QUANTIFYING THE IMPACT OF THE LAND REFORM PROGRAMME ON LAND USE AND LAND COVER CHANGES IN CHIPINGE DISTRICT, ZIMBABWE, BASED ON LANDSAT OBSERVATIONS

by

Simbarashe Sanyaruwa Jombo (1272452)

A research report submitted to the Faculty of Science, University of the Witwatersrand, Johannesburg, in partial fulfilment of the requirements for the degree of Master of Science (Geographical Information Systems and Remote Sensing) at the School of Geography, Archaeology & Environmental Studies

Supervisor: **Dr Elhadi Adam**

Johannesburg, 2016

DECLARATION

I, Simbarashe Sanyaruwa Jombo, declare that this research report is my own unaided work. It is being submitted to the Degree of Master of Science in Geographical Information Systems and Remote Sensing to the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination at any other University.

…………………………………..

Signature of candidate

.... day of......................20......................in ....

ABSTRACT

The purpose of this research was to quantify the impact of the land reform programme on land use and land cover changes (LULCC) in Chipinge district situated in Manicaland Province of Zimbabwe. The Fast Track Land Reform Programme (FTLRP) of 2000 was selected as the major cause of LULCC in the district.

This research addresses the problem of knowing and understanding if there was LULCC in the district before and after the enactment of the FTLRP in the year 2000. The research objectives of this study were as follows: to investigate the impact of the FTLRP of 2000 on land use and land cover in Chipinge district; to test the use of Landsat earth observation data in quantifying the changes on land use and cover from 1992 to 2014 in Chipinge district and to predict LULCCs in the year 2028 in Chipinge district.

The methodology for detecting the impact of LULCC was based on the comparison of Landsat MSS, TM, ETM+ and OLI/ TIRS scene p168r74 images covering Chipinge district taken on diverse dates in five different years. In order to prepare the Landsat images for change detection analysis, a number of image processing operations were applied which include radiometric calibration and atmospheric correction. The images were classified using the Support Vector Machine (SVM) and evaluation was done through accuracy assessment using the confusion matrix. The prediction of LULCC in the year 2028 was modeled by the Markov Chain Analysis (MCA) and the Cellular Automata Markov Chain Analysis (CA MCA) so as to show land distribution in the future.

The results show that agricultural farmland, estates and area covered by water bodies declined whilst there was an increase in built-up areas, forest land and bare land since the enactment of the FTLRP. The prediction results show that in the year 2028, there will be a decrease in the amount of land covered by water bodies, forest and agricultural farmland. There will be an increase in the amount of built-up in the year 2028 as a result of population growth.

It is the recommended in this study that better remedies be put in place to increase forest cover and also the use of high resolution images in further studies. There should be exploration of the relationships between LULCC, socio-economic and demographic variables would develop more understanding of LULCC. The study also recommends the preparation of a proper land use plan to deal with a reduction in the growth of settlement which is vital in the planning and management of social and economic development programs.

Dedicated to my late parents; Happy Jabulani Jombo and Margnolia Dorcas Jombo. Dedication also goes to my sisters, Shamiso Nyakuwa and Sithembinkosi Feruzi.

ACKNOWLEDGEMENTS

Praise goes to the Almighty God for his grace and mercy during my entire study time at University of the Witwatersrand in Johannesburg.

I would like to express my appreciation to my supervisor Dr Elhadi Adam for his unwavering support and supervision he offered during my research. His comments and supportive guidance provides me a chance to explore further. I will not ever forget your treatment, persistence and commitment during the research time.

I am very grateful to all offices, Wits library staff and personalities who provided me with data and use of GIS and remote sensing techniques for my study.

I would like to also extend my appreciation to my lecturers for providing me with all the fundamentals of GIS and remote sensing and their courage in helping everyone. My thanks also go to staff members in the program and the school of Geography, Archaeology and Environmental Studies.

CONTENTS

LIST OF FIGURES

LIST OF TABLES

ABBREVIATIONS AND ACRONYMS

ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
AVHRR	Advanced Very High Resolution Radiometer
CA	Cellular Automata
CA MCA	Cellular Automata Markov Chain Analysis
DEM	Digital Elevation Model
ESAP	Economic Structural Adjustment Programme
ETM	Enhanced Thematic Mapper
ETM+	Enhanced Thematic Mapper Plus
FTLRP	Fast Track Land Reform Programme
GIS	Geographic Information Systems
GSOD	Global Summary of the Day
IRSS	Indian Remote Sensing Satellites
LIDAR	Light Detection and Ranging
LULC	Land use and land cover
LULCC	Land use and land cover change
MCA	Markov Chain Analysis
MCE	Multi-Criteria Evaluation
MODIS	Moderate Resolution Imaging Spectroradiometer
MODTRAN	Moderate Resolution Atmospheric Transfer code
MOLA	Multi-Objective Land Allocation
MSS	Multi-spectral scanner
NCDC	National Climate Data Centre
NGOs	Non-Governmental Organisations
NIR	Near Infrared
NOAA	National Oceanic Atmospheric Administration
OLI	Operational Land Imager
RADAR	RAdio Detection And Ranging
RMSE	Root Mean Square Error

ROI	Region of Interest
RS	Remote Sensing
SLC	Scan Line Correcter
SPOT	Satellite Pour l'Observation de la Terre
SVM	Support Vector Machine
TIRS	Thermal Infrared Sensor
TM	Thematic Mapper
TOA	Top of Atmosphere
USGS	United States Geological Survey
UTM	Universal Transverse Mercator
WGS	World Geodetic System
ZANU-PF	Zimbabwe African National Union - Patriotic Front

CHAPTER ONE -INTRODUCTION

1.1. General Introduction

Land use and land cover change (LULCC) is one of the key processes through which human beings have an effect on the functioning of the Earth system (Turner II *et al*., 2007). LULCC results in global change and has turned out to be an important component in managing the environment (Turner II *et al*., 2007). The consequences of LULCC have great effect on humankind due to alterations in natural conditions of the environment such as degradation of the land (Sánchez-Cuervo *et al*., 2012). LULCC has impacts on biodiversity through change of home places or territory (Sala *et al*., 2000); local and regional climate change (Lambin *et al.*, 2003); global climate warming and degradation of the land (Tolba *et al*., 1992) and decrease in agricultural productivity (Lambin and Geist, 2007). The monitoring of LULCC has become an essential component in current strategies for managing natural resources and environmental changes.

LULCC in agrarian landscapes is as a result of various processes. Social, demographic, economic, cultural and policy issues are major drivers in LULCC (Lambin and Geist, 2007). LULCCs are as a result of drivers such as technological advancement, implementation of policies and environmental forces (Silva *et al*., 2011). The LULCC drivers can cause a change in land use and land cover systems where new approaches of land use dominate the landscape (Houet *et al.,* 2010). The significance of LULCC makes it important to recognise their drivers and assessing the influence of technological advancement and political changes, which is challenging as these two usually co-occur and interact (Voss and Chi, 2006).

The quantification of LULCC, change detection and assessment is essential in land use management as it helps in understanding the relations between human and natural phenomena and also on how they interact (Lu *et al*., 2004). The quantification of changes in land use and land cover is very important as it assists in understanding LULCC trends which provide important information for land use preparations and sustainable management of resources (Verburg *et al*., 1999). Historical and precise figures about LULCC are vital in finding ways for sustainable development (Wang *et al*., 2009). The analysis, mapping of both past and present LULCC over time is recognised as key in understanding and providing constructive solutions for socio-economic and environmental problems (Abd El-Kawy *et al*., 2011).

Satellite remote sensing is the commonly used data source for detection, quantification and mapping of LULCC due to its repetitiveness in acquiring data, digital format appropriate for processing using computers, and precise geo-referencing measures (Jensen, 1996; Lu *et al*., 2004; Chen *et al*., 2005; Abd El-Kawy *et al*., 2011). Remote Sensing (RS) has been greatly employed in quantifying LULCC, particularly from arable land to impermeable surfaces (Miles *et al*., 2003). RS monitors spatio-temporal LULCC at different intervals using multi-temporal Landsat images (Basnet and Vodacek, 2015). In change detection, the Landsat program has been commonly used to provide historical and up-to-date information about LULCC (Abd El-Kawy *et al*., 2011). The Landsat satellite images can be processed and represent land use and land cover for large areas and over long time spans, which is absolutely essential for monitoring, mapping, and management of LULCC (Wulder *et al*., 2008).

In Zimbabwe, approximately 41.9 % of the country is agricultural land (World Bank, 2015). One of the LULCC drivers in Zimbabwe is the agricultural policies and activities. Chipinge district is one of the large agricultural districts in Zimbabwe with great LULCC due to the land reform exercise implemented in 2000, known as the Fast Track Land Reform Programme (FTLRP) (Zamuchiya, 2011). The mapping and monitoring of LULCC in Chipinge district will help land planners and managers to understand the dynamics of the LULCC in the area and to provide tools for better agricultural planning and management.

1.2. Problem Statement

The land reform policy in Zimbabwe deals with an overall transformation of the existing farming system, institutions and structures seeking to achieve agricultural productivity (Ministry of Lands and Resettlement, 2015). Before the FTLRP in 2000, over six million landless Zimbabweans lived in rural communal lands where soil was infertile and rainfall was erratic, they had no control of water rights and were constrained from access to the bulk of the nation’s natural resources (Moyo, 2002). The land reform program started in 1980 and it changed its nature along the way and resulted in the FTLRP which started on 15 July 2000 and this was the initial phase (Zamuchiya, 2011). Vast amounts of land was taken under this program, mainly from settler farmers and redistributed to the native majority who comprised of impoverished war veterans, the poor, landless and commercial farm workers (Zamuchiya, 2011). The FTLRP resulted in the demise of the agricultural sector which led to nationwide famine as the majority of the beneficiaries of the program had little knowledge of farming practices (Richardson, 2005). The little knowledge of farming practices from the beneficiaries of the FTLRP has led to deforestation (Matsa and Muringaniza, 2010), degradation of land in Zimbabwe along with other environmental problems (Zamuchiya, 2011). There has been a lot of LULCC in many areas of Zimbabwe such as Chipinge district. LULCC in this district has become a concern to the inhabitants. Several critics of recent land reform programmes in Zimbabwe have argued that population growth and climate change have led to LULCC (Campbell, 2008), whereas others authenticate that there is huge LULCC due to the government's FTLRP of 2000 (Matsa and Muringaniza, 2011). However, the degree and impact of LULCC in Chipinge district remains unclear as no attempts have been made so far using RS imagery to come up with the rate, magnitude and even predictions of future LULCC. It is therefore the purpose of this research to quantify the impact of the FTLRP of 2000 on land use and land cover changes in Chipinge district.

1.3. Research Questions

i. Can Landsat earth observation data be used to quantify land use and land cover changes as a result of the FTLRP policy?

ii. How much land use and land cover change has occurred between 1992 and 2014?

iii. What is the impact of the FTLRP of 2000 on land use and land cover in Chipinge district?

iv. What will be the state of the land use and land cover in the year 2028 in Chipinge district under the current FTLRP policy?

1.4. Aim of the Study

i. To investigate the quantity of land use and land cover change before and after the FTLRP of 2000 in Chipinge district using Landsat images.

1.5. Objectives of the Study

i. To investigate the impact of the FTLRP of 2000 on land use and land cover in Chipinge District.
ii. To examine the use of Landsat earth observation data in quantifying the changes on land use and land cover from 1992 to 2014 in Chipinge District.
iii. To predict land use and land cover changes in the year 2028 in Chipinge District

1.6. Land use and land cover mapping in Zimbabwe

Even though there has been the application of GIS and remote sensing in Zimbabwe, its advancement is still in an infant stage, which is because of lack of finance, skill, and more essential, low level of political will. In order to change this state of affairs, GIS and remote sensing technology has to be greatly applied in the country such that it convinces politicians, land officers and various members of the government, so that they can include it when drafting policies. The quantification and prediction of LULCC has a prospective in this direction. The demonstration of the usefulness of the use or application of GIS and remote sensing must be noted in its cost effective advantages. This iterates the production of LULC data sets rapidly, consistently and less costly. Unsupervised and supervised classification methods can thus be used as they are known in giving cost effective and more accurate results as compared to those obtained by on-screen digitizing.

Chipinge district was chosen for this study as it considered to be one of the districts in the country which were affected by the FTLRP which was enacted in the year 2000 where the agrarian structure was changed which resulted in LULCC. Starting from the year 2000, the FTLRP has fundamentally transformed Chipinge district's agrarian structure from one dominated by white-owned large-scale farmers to one led by a large group of small holder producers which has a negative effect on the environment (Zamuchiya, 2011). The spatial scale of Chipinge district is 539, 303 hectares (C.S.O, 2012) and it was chosen as it represents all the five broad natural regions in Zimbabwe (Zamuchiya, 2011). The whole district was selected as the results of this study will show LULCC in all the five broad regions of the country which will help land planners and other stakeholders in coming up with ways to curb the changes.

CHAPTER TWO - LITERATURE REVIEW

This research is laid on the basis of past and current theories and concepts. This chapter comprises of concise review of the literature which is linked to this research and takes clues from those concepts and theories that support the research content and context. Amongst these include land ownership in Zimbabwe, FTLRP, role of RS in LULCC detection and the challenges of using RS in LULCC. Divergent views on the subject will also be adopted and linked with the research objectives as they function as a guide to the study.

2.1. Land Ownership in Zimbabwe

The land in Zimbabwe was distributed as outlined in the Land Apportionment Act which was signed in the House of Commons situated in London in the year 1930 (Hanlon *et al*., 2012). The Act outlined that approximately half of the land in Southern Rhodesia (now Zimbabwe) was to be utilised by whites only (Hanlon *et al*., 2012). The Act offered 51 percent of agricultural land, regarded as the best land which produced high yields to 50,000 Europeans, where 11,000 of whom actually resided on their land. Thirty percent of agricultural land was allocated to one million Africans and this land was poor, dry and infertile (Jennings, 1935). The Land Apportionment Act that was signed rewarded white veterans who fought in World War II with land. Blacks still practised agriculture in their ancestral land where the Act regarded them as “squatters” (Hanlon *et al*., 2012). Land was cleared from 1945 to 1955 where more than 100,000 black Africans were forcibly moved into areas which were infertile and tsetse ridden (Palmer, 1977).

The Lancaster House conference was held in 1979 and it stated that the transfer of land from white to black farmers could only be done following a principle named *willing seller, willing buyer* (Hanlon *et al*., 2012). A few blacks could afford to buy agricultural farms from the government as it was very expensive as they costed 10 times more than the amount which was paid by the government to acquire farms during this period (Karumbidza, 2009). The farms were bought by white farmers who were charged lower prices than what would have been proposed to the state (Hanlon *et al*., 2012).

When Zimbabwe got independence in 1980, it inherited land ownership patterns that were racially skewed. White large-scale commercial farmers who made up less than 1% of the population used up to 45% of agricultural land (Ministry of Lands and Rural Resettlement, 2015). This batch of land was situated in the country’s agricultural strongholds characterised by high rainfall and high agricultural yields. Approximately 60% of this large-scale commercial land was not fully used by the white farmers (Ministry of Lands and Rural Resettlement, 2015).

The government of Zimbabwe introduced the National Land Policy also known as the Land Acquisition Act in 1992 which had aims of creating a fair, democratic and well-organized economy and also engage majority of the people in developing the country (Coldham, 1993). The policy was also crafted to make sure that there is social and equal access to the land. One of the policy's aims was to also ensure that land tenure systems are democratic and also to safeguard the security of the tenure systems for all land holdings in the country (Ministry of Lands and Rural Resettlement, 2015).

2.2. Fast Track Land Reform Programme (FTLRP)

When Zimbabwe's Independence came in 1980, there was a first, limited land reform, as a result most land continued to be in white hands (Hanlon *et al.*, 2012). Seventy years after the signing of the Land Act and 20 years after independence, 170,000 Zimbabwean families occupied most of the remaining white farms, and took back the land (Hanlon *et al.*, 2012). The programme known as the FTLRP was launched on 15 July 2000 and designed to be undertaken in an accelerated manner with reliance on domestic resources (UNDP, 2002).

In Zimbabwe the land reform was implemented in three phases in the previous three decades (Zamuchiya, 2011). The phase which was implemented first lasted up to 1985 and consisted of market sales of land led by state land acquisition, redistribution and it also entailed intensive illegal land occupations (Moyo, 2011). The second phase ran from 1986 till 1999, during the period of the Economic Structural Adjustment Programme (ESAP), enabled the state to acquire some land through expropriation and market mechanisms and the third FTLRP phase began in 2000 where it employed intensive land expropriation alongside 'illegal land occupations' which continued until 2010 (Moyo, 2011). By 2009, 6,214 farmland properties covering above 10 million hectares had been acquired, but not all were allocated and 168,671 families gained (Moyo, 2011). By 2009, less than 400 individually owned white farms remained and also the large agro-industrial plantations or estates and conservancies were also not substantively expropriated, though they lost some land and/or were partially 'illegally' occupied (Bonarjee, 2013). Across these three land reform phases, a wide range of blacks, especially the non-landed who included; the landless, poor land-short farmers, agricultural manual workers, poor urban workers and the unemployed, wanted land reform to redress racial and class inequalities, foreign domination and historical loss (Moyo, 2011). In the country most of the land that was taken under the FTLRP of 2000 is underutilised or operating below its full potential and environmental degradation is one of the leading effects, evidence of failure to effectively address the land reform programme (Maguwu, 2007).

Zimbabwe has not been spared concerning LULCC as it has been greatly altered because of human activity (Matsa and Muringaniza, 2011). Pressure has been exerted on the environment mainly due to poverty and vulnerability (Zamuchiya, 2011). The FTLRP caused major environmental damage resulting from the indiscriminate cutting down of trees for firewood, for sale, use in tobacco kilns as well as clearance for cultivation along rivers and stream banks resulting in siltation of rivers (UNDP, 2002). Chipinge district was also affected and it is the purpose of this research to quantify the impact of FTLRP of 2000 on LULCC and this will be done through analysing changes from 1992 to 2014.

2.3. Concept and Importance of Land Use and Land Cover

The terms land cover and land use have various definitions. Land cover is defined as the observed biophysical cover on the earth's surface, including grassland, agricultural land, forest land, recreational area or a built up area (Lambin and Geist, 2006). Land use is characterized by the inputs, activities and measures that people take on in a certain land cover type to produce, change or maintain it (Briassoulis, 2000). LULCC refers to quantitative changes in the aerial extent where there might be an increase or decrease of any given type of land use or land cover (Briassoulis, 2000). Furthermore, LULCC can be grouped into two broad categories which are conversion and modification (Stolbovoi, 2002). Conversion refers to a change from one cover or use type to another, for instance the conversion of forests to pasture whilst modification involves the maintenance of the broad cover or use type in the face of change in its attributes (Duadze, 2004).

Land use and land cover (LULC) are distinct yet closely linked characteristics of the Earth’s surface (Stolbovoi, 2002). Land cover provides additional information on anthropogenic activities and also stipulates these actions in terms of factors such as identification, timing and many others (Stolbovoi, 2002). On the other hand, land use incorporates quite a number of natural, social and economic factors and also their relations (Stolbovoi, 2002). Several shifts in land use patterns are driven by a variety of social causes, that result in land-cover changes that affect water, radiation budgets, biological diversity, trace gas emissions and other processes that come together to affect climate and biosphere (Riebsame *et al*., 1994). The information on land use and land cover has emerged to be very important in a wide range of studies related to the environment.

Information on LULC is vital in many activities which involve planning and management concerning the Earth's surface as it comprises of essential environmental details for scientific, resource management, policy purposes and a range of anthropogenic activities (Duadze, 2004). This information is vital in a number of aspects that are crucial in the study of global environmental change, for instance the alterations in the Earth's surface have major consequences in energy fluxes and global radiation balance, hydrological cycles, ecological balances and complexity (Duadze, 2004). The environmental impact at local, regional and global scale brought about by anthropogenic activities or biophysical factors can have an effect on food security, world's agricultural sustainability and the supply systems of forests (Mas and Ramirez, 1996). Land cover is an important determinant of land use and also a significant value to society (Mucher *et al*., 2000), hence land cover information has become very important at local, regional and global levels in the management and planning of environmental issues (Cihlar, 2000; Duadze, 2004).

LULC studies are necessitated by the intent to quantitatively find out the nature, extent, rate of LULCC and the ideal baseline information on which to put together and evaluate environmental policies for the future (Wright and Morrice, 1997). Precise knowledge of LULC characteristics signifies the basis for land classification and management; and the absence of this precise information is a major problem in coming up with proper decisions in relation to the environment and resources of the Earth (Dai and Khorram, 1998). Quite a number of Earth systems scientists, natural resources managers, urban planners, business people and geographers look for information on the position, allocation, type, extent and accuracy of LULCC (Stow, 1999).

2.4. Role of Remote Sensing on Land Use and Land Cover Changes

LULCC studies have undergone large advancements and improvements in both planning and technical contexts. The introduction of aerial photography and satellite imagery resulted in substantial improvements in LULCC studies (Kivel, 1991). Historical and current sources of RS are quite important for measuring and monitoring changes in landscape parameters (Sohl and Sleeter, 2012). Developments in Geographical Information Systems (GIS) and RS have increased the user-friendly nature of model planning systems and allowed researchers to tackle problems previously considered analytically impossible (Lambin and Geist, 2006).

RS is an essential tool of LULCC science because it makes it possible for observations across large areas on the Earth's surface of what can be obtained using ground-based observations (Lillesand and Kiefer, 2000). This is done with the use of RADAR and LiDAR sensors mounted on air and space-borne platforms, multi-spectral scanners, cameras that yield aerial photographs and satellite imagery (Ellis, 2013). The application of RS techniques in resource management is mainly due to high reflectance from the resources which will be in different regions of the electromagnetic spectrum recorded by different sensors (Trotter, 1998; Duadze, 2004). This makes the application of RS in land use and land cover mapping a vital process in modern-day satellite sensor technology (Daudze, 2004). The application of satellite RS techniques in LULC mapping is vital as it is applicable in inaccessible areas and also in areas where aircraft-based mapping methods are difficult to apply or where traditional methods might give inherent problems (Tucker and Townsend, 2000).

In recent years the use of RS techniques has become common in LULC mapping of large areas (Cihlar, 2000). The use of satellite RS in mapping vegetation in developing countries has not been commonly used until recently (Trotter, 1998). There has been a great need to apply satellite RS in resource mapping due to the growing need of new information and also because of new technological development (Cihlar, 2000). In its development, the mainly consistent, precise and in depth local, regional and global LULC classifications have been acquired using multi-temporal imagery (Wright and Morrice, 1997).

The imagery from RS plays a vital role in various spatial information systems (Wright and Morrice, 1997) and offers a feasible data source where updated land cover information is obtained efficiently with regular repeat coverage, scale which is consistent and at low cost for professional change detection (Kressler and Steinnocher, 1996). Satellite image data provides the potential to obtain land cover information at more frequent intervals and more economical than those obtained by traditional methods (Martin and Howarth, 1989). Information on vegetation cover from multi-temporal images is fundamental in supervision of biotic resources' rates and the response of vegetation to drought conditions which is essential for rangelands, grazing lands and crops (Duadze, 2004).

There are a number of satellite data sources that allow for the analysis of ecological or environmental variables (Duadze, 2004). The satellite RS data available differ from high resolution (e.g. IKONOS and Quickbird) to regional datasets which are produced at regular intervals (e.g. Landsat and SPOT) and those with low resolution (> 250 m) datasets like Moderate Resolution Imaging Spectroradiometer (MODIS) (Ellis, 2013). The datasets include the Advanced Very High Resolution Radiometer (AVHRR) obtained from National Oceanic Atmospheric Administration (NOAA), which is very important in the monitoring of global processes (Schmidt and Gitelson, 2000); the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER); Satellite Pour I'Observation de la Terre (SPOT); MODIS; IKONOS and the Indian Remote Sensing Satellites (IRSS) (Duadze, 2004).The datasets also include the Landsat series which incorporates Landsat 1, 2 and 3 which are referred to as the Multi-spectral scanner (MSS); Landsat 4, 5 and 7 referred to as Thematic Mapper (TM) and Enhanced Thematic Mapper (ETM) for Landsat 7 (Duadze, 2004). The Landsat series now includes Landsat 8 which has the Operational Land Imager (OLI) sensor and the Thermal Infrared Sensor (TIRS) which have better noise performance thus enabling better classification of the state of LULC and their condition (USGS, 2014). Landsat series can be taken as a good example of showing continuous improvement in radiometric and spectral property of images enabling better understanding of land resources (Oumer, 2009). Change detection has greatly applied RS imagery due to its coverage which is repetitive at short intervals with image quality that is consistent (Mas, 1999).

