An Assessment of Land Cover Change Patterns using Remote Sensing: A case study of Dube and Esikhawini, KwaZulu-Natal, South Africa

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As the candidate's supervisor I have/~~have not~~ approved this ~~thesis~~/dissertation for submission.

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ABSTRACT

During the past two centuries, land cover has been changing at an alarming rate in space and time and it is humans who have emerged as the dominant driver of change in the environment, resulting in changes of extraordinary magnitudes. Most of these changes occur due to demands placed on the land by the ever-increasing human population and their need for more land for both settlement and food production. Many researchers underscore the importance of recognizing and studying past land-use and land cover changes as the legacies of these changes continue to play a major role in ecosystem structure and function. The objectives of this study were to determine the extent of land cover changes between 1992 and 2008 in the study areas, Esikhawini and Dube located in the uMhlathuze municipality, KwaZulu-Natal, and to both predict and address the implications of the extent of future changes likely to occur in the area by 2016. Three Landsat satellite images of the study area were acquired for the years, 1992, 2000 and 2008. These images were classified into nine classes representing the dominant land covers in the area. An image differencing change detection method was used to determine the extent of the changes which took place during the specified period. Thereafter, a Markov chain model was used to determine the likely distribution of the land cover classes by 2016. The results revealed that aside from Waterbodies and Settlements, the rest of the classes exhibited a great degree of change between 1992 and 2008, having class change values greater than 50%. With regards to the predicted change in the land cover classes, the future land cover change pattern appears to be similar to that observed between 1992 and 2008. The Settlements class will most likely emerge as the dominant land cover in the study area as many of the other classes are increasingly being replaced by this particular class. The overall accuracy of the classification method employed for this study was 79.58% and the results have provided a good overview of the location and extent of land cover changes in the area. It is therefore plausible to conclude that these techniques could be used at both local and regional scales to better inform land management practices and policies.

DECLARATION

I, Zaakirah Bassa declare that:

1. The research reported in this dissertation, except where otherwise indicated, is my original research.
2. This dissertation has not been submitted for any degree or examination at any other university.
3. This dissertation does not contain other persons’ data, pictures, graphs or other information, unless specifically acknowledged as being sourced from other persons.
4. This dissertation does not contain other persons' writing, unless specifically acknowledged as being sourced from other researchers. Where other written sources have been quoted, then:
    a. Their words have been re-written but the general information attributed to them has been referenced
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5. This dissertation does not contain text, graphics or tables copied and pasted from the Internet, unless specifically acknowledged, and the source being detailed in the dissertation and in the References sections.

Signed__________________________

PREFACE

The work undertaken in this study was carried out at School of Agricultural, Earth and Environmental Sciences, College of Agriculture, Engineering and Science, University of KwaZulu-Natal, Durban, University of KwaZulu-Natal. This research was completed under the supervision of the following academic staff:

Prof. U. Bob, Senior Lecturer, School of Agricultural, Earth and Environmental Sciences, College of Agriculture, Engineering and Science, University of KwaZulu-Natal.

Dr. R. Ismail, Research Fellow at the University of KwaZulu-Natal.

The duration of this study was from March 2009 to September 2012.

The contents of this work have not been submitted in any form to another University and, except where the work of others is acknowledged in the text, the results are the author's own investigation.

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Zaakirah Bassa

October 2012

We certify that the above statement is correct:

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Prof. U. Bob Dr. R. Ismail

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LIST OF ABBREVIATIONS

LUCC	– Land-use and Land Cover Change
GIS	– Geographic Information System
NASA	– National Aeronautics and Space Administrations
MSS	– Multispectral Scanner System
TM	– Thematic Mapper
ETM+	– Enhanced Thematic Mapper Plus
IR	– Infrared
MMU	– Minimum Mapping Unit
CVA	– Change Vector Analysis
RMSE	– Root Mean Square Error
SANSA	– South African National Space Agency
DN	– Digital Number
DWAF	– Department of Water Affairs and Forestry
W	– Waterbodies
Ws	– Wetlands
FW	– Forest and Woodlands
P	– Plantations
CL	– Cultivated land
B	– Bushveld
S	– Settlements
C	– Clearfelled
ROI	– Region of Interest
J-M	– Jeffries-Matusita
SID	– Spectral Information Divergence
DOS	– Dark Object Subtraction
MDM	– Minimum Distance to Means
ML	– Maximum Likelihood
OA	– Overall Accuracy
PA	– Producer's Accuracy
UA	– User's Accuracy
DAFF	– Department of Agriculture, Forestry and Fisheries

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There are several people without whose help, the undertaking of this research would not have been entirely successful. I am deeply indebted to the below mentioned people for their assistance and guidance throughout the course of this study. First and foremost, warm and heartfelt appreciation is extended to my supervisor, Professor U. Bob. Prof. Bob has played a vital role during the course of this research serving not only as a mentor but a big sister of sorts. Her open door policy, ready advice and enthusiastic outlook towards research, and life in general, have made working with her a joyful and educational experience which I will treasure for a very long time. I am also thankful to her for involving me in other research projects which she was conducting during my time as a Masters student. My participation in these projects has exposed me to both the wonders and frustration of undertaking research and at the same time instilled in me a desire to become a researcher in the future.

I am enormously grateful to my co-supervisor, Dr. Ismail, who helped me complete this study when I lost faith and thought all was lost. His almost instant replies to emailed questions and willingness to give up his weekends in order to ensure that I was on the right track are sincerely appreciated. I am in constant awe of the remote sensing knowledge possessed by Dr. Ismail and indebted to him for his valuable technical support and advice.

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CHAPTER 1: INTRODUCTION

1.1. Background

In the past two centuries, it is humans who have emerged as the dominant force of change in the environment, resulting in changes of extraordinary magnitudes, rates, and spatial scales in the landscape (Moran, 2001; Schulz *et al.*, 2010; Turner *et al.*, 1994). Anthropogenic changes in relation to the demand and consumption of land-related resources and services have resulted in significant land clearing as well as changes in land cover and use patterns over the years (Barnett and Adger, 2007; Bob, 2010; Kagwanji, 2009). The authors further argue that these changes and stressors have contributed significantly to increasing vulnerabilities, undermining existing livelihoods (specifically in relation to concerns pertaining to climate change) and in some instances have been the key driver of land related conflicts. These have been particularly acute in marginalized communities in Africa, such as rural areas.

The ever-increasing human need for more land for activities such as agriculture and housing has led to an increase in land cover conversions, land degradation and land-use intensification (Houlbrooke *et al*., 2011; Jones *et al*., 2011; Lambin, 1997). The aforementioned effects of land-use and land cover change (LUCC) has a sometimes negative effect on humans as well, most especially the poor who are dependent on the environment for survival and a range of livelihoods. Thus, it is for this very reason that many authors (such as Lillesand and Kiefer, 2000 and Sherbinin, 2002) believe there to be a need for a better understanding of the relationship and interaction between humans and the terrestrial environment. In addition, Veldkamp and Lambin (2001) emphasize the fact an understanding of the factors which result in LUCCs are essential for the development of LUCC models. These models, according to Guan *et al*. (2011), are useful for exploring and predicting future LUCCs under different scenario conditions, and are therefore regarded as indispensible tools for sustainable land-use planning.

Human and natural systems interact on a dynamic canvas we call land (Parker *et al.*, 2003). Land is one of the most important natural resources as it is from here that humans draw most of their food, shelter, freshwater and fuel (Foley *et al.*, 2005). Land tenure in Africa takes a range of forms including freehold/private titles (includes large tracts of commercial land for activities such as farming and forestry plantations), communal/traditional systems, public/state land (includes natural resource areas for conservation purposes) and informal squatting (Rugege *et al*., 2007). Furthermore, Rugege *et al*. (2007) state that in the South African context in particular, colonial and apartheid processes and legacies have resulted in skewed land ownership patterns as well as contestations over rights and use. In terms of the global land usage, the most economically important human uses include agriculture, timber extraction, settlement and construction, and reserves and protected lands (Lambin *et al*., 2006; Turner *et al.*, 1994). These land-uses, combined with other human activities, have had wide and varied cumulative impacts on the environment. The effects range from direct physical impacts on the terrestrial environment, such as deforestation, to indirect consequences, such as global warming (Foster *et al.*, 2003). Thus, LUCC can negatively impact climate, biodiversity, soil conditions, water flows, and the human population (Turner *et al.*, 1994; Verburg *et al*., 2009).

It is worth noting that much of the research on LUCC has focused primarily on and been applied to urban environments with very few studies assessing LUCCs in rural contexts. In the case of this research, the study area is a typical rural community within the KwaZulu-Natal province. It has a built-up residential area (commonly referred to as 'township'), Esikhawini, and a more agriculturally-based rural area called Dube. Additionally, it is surrounded by or in close proximity to several land-uses typical of rural landscapes such as forest plantations, commercial agriculture and mining interests. These are key LUCC drivers in rural areas and therefore this case study is appropriate to examine LUCCs in these environments.

1.2. Land-use and land cover assessments

In order to understand LUCC, one has to first understand what these terms mean. Land cover refers to the type of feature which occurs on the earth's surface while land-use describes the actual human activity that is taking place on a specific piece of land (Lillesand and Kiefer, 2000). Timely and reliable LUCC information is rapidly becoming one of the most important requirements in decision-making processes at local, regional and global levels (Jansen and Di Gregorio, 2003).

Changes made to the landscape by humans are probably the most ancient of all human-induced environmental impacts (Serra *et al*., 2008; Sherbinin, 2002). These changes generally occurred due to demands placed on the land by the ever-increasing human population. With an increase in population, there is a need for more land for both settlement and the production of food (agriculture). Foster *et al.* (2003) underscore the importance of recognizing and studying past LUCC as the legacies of these changes continue to play a major role in ecosystem structure and function. This will further our understanding of modern changes at both local and global scales, thereby allowing for better predictions of future changes in the terrestrial environment (Deng *et al*., 2009; Foster *et al.*, 2003). Although the importance of assessing both land-use and land cover changes has been underscored above, it should be noted that the primary aim of this research is the assessment of land cover changes.

Change detection provides a means of assessing these land cover changes. A commonly accepted definition of change detection is that of Singh (1989), who defines this term as the "process of identifying differences in the state of an object or phenomenon by observing at different times". Due to the fact that change detection provides a user with repetitive data and short time intervals as well as consistent image quality, it is often regarded as one of the most significant and indispensable applications of remote sensing (Jansen and Di Gregorio, 2002; Mas, 1999).

