78.13% and Overall Kappa Statistics of 0.76 (Table 6, Appendix 5). Producer accuracy varied from 100% for natural water and active sand dunes to 66% for farm on clay while user accuracy varied from 100% for natural water bodies to 52% for fallow on clay.

Table 6a: Accuracy totals of classified image (January, 2001)

Class Name	Reference	Totals Classified	Correct Number	Producers Accuracy	Users Accuracy
Natural water bodies	10	10	10	100.00%	100.00%
Burnt/wetland	32	25	23	71.88%	92.00%
Farm on sand	27	25	20	74.07%	80.00%
Fallow on sand	21	25	17	80.95%	68.00%
Active sand dunes	20	21	20	100.00%	95.24%
Forest	18	18	13	72.22%	72.22%
Mixed woodland	35	25	23	65.71%	92.00%
Grassland	20	25	18	90.00%	72.00%
Farm on clay	27	25	18	66.67%	72.00%
Fallow on clay	14	25	13	92.86%	52.00%
Totals	224	224	175		

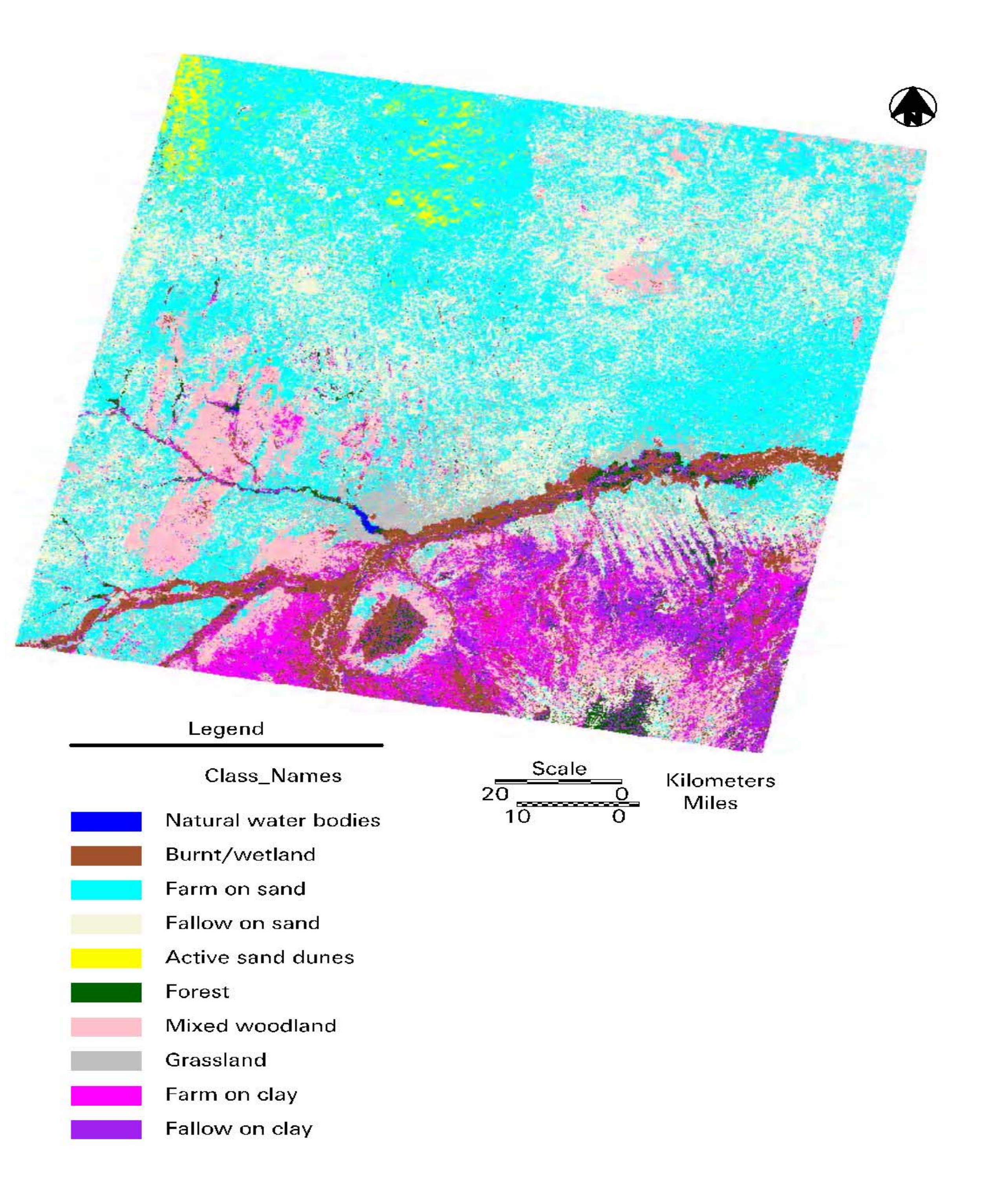


Figure 10: Dominant land use/land cover classes of classified image (January, 2001)

Table 6b: Conditional Kappa for each category of image (January, 2001)

Class Name	Kappa
Natural water bodies	1.00
Burnt/wetland	0.90
Farm on sand	0.77
Fallow on sand	0.64
Active sand dunes	0.95
Forest	0.70
Mixed woodland	0.90
Grassland	0.69
Farm on clay	0.68
Fallow on clay	0.48

5.3.2.2 PCA Image 2001

The spectral signatures of the information classes were tested by means of contingency and separability (Appendix 7). The first three principal components were used in the classification of the image of January, 2001. Tables (7) and Figure 11 show the land use/land cover classes in the study area. Farm on sand (21.69%), and fallow on sand (37.21%) constituted the major land uses. Mixed woodland covered 14.66% while Forest 9.92%. Farm on clay and fallow on clay covered 1.57% and 3.40, respectively. Natural water bodies covered 0.05% while burnt/wetland covered 2.20%.

Table 7: Area and percentage of the dominant land use/land cover classes in the study area based on classification of PC image (January, 2001)

Class Name	Area (Ha)	%
Natural water bodies	1,247.13	0.05
Burnt/wetland	59,719.95	2.20
Farm on sand	587,203.47	21.69
Fallow on sand	100,7557.65	37.21
Active sand dune	65,051.01	2.40
Forest	268,487.64	9.92
Mixed woodland	396,945.99	14.66
Grassland	186,800.49	6.90
Farm on clay	42,449.13	1.57
Fallow on clay	92,147.58	3.40
Total	2,707,610.04	100.00

Table (8) and appendix (8) showed that the overall classification accuracy of the classified PCA image was 78.21% and overall Kappa statistics was 0.76. It is obvious that PCA data had increased the accuracy. This could be attributed to the fact that PCA extended the possibility for pattern recognition since the imagery data were transformed into a new, uncorrelated co-ordinate system or vector space (Richard and Jia, 1999).

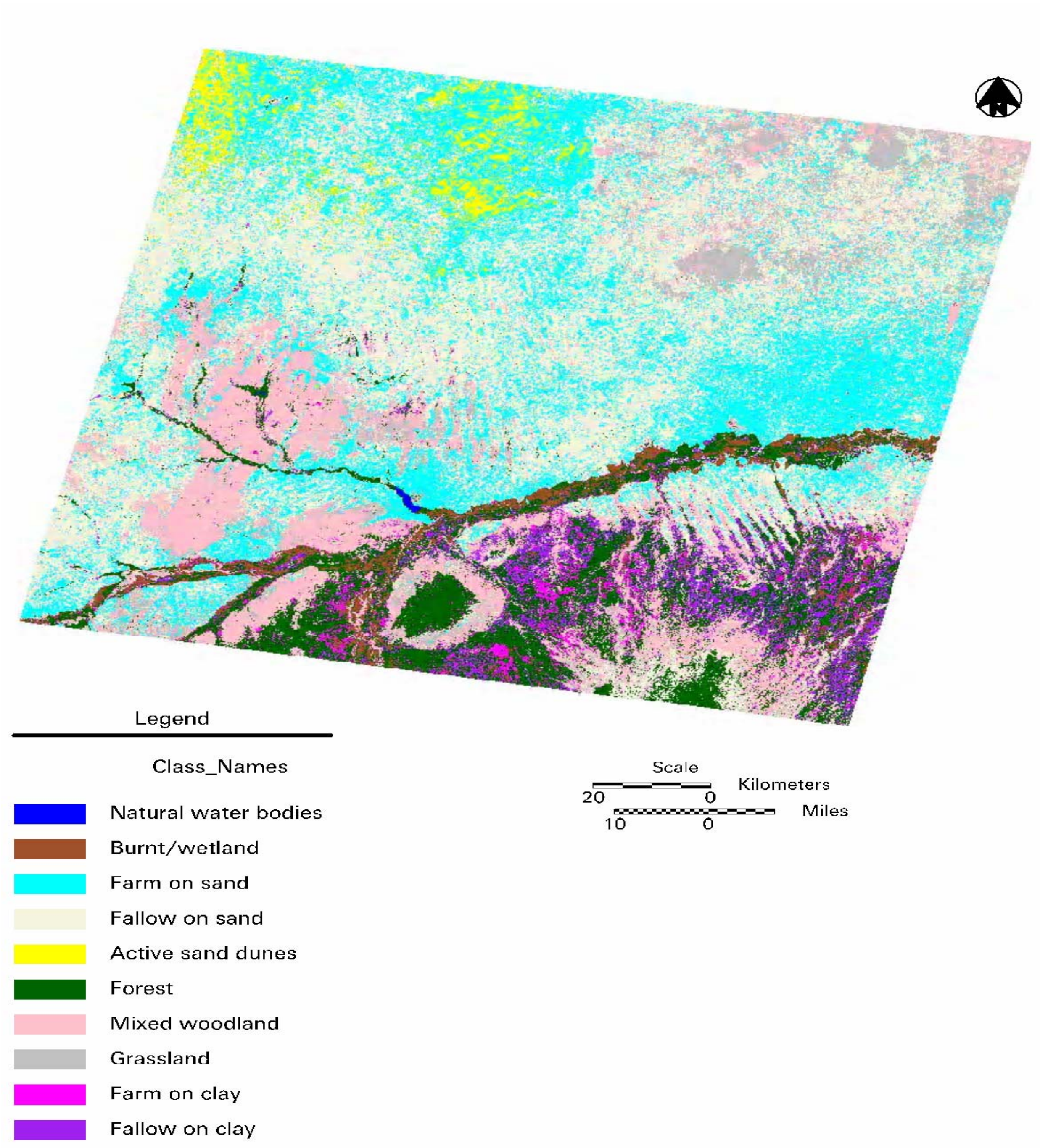


Figure 11: Dominant land cover/land use classes of classified PC image (January, 2001)

Table 8a: Accuracy totals of classified PC image (January, 2001)

Class Name	Reference	Totals Classified	Correct Number	Producers Accuracy	Users Accuracy
Natural water bodies	9	9	9	100.00%	100.00%
Burnt/wetland	24	25	21	87.50%	84.00%
Farm on sand	24	25	18	75.00%	72.00%
Fallow on sand	32	25	20	62.50%	80.00%
Active sand dunes	19	25	19	100.00%	76.00%
Forest	28	25	21	75.00%	84.00%
Mixed woodland	29	25	20	68.97%	80.00%
Grassland	24	25	16	66.67%	64.00%
Farm on clay	26	25	21	80.77%	84.00%
Fallow on clay	26	25	21	80.77%	84.00%
Totals	19	25	18		

Table 8b: Conditional Kappa for each category PC (image, 2001)

Class Name	Kappa
Natural water bodies	1.00
Burnt/wetland	0.82
Farm on sand	0.69
Fallow on sand	0.77
Active sand dunes	0.74
Forest	0.82
Mixed woodland	0.77
Grassland	0.60
Farm on clay	0.82
Fallow on clay	0.69

5.3.2.3 TCA Image 2001

Spectral signatures of class information were tested by means of mean plots and contingency (Appendix 9). With use of the TCA components brightness, greenness and yellowness, dominant land use/land cover classes were determined as shown in Figure (12) and Table (9).

The overall classification accuracy of classified TCA image was 72.64% and Overall Kappa Statistics was 0.69 (Table 10 and appendix 10). TC is sensor dependent and was originally applied to assess crop development in USA. TCA did not improve significantly the classification in this study. This could be attributed to sparse nature of the vegetation in the study area.

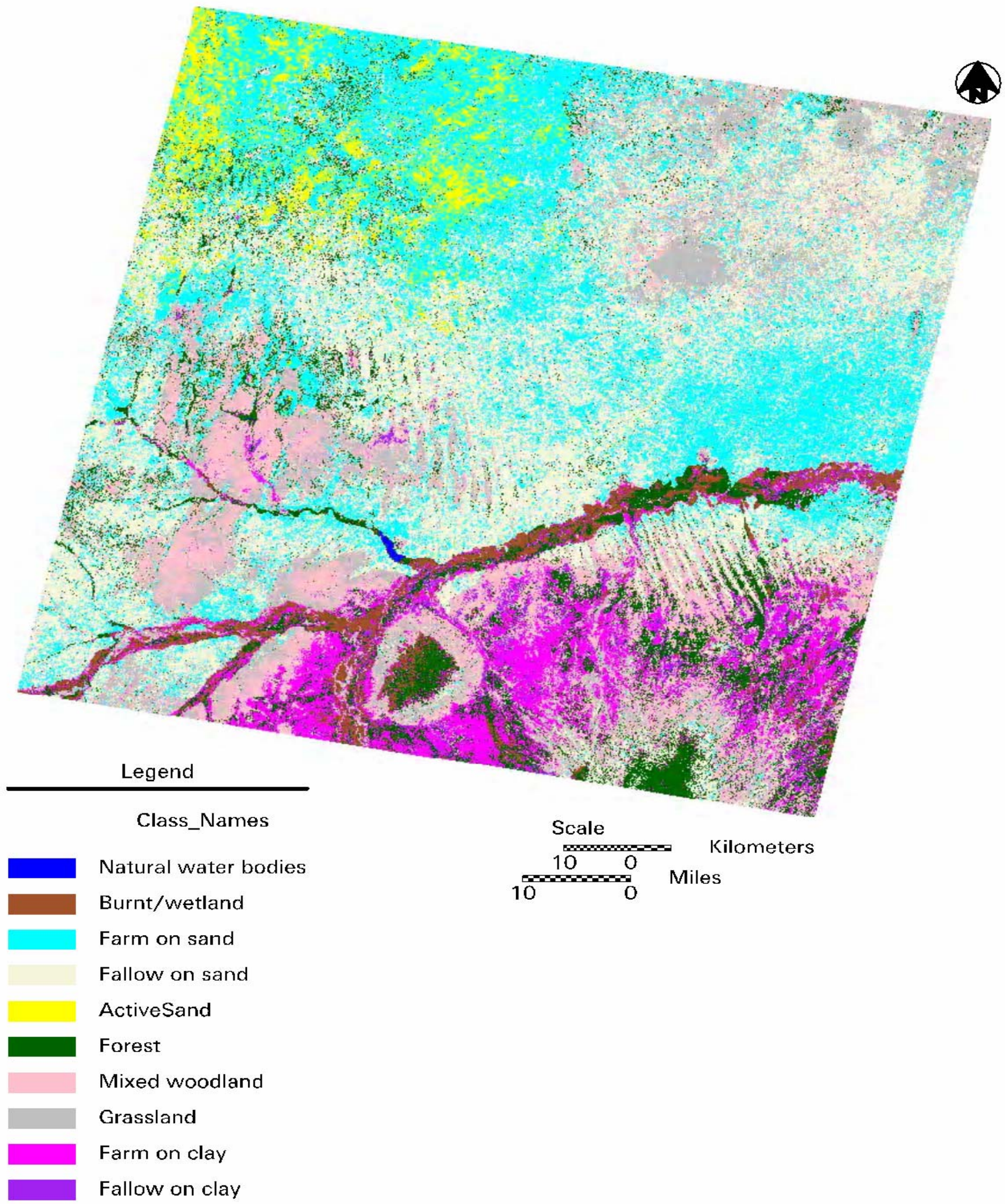


Figure 12: Dominant land cover/land use classes of classified TC image (January, 2001)

Table 9: Area and percentage of the dominant land use/land cover classes in the study area based on classification of TC image (January, 2001)

Class Name	Area (Ha)	%
Natural water bodies	1284.93	0.05
Burnt/wetland	72488.79	2.68
Farm on sand	602285.49	22.24
Fallow on sand	857321.37	31.66
Active sand dunes	107797.95	3.98
Forest	235377.72	8.69
Mixed woodland	366675.84	13.54
Grassland	261536.4	9.66
Farm on clay	154019.34	5.69
Fallow on clay	48822.21	1.81
Total	2,707,610.04	100.00

Table 10a: Accuracy totals of classified TC image (January, 2001)

Class Name	Reference	Totals Classified	Correct Number	Producers Accuracy	Users Accuracy
Natural water bodies	11	11	11	100.00%	100.00%
Burnt/wetland	17	18	13	76.47%	72.22%
Farm on sand	36	25	22	61.11%	88.00%
Fallow on sand	29	25	18	62.07%	72.00%
Active sand dunes	16	25	16	100.00%	64.00%
Forest	23	25	16	69.57%	64.00%
Mixed woodland	29	25	18	62.07%	72.00%
Grassland	28	25	22	78.57%	88.00%
Farm on clay	16	25	14	87.50%	56.00%
Fallow on clay	7	8	4	57.14%	50.00%
Totals	212	212	154		

Table 10b: Conditional Kappa for each category of classified TC image (January, 2001)

Class Name	Kappa
Natural water bodies	1.00
Burnt/wetland	0.70
Farm on sand	0.85
Fallow on sand	0.68
Active sand dunes	0.61
Forest	0.60
Mixed woodland	0.67
Grassland	0.86
Farm on clay	0.52
Fallow on clay	0.48

5.3.2.4 CA Image 2001

Spectral signatures were tested by means of contingency and mean plots (Appendix 11). With use of the first three bands produced from the canonical transformation, the dominant land use/land cover classes were determined as shown in Figure (13) and Table (11).