Remote sensing has long been used successfully for LULCC change across different landscapes. Daniel *et al.* (2002) who compared LULCC detection methods and made use of five methods which are: cross correlation analysis, traditional post-classification cross tabulation, knowledge-based expert systems, image segmentation and neural networks. The study concluded that the five methods have a number of advantages and no single method can solve the change detection problem (Rawat and Kumar, 2015). Yuan *et al.* (2005) developed a method to map and monitor land cover change using multi-temporal Landsat TM satellite images in the seven-county Twin Cities Metropolitan Area of Minnesota for the years: 1986, 1991, 1998 and 2002. They observed that between 1986 and 2002, there was an increase in urban land and it rose from 23.7 % to 32.8 %, whilst rural cover types of wetland, forest and agriculture decreased from 69.6 % to 60.5 %.

GIS and remote sensing techniques have also emerged as the most valuable data source in measuring and quantifying LULCC in many parts of the world including Africa. Adam *et al*. (2014) quantified land cover change using modern geoinformatics technology in Wadi El Kanga, Sudan. Four Landsat images were used in the study which were for the years: 1973, 1987, 2001 and 2011. The study noted the trend and magnitudes of land cover change, causes and LULCC maps in the area. They also investigated the potential use of remote sensing and GIS as a powerful tool for assessing, monitoring and mapping land cover changes in the semi-arid environment. The results of the study indicated an increase and decrease of vegetation cover as it was 6.14 % in 1973, 7.31 % (1987), 6.1 % (2000) and 7.16 % (2011) of the total study area. Other studies from the African continent include that by Adejuwon and Jeje (1973) who mapped vegetation or land use associations in the Ife area in Nigeria with the use of 1: 40 000 panchromatic aerial photographs. Salami and Akinyende (2006) used GIS and remote sensing techniques in conducting LULCC studies in south west Nigeria using Landsat satellite imagery of December 1986 and NigeriaSat-1 imagery of December 2004.

Previous studies on LULCC have been done in Zimbabwe with the use of GIS and remote sensing techniques. Scholars like Matsa and Muringaniza (2011) used GIS and remote sensing skills in assessing land use and land cover changes in Shurugwi district, Zimbabwe. They established the status of LULCC for Shurugwi district as well as determining the extent of these changes using GIS and remote sensing techniques. The study used three satellite images from different years which are 1991, 2000 and 2009. Change detection methods were used and that cultivation and bare land dominated the LULC of the district and that there was significant LULCC. Other studies which were done in Zimbabwe using GIS and remote sensing techniques on LULC include Fakarayi *et al*. (2015) who assessed LULCC in Driefontein Grasslands Important Bird Area (Driefontein IBA), Zimbabwe. Landsat images and various GIS techniques were used in the study. There have been no attempts to quantify and predict future LULCC in Chipinge district which is one of the affected districts by the FTLRP in Zimbabwe. It is against this background that this study investigates the impact of the FTLRP of 2000 on LULCC and also examines the use of Landsat earth observation data in quantifying LULCC from 1992 to 2014 in Chipinge District. The study also predicts LULCC in the year 2028 in Chipinge district.

2.5. Challenges of Using Remote Sensing in Land Use and Land Cover Change

RS has been widely used in LULC detection and it has its own limitations. One of the challenges includes the inability of many sensors to obtain data and information on LULC due to the presence of cloud cover (Fonji and Taff, 2014). In studying LULCC, distinct phenomena can be confused if they look the same to the sensor as their spectral reflectance might be in the same range (Fonji and Taff, 2014). The other challenge is that the resolution of the satellite imagery might be too coarse for LULC mapping and for distinguishing small contrasting areas. There are also challenges of RS when using multispectral data which have either high spatial resolution but with a few bands like red, green, blue and near infrared (NIR), or offer fairly more bands but with lower spatial resolution (Omer *et al*., 2015). Multispectral sensors with low spatial resolution might not map LULC classes accurately in a fragmented and heterogeneous environment (Cho *et al*., 2012; Omer *et al*., 2015). Multiple objects that are in a pixel in such a case can lead to poor distinction and spectral confusion amongst continuous and discreet cover types resulting in LULC classes that are ambiguous (Cingolani *et al*., 2004). Hyperspectral data can be used in studying and analysing LULCC though it has its own challenges. The use of hyperspectral data has a challenge in terms of availability, high dimensionality, processing and cost (Dalponte *et al*., 2009; Omer *et al*., 2015).

2.6. Impact of Rainfall and Temperature Variability on Land Use and Land Cover Change

A combination of climate variability, deforestation, overgrazing and other human activities results in significant land cover changes (Yan and Zheng-Hui, 2013). Variability in climate has an effect on LULCC and this can affect agricultural patterns (CARA, 2006). Alterations in water, carbon fluxes and energy are products of climate change (Galloway *et al*., 2014). The variability in climate that has an effect on LULCC due to factors such as rainfall patterns, temperatures especially the ones at night and carbon dioxide enrichment (Batlle *et al*., 2014). Rainfall and temperature variability yields environmental disturbances that affect LULC directly or indirectly (CARA, 2006).

A number of controlled experiments have brought to light that huge variability in rainfall patterns cause low plant growth as a result of reduced water availability in the soil, mostly the upper 30 centimetres (Kochy, 2008). Temperatures which are higher are most likely to make growing seasons longer, thereby permitting the possibility of more than one cropping cycle within the same season and the expansion of forest and agricultural land towards higher elevations and the poles (Reddy and Hodges, 2000). An increase in night time temperatures may have an effect on biological processes like respiration which can result in a decline of agricultural yields (Cheesman and Winter, 2013).

Human beings can respond to the variations in rainfall and temperature in terms of migration (Bohra-Mishra *et al*., 2014). If warmer places are regarded amenities to human beings, there might be population density increase in areas with higher temperatures (CARA, 2006). LULC is affected by the new population settlements as more development and land fragmentation occurs in these areas (Bohra-Mishra *et al*., 2014). Rainfall and temperature variability can have negative or positive results (Omoyo *et al*., 2015). If climate changes in an area, it may result in less agricultural productivity, then more land will have to be converted to other land uses. Conversely, if climate change makes agriculture more productive in an area, land that is currently a forest or grassland maybe converted to agricultural uses (CARA, 2006).

CHAPTER 3 - MATERIALS AND METHODS

3.1. Study Area

Chipinge district is located in south eastern Zimbabwe which is in the Manicaland province as shown in Figure 1 below. Chipinge district is divided into urban and rural; it covers a total area of 539,303 hectares (CSO, 2012). The district is geo-physically divided into five broad natural regions depending on annual patterns of rainfall. These regions' soil type, land coverage, annual rainfall and the major farming systems are illustrated in Table 1 below:

Table 1: Zimbabwe's Natural Regions and the major farming methods (Vincent and Thomas, 1962)

Region	Soil type	Land coverage (km^2)	Annual rainfall (mm)	Major farming system
I	Red clay	7 000	>1 000	Diversified and specialised
II	Sandy loams	58 600	750 – 1 000	Intensive
III	Sandy, acid (low fertility)	72 900	650 - 800	Semi-intensive
IV	Sandy, acid (low fertility)	147 800	450 - 650	Semi-intensive
V	Sandy (infertile)	104 400	< 450	Extensive

Chipinge district can be broadly divided into the high veld covering region I (1) and II (2)and the low veld covering regions III (3) to V (5) (GoZ, 1986). The district consists of a town named Chipinge, commercial farms, rural areas, and communal farms and agriculture varies from region to region (Cliffe *et al.*, 2014). In the whole country, Chipinge is the only district that covers all the five agricultural regions, so it is representative of the country's geography and it provides an opportunity to capture regional variation and the underlying dynamics between households resettled in the high veld and those left out in the low veld regions (Zamuchiya, 2011). Chipinge district has various soil types and they differ with regions where it has red clay, sandy loams and acid soils as shown in Table 1 above. The district also consists of corporate estates, large scale commercial farms, small scale commercial farms, resettlement and communal farms where tea, coffee, macadamia nuts farming is done (Zamuchiya, 2011).

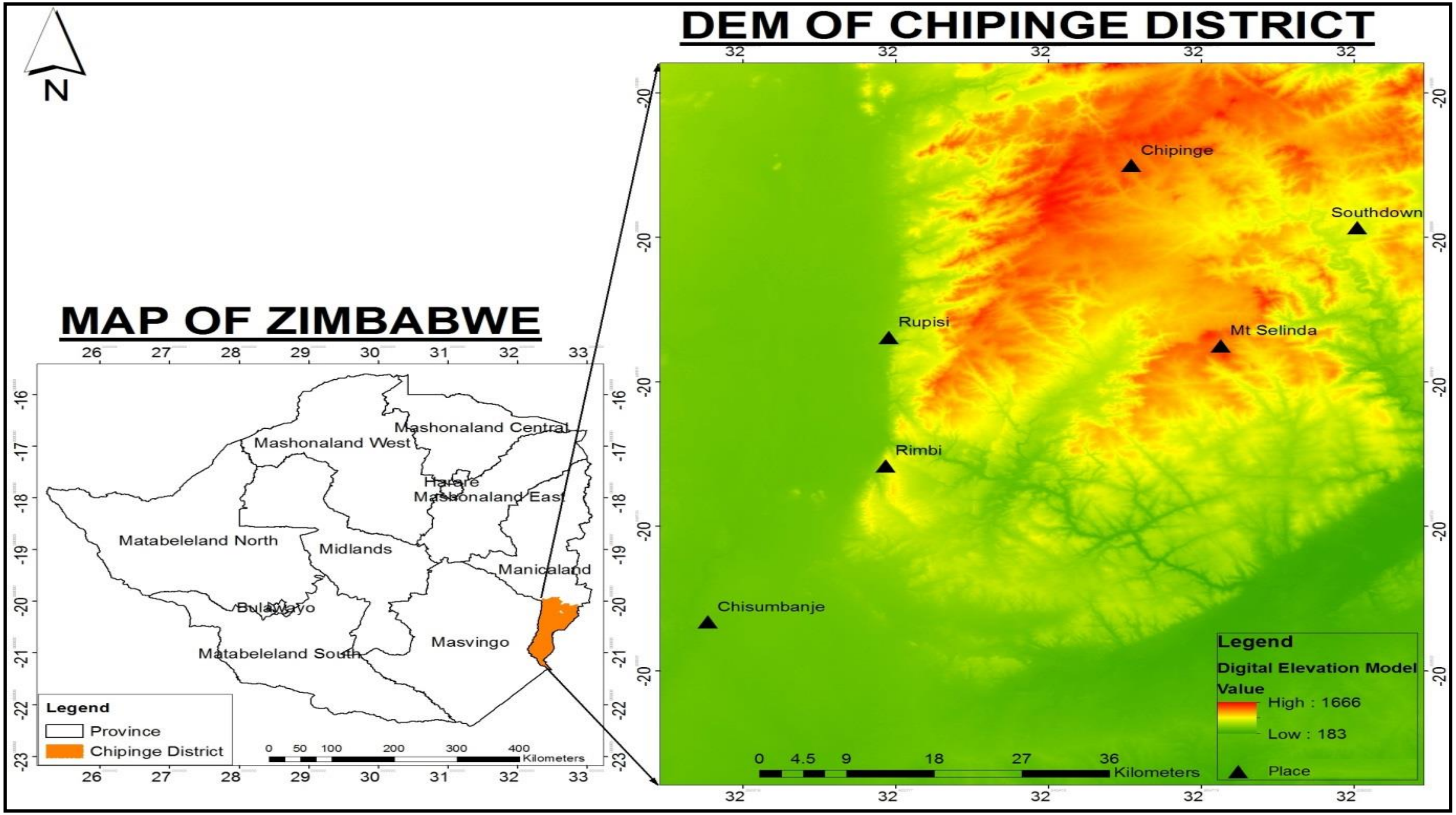

Figure 1: Map of Chipinge district

3.2. Materials

Data that was used in this study was collected from various sources so as to increase the accuracy of its results. Data used in this study included annual rainfall and temperature means, Landsat images and ground truth data.

3.2.1. Remote Sensing Data

The use of RS data in the assessment of the state of the landscape and its transformation in developing countries is not new and it was used in this study, in form of Landsat imagery. Present and past information on LULCC in Chipinge district was used in this study. Satellite images from Landsat for the years 1992, 2000, 2006, 2011 and 2014 were used as shown in Table 2. The satellite images used in this study differed in their sensor and spectral range as illustrated in table 2. The image for 1992 was from Landsat 4 TM; 2000 (Landsat 7 ETM+ SLC on); 2006 (Landsat 5 TM); 2011 (Landsat 5 TM) and 2014 (Landsat 8 OLI/TIRS). There are a number of ways of detecting and monitoring of LULCC over time. In the past, scientists used field data and aerial photographs to map LULCC over small areas. As the study area's size increased, these methods became very costly and also time consuming (Fonji and Taff, 2014). High spatial resolution imageries such as IKONOS, QuickBird, WorldView and RapidEye have been used recently in LULC scale mapping across large areas as they provide good landscape characteristics and information about the shape and size of targets (Hu *et al*., 2013). Landsat imagery was used in this study as the high spatial imageries have narrow spatial coverage and high economic costs and are generally used for LULC mapping in small areas (Hu *et al*., 2013). The use of Landsat observations was also of their representation of valuable and continuous records of the earth's surface (USGS, 2014). The entire Landsat archive is now accessible free-of-charge and provides a wealth of information for the identification and monitoring of changes in the physical and manmade environments (Chander *et al*., 2009).

The satellite images were obtained from the United States Geological Survey (USGS) on Earth Science Data Interface (http://www.usgs.gov/). Chipinge district is found within Scene path 168 and Row 74. A deliberate effort was made to ensure that the images were acquired in the hot-wet season and the cold-dry season which are the agricultural seasons in Zimbabwe. Satellite images were collected during the summer seasons except the one for the year 1992. The images collected in the summer season were used in order to see the spectral differences between vegetated, cropped and degraded areas in the rainy agricultural seasons.

The image for the year 1992 is in the winter season as there are no summer images for this year on the Earth Science Data Interface. Change differences that occurred in the seasons selected in this study were noted for the different years used. The 1992, 2000, 2006, 2011 and 2014 images were acquired from the months of April, November and December as shown in Table 2. The time gap between the five satellite imagery is wide enough to show changes and trends in LULCC in Chipinge district. In the study, the time gap was supposed to be four years starting from 1995 to 2014 but some of the images are not available on the Earth Science Data Interface and that is the reason why the time interval changed. These sources of information were used to quantify the impact of LULCC over the years for the study area. Table 2 below shows the acquisition dates, years, sensor, paths and rows of Landsat images acquired.

Table 2: Landsat data source, dates and resolution (USGS, 2014)

Year	**Acquisition date**	**Sensor and spectral range**	**Path**	**Row**	**Resolution (meters)**
1992	19 April 1992	Landsat 1 – 5 MSS Band 1: 0.5 – 0.6 µm Band 2: 0.6 – 0.7 Band 3: 0.7 – 0.8	168	74	60
2000	05 December 2000	Landsat 7 ETM+ (SLC on)	168	74	30
2006	14 December 2006	Landsat 4 - 5 TM	168	74	30
2011	10 November 2011	Landsat 4 - 5 TM	168	74	30
2014	4 December 2014	Landsat 8 OLI/TIRS	168	74	15 and 30

3.2.2. Rainfall and Temperature Data

There are three seasons that are recognised in Zimbabwe and these are: summer, which is the hot wet season (mid-November to March); a hot dry season from the month of August to mid-November and winter, a cold dry season (April to July) (Gambiza and Nyama, 2000). The historical daily precipitation and temperature data from Chipinge weather station which has Weather Meteorological Organization (WMO) ID number: 67983, was obtained and used in analysing significant trends. The weather station that was chosen is in Chipinge town with an altitude of 1132 metres, longitude of 32º37´E and also latitude of 20º12´S (Aguilar *et al*., 2009). The yearly mean rainfall and temperature values cover years from 1992 to 2014. They were used to analyse if the LULCC was mainly as a result of the FTLRP, climate change or the combination of both. The climate data was collected from the Global Summary of the Day (GSOD) that is on the website of the United States, National Oceanic and Atmospheric Administration (NOAA) National Climate Data Centre (NCDC) (http://www7.ncdc.noaa.gov/CDO/cdodata.cmd).

Summary statistics which include the standard deviation, annual rainfall and temperature means were produced using Stata 11.1 software. A one sample mean comparison test was conducted so as to investigate whether differences are statistically significant in the annual mean rainfall and temperature values for the period 1992 to 2014. A one sample t test is used in testing the null hypothesis to see if that sample comes from a population that has a particular mean (Norusis, 1997). A one sample *t-test* used in this study is the one which compares the mean score that is found in an observed sample to a value that is hypothetically assumed (McDonald, 2008). The hypothetically assumed value is in most cases the population mean or a figure that is theoretically derived (McDonald and Dunn, 2013). The hypothesized values that were used in this study were theoretically derived where a value of 1 105 millilitres (mm) and 21 ºC were used for annual mean rainfall and temperature respectively. The null and alternative hypotheses were also written out in this study. The null hypothesis which is denoted as H_0 is referred to as a statement that no difference exists between the parameter and the statistic that is being compared to it (McDonald, 2008). The hypotheses in this study were tested at a significance level of 5 %. The test produced values which included the t statistic, p-value and the 95 % confidence interval which were used to note if the variations in mean annual rainfall and temperature had a huge effect on the occurrence of LULCC in Chipinge district. The test statistic (t_s) was calculated using the following formula:

$$t_S = (\bar{x} = \mu_0) / (s / \sqrt{\ } \bar{n})$$

where $\bar{x}$ represents the sample mean; μ is the mean that is expected under the null hypothesis; *s* stands for the sample standard deviation and *n* represents the sample size (McDonald and Dunn, 2013).

3.3. Land Use and Land Cover Mapping

In this study, a number of steps were taken in LULC mapping of Chipinge district. These steps include image pre-processing, acquiring of reference data, image classification and accuracy assessment.

3.3.1. Image pre-processing

Prior to the use of satellite images in analysis, Landsat images were pre-processed. Mapping processes for historical and modern-day time requires images that have high-level geometric precision, radiometric and atmospheric correctness (Lu *et al*., 2004). This is done due to several factors which include earth-sun distance, angle of the zenith and view, the topography, conditions of the atmosphere and also temporal evolution of target characteristics that affect satellite images (Chandra, 2012). These irregularities affect the mapping results from LULCC mapping if they are not corrected.

The sample set in the study was obtained with the use of the combination: 2, 4, 1 (1992 and 2006 images); 3, 2, 1 (image for 2000, 2006, 2011) and 4, 3, 2 for 2014 image for visual interpretation of the images in their true colour. The sensor bands for MSS (1, 2, 3 and 4) encompass spectral ranges which are between 0.45 to 1.10 µm (USGS, 2014). The TM and the ETM+ sensor bands (1, 2, 3, 4, 5, 6, 7 and 8) have spectral ranges which are from 0.45 to 12.50 µm. Landsat 8 OLI and TIRS sensor bands (1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11) have spectral ranges which are from 0.43 to 12.52 µm (USGS, 2014).

Landsat images were converted to top-of-atmosphere (TOA) radiance through the use of radiometric calibration coefficients. There are quite a number of techniques that can be used to radiometrically correct satellite images. These techniques include dark subtraction, FLAASH, emissivity normalization and many more. The radiance calibration was processed with the FLAASH module in ENVI SAT 5.2. This was done to atmospherically correct surface reflectance where it also removed unwanted materials such as errors of the sensor and noise (Lu *et al*., 2004). The MODTRAN4 radiation transfer code that is embedded in the FLAASH module was used as it is considered to be a worthy solution for atmospheric corrections (Kaufman *et al*., 1997; Han *et al*., 2014). The processes in the FLAASH module were chosen as: Rural for aerosol model (as most parts of the district are far from Chipinge town), 2-Band (K-T) for the aerosol retrieval and the initial visibility were chosen at 20-40 km as this depended on the quality of Landsat images that were acquired.

In order to match the spatial resolution of the four Landsat images (TM, ETM+ SLC on and OLI/TRS in Table 2), the 1992 MSS image was re-sampled from 60 metres to 30 metres using the nearest neighbour resampling method (Han *et al*., 2014) so as to match that of the TM, ETM+ SLC on and OLI/TRS images. Resampling was done using the nearest neighbour algorithm in ArcMap 10.2 so as to maintain the pixel's original brightness values so that they remain unchanged on the images. The nearest neighbour algorithm was used as its output values comes from the original input values which is vital in the discrimination of class type (Khuman, 2013). There was a limitation in that the total area on the 1992 MSS image as it was greater than that of the TM, ETM+ SLC on and OLI/TRS images by 18 hectares. This was as a result of position error of pixels along the Chipinge district shapefile after the application of the nearest neighbour resampling method. This is supported by Baboo and Devi (2010) who stated that one of the disadvantages of using the nearest neighbour resampling method is that of position errors mostly seen along linear features where it is very easy to note the realignment of pixels.

The images were geometrically corrected using the Root Mean Square Error (RMSE) where it should have to be less than 0.5. RMSE is a measure of the difference between locations that are known and locations that have been interpolated or digitized (Barreto and Howland, 2006). The 1992, 2000, 2006 and 2011 images were geometrically corrected to the 2014 image in ENVI 5.2 Classic using the *Image to Image Registration* function. The term image registration is defined as a process of making an image conform to another image and it incorporates georeferencing which is done when the reference image has already been rectified to a map projection type (Zitova and Flusser, 2003). This process involves overlaying two or more images that are of the same scene and taken at different times from different sensors and /or viewpoints that are different (Zitova and Flusser, 2003). The *Ground Control Points* used for base were from the 2014 image whereas the warp GCP's were for the other four images. The 1992, 2000, 2006 and 2011 images were warped to match the 2014 image. The RMSE was ≤ 0.5 as this is the value regarded as good in terms of image rectification (Jensen, 1996). All the Landsat images were rectified to Universal Transverse Mercator (UTM) projection, World Geodetic System (WGS) 1984 and Zone 36 South for the analysis to be accurate.

3.3.2. Reference Data and Image Classification

Image classification is a process which involves identification of pixels and statistically grouping, seeing if they have similar digital numbers and/or spatial orientation of pixels in order to come up with geographic features that are meaningful (Mesev, 2010). The comparison of pixels that will be done assists and aggregate them into classes which represent information of interest to land managers or researchers (Mas, 1999). The land use and land cover types were categorised using the acquired Landsat images. Supervised classification was used where training and validation samples were obtained in order to develop a classifier which is efficient. Representative samples were selected for each LULC class from the satellite images. The training samples which were collected are for estates, bare land, water bodies, built up areas and forests. The training samples that were collected for each and every class were equal or more than 80 so as to make the classification more efficient. The land cover and land use classification scheme and attributes are shown in table 3 below:

Table 3: Land use and Land cover classification scheme

Land use and land cover classes	Attributes
1. Water bodies	Streams, rivers, ponds, dams and reservoirs
2. Built up areas	Industrial, residential, factories and commercial structures.
3. Bare land	Unvegetated land and exposed rocks. This is the type of land with less ability of supporting life where less than one-third of the area has vegetation or other cover.
4. Estates	Large commercial farms and corporate estates including tea estates and cotton farms
5. Forest	Reserved and protected forest. This type of land has a tree-crown areal density of up to 10% or more and stocked with trees that produce timber and a number of wood products.
6. Agricultural farms	Land that is used for the production of fibre and food primarily. This type of land also includes the ones with commercial and horticultural crops.