In order to detect both short- and long-term changes in the landscape, change detection employs the use of multi-temporal datasets (Lillesand and Kiefer, 2000). The best results from change detection techniques can be produced through the use of data which was acquired by the same/similar sensor and that was recorded using the same "spatial resolution, viewing geometry, spectral bands, radiometric resolution, and time of day" (Lillesand and Kiefer, 2000: 578). It is important to note that various environmental factors play a role in influencing the reliability of change detection (Lillesand and Kiefer, 2000). There are a variety of change detection techniques available that can be employed to assess changes in the landscape and one of the main challenges the many remote sensing users face with regards to change detection, is an understanding of how to match a particular technique to an application as no single method has proven to be applicable in all cases (Collins and Woodcock, 1996; Deng *et al*., 2009).

The present research will provide a brief description of some of the most commonly used change detection methods before establishing why 'image differencing' was the method of choice. This choice took into account the remote sensing data available, time limit and the aim and objectives stated below.

1.3. Aim and Objectives

The aim of this research endeavor is to detect and assess land cover changes in Dube and Esikhawini from 1992 to 2008. Specifically, the study will focus on examining changes in relation to the natural resource base.

The objectives of the study are:

1. To determine the dominant land cover changes that have occurred during the 16 year period.
2. To evaluate the extent of these changes.
3. To predict the extent of future changes.
4. To examine potential impacts of these changes on the natural resource base.

1.4. Chapter Outline

This dissertation is divided into seven chapters, with the present Chapter briefly outlining the importance of LUCC research and the aim and objectives of the study. Chapter 2 provides an overview of the recent literature regarding LUCC and change detection. It also discusses in detail how remote sensing data is utilized for change detection and reviews some of the existing change detection techniques and their associated advantages. Chapter 3 describes the background to the study area. Chapter 4 provides a description of the data and methodology used to undertake this research. The findings of the study are described and analyzed in Chapter 5. Chapter 6 discusses in detail the changes observed in the area and the likely impacts of current and future land cover trends. The final Chapter provides a brief overview of the key findings, addresses the implications of this study and provides recommendations for future research.

1.5. Summary

The land-use and land cover trends that exist today allow humans to use increasingly greater amounts of environmental goods and services, thus resulting in an inability of the global ecosystems to perform various functions, such as sustain food production, maintain freshwater and forest resources and regulate climate and air quality (Foley *et al.*, 2005). Changes in the terrestrial environment are closely associated with issues of sustainable development since and, as mentioned before, these changes affect climate, soils, vegetation, water resources and biodiversity, all of which form part of our most essential natural capital (Foley *et al.*, 2005; Mather and Sdasyuk, 1991). Perhaps the most important fact to consider about land resources is that they are “finite, fragile, and non-renewable” (Son and Tu, 2008: 1). These resources also form the basis of human and other terrestrial ecosystems, as well as agricultural production (Son and Tu, 2008). Thus, it is clearly evident that there is a need for the assessment of the broader impact of these changes on both the natural and human environment, especially since these changes often lead to global environmental change (Foster *et al.*, 2003; Lambin, 1997). The foundation for a better understanding of the interactions between humans and the environment can therefore be provided by timely and accurate change detection data of features on the Earth’s surface.

According to Zeleke and Hurni (2001: 184), LUCC assessments should strive to answer the following questions:

- What is the degree and extent, in both temporal and spatial terms, of the changes?
- What are the major consequences of these changes?
- What will the future trends in be in land-use and land cover dynamics?
- Are these dynamics well understood by the relevant stakeholders?
- What are their implications at the regional, national, and international levels?

Assessments of changes in the landscape could lead to the improved use and management of natural resources both in the short- and long-term (Lu *et al.*, 2004). The information gained from such assessments can also be used to inform land management policies (Jansen and Di Gregorio, 2004). In addition, Peterson *et al.* (2004) state that these assessments will also result in better conservation planning and environmental monitoring of all natural resources.

Rural areas, given the extent and nature of persistent poverty, are widely regarded as being socially, economically and ecologically vulnerable. This situation is expected to worsen as a result of climate variability and extreme weather conditions linked to global warming as highlighted earlier. African rural areas in particular are likely to bear the brunt of these changes. In this context, LUCC research that focuses on rural communities will assist in identifying developmental trajectories that can improve the quality of life of rural residents without undermining the natural resource base. Thus, this research contributes to the increasing body of knowledge on how spatial approaches can enhance our understanding of LUCC in rural contexts.

CHAPTER 2: LITERATURE REVIEW

2.1. Introduction

In the past few years, remote sensing has played a substantial role in assessing LUCC. The valuable information supplied by these assessments coupled with developments in remote sensing technologies has led to a rapid increase in the number of change detection studies conducted over the years. This chapter seeks to first understand what exactly is meant by the terms 'land-use' and 'land cover', before addressing the determinants of LUCC and their significance thereof. A large portion of the literature review is dedicated to describing the impacts of LUCC and the role of remote sensing in assessing these changes.

2.2. Land-use and Land cover

Land-use and land cover are two closely related criteria and as such are easily confused with one another even though they are used to describe different aspects of the landscape (Fairbanks *et al.*, 2000). In order to fully comprehend the interaction between and changes in land-use and land cover, Jansen and Di Gregorio (2002) believe that it is vital to understand and know the difference between them. These two terms are often used to describe the terrestrial environment in relation to whether it has been shaped by anthropogenic activity or nature (Chilar and Jansen, 2001).

Land cover refers to the physical cover that one can observe on the earth's surface (Brown and Duh, 2004; Jansen and Di Gregorio, 2003). It can be defined as "all the natural and human features that cover the earth's immediate surface, including vegetation (natural or planted) and human constructions (buildings, roads), water, ice, bare rock or sand surfaces" (Fairbanks *et al.*, 2000: 70). Thus, it is apparent that land cover can be either of natural origin or it can also be created by people's use of the land (Chilar and Jansen, 2001). Moreover, Meyer and Turner (1992: 41) state that land cover change can take one of two forms: "conversion of one category of land to another and modification of condition within a category".

On the other hand, land-use basically refers to the purpose for which the land is used or rather the manner in which the biophysical assets on the earth's surface are used by humans (Brown and Duh, 2004; Jansen and Di Gregorio, 2003; Lambin *et al.*, 2000). Land-use is based more on function, with a specific use referring to the activities which are undertaken to produce goods and services (Fairbanks *et al.*, 2000). A land-use in a particular area is typically influenced by economic, social, political and historical factors (Brown *et al.*, 2000). Furthermore Chilar and Jansen (2001) state that since use of the land depends largely on the characteristics of the landscape, a close relationship exists between land-use and land cover and as such land cover characteristics play a role in influencing land-use. However, it is important to note that although there can be only one land cover type associated with a single point on the earth's surface, that point can be associated with different land-use types (Fairbanks *et al.*, 2000).

From a remote sensing point of view, the difference between land-use and land cover stems from how observable the two are in remotely sensed images. Land cover was found to be more easily observed, both in the field and from images, as it comprises the physical cover of the landscape, such as vegetation, crops and soils (Verburg *et al.*, 2009). In contrast, it is more difficult to distinguish land-use and in many cases land-use is inferred from either observable activities (e.g. grazing) or structural elements in the landscape (e.g. the presence of logging roads) (Verburg *et al.*, 2009).

2.3. The significance of land-use/land cover change research

In recent years increasing importance has been placed on the assessment of LUCC since these changes are closely linked to other environmental issues such as climate change, sustainability of the agricultural sector and provision of safe drinking water in developing countries (Lepers *et al.*, 2005). Consequently, changes in the terrestrial environment are a major environmental global problem along with changes in biodiversity, atmospheric composition and climate change (Jansen and Di Gregorio, 2003). Since LUCC affect both the climate and biogeochemistry of the Earth's ecosystem, they influence land management practices, economic health and social processes at both the national and global scale (Dwivedi *et al.*, 2005; Ojima *et al.*, 1994). Therefore, information regarding changes in the landscape can help in modeling global climate change and terrestrial hydrology (Lambin and Strahler, 1994). Perhaps the most vital reason for assessing LUCC is that it will allow for a greater understanding of environmental change over the next few decades which will in turn allow for a more timely response to these changes (Jansen and Di Gregorio, 2003).

Other advantages associated with the monitoring of LUCC include the fact that the assessment of these changes will facilitate improved conservation planning and environmental monitoring, as well as assist in establishing rates of change in the landscape (Fairbanks *et al.*, 2000; Huston, 2005). Furthermore, information regarding these changes plays a role in the modeling of land-use and environmental change, sustainable management of resources and the development of relevant policies. The aforementioned advantages will result in a better understanding of the landscape thereby leading to a more efficient use of this resource (Jansen and Di Gregorio, 2004).

2.4. Determinants of land-use and land cover change

In order to address the impacts of LUCC, it is imperative that one also understands the causes of these changes. This understanding will not only lead to better decision-making and land-use policies but will also allow for prediction of future changes in the landscape (Lambin *et al.*, 2001; Verburg *et al.*, 2004). Lambin *et al.* (2003) divide the determinants of LUCC into two distinct categories, namely, proximate (direct) and underlying (indirect) causes. Proximate causes refer to anthropogenic activities which result in a physical change in land cover (Lambin *et al.*, 2003; Zak *et al.*, 2008). These causes mainly occur at the local level (Lambin *et al.*, 2003). Underlying causes on the other hand refer to the fundamental forces which underpin proximate causes of land cover changes. Underlying causes, which are formed by a mix of social, political, economic, demographic, technological, cultural, and biophysical variables, can operate at either the local level or be influenced by impacts at the regional and global levels (Lambin *et al.*, 2003; Zak *et al.*, 2008). Lambin *et al.* (2003) stress that not all determinants of LUCC are equally important, and when attempting to predict the trend of change for a particular human-environment system, only a few determinants need to be considered.

2.4.1. *Economic factors*

Economic factors have often been regarded by many researchers as one of the more dominant determinants of LUCC (Lambin *et al.*, 2003; Verburg *et al.*, 2004). The assumption that, in equilibrium, land is used for the activity which produces the highest potential profitability forms the basis of many of the economic models which economists use to understand the relationship between land and location factors (Verburg *et al.*, 2004). Lambin *et al.* (2003) note that changes in the landscape often occur as a consequence of individual and social responses to fluctuating economic conditions, which are mediated by institutional factors.

Decisions made by land managers are influenced by a variety of economic factors and policies such as taxes, subsidies, technology, etc. Furthermore Lambin *et al.* (2003) argue that local consumption has less of an effect on land in comparison to external demand. Increasing external demand leads to a decrease in subsistence croplands and an increase in both land for market crops and agricultural intensity.

The unequal distribution of wealth amongst households and countries is also a factor which influences change in the landscape (Lambin *et al.*, 2003; Turner *et al.*, 1993). According to Turner *et al.* (1993), there exists a mixed relationship between level of wealth or economic development and environmental change. For example, wealth has often been associated with an ability to easily develop and exploit land and natural resources thereby increasing per capita consumption (Lambin *et al.*, 2003). This increase means higher resource demands resulting in some form of environmental change, which can be mitigated through the use of advanced technologies (Turner *et al.*, 1993).