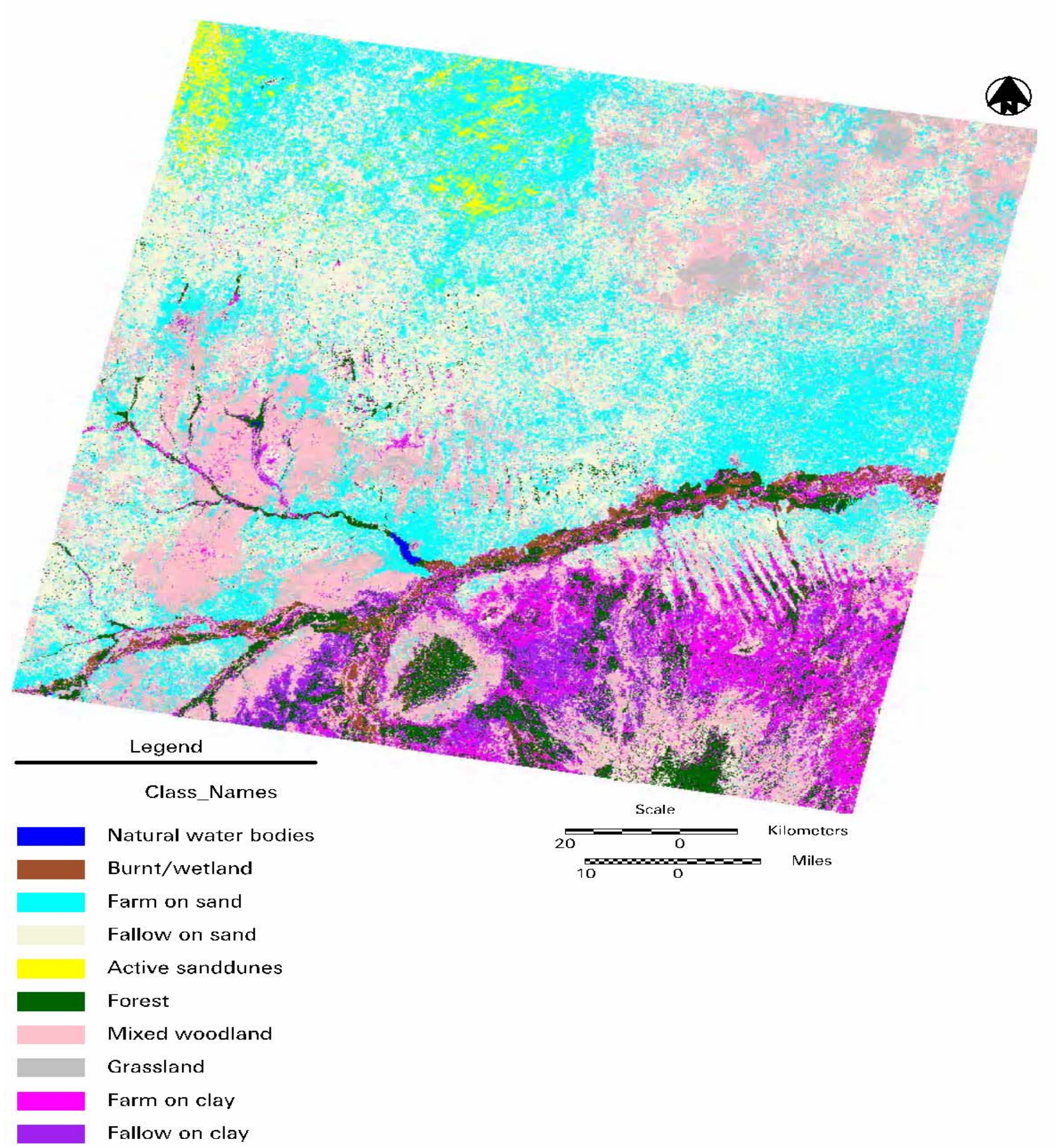


Figure 13: Dominant land cover/land use classes of classified CA image (January, 2001)

Table 11: Area and percentage of the dominant land use/land cover in the study area based on classification of CA image (January, 2001)

Class Name	Area (ha)	%
Natural water bodies	1,629.63	0.06
Burnt/wetland	42,334.65	1.56
Farm on sand	535,665.87	19.78
Fallow on sand	835,137.18	30.84
Active Sand dune	43,068.42	1.59
Forest	150,950.88	5.57
Mixed woodland	767,075.31	28.33
Grassland	57,641.04	2.13
Farm on clay	153,248.22	5.67
Fallow on clay	120,853.71	4.47
Total	2,707,604.91	100.00

Overall classification accuracy of classified CA image was 82.91% and overall Kappa statistics was 0.81 (Table 12, Appendix 12). Canonical analysis, as expected, increased accuracy since it maximized the between-classes variance and minimized the within-class variance. This in turn, led to an increased separability between classes (Richard and Jia, 1999; Lee *et al.*, 1999).

Table 12a: Accuracy totals of classified CA image (January, 2001)

Class Name	Reference	Totals Classified	Correct Number	Producers Accuracy	Users Accuracy
Natural water bodies	11	11	11	100.00%	100.00%
Burnt/wetland	14	14	13	92.86%	92.86%
Farm on sand	27	25	19	70.37%	76.00%
Fallow on sand	21	25	20	95.24%	80.00%
Active sand dunes	10	10	9	90.00%	90.00%
Forest	31	25	24	77.42%	96.00%
Mixed woodland	26	25	20	76.92%	80.00%
Grassland	18	14	11	61.11%	78.57%
Farm on clay	19	25	17	89.47%	68.00%
Fallow on clay	22	25	21	95.45%	84.00%
Totals	199	199	165		

Table 12b: Conditional Kappa for each category of classified CA image (January, 2001)

Class Name	Kappa
Natural water bodies	1.00
Burnt/wetland	0.92
Farm on sand	0.72
Fallow on sand	0.77
Active sand dunes	0.89
Forest	0.95
Mixed woodland	0.77
Grassland	0.76
Farm on clay	0.64
Fallow on clay	0.82

5.3.2.5 Overall Evaluation of the Classification Results of the 2001 Image

In the classification of image 2001 two new classes were introduced, namely farm and fallow on clay. However, the class woodyland disappeared. Different classified images had clearly shown the different land use/land cover classes. However, there were differences in areas covered by each land use/land cover classes between the classified image of the original DNs image and transformed ones (Fig. 14).

With reference to accuracy assessment, classified image from canonical analysis showed higher value of overall accuracy followed with PCA, original (DNs pixel) image and finally TCA. This result indicated that data transformation had improved the classification. The classified image based on PCA image showed well spatial distribution of classes. Moreover, PC transformation was found easier to handle than CA. Thus classified image based on PCA was used for change detection.

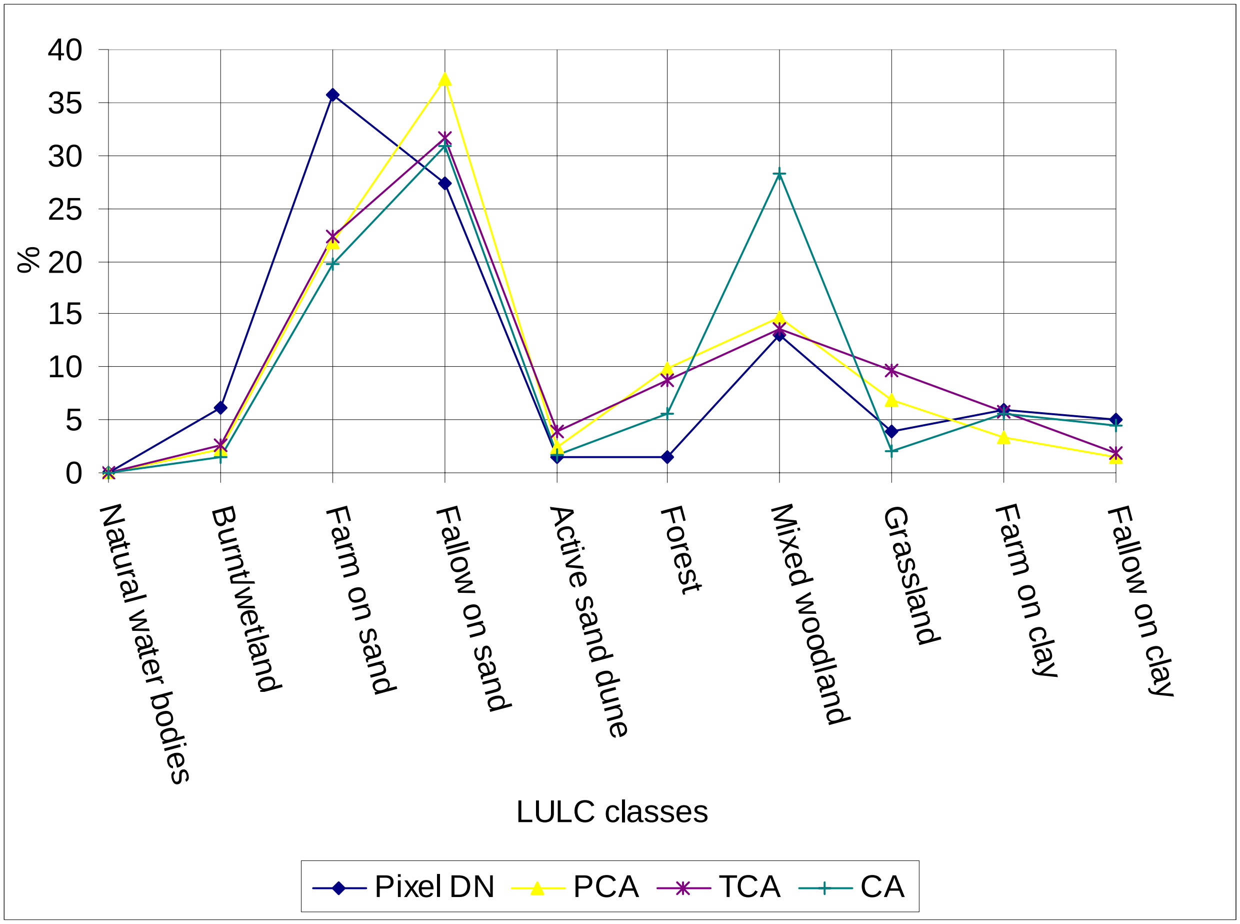


Figure 14: Comparison of land use/land cover types with use of different classification methods

5.4 Change Detection

5.4.1 Visual Interpretation

Visual interpretation showed change in vegetation cover around Elobeid, the biggest city in the state. Interviewers said that forest was surrounding the city in the past. This claim was obvious in the image 1973, but lately the forest around Elobeid was cleared and transformed into grassland and rainfed agriculture. This could be due to heavy immigration of people from rural areas towards urban areas during the drought period of 1980s. The immigrants used trees as fuel wood and building material. Domkyia forest, which is located east from Elobeid city, was transformed into grassland, mixed woodland and rainfed agriculture. This was in line with the general trend of increasing farming land at the expense of forest to meet the increasing demand for crops (e.g Olsson, 1985, Aclhrona, 1988, Ardö and Olsson, 2003, Hinderson, 2004). Part of Shikan forest, which is located south of Elobeid city and was mainly covered by *Kitir* (*Acacia mellifera*), was cleared by Forestry National Corporation (FNC) and planted with *Hashab* (*Acacia Senegal*) by Gandail Corporation to produce Gum Arabic. However, although this plantation is more than 3 years old, it is very stunt and dwarf. This might be due to the low water permeability of *gardud* soil (heavy compact clay soil) (Taha, 2005). In general farming land had increased. This could be attributed to the tendency of people to increase the area of land under cropping to compensate for the low crop yield/ unit area. This increase in cultivated land was obvious especially in the southern part of the area, which was characterised by pattern of farms. This could have possibly been driven by the policy of the Government of North Kordofan State which encouraged expansion of arable lands in the 1990s under what was then called Food Security Policy. This policy, however, had lead to the deterioration of vegetation cover. This was so because the farmers had to cut trees and sell their wood to finance the agricultural operations and to maintain their living. This, in turn, had very adverse effects on the environment since the dominant tree species in that area were very tolerant and took very long time to reach maturity. Moreover, the problem was further aggravated by the presence of the compact *gardud* soil characterised by low water permeability.

5.4.2 Field Work Observation

Interviews and group discussions with the inhabitants of the study area illustrated that vegetation cover was transformed; some trees and grass were replaced by new ones. Moreover, the people proclaimed a decrease in crops productivity and attributed this to desertification. Desertification according to their definition was positively correlated with low rainfall and sand encroachment. The people of the southern part of the study area claimed that some tree species like ebony (*Dalbergia melanoxylon*) were scarce, while others like *kerssan* (*Bosica senegalensis*) were extremely dominant. On the other hand, the people of the northern part stated that tree coverage had increased during the last years in comparison with the drought period of the 1970s. This might have been due to the rehabilitation programmes executed by UN and FNC within the domain of the programme “Work for Food” (Kowrak, 1998, Zaroug, 2000, Tagelsir, 2005). This fact confirmed the recent research findings which showed a significant increase in the pattern of NOAA-NDVI observed along the Sahel region during the period 1982-1999 (Eklundh and Sjöström, 2002, Eklundh and Olsson, 2003, Hermann *et al.*, 2005). In contrast the people of the southern part mentioned that trees are less now in comparison with the past and that ke*rssan* (*Bosica senegalensis*) and *Ushr* (*Calotropis procera*) become dominant.

5.4.3 Pre-Classification Methods

Pre-classification methods included image differencing, composite analysis of PCA and change vector analysis with use of tasseled cap components brightness and greenness.