Source: Anderson *et al*. (1976)

The classification of the representative samples for land use and land cover was based on the spectral signatures which were defined in the training set. The reference data that was used was obtained from air photographs from Chipinge which covers the years: 1992, 2000 and 2014. Other images that were used were of high-resolution and these covered the years 2006 and 2011. These images were acquired from Google Earth TM (http://earth.google.com) for the ground-truth of LULC classification (Knorn *et al*., 2009; Han *et al.*, 2014).

The Support Vector Machine (SVM) is a non-parametric method of supervised classification which was used in LULC classification (Adam *et al.,* 2014). SVM classifier is a statistical approach where a hyperplane is built in order to separate examples of different classes, maximizing the distance or margin of those examples that lie closer to it (Saez *et al*., 2013).

The longer the distances form the pair class examples to the hyperplane are, the better the generalization achieved (Saez *et al*., 2013). The SVM method was used as it proved to have better performance compared to other classification methods as it determines higher accuracy level, producer accuracy and values of the kappa coefficient (Congalton, 1992). The SVM employs a kernel function to map a set of non-linear decision boundaries in the original dataset into linear boundaries of a higher-dimensional construct (Han *et al.*, 2007).The SVM make a distinction between classes with a decision surface known as the optimal hyper-plane and this increases the variations of the classes (Liu *et al*., 2014). The operation of SVM involves the generation of regions of interest as the training data and the kernel type which consists of radial basis function, polynomial, linear and sigmoid, gamma in kernel function, penalty parameter, pyramid levels and classification probability threshold which are vital in the output of classification (Zhu and Blumberg, 2002). The kernel type commonly used is the radial basis function as it produces better results (Liu *et al*., 2014). In this study, the SVM classification method with radial basis function as the kernel type, gamma in kernel function of 0.143, penalty parameter of 120 and classification probability threshold of 0.05.

The Landsat images that were used in this study are from five different sensors and this had an effect on the spectral responses and band configurations. This problem was solved by developing image-specific classifiers for each Landsat image that was selected, however it is not possible to attain reference data for images that were acquired a long time ago, like MSS data (Han *et al.*, 2014). In this study, the OLI-based classifier for every Landsat image and sensor-associated differences (like spectral responses and wavelengths) between OLI and other sensors were corrected. In the adjustment of the variations between the atmospherically corrected surface reflectance of OLI and other sensors, an empirical line method was used. The surface reflectance of the OLI image in 2014 was used so as to establish the linear relationship between the OLI and other Landsat images (TM and ETM+ SLC on). This was done and the relationship for each band was determined.

3.3.3. Accuracy Assessment

The inclusion of images collected years ago or historical images in analysing LULCC is often affected by unavailability of ground reference data (Witmer, 2008). The images that are classified often have classification errors due to spectral confusion, noise and even weaknesses of classification algorithms (Liu and Cai, 2012). The quality of each classified Landsat image was assessed for post-classification analysis which is meaningful (Lu *et al*., 2004). The main objective was to determine quantitatively how the pixels were grouped effectively into the appropriate feature classes in the area of study. In order to assess the accuracy of LULC maps extracted from Landsat data, a number of stratified random pixels were generated from all the maps. The assessment of LULC maps was done using air photographs for the years: 1992, 2000 and 2014; and Google Earth ™ images for 2006 and 2011. The air photographs went through image enhancement in order to improve their appearance for human visual analysis. The confusion matrix using ground truth regions of interest (ROIs) was constructed to compute the kappa statistic, overall accuracy, producer and user accuracies (Cohen 1960; Congalton and Green 2008; Adam *et al*., 2014). The overall accuracy is a percentage which represents the probability that a randomly selected point is correctly classified on the land use and land cover map (Richards, 2012). The overall accuracy in this study was determined using the following formula:

$$\text{Overall accuracy} = \frac{\Sigma\,(classes\ correctly\ classified\ along\ diagonal)}{\Sigma(Row\ total\ or\ Column\ total)}$$

The producer's accuracy represents the probability that the labelling of the classifier is correct in an image pixel (Richards, 2012). The producer's accuracy also known as the error of omission is determined by dividing the number of correctly classified samples by the reference samples total number. The formula for determining the producer's accuracy is as follows:

$$\text{Producer's accuracy} = \frac{Number\ of\ the\ correctly\ classified\ class\ in\ a\ column}{Verified\ items\ total\ number\ in\ that\ column}$$

The user's accuracy also known as the errors of commission is produced by the division of the correctly classified samples number of the respective class by its total number of verified samples belonging to the class (Richards, 2012). The formula for determining the user's accuracy is as follows:

$$\text{User's accuracy} = \frac{Correctly\ classified\ number\ of\ item\ in\ a\ row}{Verified\ items\ total\ number\ in\ that\ row}$$

The producer and user accuracies were produced so as to show if the error was or was not evenly distributed (Congalton, 1992).

Kappa coefficient which lies between a value of 0 and 1 provides a measure of the difference between the actual agreement and the agreement that would have been expected by chance (Adam *et al.,* 2014). The value of 1 in kappa coefficient shows prefect agreement between classification and ground truth pixels whereas a value of 0 shows no agreement (Dorn *et al*., 2015). The kappa coefficient is calculated using the equation below:

$$\kappa = \frac{N \sum_{i=1}^{n} m_{i,i} - \sum_{i=1}^{n} (G_i \, C_i)}{N^2 - \sum_{i=1}^{n} (G_i \, C_i)}$$

where; $\boldsymbol{i}$ represents the class number, $\boldsymbol{N}$ is the total number of the pixels classified that are being compared to ground truth, $\boldsymbol{m_{i,i}}$ represents the pixels that belong to the ground class $\boldsymbol{i}$, that have also been classified with a class $\boldsymbol{i}$ (refers to the values that are found diagonally in a confusion matrix), $\boldsymbol{C_i}$ represents the number in total of classified pixels that belong to class $\boldsymbol{i}$ and $\boldsymbol{G_i}$ represents the number in total of ground truth pixels that belong to class $\boldsymbol{i}$ (Foody, 2002).

The overall accuracy, kappa coefficient, user and producer accuracies were used to observe the level of accuracy and reliability of the LULC maps produced. The confusion matrix using ground truth ROIs was conducted under post classification tools in ENVI 5.2 software.

3.4. Change Detection

Change detection is known as a process of identifying the differences in a feature's state observing it at dissimilar moments in time (Chen *et al*., 2012). Identification and understanding the nature of change in the use of land resources is essential in the planning, regulation and even the management of their uses (Sunar, 1998). Change detection has a number of aspects in monitoring natural resources which are to detect changes that have occurred, identify nature of change, extent of change and also the spatial pattern of the change (Macleod and Congalton, 1998).

The estimation of change using RS data uses a number of algorithms or techniques (Singh, 1989). These techniques are based on a variety of statistical and/or mathematical relationships, assumptions and principles (Singh, 1989). The algorithms or techniques used include image digitizing, image rationing, image overlay, image regression, principal component analysis, background subtraction, change vector analysis, spectral/temporal classification, vegetation index differencing, image differencing and post classification comparison (Singh, 1989; Sunar, 1998). These techniques have been applied in monitoring changes in various applications and yielded good results though there is no consensus as to which change detection approach is the best (Singh, 1989). Change detection techniques used hugely depends on available data, study area's geography, computing constraints and also the type of application (Lu *et al*., 2004).

The study used the change detection statistics in ENVI 5.2 software which provides a detailed tabulation of LULC changes between two classified images. The change detection statistics give a class for class difference in the images where the earlier image is identified by way of initial state classification and the later image as the final state classification (Canty, 2009). This change detection statistics identified the classes where the pixels changed in the final state image. The changes can be reported in form of pixel counts, percentages or areas (in this study was put in hectares). The change detection statistics were produced between images from 1992-2000; 2000-2006; 2006-2011 and 2011-2014. All the classified images were georeferenced before classification and change detection analysis in order to get results which are accurate. The change detection statistics between 1992 and 2000 images gives LULCC before the FTLRP and those from 2000 to 2014 show the impact of the FTLRP on LULCC. The technique generated four change detection statistics which were assessed. The change detection statistics produced a report containing LULC changes in hectares and percentages. The report had a reference tab with information about the analysis which includes the input images and equivalent class pairings.

The change detection analysis in ENVI 5.2 was utilised for the identification, description and quantification of differences between classified images of the same scene at times or conditions which are different (Hegazy and Kaloop, 2015). The technique signifies all changes found within two respective images. Therefore in the light of this study it enabled the researcher to take note of all the changes that had occurred between the 1992 and 2000 images, 2000 and 2006 images, 2006 and 2011 images and the 2011 and 2014 images.

3.5. Markov Chain Analysis (MCA)

The modelling of future LULCC was done in this study with the use of two techniques. In predicting LULCC changes in the year 2028, Markov Chain Analysis (MCA) and the

Cellular Automata Markov Chain Analysis (CA MCA) were used as shown in figure 2 below. The two techniques were used as they are complementary to each other. Markov Chain Analysis determines the amount of change in the future by using the earlier and later LULC images along with their specified dates (Mishra *et al.,* 2014). This procedure determines precisely the amount of land that would be expected to change from the later date to the predicted date basing it on a projection of the transition potentials into the future where it creates a transition probabilities file (Mishra *et al.,* 2014). This transition probabilities file is known as a matrix that records the probability that each land cover class will transform to every other category (Behera *et al*., 2012).

For LULCC, one may articulate a principle like the one of classical physics: the possibility that the system will be in a specified state at a given time referred to as t_2, may be derived from the knowledge of its state at any earlier time known as t_1, and this is not determined by history of the system before time t_1 i.e. it is a first-order process (Parzen, 1964).

The Markov chain can be expressed as:

$$vt_2 = M \times vt_1$$

where vt_1 is the input land use and land cover proportion column vector whereas vt_2 is known as the output land use and land cover proportion column vector and M is an $m \times m$ transition matrix for the time interval $\Delta t = t_2 - t_1$ (Lambin, 1994). The probability (p^{ij}) of transition between a pair of states is calculated by dividing the cell (n^{ij}) of the change/no change matrix by its row marginal frequency ($n^{i\cdot}$):

$$p^{ij} = n^{ij} / n^{i\cdot}$$

where $ni. = \sum_{j=1}^{q} ni\ j$

In the MCA, the transition probabilities are influenced by the time interval (t) where if the time period at which the process is being looked at is of no relevance, the Markov chain is regarded as homogeneous or stationary in the period observed (Karlin and Taylor, 1975).

The probability or chance of future states for a cell is calculated using the equation:

$$p\ (t) = p\ (t - 1).\ p$$

where p is the probability matrix of n states; t is for time (Serra *et al*., 2008). An increase in the time steps of the Markov process, $p\ (t)$ approaches to limiting distribution which is referred to as the constant probability vector (Weng, 2002).

$$p\ (\infty) = \lim_{t\to\infty} p\ (0).\ p^t$$

The transition matrices were constructed from the change/no change matrices that were acquired from change detection analysis. The processes for modelling were implemented using algorithms supplied with the IDRISI Selva software. The researcher used Markov models were used as they are easy to derive from successional data and do not require deep understanding of the dynamic change system, but it can contribute in specifying areas where such insight would be vital and therefore perform as both a stimulant and guide to further research. (Kau, 2014).

3.5.1. Cellular Automata Markov Model (CA MCA)

The Markov model emphasises on the quantity in LULCC prediction (Sang *et al*., 2011). The spatial parameters for the Markov model are weak and do not show the various types of land use or land cover change in their spatial extents (Wickramasuriya *et al*., 2009). A stochastic model known as CA-Markov was used in this study and it is widely used in the assessment of change in a certain area. The CA Markov model was used in this study to correct the spatial contiguity of the model and produce the 2028 map. The CA models are spatial models with cell as their basis. The cell is affected by its neighbouring cells where it is capable of adopting various states. The CA Markov model which is a combination of the Cellular Automata, Markov Chain, Multi-Criteria Evaluation (MCE) and Multi-Objective Land Allocation (MOLA) prediction method for land cover enhances spatial contiguity and knowledge of the probable transition's spatial distribution to Markov chain analysis (Sayemuzzaman and Jha, 2014). The CA Markov model produces better simulation for both the temporal and spatial patterns of LULCC in space and quantity (Sang *et al*., 2011).

The model is a hybrid of the Cellular Automata (CA) and the Markov chain. The CA is a model which utilises mathematical processes in modelling physical structures and time where space can be distinct in these physical systems (Wolfram, 1998). The CA encompasses the physical space which is characterised by cells where the CA mechanism occurs (Barredo *et* *al*., 2003). It also consists of a cell where the CA mechanism inhabits the neighbourhood surrounding this cell, transition rules that define the CA's performance and the time-based space where the mechanism entirely exists (Li and Yeh, 2000). The mathematical notation for CA is as follows:

$$s^{t+1} = f\,(s^{t}, N)$$

where s is the set of all possible states of CA; *N* represents the neighbourhood of all the cells and *f* is the transition function that defines change from *t* to *t + 1* (Zhang *et al*., 2011).

3.5.2. Simulation with CA Markov Model

The CA Markov utilises a contiguity filter, which is demarcated by the user. The contiguity filter integrates the suitability image of all the classes and is then input into the model. The contiguity rule pixel is used in the Markov model where it applies to a certain LULC class, which will in greatest probability remain the same LULC class as earlier. In this study, a Gaussian 5 x 5 filter size was used for the modelling purposes as illustrated in Figure 2. The filter was then used on the suitability images for each LULC class. The process employed outlined the neighbourhood and the 5 x 5 filtering window controls the pixel's suitability. If the number of pixels with the same class in the same neighbourhood is high then the higher the suitability value of that particular land cover class in that specific area. The pixel remains the same as it was earlier if it is of another class. In the CA MCA, suitability assists in the definition of those pixels, which will alter subject to the highest suitability of each and every LULC class.

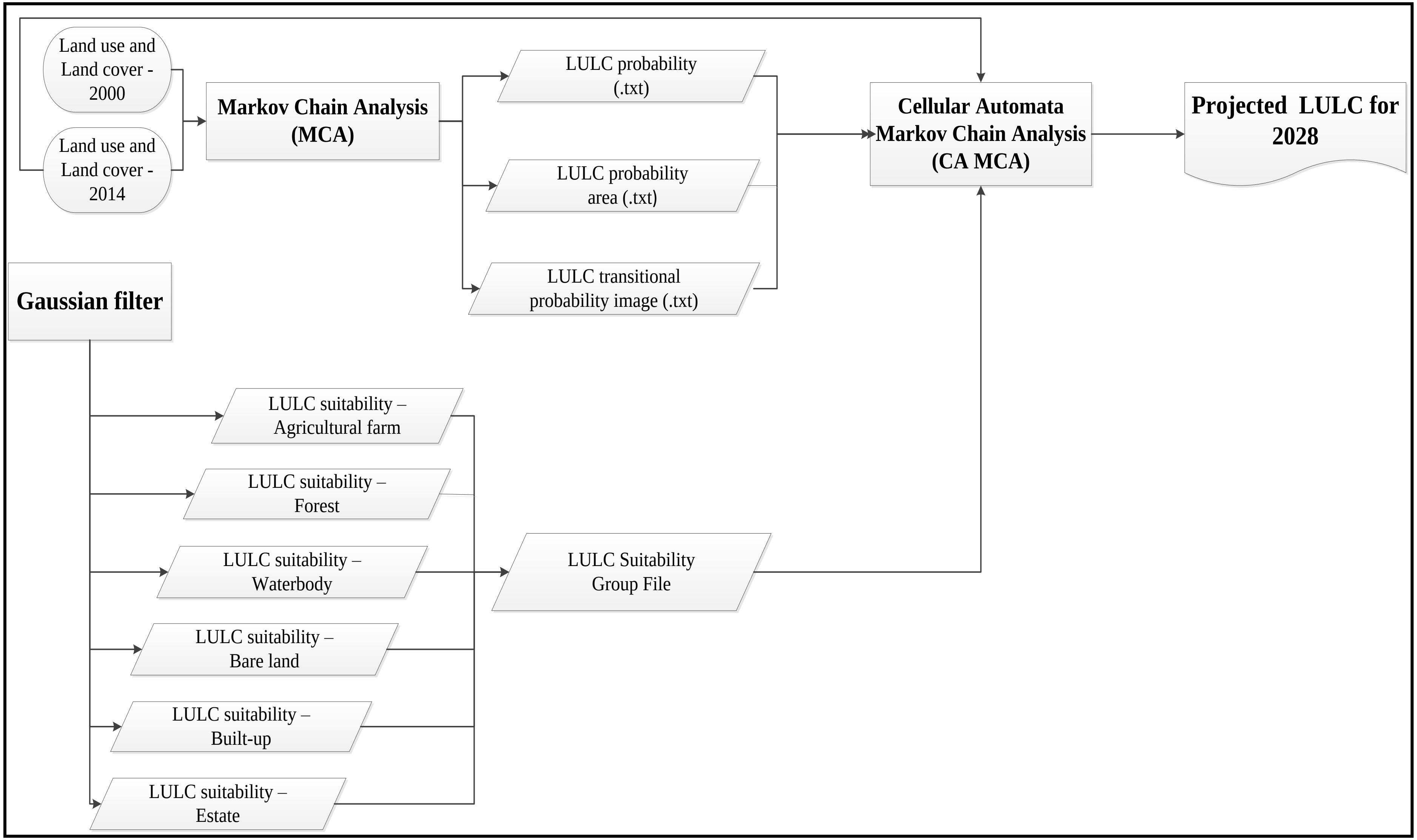

Figure 2: A flow diagram of the Markov Chain Analysis and CA Markov Chain Analysis Modeller

3.5.3. Transitional Probability Mapping

The transitional probability areas that were obtained from the MCA were used as input to the CA Markov module. This was done as the CA Markov module uses cellular automata actions work in combination with MCA and MCE or MOLA. The transition areas file from MCA which was obtained from the Markov module in IDRISI Selva of two LULC maps (2000 and 2014) established the quantity of expecting LULCC from each existing category to any other in the next 14 years. The classified 2014 LULC image was used as the base image and as a starting point for change simulation as shown in figure 2 above. Within each time step, every LULC is considered in turn as a host category. All the other LULC classes act as claimant classes and compete for land (only within the host class) using the MOLA procedure. The area requirements for each and every claimant class within each host were equal to the total established by the transition areas file divided by the number of iterations. The MOLA operation produced results which were overlaid using a COVER operation to come up with a new LULC map at the end of each iteration. The CA Markov module used in this study is the one in IDRISI Selva which incorporates the functions of cellular automaton filter as well as Markov processes, with the use of conversion tables and conditional probability from the conversion map so as to predict the states of LULCC. This makes it better in carrying out LULCC simulations. Figure 3 below shows all the data and steps that were taken in this research.

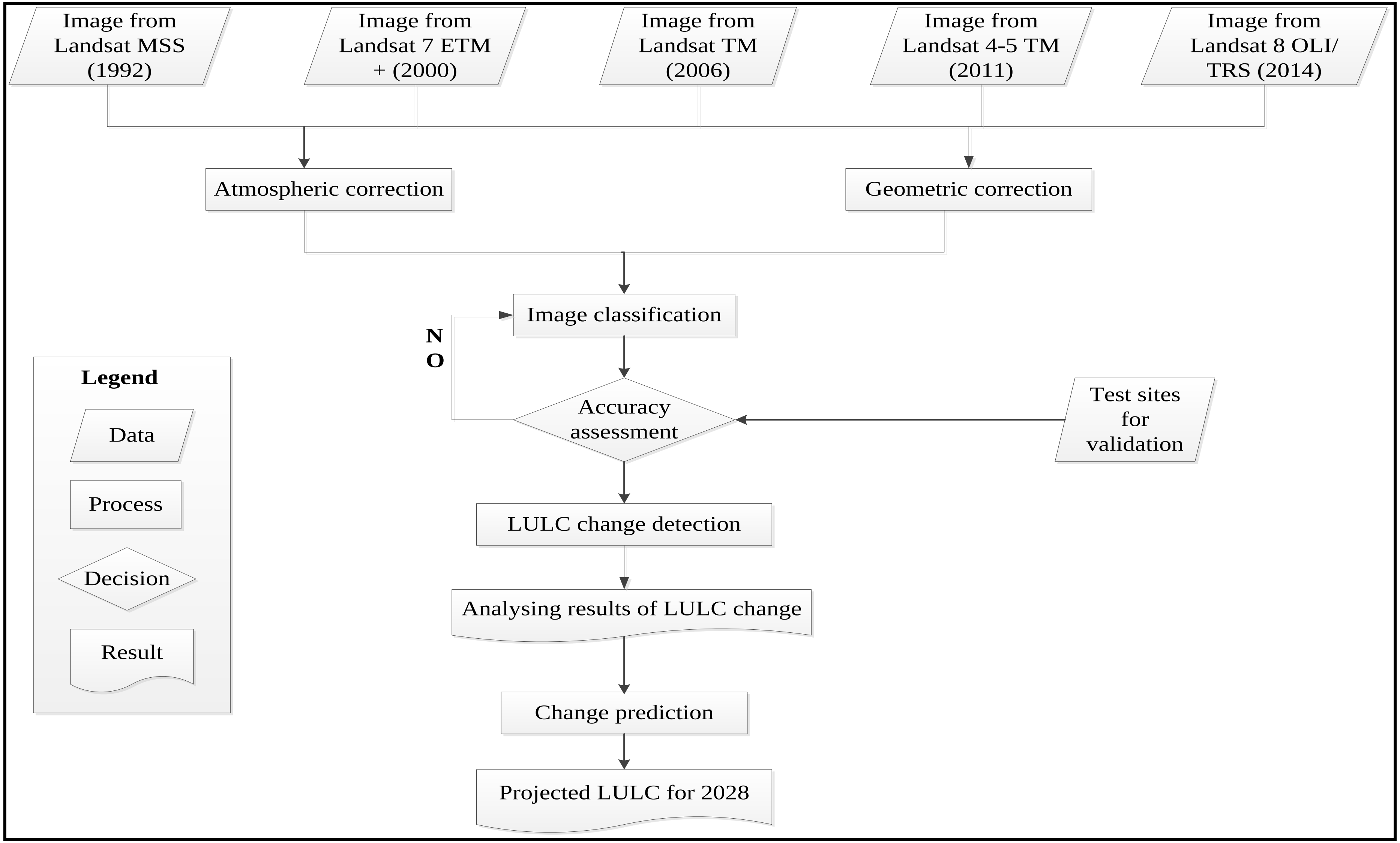

Figure 3: Data steps taken in processing Landsat imagery of Chipinge district

CHAPTER 4 - RESULTS AND DISCUSSION

4.1. Land use and Land Cover Mapping

The LULC map for the year 1992 in figure 4 and the histogram showing LULC classes in figure 5 illustrate that about 36 % of Chipinge district was bare land. It is also illustrated in figure 5 that 2 % of the land was covered by estates, 17 % by forest, 20 % by built-up, 5 % by water bodies and 20 % by agricultural land. The distribution of LULC as shown in the classified map (Figure 4) shows that the distribution of agricultural farms was found in the north and eastern part of the district. These are high rainfall areas which cover agricultural regions I and II where they also have fertile soils. In these areas annual rainfall amount in region I is above 1 000 millimetres and in region II, it is in a range of 750 to 1000 millimetres (Zamuchiya, 2011). The western part of the district and mostly in the south western part had a lot of bare land. These are low veld areas which covers regions III to V. These are areas with little rainfall where they practice livestock farming and the growing of drought resistant crops (Mugandani *et al*., 2012).