2.4.2. *Technological factors*

The development and application of new technologies, over the years, has allowed humans to change or adapt the landscape in ways which severely impact the natural environment (Huston, 2005). Huston (2005) states that the history of human civilization and environmental impacts can be divided into three phases. The first phase is the “agrarian stage” and portrays the growth in human population as a consequence of both primary and secondary production (Huston, 2005: 1864). Agricultural activity, driven mainly by primary production, is included in this stage. The second phase describes the independence of humans from any environmental constraints on primary productivity. The change from the agrarian to industrial phase and development of new transportation system allowed for human settlements to be located away from agricultural production (Huston, 2005). The third and final phases demonstrate a further independence of humans from both industrial and agricultural centers. This independence is attributed mainly to the development and efficiency of electronic communication and new transport systems (Huston, 2005). Huston (2005) notes that this phase has allowed humans to occupy any portion of the landscape and remain completely independent of any primary or secondary productivity centers. The aforementioned phases result in the creation of varying patterns of human populations, land-use changes as well as environmental impacts, constrained only by the availability and location of natural resources.

In addition, Lambin *et al.* (2003) note that although improvements in agricultural technology can have the advantage of ensuring that farmers have access to credit and markets as well providing them with secure land tenure, it can also lead to an increase in environmental degradation. A change in the demand and usefulness of certain natural resources occurs as a consequence of the development of new technologies. Furthermore improvements made to transport infrastructure, such as the building of new roads, allows for greater access to previously inaccessible areas, thereby increasing natural resource exploitation and land degradation (Turner *et al.*, 1993).

2.4.3. *Social and Cultural Factors*

The focus of social models and theories is one of the factors which play a role in the choice of location made by communities. These factors include "individuals' cultural values, norms, and preferences (lifestyles), and their financial, temporal, and transport means" (Verburg *et al.*, 2004: 127). In addition to the aforementioned factors, site characteristics, such as land property value and topographical quality, and historical events also influence locational choices (Verburg *et al.*, 2004).

According to Lambin *et al.* (2003), cultural values are also taken into account in the land-use decision-making process. When making land-use decisions, land managers are influenced by their own attitudes, values, beliefs and individual perceptions. Cultural factors together with political and economic inequalities affect resource access and land-use, and thus understanding of the various factors may better describe the way by which resources are managed, peoples' compliance or resistance to certain government policies as well as social flexibility during environmental change (Lambin *et al.*, 2003).

2.4.4. *Demographic Factors*

Fluctuations in population size have a significant impact on land-use, especially in developing and underdeveloped countries (Lambin *et al.*, 2003; Turner *et al.*, 1993; Zak *et al.*, 2008). As human population increases so does the pressure it exerts on the terrestrial environment, due to a greater demand for resources such as food, fiber, fuel and water (Ojima *et al.*, 1993). Despite the fact that population growth can be positively correlated to expansion of agricultural lands, land intensification and deforestation, Turner *et al.* (1993) argue that some studies prove this correlation to be weak and dependant on the inclusion and exclusion of statistical outliers. Meyer and Turner (1992) assert that some theories, such as the Faustian and Neoclassical theories, found population to be a secondary determinant of LUCC. These theories believe that growing populations serve to only worsen degradation caused by other major determinants, such as the development of new technologies (Meyer and Turner, 1992).

Other demographic factors which contribute to LUCC are life-cycle features, migration and urbanization. Life-cycle features refer mainly to labor availability at household level which is in it-self linked to migration and urbanization (Lambin *et al.*, 2003). Although these features arise from rural environments they also affect urban environments. Life-cycle features occur as a consequence of households' responses to economic constraints and opportunities and are thus responsible for shaping the trajectory of change in land-use and land cover patterns, which in turn impacts on households' economic status (Lambin *et al.*, 2003).

Lambin *et al.* (2003) consider migration to be the most important demographic factor responsible for change in the landscape. Together with other non-demographic factors, such as globalization, government policies and change in consumption patterns, migration operates as a major driver of change (Lambin *et al.*, 2003).

Over the next few decades, Lambin *et al.* (2003) predicts that urbanization will become a significant driving force of land-use change, not only in the main urban and peri-urban areas but in remote areas as well. This is due to the fact that although urban growth has the advantage of creating new markets for agricultural products, timber and livestock, it still results in an increase in urban remittances to rural areas (Lambin *et al.*, 2003).

2.4.5. *Biophysical Factors*

In comparison to the abovementioned determinants of LUCC, biophysical factors play a lesser role. The natural environment is more important in terms of the constraints and possibilities it provides for the way in which land can be exploited (Verburg *et al.*, 2004). Despite the fact that environmental conditions provide significant constraints to new land-uses, Chilar and Jansen (2001) believe that these can be mitigated through the investment of energy and materials.

Some of the biophysical factors which influence land-use and land cover in area are climate, topography, soils, geology, vegetation and the presence or availability of water (Chilar and Jansen, 2001). The aforementioned factors frequently interact with anthropogenic determinants of land-use change and often changes in the landscape lead to an increase in the vulnerability of human-environment systems to climatic fluctuations resulting in land degradation (Lambin *et al.*, 2003).

2.4.6. *Policy Factors*

In order to fully understand the causes behind LUCC, one has to also recognize the role which institutions (i.e. political, economic, legal and traditional) play in individual decision making. Local and national policies together with institutions structure the way in which land, labor, capital and technology can be accessed (Lambin *et al.*, 2003). These policies can have both negative and positive outcomes. Land-use changes can occur as a product of ill-defined polices as well as inadequate institutional responses. However, well designed and properly implemented policies can have a positive impact in the recovery and restoration of natural resources (Lambin *et al.*, 2003).

In the case of developing countries, such as South Africa, land policy, land rights and land reform constitute important elements for poverty reduction in both urban and rural sectors (Tukahirwa, 2002). Since the new government came into power in 1994, various new policies and legislations have been developed to address the injustices of the past (Bradstock, 2006; Fourie, 2000). South Africa's land reform programme comprises of three major components, namely, Land Tenure Reform, Land Restitution and Land Reform (Bradstock, 2006).

2.4.7. *Spatial Interactions and Neighborhood Characteristics*

Analysis of land-use patterns reveals that these patterns are often a consequence of spatial interactions. The occurrence of a type of land-use (be it residential, commercial, etc.) does not develop independently, but is rather influenced by land-uses in neighboring locations (Verburg *et al.*, 2004). Thus, each land-use type impacts the conditions of both adjacent and distant locations. Interregional and international networks of economic, social and political relations are also factors which are considered in the location of a particular land-use (Verburg *et al.*, 2004).

2.5. The impact of land-use and land cover changes

According to Walker and Steffen (1997), LUCC "comprise one of four major, large-scale environmental perturbations of the earth, together with biodiversity, atmospheric composition, and climatic changes". Agricultural growth and urban expansion are two major land-use activities responsible for the transformation of one-third to one-half of the Earth's land surface. This transformation, which generally occurs in the form of deforestation, agricultural practice and urban growth, has significant impacts on the environment, ecosystem services and food production (Yan *et al.*, 2009).

At the global level, land-use is responsible for the dramatic change in land cover, most especially in the tropics (Lambin, 1997). Most land cover changes are a consequence of anthropogenic activities and driven by either land cover conversions, land degradation or land-use intensification (Lambin, 1997). Land cover conversions, which simply entails the change in land cover from one type to another, has devastating impacts on the environment and two of its main causes are urbanization and tropical deforestation (Lambin, 1997). Land degradation is a term which describes the deterioration in the natural resource base via processes such as soil erosion and soil salinisation. It negatively impacts food supply and is prevalent mainly in semi-arid regions (Lambin, 1997). Land-use intensification, associated mainly with the agricultural sector, is driven by population growth and market demand (Lambin, 1997). The impacts of both LUCC will be discussed in greater detail below.

2.5.1. *Impacts associated with food production*

Advances in agricultural technologies together with changing land practices have allowed humans to significantly increase both world food production and the extent of agricultural lands, making it one of the largest terrestrial biomes (Foley *et al.*, 2005). However, these advances have occurred at a huge cost resulting in widespread environmental damage. The conversion of land cover into cropland has been occurring for more than a hundred years, resulting in significant impacts on almost all major biomes as well as huge losses in soil carbon (Ojima *et al.*, 19994). Tillage, drainage and grazing are just a few of the agricultural activities which impact on the native flora and fauna of an area (McLaughlin and Mineau, 1995). The loss of these native species is detrimental in the fact that it also affects agricultural production through the degrading of the services provided by pollinators, such as bees (Foley *et al.*, 2005).

In light of the abovementioned impacts of some agricultural activities, Foley *et al.* (2005) conclude that modern agricultural practices may be trading short-term increases in food production for long-term losses in ecosystem services, many of which are vital to food production itself.

2.5.2. *Impacts on the hydrological cycle*

LUCC can disrupt the hydrological cycle in both the long- and short-term. Short-term disruptions may increase water yield or in cases of low flow, eliminate the flow altogether. Reductions in evapotranspiration and water recycling, which can ultimately result in rainfall reduction, are examples of long-term disruptions (Li *et al.*, 2007). These changes are also responsible for modifying the surface water balance, runoff and groundwater flow (Foley *et al.*, 2005). The aforementioned negative impacts on freshwater resources frequently arise as consequence of deforestation, vegetation removal and the conversion of one land cover type to another (Costa *et al.*, 2003; Foley *et al.*, 2005).

Many land-use activities require large amounts of water, none more so than agriculture. Gleick (2003) estimates that global water withdrawals now total approximately 4 324 km^3 yr^{-1} and the consumptive use of water is estimated to be 2 501 km^3 yr^{-1}, with agriculture responsible for approximately 85% of this consumption. The consequences of such large demands on freshwater has led to both a decline in groundwater tables in some regions as well many large rivers experiencing reduced flow or even drying up altogether (Foley *et al.*, 2005).

Urbanization and agriculture are two land-use activities which are responsible for the degradation of water quality in many rivers and streams throughout the world (Foley *et al.*, 2005). In their study on the relationship between land-use and surface water quality, Yong and Chen (2002) prove that runoff from both agricultural and urban land-use increase the amount of nitrogen and phosphorous thus resulting in contamination of freshwater resources. In cases where wastewater treatment is absent, urbanization can result in water quality degradation which affects inland and coastal waters thus resulting in oxygen depletion, aquatic ecosystem disruptions and increases the occurrence of waterborne diseases (Foley *et al.*, 2005).