5.4.3.1 Image Differencing

Image differencing was carried out with the use of original near-infrared bands and NDVI.

A. Subtraction of Near-Infrared Band

The normalised band 7 of MSS 1973 was subtracted from band 4 of ETM. The output image was categorised into positive, negative and no-change based on standard deviation threshold (Fig. 15, Table 13). The mean of the output image was -1.684 and the standard deviation was 11.017. So positive change pixels had values greater than 9.33 while the values of negative ones were less than -12.701 and those with no-change had values ranging from -12.701 to 9.33.

Table 13: Areas of vegetation change calculated by difference of near-infrared bands 1973-2001

Degree of change	Area (ha)
Positive change	361,035.45
No change	3,010,887.54
Negative change	365,184.81

B. NDVI Subtraction

The difference image resulting from subtraction of NDVI 1973 from NDVI 2001 was categorized into positive, negative and no-change using one standard deviation (0.065) threshold from the mean (0.02) (Fig. 16, Table 14).

Table 14: Areas of vegetation change calculated by difference of NDVI 1973-2001

Degree of change	Area (ha)
Positive change	250,410.24
No change	3,239,459.28
Negative change	247,238.28

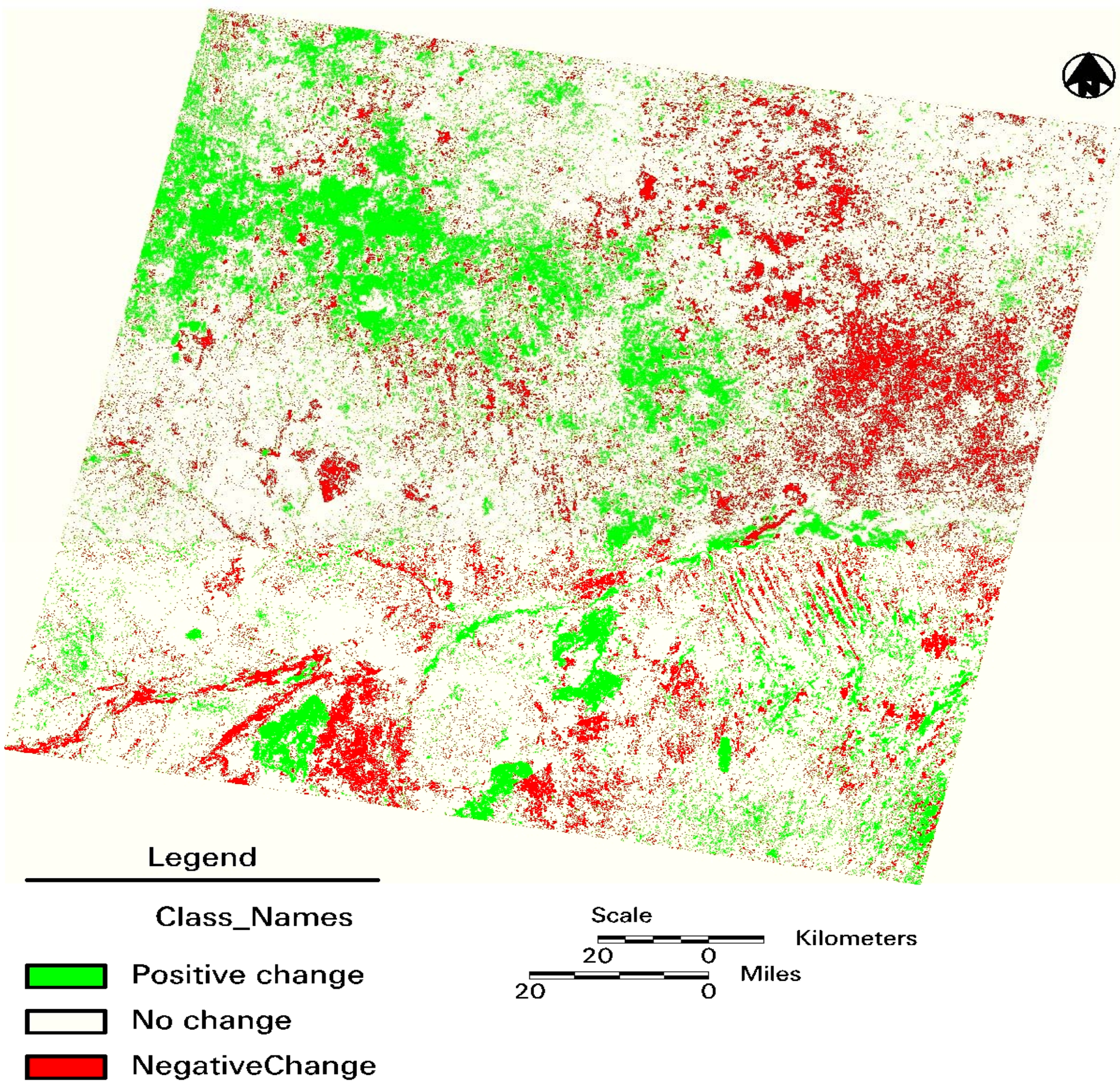


Figure 15: Vegetation change pattern with use difference of near-infrared bands of image 1973 and image 2001

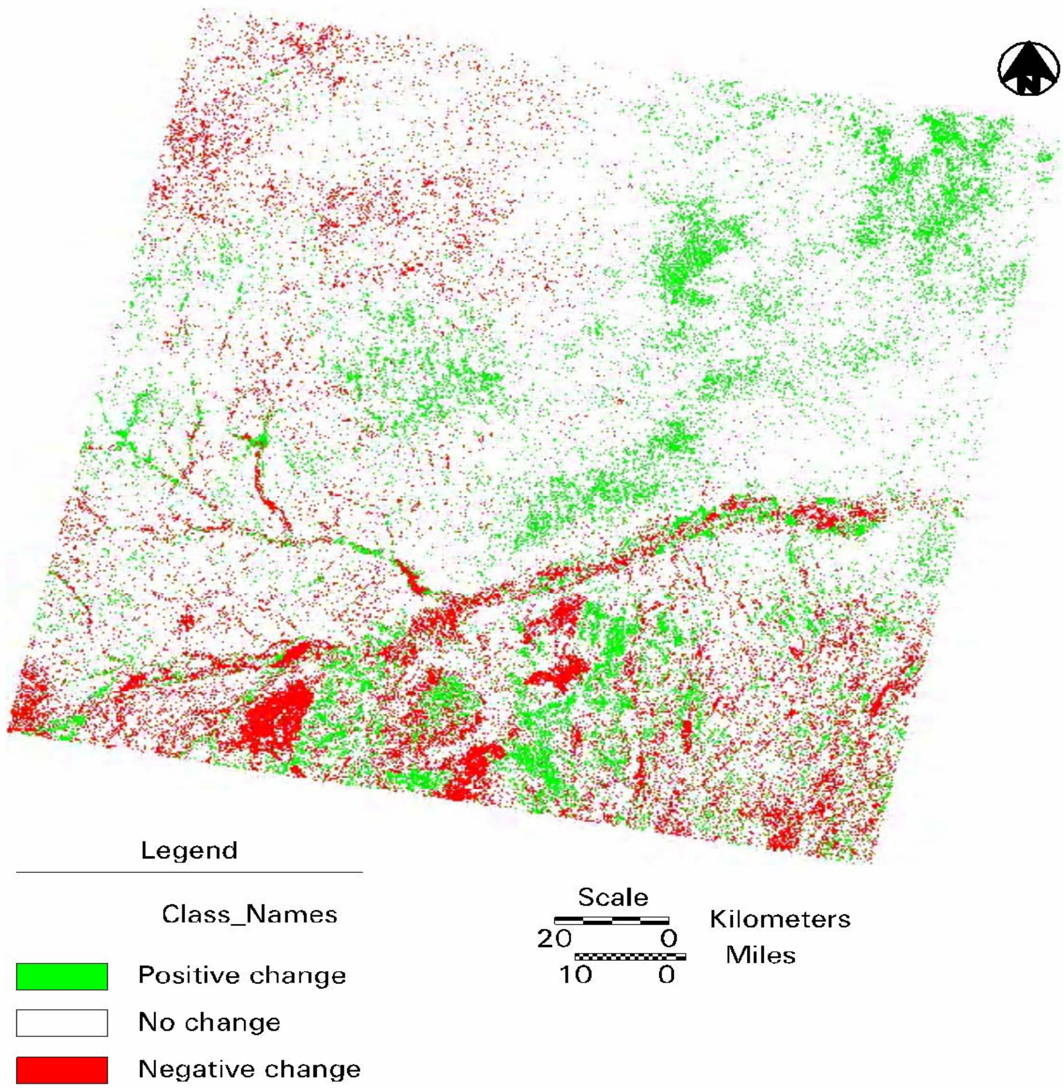


Figure 16: Vegetation change pattern with the use of difference of NDVI of 1973-2001 images

C. Overall Evaluation of the Image Differencing Change Detection Method

The difference images which resulted from subtraction of near-infrared bands and NDVI values 1973-2001 showed the same pattern; the northern part with dominant positive change while the southern part with dominant negative change. This finding agreed with recent research which indicated an increasing trend in NDVI values in the Sahel region (Elkundh and Olsson, 2003). However, the far north-western part of the image showed a positive change with the use of near-infrared bands while negative change with the use of NDVI values was encountered. This result was not contradictory, since a bare soil reflects electromagnetic energy at the same proportion, while NDVI decreases as the soil becomes more and more bare. Therefore, increase obtained from near-infrared band subtraction might have also been a sign of vegetation decrease, thus similar to the results arrived from NDVI difference. The middle-eastern part of the image also showed a decrease in the case of near-infrared bands subtraction while no change was detected in the case of NDVI difference. This result could be interpreted by using the previous principle; the decrease of near-infrared might have been good sign for a better vegetation condition, since these areas were heavily used for rainfed agriculture. Thus the land might have been covered with grasses and crop residues which lead to a decrease of near-infrared and visible reflection especially from a light bare soil. On the other hand, this might have lead to a slight increase in NDVI values. However, this result revealed that it was justifiable to use vegetation indices to interpret changes rather than the original NIR bands.

5.4.3.2 PCA

The first principal component which was derived from the six ETM+ bands of 2001 and the four MSS bands of the year 1973 accounted for 88.9% of the variation in the data, while the others represented the remaining variability (Table 15). Information on type of change represented by each component could be inferred partly by examination of the algebraic signs of the eigenvectors corresponding to each band at each date (Table 15). The first component was an overall product of all the bands, which was deemed to represent the overall variations across all pixels in the study area. The second component was a product of the subtraction of the first 4 bands of image (1973) from all bands of image 2001, which was deemed to represent change. PC3 was a product of subtraction of the all bands from two dates from band 5 and band 7 of ETM+. This could be an indication of moisture variation of plants and/or soils in the study area, since bands 5 and 7 are sensitive to these parameters. This result agreed with findings of Byrne et al. (1980) and Hayes *et al.* (2001).

Visual interpretation of the second and third components showed distinct changed areas such as the *hashab* plantation by Jandail (A), burnt/wetland (B) near Jebel Eddair, woodyland (C) in the southern part of Shikan forest and grassland (D) (Fig. 17C and D).

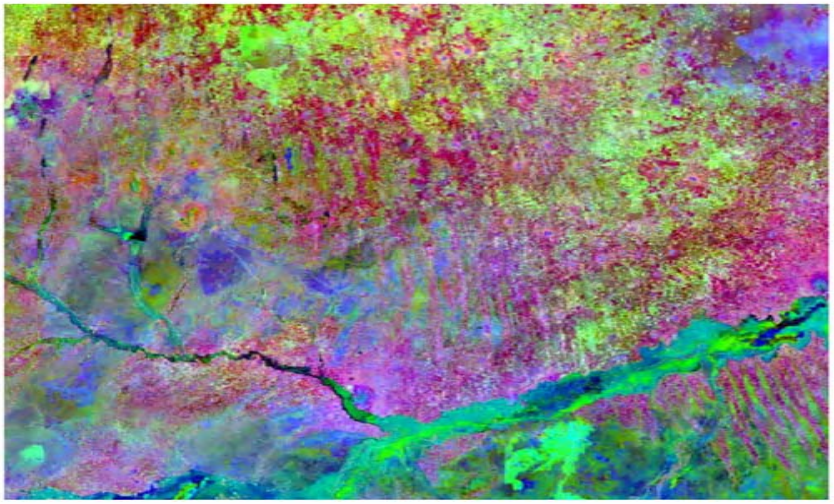
Table 15: PCA eigenvectors

		C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
MSS	B1	0.08	-0.19	-0.02	-0.40	-0.05	0.20	-0.45	0.41	-0.58	0.11
	B2	0.23	-0.51	-0.03	-0.28	-0.4	-0.43	0.04	0.22	0.41	0.01
	B3	0.25	-0.61	-0.00	0.25	0.55	0.39	0.04	0.10	0.18	-0.03
	B4	0.18	-0.39	-0.04	0.06	-0.16	-0.15	0.09	-0.71	-0.50	-0.01
ETM	B1	0.05	0.07	-0.19	-0.46	0.00	0.37	0.063	-0.33	0.28	0.64
	B2	0.16	0.12	-0.26	-0.51	0.12	0.18	-0.02	-0.20	0.13	-0.73
	B3	0.41	0.21	-0.40	-0.08	0.40	-0.42	0.38	0.21	-0.24	0.18
	B4	0.34	0.15	-0.49	0.40	-0.14	-0.03	-0.63	-0.11	0.17	0.05
	B5	0.52	0.18	0.11	0.19	-0.49	0.46	0.39	0.17	-0.09	-0.06
	B7	0.50	0.21	0.69	-0.13	0.23	-0.19	-0.29	-0.16	0.09	0.05
	Eigenvalue	1819.63	130.27	58.99	18.57	11.11	9.53	4.32	3.88	1.98	1.01
	% of variation	88.36	6.32	2.86	0.90	0.54	0.46	0.21	0.19	0.10	0.04

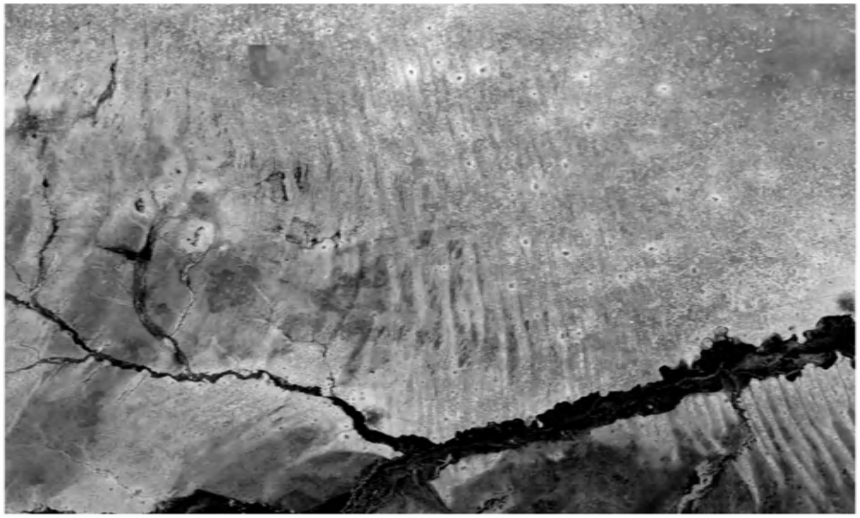
Hybrid supervised/unsupervised classification of the PCA composite image produced five change classes, which could be interpreted to be due to: change in forest vegetation (class1), changes in farming on clay (class 2), changes in mixed woodland (class 3), changes in sand dunes (class 4), and changes in farming on sand (class 5) (Fig. 18). It was difficult to investigate the levels of change, but in general the trend was negative (Table 16).