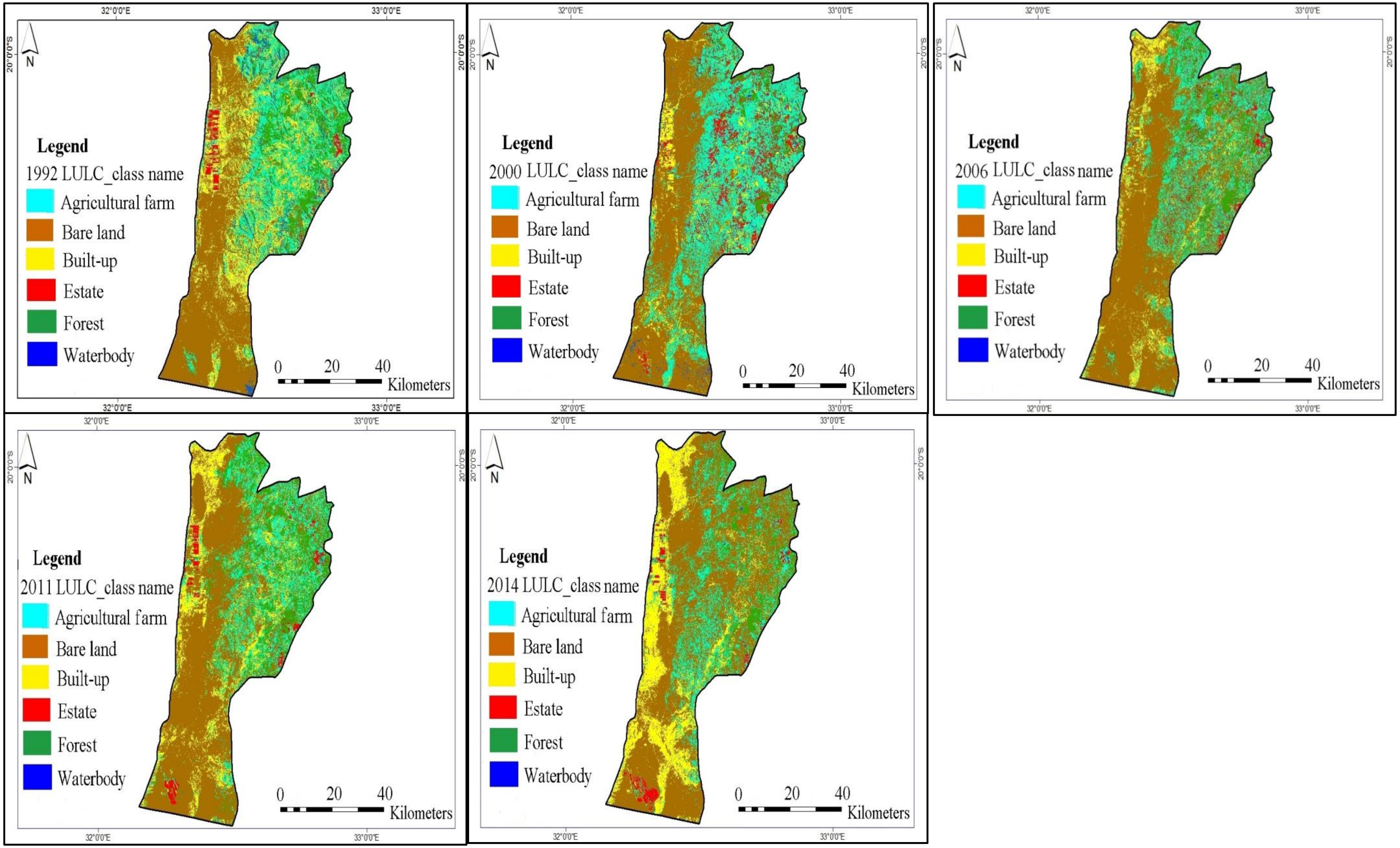

Figure 4: LULC maps for Chipinge district in 1992, 2000, 2006, 2011 and 2014

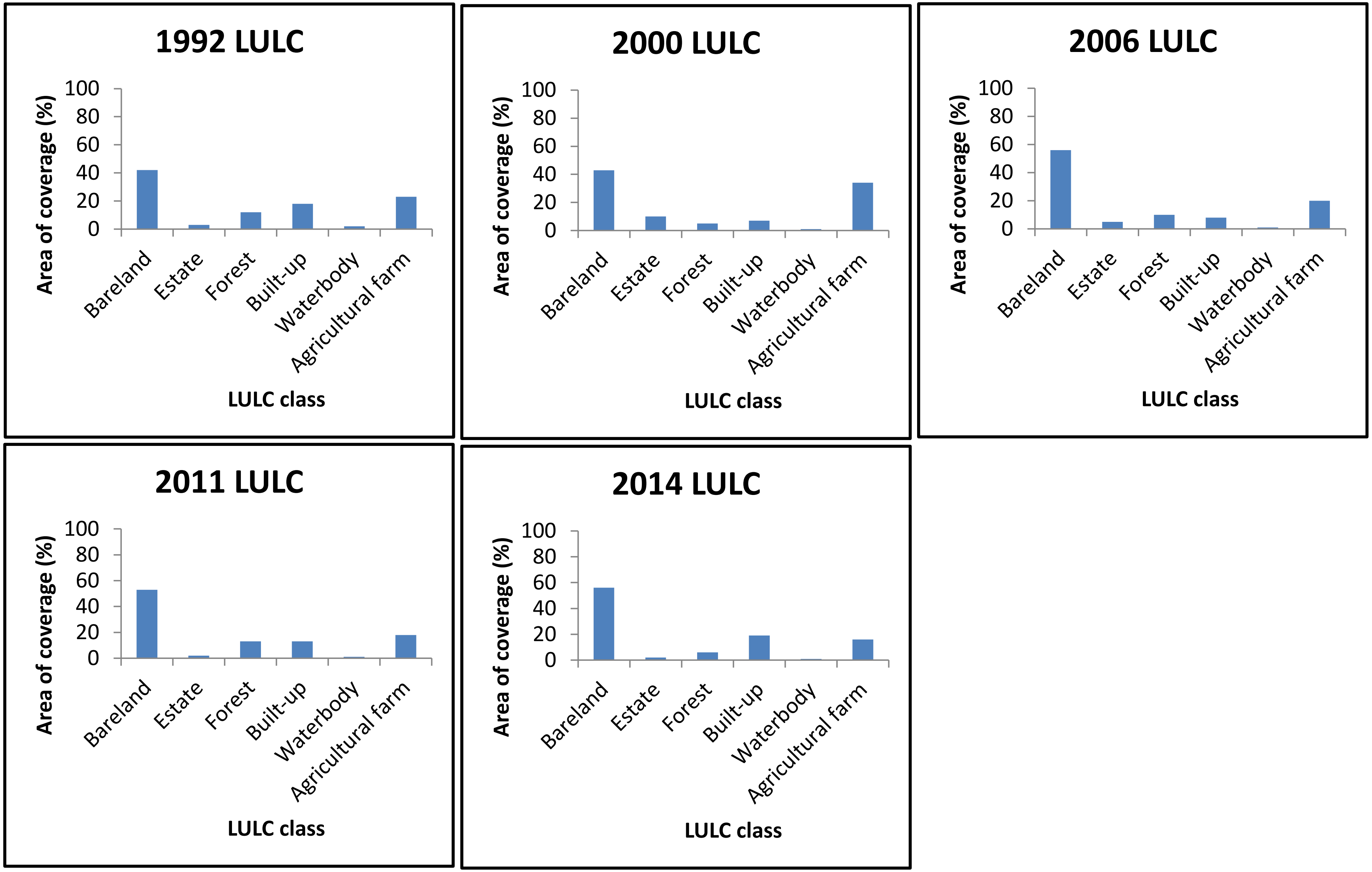

Figure 5: Histograms of LULC coverage for 1992, 2000, 2006, 2011 and 2014

The LULC map of Chipinge district in the year 2000 as shown in figure 4 and the area of coverage (in hectares) in figure 5 show that the district had a lot of bare land which amounted to 45 %. Land area covered by agricultural farms amounted to 23 %, 6 % by estate, 9 % by forest, 15 % by built-up and 2 % by water bodies. During this year there was an increase in the total bare land area as it increased from 36 % in the year 1992 to 45 % in 2000. There was also an increase in the total area covered by agricultural farmlands as they covered 23 % in 2000 from 20% in 1992.

For the year 2006 the LULC map is shown in figure 4 and the area of coverage in percentage is shown in the histogram (Figure 5). It is illustrated that agricultural farms covered 19 % whilst bare land, estate, forest, built-up and water body covered 54 %, 4 %, 10%, 10 % and 3 % of the district’s land respectively. The land covered by agricultural farmland decreased in this year due to the FTLRP where people given the land did not have farm machinery to plough in their farms. There was an increase in the bare land area from 45 % in 1992 to 54 % in 2006 as some agricultural land was now turned into bare land.

The LULC map for the year 2011 as shown in figure 4 and the area of coverage in percentage (figure 5). The histogram (figure 5) illustrates that 15 % of the land was covered by agricultural farms, 2 % by estates, 15 % by forests, 15 % by built-up, 2 % by water bodies and 51 % was bare land. There was a reduction in the percentage of land covered by agricultural farms from 19 % in 2006 to 15 % in 2011. This must be due to the lack of farming equipment amongst the farmers and also the economy of the country where there was high inflation. Most of the agricultural farms were now changing into bare land and built-up. The built-up area’s percentage increased from 10 % in 2006 to 15 % in 2011 due to population increase in the district.

The LULC map of the year 2014 as shown in figure 4 and also the histogram of the LULC coverage in figure 5 illustrates that bare land covered 53 % of Chipinge district in this year. The land covered by agricultural farms was 16 %, 3 % by water bodies, 18 % by built-up, 8 % by forest and 2 % by estate. The distribution of LULC classes as shown in the map (figure 4), agricultural farms were mostly spread in the north-eastern part of the district. It can also be seen that built-up areas were in the north-western part of the district. The north-western part of the district with a lot of built-up structures reflects areas nearer to the farms where people working in the redistributed farms stay. The increase in the built-up areas must also be as a result of population growth in the district as this class also includes households of where people stay.

4.1.1. Accuracy Assessment

Accuracy of each and every Landsat image that was classified using SVM was produced with the use of a confusion matrix done using ENVI 5.2 software. The confusion matrix produced was constructed with the use of ground control points which were not used as training samples in classification. A number of 30 ground control points for each class was used in the validation of the classified image. The ground control points for the years 1992, 2000 and 2014 were derived from air photographs of Chipinge district. The ground control points for the years 2006 and 2011 were derived from Google Earth. The error matrix technique that was used from ground truth data produced a level of accuracy and reliability that meets the 85 % threshold value that is recommended for accuracy assessment (Anderson *et al*., 1976), as illustrated in table 4. The overall accuracy for all the five classified Landsat images ranged from 85.6 % to 93.9 %.

In table 4, when comparing the user and producer accuracies for the different LULC classes, it can be noted that water body has higher value than the other classes meaning there was greater level of accuracy. The agricultural farms class was 56.9 % in the year 2000 which is the lowest producer's accuracy as shown in table 4. The user's accuracy for estate class was the lowest in the year 2000 with a value of 57.7%. The low figures in the estates and the agricultural farms is due to the reason that they looked similar in the images hence spectral reflectance of crops in the agricultural farms is at some point similar to that of plants in estate farms. This caused mixed pixels resulting in misclassification of some pixels and low producer and user accuracies for both the agricultural farms and estate classes. The classification accuracy assessment results in table 4 met the recommended 85 % threshold value (Anderson *et al*., 1976). The lowest overall accuracy of the 1992 Landsat imagery as compared to the other four years can be due to the resampling of the image from 60 meters to 30 meters resolution for consistency with the other images.

Table 4: Confusion matrices for validation of 1992, 2000, 2006, 2010 and 2014 LULC maps

Year	Overall accuracy (%)	Kappa Coefficient	Accuracy type	Agricultural farms (%)	Estate (%)	Water body (%)	Built-up (%)	Forest (%)	Bare land (%)
1992	85.5	0.78	Producer's	73.7	96.7	73.3	72.7	100	96.7
			User's	81.0	72.5	100	95.2	93.8	66.0
2000	85.6	0.79	Producer's	56.9	100	100	76.7	83.3	96.7
			User's	87.5	57.7	100	95.2	100	80.6
2006	88.6	0.82	Producer's	86.7	75.0	100	70.0	100	100
			User's	68.4	81.8	100	100	96.8	77.5
2011	88.8	0.83	Producer's	86.7	84.1	88.6	75.5	97.7	100
			User's	72.2	92.5	100	100	91.3	69.6
2014	93.9	0.92	Producer's	96.7	100	100	66.7	100	100
			User's	100	100	100	100	100	73.2

4.1.2. Summary of Land Use and Land Cover Classes

The LULC maps of Chipinge district were generated and they were for the 5 years analysed in this study which are: 1992, 2000, 2006, 2011 and 2014. The LULC class and their change statistics for all the five years are summarised in table 5 below:

Table 5: Summary of LULC type in Chipinge district for 1992, 2000, 2006, 2011 and 2014.

	1992		**2000**		**2006**		**2011**		**2014**	
LULC class	ha	%	ha	%	ha	%	ha	%	ha	%
BL	188318	42.46	189 574	42.75	247 546	55.82	232 720	52.48	248 467	56.03
ES	12555	2.83	42721	9.63	21 030	4.74	10 610	2.39	9655	2.18
F	46071	10.39	22 675	5.11	45 432	10.24	59 331	13.38	29 365	6.62
BU	71129	16.04	31 044	7.00	34 275	7.73	59 009	13.31	84 039	18.95
WB	13560	3.06	4 253	0.96	615	0.14	291	0.07	600	0.14
AF	111861	25.22	153 209	34.55	94 578	21.33	81 515	18.38	71 350	16.09

Note: BL = Bare land, ES = Estate, F = Forest, BU = Built-up, WB = Water body, AF = Agricultural farm. Percentage figures rounded off to two decimal places.

4.1.3. Change Detection Statistics

In the assessment of LULCC in Chipinge district, change detection statistics between 1992 and 2000, 2000 and 2006, 2006 and 2011 and 2011 and 2014 images were produced. Change was detected by assessing the differences from the specified date on the Landsat image used to another by comparing change in the raster cells. The change was compared on the 1992 - 2000, 2000 - 2006, 2006 – 2011 and the 2011 – 2014 images. The change detection statistics produced a table which shows the initial and the final state. A change matrix was also produced which has data from the initial year in the rows and data from the final year in the columns. The change matrix that was produced shows changes in the classes which indicates total changed areas for each LULC class in the initial stage. The value for class total for the column illustrates the total area for initial stage image of each LULC class whereas the row total shows the final stage for the LULC classes. The image difference value represents the total net change for the two time images. Negative image difference shows a decrease in the state of a certain LULC class whereas positive values demonstrate increment. The class change indicates the total areas of each land use or land cover class that was transformed in to another LULC type.

The change detection matrix of LULC types in Chipinge district between 1992 and 2000 in hectares is shown in table 6. Table 7 shows the change detection matrix between 1992 and 2000 in percentages. The areas which are in bold are areas that did not change within the period of initial and final state.

Table 6: Change detection matrix of LULC types in Chipinge district between 1992 and 2000 in hectares (ha)

Year		1992 (Initial State)						
2000 (Final State)	Class name	BL	ES	F	BU	WB	AF	Row Total
	BL	**143085**	1865	1066	30827	2093	10658	189443
	ES	2321	**2545**	14771	1253	2798	19023	42697
	F	823	139	**13355**	350	4859	3154	22650
	BU	12800	3065	876	**8337**	81	5945	31031
	WB	2384	45	285	233	**698**	611	4247
	AF	26905	4896	15718	30129	3030	**72469**	153081
	Class Total	188318	12555	46071	71129	13559	111860	
	Class Changes	45384	10023	32745	62865	12871	39457	
	Image Difference	1256	30167	-23395	-40085	-9307	41348	

Note: BL = Bare land, ES = Estate, F = Forest, BU = Built-up, WB = Water body, AF = Agricultural farm.

Table 7: Change detection matrix of LULC types in Chipinge district between 1992 and 2000 in percentage (%)

Year		1992 (Initial State)					
2000 (Final State)	Class name	BL	ES	F	BU	WB	AF
	BL	**76.00**	14.86	2.31	43.34	15.44	9.53
	ES	1.23	**20.27**	32.06	1.76	20.64	17.01
	F	0.44	1.11	**28.99**	0.49	35.83	2.82
	BU	6.80	24.41	1.90	**11.72**	0.60	5.31
	WB	1.27	0.36	0.62	0.33	**5.15**	0.55
	AF	14.29	39.00	34.12	42.36	22.34	**64.79**
	Class Total	100	100	100	100	100	100
	Class Changes	24.10	79.83	71.08	88.38	94.92	35.27
	Image Difference	1256	30167	-23395	-40085	-9307	41348

Note: BL = Bare land, ES = Estate, F = Forest, BU = Built-up, WB = Water body, AF = Agricultural farm.

As shown in table 6, the image difference for bare land, estate and agricultural farm increased by 1 256, 30 167 and 41 348 ha respectively. It is also illustrated in the table that forest, built-up and water body decreased by 23 395, 40 085 and 9307 ha respectively.

As shown in table 6 and 7 above, the agricultural farm class had a total of 111 860 ha (100 %) by the year 2000 and 72 469 ha (64.79 %) did not change within the period from 1992 to 2000. It is shown that most agricultural farmland was transformed into estate land with a value of 19 023 ha (17.01 %). The second highest transformation was the one into bare land with a value of 10 658 ha (9.53 %). The class changes for agricultural farmland to other LULC classes amounted to 39 457 ha (35.27 %). Some of the agricultural farmland was transformed to forest land (3 154 ha), built up (5 945 ha) and water body (611 ha). This was converted into percentage as shown in table 7 where agricultural farmland transformed into forest is 2.82 %, built up (5.32 %) and water body (0.55 %).

Of the 188 318 ha that were bare land in 1992, only 143 085 ha did not change by the year 2000. This is also shown in table 7 that of the 100 % of bare land in 1992, 76 % did not change by the year 2000. It is shown that the class changes for bare land to other LULC classes amounted to 45 384 ha (24.10 %). Most of the bare land transformed into agricultural farmland with a value of 26 905 ha (14.29 %) whilst the least transformation was into forest where it had a value of 823 ha (0.44 %). Bare land also transformed into estate, built-up and water body with values of 2 321 ha (1.23 %), 12 800 ha (6.80 %) and 2 384 ha (1.27 %) respectively.

As shown in table 6 and table 7, land covered by estates was an area of 12 555 ha (100 %) where 2 545 ha (20.27 %) did not change between the period 1992 and 2000. It is illustrated that the class changes for estate to other LULC classes was 10 023 ha (79.83 %). Within the period of 1992 and 2000, land covered by estate transformed into bare land, forest, built-up, water body and agricultural farmland with values of 1 865 ha (14.86 %), 139 ha (1.11 %), 3 065 ha (24.41 %), 45 ha (0.36 %) and 4 896 ha (39.00 %) respectively. The greatest transformation of estate was into agricultural farmland with a value of 4 896 ha (39.00 %) and the lowest was into water body with a value of 45 ha (0.36 %) between 1992 and 2000.

The land that was covered by built-up had a total area of 71 129 ha (100 %) where 8 337 ha (11.72 %) did not change between the period 1992 and 2000 as shown in table 6 and table 7. It was observed that the class changes for built-up to other LULC classes amounted to 62 865 ha (88.38 %). Within the period of 1992 and 2000, land covered by built-up transformed into bare land, estate, forest, water body and agricultural farmland with values of 30 827 ha (43.34 %), 1 253 ha (1.76 %), 350 ha (0.49 %), 233 ha (0.33 %) and 30 129 ha (42.36 %) respectively. It can be noted in table 6 and table 7 that the greatest transformation of built-up land was into bare land with a value of 30 827 ha (43.34 %) whilst the lowest transformation was into water body with a value of 233 ha (0.33 %).

Water bodies covered an area of 13 559 ha (100%) in 1992 where 698 ha (5.15 %) did not change from the year 1992 to 2000. The class changes for water body to other LULC classes were 12 871 ha (94.92 %). The land covered by water bodies transformed into bare land, estate, forest, built-up and agricultural farmland with values of 2 093 (15.44 %), 2 798 ha (20.64 %), 4859 ha (35.83 %), 81 ha (0.60 %) and 3 030 ha (22.34 %) respectively. The greatest transformation for water body was into forest with a value of 4 859 ha (35.83 %) and the lowest was into built-up with a value of 81 ha (0.60 %) between 1992 and 2000.

The change detection matrix of LULC types in Chipinge district between 2000 and 2006 in hectares is shown in table 8 below. Table 9 as illustrated below shows the change detection matrix between 2000 and 2006 in percentages.

Table 8: Change detection matrix of LULC types in Chipinge district between 2000 and 2006 in hectares (ha)

Year		**Initial State (2000)**						
2006 (Final State)	Class	BL	ES	F	BU	WB	AF	Row Total
	BL	**157945**	6568	3032	18434	2372	59194	247546
	ES	337	**8926**	1106	355	68	10239	21030
	F	2498	16202	**15475**	198	739	10320	45432
	BU	17274	447	60	**7254**	98	9142	34275
	WB	28	6	14	6	**554**	8	615
	AF	11492	10572	2988	4797	421	**64305**	94577
	Total	189574	42721	22675	31044	4252	153209	
	Class Changes	31629	33796	7200	23790	3699	88904	
	Image Difference	57972	-21691	22757	3231	-3637	-58632	

Note: BL = Bare land, ES = Estate, F = Forest, BU = Built-up, WB = Water body, AF = Agricultural farm.

Table 9: Change detection matrix of LULC types in Chipinge district between 2000 and 2006 in percentage (%)

Year		Initial State (2000)						
2006 (Final State)	Class	BL	ES	F	BU	WB	AF	Row Total
	BL	**83.32**	15.37	13.37	59.38	55.78	38.64	247546
	ES	0.18	**20.89**	4.88	1.14	1.61	6.68	21030
	F	1.32	37.93	**68.25**	0.64	17.37	6.74	45432
	BU	9.11	1.05	0.27	**23.37**	2.31	5.97	34275
	WB	0.02	0.01	0.06	0.02	**13.02**	0.01	615
	AF	6.06	24.75	13.18	15.45	9.91	**41.97**	94577
	Total	100	100	100	100	100	100	
	Class Changes	16.68	79.11	31.75	76.63	86.98	58.03	
	Image Difference	30.58	-50.77	100.36	10.41	-85.53	-38.27	

Note: BL = Bare land, ES = Estate, F = Forest, BU = Built-up, WB = Water body, AF = Agricultural farm.

Table 8 and table 9 show the transformations of LULC types between the year 2000 and 2006. Table 8 shows the transformation in hectares whereas table 9 shows transformation in percentage. Table 8 shows that estate, water body and agricultural farmland decreased by 21 691, 3 637 and 58 632 ha respectively. This decrease is shown in percentage in table 9 where for estate is 50.77 %, water body (85.33 %) and agricultural farm (38.27 %). Bare land, forest and built up land increased by 57 972 ha (30.58 %), 22 757 ha (100.36 %) and 3 231 ha (10 .41 %).

Table 8 and 9 show that most agricultural farmland transformed into bare land with a value of 59 194 ha (38.64 %) followed by forest which was 10 320 ha (6.74 %). It is shown that the class changes for agricultural farmland to other LULC classes amounted to 88 904 ha (58.03 %). Agricultural farmland also transformed to estate (10 239 ha), built up (9 142 ha) and water body (8 ha). This was converted into percentage as shown in table 9, where the agricultural farmland which transformed into estate was 6.68 %, built up (5.97 %) and water body (0.01%). It is also shown that of the 153 209 ha (100 %) of agricultural farmland in 2 000, a value of 64 305 ha (41.97 %) did not change between the 2000 and 2006 period.

It is shown in table 8 and table 9 that of the total value of 189 574 ha (100 %) for bare land in the year 2000, 157 945 ha (83.32 %) did not change by the year 2006. It is illustrated that the class changes for bare land to other LULC classes amounted to 31 629 ha (16.68 %). The amount of bare land that transformed into estate, forest, built-up, water body and agricultural farmland was 337 ha (0.18 %), 2 498 ha (1.32 %), 17 274 ha (9.11 %), 28 ha (0.02 %) and 11 492 ha (6.06 %) respectively. This indicates that a large amount of bare land transformed into built-up land with a value of 17 274 ha (9.11 %) whilst the least transformation was from bare land to water body with a value of 28 ha (0.02 %) between the period of 2000 and 2006.