2.5.3. *Impacts associated with forest resources*

In the past 300 years, various land-use activities have contributed to the net loss of about 7 to 11 million km^2 of forests (Foley *et al.*, 2005; Ramankutty and Foley, 1999). Agricultural expansion, road building, logging, fuelwood collection and forest grazing are some of the land-use practices which negatively affect forest ecosystems (Foley *et al.*, 2005; Moran, 1993). Changes and development of land-uses is especially troubling in tropical forests, which although cover only 17% of the earth's land surface, sustain over half of the planet's animal and plant species (Laurance, 1999). Forest loss and habitat fragmentation have severe negative implications for biodiversity through increasing habitat isolation and thereby endangering species and modifying their population dynamics (Echeverria *et al.*, 2006; Verburg *et al.*, 2006). Deforestation and fragmentation also negatively impact on forest productivity, biomass, stand structure and species richness (Echeverria *et al.*, 2006; Foley *et al.*, 2005).

In addition to the previously mentioned impacts, Laurance (1999) believes that loss of ecosystem services is by far the greatest and most severe effect of deforestation. The loss of these services are detrimental not only to the environment but to humans as well. For example, the flooding of the Yangtze River in China, which resulted in 3 000 deaths and extensive infrastructural damage, was further exacerbated by the forest removal which took place near the headwaters of the river (Gorman, 1999). Thus, it is evident that forests play an important role in maintaining both the stability of rivers and soils (Laurance, 1999). Furthermore, forest removal also affects climate, as discussed in greater detail below.

2.5.4. *Impacts associated with climate change*

Climate change both drives and is impacted by LUCC (Zak *et al.*, 2008). Land conversions change the physical properties of the land surface thereby impacting on regional climate through its effects on net radiation, the diversion of energy into sensible and latent heat, and the partitioning of precipitation into evapotranspiration, soil water and runoff (Foley *et al.*, 2005; Pielke *et al.*, 2002). In tropical regions, the replacement of tropical forests with pastures and other land-uses is of particular importance as it significantly affects the global climate (Bonan, 1997; Foley *et al.*, 2005; Pielke *et al.*, 2002). In contrast to the cooling brought about by the removal of temperate and boreal forest vegetation, tropical deforestation both results in a warmer and drier climate and negatively impacts on the climate-related ecosystem services provided by tropical forests (Bonan *et al.*, 1992; Foley *et al.*, 2005; Pielke *et al.*, 2002).

The changing spatial and temporal pattern of thunderstorms is another example of the negative climatic impacts of LUCC (Pielke, 2005). These changes affect the surface fluxes of heat and water vapor which in turn impacts on the atmospheric boundary and the energy available for thunderstorms. Alterations in the spatial patterning of thunderstorms have global climate consequences in the form of modifying atmospheric and oceanic circulation patterns (Pielke, 2005). Thus, Pielke (2005) concludes that since most thunderstorms form over land, LUCC can be recognized as an important determinant of climate change.

Changes in the landscape can sometimes result in the formation of "urban heat islands" (Foley *et al.*, 2005: 571). These islands form as a result of the combination of reduced vegetation cover, impervious surface area and the morphology of buildings, all of which lead to a decrease in evaporative cooling, storage of heat and warming of surface air (Foley *et al.*, 2005). Furthermore Foley *et al.* (2005) state that land-use activities also negatively impact air quality and causes air pollution through by altering emissions and atmospheric conditions.

The abovementioned impacts of LUCC are just a few of the destructive consequences posed by changes in the landscape. These impacts were mentioned in order to reiterate the importance of assessing and providing solutions to LUCC. Present land-use practices have developed over many years and under different political, environmental, social and demographic conditions (Ojima *et al.*, 1994). The goal of most modern land-use activities is to meet local needs and increase the supply of material goods and services in the short-term. This practice is destructive as it often has severe negative consequences on the natural environment at both the regional and global scales (Foley *et al.*, 2005; Ojima *et al.*, 1994). Thus, not only is it vital to understand how people responded to past LUCC, but it is equally important to develop sustainable land management practices and policies that will allow humans to meet their present needs, whilst still maintaining the ability of the environment to supply goods and services in the future (Foley *et al.*, 2005; Ojima *et al.*, 1994).

2.6. The importance of LUCC research in developing countries

Several researchers have shown that the assessment of LUCC can be of great benefit to developing countries. One such study which addresses these changes is that of Brink and Eva (2009). In their study on land cover changes in sub-Saharan Africa, the authors made note of the fairly recent impacts which the area has undergone and the associated impacts. Brink and Eva (2009) state that in the last 25 years sub-Saharan Africa has been subjected to both natural and anthropogenic disturbances which resulted in unprecedented LUCC. These changes were and continue to be the product of various factors such as droughts, civil wars, floods, population increase and globalization, all of which serve to enhance the degradation of natural resources and ecosystem services (Brink and Eva, 2009). This has both environmental and socioeconomic consequences. With regards to the environmental impacts, Brink and Eva (2009) assert that the removal of natural vegetation not only results in biodiversity, stored carbon and habitat loss, but also causes the loss of pastures, fuelwood and bush meat as well increasing the occurrence of natural hazards. Loss of ecosystem services has socioeconomic consequences in the form of deterioration of livelihoods and cultural values, which may in turn affect the income generated from tourism to these areas (Brink and Eva, 2009). Thus, Brink and Eva (2009) conclude that it is essential to understand the impacts of LUCC in sub-Saharan Africa and thereafter develop appropriate land management practices to deal with them.

Other studies which also highlight the importance of LUCC research in developing countries, especially with regards to African countries, include that of Sedano *et al.* (2005) and Tekle and Hedlund (2000). Sedano *et al.* (2005) found that poverty alleviation and food security in Africa is influenced by natural resource management and environmental monitoring. As such the authors advocate the use of land cover information, since it will be of great benefit in monitoring the impacts and effectiveness of management practices, thereby assisting in the creation of better sustainable development policies (Sedano *et al.*, 2005). According to Tekle and Hedlund (2000), a recurring problem in many developing countries is the fact that agricultural production has not kept pace with increasing population growth. The focus of their study was on LUCC in Southern Wello, Ethiopia. The authors found that the study area had undergone significant changes as a result of anthropogenic activities which contributed to the problem of land degradation in the country (Tekle and Hedlund, 2000). Consequently, Tekle and Hedlund (2000) state that there is a need to better understand the cause and effects of LUCC so as to allow for better management of the available resources.

With regards to South Africa, Fairbanks *et al.* (2000) assert that in order for strategic environmental assessments and sustainable land-use planning to be successful, there is critical need for good quality information regarding the characteristics and spatial distribution of the country's land cover. Thus, in light of the aforementioned case studies, it can be concluded that LUCC research is of vital importance to developing countries.

2.7. The Role of Remote Sensing for LUCC Research

According to Lillesand and Kiefer (2000: 1), remote sensing is the "science and art of obtaining information about an object, area, or phenomenon through the analysis of data acquired by a device that is not in contact with the object, area or phenomenon under investigation. In the last few decades remote sensing technologies and methods have evolved dramatically and resulted in the creation of a group of different sensors operating at a variety of imaging scales (Rogan and Chen, 2004). Current remote sensing technologies have a variety of applications in all fields of study and the fact that remote sensing also provides historical data that is both cost-effective and of a good resolution, implying that the technology will make an even greater impact in the future (Franklin, 2001; Rogan and Chen, 2004). According to Rogan and Chen (2004: 304), the rapid advancements in the field of remote sensing are driven by three main factors: "(1) advancements in sensor technology and data quality, (2) improved and standardized remote sensing methods, and (3) research applications".

Remote sensing has played a vital role in LUCC research since the 1940s, when changes in the landscape were assessed through the use of aerial photographs (Al-Bakri *et al.*, 2001). Although visual interpretation of high resolution aerial photography is still presently regarded as a standard tool for monitoring changes in the landscape, it is an expensive and time consuming process (Bauer and Steinnocher, 2001; Treitz and Rogan, 2004). The use of satellite images provides an alternative to this traditional method and allows for cartographic and geographic databases to be updated and maintained more efficiently (Bauer and Steinnocher, 2001).

The benefits of remote sensing to LUCC assessments are many and are summarized below. Remote sensing can be used for:

- understanding, mapping and monitoring changes in the landscape since it provides multispectral and multitemporal data that can be easily converted into useful information (Mas, 1999; Nelson *et al.*, 2005; Weng, 2002).
- mapping and monitoring of vast areas of the landscape (Jansen and Di Gregorio, 2004; Thompson, 1996) at both regional and global scales (Lepers *et al.*, 2005).
- supplying spatial information of areas where data collection was previously difficult due to inaccessibility and high costs (Sedano *et al.*, 2005).

Remote sensing technology is thus rapidly proving to be an invaluable information source to planning departments and land managers as it both provides and analyses digital data from ground-based, atmospheric and Earth-orbiting sensors. The fact that this data can be linked to GPS data, GIS vector layers and be used to model different scenarios, is a further advantage of utilizing the technology (Rogan and Chen, 2004).

2.8. Change detection analysis and remote sensing

According to Rogan and Chen (2004: 314), digital change detection is “the process of determining and/or describing changes in land cover and land-use properties based on co-registered multi-temporal remote sensing data”. This technique is essentially used to identify those areas on digital images (i.e. both satellite and aerial photographs) that show change in features of interest, between any two or more dates (Muttitanon and Tripathi, 2005; Rogan and Chen, 2004). Macleod and Congalton (1998) assert that there are four main aspects of change detection for monitoring natural resources: detecting if a change has occurred, identifying the nature of the change, measuring the areal extent of the change, and assessing the spatial pattern of the change. There are several advantages associated with change detection analysis such as the fact that it is repetitive, facilitates the inclusion of biophysically relevant features from the electromagnetic spectrum, and has relatively cheap operational costs (Nackaerts *et al.*, 2005). It also has the ability to not only show the location of the change, but also the type of change and the manner in which this change is occurring (Jansen and Di Gregorio, 2002).

There are numerous change detection methods available that can be used to assess LUCC. However before selection can take place, there are several factors that need to be considered. Firstly, Jansen and Di Gregorio (2002) make reference to the fact that land cover change takes two forms, namely, conversion from one category to another and modifications within a single category. This has implications for selection of an appropriate method when describing and classifying land cover. Conversion implies an obvious or clear change, whilst modification implies a less apparent change and therefore requires a greater level of detail (Jansen and Di Gregorio, 2002). In comparison to modifications in land cover, conversions are easier to notice, as long as the categories are not too broad or too few. Consequently conversions from one land cover type to another are a well-documented unlike modifications which are subtle and often very hard to notice, especially at a global level (Jansen and Di Gregorio, 2002; Lambin, 1997). Other factors to consider when selecting a method for change detection is the remote sensor system, environmental characteristics, and most importantly that this type of analysis is subject to spatial, temporal, thematic and spectral constraints (Coppin and Bauer, 1996; Lu *et al.*, 2004; Muttitanon and Tripathi, 2005). Therefore the type of method chosen can greatly affect the qualitative and quantitative estimates of the change and sometimes, even in the same environment, different change detection methods may produce different change maps (Coppin and Bauer, 1996; Muttitanon and Tripathi, 2005). A detailed review of various change detection methods is provided by Coppin *et al*. (2004) and Lu *et al*. (2004). The methods referred to below, namely post-classification comparison, image ratioing, Change Vector Analysis (CVA) and image differencing, are just four of the most popular change detection techniques employed by researchers in studies on LUCCs. The purpose of mentioning these methods is to highlight the fact that choice of a specific change detection method depends on several factors and no one method is perfect for every scenario.