Table 16: Statistical parameters of change-classes of PC image of 1973 and 2001

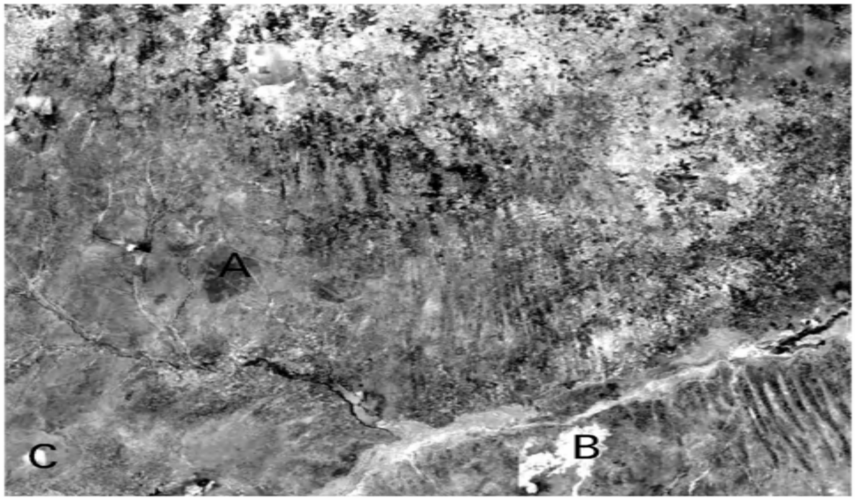
Class name	Mean of PC1	Mean of PC2	Mean PC3
Class 1	90.10	-13.31	1.44
Class 2	122.71	-8.72	-3.384
Class 3	152.83	-11.96	-3.624
Class 4	247.73	-4.94	-2.204
Class 5	197.45	-14.07	-1.08



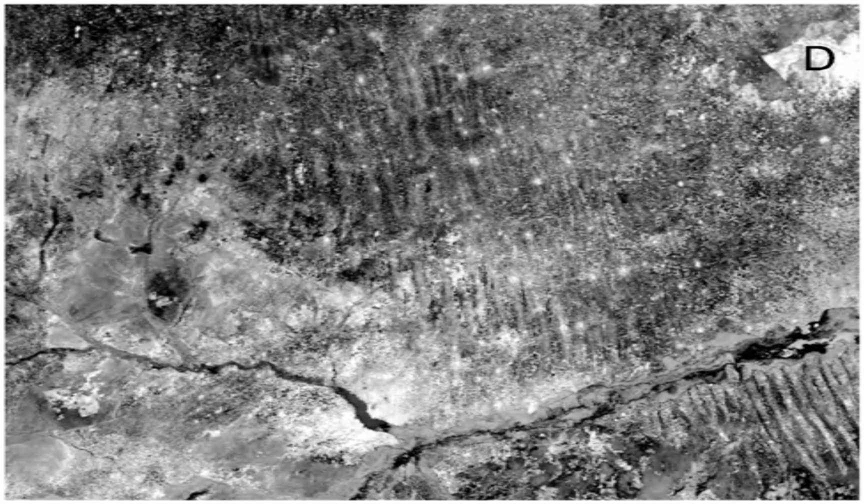
a. PC1, 2, 3 (RGB)



b. PC1



c. PC2



d. PC3

Figure 17: Principal components of image 1973 and 2001

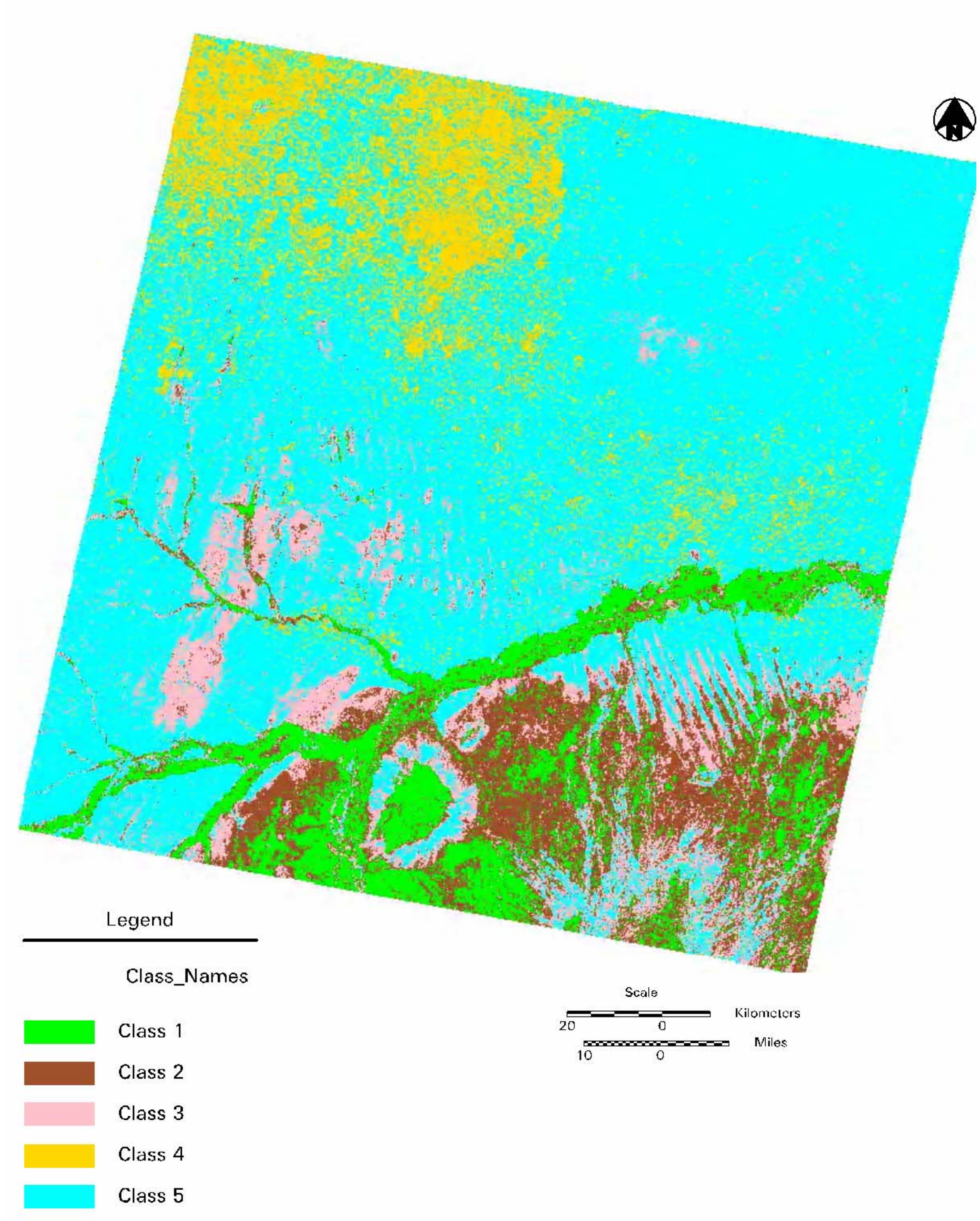


Figure 18: Changes classes of PC image of 1973 and 2001

5.4.3.3 CVA

Absolute correlation analysis of TCA components of 1973 and 2001 indicated a positive correlation between first components and a negative correlation between second and third components (Table 17). This might indicate some changes in vegetation and moisture status.

Table 17: Correlation matrix of TC components for images 1973 and 2001

	TC1-73	TC2-73	TC3-73	TC1-01	TC2-01	TC3-01
TC1-73	1.00	0.54	0.59	0.73	-0.47	-0.65
TC2-73	0.54	1.00	0.47	0.36	-0.07	-0.35
TC3-73	0.59	0.47	1.00	0.44	-0.16	-0.42
TC1-01	0.73	0.36	0.44	1.00	-0.67	-0.79
TC2-01	-0.47	-0.07	-0.16	-0.67	1.00	0.64
TC3-01	-0.65	-0.35	-0.42	-0.79	0.64	1.00

The CVA of brightness and greenness components of TCA produced a magnitude and direction image. The magnitude ranged from 4 to 162 while the angle of direction ranged from -87º to -4º. It was obvious that the direction of change was negative. This result was contradictory with findings of the image subtraction method but agreed with the outcomes of PCA analysis. On the other hand, this result disagreed with the positive finding of Eklundh and Olsson (2003). Hybrid supervised/unsupervised classification produced five change classes, explicitly slight, low, medium, high and extreme changes (Table 18, Fig. 19).

Table 18: Change degrees of change vector analysis

Change degree	Area (ha)
Slight	134,939.16
Low	563,679.72
Medium	1,128,878.19
High	656,312.76
Extreme	224,980.11

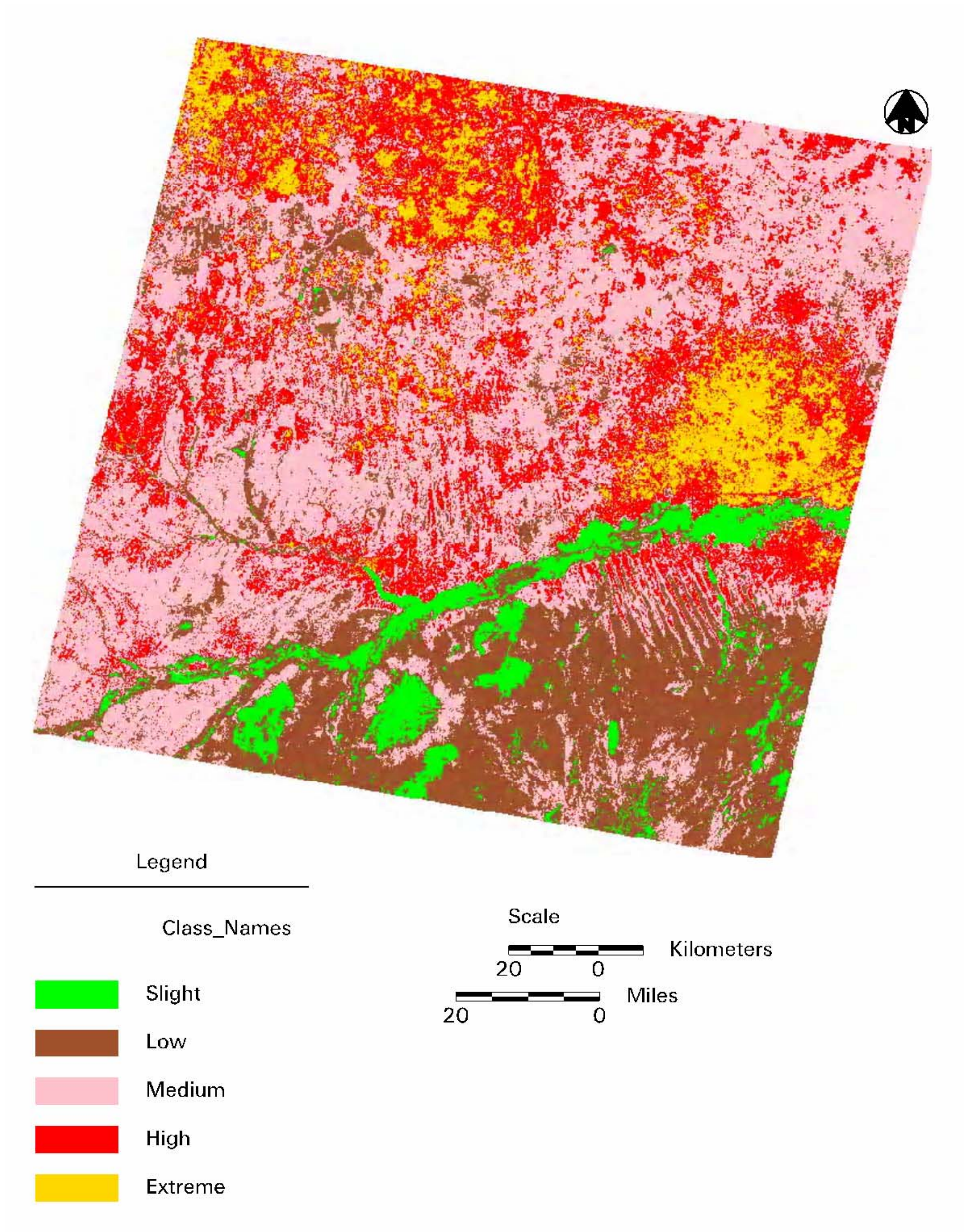


Figure 19: Change pattern of change vector analysis

5.4.3.4 Evaluation of Pre-Classification Change Detection Methods

Pre-classification methods determined changes, but did not give precise detailed quantitative information about the change of each LULC class. In this study these methods hardly gave information about changes of specific LULC classes such as change in sand dunes, farm on sand, vegetation on hilly area and water courses. It is worth to mention that PCA and CVA comparatively gave similar results, while image subtraction of NDVI and Near-Infrared bands also gave similar results. Image subtraction outcomes indicated an increase in vegetation cover while PCA and change vector methods indicated a negative change. Although these methods are very sensitive to data normalization and co-registration of multi-temporal data, they are fast and can process massive huge data.

5.4.4 Post-Classification Method

The change matrix based on classified images 1973 and 2001 revealed that significant changes in land use/land cover classes occurred. New classes such as farm and fallow on clay were introduced in 2001, while woodyland in 1973 was completely shifted to other classes in 2001 (Table 19).

Table 19: Change matrix of image 1973 and 2001

1973	2001											Total 1973
	1	2	3	4	5	6	7	8	9	10	11	
1	707.49	4.59	0.00	0.09	0.00	152.64	0.00	27.99	0.00	12.24	5.13	910.17
2	299.97	8286.48	120.51	1378.44	21.69	40153.95	0.00	12143.88	302.04	4773.6	6380.10	73860.66
3	0.18	8.37	170157.42	175067.37	31636.35	471.69	0.00	24307.92	25754.4	38.97	72.00	427514.67
4	4.05	64.44	284757.93	486017.91	24069.06	4236.75	0.00	79596.45	81244.26	399.6	1385.28	961775.73
5	0.00	0.00	68.94	42.12	2971.71	1.80	0.00	1.98	0.81	0.00	0.09	3087.45
6	58.23	8540.91	20717.28	79774.56	2458.71	70049.34	0.00	78860.25	12381.21	9531.27	17074.71	299446.47
7	99.63	39306.42	1573.47	11720.52	276.3	112762.35	0.00	30955.32	661.68	18402.12	47629.17	263386.98
8	14.76	591.03	17651.16	88870.68	510.66	7661.97	0.00	109055.7	39707.55	2383.74	5669.19	272116.44
9	62.82	2915.91	92115.81	164522.88	3065.67	32979.42	0.00	61959.51	26738.73	6906.24	13927.59	405194.58
Total 2001	1247.13	59718.15	587162.52	1007394.57	65010.15	268469.91	0.00	396909.00	186790.68	42447.78	92143.26	

Where numbers refer to natural water (1), Burnt/wetland (2), farm on sand (3), fallow on sand (4), Active sand dune (%), forest (6), woodyland (7), mixed woodland (8), grassland (9), farm on clay (10) and fallow on clay (11).

It was obvious, that cropping lands on sand and clay had increased. This agreed with findings of Zaroug (2000), Poussart (2002), Ardö and Olsson (2003) and Elmqvist (2004). The latter however found that the increase of population was much higher than the correlated increase in cropping lands. Forest, woodyland, grassland and burnt/wetland areas had decreased. This could be attributed to the increase of cropland to face the increasing food demand due to population increase. This agreed with findings of Olsson (1985), Zaroug (2000) and Ardö and Olsson (2003). Moreover, active sand dunes had increased which could be an indicator of desertification. Mixed woodland had also increased which could be due to afforestration effort adopted by the Ministry of Agriculture and Forestry (Zaroug, 2000, Tagelsir, 2005) (Table 20).