Land covered by estates covered an area of 42 721 ha (100 %) where 8 926 ha (20.89 %) did not change between the period 2000 and 2006 as shown in table 8 and table 9. It is illustrated that the class changes for estate to other LULC classes amounted to 33 796 ha (79.11 %). Within the period of 2000 and 2006, land covered by estate transformed into bare land, forest, built-up, water body and agricultural farmland with values of 6 568 ha (15.37 %), 16 202 ha (37.93 %), 447 ha (1.05 %), 6 ha (0.01 %) and 10 572 ha (24.75 %) respectively. The greatest transformation of estate was into forest with a value of 16 202 ha (37.93 %) and the lowest was into water body with a value of 6 ha (0.01 %) between 2000 and 2006.

As shown in table 8 and table 9, the land that was covered by forest covered an area of 22 675 ha (100 %) where 15 475 ha (68.25 %) did not change between the period 2000 and 2006. These show that the class changes from forest to other LULC classes amounted to 7 200 ha (31.75 %). Within the period of 2000 and 2006, land covered by forest transformed into bare land, estate, built-up, water body and agricultural farmland with values of 3 032 ha (13.37 %), 1 106 ha (4.88 %), 60 ha (0.27 %), 14 ha (0.06 %) and 2 988 ha (13.18 %) respectively. The greatest transformation of forestry was into bare land with a value of 3 032 ha (13.37 %) and the lowest was into water body with a value of 14 ha (0.06 %).

Land covered by built-up had an area of 31 044 ha (100 %) where 7 254 ha (23.37 %) did not change between the period 2000 and 2006 as shown in table 8 and table 9. It is shown that the class changes for built-up to other LULC classes amounted to 23 790 ha (76.67 %). Within the period of 2000 and 2006, land covered by built-up transformed into bare land, estate, forest, water body and agricultural farmland with values of 18 434 ha (59.38 %), 355 ha (1.14 %), 198 ha (0.64 %), 6 ha (0.02 %) and 4 797 ha (15.45 %) respectively.

It is shown in table 8 and table 9 that land covered with water body was 4 252 ha (100%) where 554 ha (13.02 %) did not change from the year 2000 to 2006. The class changes for water body to other LULC classes was 3 699 ha (86.98 %). The land covered by water bodies transformed into bare land, estate, forest, built-up and agricultural farmland with values of 2 372 (55.78 %), 68 ha (1.61 %), 739 ha (17.37 %), 98 ha (2.31 %) and 421 ha (9.91 %) respectively. The greatest transformation of water bodies was into bare land with a value of 2 372 ha (55.78 %) and the lowest was into estate with a value of 68 ha (1.61 %) between 2000 and 2006.

The change detection matrix of LULC types in Chipinge district between 2006 and 2011 in hectares is shown in table 10 below. Table 11 below shows the change detection matrix between 2006 and 2011 in percentage.

Table 10: Change detection matrix of LULC types in Chipinge district between 2006 and 2011 in hectares (ha)

Year		**Initial state (2006)**						
2011 (Final State)	Class	BL	ES	F	BU	WB	AF	Row Total
	BL	**190527**	1899	6095	8277	95	25825	232718
	ES	3500	**3622**	1560	558	7	1363	10610
	F	5785	6995	**33581**	99	184	12686	59330
	BU	28684	299	229	**21845**	40	7912	59009
	WB	23	0	0	2	**265**	1	291
	AF	19027	8214	3968	3492	24	**46789**	81514
	Class Total	247526	21030	45432	34275	615	94577	
	Class Changes	57019	17408	11852	12430	350	47787	
	Image Difference	-14827	-10421	13898	24734	-324	-13061	

Note: BL = Bare land, ES = Estate, F = Forest, BU = Built-up, WB = Water body, AF = Agricultural farm.

Table 11: Change detection matrix of LULC types in Chipinge district between 2006 and 2011 in percentage (%)

Year		Initial state (2006)					
2011 (Final State)	Class	BL	ES	F	BU	WB	AF
	BL	**76.97**	9.03	13.42	24.15	15.42	27.31
	ES	1.41	**17.22**	3.43	1.63	1.08	1.44
	F	2.34	33.26	**73.91**	0.29	29.96	13.41
	BU	11.59	1.42	0.50	**63.74**	6.54	8.37
	WB	0.01	0	0	0.01	**43.10**	0.001
	AF	7.69	39.06	8.73	10.19	3.89	**49.47**
	Class Total	100	100	100	100	100	100
	Class Changes	23.03	82.78	26.09	36.26	56.90	50.53
	Image Difference	-5.99	-49.55	30.59	72.17	-52.7	-13.81

Note: BL = Bare land, ES = Estate, F = Forest, BU = Built-up, WB = Water body, AF = Agricultural farm.

Table 10 and table 11 above show the transformations of LULC types between the year 2006 and 2011. Table 10 shows that bare land, estate and water body and agricultural farmland decreased by 14 827 ha, 10 421 ha and 324 ha respectively. This decrease is shown in percentage in table 11 where the decline for bare land is 5.99 %, estate (49.55 %), water body (52.7 %) and agricultural farm (13.81 %). Forest and built up land increased by 13 898 ha (30.59 %), and 24 734 ha (72.17 %) respectively.

It is illustrated in table 10 and 11 that most agricultural farmland transformed to bare land with a value of 25 825 ha (27.31 %) followed by forestry which was 12 686 ha (13.41 %). Agricultural farmland also transformed to estate (1 363 ha), built up (7 912 ha) and water body (1 ha). This was converted into percentage as shown in table 11 where agricultural farmland which transformed into estate is 1.08 %, built up (8.37 %) and water body (0.001%). The class changes for agricultural farmland to other LULC classes amounted to 47 787 ha (50.53 %). It is also shown that of the total 94 577 ha (100 %) of agricultural farmland in 2006, a value of 46 789 ha (49.47 %) did not change between the 2006 and 2011 period.

In table 10 and table 11 above the total value of 247 526 ha (100 %) for bare land in the year 2006, 190 527 ha (76.97 %) did not change by the year 2011. It is demonstrated that the class changes for bare land to other LULC classes amounted to 57 019 ha (23.03 %). The amount of bare land that transformed into estate, forest, built-up, water body and agricultural farmland was 3 500 ha (1.41 %), 5 785 ha (2.34 %), 28 684 ha (11.59 %), 23 ha (0.0.1 %) and 19 027 ha (7.69 %) respectively. This indicates that a large amount of bare land transformed into built-up land with a value of 28 684 ha (11.59 %) whilst the least transformation was from bare land to water body with a value of 23 ha (0.01 %) between the period of 2006 and 2011.

The land covered by estates in 2006 covered an area of 21 030 ha (100 %) where 3 622 ha (17.22 %) did not change between the period 2006 and 2011 as shown in table 10 and table 11. It is shown that the class changes for estate to other LULC classes amounted to 17 408 ha (82.78 %). Land covered by estates transformed into bare land, forest, built-up, water body and agricultural farmland with values of 1 899 ha (9.03 %), 6 995 ha (33.26 %), 299 ha (1.42 %), 0 ha (0 %) and 8 214 ha (39.06 %) respectively. The greatest transformation of land covered by estates within the period of 2006 to 2011 was to agricultural farmland with a value of 8 214 ha (39.06 %) and the lowest transformation was to water body with 0 ha (0%) as shown in table 10 and 11.

As illustrated in table 10 and table 11, the land that was covered by forest covered an area of 45 432 ha (100 %) where 33 581 ha (73.91 %) did not change between the period 2006 and 2011. It is also shown that between 2006 and 2011, the class changes for forest to other LULC classes amounted to 11 852 ha (26.09 %). Within the period of 2006 and 2011, land covered by forest transformed into bare land, estate, built-up, water body and agricultural farmland with values of 6 095 ha (13.42 %), 1 560 ha (3.43 %), 229 ha (0.50 %), 0 ha (0 %) and 3 968 ha (8.73 %) respectively. The greatest transformation of forest was into bare land with a value of 6 095 ha (13.42 %) and the lowest was into water body with a value of 0 ha (0 %).

Table 10 and table 11 show that land covered by built-up was an area of 34 275 ha (100 %) where 21 845 ha (63.74 %) did not change between the period 2006 and 2011. It is also shown that the class changes for built-up to other LULC classes amounted to 12 430 ha (36.26 %). Within this period, land covered by built-up transformed into bare land, estate, forest, water body and agricultural farms with values of 8 277 ha (24.15 %), 558 ha (1.63 %), 99 ha (0.29 %), 2 ha (0.01 %) and 3 492 ha (10.19 %) respectively. There was greater transformation from built-up to bare land with a value of 8 277 ha (24.15 %) whilst the lowest was into water body with a value of 2 ha (0.01 %).

Water bodies covered land of a value of 615 ha (100%) where 265 ha (43.10 %) did not change from the year 2006 to 2011as shown in table 10 and 11. The class changes from water body to other LULC classes were 350 ha (56.90 %). The land covered by water bodies transformed into bare land, estate, forest, built-up and agricultural farmland with values of 95 ha (15.42 %), 7 ha (1.08 %), 184 ha (29.96 %), 40 ha (6.54 %) and 24 ha (3.89 %) respectively. The greatest transformation for water body was into forest with a value of 184 ha (29.96 %) and the lowest was into estate with a value of 7 ha (1.08 %) between 2006 and 2011.

The change detection matrix of LULC types in Chipinge district between 2011 and 2014 in hectares is shown in table 12 below. Table 13 as illustrated below shows the change detection matrix between 2011 and 2014 in percentage.

Table 12: Change detection matrix of LULC types in Chipinge district between 2011 and 2014 in hectares (ha)

Year		**Initial state (2011)**						
2014 (Final State)	Class	BL	ES	F	BU	WB	AF	Row Total
	BL	**168068**	1298	19959	18293	17	40832	248467
	ES	2310	**4597**	706	610	0	1432	9655
	F	1305	1421	**25357**	26	0	1257	29366
	BU	45201	923	142	**35335**	3	2434	84038
	WB	41	2	256	15	**271**	14	599
	AF	15794	2368	12910	4730	0	**35547**	71349
	Class Total	232719	10610	59331	59009	291	81515	
	Class Changes	64651	6013	33974	23674	20	45968	
	Image Difference	15748	-955	-29966	25030	309	-10166	

Note: BL = Bare land, ES = Estate, F = Forest, BU = Built-up, WB = Water body, AF = Agricultural farm.

Table 13: Change detection matrix of LULC types in Chipinge district between 2011 and 2014 in percentage (%)

Year		Initial state (2011)					
2014 (Final State)	Class	BL	ES	F	BU	WB	AF
	BL	**72.22**	12.24	33.64	31.00	5.75	50.09
	ES	0.99	**43.33**	1.19	1.03	0	1.76
	F	0.56	13.39	**42.74**	0.04	0	1.54
	BU	19.42	8.70	0.24	**59.88**	1.14	2.99
	WB	0.02	0.02	0.43	0.03	**93.11**	0.02
	AF	6.79	22.32	21.76	8.02	0	**43.61**
	Class Total	100	100	100	100	100	100
	Class Changes	27.78	56.67	57.26	40.12	6.90	56.39
	Image Difference	6.77	-9.00	-50.51	42.42	106.09	-12.47

Note: BL = Bare land, ES = Estate, F = Forest, BU = Built-up, WB = Water body, AF = Agricultural farm.

The transformations of LULC types between the year 2011 and 2014 is shown in table 12 and table 13. Table 12 shows that there was a decrease in the amount of land used or covered by estate, forest and agricultural farms where they declined by 955 ha, 29 966 ha and 10 166 ha respectively. This decrease is shown in percentage in table 13 where for estate is – 9 %, forest (- 50.51 %) and agricultural farm (-12.47 %). Bare land, built-up and water body increased by 15 748 ha (6.77 %), 25 030 ha (42.42 %) and 309 ha (106.09 %) respectively.

As shown in table 12 and 13, most agricultural farmland transformed into bare land with a value of 40 832 ha (50.09 %) followed by built-up which was 2 434 ha (2.99 %). Agricultural farmland also transformed to estate (1 432 ha), forest (1 257 ha) and water body (14 ha). This was converted into percentage as shown in table 13 where agricultural farmland that transformed into estate is 1.76 %, forest (1.54 %) and water body (0.02 %). The class changes for agricultural farmland to other LULC classes amounted to 45 968 ha (56.39 %). It is also shown that of the total 81 515 ha (100 %) of agricultural farmland in 2011, a value of 35 547 ha (43.61 %) did not change between the 2011 and 2014 period.

As illustrated in table 12 and table 13, the total value for bare land was 232 719 ha (100 %) in the year 2011 and 168 068 ha (72.22 %) did not change till the year 2014. The class changes for bare land to other LULC classes amounted to 64 651 ha (27.78 %). The amount of bare land which transformed into estate, forest, built-up, water body and agricultural farmland was 2 310 ha (0.99 %), 1 305 ha (0.56 %), 45 201 ha (19.42 %), 41 ha (0.02 %) and 15 794 ha (6.79 %) respectively. This indicates that a large amount of bare land transformed into built-up land with a value of 45 201 ha (19.42 %) whilst the least transformation was into water body with a value of 41 ha (0.02 %) between the period of 2011 and 2014.

The total land covered by estates was an area of 10 610 ha (100 %) where 4 597 ha (43.33 %) did not change between the period 2011 and 2014 as shown in table 12 and table 13. It can be noted that the class changes for estates to other LULC classes amounted to 6 013 ha (56.67 %). Land covered by estates also transformed into bare land, forest, built-up, water body and agricultural farmland with values of 1 298 ha (12.24 %), 1 421 ha (13.39 %), 923 ha (8.70 %), 2 ha (0.02 %) and 2 368 ha (22.32 %) respectively. Large amount of land covered by estates transformed into agricultural farmland with a value of 2 368 ha (22.32%) whilst the lowest transformation was to water body which was 2 ha (0.02 %).

In table 12 and table 13, it can be seen that forest covered an area of 59 331 ha (100 %) where 25 357 ha (42.74 %) did not change between 2011 and 2014. It can be noted that during this period, the class changes for forest to other LULC classes amounted to 33 974 ha (57.26 %). Land covered by forest transformed into bare land, estate, built-up, water body and agricultural farmland with values of 19 959 ha (33.64 %), 706 ha (1.19 %), 142 ha (0.24 %), 256 ha (0.43 %) and 12 910 ha (21.76 %) respectively. The largest value of transformation was that of forest into bare land with a value of 19 959 ha (33.64 %) and the lowest was into built-up with a value of 142 ha (0.24 %).

The land covered by built-up in 2011 was 59 009 ha (100 %) where 35 335 ha (59.88 %) did not change between the period 2011 and 2014 as shown in table 12 and table 13. It can be noted that the class changes for built-up to other LULC classes amounted to a value of 23 674 ha (40.12 %). During the period of 2011 and 2014, land covered by built-up transformed into bare land, estate, forest, water body and agricultural farmland with values of 18 293 ha (31.00 %), 610 ha (1.03 %), 26 ha (0.04 %), 15 ha (0.03 %) and 4 730 ha (8.02 %) respectively. It is clear that the most significant transformation of built-up was to bare land with a value 18 293 ha (31.00 %) and the lowest was to water body with a value of 15 ha (0.03 %).

Water bodies covered land of a value of 291 ha (100 %) where 271 ha (93.11 %) did not change from the year 2011 to 2014 as shown in table 12 and table 13. The class change for the water body class to other LULC classes was 20 ha (6.90 %). The land covered by water bodies transformed into bare land, estate, forest, built-up and agricultural farmland with values of 17 ha (5.75 %), 0 ha (0 %), 0 ha (0 %), 3 ha (1.14 %) and 0 ha (0 %) respectively. The greatest transformation for water body was into bare land with a value of 17 ha (5.75 %). The lowest can be observed in table 12 and table 13 that it was from water body to estate, forest and agricultural farmland where all the values were 0 ha (0%).

4.2. Evaluating Future LULC Changes in Chipinge District using Cellular Automata Markov Chain Analysis (CA MCA) Modeller

The modelling of future LULCC was done using the MCA and the CA MCA. The MCA modeler was used to predict the future scenarios of LULC changes based on the state of the changes observed in 2014 and the transitional probability areas between 2000 and 2014. Both the transitional probability area and the spatial transitional probabilities as shown in figure 2 were used as input to the CA MCA module where the 2014 LULC image was used as the base image.

The conditional probabilities for estate, built-up, bare land, waterbody, forest and agricultural farmland were calculated using the images from when the FTLRP was enacted in 2000 up to the year 2014. The conditional change probabilities as shown in table 14 below indicate varying probabilities of changing for all land use and land covers. Bare land and forest showed high probabilities of remaining unchanged (53 and 43 % respectively). It is also shown that the highest probability of agricultural farmland transition was to estate with a value of 30 %. Waterbody recorded the lowest probability of transition (0 %) into any other LULC with a value of 9 % remaining unchanged.

Table 14: Conditional probability of LULC class changing to any other classes

Conditional probability of being any other class						
Given probability of transitioning to:	**ES**	**BU**	**BL**	**WB**	**F**	**AF**
ES	**0.06**	0.03	0.38	0.00	0.23	0.30
BU	0.05	**0.35**	0.49	0.00	0.01	0.10
BL	0.02	0.36	**0.53**	0.00	0.01	0.07
WB	0.04	0.05	0.67	**0.09**	0.08	0.07
F	0.01	0.01	0.43	0.00	**0.43**	0.12
AF	0.01	0.10	0.61	0.00	0.04	**0.24**

Note: BL = Bare land, ES = Estate, F = Forest, BU = Built-up, WB = Water body, AF = Agricultural farm.

4.2.1. Spatial Distribution of Probabilities for LULCC

The spatial distribution of transitional probabilities as illustrated in figure 6 below shows the probability of each cell changing to any other LULC classes. The spread of transitional probabilities decreased as the distance from the feature class increased. The probability of a cell that is currently occupied by forest being waterbody after 14 years will be high in cells already occupied by forest than in cells occupied by waterbodies, estate, agricultural farmland, built-up and bare land, and the probability will decrease as the distance from the forest land increases. Figure 6 below shows the spatial distribution of transitional probabilities of all the LULC classes that were used in this study. These LULC classes are: estate, built-up, bare land, waterbody, forest and agricultural farmland.

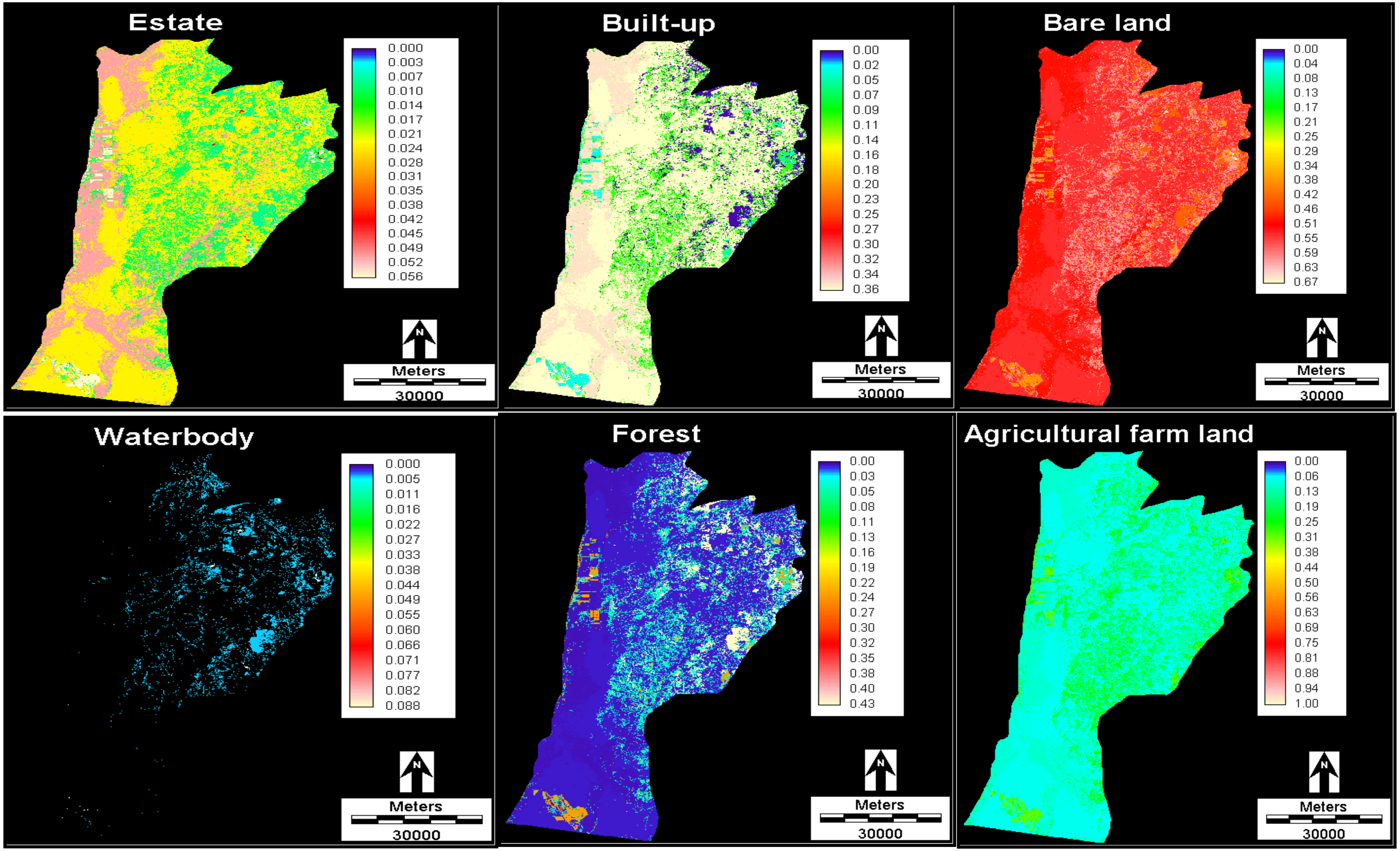

Figure 6: Spatial distribution of transitional probabilities of each LULC class.

High probabilities were observed in bare land transitioning to waterbody and agricultural farmland with values of 67 % and 61 % respectively as shown in table 14. The high probability of transition of bare land into waterbody will happen as a result of water sources such dams and rivers expanding into nearby areas by the year 2028. Bare land has also a high transition value into agricultural farmland as farmers will probably increase their farming land into areas which were bare. The whole district of Chipinge has high probability of land transition into bare land as shown in figure 6. There is less probability of land transition into bare land in areas covered by estates and forests. The eastern and southern part of the district exhibited more areas with high probabilities of land transitioning to estate land. In the eastern part of the district, functioning estates will expand into its neighbouring areas. There is also high probability of land transitioning to built-up which was observed in the southern and in the western part of the district while there are low probabilities of transitioning to agricultural farmland in the same areas of the district. The high probability in transitioning to built-up is caused by population increase in the district and the low probability of transitioning into agricultural farmland is as a result of shrinking in size of land holdings and a decline in land productivity. This is supported by Chifamba and Mashavira (2011) who state that as a consequence of high population growth rate in Chipinge district, land holdings shrink in size and there is also a decline in land productivity which in the end results in poverty increase and out-migration.

There are low probabilities of transition into forestry mostly in the southern and western parts of the district. High probabilities of transition into forests were observed in areas currently occupied by forests or in areas with estate farms which are located in the eastern part of the district as shown in figure 6. Figure 6 also shows that there was low probability of LULC transition to waterbody for the whole district with a bit of higher probabilities of transition in the north-eastern part of the district. The higher probabilities of transition into waterbody are in eastern part of the district as these are the areas where most waterbodies are currently located meaning that there will be expansion of these features.