The post-classification method involves the comparison of multiple remotely sensed classified images, collected at different time intervals, on a pixel to pixel basis (Peterson *et al*., 2004). Kamusoko and Aniya (2009) used this approach to analyze the LUCCs which occurred from 1973 to 2000 in the Bindura district of Zimbabwe. The authors chose this method specifically because it provides information on the nature of class changes, and compensates for variations in vegetation phenology and atmospheric conditions between two dates. The pixel-by pixel comparison nature of the resultant change detection matrix allowed Kamusoko and Aniya (2009) to quantify both the areal extent and spatial distribution of the LUCCs. Xu *et al*. (2010) also favored the post-classification comparison method, combined with background subtraction (i.e. the exclusion of all other classes other than those of interest), for similar reasons in their study on the change in an earthquake-induced barrier lake. Using images from before and after the 2008 Wenchaun Earthquake, the results of this change detection method showed that the earthquake led to a widening of the river and an increase in the surface area of the barrier lake in the study area.

Image ratioing is a quick easy method which basically entails ratioing of remotely sensed images on a pixel to pixel basis. A pixel which has not changed will have a ratio value of one, whilst areas of change will have values that are either higher or lower than one (Coppin and Bauer, 1996; Coppin *et al*., 2000). Chi *et al*. (2009) used both the image ratioing and post-classification comparison methods to assess urban dynamic changes in southeastern China. The authors found that whilst post-classification comparison yielded better results on the macro-scale, image ratioing displayed in more detail the changes which occurred in the inner city.

With regards to CVA, this technique is ideal for defining thresholds and identifying change trajectories (Lu *et al*., 2004). It uses multitemporal datasets to calculate both the magnitude and nature of LUCC (Rogan and Chen, 2004). Two outputs are generated: (1) a spectral change vector which describes the direction and magnitude between the two dates, and (2) the total change magnitude per pixel (Lu *et al*., 2004). It is for these very reasons that Yun-hao *et al*. (2001) chose CVA to determine the trends and characteristics in terrestrial vegetation change in China over a ten year period, from 1989 to 1999. The results of the CVA method showed that most of the observed land cover changes took place in eastern China, where climate and human activities were cited as key drivers. Yun-hao *et al*. (2001) advocate CVA as this method, in comparison to many of the other methods, allows for processing of as many spectral bands as desired in order to find changed pixels. Other authors who have used CVA include Palmer and van Rooyen (1998). The authors employed this method in their study on vegetation change in the southern Kalahari, with the specific aim of determining whether land cover changes around water points and fence-lines could be determined using satellite imagery. Using CVA, Palmer and van Rooyen (1998) explored three bands (visible, red and near-infrared) and their results showed that there was a definite change in near-infrared activity near water points from 1989 to 1994.

Image differencing, the change detection method on which this particular research is based, assesses LUCC by subtracting, pixel by pixel, the first-date image from the second-date image (Lu *et al*., 2004). The popularity of this method stems from the fact that it is simple, straightforward and the results can be easily interpreted (Lu *et al*., 2004). Weng (2001) used image differencing to evaluate changes in surface runoff over time in order to analyze the impact of LUCC on the environment. His findings showed that the Zhujang Delta of China experienced significant urban growth between 1989 and 1997, which led to an increase in surface runoff and caused severe problems for water resource management. In their study on measuring woody encroachment along a forest-savanna boundary in Central Africa, Mitchard *et al*. (2009) preferred image differencing as this change detection method made it possible to examine changes in woody cover, even though the satellite images used were collected from different sensors and under unknown atmospheric conditions.

2.9. Modeling LUCC using remote sensing

Prior to the 1960s, LUCC was studied from a disciplinary perspective. In recent years this has changed to a more interdisciplinary approach, as researchers seek to understand the interactions in land systems from a more holistic point of view (Verburg *et al.*, 2009). Advances in remote sensing and classification and change detection methods have enabled researchers to more accurately assess current land resources as well as identify trajectories of land cover change processes, and hot-spots of LUCC (Herold, 2006). The recent advances in land change science enhance our understanding of changes in the landscape, however, Parker *et al.* (2003) stress that these direct measurements are not sufficient. A comprehensive understanding of the drivers of LUCCs, according to Parker *et al.* (2003), can only be gained by linking observations at spatial and temporal scales to empirical models.

Over the last few decades a range of different LUCC models have been developed to meet the specific needs of land managers and to provide better information about the future role of LUCC in the functioning of the earth system (Veldkamp and Lambin, 2001; Verburg *et al*., 2006). The objective of many LUCC models is to address when, where, and why LUCC occurs (Brown *et al.*, 2000; Lambin, 2004; Lambin *et al.*, 2000). These models are regarded as powerful tools that can be used to not only conceptualize and analyze the influence of socioeconomic processes on land development, agricultural activities and natural resource management strategies, but to also understand the ways in which these changes affect ecosystem structure and function (Brown *et al.*, 2000; Schneider and Pontius, 2001; Verburg *et al.*, 2004b; Verburg *et al.*, 2009). Furthermore, Veldkamp and Lambin (2001) state that if LUCC modeling is conducted in a spatially explicit, integrated and multi-scale manner, these models could then be effectively used to explore scenarios of future developments, perform experiments that test our understanding of key LUCC processes and drivers and lastly, describe the latter using a more quantitative approach. Verburg and Veldkamp (2001) add that these models will allow policy makers, researchers and other stakeholders to make more informed decisions through the provision of vital information on possible future changes, should policies or other land-use determinants change.

A range of land-use and land cover models, from different disciplinary backgrounds, have been developed over the years (Verburg *et al.*, 2004b). Initially these models were based on the use of biophysical attributes (such as slope, altitude or geology) as there was generally good data available for them (Veldkamp and Lambin, 2001). However, in order to be truly effective, these models had to incorporate social, economic and political factors, which proved to be difficult due to a lack of spatially explicit data and problems linking social and natural data (Veldkamp and Lambin, 2001). One of the main challenges associated with monitoring, modeling and communicating LUCC, is the relation between land-use, land cover and land functions (i.e. the provision of goods and services by the land system). Verburg *et al.* (2009) note that most studies have focused on the socioeconomic and environmental consequences of LUCC as a post-analysis or impact assessment, with many of these studies not taking into consideration the fact that in reality, the functionality of land is intricately linked to land cover. Thus, the authors stress the need for more attention to be paid to this link between land cover and ecosystem functioning as land cover changes do not only alter the provision of goods and services, but are also important driving forces of future land cover dynamics. However, it is difficult to model or conduct an assessment between land cover and land function for several reasons. Firstly, there is no one-to-one relationship between land cover and functionality, and the standard techniques used to observe and monitor land cover cannot necessarily be applied to land functions. Also, in many cases land function may change without any alterations in land cover or vice versa. Furthermore, since land cover is not always a good indicator for the actual functions performed by the land at a location, it is difficult to quantify these functions bases on land cover information (Verburg *et al.*, 2009).

There are four broad categories of modeling which have evolved, namely empirical-statistical, stochastic, optimization and dynamic (process-based) simulation models (Lambin, 2004; Lambin *et al.*, 2000). It is important to note that all of these models, different though they may be, have three main components: maps of land cover from more than one point in time, a function of change that modifies the values and spatial arrangement of an initial land cover map, and the resulting prediction map (Schneider and Pontius, 2001). Additionally when modeling LUCC, it is essential that the level of analysis, cross-scale dynamics, driving factors, spatial interaction and neighborhood effects, temporal dynamics, and level of integration are all considered before a model is chosen (Verburg *et al.*, 2004b). Discussed below are a few examples of cases where a LUCC model has been used with great success.

In order to aid water resource management and predict the effect of land-use change on the Luvuvhu Catchment in South Africa, Jewitt *et al*. (2004) utilized the HYLUC (Hydrological Land Use Change) and ACRU (Agricultural Catchments Research Unit) models. The models predicted that increasing either forestry or irrigation in the study area will have a significant negative impact on the catchment. The authors stated that using GIS and remote sensing to model LUCC enables policy-makers and managers to quickly and easily understand the implications of LUCC on water resources.

Richardson *et al*. (2010) used a cellular-automata simulation model to estimate the dynamics of *Schinus molle*, an invasive tree species from central South America introduced to South Africa in 1850, under future climates and different management scenarios. By using the modeling approach outlined in their paper, Riachardson *et al*. (2010) conclude that it will be possible to predict the invasion potential of alien plant species not only in South Africa but in other countries as well. Cellular-automata models are quite popular and another example featuring this model, this time in an urban context, is the research presented by Han *et al*. (2009). The authors used an integrated systems dynamics and cellular-automata model to analyze socioeconomic driving forces and evaluate the urban spatial pattern. The integrated model proved to be adept at monitoring and projecting the dynamics of urban growth and also predicted a 3% increase in the urban area of Shanghai from 2000 to 2020. Han *et al*. assert that information provided by models such as this is necessary for understanding environmental impacts and implementation of sustainable urban development strategies.

Agent-based modeling is a relatively new approach to LUCC assessments and one that has been gaining popularity, as it offers a way to mechanistically and spatially explicitly incorporate the influence of human decision making on LUCC (Matthews *et al*., 2007). Examples of cases where this approach was applied include studies by Bharwani *et al*. (2005) and Valbuena *et al*. (2010). Bharwani *et al*. (2005) used a multi-agent model to model the effects climate outlooks and food security on a community garden scheme in Limpopo, South Africa. Their model took into account the drivers of decision-making with a focus on the role of climate, market and livelihood needs. This innovative approach used by Bharwani *et al*. (2005) not only highlights the effect of climate on small-scale agriculture in South Africa, but also allows analysts to experiment with scenarios which do not currently exist. Valbuena *et al*. (2010) study on the other hand explored the effect of voluntary mechanisms on LUCC in rural Queensland, Australia. The authors deduced that in rural areas, LUCC were very often the result of decision-making on the part of the individual farmers, and both compulsory and voluntary mechanisms were implemented to influence these decisions. Valbuena *et al*. (2010) applied their model to an area where farmers were asked to voluntarily participate in restoring native vegetation. The results of this approach were in the form of three scenarios which depicted how changes in farmers' willingness to participate in restoration progammes can affect the landscape.