Table 20: Changes of land use/land cover classes during 1973-2001

Class name	Area 2001	Area 1973	Difference
Natural water bodies	1247.13	910.69	336.43
Burnt/wetland	59719.95	73918.32	-14198.37
Farm on sand	587203.47	427719.15	159484.31
Fallow on sand	1007557.65	962104.27	45453.37
Active sanddunes	65051.01	3097.59	61953.41
Forest	268487.64	299539.93	-31052.29
Woodyland	0.00	263450.68	-263450.68
Mixed woodland	396945.99	272279.84	124666.14
Grassland	186800.49	405452.13	-218651.64
Farm on clay	42449.13	0.00	42449.13
Fallow on clay	92147.58	0.00	92147.58

5.5 Soil Types

Mineral composition indices of iron oxide, clay and ferrous minerals showed distinct patterns of soil types in the study area (Fig. 20). Sandy soils appeared in bluish colours in the northern part of the study area, while alluvial cracking clays showed reddish colours covering water depressions and water courses. Finally the non-cracking heavy clay soils mixed with aeolian sand, locally known as *Gardud* soil, appeared in greenish colours covering the southern part of the study area.

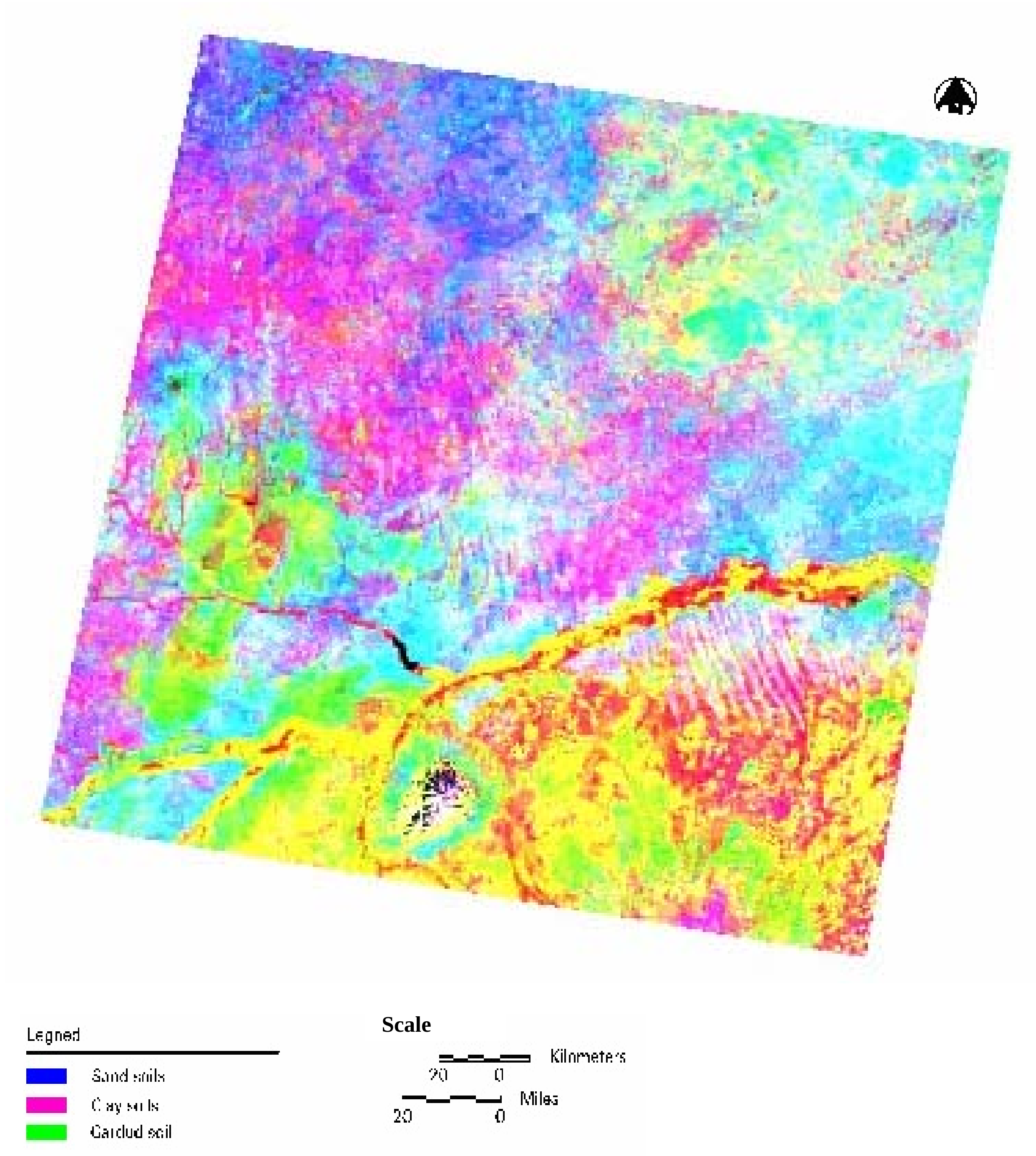


Figure 20: Soil types in the study area

Table (21) and Appendix (13) showed the results of the chemical and physical analysis of soil samples collected from the study area. Soils are neutral to slightly acidic (4.35-8.1) and are nonsaline (ECe<4) and non-sodic (SAR<13) with low organic matter percentage (0.05%). The texture varies from sand to clay. Infiltration rate and hydraulic conductivity are generally high and vary considerably with texture.

Table 21: Some chemical and physical properties of soil samples

	SP	pH	EC dS/m	Ca+Mg (mmol/l)	Na (mmol/l)	SAR	OM%	HC (cm^3/min)	IR (cm^3/min)
Mean	20.24	6.25	0.48	2.17	2.64	2.46	0.05	0.854	7.39
Std	7.75	0.97	0.46	2.18	3.33	2.6	0.036	1.05	6.83
Range	38.03	3.75	2	14.25	12.97	10.14	0.139	6.03	19.68
Min.	16.1	4.35	0.15	0.75	0.13	0.14	0.005	0.02	0.32
Max.	54.13	8.1	2.15	15	13.1	10.28	0.144	6.05	20.00

5.6 Effect of Soils Types on Land Use/Land Cover

The study area is generally covered by two soil types: sand and clay in the northern and southern parts, respectively. Rainfed agriculture is practiced in the northern and southern part, but grassland and sand dunes are dominant in the northern part, while forest and woodyland are more common in the southern part.

The introduction of rainfed agriculture in the southern part is obvious and it may represent the causative factor for land degradation in this area as a result of continuous tree cutting. Millet and Karkade are grown on sand, while sorghum is grown on clay (Ahlcrona, 1988, Poussart, 2002, Ardö and Olsson, 2003). Each soil type supports certain tree and shrub species, for example sandy soils support species like *Marekh* (*Leptadenia pyrotechnica*), *Hashab* (*Acacia Senegal*) and *Sirih* (*Maerua crassifolia*). On the other hand clay soils support species like *Kitir* (*Acacia millifera*), *Sunt* (*Acacia nilotica*) and *Talh* (*Acacia seyal*). However shrubs like *Kerssan* (*Boscia senegalensis*) and *Ushr* (*Calatropis procera*) grow on both soil types and it is considered as a sign of land degradation by local people.

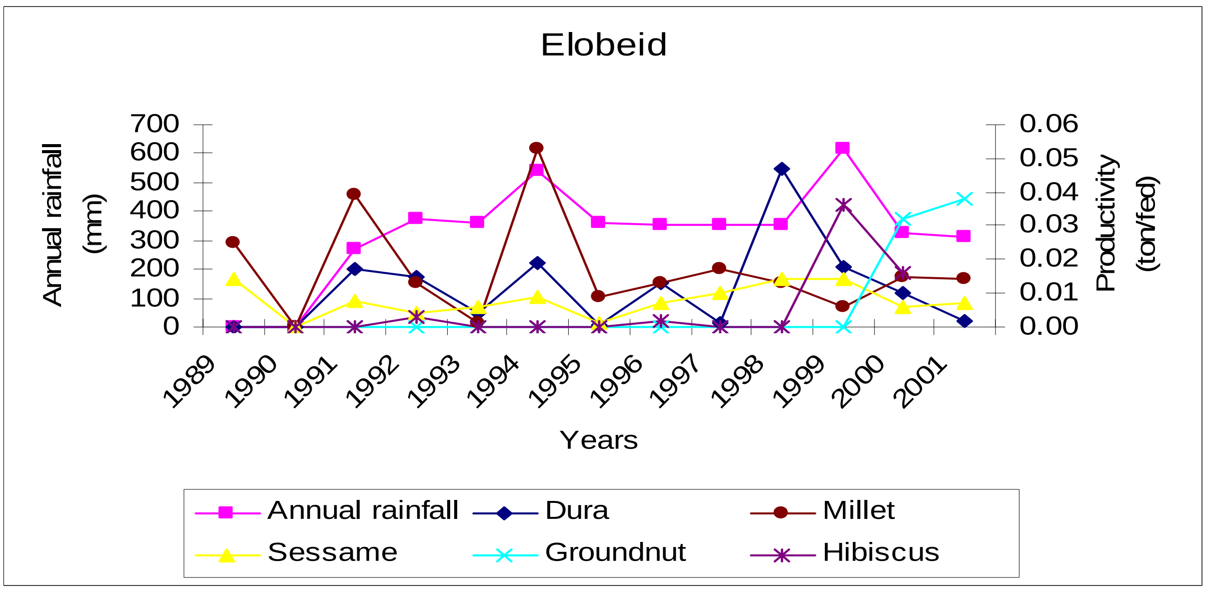
5.7 Desertification

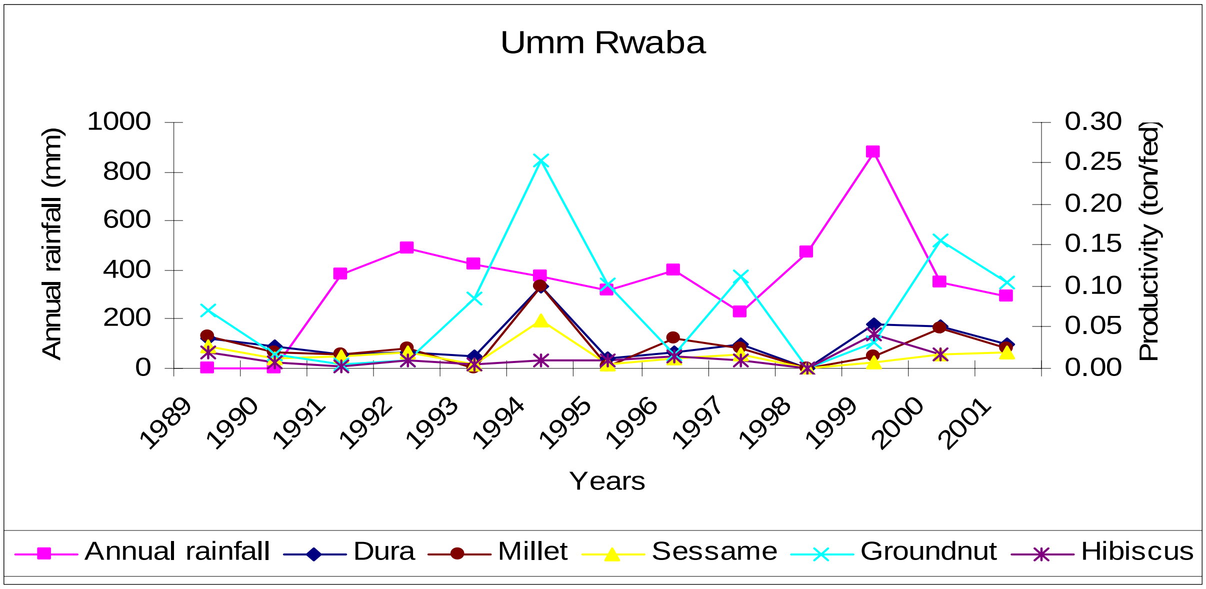
This study revealed different signs of desertification in the study area related to change patterns in land use/land cover, such as increase of farming land on sand and clay at the expense of woodyland and grassland. These signs could be revised with the use of agricultural indicators.

Land degradation as reduction in biological productivity can be interpreted from crop and animal production.

5.7.1 Crop Production

Crop production is generally very low and varies from year to year (Fig. 21). It is difficult to conclude that there is a systematic desertification process however this fluctuation could be attributed to variations in annual rainfall and low soil fertility due to continuous cultivation of the land to face the increased demand for food resulting from population increase combined with decreasing yields (Poussart, 2002, Ardö and Olsson, 2003).





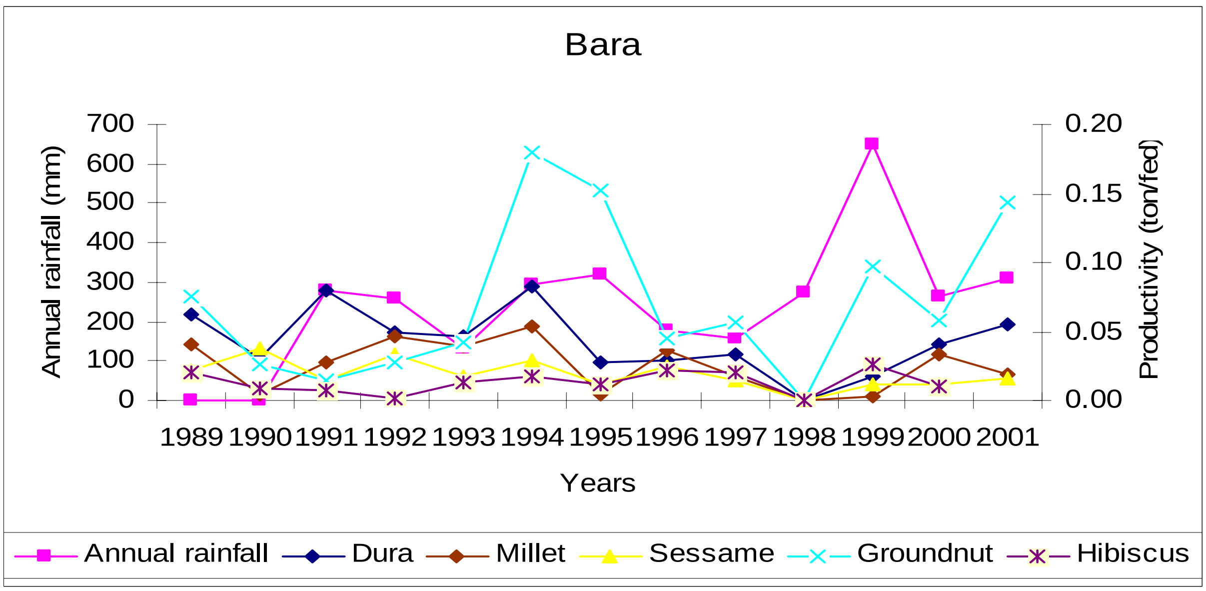


Figure 21: Crop production at different administrative units in North Kordofan State
Source: Ministry of Agriculture and Forestry, North Kordofan State, Sudan (2005)

5.7.2 Livestock

Figure (22) showed that livestock had increased in all sites except in the Bara area, which is characterised by low annual rainfall. Bara area showed reduction in growth rate of goat and sheep. This could be an indicator of reduction in biological productivity in the northern part of the study area and hence desertification. On the other hand, in Elobeid and Umm Rwaba areas the increase in animal numbers could be a sign of overgrazing although there were no clear statistics about the carrying capacity of the land cover classes of the study area. Nevertheless overgrazing is considered one of the causative factors of desertification.