4.2.2. Simulated Land Use and Land Cover Changes: 2014 – 2028

The CA Markov module was ran in IDRISI Selva using the 2000 and 2014 classified images, LULC suitability and LULC probability images and this predicted a number of scenarios in LULCC from 2014 to 2028. The model predicted that land covered by forests will decrease by 7 509 ha (1.69 %) as shown in table 15 and table 16 whilst the amount of land covered by built-up will increase by 31 116 ha (7.02 %) from the year 2014 till 2028. Bare land would increase by 0.22 % (1006 ha) by the year 2028 as illustrated in table 15 and table 16. This will happen at the expense of agricultural farmland which will decrease by 5.48 % from 71 350 ha in the year 2014 to 47 061 ha in 2028 as shown in table 15 and 16. The amount of land covered by estates will slightly increase by 3 ha from 9 655 ha in 2014 to 9 658 ha by the year 2028 as shown in table 15. Waterbodies are expected to decrease by 327 ha (0.08%) within the years 2014 and 2028 as illustrated in table 15 and table 16 below.

Table 15: Projected status of LULC changes by the year 2028 in hectares (ha)

LULC	2014 (ha)	Projected - 2028 (ha)	Change in ha (2014 - 2028)
ES	9 655	9 658	3
BU	84 039	115 155	31116
BL	248 467	249 473	1006
WB	600	273	-327
F	29 365	21 856	-7509
AF	71 350	47 061	-24289

Note: BL = Bare land, ES = Estate, F = Forest, BU = Built-up, WB = Water body, AF = Agricultural farm.

Table 16: Projected status of LULC changes by the year 2028 in percentage (%)

LULC	2014(ha)	Projected percentage for 2028	Percentage change (2014 - 2028)
ES	2.18	2.18	0.00
BU	18.95	25.97	7.02
BL	56.03	56.25	0.22
WB	0.14	0.06	-0.08
F	6.62	4.93	-1.69
AF	16.09	10.61	-5.48

Note: BL = Bare land, ES = Estate, F = Forest, BU = Built-up, WB = Water body, AF = Agricultural farm. Percentage figures rounded off to two decimal places.

4.2.3. Spatial Distribution of Simulated Changes: 2028

Figure 7 indicates that the major LULC changes are expected to be mostly in the southern part of the district where there will be an increase in built-up areas. This increase will be as a result of population growth, which has been increasing even after the enactment of the FTLRP in 2000. The southern part of Chipinge district has biodiversity loss since the enactment of the FTLRP in 2000 and this is due to the increase in population growth, political and socio-economic problems (Chibisa *et al*., 2010). There will be a slight increase in the amount of bare land, which covers the western and southern part of the district as shown in figure 7; this will be at the expense of forest and agricultural farmland. The increase in bare land will be as a result of deforestation, which will result in a reduction in land, covered by forest and also due to low production in agricultural farms in the district. This is supported by Zamuchiya (2011) who states that in Chipinge district there has been a high rate of deforestation and low productivity in the agricultural farmlands since the enactment of the FTLRP in 2000. The estate land will remain stable even though it will increase its cover in the eastern part of the district as illustrated in figure 7. An explanation which may result in the amount of estate land remaining stable may be due to a reason that the land that was not taken during the course of the FTLRP will remain in the farmer's hands where production will not be affected. The results of the model showed that the distribution of waterbodies remained the same but their capacity and area will continue to deteriorate as shown in table 15.

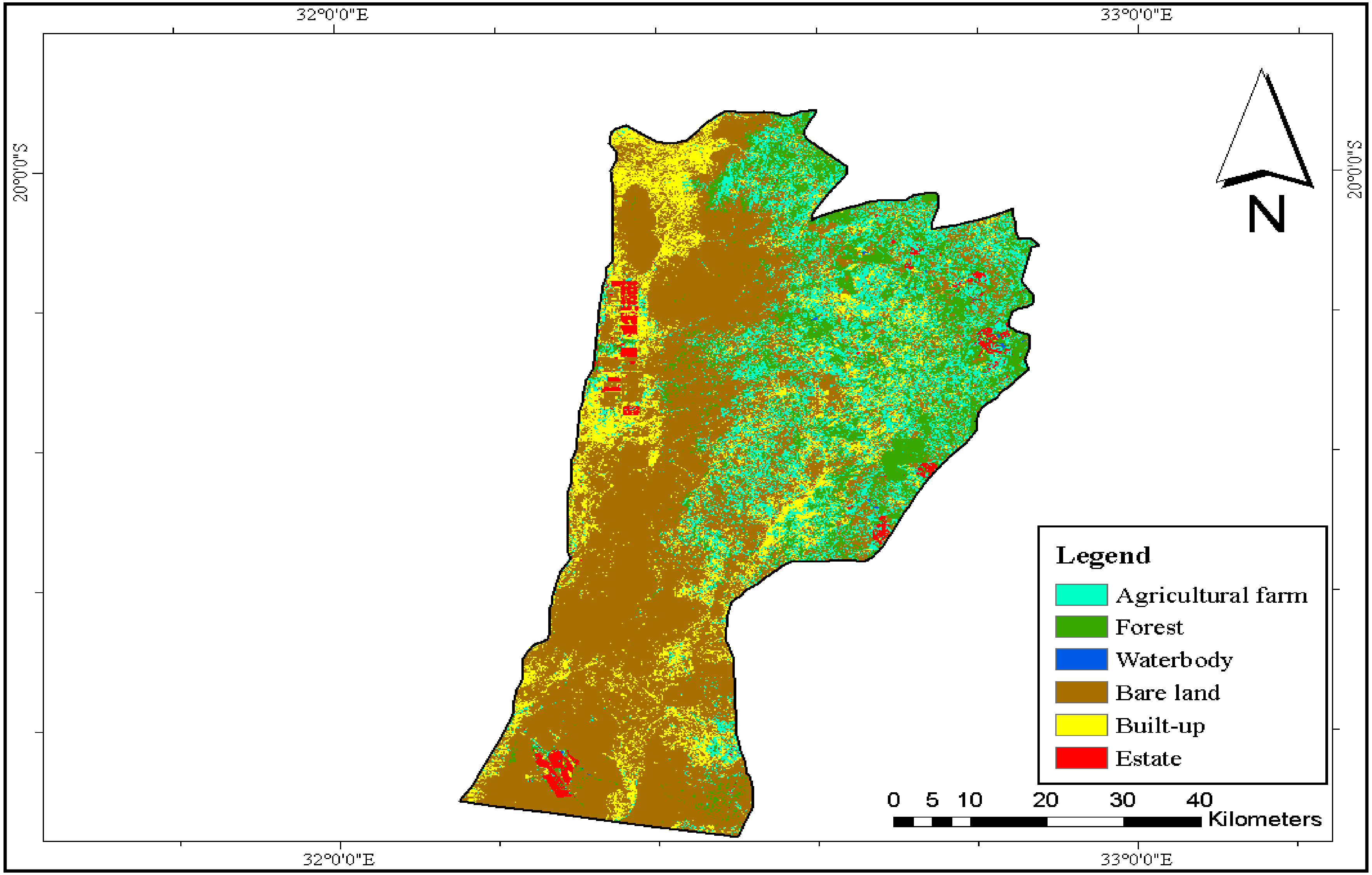

Figure 7: CA Markov projected LULC for 2028.

4.3. Rainfall and Temperature for Chipinge District

Annual rainfall and temperature mean values from the year 1992 to 2014 were taken from Chipinge weather station with WMO ID number: 67983. The values were derived from the GSOD on the NOAA website. The annual mean rainfall and temperature values for Chipinge district from the year 1992 to 2014 are shown in table 17 below.

Table 17: Annual mean rainfall and temperature values for Chipinge district from 1992 to 2014

Year	Annual rainfall mean (mm)	Annual temperature mean (ºC)
1992	325.80	20.61
1993	925.90	18.72
1994	1020.60	21.52
1995	846.40	24.00
1996	1231.20	18.01
1997	1480.50	22.23
1998	699.50	20.44
1999	1286.80	19.74
2000	1910.10	17.03
2001	1180.00	23.09
2002	1050.58	20.22
2003	1205.30	21.35
2004	782.91	22.24
2005	1128.76	20.55
2006	529.15	21.32
2007	850.00	19.22
2008	804.43	20.31
2009	863.40	21.74
2010	745.20	20.36
2011	900.00	20.35
2012	932.60	21.26
2013	803.30	20.79
2014	822.00	21.08

One sample *t-tests* were carried out for both the annual mean rainfall and temperature from the year 1992 to 2014.The one sample *t-tests* were carried out so as to see how variability in annual rainfall and temperature played a part in the causing LULCC in Chipinge district from the year 1992 to 2014.

4.3.1. Summary Statistics for Annual Mean Rainfall and Temperature

The summary statistics of the mean annual rainfall and the mean annual temperature are shown in table 18 below.

Table 18: Summary statistics for annual mean rainfall and temperature for Chipinge district

Variable	Mean	Standard deviation	Min	Max	N
Rainfall	970.63	326.21	325.80	1910.10	23
Temperature	20.70	1.55	17.03	24.00	23

The values for both annual mean rainfall and temperature were 23 from the year 1992 to 2014 as illustrated in table 18 above. The maximum mean annual rainfall amount was 1910.10 mm whereas the minimum annual mean rainfall was 325.80 mm. The mean rainfall amount for the 23 years (1992 to 2014) was 970.63 mm. Table 17 shows that four years before the enactment of the FTLRP in 2000 had values above the mean. These years are 1994, 1996, 1997 and 1999. The remaining four years before the FTLRP had values that are below the mean. It can also be seen that from the year 2000 when the FTLRP was enacted, five years had values above the mean value whereas the other ten years had values which are below the mean. This shows that rainfall had been varying over the years and LULCC had been occurring. It is evident that LULCC occurred in the district whilst receiving high rainfall or with less rainfall, meaning rainfall did not have much impact on LULCC.

As shown in table 18, the maximum mean annual temperature was 24.00 ºC whilst the minimum was 17.03 ºC. The mean temperature amount for the 23 years (1992 to 2014) was 20.70 ºC. It is shown in table 17 that a total of three years before the enactment of the FTLRP in 2000 had values above the mean temperature of 20.70 ºC. The remaining five years had values which were below the mean temperature for all the 23 years. These years are 1992, 1993, 1996, 1998 and

1999 as shown in table 17. It can be noted from table 17 that a total of seven years starting from when the FTLRP was enacted in the year 2000 had annual mean temperatures that were above the mean. These years are 2001, 2003, 2004, 2006, 2009, 2012 and 2014. The remaining eight years had values that were below the mean temperature value. This indicates the variation in temperature over the years which show that whether the temperatures were high or low, LULCC occurred in the district.

It is shown in table 18 that the standard deviation for rainfall was 326.21. This standard deviation is high showing that the annual mean rainfall values are farther away from the mean, on average. This indicates that rainfall varied a lot in Chipinge district at the time when LULCC was occurring. The standard deviation for temperature was 1.55 as shown in table 18. This standard deviation value is low which means the mean annual temperature values from the year 1992 to 2014 in Chipinge district were closer to the mean of the whole dataset which is 20.70 ºC. This means temperature variation did not play a bigger role in the occurrence of LULCC in Chipinge district as there were less variations in annual mean temperatures.

The average annual rainfall for Chipinge district is approximately 1 105 mm (Dube and Guveya, 2013). It can be noted from table 17 that only three years that are within the period before the enactment of the FTLRP had annual mean rainfall that is above the approximate value of average annual rainfall which is 1 105 mm. As shown in table 17, the period before the FTLRP had a total of five years which had annual rainfall mean which was less than the approximate annual rainfall mean of 1 105 mm. This shows that rainfall varied within the period from 1992 to 1999 in which LULCC was also occurring. The period starting from time when the FTLRP was enacted in 2000 till 2014 had a total of four years which had an annual rainfall mean which was above the approximate annual rainfall mean of 1 105 mm as noted from table 17. The remaining eleven years had annual mean rainfall values which were below the approximate average annual rainfall amount of 1 105 mm. This shows that most annual rainfall amounts were below the approximate figure of 1 105 mm. This means that rainfall did not play a huge impact in promoting the occurrence of LULCC in the district.

In Chipinge district, the mean annual temperature is 21 ºC and with significant frost occurrences occurring in the months of June and July (Masaka and Khumbula, 2007). It is shown in table 17 that a total of three years before the enactment of the FTLRP had values that were above the mean annual temperature of 21 ºC. These years are 1994, 1995 and 1997.The other five years before the enactment of the FTLRP had values that were below 21 ºC. The period starting from the year when the FTLRP was enacted in 2000 had seven years that were above the annual mean temperature of 21 ºC. The other eight years after the enactment of the FTLRP had values that were below the annual mean temperature of 21 ºC. This indicates that values for both before and after the enactment of the FTLRP varied. This shows that temperature variability did not have much impact on LULCC in the district as it occurred under these conditions.

4.3.2. One sample *t-test* for mean annual rainfall

A single sample *t-test* was carried for both mean annual rainfall and temperature values from the year 1992 to 2014. The *t-test* was done for the annual mean rainfall and temperature values against hypothesized annual means.

A one sample *t-test* for mean annual rainfall was conducted in which a value of 1 105 mm was put as the hypothesized mean. The results of the *t-test* are shown in table 19 below.

Table 19: One sample *t-test* for mean annual rainfall

	Test Value = 1 105					
	t	**df**	**Std. Error Mean**	**Pr (|T| > | t|)**	**95 % Confidence Interval**	
					Lower	**Upper**
Annual mean rainfall	-1.98	22	68.02	0.06	829.56	1 111.69

Hypothesis

H_0: µ = 1 105

H_a: µ ≠ 1 105

As shown in table 19 above, the *t* statistic is -1. 98 and it measures the degree of agreement which is between a sample of data analysed and the null hypothesis (McDonald and Dunn, 2013). The degrees of freedom for the test is 22 which is the total number of valid observations minus 1. The standard error mean is 68.02 and this represents the estimated standard deviation of the sample mean. The Pr (|T| > |t|) is 0.06 which is greater than the level of significance (0.05), therefore we fail to reject the null hypothesis at 95 % confidence level. The 95 % confidence interval (829.56; 1 111.69) contains the value of 1 105 (test value) which means the null hypothesis cannot be rejected. There is a 95 % chance that the confidence interval calculated contains the true population mean of 1 105 mm. This means that the annual rainfall mean is not significantly different from the test value of 1 105. This shows that there wasn't much variation in annual rainfall mean which illustrates that rainfall did not play a huge part in LULCC but other factors such as the FTLRP.

4.3.3. One sample *t-test* for annual mean temperature

A one sample *t-test* for annual mean rainfall was conducted in which the mean annual temperature of 21 ºC was put as the hypothesized mean. Table 20 below shows the results of the one sample *t-test* carried out for mean annual temperature of Chipinge district from the year 1992 to 2014.

Table 20: One sample *t-test* for annual mean temperature

	Test Value = 21					
	t	**df**	**Std. Error Mean**	**Pr (|T| > | t|)**	**95 % Confidence Interval**	
					Lower	**Upper**
Annual mean temperature	-0.92	22	0.32	0.36	20.03	21.37

Hypothesis

H_0: μ = 21

H_a: μ ≠ 21

As shown in table 20, that the *t* statistic is -0. 92 and this is the ratio of the mean of the difference to the standard error of the difference. The degrees of freedom for the test is 22 which is the total number of valid observations minus 1. The standard error mean is 0.32 which represents the estimated standard deviation of the sample mean. The Pr (|T| > |t|) is 0.36 which is greater than the level of significance (0.05), therefore we fail to reject the null hypothesis at 95 % confidence level. The 95 % confidence interval (20.03; 21.37) contains the value 21 which means that the null hypothesis cannot be rejected. There is a 95 % chance that the confidence interval calculated contains the true population mean of 21 ºC. This means that the annual temperature mean is not significantly different from the test value of 21. This shows that there wasn't much variation in annual temperature mean which illustrates that temperature did not play a huge part in LULCC in Chipinge district. This illustrates that the FTLRP played a major role in LULCC in the district from the year 1992 to 2014.

4.4. Discussion

This discussion is based on the change detection statistics that were acquired by looking at changes in two classified images which are 1992-2000; 2000-2006; 2006-2011 and the 2011-2014 images. Rainfall and temperature variation did not have much effect on the occurrence of LULCC in Chipinge district. The study findings show that there were notable LULCC in the district particularly after the enactment of the FTLRP in the year 2000. In the previous sections, each of the research questions is evaluated as explained below:

Research Question: 1: ***How much land use and land cover change has occurred between 1992 and 2014?***

Change detection analysis done on the five Landsat images shows some notable changes. The results indicate that the LULCC was significant in Chipinge district from the year 1992 to 2014. Summary of LULCC in the district from 1992 up to 2014 is shown in table 21 below:

Table 21: Summary of LULC changes in Chipinge district for the period of 1992-2000, 2000-2006, 2006-2011 and 2011-2014

	1992 - 2000	2000 - 2006	2006 - 2011	2011 - 2014
LULC class	%	%	%	%
BL	0.29	13.07	-3.34	3.55
ES	6.80	-4.89	-2.35	-0.21
F	-5.28	5.13	3.14	-6.76
BU	-9.04	0.73	5.58	5.64
WB	-2.10	-0.82	-0.07	0.07
AF	9.33	-13.22	-2.95	-2.29

Note: BL = Bare land, ES = Estate, F = Forest, BU = Built-up, WB = Water body, AF = Agricultural farm. Percentage figures rounded off to two decimal places.

In table 21 above, the negative and positive sign shows decrease and increase in relation to the LULC class for the time period specified.

In table 21, it can be noted that in the period 1992 to 2000, agricultural farm area increased by 9.33 % whilst forest, built-up and water body decreased by a value of 5.28 %, 9.04 % and 2.10% respectively. The increase in agricultural farmland and estate land during this period was as a result of the introduction of the 1992 Land Acquisition Act which removed the “willing seller, willing buyer” clause. This is supported by Madhuku (2004) who states that the Land Acquisition Act demolished “prompt and adequate” compensation measure with the one on fair compensation which had less market value than the willing seller, willing buyer principle. This led agricultural farm and estate land to increase in the country hence might have led to the transformation of some forests and water bodies in Chipinge district. The decrease in built-up areas might have been led by the point that some of the people being resettled in the district under the Land Apportionment Act were not allowed to build permanent residences in the land they were being allocated. This is supported by Human Rights Watch (2002) stating that farmers who were allocated land after the Land Apportionment Act of 1992 were told not to build permanent shelters.

The period between 2000 and 2014 saw an increase in the amount of bare land between the years 2000 to 2006 (13.07 %) and 2011 to 2014 (3.55 %) as shown in table 21. The amount of bare land decreased by 3.34 % within the years 2006 and 2011 and then increased within the 2011 and 2014 era as shown in table 21. During this period, the amount of land covered by agricultural farms decreased by 13.22 % during 2000-2006, 2.95 % (2006-2011) and 2.29 % (2011-2014) as shown in table 21. The decrease in the amount of land covered by agricultural farmland decreased at the expense of bare land and built-up land. The decrease in agricultural farm and an increase in bare land might have been caused by less agricultural activity in the land acquired during the FTLRP in 2000 and also the invasion of some of the protected forests during the programme. There was a drop in agricultural production in farms acquired during the FTLRP which was as a result of farm disturbances (Masiiwa, 2004). As shown in table 21, there was an increase in the amount of land covered by forest and built-up area where they rose by 5.13 % and 0.73 % respectively. The amount of land covered by built-up increased from the year 2000 to 2014 as shown in table 21. The increase in built-up areas in this period was as a result of a rise in population where houses were being built in the district. There has been population increase in all the districts in Zimbabwe since the population census done in the year 1992 (C.S.O, 2012).

Results of this assessment contribute to the LULCC literature, as it extends the understanding of LULCC trajectories and landscape fragmentation before and after the FTLRP of 2000. This study is aligned with the findings of Matsa and Muringaniza (2011) who noted LULCC in Shurugwi district between the year 1991 and when the FTLRP was enacted in the year 2000 in Zimbabwe. Both studies noted a decrease in water bodies and an increase in agricultural farm land and bare land. However, these studies differed in the classes used where Matsa and Muringaniza (2011) had vegetation and degraded whilst this study had built-up, forest and estate, hence results were not the same. This study also differs with other existing studies as it is the first to undertake such detailed LULCC analysis in Chipinge district.

Research Question 2: ***What are the impacts of the FTLRP of 2000 on LULCC in Chipinge district?***

The question was responded to by looking at the change detection statistics starting from the year when the FTLRP was enacted that is the year 2000 till 2014.

From the year 2000 to 2014, agricultural farmland decreased in size. As shown in table 21 above, agricultural farmland decreased by 13.22 % (2000-2006); 2.95 % (2006-2011) and 2.29 % (2011-2014). When agricultural farmland decreased in 2000-2006 and 2011-2014, there was an increase in bare land during these periods with values of 13.07 % (2000-2006) and 3.55 % (2011-2014). Land covered by estates in the district decreased since the start of the FTLRP. This land decreased by 4.89 % (2000-2006); 2.35 % (2006-2011) and 0.21 % (2011-2014). This was caused by the farm disturbances, lack of farm workers and farm inputs in the newly resettled farms. This is supported by Madhuku (2004) who states that after the FTLRP of 2000 there was a drop in agricultural production due to several reasons which include farm disturbances, lack of capital to purchase farm inputs and massive unemployment as most of the farms stopped employing farm workers. This is also supported by Chiremba and Masters (2003) who state that newly resettled farmers do not have enough farm equipment, capital to support farming activities, agricultural education and experience.

The period after the FTLRP in 2000, land covered by estates also decreased as noted in table 21 above. The land covered by estates decreased by 4.89 % (2000-2006), 2.35 % (2006-2010) and 0.21 % (2011-2014). The decrease could also have led to an increase in the amount of bare land in the district as shown in table 21 that bare land increased by 13.07 % (2006-2010) and 3.55 % in 2011-2014). The decrease in estate land was due to less farming activities as most foreign investors who owned farming estates left the country as they were chased away by the ruling Zimbabwe African National Union – Patriotic Front (ZANU-PF) party. Foreign investors were also worried about the government's land reform policy which eroded the rule of law and also undermined the security of property rights. This is supported by KPMG (2012) who argue that the uncertainty of the domestic political environment in Zimbabwe tends to amplify risks for foreign investors to come into the country and pursue agricultural activities. The decrease in land covered by agricultural farms was also as a result of low farming activities due to lack of knowledge and machinery amongst the newly resettled farmers to produce cash crops which covered a huge area before the FTLRP of 2000. The newly resettled had to resort to subsistence farming where they grew food crops which covered smaller areas as compared to the cash crops grown before the FTLRP. This is supported by Zamuchiya (2011) who states that in Chipinge district, there is a new trajectory from growing cash crops to food crops and this is caused by the need for food consumption at household level, less knowledge on cash crop production and also the lack of adequate farming production technology.

Since the start of the FTLRP, the area covered by built-up increased as noted in table 21 above. Built-up increased by 0.73 % (2000-2006), 5.58 % (2006-2011) and 5.64 % (2011-2014). The increase in the land covered by built-up could have led to a reduction in agricultural farmland as it decreased during this period. The increase in built-up areas was as a result of population growth where more houses were built which also included structures in the newly resettlement farms. This supported by Zamuchiya (2011) who states that from the year 2000, there has been an increase in black farmers occupying former white commercial farms in the district where they build shelter to stay in.

When the FTLRP started, area covered by forest increased up to the year 2011. This is shown in table 21 above that area covered by forest increased by 5.13 % (2000-2006) and 3.14 % (2006-2011). The area covered by forest decreased between the years 2011 and 2014. This was due to deforestation where newly resettled farmers cut down trees even in protected forests for various uses which include expansion of arable land, need of fuel wood and construction poles, and expansion of the urban area. This is supported by Njaya and Mazuru (2014) who state that the reason why deforestation has increased after the FTLRP in resettled farms include the need for farm expansion, home construction, firewood, cattle pens, sale in towns as fuel, domestic use, tobacco drying, hunting and gold panning.