The last few case studies described here are in reference to Markov Chain models, an approach used in the present study. The usefulness of this type of modeling approach, according to Wu *et al*. (2006), lies in its ability to describe, analyze and predict LUCC. The authors used Markov chains together with regression analyses to predict how land-use would change in 2021 in Beijing. Both these models forecasted a significant increase in urban land and a subsequent decrease in agricultural land. Wu *et al*. (2006) concluded that the LUCC measurements and predictions provided by Markov and regression models have important implications for urban planning and management in Beijing. Unlike Wu *et al*. (2006), Guan *et al*. (2011) used a combined Markov-Cellular Automata model to analyze temporal change and spatial distribution of land-use in Saga, Japan using natural and socioeconomic data. The purpose of the model was to predict future land-use changes between 2015 and 2045, with the results indicating that there would be a continuing downward trend in agricultural land and forestland areas and an upward trend in built-up areas. Guan *et al*. (2011) believe that these predictions will assist local authorities in understanding and addressing this complex land-use system and lead to the development of land-use management strategies which will better balance urban expansion and ecological conservation.

The case studies described in this section represent just a small number of the many models which are available and used by researchers. These examples were mentioned in order to show the range, diversity and extreme usefulness of LUCC models.

2.10. Challenges facing LUCC research

Researching and understanding exactly how the landscape has and continues to evolve is a difficult process which is fraught with a range of data, methodological and analytical difficulties (Rindfuss *et al.*, 2004; Turner *et al*., 2007). Some of the main problems which hamper LUCC research are mentioned below.

According to Rindfuss *et al.* (2004: 13976), data as well as methodological and analytical difficulties arise as a result of the "complexity of integrating diverse phenomena, space–time patterns, and social–biophysical processes, and the different disciplinary means of addressing them" (Rindfuss *et al.*, 2004: 13976). These difficulties are exacerbated by the need to address issues of how, why, where and when LUCCs. Of particular importance is that of location and time, since it often involves dynamic human aspects linked to land-use, which are investigated at the individual, household, community, parcel, or pixel level (Rindfuss *et al.*, 2004). Additional challenges to LUCC research emerge as one considers the many dimensions of land-use and land cover systems. Rindfuss *et al.* (2004) note that not only does there exist a wide variety of land-use types worldwide, but also that several of these land-uses may be present on a single land unit or parcel, simultaneously. Furthermore, the land-use and land cover types of one parcel may influence the land management decisions of neighboring parcels. These decisions and the actual behavior of land managers are further influenced by the productivity of a particular parcel, i.e. whether the land parcel is used for subsistence or commercial purposes (Rindfuss *et al.*, 2004). LUCC research is particularly problematic in cases where households engage in both subsistence and market cultivation on the same land parcel and when households own several, spatially disconnected parcels (Rindfuss *et al.*, 2004).

One of the key remote sensing issues which surface during LUCC studies is that of linking individual land-uses to pixels as well as linking land managers or owners to the land parcel which they have authority over. This is often an arduous process due to the fact that data about people and land parcels are collected in different ways. The different methods used means that there are spatiotemporal implications to consider, thus making the analytical process of combining the two datasets problematic (Rindfuss *et al.*, 2004). Furthermore although a land parcel remains stationary, other than slight changes in its boundary over time, land managers move, change and combine in a variety of ways, which affect the land-use or land cover of a parcel (Rindfuss *et al.*, 2004).

LUCC research which integrates remote sensing, GIS and the social sciences, in order to better understand changes in the landscape, will have to deal with issues of data quality and validity. Rindfuss *et al.* (2004) state that there are two main issues which arise during interpretation of a remotely sensed image, firstly the problem of accuracy and validity of the link between social science measures, land parcels and pixels, and secondly the appropriate combination of remote sensing, social science and natural science skills to use to address these issues of accuracy and validity. Additional remote sensing problems include that of matching spatial and temporal data from different sources and the use of ancillary data during classification, which may undermine the assumption of independence when conducting statistical tests (Rindfuss *et al.*, 2004).

2.11. Summary

This chapter has presented a detailed account of the determinants of LUCC and the associated impacts of such changes. The role of remote sensing and the various models used to assess LUCC has also been provided. It should be noted that although the literature has focused extensively on both land-use and land cover, given the level of scale of analysis used in this study, it was easier to detect land cover rather than land-use. Thus, from here onwards only the term land cover will be used.

CHAPTER 3: GEOGRAPHICAL CONTEXT

3.1. Introduction

This chapter describes the geographical context of the study area, i.e. Dube and Esikhawini. The first section briefly describes the district council and municipality within which the study area is located. Thereafter a concise history of the area is provided followed by short descriptions of the topography, climate, geology and soils, water resources, biological characteristics and demographic characteristics.

3.2. The uMhlathuze Municipality

Esikhawini and Dube fall under the uMhlathuze municipality, which is one of the six local municipalities forming part of the uThulungu District Council. The municipality was established on 5 December 2000 and is named after the uMhlathuze River which meanders through the area and symbolically unifies all of the towns, suburbs and traditional areas (City of uMhlathuze, 2010). The municipality is situated on the north-east coast of KwaZulu-Natal, South Africa between latitudes 28º37'S and 28º57'S and longitudes 31º42'E and 32º09'E. The area comprises the towns and settlements of Richards Bay, Empangeni, Esikhawini, Ngwelezane, Nseleni, Felixton and Vulindlela. Included in the municipality are also five tribal authority areas namely, Dube, Mkhwananzi, Khoza, Mbuyazi and Zungu, twenty-one rural settlements and sixty-one farms (City of uMhlathuze, 2008). Surrounding the towns in the municipality are sugar cane fields, timber plantations, wetlands and fresh waters lakes. The municipality also boasts the country's largest deep-water port which is connected via national roads and railway lines to the rest of South Africa (City of uMhlathuze, 2008; City of uMhlathuze, 2010).

The uMhlathuze municipality covers an area of approximately 796 km^2, with an estimated population of 345 776 and with an average of 372 people per square kilometer. Of all the municipalities in the uThulungu District Council, this uMhlathuze is the smallest, covering only 9.7% of the total district area (City of uMhlathuze, 2011). Despite its small size, the uMhlathuze municipality contains approximately 32% of the district's population and 88% of the economic activity is centralized within the municipality, making it the third largest economy in KwaZulu-Natal (City of uMhlathuze, 2011).

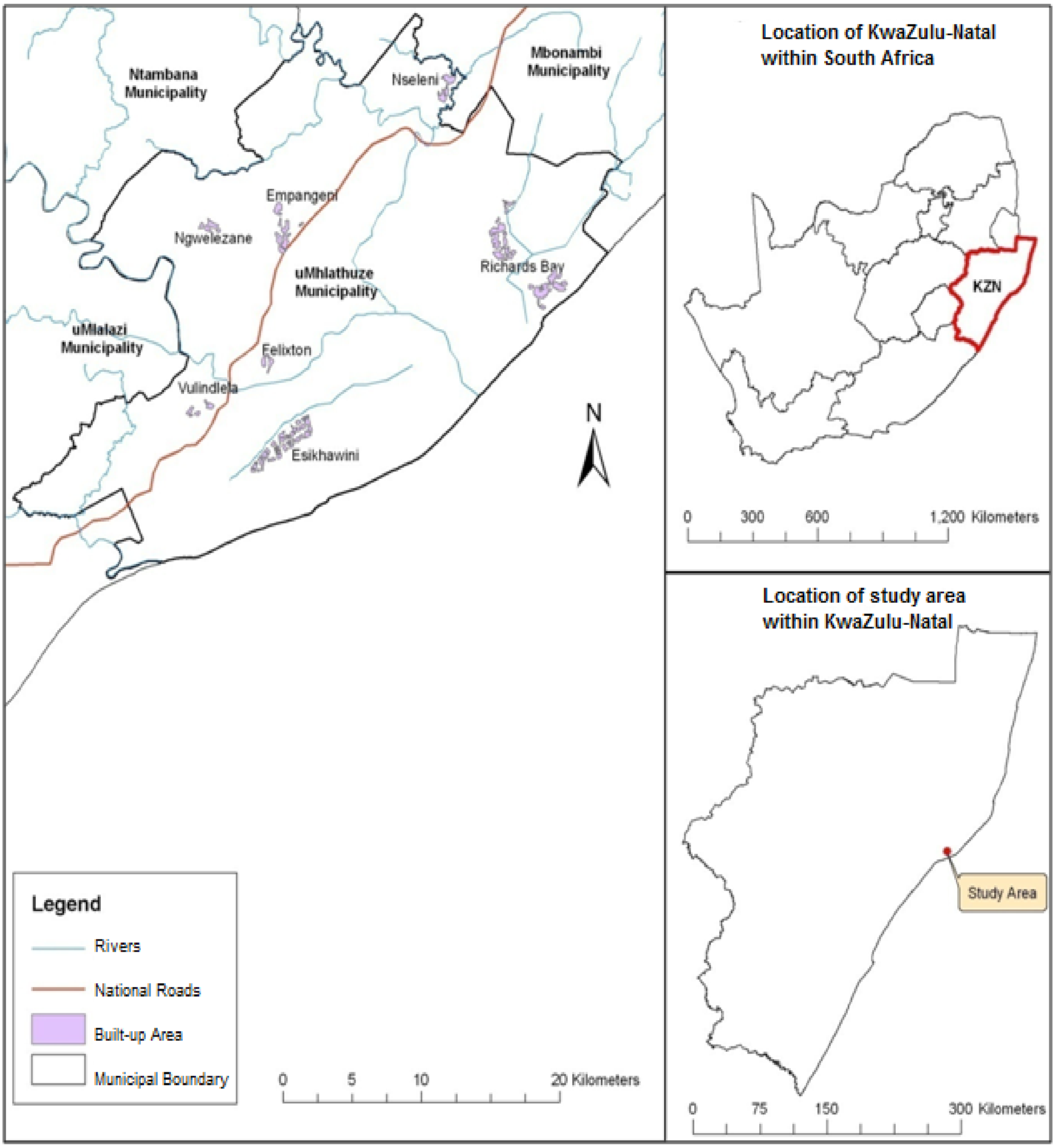


Figure 3.1: Map of the study area

3.3. History of the uMhlathuze Municipality

As mentioned in the previous section, much of the uMhlathuze municipality is rural with the majority of the population occupying the towns of Richards Bay and Empangeni. This section will provide a brief overview of the formation and history behind these two towns.

The present town of Empangeni was established in 1841 when a mission station was built next to the Mpangeni River. Empangeni achieved official village status on 19 June 1906, three years after the birth of Empangeni Rail in 1903. Soon after this, Empangeni Sugar Mill was built and this industry together with the railway line allowed for formation of the first Town Board of Empangeni and subsequently, in 1960, Empangeni achieved borough status (City of uMhlathuze, 2005).