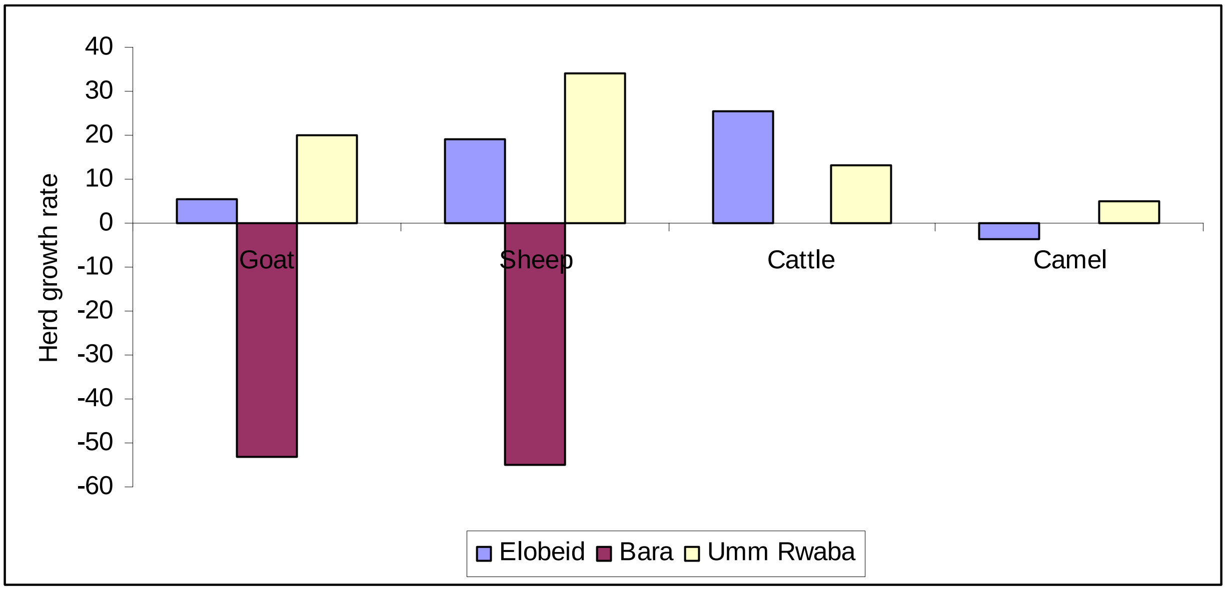


Figure 22: Herd growth rate at different administrative units in North Kordofan State
Source: Ministry of Agriculture and Forestry, North Kordofan State, Sudan (2005)

5.7.3 Discussion

Agricultural statistics did not indicate clear trends of desertification but showed a slightly fluctuating pattern of crop production and an increased trend in livestock. These two indicators could confirm the occurrence of localised desertification at certain parts in the study area especially in terms of reduction in biological productivity. However the short period for these measurements affects its reliability.

CHAPTER SIX
CONCLUSION AND LIMITATION

6.1 Conclusion

This study aims to determine the major land use/land cover (LULC) classes for the study area in the years 1973 and 2001 and to analyse the process of desertification with relation to changes of LULC classes and vegetation cover for the above addressed period. Moreover, the study aims to map soil types using Landsat ETM+ 2001 and field data. Finally the study attempts to improve accuracy of digital classification by different data transformation methods such as PCA, TCA and CA.

The major LULC classes present in the study area are forest, farm on sand, farm on clay, fallow on sand, fallow on clay, woodyland, mixed woodland, grassland, burnt/wetland and natural water bodies. Farm and fallow on sandy and clay soils constitute the major land uses in the area, while mixed woodlands constitute the major land cover. This increase in cropping areas implies the overexploitation of natural resources on behalf of agriculture. This is confirmed by the decreasing areas of forest and also coincides with the vegetation cover decrease as indicated by NDVI from both images. This finding leads to accept the first hypothesis which stated that amount/degree of vegetation cover change is large enough to state that desertification occurs in the study area. Moreover, this finding leads to accept the second hypothesis which relates desertification process to change in land uses pattern. Remote sensing methods used in this study prove a high potential to illustrate vegetation cover changes. Therefore, the third hypothesis asking if remote sensing is a suitable tool for detection of vegetation cover change is accepted. However, results shows that vegetation cover in the southern part covered with clay soil type is more deteriorated in comparison with the northern part which is predominately covered with sandy soils. Hence, the fourth hypothesis stating that different soil types in the study area are related to different vegetation change patterns is accepted. Based on these results this study concludes the following:

1. Remote sensing techniques give reasonable classification for LULC in the study area.

2. Digital image classification of transformed data with use of TCA, PCA and CA improves the classification accuracy for LULC.

3. NDVI effectively measures vegetation cover change in the area and is a significant indicator of vegetation desertification in the study area.

4. Post classification change detection methods show direct patterns of change in LULC classes while pre-classification methods are contradictory with each other and give general indications.

5. Remote sensing techniques allow for reasonably mapping of the soil types in the study area.

6.2 Limitations of the Study

This study attempted to overcome and minimise the affects of many limitations. These limitations include scarcity of historical spatial data concerning natural resource such as land use/land cover maps and climatic information. On the other hand the remotely sensed data used represent only two selected dates are not sharpened by additional data. MSS data of 1973 is characterised by moderate spatial resolution of 79x79m and multi-spectral resolution of 4 bands. This low spatial and spectral resolution constrains the recognition of LULC classes. In addition the MSS dataset was affected by line stripping in bands 4 and 6 which influenced its spectral reliability. The time lag between acquisitions dates of these imageries and dates of field works constrains the full use of information collected during the field works in 2004. The study area is considered large with many inaccessible locations. These conditions lead to adoption of a sampling technique which coincides with roads and settlements areas. In addition the study area is rural and has no or only few man-made features which hinder the possibility for further georeferencing with use of ground control points. As consequence this affects the quality of image to image registration.

6.3 Recommendation

Based on the findings of this study under the above mentioned limitation and concerning available data the study recommends the followings:

1. Conduction of periodical assessment and monitoring of natural resources with use of remote sensing methods.
2. Adoption of governmental agricultural policy based on the above recommended method of periodical and up-to-date natural resource assessment which can conserve the natural resources.

3. Continuation of afforestation programmes which have been conducted in the last decade by FNC.
4. Encouragement of the people in the study area to adopt land uses which are friendly to the environment such as plantation of *hashab* (*Acacia senegal*) which is tapped for Gum Arabic production and of animal husbandry instead of rainfed agriculture especially in the northern part.
5. Adoption of remote sensing techniques as the most cost- and time-effective method for land use/land cover mapping and assessment.
6. Use of remotely sensed data in soil mapping.
7. Conduction of in-depth detailed studies in this area with high emphasis at local level of land use/land cover changes and vegetation cover by means of remotely sensed hyper-spectral data and advanced digital analysis techniques such as spectral un-mixing analysis.

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Appendix 1: Annual rainfall (mm) for different towns in the study area for the period 1991-2005

Place	Years													
	91/92	92/93	93/94	94/95	95/96	96/97	97/98	98/99	99/00	00/01	01/02	02/03	03/04	04/05
Elobeid	268	373	358	543	362	356	352	351	618	324	315	216	400	290
Kazgil	*	*	*	*	*	*	267	*	*	*	332	*	*	73
Umm A'shirra	*	*	*	*	*	*		*	*	*	*	142	641	114
Abuharaz	*	*	*	*	*	*		*	*	*	438	270	*	271
Khor Taggat	*	*	*	*	*	*		*	*	*	*	85	*	*
Umm Rwaba	386	490	420	370	315	400	231	475	877	353	294	223	369	263
Errahad	*	*	338	309	343	329	512	376	266	253	349	359	371	269
Elsemih	*	*	*	*	*	*	*	422	584	307	317	395	406	151
Ummdamm	*	*	*	*	*	*	*	*	304	147	287	103	*	105
Sidra	*	*	*	*	*	*	*	*	*	*	*	625	*	*
Wada'shana	*	*	*	*	*	*	*	*	*	*	245	165	*	204
Shirkilla	*	*	*	*	*	*	*	*	*	*	84	244	*	*
Bara	280	257	133	296	322	180	157	272	651	266	310	112	411	281
Umm Seyalla	*	*	*	*	*	*	*	250	253	*	294	119	192	91

Source: Ministry of Agriculture and Forestry, North Kordofan State, Sudan (2005)

Appendix 2a: Area, production and productivity of sorghum in different administrative sectors

Season	Bara			Shikan			Umm Rwaba		
	Area (fed.)*	Production (ton)	Productivity (ton/fed.)	Area (fed.)	Production (ton)	Productivity (ton/fed.)	Area (fed.)	Production (ton)	Productivity (ton/fed.)
1989	0	0	0.00	25251	909	0.04	74337	4757	0.06
1990	0	0	0.00	5468	146	0.03	21161	636	0.03
1991	11116	194	0.02	9120	148	0.02	131190	10387	0.08
1992	77326	1083	0.02	54869	1043	0.02	381918	18714	0.05
1993	9511	38	0.00	109541	1643	0.01	259215	11923	0.05
1994	130368	2477	0.02	132551	13388	0.10	359144	29450	0.08
1995	64129	21	0.00	51664	619	0.01	393970	11067	0.03
1996	135032	1753	0.01	66423	3201	0.02	303355	8841	0.03
1997	34040	50	0.00	65573	1983	0.03	259018	8827	0.03
1998	17070	802	0.05	135213	0	0.00	436967	0	0.00
1999	128751	2345	0.02	192780	10419	0.05	590084	9966	0.02
2001	191480	1977	0.01	214814	11036	0.05	498049	11912	0.04
2002	68029	163	0.00	182071	5370	0.03	311745	17226	0.06

Source: Ministry of Agriculture and Forestry, North Kordofan State, Sudan (2005)
* fed = feddan; 1 feddan = $4200m^2$.

Appendix 2b: Area, production and productivity of millet in different administrative sectors

Season	Bara			Shikan			Umm Rwaba		
	Area (fed.)*	Production (ton)	Productivity (ton/fed.)	Area (fed.)	Production (ton)	Productivity (ton/fed.)	Area (fed.)	Production (ton)	Productivity (ton/fed.)
1989	21498	557	0.02	49428	1977	0.04	171356	6854	0.04
1990	0	0	0.00	40055	761	0.02	18318	831	0.00
1991	324352	12616	0.04	47244	795	0.02	532141	14789	0.03
1992	81082	14054	0.01	289595	7240	0.02	486755	22695	0.05
1993	59779	537	0.00	93515	103	0.00	153862	6031	0.04
1994	112424	59594	0.05	300529	30053	0.10	1049887	56694	0.05
1995	30374	366	0.01	74512	223	0.00	482585	2620	0.01
1996	420809	5617	0.01	105900	3778	0.04	267025	9642	0.04
1997	933381	15064	0.02	215675	5214	0.02	529646	8765	0.02
1998	793868	10320	0.01	195606	0	0.00	743317	0	0.00
1999	1192713	7062	0.01	183130	2674	0.02	587770	14638	0.00
2001	514790	7787	0.01	84796	4134	0.05	127244	4293	0.03
2002	318869	5929	0.01	141822	3442	0.02	289043	5626	0.02

Source: Ministry of Agriculture and Forestry, North Kordofan State, Sudan (2005)
* fed = feddan; 1 feddan = $4200m^2$

.

Appendix 2c: Area, production and productivity of sesame in different administrative sectors

Season	Bara			Shikan			Umm Rwaba		
	Area (fed.)*	Production (ton)	Productivity (ton/fed.)	Area (fed.)	Production (ton)	Productivity (ton/fed.)	Area (fed.)	Production (ton)	Productivity (ton/fed.)
1989	20501	295	0.01	34470	896	0.03	397995	9815	0.02
1990	0	0	0.00	1499	18	0.01	24579	954	0.04
1991	41635	315	0.01	25550	378	0.01	164650	2254	0.01
1992	199252	797	0.00	162582	3089	0.02	468522	15836	0.03
1993	74183	445	0.01	108230	530	0.00	638394	11491	0.02
1994	144597	1301	0.01	159593	9256	0.06	664745	19278	0.03
1995	113686	220	0.00	88588	354	0.00	565231	6203	0.01
1996	125222	902	0.01	116377	1475	0.01	378717	8938	0.02
1997	145930	841	0.01	122050	1933	0.02	411838	5586	0.01
1998	68678	961	0.01	122719	0	0.00	850413	0	0.00
1999	269916	3677	0.01	191810	1291	0.01	748268	8253	0.01
2001	92120	582	0.01	82060	1399	0.02	287442	5292	0.01
2002	176275	2651	0.01	85588	1629	0.02	425367	6600	0.02

Source: Ministry of Agriculture and Forestry, North Kordofan State, Sudan (2005)
* fed = feddan; 1 feddan = 4200m^2

Appendix 2d: Area, production and productivity of groundnut in different administrative sectors

Season	Bara			Shikan			Umm Rwaba		
	Area (fed.)*	Production (ton)	Productivity (ton/fed.)	Area (fed.)	Production (ton)	Productivity (ton/fed.)	Area (fed.)	Production (ton)	Productivity (ton/fed.)
1989	0.00	0.00	0.00	4320	239	0.07	70328	5344	0.08
1990	0.00	0.00	0.00	13130	210	0.02	19545	522	0.03
1991	11317	0.00	0.00	1433	80	0.01	446	7	0.01
1992	0.00	0.00	0.00	15134	136	0.01	38485	1078	0.03
1993	0.00	0.00	0.00	84368	7171	0.08	9422	395	0.04
1994	0.00	0.00	0.00	61541	15570	0.25	19133	3444	0.18
1995	0.00	0.00	0.00	28058	2890	0.10	42534	6465	0.15
1996	0.00	0.00	0.00	37151	659	0.02	37193	1667	0.04
1997	0.00	0.00	0.00	32856	3768	0.11	34258	1952	0.06
1998	0.00	0.00	0.00	33840	0.00	0.00	64755	0	0.00
1999	0.00	0.00	0.00	47268	1449	0.03	31312	3052	0.10
2001	13835	447	0.03	62519	9666	0.15	72200	4197	0.06
2002	20696	787	0.04	64518	6834	0.11	49250	6978	0.14

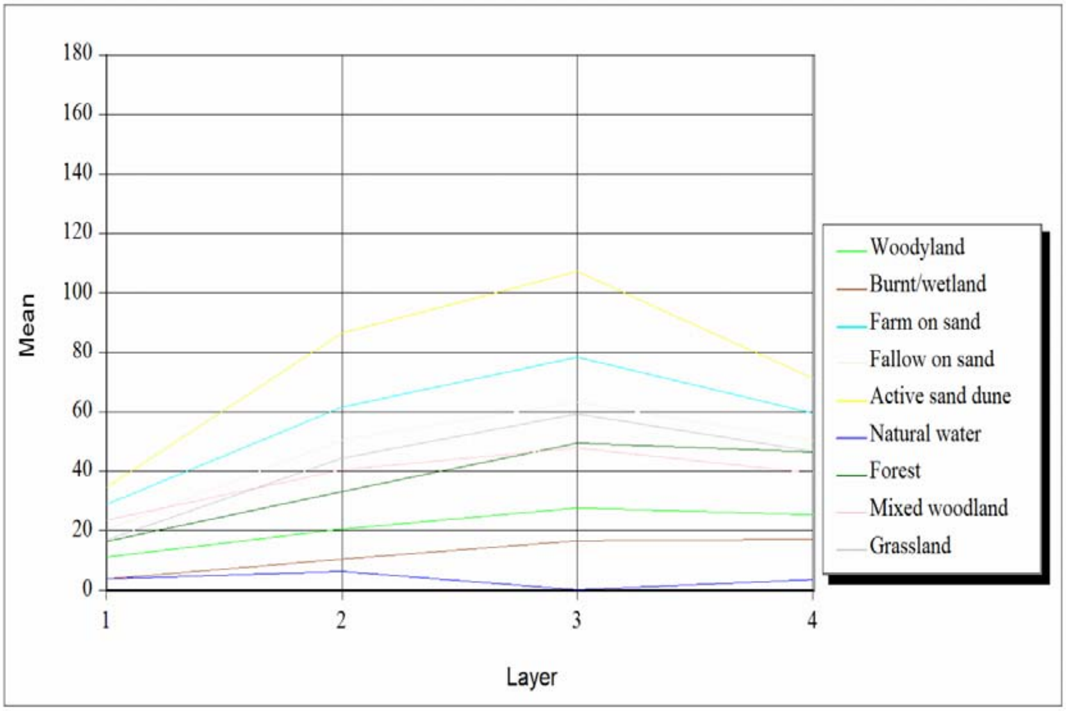
Source: Ministry of Agriculture and Forestry, North Kordofan State, Sudan (2005)
* fed = feddan; 1 feddan = $4200m^2$