After the enactment of the FTLRP in 2000, the land covered by water bodies decreased till the year 2011 as shown in table 21 above. The land covered by water bodies decreased by 0.82 % (2000-2006) and 0.07 % (2006-2011). The decrease in the land covered by water bodies might be as a result of the farming methods of the newly resettled farmers which led to the siltation of rivers. The siltation of rivers might have been as a result of bad farming methods and lack of conservation. This is supported by Zembe *et al*. (2014) who state that after the FTLRP in Zimbabwe, bad farming practices and utilization of natural resources to support their livelihoods has negative impacts on the environment which include deforestation and the siltation of rivers.

The area covered by water bodies increased by 0.07% within the period of 2011-2014 as shown in table 21 above.

On the question of the impact of the FTLRP of 2000 on LULCC in Chipinge district, the study observed that there was a decrease in the amount of land covered by agricultural farms and estates. These findings align with a study done by Lidzhegu and Palamuleni, 2012 who noted a decrease in agricultural cropland from 78.04 ha in 1994 to 20.43 ha (2007) on their study on land use and land cover changes as a consequence of the South African land reform program. The results of this study differ with those of Matsa and Muringaniza (2011), in that they noted a rise in cultivated land from the year 2000 (25.2 %) to 2009 (26.6 %) in Shurugwi district. These results differ with the ones of this study as they noted a decrease in agricultural farm land from 34.55 % in 2000 to 16.09 % in 2014.

Research Question 3: *Can Landsat earth observation data be used to quantify land use and land cover changes as a result of the FTLRP policy?*

This study showed that Landsat earth observation data can be used in quantifying LULCC that is as a result of the FTLRP. In the study Landsat earth observation data was analysed using change detection analysis in ENVI 5.2 software, which identified, described and quantified the differences on two images of an identical scene at times which are different (Harris geospatial solutions, 2016). Change detection statistics were produced from the year 2000 when the FTLRP was enacted. The researcher used tables to show differences between two classified images. The images were for the years starting from the period when the FTLRP was enacted in 2000 up to 2014. These images were for the years: 2000, 2006, 2011 and 2014. The change detection statistics also showed class-for-class image difference from the classified Landsat image, which focused primarily on classification of the initial state so as to see how the pixels transformed in the image of the final state. The change detection statistics indicated how the FTLRP resulted in LULCC in Chipinge district by looking at the changes on the classified Landsat images from the year 2000 up to 2014. Satellite remote sensing, which includes Landsat earth observation data is the commonly used data source in the detection, mapping and quantification of LULC patterns with data acquisition which is repetitive and georeferencing procedures which are accurate (Lu *et al.*, 2004). The change detection statistics report in this study for all the images including the ones starting from the year when the FTLRP was enacted in 2000 shows LULCC in hectares and percentages.

The findings of this research noted that Landsat earth observation data can be used in quantifying LULCC as a result of the FTLRP. These findings align with those for Matavire *et al. (2015)* who assessed the role of the FTLRP of 2000 on LULCC in Quagga Pan Ranch, Zimbabwe using Landsat images for the years 1989 and 2000. The results from the study align with this research in that they both observed the use and importance of Landsat observations in quantifying LULCC as a result of the FTLRP of 2000 in Zimbabwe. The findings of this study differ with the ones for Matavire *et al.* (2015) on the objectives of the study where Matavire *et al.* (2015) tested if there were significant differences in species diversity and also on tree species. The findings are different from the ones of this study as it focused on six classes which are estate, waterbody, forest, built-up, bare land and agricultural farm land.

Research Question 4: ***What will be the state of the land use and land cover in the year 2028 in Chipinge District under the current FTLRP policy?***

In this study, historical and current Landsat earth observation data was used to measure and monitor the changes in landscape parameters. The state of the LULC in the year 2028 shows that there will be a decrease in land covered by water bodies, forests and agricultural farms as shown in table 15 and table 16. Between 2014 and 2028, the land covered by waterbodies will decrease by 0.08 %, forest (1.69 %) and agricultural farmland (5.48 %) as illustrated in table 16. The decrease in the amount of land covered by forest and agricultural farmland will be as a result of increasing deforestation rates and less farming activities in the farming lands. As shown in table 16, by the year 2028 there will be an increase in the amount of land covered or used for built-up (7.02 %) and bare land (0.22 %). The increase in the built-up area will be as a result of increasing population growth in the district. During this period in time the amount of land covered by estate will have a slight increase of 3 hectares as shown in table 15.

By the year 2028, the built-up areas will be mainly in the north-western and southern part of the district. Bare land will cover mainly the southern and western part of the district as shown in figure 7. The land covered by forest will be mainly in the north eastern part of the district. The land with estate farms by the year 2028 will cover the north eastern part of the district as shown in figure 7. By the year 2028, the land covered by agricultural farmland will cover mainly the eastern part of the district. Waterbodies will cover mostly the eastern part of the district in the year 2028.

The findings of this research are aligned to the ones by Kamusoko *et al*. (2009) who simulated LULCC (up to 2030) in the Masembura and Musana communal areas of the Bindura district, Zimbabwe based on the Markov-cellular automata model which combines MCA and cellular automata models. Both studies used satellite images before and after the implementation of the FTLRP of 2000 where Kamusoko *et al*. (2009) used the ones for 1973, 1989, 2000 and 2005. The findings from both studies show an increase in the amount of bare land and a decrease in agricultural areas. However, the findings of these studies differ in that the study by Kamusoko *et al*. (2009) produced projection for the year 2030 whilst the ones for this study are for the year 2028.

4.5. Limitations of the Research

Despite the favorable findings and timely completion of this research, a number of limitations were faced in the process. Some of them are:

i. Absence of consistent multi-temporal Landsat earth observation data from the same season in all the targeted years which would have permitted change analysis with consistent time intervals.
ii. The use of Landsat images with different spatial resolution led to the resampling of the 1992 image from 60 meters to 30 meters so as to match with the ones for the years 2000, 2006, 2011 and 2014. The limitation is that the total area of the district from the 1992 MSS image was greater than those of the TM, ETM+ SLC on and OLI/TRS images by 18 hectares.
iii. Inadequate access to different aerial photos with full coverage of the district from several years to collect training samples from the study area generated a limitation on visual interpretation and the classification process.
iv. Inconsistency in geo-referencing Landsat images and also the local datum. A lot of time was consumed in making the data formats of different layer files consistent.

v. The absence of socio-economic data, high resolution imageries like WorldView-3 GeoEye-2 and other ancillary data hindered the production of more accurate results.

CHAPTER 5 - CONCLUSIONS AND RECOMMENDATIONS

This final chapter consists of the conclusions and recommendations of this study. The analysis of Landsat earth observation data gave quantification and projection results which provided an in-depth understanding of LULCC in Chipinge district.

5.1. Conclusions

In this study, five Landsat images were used to quantify the impact of the land reform programme on LULCCs in Chipinge district. The use of Landsat earth observation data with GIS and remote sensing techniques was found to be useful in quantifying the changes on LULC from the year 1992 to 2014 in Chipinge district. The change detection techniques were used to detect LULCC and analysis was done so as to see spatiotemporal LULC dynamics. These techniques were used so as to see the impact of the FTLRP on LULCC in Chipinge district. The analysis of Landsat observations focused on change patterns and transitions over a 22-year period and divided into the following two levels: (1) before the FTLRP to the year it began (1992 – 2000), (2) after enactment of the FTLRP (2000 – 2014). The Markov chain analysis and the CA Markov model were used in predicting LULCC in the year 2028 in Chipinge district. The results were obtained and the main objective and sub objectives were achieved. In relation to the objectives, the research questions were answered based on the results that were obtained and analysis done. The following conclusions are drawn from this study:

i. The amount of LULC that occurred in Chipinge district between 1992 and 2014 was acquired in this study. The LULCC in the district from the year 1992 to 2014 shows that the amount of area with bare land increased as shown by the increase percentage of land cover from 42.46 % in 1992, 42.75 % in 2000, 55.82 % in 2011 and 56.03 % in 2014.

   The amount of land covered by agricultural farmland rose from 1992 to 2000. There was a rise from 25.22 % in 1992 to 34.55 % in 2000. It then declined from the year 2000 up to 2014. During this period, there was a decline of 13.22 % from the year 2000 to 2006, 2.95 % (2006-2011) and 2.29% (2011-2014).

   The amount of land covered by estates rose by 6.80 % from the year 1992 to 2000 as it was 2.83 % in 1992 to 9.63 % in 2000. The amount of land covered by estates declined from the year 2000 up to 2014. The amount declined from 9.63 % in 2000 to 2.18 % in the year 2014.

Land covered with forests declined from the year 1992 to 2000. This amount declined from 10.39 % in 1992 to 5.11 % in 2000. The land covered by forestry however increased to 10.24 % in 2006 from 5.11 % in the year 2000. There was a further increase from 10.24 % in 2006 to 13.38 % in the year 2011. The 2011 amount declined to 6.62 % in 2014 which represents a reduction of 6.76 %.

There was a decrease in the amount of land covered by water bodies in Chipinge district from the year 1992 up to 2014. This amount declined from 3.06 % in 1992 to 0.14 in the year 2014.

The built up area decreased from 16.04 % in 1992 to 7 % in the year 2000. The amount of land covered by built up increased from the year 2000 to 2014. The amount increased from 7 % in 2000 to 18.95 % in 2014.

ii. The impact of the FTLRP of 2000 on LULC in Chipinge district was observed in this study. The classified images for the years after the enactment of the FTLRP (2000, 2006, 2011 and 2014) show that there was LULCC in Chipinge district where there was a reduction in the amount of land covered by agricultural farms, water bodies and estates from the year 2000 to 2014. The amount of agricultural farmland decreased from 34.55 % in the year 2000 to 16.09 % in 2014. The land covered by water bodies in the district also decreased after the start of the FTLRP from 0.96 % in the year 2000 to 0.14 % in 2014. The land covered by estate also decreased from 9.63 % in 2000 to 2.18 % in 2014. The FTLRP also led to an increase in the amount of land covered by built up, forests and bare land from the year 2000 to 2014. The amount of land covered by built up increased to 18.95 % in 2014 from 7.00 % in the year when the FTLRP was commenced in 2000. Land covered by forests also increased after the start of the FTLRP from 5.11 % in 2000 to 6.62 % in the year 2014. The other impact of the FTLRP on LULCC in Chipinge district was that there was an increase in the amount of bare land from 42.75 % in the year 2000 to 56.03 % in 2014.

iii. Landsat earth observation data can be used to quantify LULCC as a result of the FTLRP policy as shown in this study. This study shows the LULCC in terms of hectares and even in percentage. Landsat earth observation data shows LULCC with the use of change detection methods and other GIS and RS techniques to come up with results which are more accurate. This study used change detection techniques from ENVI 5.2 software with Landsat earth observation data to quantify the impact of the FTLRP on LULCC in Chipinge district and produced results which are accurate as reflected by the accuracy assessment that was undertaken.

iv. The projection results of the MCA and CA MCA indicate the state of LULC in 2028 both spatially and quantitatively in Chipinge district. There will a huge increase in the built-up area where it will grow by 7.02 % from the year 2014. This increase will be as a result of increasing population growth in the district where people will be building houses to stay in. The amount of bare land will also increase with a value of 0.22 % by the year 2028. During the period between 2014 and 2028, there will be a slight increase in the amount of estate land where it will rise by an amount of 3 hectares. There will be a decline in the amount of land covered by water bodies (-0.08 %), forest (-1.69 %) and agricultural farmland (-5.48 %). The decrease in the amount of agricultural farmland in the district will be due to low agricultural activities in the farms that were acquired during the FTLRP. The projected LULC for the year 2028 indicate that estate and bare land will cover mostly the western side of the district whereas agricultural farmland and forests will mostly cover the eastern part of the district. There will be an increase in the amount of built-up area from 2014 to the year 2028 and it will cover mostly the western side of the district and this will be due to continuing population growth in the district. Waterbodies will cover mainly the eastern part of the district as there will be expansion of the current water sources.

5.2. Recommendations

i. This study quantified LULCC which has occurred between 1992 and 2014 in Chipinge district. The results show that there was a decrease in the amount of land covered by forest, water bodies and agricultural farmland. This is coupled with an increase in the amount of land covered by built-up areas in the district, which is as a result of an increase in population density. This shows that an increase in population density accelerated LULCC dynamics in the district, so as to lessen the pressure of population on LULCC and dynamics, resettlement will help. The reduction in the amount of forest cover in the district was as a result of deforestation in the district. It would be prudent for better remedies to be put in place by the government, companies and Non-Governmental Organisations (NGOs) for example prioritise the need to increase the amount of forest cover in the district. These remedies include the protection of existing forests in the district, planting of trees and the encouragement of individual tree growing etc.

ii. This study produced results on the impacts of the FTLRP of 2000 on LULCC in Chipinge district. In future studies, it would be interesting as an extension of this study to do a comparative investigation into LULCC in an environment that was not affected by the FTLRP, but with increased population from various causes such as rural-urban migration using comparable datasets. This would be vital in identifying whether the FTLRP indeed plays a unique role in LULCC, or whether the increase in population is the main driving force. Research that explores the relationships between LULCC, socio-economic and demographic variables (population, gross agricultural output, per capita GDP) would develop understanding of LULCC. These studies will assist in identifying the role of socio-economic processes, if any, contribute to LULCC.

iii. This study used Landsat earth observation data to quantify LULCCs as a result of the FTLRP policy. In future researches, high resolution images such as World View 3 can be used so as to improve the kappa coefficient, overall accuracy, producer and user accuracies.

iv. The MCA and CA MCA models were used in the prediction of the state of LULC in the year 2028 in Chipinge district under the current FTLRP policy. The LULC prediction for the year 2028 in this study indicates that there will be a decrease in agricultural farmland, water bodies and forestry. The government and NGOs should put more capital into farming, protection of forests and water bodies in the district so as to enhance their growth and survival. The prediction also shows that by the year 2028, there will be an increase in the built-up area in the district which will be as a result of factors such as population's continuous growth and development of infrastructure. It is therefore recommended that bodies which are concerned such as the government and NGOs like health office, population office, agricultural offices, Ministry of Lands and Rural Resettlement offices etc. prepare a land use plan which is proper in order to reduce the growth of settlement. The prediction of future LULCC is vital to land use planners in terms of planning and implementation of social and economic development programs. I also recommend that people in the district be made aware on the importance of utilizing lands intensively than using it extensively. Further research should be prepared to achieve LULC prediction which is better in the same way by adding information that is necessary, data that is applicable and by filling limitations mentioned in the study.

5.3. Future Research

This research contributes to the broader understanding of the impact of the land reform policies on LULCC. For future comprehensive study of LULCC in Chipinge district, the kappa coefficient, overall accuracy, producer and user accuracies can be improved with the use of high spatial resolution images such as WorldView and GeoEye. In future researches, misclassifications seen in this study can be avoided by using alternative approaches such as object-based classification.

In future studies, a research showing a better understanding of LULCC in Chipinge district can be done based on a socio-geospatial approach. The research can be done using theories such as Malthusian and Boserupian ideas on population and environment. The research can also discover the relationships between LULCC, socio-economic and demographic variables.

REFERENCES

Abd El-Kawy, O.R., Rod, J.K., Ismail, H.A., Suliman, A. S. (2011) Land use and land cover change detection in the western Nile delta of Egypt using remote sensing data, *Applied Geography*, vol. 31, no. 2, pp. 483-494.

Adam, E., Mutanga, O., Odindi, J., Abdel-Rahman, E. M. (2014) Land-use/cover classification in a heterogeneous coastal landscape using RapidEye imagery: Evaluating the performance of random forest and support vector machines classifiers, *International Journal of Remote Sensing, 2014*, vol. 35, no. 10, pp. 3440-3458.

Adam, H. A. M., Elhag, A. M. H and Hassan, T. K (2014) Quantifying Land Cover Change Using Modern Ceoinformatics Technology, *Journal of Natural Resources & Environmental Studies*, vol. 10, pp. 18-28.

Adejuwon, J. O., Jeje, L. K. (1973) *Land use map of Ife area*, Lagos, Nigeria: Federal Surveys Department.

Aguilar, E., Barry Azziz, A., Brunet, M., Ekang, L., Fernandes, A., Massoukina, M., Mbah, J., Mhanda, A., do Noscimento, D.J., Peterson, T.C., Thamba Umba, O, Tumou, M. and Zhang, X. (2009) Changes in Temperature and Precipitation Extremes in Western Central Africa, Guinea Conakry, and Zimbabwe, 1955-2006, *Journal of Geophysical Research*, vol. 114, no. 2, pp. 2156-2202.

Anderson, J.R., Roach, J.T and Witmer., R.E. (1976) *A Land Use and Land Cover Classification System For Use With Remote Sensor Data, Geological Survey Professional Paper,* Washington: US Government Printing Office.

Baboo, S.S. and Devi, M.R. (2010) An Analysis of Different Resampling Methods in Coimbatore, District, *Global Journal of Computer Science and Technology*, vol. 10, no. 15, pp. 61-66.

Barredo, J.I., Kasanko, M., McCormick, N. and C. Lavalle. (2003) "Modelling Dynamic Spatial Processes: Simulation of Urban Future Scenarios through Cellular Automata," *Landscape and Urban Planning*, vol. 64, no.3, pp. 145-160.

Barreto, H. and Howland, F. (2006) *Introductory Econometrics: Using Monte Carlo Simulation with Microsoft Excel*, Cambridge University Press: USA.

Basnet, B. and Vodacek, A. (2015) Tracking Land Use/ Land Cover Dynamics in Cloud Prone Areas Using Moderate Resolution Satellite Data: A Case Study in Central Africa, *Remote Sensing*, vol. 7, no. 6, pp. 6683-6709.

Batlle, B.L., van den, H.B.J., Strengers, B.J. and Minnen, J.G. (2014) A Framework to Explore Regional Feedbacks under Changing Climate and Land-use Conditions, Journal of Earth Science and Climatic Change, vol. 5, no.3, pp. 1-11.

Behera, M. D., Borate, S. N., Panda, S. N., Behera, P. R. and Roy, P.S. (2012) Modelling and Analyzing the Watershed Dynamics using Cellular Automata (CA) – Markov Model – A Geo-Information Based Approach, *J. Earth Syst. Sci*, vol. 121, no. 4, pp. 1011-1024.

Bohra-Mishra, P., Oppenheimer, M and Hsiang, S.M. (2014) Nonlinear Permanent Migration Response to Climatic Variations but Minimal Response to Disasters, Proceedings *of the National Academy of Sciences of the United States of America*, vol. 111, no.27, pp. 9780-9785.

Bonarjee, B. M. (2013) 3 Decades of Land Reform in Zimbabwe: Perspectives of Social Justice & Poverty Alleviation [online], available: http://www.uib.no/filearchive/seminar-paper-25-oct-2013-mfbb.pdf/ [accessed 07 May 2015].

Briassoulis, H. (2000) Analysis of Land Use Change: Theoretical and Modeling Approaches [online], available: http://www.rri.wvu.edu/Webbook/Briassoulis/contents.htm 12/ [accessed 23 March 2015].

Campbell, H. (2008) ‘‘Mamdani, Mugabe and the African Scholarly Community.’’ [online], available: http://www.pambazuka.org/en/category/features/52845/ [accessed 01 April 2015].

Canty, M. J. (2009) *Image Analysis, Classification, and Change Detection in Remote Sensing: With Algorithms for ENVI/IDL*, USA: CRC Press.

Central Statistics Office (CSO). (2012) *Zimbabwe Population Census 2012*, Harare: Government Printers.

Chander, G., Markham, B.L and Helder, D.L. (2009) Summary of Current Radiometric Calibration Coefficients for Landsat MSS, TM, ETM+ and EO-1 ALI Sensors, *Remote Sensing Environment*, vol. 113 (5), pp. 893-903.

Chandra, P.G. (2012) *Remote Sensing of Land Use and Land Cover Principles and Application* pp. 113-126, Boca Raton, New York: CRC Press.

Cheesman, A.M. and Winter, K. (2013) Elevated Night-Time Temperatures increase Growth in Seedlings of Two Tropical Pioneer Tree Species, *New Phytologist*, vol. 197, no. 4, pp. 1185-1192.

Chen, G., Hay, G.J., Carvalho, L.M.T and Wulder, M.A. (2012) Object-based Change Detection, *International Journal of Remote Sensing*, vol. 33, no. 14, pp. 4434-4447.

Chen, X., Vierling, L. and Deering, D. (2005) A simple and effective radiometric correction method to improve landscape change detection across sensors and across time. *Remote Sensing of Environment*, vol. 98, no. 1, pp. 63-79.

Chibisa, P., Ruzive, A and Mandipa, C. T. (2010) The 2000-2004 Fast Track Land Reform Program and Biodiversity Issues in the Middle Save Conservancy, *Journal of Sustainable Development in Africa*, vol. 12, no. 6, pp. 74-100.

Chifamba, E and Mashavira, N. (2011) Adaptation and Mitigation Strategies in Sustainable Land Resource Management to Combat the Effects of Climate Change in Chipinge, Zimbabwe, *Journal of Sustainable Development in Africa*, vol. 13, no. 2, pp. 15-27.

Chiremba, S and Masters, W. (2003) The Experience of Resettled Farmers in Zimbabwe, African Studies Quarterly [online], available: http://asq.africa.ufl.edu/files/Chiremba-Masters-Vol-7-Issues-23.pdf/ [accessed 30 November 2015].

Cho, M. A., Debba, P., Mutanga, O., Dudeni-Tlhone, N., Magadla, T and Khuluse, S. A. (2012) Potential utility of the spectral red-edge region of SumbandilaSat imagery for assessing indigenous forest structure and health, *International Journal of Applied Earth Observation and Geoinformation*, vol. 16, pp. 85-93.

Cihlar, J. (2000) Land Cover Mapping of Large Areas from Satellites: Status and Research Priorities, *International Journal of Remote Sensing*, vol. 21, no. 6 &7, pp. 1093-1114.

Cingolani, A. M., Renison, D., Zak, M. R and Cabido, M. R. (2004) Mapping Vegetation in a Heterogeneous Mountain Rangeland using Landsat data: An Alternative Method to define and Classify Land-cover Units, *Remote Sensing of Environment*, vol. 92, no. 1, pp. 84-97.

Cliffe, L, Alexander, J, Cousins, B and Gaidzanwa, R. (2014) *Outcomes of Post-2000 Fast Track Land Reform in Zimbabwe*, New York: Routledge.

Cohen, J. (1960) “A Coefficient of Agreement for Nominal Scales.” *Educational and Psychological Measurement*, vol. 20, no. 1, pp. 37-46.

Coldham, S. (1993) The Land Acquisition Act, 1992 of Zimbabwe, *Journal of African Law,* vol. 37, no. 1, pp. 82-88.

Congalton, R.G. (1992) A review of assessing the accuracy of classifications of remotely sensed data, *Remote Sensing of Environment,* vol. 37, pp. 35-46.

Congalton, R. G and Green, K. (2008) *Assessing the Accuracy of Remotely Sensed Data: Principles and Practices,* New York: Taylor and Francis.

Dai, X. and Khorram, S. (1998) A hierarchical methodology framework for multisource data fusion in vegetation classification. *International Journal of Remote Sensing, 1998,* vol. 19, no. 18, pp. 3697-3701.

Dalponte, M., Bruzzone, L., Vescovo, L and Gianelle, D. (2009) The Role of Spectral Resolution and Classifier Complexity in the Analysis of Hyperspectral Images of Forest Areas, *Remote Sensing of Environment*, vol. 113, no. 11, pp. 2345-2355.

Daniel, L. C., James, D. H., Emily, H. Mingjun, S and Zhenkui, Z. (2002) A Comparison of Land Use and Land Cover Change Detection Methods, *ASPRS-ACSM Annual Conference and FIG 22 nd Congress*, pp. 2.

Dorn, H., Tornros, T and Zipf, A. (2015) Quality Evaluation of VGI Using Authoritative Data: A Comparison with Land Use Data in Southern Germany, *International Journal of Geo-Information*, vol. 4, no. 3, pp. 1657-1671.