Unlike Empangeni, Richards Bay grew very slowly and remained a small fishing village until the late 1960's. The development of both a deep-water harbor and railway link to Witwatersrand provided a much needed boost for development in the town. Richards Bay has since evolved into a modern and dynamic port town and despite the fact it has undergone serious periods of national recession, international economic pressures and nationwide political uncertainty, the town has continued to grow (City of uMhlathuze, 2005). The fact that Richards Bay is officially recognized as a 'port city' has resulted in it usurping Empangeni as the most prominent town in the uMhlathuze municipality. However, it is important to note that both towns provide very different functions. Empangeni functions as a service centre with higher order commercial, retail, administrative, social, business transportation, storage, institutional and light industrial uses, whilst Richards Bay's main function is the harbor and its associated heavy industries. Both towns attract considerable investment and development to the uMhlathuze municipality as a whole and are thus vital for the sustainable development and functioning of the area (City of uMhlathuze, 2005).

3.4. Topography

The regional geology of the uMhlathuze municipality has given rise to considerable diversity of relief throughout the area. Most of the interior is characterized by relatively gentle slopes with gradients less than 1:4. However, slopes in the north-west sections of the area as well parts of the North-Eastern and Western sections can have gradients as steep as 1:3 (Govender and Hounsome, 2002). The altitude throughout the study area varies from sea level to approximately 450 meters above sea level. The Northern and Western sections of Empangeni are characterized by a range of rounded conical hills. These hills, which were built by the Letaba Formation, have generally steep slopes and are closely spaced. In contrast, the topographical undulation of the Eastern and Southern sections of Empangeni are not as noticeable, with a range of low hills, which originated as a result of the Empangeni-Etesa fault, flattening out onto the coastal plains (City of uMhlathuze, 2005; Govender and Hounsome, 2002).

Towards the coastal plains, the dominant feature of the area is the low lying sandy coastal plain, and broad alluvial plain of the Mhlathuze River and former Richards Bay estuary. Levies, marginal lakes and ponds in the tributary valleys, and a low plateau north and south of the Mhlathuze floodplain all form part of the coastal plain. The coastal barrier dune complex is both very young and stable. The stability is due to the presence of relatively unspoiled dune vegetation. As one moves away from the coastal plain, the topography changes to become steeply undulating with deeply incised drainage courses. There is a deep subsurface trough below the harbor sediments and out to sea, which presents engineering and geotechnical complications to development (Govender and Hounsome, 2002).

3.5. Climate

The uMhlathuze municipality experiences a sub-tropical, maritime climate throughout the year with temperatures rarely lower than 12 to 14 degrees in winter and reaching 32 to 35 degrees in summer. The winters are generally warm and dry, with occasional frost in the interior areas while summers are hot and humid, and experience the majority of the municipality's rainfall (City of uMhlathuze, 2008). The average daily temperature during winter is 22 degrees and 28 degrees in summer. The winds along the coast of the uMhlathuze municipality are stronger than those experienced inland. The prevailing winds in the area are North-Easterly, associated with high pressure systems and fine weather, and South-Westerly winds associated with the ridging Indian Ocean Anticyclone (Govender and Hounsome, 2002).

Most of the rainfall occurs between January and May, with the average annual rainfall for the Richards Bay area about 1 200 mm and decreasing to about 1 000 mm inland towards Empangeni. During the past three decades, the municipality has experienced prolonged periods of droughts during the years 1981 to 1983 and 1992 to 1994. Furthermore, the area has also been subjected to destructive floods generated by the cyclones Demonia and Mboa in 1984 and followed by the flood disasters in 1987 and 2000 (City of uMhlathuze, 2008).

3.6. Geology and Soils

The geology of the uMhlathuze municipality is complex and the age of the rock formations range from more than 1000 million years to less than 1 million years. The outcrops of the Tugela Complex (1 100 million years old) underlie the central part of the area and overlying this complex are sediments (consisting of sandstones, shale and basal conglomerates) of the

Natal Supergroup. The Northern and North-Western parts of the municipality are underlain by basalts of the Letaba Formation, whilst the Eastern parts of the area are covered by Quaternary age red clayey sand as well as alluvial sand, silt and clay. The sands of this part of the area have very good agricultural potential (City of uMhlathuze, 2005; Govender and Hounsome, 2002).

The entire coastal plain of the area is underlain by marine deposits of the Cretaceous Age and a relatively thin layer of Miocene deposits of the Tertiary Age. The coastal dune barrier complex is thought to be very young and in some places still being formed and is only, as stated before, stable because of the vegetation cover. The sands of the dune barrier complex are fine-grained, well-sorted and contain rich deposits of minerals. These minerals, namely ilemite, rutile and zircon, are extracted commercially (City of uMhlathuze, 2005; Govender and Hounsome, 2002).

Towards the coast, the Port Dunford Formation is covered by red, brown and grey sand which have low to very low natural fertility. This is mainly due to their high permeability, rapid leaching of nutrients and the fact that they are very thin. Despite the low agricultural potential of these sands, they occur in an area which has good rainfall, high temperatures and mild topography, thereby favoring the production of both sugarcane and timber (Govender and Hounsome, 2002).

3.7. Water Resources

The Mhlathuze River is the dominant river which flows through the municipality from the southwest of Empangeni and Ngwelezane to the south of Felixton, thereafter connecting with the Indian Ocean via the Mhlathuze Estuary. This river, along with several other subsidiary rivers form part of the Mhlathuze River Basin, and are heavily utilized in the Richards Bay area for both commercial and residential purposes. Other water resources in the area include natural lakes and dams. There are three coastal lakes in the municipality, namely Lake Mzingazi, Nhlabane and Cubhu, and various other smaller inland lakes. The main dam in the area, Goedertrouw Dam, was built on the Mhlathuze River and it, together with a few of the natural lakes in the lower part of the Mhlathuze catchment, supplies water to the majority of the uMhlathuze municipality (City of uMhlathuze, 2005; Govender and Hounsome, 2002).

3.8. Biological Characteristics

The uMhlathuze municipality, which falls within the Maputaland-Pondoland-Albany Biodiversity Hotspot, is characterized by a diverse and rich mix of both floral and faunal species. The area is floristically, climatologically and geologically complex and provides a range of different habitats. Consequently, the municipality is regarded as an area of great conservation significance, especially in terms of biodiversity. With regards to the floral characteristics of the uMhlathuze municipality, the area falls within the Savanna biome and according to Low and Rebelo (1996) comprises six main vegetation types: Afromontane Forest, Coast-hinterland Bushveld, Coastal Bushveld/Grassland, Natal Lowveld Bushveld, Sand Forest and Valley Thicket. Due to the type of soils and climate experienced by the municipality, it has great potential for crop farming and as such the area is characterized by intensive agricultural activities, in particular sugar cane and timber (City of uMhlathuze, 2005; Govender and Hounsome, 2002).

3.9. Demographic Characteristics

As stated above the estimated population of the uMhlathuze municipality is 345 776, with the major ethnic group being the African population who represent 86% of the total population. The gender ratio is similar (51% female and 49% male) (City of uMhlathuze, 2008; City of uMhlathuze, 2010). The majority of the population is between the ages of 15 and 34 and the total unemployment rate is 36%, although this figure only relates to the formal sector (City of uMhlathuze, 2008). The municipality has approximately 75 000 households with an average of 4.4 persons per household (City of uMhlathuze, 2011). Although a large percentage of these households are located within the urban area, more than 40% of the municipality's population resides in rural and tribal areas, which is indicative of a densely populated rural area (City of uMhlathuze, 2008).

3.10. Summary

The geographical context described above serves to highlight the appropriateness of this study area

CHAPTER 4: METHODOLOGY

4.1. Introduction

The purpose of this chapter is to provide a detailed account of the data and methodology used to achieve the aims and objectives of this research. The first part of this chapter describes the satellite imagery used as well the field data. This information is then used to identify the main land cover classes in the study area. The bulk of this chapter is dedicated to explaining the methodology employed during the course of the research, from data pre-processing to post-classification.

4.2. Data Acquisition

4.2.1. *Satellite Imagery*

As mentioned earlier, one of the basic requirements for LUCC detection is the use of remotely sensed imagery, acquired from sensors with similar spectral, spatial, radiometric and temporal resolutions. However, there are many factors which hinder the acquisition of such images because images are often selected based on availability, project requirements and objectives. For this study, images from the Landsat 5 TM sensor (Table 4.1) were selected due to the finer spectral (i.e. 7 bands) and temporal resolution (i.e. 16 day revisit) of the sensor in comparison to other commonly available sensors such as SPOT 4/5. Additionally, temporal images for South Africa from the Landsat 5 TM sensor are more readily available and accessible from the South African National Space Agency (SANSA). Three images, acquired during 1992 (July), 2000 (October) and 2008 (September), were obtained from the SANSA archive (Figure 4.1).

Landsat 5 TM was launched on 1 March 1984 and has a 16 day revisit period (Lillesand and Kiefer, 2000). The satellite has both the Multispectral Scanner System (MSS) and the Thematic Mapper (TM) instruments onboard. The MSS instrument has a swath of 185 km, ground resolution of 82 m and four spectral bands. The TM instrument has seven spectral bands with 8-bit radiometric resolution and a ground resolution of 30 m for every band except the thermal band (band 6), which has a ground resolution of 120 m (Lillesand and Kiefer, 2000).

Table 4.1: Landsat 5 TM spatial and spectral resolution characteristics

Band	Spatial Resolution (m)	Spectral Resolution (nm)	Full-Width Half-Maximum (nm)
1 – Blue	30	450-520	70
2 – Green	30	520-600	80
3 – Red	30	630-690	60
4 – Near IR	30	760-900	140
5 – Mid-IR	30	1 500-1 750	200
6 – Thermal IR	120	10 400-12 500	210
7 – Mid-IR	30	2 080-2 350	270

4.2.2. *Field Data and identification of land cover classes*

In order to determine the number and type of land cover classes present in the study area a field assessment was undertaken in 2009. Additionally, the latest available aerial photographs (taken during 2008, 2006, 2005) and land-use maps (EKZN Wildlife, 2008) were used to aid and verify the field assessments. The field assessment was conducted using a Leica GPS, which has a Root Mean Square Error (RMSE) of approximately 10 m. A total of 340 ground points representing the various land cover classes were collected and thereafter the dataset was partitioned in two subsets. Seventy percent (n = 238) of the points were used as a training set (approximately 30 points per class), whilst the remaining 30% (n = 102) were used as a test set (also commonly referred to as a hold-out sample).