Appendix 2e: Area, production and productivity of karkade in different administrative sectors

Season	Bara			Shikan			Umm Rwaba		
	Area (fed.)*	Production (ton)	Productivity (ton/fed.)	Area (fed.)	Production (ton)	Productivity (ton/fed.)	Area (fed.)	Production (ton)	Productivity (ton/fed.)
1989	0	0	0.00	2649	50	0.02	55547	1166	0.02
1990	0	0	0.00	10814	76	0.01	2932	26	0.01
1991	4203	0	0.00	2105	3	0.00	26278	197	0.01
1992	1482	4	0.00	13767	140	0.01	128595	1800	0.00
1993	0	0	0.00	20954	117	0.00	49670	646	0.01
1994	0	0	0.00	17791	178	0.01	49053	883	0.02
1995	0	0	0.00	12611	127	0.01	119931	1345	0.01
1996	5152	10	0.00	11434	180.5	0.01	76651	1720	0.02
1997	11607	0	0.00	3180	34	0.01	58034	1197	0.02
1998	645	0	0.00	27651	0	0.00	153165	0	0.00
1999	8118	291	0.04	17719	750	0.04	182020	4732	0.03
2001	12220	197	0.02	29651	527	0.02	129979	1318	0.01

Source: Ministry of Agriculture and Forestry, North Kordofan State, Sudan (2005)
* fed = feddan; 1 feddan = 4200m^2

Appendix 3a: Mean plots of spectral signatures (1973)



Appendix 3b: Contingency error matrix for classified image 1973

Classified data	Reference data %									Total pixel
	A	B	C	D	E	F	G	H	I	
A	99.28	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	274
B	0.72	100.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	215
C	0.00	0.00	100.00	0.00	0.00	1.85	0.00	0.00	0.00	841
D	0.00	0.00	0.00	97.50	0.00	0.00	0.00	0.00	4.04	612
E	0.00	0.00	0.00	0.00	100.00	0.00	0.00	0.00	0.00	855
F	0.00	0.00	0.00	0.00	0.00	98.14	0.00	0.00	0.00	369
G	0.00	0.00	0.00	0.00	0.00	0.00	100.00	0.00	0.16	660
H	0.00	0.00	0.00	0.00	0.00	0.00	0.00	100.00	0.00	5334
I	0.00	0.00	0.00	2.50	0.00	0.00	0.00	0.00	95.8	631
Total pixels	276	213	834	501	866	376	659	5334	643	9802

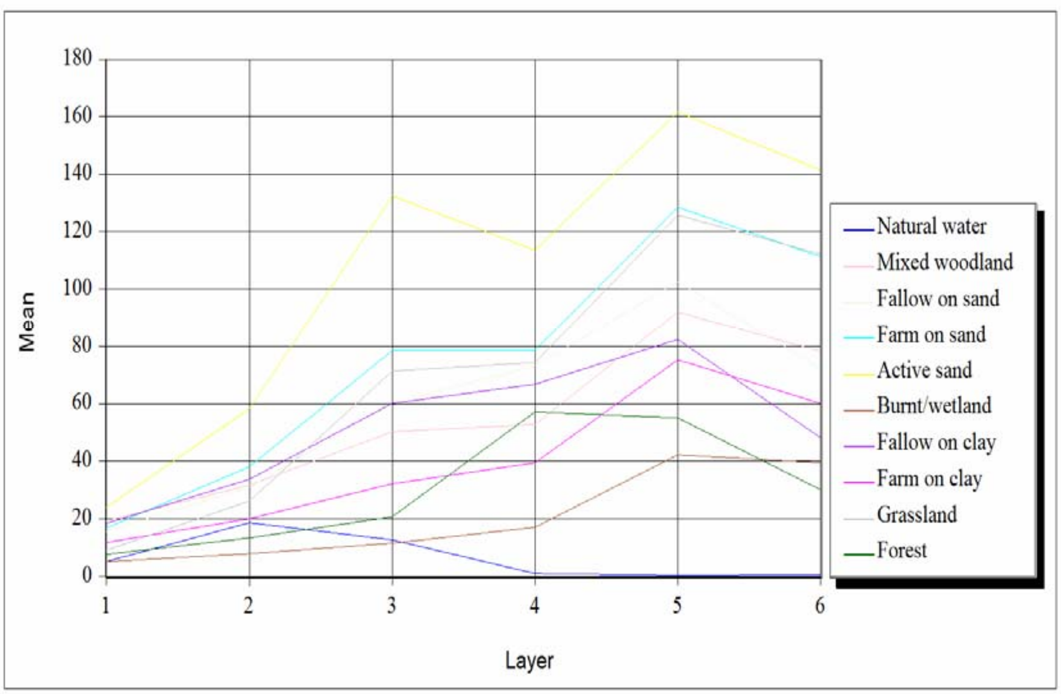
In this appendix and other successive ones, letters refer to following:

A	= Natural water	E	= Woodyland	I	= Grassland
B	= Burnt/wetland	F	= Active sand dunes	J	= Farm on clay
C	= Farm on sand	G	= Forest	K	= Follow on clay
D	= Fallow on sand	H	= Mixed woodland		

Appendix 4: Accuracy error matrix of classified image 1973

Classified data	Reference data									Total pixels
	A	B	C	D	E	F	G	H	I	
A	9.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	9.00
B	0.00	8.00	0.00	0.00	0.00	0.00	2.00	0.00	0.00	10.00
C	0.00	0.00	9.00	1.00	0.00	0.00	0.00	4.00	2.00	16.00
D	0.00	0.00	2.00	14	0.00	0.00	0.00	2.00	4.00	10.00
E	0.00	0.00	0.00	0.00	8.00	0.00	4.00	0.00	0.00	12.00
F	0.00	0.00	0.00	0.00	0.00	13.00	0.00	0.00	0.00	13.00
G	0.00	0.00	0.00	0.00	0.00	0.00	14.00	0.00	0.00	14.00
H	0.00	0.00	0.00	0.00	0.00	0.00	0.00	10.00	1.00	11.00
I	0.00	0.00	1.00	1.00	0.00	0.00	1.00	0.00	11.00	14.00
Total pixels	9.00	8.00	12.00	16.00	8.00	13.00	21.00	16.00	16.00	

Appendix 5a: Spectral signatures of original DN pixel of image 2001



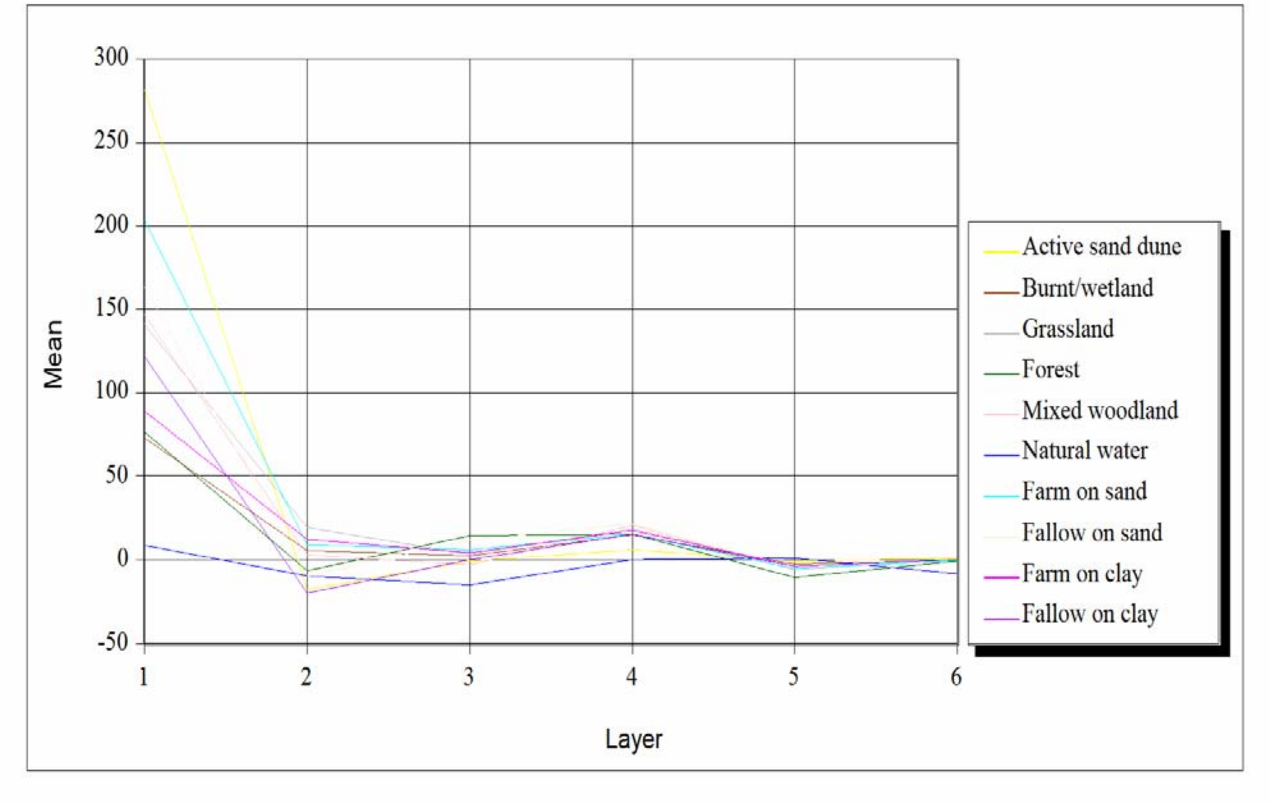
Appendix 5b: Contingency error matrix of classified original DN pixel of image 2001

Classified data	Reference data %										Total pixels
	A	B	C	D	F	G	H	I	J	K	
A	99.85	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3335
B	0.050	98.31	0.00	0.00	0.00	0.00	0.00	0.00	0.23	0.00	817
C	0.00	0.00	99.49	0.00	0.00	0.00	0.00	0.00	0.00	0.00	584
D	0.00	0.00	0.51	100.00	0.00	0.00	0.01	0.00	0.00	0.00	251
F	0.00	0.00	0.00	0.00	100.00	0.00	0.00	0.00	0.00	0.00	1180
G	0.00	0.00	0.00	0.00	0.00	100.00	0.00	0.00	0.00	0.09	69
H	0.00	0.00	0.00	0.00	0.00	0.00	99.56	0.00	0.23	0.00	7691
I	0.00	0.00	0.00	0.00	0.00	0.00	0.00	100.00	0.00	0.00	2525
J	0.00	1.69	0.00	0.00	0.00	0.00	0.43	0.00	99.54	0.00	483
K	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	99.91	1135
Total pixels	3341	828	587	247	1180	65	7724	2525	438	1135	

Appendix 6: Accuracy error matrix of classified original DN pixel of image 2001

Classified data	Reference data										Total pixels
	A	B	C	D	F	G	H	I	J	K	
A	10.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	10.00
B	0.00	23.00	0.00	0.00	0.00	0.00	1.00	0.00	1.00	0.00	25.00
C	0.00	0.00	20.00	3.00	0.00	0.00	1.00	1.00	0.00	0.00	25.00
D	0.00	0.00	1.00	17.00	0.00	2.00	5.00	0.00	0.00	0.00	25.00
F	0.00	0.00	0.00	0.00	20.00	0.00	0.00	1.00	0.00	0.00	21.00
G	0.00	2.00	0.00	0.00	0.00	13.00	1.00	0.00	1.00	1.00	18.00
H	0.00	0.00	0.00	0.00	0.00	0.00	23.00	0.00	2.00	0.00	25.00
I	0.00	0.00	6.00	1.00	0.00	0.00	0.00	18.00	0.00	0.00	25.00
J	0.00	5.00	0.00	0.00	0.00	0.00	2.00	0.00	18.00	0.00	25.00
K	0.00	2.00	0.00	0.00	0.00	3.00	2.00	0.00	5.00	13.00	25.00
Total pixels	1.00	32.00	27.00	21.00	20.00	18.00	35.00	20.00	27.00	14.00	

Appendix 7a: Spectral signatures of dominant land use/land cover classes of PC image 2001



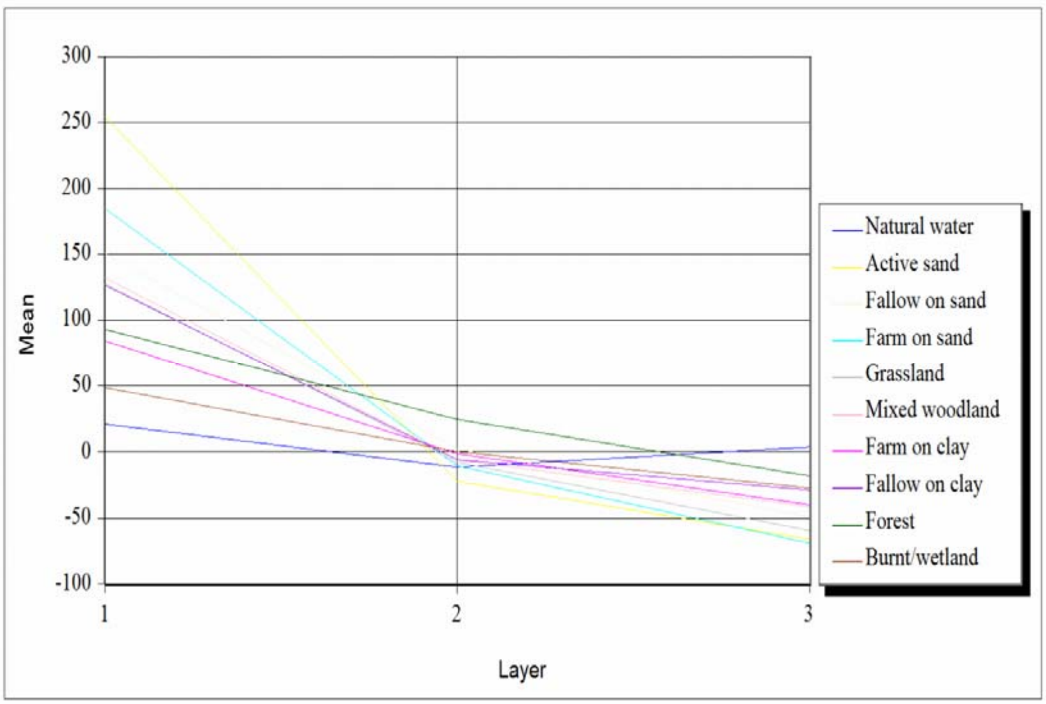
Appendix 7b: Contingency error matrix of classified image of PC image 2001

Classified data	Reference data %										Total pixels
	A	B	C	D	F	G	H	I	J	K	
A	99.83	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3011
B	0.00	99.64	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1098
C	0.00	0.00	99.88	0.00	0.00	0.00	0.00	0.00	0.00	0.00	848
D	0.00	0.00	0.12	100.00	0.00	0.00	0.00	0.00	0.00	0.00	524
F	0.00	0.00	0.00	0.00	100.00	0.00	0.00	0.00	0.00	0.00	887
G	0.17	0.36	0.00	0.00	0.00	99.87	0.00	0.00	0.62	0.00	780
H	0.00	0.00	0.00	0.00	0.00	0.00	100.00	0.00	0.00	0.00	2877
I	0.00	0.00	0.00	0.00	0.00	0.00	0.00	100.00	0.00	0.00	2168
J	0.00	0.00	0.00	0.00	0.00	0.13	0.00	0.00	99.38	0.00	1434
K	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	100.00	664
Total pixels	3016	1102	849	523	887	763	2877	2168	1442	664	14291