Duadze, S. E. K. (2004) Land *Use and Land Cover Study of the Savannah Ecosystem in the Upper West Region (Ghana) Using Remote Sensing*, Germany: Cuvillier Verlag.

Dube, L and Guveya, E. (2013) Land Tenure Security and Farm Investments amongst Small Scale Commercial Farmers in Zimbabwe, *Journal of Sustainable Development in Africa*, vol. 15, no. 5, pp. 107-121.

Ellis, E. (2013) Land-use and land-cover change [online], available: http://www.eoearth.org/view/article/154143/ [accessed 07 May 2015].

Fakarayi, T., Mashapa, C., Gandiwa, E and Kativu, S. (2015) Pattern of Land Use and Land Cover Changes in Driefontein Grassland Important Bird Area, Zimbabwe, *Tropical Conservation Science*, Vol 8 (1), pp.274-283.

Fonji, S.F and Taff, G.N. (2014) Using Satellite Data to Monitor Land-use Land-cover Change in North-Eastern Latvia, *SpringerPlus*, 3:61, doi:10.1186/2193-1801-3-61.

Foody, G.D. (2002) Status of Land Cover Classification Accuracy Assessment, *Remote Sensing of the Environment*, vol. 80, no. 1, pp. 185-201.

Galloway, J. N., Schlesinger, W.H., Clark, C.M., Grimm, N.B., Jackson, R.B., Law, B.E., Thornton, P.E., Townsend, A.R and Martin, R. (2014) Biogeochemical Cycles, *Climate Change Impacts in the United States: The Third National Climate Assessment*, J. M. Melillo, Terese (T.C.) Richmond, and G. W. Yohe, Eds., U.S. Global Change Research Program, pp. 350-368.

Gambiza, J and Nyama, C. (2000) Country Pasture/ Forage Resource Files [online], available: http://www.fao.org/ag/agp/agpc/doc/counprof/zimbabwe/zimbab.htm/ [accessed 10 August 2015].

Government of Zimbabwe (GoZ). (1986) *Land use in Zimbabwe*, Harare: Ministry of Lands, Agriculture and Rural Resettlement.

Han, D., Chan, L., Zhu, N. (2007) Flood forecasting using support vector machines, *J. Hydroinf*, vol. 9, no.4, pp. 267-276.

Han, X., Chen, X. and Feng, L. (2014) Four decades of winter wetland changes in Poyang Lake based on Landsat observations between 1973 and 2013, *Remote Sensing of Environment*, vol. 156, no.1, pp. 426-437.

Hanlon, J., Manjengwa, J. and Smart, T. (2012) *Zimbabwe Takes Back Its Land*, Virginia: Stylus Publishing.

Harris Geospatial Solutions. (2016) Change Detection Analysis [online], available: http://www.exelisvis.com/docs/ChangeDetectionAnalysis.html/ [accessed 25 February 2016].

Hegazy, I.R and Kaloop, M. R. (2015) Monitoring urban growth and land use change detection with GIS and remote sensing techniques in Daqahlia governorate Egypt, *International Journal of Sustainable Built Environment*, vol. 39, no. 4, pp. 117-124.

Houet, T., Loveland, T., Hubert-Moy, L., Gaucherel, C., Napton, D., Barnes., C.A and Sayler, K. (2010) Exploring subtle land use and land cover changes: A framework for future landscape studies, *Landscape Ecology*, 25 (2), 249-266.

Hu, Q., Wu, W., Xia, T., Yu, Q., Yang, P., Li, Z and Song, Q. (2013) Exploring the Use of Google Earth Imagery and Object-Based Methods in Land Use/ Cover Mapping, *Remote Sensing*, vol.5, pp. 6026-6042.

Human Rights Watch. (2002) Zimbabwe: Fast Track Land Reform in Zimbabwe [online], available:https://www.hrw.org/reports/2002/zimbabwe/ZimLand0302-07.htm#P739_179026/ [accessed on 15 December 2015].

Jennings, A. C. (1935). 'Land Apportionment in Southern Africa,' *Journal of the Royal African Society*, vol. 34, no. 136, pp. 296-312.

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

Kamusoko, C., Aniya, M., Adi, B and Manjoro, M. (2009) Rural Sustainability Under Threat in Zimbabwe – Simulation of Future Land Use/ Cover Changes in the Binidura District

Based on the Markov-Cellular Automata Model, *Applied Geography*, vol. 29, pp. 435-447.

Karlin, S and Taylor, H. M. (1975) *A First Course in Stochastic Processes*, New York: Academic Press.

Karumbidza, J. B. (2009). '*A Fragile and Unsustained Miracle: Analysing the Development Potential of Zimbabwe's Resettlement Schemes, 1980-2000*' unpublished thesis (PhD) thesis, University of KwaZulu-Natal, South Africa.

Kau, H. (2014) Algorithm used in Intrusion Detection Systems: A Review, *International Journal of Innovative Research in Computer and Communication Engineering*, vol. 2, no. 5, pp. 4438-4446.

Khuman, M.B. (2013) Classification of remote sensing data using K-NN method, *Journal of Information, Knowledge and Research in Electronics and Communication Engineering*, vol. 2, no. 2, pp. 817-821.

Kivel, P. (1991) *Urban Land Use*, New York: Longman Scientific and Technical.

Knorn, J., Rabe, A., Radeloff, V.C., Kuemmerle, T., Kozak, J. and Hostert, P. (2009) Land cover mapping of large areas using chain classification of neighboring Landsat satellite Images, *Remote Sensing of Environment*, vol. 113, no. 1, pp. 957-964.

Kochy, M. (2008) Effects of Simulated Daily Precipitation Patterns on Annual Plant Populations Depend on Life Stage and Climatic Region, *BMC Ecology*, vol. 8, no. 1, pp. 1-23.

KPMG. (2012) Investing in Zimbabwe [online], available: https://www.kpmg.com/ZW/Lists/Copied%20Documents/Investing%20in%20Zimbabwe%202012-Final.pdf/ [accessed 10 December 2015].

Kressler, F. and Steinnocher, K. (1996) Changes Detection in Urban Area using Satellite images and Spatial Mixture Analysis. *International Achieves of Photogrammetry and Remote Sensing*, vol. 31, no. 7, pp. 379-383.

Lambin, E. F. (1994) Modelling deforestation processes: A review. TREES series B: Research Report 1, European Commission, *International Journal of Remote Sensing*, vol. 17, pp. 1061-1062.

Lambin, E. F. and Geist, H. (2007) Causes of land-use and land-cover change [online], available: http://www.eoearth.org/view/article/150964/ [accessed 07 April 2015].

Lambin, E. F. and Geist, H. (2006) *Land-Use and Land-Cover Change: Local Processes and Global Impacts*, Berlin: Springer Verlag.

Lambin, E. F., Geist, H. J. and Lepers, E. (2003) Dynamics of land-use and land-cover change in tropical regions, *Annual Review of Environment and Resources*, vol. 28, no. 1, pp. 205-241.

Li, X. and Yeh, A.G.O. (2000) Modelling Sustainable Urban Development by the Integration of Constrained Cellular Automata and GIS, *International Journal of Geographical Information Science*, vol. 14, no. 2, pp. 131-152.

Lidzhegu, Z. and Palamuleni, L.G. (2012) Land use and Land cover change as a consequence of the South African land reform program: A remote sensing approach, *Journal of Food, Agriculture and Environment*, vol.1, pp. 1441-1447.

Lillesand, T. M. and Kiefer, R. W. (2000) *Remote Sensing and Image Interpretation*, New York: John Wiley and Sons.

Liu, D. And Cai, S. (2012) A Spatio-Temporal Modelling Approach to Reconstructing Land-Cover Change Trajectories from Multi-Temporal Satellite Imagery, *Annals of the Association of American Geographers*, vol. 102, no. 6, pp. 1329-1347.

Liu, Q., Gou, Y., Liu, G. and Zhao, J. (2014) Classification of Landsat 8 OLI Image Using Support Vector Machine With Tasseled Cap Transformation, *2014 10th International Conference on Natural Computation*, vol. 10, no. 1, pp. 665-669.

Lu, D., Mausel, P., Brondizios, E. and Moran, E. (2004) Change detection techniques, *International Journal of Remote Sensing*, vol. 25, no. 12, pp. 2365-2407.

Macleod, R.D. and Congalton, R.G. (1998) A Quantitative Comparison of Change-Detection Algorithms for Monitoring Eelgrass from Remotely Sensed Data, *Photogrammetric Engineering & Remote Sensing*, vol. 64, no. 3, pp. 207-216.

Madhuku, L. (2004) "Law, Politics and the Land Reform Process in Zimbabwe" in Masiiwa, M. (ed), 2004, *Post-Independence Land Reform in Zimbabwe: Controversies and Impact on the Economy*, Harare: Friedrich Ebert Stiftung and Institute of Development Studies, University of Zimbabwe.

Maguwu, F. (2007) Land Reform, Famine and Environmental Degradation in Zimbabwe, *Journal of Human Security*, vol. 3, no. 32, pp. 32-46.

Martin, L. R. G. and Howarth P.J. (1989) Change Detection Accuracy Assessment using SPOT Multispectral Imagery of the Rural – Urban Fringe, *Remote Sensing of Environment*, vol. 30, pp. 55-56.

Mas, J. F. (1999) Monitoring Land-cover Changes: A comparison of Change Detection Techniques, *International Journal of Remote Sensing*, vol. 20, no. 1, pp. 139-152.

Mas, J. F. and Ramirez, I. (1996) Comparison of Land use Classifications obtained by Visual Interpretation and Digital Processing, *ITC Journal*, vol. 3, no. 4, pp. 278-283.

Masaka, J. and Khumbula, N. (2007) The Effect of Soil Compaction Levels on Germination and Biometric Characteristics of Coffee (*Coffee arabica*) Seedlings in the Nursery, *International Journal of Agricultural Research*, vol. 2, no. 7, pp. 581-589.

Masiiwa, M. (2004) Land Reform Programme in Zimbabwe: Disparity between Policy Design and Implementation [online], available: http://www.sarpn.org/documents/d0000858/P956-Masiiwa Zimbabwe_landreform_May2004.pdf/ [accessed 23 February 2016].

Matavire, M. M., Sibanda, M. and Dube, T. (2015) Assessing the Aftermath of the Fast Track Land Reform Programme in Zimbabwe on Land-use and Land-cover Changes, *Transactions of the Royal Society of South Africa*, vol. 70 (2), pp. 181-186.

Matsa, M. and Muringaniza, K. (2010) Rate of Landuse/ Landcover Changes in Shurugwi District, Zimbabwe: Drivers for Change, *Journal of Sustainable Development in Africa*, vol. 12, no. 3, pp. 107-121.

Matsa, M and Muringaniza, K. (2011) An Assessment of the Land Use and Land Cover Changes in Shurugwi District, Midlands Province, Zimbabwe. *Ethiopian Journal of Environmental Studies and Management*, vol. 4, no. 2, pp. 88-100.

McDonald, J.H. (2008) *Handbook of Biological Statistics*, Baltimore: Sparky House Publishing.

McDonald, J.H., and Dunn, K.W. (2013) Statistical Tests for Measures of Colocalization in Biological Microscopy, *Journal of Microscopy*, vol. 252, no. 3, pp. 295-302.

Mesev, V. (2010) Classification of Urban Areas: Inferring Land Use from the Interpretation of Land Cover in Rashed, T and C. Jurgens., eds., *Remote Sensing and Digital Image Processing: Remote Sensing of Urban and Suburban Areas*, New York: Springer, vol. 10, pp. 144-164.

Miles, V. V., Bobylev, L.P and Maximov, O.M. (2003) An approach for assessing boreal forest conditions based on combined use of satellite SAR and multi-spectral data, *International Journal of Remote Sensing*, vol. 24, no. 22, pp. 4447-4466.

Ministry of Lands and Resettlement (2015) Land Reform Programme 2015 [online], available: http://www.lands.gov.zw/land-reform-program/ [accessed 07 May 2015].

Mishra, V. N, Rai, P. K and Mohan, K. (2014) Prediction of Land use Changes based on Land Change Modeler (LCM) using Remote Sensing: A Case Study of Muzaffarpur (Bihar), India, *Journal of the Geographical Institute 'Jovan Cvijic'* vol. 64, no. 1, pp. 111-127.

Moyo, S. (2002) ‘Peasant Organisations and Rural Civil Society in Africa: An Introduction’, in S. Moyo and B. Romdhane, eds., *Peasant Organisations and Democratisation in Africa*, Dakar, CODESIRA, pp. 1-26.

Moyo, S. (2011) Three decades of agrarian reform in Zimbabwe, *Journal of Peasant Studies*, vol. 38, no. 3, pp. 493-531.

Mucher, C.A., Steinnocher, F.P. and Heunks, C. (2000) Land Cover Characterisation and Change Detection for Environmental Monitoring of Pan-Europe, *International Journal of Remote Sensing*, vol. 21, no. 6, pp. 1159-1181.

Mugandani, R., Wuta, M., Makarau, A. and Chipindu, B. (2012) Reclassification of Agro-ecological Regions of Zimbabwe in Conformity with Climate Variability and Change, *African Crop Science Journal*, 20, 361-369.

Njaya, T. and Mazuru, N. (2014) Emerging New Farming Practices and their Impact on the Management of Woodlots in A1 Resettlement Areas of Mashonaland Central Province in Zimbabwe, *Asian Developing Policy Review*, vol. 2, no. 1, pp. 1-19.

Norusis, M. (1997) SPSS 7.5: *Guide to Data Analysis*, Upper Saddle River NJ: Prentice Hall.

Omer, G., Mutanga, O., Abdel-Rahman, E.M and Adam, E (2015) Exploring the Utility of the

Additional WorldView-2 bands and Support Vector Machines in Mapping Land use/ Land cover in a Fragmented Ecosystem, South Africa, *South African Journal of Geomatics*, vol. 4, no. 4, pp. 414 – 433.

Omoyo, N.N., Wakhungu, J and Otengi, S (2015) Effects of Climate Variability on Maize Yield in the Arid and Semi Arid Lands of Lower Eastern Kenya, *Agriculture & Food Security*, vol. 4, no. 8, pp. 1-13.

Oumer, H.A. (2009) *Land use and Land cover Change, Drivers and its Impact: A Comparative Study from Kuhar Michael and Lenche Dima of Blue Nile and Awash Basins of Ethiopia*, Masters Theses, Cornell University: New York.

Palmer, R. (1977) *Land and Racial Domination in Rhodesia*, Berkeley: University of California Press.

Rawat, J.S. and Kumar, M. (2015) Monitoring Land Use/ Cover Change Using Remote Sensing and GIS Techniques: A Case Study of Hawalbagh Block, District Almora, Uttarakhand, India, *The Egyptian Journal of Remote Sensing and Space Sciences*, vol.18, pp. 77-84.

Reddy, K.R. and Hodges, H.F., eds. (2000) *Climate Change and Global Productivity*, New York: CABI Publishing.

Richards, J.A. (2012) *Remote Sensing Digital Image Analysis: An Introduction*, Australia: Springer Science & Business Media.

Richardson, C. J. (2005) "The Loss of Property Rights and the Collapse of Zimbabwe," *Cato Journal*, vol. 25, no. 3, pp. 541-565.

Riebsame, W.E., Meyer, W. B. and Turner, B. L. (1994) Modeling Land-use and Cover as Part of Global Environmental Change, *Climate Change*, vol. 28, no. 1, pp. 45-64.

Sáez, J.A., Galar, M., Luengo, J. and Herrera, F. (2013) Tackling the problem of classification with noisy data using multiple classifier systems: Analysis of the performance and robustness, *Information Sciences,* vol. 247, no.1, pp. 1-20.

Sala, O. E., Chapin, F.S., Armesto, J. J., Berlow, E., Bloomfield, J., Dirzo, R., Huber- Sanwald, E., Huenneke, L. F., Jackson, R. B., Kinzig, A., Leemans, R., Lodge, D. M., Mooney, H. A., Oesterheld, M., Poff, N. L., Sykes, M. T., Walker, B. H., Walker, M. and Wall, D. H. (2000) Global biodiversity scenarios for the year 2100, *Science***,** vol. 287, pp. 1770-1774.

Salami, A. T and Akinyede, J. (2006) Space technology for monitoring and managing forest in Nigeria, *A paper presented at the International Symposium on Space and Forests*, United Nations Committee on Peaceful Uses of Outer Space (UNOOSA), Vienna, Austria.

Sánchez-Cuervo, A.M., Aide, T.M., Clark, M.L., Etter, A. (2012) Land Cover Change in Colombia: Surprising Forest Recovery Trends between 2001 and 2010. *PLoS ONE*, vol. 7, no. 8, pp. 1-14.

Sang, L., Zhang, C., Yang, J., Zhu, D. and Yun, W. (2011) Simulation of Land Use Spatial Pattern of Towns and Villages based on CA-Markov model, *Mathematical and Computer Modelling*, vol. 54, no. 3-4, pp. 938-943.

Sayemuzzaman, M and Jha, M.K (2014) Modelling of Future Land Cover Land Use Change in North Carolina Using Markov Chain and Cellular Automata Model, *American Journal of Engineering and Applied Sciences*, vol. 7, no. 3, pp. 295-306.

Schmidt, H and Gitelson, A. (2000) Temporal and spatial vegetation cover changes in Israeli transition zone: AVHRR-based assessment of rainfall impact, *International Journal of Remote Sensing*, vol. 21, no. 5, pp. 997-1010.

Serra, P., Pons, X and Saurí, D. (2008) “Land-Cover and Land-Use Change in a Mediterranean Landscape: A Spatial Analysis of Driving Forces Integrating Biophysical and Human Factors,” *Applied Geography*, 28, 189-209.

Silva, J.S., Vaz, P., Moreira, F., Catry, F and Rego, F.C. (2011) Wildfires as a major driver of landscape dynamics in three fire-prone areas of Portugal, *Landscape Urban Planning*, vol. 101, no. 4, pp. 349-358.

Singh, A. (1989) Digital Change Detection Techniques using Remotely Sensed Data, *International Journal of Remote Sensing*, vol. 10, no. 6, pp. 989-1003.

Sohl, T.L and Sleeter B. M. (2012) Role of Remote Sensing for Land-Use and Land-Cover Change Modeling, *Remote Sensing and Land Cover: Principles and Applications*, vol. 15, pp. 225-239.

Stolbovoi, V. (2002) Carbon in Russian soils, *Climatic Change*, vol. 55, no. 1, pp. 131-156.

Stow, D. A. (1999) Reducing the effects of misregistration on pixel-level change detection. *International Journal of Remote Sensing*, vol. 20, no. 12, pp. 2477-2483.

Sunar, F. (1998) Analysis of Changes in Multidate Data Set: A Case Study in Ikitelli Area, Istanbul, Turkey, *International Journal of Remote Sensing*, 19, 225-236.

Tolba, M. K. and El-Kholy, O. A. (1992) *The World Environment 1972–1992: Two Decades of Challenge*, London: Chapman & Hall.

Trotter, C. M. (1998) Characterising the Topographic Effect at Red Wavelengths using Juvenile Conifer Canopies, *International Journal of Remote Sensing*, vol. 19, no. 11, pp. 2215-2221.

Tucker, C.J. and Townsend, J.R.G. (2000) Strategies for monitoring tropical deforestation using satellite data, *International Journal of Remote Sensing 2000*, vol. 21, no. 6 &7, pp. 1461-1471.

Turner II, B. L., Lambin, E. F. and Reenburg, A. (2007) The Emergence of Land Change Science for Global Environmental Change and Sustainability, *Proceedings of the National Academy of Sciences*, vol. 105, no. 7, pp. 20666-20671.

United Nations Development Programme. (2002) *An Assessment and Review of Land Reform Programme of Zimbabwe*, Harare: UNDP Publishers.

United States Geological Survey (2014) Landsat Missions [online], available: http://landsat.usgs.gov/band_designations_landsat_satellites.php/ [accessed 07 May 2015].

Verburg, P.H., de Koning, G.H.J., Kok. K., Veldkamp, A., Fresco, L.O. and Bouma, J. (1999) A Spatial Explicit Allocation Procedure for Modelling the Pattern of Land Use based upon Actual Land Use, *Ecological Modelling*, vol. 116, no. 1, pp. 45-61.

Vincent, V and Thomas, R.G. (1962) *An Agricultural Survey of Southern Rhodesia Part I Agro-ecological Survey*, Harare: Government Printers.

Voss, P.R and Chi, G. (2006) Highways and Population Change, *Rural Sociology*, vol. 71, no. 1, pp. 33-58.

Wang Y., Mitchell B. R., Nugranad-Marzilli J., Bonynge G., Zhou Y. and Shriver G. (2009) Remote sensing of land-cover change and landscape context of the National Parks: A case study of the North-east Temperate Network, *Remote Sensing of Environment*, vol. 113, pp. 1453-1461.

Weng, Q. (2002) "Land Use Change Analysis in the Zhujiang Delta of China using Satellite Remote Sensing, GIS and Stochastic Modelling," *Journal of Environmental Management*, vol. 64, no. 3, pp. 273-284.

Wickramasuriya, R. C., Bregt, A.K., van Delden, H. and Hagen-Zanker, A. (2009) The Dynamics of Shifting Cultivation Captured in an Extended Constrained Cellular Automata Land Use Model, *Ecological Modelling*, vol. 220, no. 18, pp. 2302-2309.

Witmer, F.D.W. (2008) Detecting War-induced Abandoned Agricultural Land in Northeast Bosnia using Multispectral, Multitemporal Landsat Imagery, *International Journal of Remote Sensing*, vol. 29, no. 13, pp. 3805-3831.

Wolfram, S. (1998) Cellular Automata as Models of Complexity, *Nature*, 311, 419-424.

World Bank (2015) Agricultural Land [online], available: http://data.worldbank.org/indicator/AG.LND.AGRI.ZS/countries/ [accessed 10 March 2015].

Wulder, M. A., White, J. C., Goward, S. N., Masek, J. G., Irons, J. R., Herold, M., Cohen, W.B., Loveland, T.R. and Woodcock, C.E. (2008) Landsat Continuity: Issues and opportunities for land cover monitoring, *Remote Sensing of Environment*, vol. 112, no. 3, pp. 955-969.

Wright, G.G. and Morrice, J.G. (1997) LANDSAT TM Spectral Information to Enhance the Land Cover of Scotland 1988 Dataset, *International Journal of Remote Sensing 1997*, vol. 18, no. 18, pp. 2427-2436.

Yan, Y.U. and Zheng-Hui, X. (2013) A Simulation Study on Climate Effects of Land Cover Change in China, *Advances in Climate Change Research*, vol. 4, no. 2, pp. 117-126.

Yuan, F., Sawaya, K.E., Loeffelholz, B and Bauer, M.E. (2005) Land Cover Classification and Change Analysis of the Twin Cities (Minnesota) Metropolitan Area by Multi-temporal Landsat Remote Sensing, *Remote Sensing Environment*, vol.98, pp.317-328.

Zamuchiya, P. (2011) 'A Synopsis of Land and Agrarian Change in Chipinge District, Zimbabwe', *Journal of Peasant Studies*, vol. 38, pp. 1093-1122.

Zembe, N., Mbokochena, E., Mudzengere, F.H and Chikwriri, E. (2014) An Assessment of the Impact of the Fast Track Land Reform Programme on the Environment: The Case of Eastdale Farm in Gutu District, Masvingo, *Journal of Geography and Regional Planning*, vol. 7, no. 8, pp. 160-175.

Zhang, R., Tang, C., Ma, S., Yuan, H., Gao, L and Fan, W. (2011) "Using Markov Chains to Analyze Changes in Wetland Trends in Arid Yinchuan Plain, China," *Mathematical and Computer Modelling*, vol. 54, pp. 924-930.

Zhu, G.B. and Blumberg, D.G. (2002) "Classification using ASTER data and SVM Algorithms: The Case Study of Beer Sheva, Israel," *Remote Sensing of Environment*, vol. 80, no. 2, pp. 233-240.

Zitova, B. and Flusser, J. (2003) Image registration methods: A survey, *Image and Vision Computing*, vol. 21, no. 1, pp. 977-1000.