Appendix 8: Accuracy error matrix of classified image of PC image 2001

Classified data	Reference data										Total pixels
	A	B	C	D	F	G	H	I	J	K	
A	9.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	9.00
B	0.00	21.00	0.00	0.00	0.00	0.00	1.00	1.00	2.00	0.00	25.00
C	0.00	0.00	18.00	2.00	0.00	0.00	2.00	3.00	0.00	0.00	25.00
D	0.00	0.00	1.00	20.00	0.00	0.00	1.00	3.00	0.00	0.00	25.00
F	0.00	0.00	3.00	3.00	19.00	0.00	0.00	0.00	0.00	0.00	25.00
G	0.00	0.00	0.00	0.00	0.00	21.00	4.00	0.00	0.00	0.00	25.00
H	0.00	0.00	0.00	1.00	0.00	3.00	20.00	1.00	0.00	0.00	25.00
I	0.00	0.00	2.00	6.00	0.00	0.00	1.00	16.00	0.00	0.00	25.00
J	0.00	2.00	0.00	0.00	0.00	1.00	0.00	0.00	21.00	1.00	25.00
K	0.00	1.00	0.00	0.00	0.00	3.00	0.00	0.00	3.00	18.00	25.00
Total pixels	9.00	24.00	24.00	32.00	19.00	28.00	29.00	24.00	26.00	19.00	

Appendix 9a: spectral signatures of classified image of TC image 2001



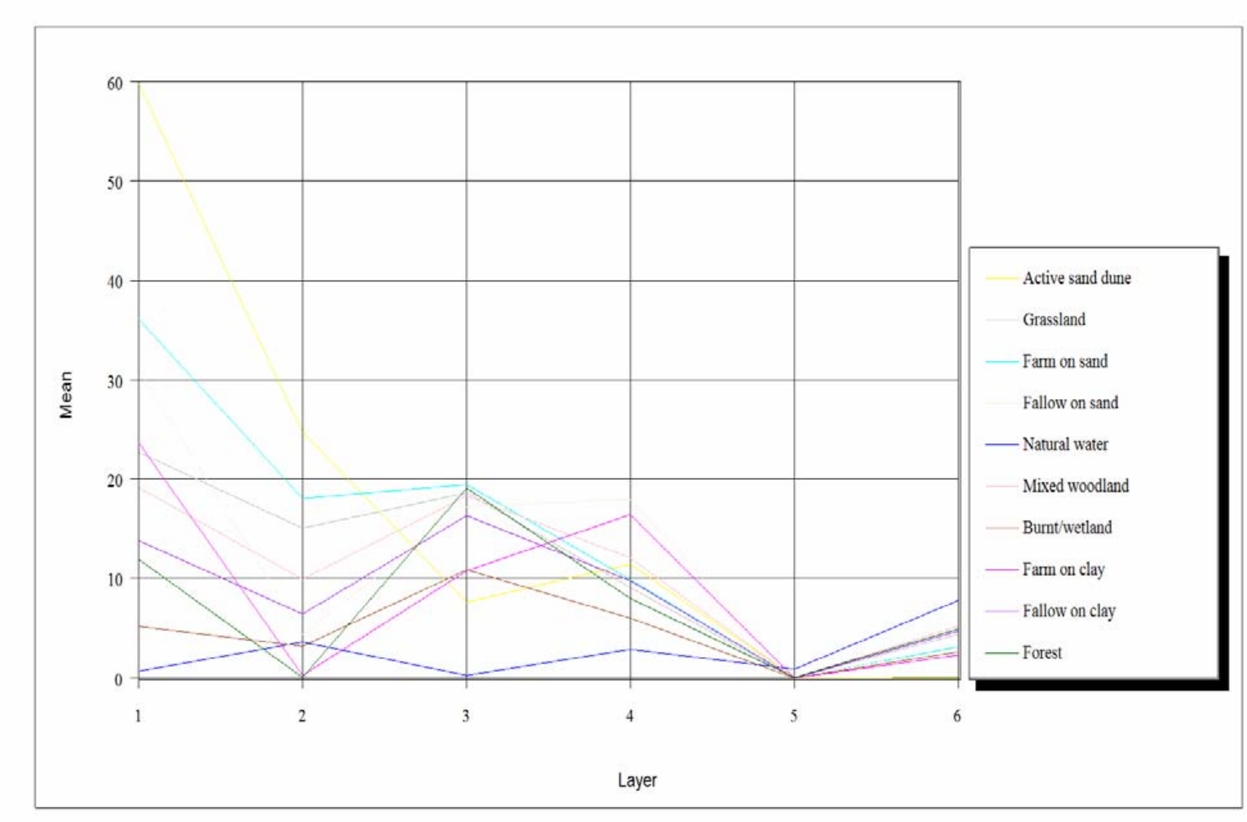
Appendix 9b: Contingency error matrix of TC image 2001

Classified data	Reference data %										Total pixels
	A	B	C	D	F	G	H	I	J	K	
A	99.76	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	4159
B	0.05	100.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2571
C	0.00	0.00	100.00	0.10	0.00	0.00	0.00	0.00	0.00	0.00	564
D	0.00	0.00	0.00	98.71	0.00	0.00	0.00	0.00	0.00	0.00	998
F	0.00	0.00	0.00	0.00	100.00	0.00	0.00	0.00	0.00	0.00	622
G	0.19	0.00	0.00	1.19	0.00	100.00	0.10	0.00	0.00	0.00	398
H	0.00	0.00	0.00	0.00	0.00	0.00	98.87	0.11	0.00	0.80	2024
I	0.00	0.00	0.00	0.00	0.00	0.00	0.00	99.89	0.00	0.00	1871
J	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	99.71	0.00	339
K	0.00	0.00	0.00	0.00	0.00	0.00	1.03	0.00	0.29	99.20	270
Total pixels	4169	2569	563	1011	622	376	2043	1873	340	250	13816

Appendix 10: Accuracy error matrix of classified image of TC image 2001

Classified data	Reference data										Total pixels
	A	B	C	D	F	G	H	I	J	K	
A	11.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	11.00
B	0.00	13.00	0.00	0.00	0.00	4.00	1.00	0.00	0.00	0.00	18.00
C	0.00	0.00	22.00	2.00	0.00	0.00	0.00	1.00	0.00	0.00	25.00
D	0.00	0.00	4.00	18.00	0.00	0.00	1.00	2.00	0.00	0.00	25.00
F	0.00	0.00	7.00	2.00	16.00	0.00	0.00	0.00	0.00	0.00	25.00
G	0.00	0.00	2.00	2.00	0.00	16.00	1.00	3.00	1.00	0.00	25.00
H	0.00	0.00	0.00	3.00	0.00	0.00	18.00	0.00	1.00	3.00	25.00
I	0.00	0.00	1.00	2.00	0.00	0.00	0.00	22.00	0.00	0.00	25.00
J	0.00	3.00	0.00	0.00	0.00	3.00	5.00	0.00	14.00	0.00	25.00
K	0.00	1.00	0.00	0.00	0.00	0.00	3.00	0.00	0.00	4.00	8.00
Total pixels	11.00	17.00	36.00	29.00	16.00	23.00	29.00	28.00	16.00	7.00	

Appendix 11a: Spectral signatures of CA image of 2001



Appendix 11b: Contingency error matrix of CA image of 2001

Classified data	Reference data %										Total pixels
	A	B	C	D	F	G	H	I	J	K	
A	98.86	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	87
B	0.00	100.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	105
C	0.00	0.00	100.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	172
D	0.00	0.00	0.00	100.00	0.00	0.00	0.00	0.00	0.00	0.00	77
F	0.00	0.00	0.00	0.00	100.00	0.00	0.00	0.00	0.00	0.00	1028
G	1.14	0.00	0.00	0.00	0.00	99.25	0.00	0.00	0.00	0.00	133
H	0.00	0.00	0.00	0.00	0.00	0.00	99.04	0.27	0.00	0.00	518
I	0.00	0.00	0.00	0.00	0.00	0.00	0.00	99.73	0.00	0.00	363
J	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	100.00	0.00	378
K	0.00	0.00	0.00	0.00	0.00	0.75	0.96	0.00	0.00	100.00	113
Total pixels	88	105	172	77	1028	133	522	364	378	107	2974

Appendix 12: Accuracy error matrix of classified image of CA image of 2001

Classified data	Reference data										Total pixels
	A	B	C	D	F	G	H	I	J	K	
A	11.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	11.00
B	0.00	13.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	14.00
C	0.00	0.00	19.00	0.00	1.00	0.00	3.00	2.00	0.00	0.00	25.00
D	0.00	0.00	1.00	20.00	0.00	0.00	0.00	3.00	1.00	0.00	25.00
F	0.00	0.00	1.00	0.00	9.00	0.00	0.00	0.00	0.00	0.00	10.00
G	0.00	1.00	0.00	0.00	0.00	24.00	0.00	0.00	0.00	0.00	25.00
H	0.00	0.00	3.00	1.00	0.00	1.00	20.00	0.00	0.00	0.00	25.00
I	0.00	0.00	3.00	0.00	0.00	0.00	0.00	11.00	0.00	0.00	14.00
J	0.00	0.00	0.00	0.00	0.00	4.00	1.00	2.00	17.00	1.00	25.00
K	0.00	0.00	0.00	0.00	0.00	2.00	1.00	0.00	1.00	21.00	25.00
Total pixels	11.00	14.00	27.00	21.00	10.00	31.00	26.00	18.00	19.00	22.00	

Appendix 13: Soil physical and chemical analysis

No.	SP	pH	ECe (dS/m)	Ca+Mg (mmol/l)	Na (mmol/l)	SAR	OM%	Clay%	Silt%	Sand%	Class	HC (cm^3/min)	IR (cm^3/min)
1	16.2	4.89	0.25	1.50	1.10	1.3	0.010	17.00	4.00	79	Sandy loam	1.05	5.56
2	16.2	5.56	0.20	1.50	0.51	0.6	0.031	13.40	1.50	85.1	Loamy sand	0.68	1.25
3	17.4	7.27	0.20	1.25	0.30	0.4	0.052	25.50	6.30	68.2	Sandy clay loam	0.20	5.00
4	16.4	5.64	0.20	1.75	0.13	0.1	0.031	12.20	0.30	87.5	Loamy sand	0.90	16.67
5	54.1	7.17	0.40	2.25	1.60	1.5	0.103	76.30	14.00	9.70	Clay	0.06	0.68
6	16.4	4.95	0.15	1.00	0.51	0.7	0.010	17.00	0.30	82.70	Sandy loam	2.30	10.00
7	16.4	6.72	0.60	2.00	4.20	4.2	0.041	9.80	0.30	89.90	Sand	1.20	16.67
8	16.4	6.51	0.20	2.00	0.19	0.2	0.010	13.40	0.30	86.30	Loamy sand	2.40	16.70
9	16.4	6.14	0.85	2.00	6.60	6.6	0.021	11.30	0.30	88.40	Loamy sand	1.80	20.00
10	33.9	7.63	0.80	3.00	5.30	4.3	0.005	44.90	10.30	44.80	Clay	1.27	2.50
11	31.4	6.06	0.90	2.50	6.50	5.8	0.052	48.50	3.00	48.50	Sandy clay	0.19	1.39
12	16.1	7.00	0.50	1.00	3.90	5.5	0.010	7.70	0.00	92.30	Sand	0.70	16.70
13	16.4	5.79	0.15	1.00	0.60	0.8	0.124	13.40	0.30	86.30	Loamy sand	1.00	16.67
14	16.4	5.87	0.20	1.00	0.80	1.1	0.021	13.40	4.00	82.60	Sandy loam	0.63	8.33
15	16.4	4.95	0.15	1.00	0.50	0.7	0.010	13.40	0.30	86.30	Loamy sand	0.95	16.67
16	24.6	5.85	2.15	15.00	6.50	2.4	0.062	26.00	24.90	49.10	Loam	0.10	0.82
17	24.2	5.02	0.15	1.00	0.52	0.7	0.031	19.40	5.10	75.50	Sandy loam	0.65	3.45
18	16.4	4.35	0.20	1.25	0.60	0.8	0.031	19.40	1.50	79.10	Sandy loam	0.36	3.125
19	16.4	4.50	0.50	2.25	2.70	2.5	0.062	19.40	1.50	79.10	Sandy loam	0.38	11.10
20	24.9	7.23	1.75	4.50	13.10	8.7	0.031	38.70	17.70	43.60	Clay loam	0.06	0.88
21	16.4	6.51	0.20	1.00	1.10	1.6	0.062	26.70	9.90	63.40	Sandy clay loam	0.12	0.83
22	29.6	7.29	0.45	2.50	1.90	1.7	0.072	39.80	10.30	49.90	Sandy clay	0.60	2.50
23	22.3	7.05	0.35	3.00	0.44	0.4	0.103	33.50	6.50	60.00	Sandy clay loam	0.39	3.33
24	16.4	6.28	0.20	1.75	0.23	0.2	0.010	11.00	0.30	88.70	Loamy sand	0.56	10.00
25	16.4	7.00	0.30	2.25	0.70	0.7	0.072	10.10	0.00	89.90	Loamy sand	0.83	12.50
26	16.4	6.74	0.25	2.25	0.20	0.2	0.103	11.30	0.30	88.40	Loamy sand	1.00	20.00
27	16.4	5.15	0.35	2.00	1.40	1.4	0.072	17.00	1.50	81.50	Sandy loam	2.60	4.54
28	16.4	6.70	0.25	1.50	1.10	1.3	0.021	11.00	3.90	85.10	Loamy sand	6.05	2.50
29	16.4	6.06	0.20	1.00	1.10	1.6	0.021	11.00	1.50	87.50	Loamy sand	0.75	16.67
30	16.5	6.98	0.35	3.00	0.45	0.4	0.145	36.10	14.00	49.90	Sandy clay	0.03	0.64
31	22.3	5.59	1.45	3.00	11.50	9.4	0.031	32.30	3.00	64.70	Sandy clay loam	0.15	2.20
32	16.1	7.05	0.25	2.00	0.60	0.6	0.010	7.70	0.00	92.30	Sand	1.00	20.00
33	16.4	6.42	0.30	2.25	0.66	0.6	0.062	20.70	13.50	65.80	Sandy clay loam	0.09	1.25
34	22.3	6.75	0.55	1.25	4.10	5.2	0.103	34.10	11.30	54.60	Sandy clay	0.02	0.32
35	16.4	6.24	0.50	1.50	3.40	3.9	0.083	19.60	8.90	71.50	Sandy clay loam	0.80	1.85
36	32.1	7.55	1.55	3.00	12.60	10.3	0.093	32.50	22.70	44.80	Clay loam	0.40	1.35
37	16.4	5.62	0.15	0.75	0.70	1.1	0.021	20.60	2.70	76.70	Sandy clay loam	0.35	5.56
38	36.5	7.53	0.75	3.00	4.50	3.7	0.052	48.70	20.30	31.00	Clay	0.21	2.78
39	16.4	7.34	0.50	2.50	2.50	2.2	0.010	11.00	0.30	88.70	Loamy sand	1.65	16.67
40	16.4	4.81	0.20	1.25	0.60	0.8	0.031	18.20	1.50	80.30	Sandy loam	0.34	4.54
41	16.4	4.82	0.20	0.75	1.10	1.8	0.021	20.60	1.50	77.90	Sandy clay loam	0.70	5.56
42	16.4	8.10	0.50	1.00	3.90	5.5	0.062	25.60	6.40	68.00	Sandy clay loam	0.10	0.83