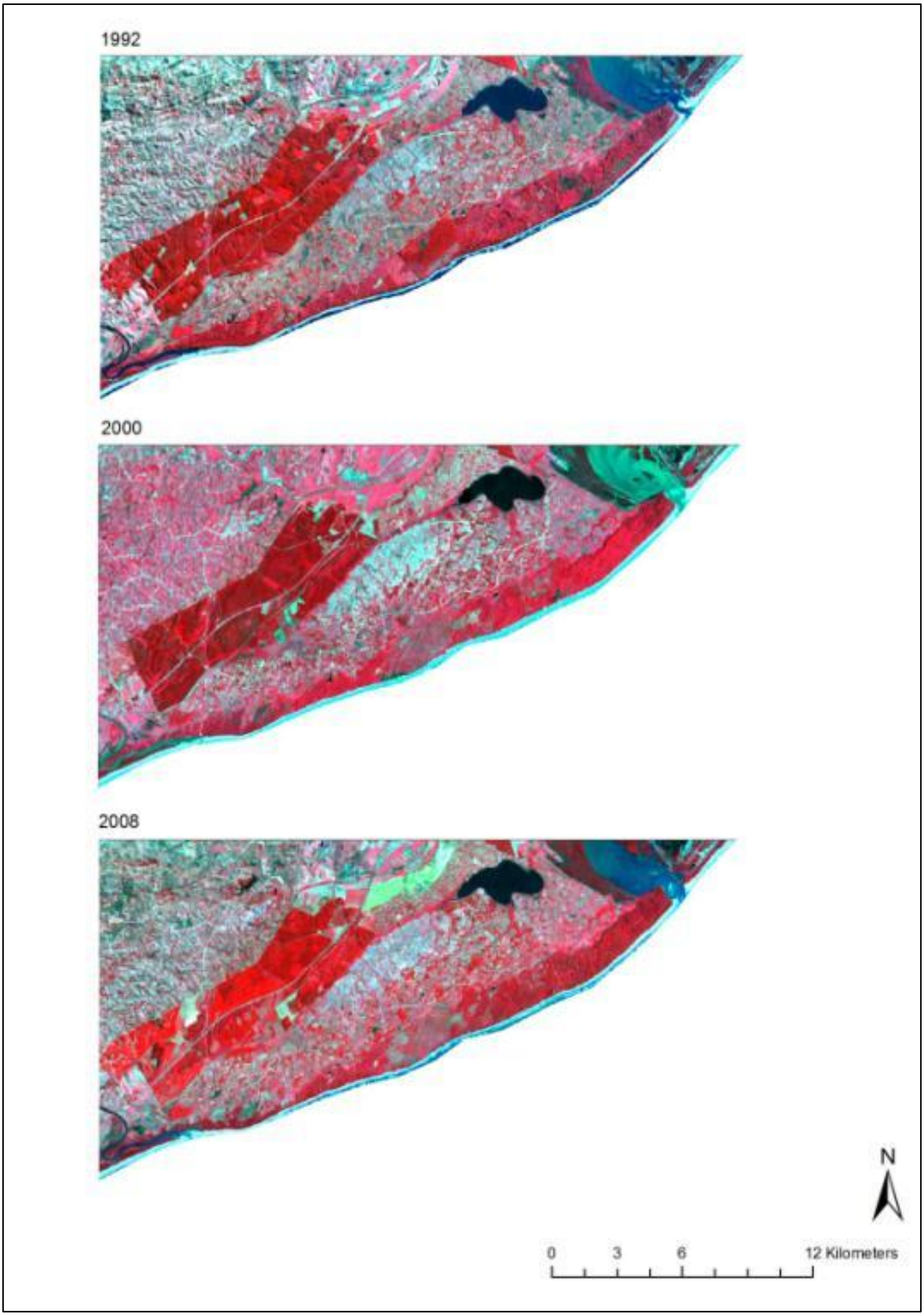


Figure 4.1: Landsat 5 TM images of study area, displayed using bands 4, 3 and 2 (i.e. false color composite)

Traditional land-use and land cover classification systems often (i) do not sufficiently distinguish between land-use and land cover, (ii) are limited in the number of classes they provide and (iii) do not contain the wide variety of occurring land-uses and land covers (Jansen and Di Gregorio, 2002). Furthermore, Thompson (1996: 34) notes that many of these classifications "have been developed around specific user objectives (namely, agriculture and conservation), and are often influenced by geographical location and actual data capabilities", thus making meaningful comparisons of classes from different study areas difficult. For the purposes of this study, the land-use and land cover classification system used was based on the classes defined by Thompson (1996). Thompson's (1996) classification system is a structured hierarchical framework that is based on three levels and is designed to suit the South African environment while still conforming to international classification standards. Additionally, in light of the spectral and spatial limitations associated with Landsat 5 TM images, a level 1 classification was deemed more appropriate for this study rather than a level 2 or 3 classification scheme. Landsat 5 TM images have a 30 m spatial resolution and thus it is difficult to accurately classify land cover classes which occupy a small area. Subsequently, the following eight land cover classes were identified: Waterbodies (W), Wetlands (Ws), Forest and Woodlands (FW), Bushveld (B), Plantations (P), Cultivated land (CL), Settlements (S), and Clearfelled (C) (Table 4.2).

Table 4.2: Description of the land cover classes used in the study (adapted from Thompson, 1996)

Class	Description
Waterbodies	Areas of (generally permanent) open water. This category includes natural and man-made waterbodies.
Wetlands	Natural or artificial areas where the water level is at (or very near) the land surface on a permanent or temporary basis, typically covered in either herbaceous or woody vegetation cover.
Forest and Woodlands	All wooded areas with greater that 10% tree canopy cover, where the canopy is composed of mainly self-supporting, single stemmed, woody plants greater than 5 m in height. Essentially indigenous tree species, growing under natural or semi-natural conditions.
Plantations	All areas of systematically planted, man-managed tree resources composed primarily of exotic species. This category includes both young and mature plantations that have been established for commercial timber production, seedling trials, and woodlots/wind breaks of sufficient size to be identified on satellite imagery.
Cultivated land	Areas of land that are ploughed and/or prepared for raising crops (excluding timber production). This category includes areas currently under crop, fallow land, and land being prepared for planting.

Bushveld	Communities typically composed of tall, woody, self-supporting, single and/or multi-stemmed plants (branching at or near the ground), with, in most cases, no clearly definable structure. Essentially indigenous species, growing under natural or semi-natural conditions.
Settlements	An area where there is a permanent concentration of people, buildings and other man-made structures and activities, from large village to city scale.
Clearfelled	Areas from which plantation trees have been removed.

4.3. Data Pre-processing

4.3.1. *Geometric Correction*

All three Landsat 5 TM images were geo-referenced to UTM Zone 36 South using a WGS-84 datum and thereafter geometrically rectified. Geometric corrections are particularly important as change detection analysis is performed on a pixel-by-pixel basis and misregistrations greater than one pixel can result in substantial errors. As such, it is recommended that the RMSE between two images not exceed 0.5 pixels (Deng *et al*., 2008). In this study, the 2008 image served as the reference image and was geometrically rectified using ground control points and 20 m digital elevation model. The resulting RMSE error was less than 1 pixel. Subsequently, the other two images were then registered to the 2008 reference image and resampled using the nearest neighbor method. Thereafter all images were clipped to the boundary of the study area.

4.3.2. *Radiometric Correction*

Radiometric correction of multi-date images is a prerequisite for change detection analysis in order to reduce the influence of sensor characteristics, atmospheric condition, solar angle and sensor view angle (Chen *et al.*, 2005). These corrections can be grouped into two broad categories, absolute corrections, where a digital number (DN) is converted to surface reflectance, or relative corrections, which involve the normalization of multiple satellite images to one reference image (Lu *et al.*, 2002; Sahu, 2008). It should be noted that the data used for this particular study displayed none of the radiometric artifacts (i.e. memory effect, scan-correlated shift and coherent noise) mentioned by Helder *et al.* (1996) and Vogelmann *et al.* (2001) and was radiometrically corrected using an absolute correction method.

The Dark Object Subtraction (DOS) method (Chavez, 1996) was utilized to correct all the images used in this study. Although DOS is the most simplest of all absolute correction methods, it is the most widely used approach for classification and change detection applications (Song *et al.*, 2001). It is based on the assumption that the atmospheric impact on the whole study area is uniform and that any radiance received at the sensor for a dark object pixel (i.e. a pixel with near-zero percent reflectance) is purely a result of atmospheric scattering (path radiance) and can therefore be subtracted from the signals produced by other features in the image (Chavez, 1996; Lu *et al.*, 2002; Sahu, 2008; Schroeder *et al.*, 2006). Chavez (1996) further states that the aforementioned assumptions are combined with the fact that there are very few features on the earth's surface which are completely black and thus an assumed one-percent minimum reflectance is better than zero percent. DOS, which is calculated using Equation 4.1, is strictly an image-based method and while it can correct for sun zenith angle, solar radiance and atmospheric scattering, it cannot correct for atmospheric absorption (Lu *et al.*, 2002).

$$R_\lambda = \frac{PI * D^2 * (L_{\lambda sensor} - L_{\lambda haze})}{(Esun_\lambda * COS(\theta))} \tag{4.1}$$

Where R_λ = surface reflectance

PI = 3.141592

D = distance between Earth and sun

$L_{\lambda sensor}$ = apparent at satellite radiance

$L_{\lambda haze}$ = path radiance

$Esun_\lambda$ = exo-atmospheric solar irradiance

θ = sun zenith angle

4.4. Statistical Analysis

4.4.1. *Signature extraction and separability*

The first step of the classification procedure is the extraction of the class signatures (see Table 4.2 for the land cover class descriptions) from the reference image (2008 Landsat 5 TM image) and the development of a spectral library. In order to develop the spectral library, the training data (n = 238) were converted to Region of Interests (ROI) and the spectral signatures for all the classes (n = 8) were then extracted from the reference image and saved as a spectral library utilizing ENVI 4.7 (ITT, 2009).

Once the spectral library was developed, individual class signatures were evaluated using the Jeffries-Matusita (J-M) distance measure of separability. The J-M distance algorithm evaluates the separability between two class signatures and outputs a value between 0 and 2 utilizing Equations 4.2 and 4.3. Class separability values approaching zero indicate a low degree of separability, while values close to two indicate a high degree of separability (Ismail *et al.*, 2008; Thomas *et al.*, 2002; Trigg *et al.*, 2001).

$$\alpha = \frac{1}{8}\left(\mu_i - \mu_j\right)^T \left[\frac{C_i + C_j}{2}\right]^{-1} \left(\mu_i - \mu_j\right) + \frac{1}{2}\ln\left[\frac{\left(\left|C_i + C_j/2\right|\right)}{\sqrt{\left|C_i\right| * \left|C_j\right|}}\right] \tag{4.2}$$

$$JM_{ij} = \sqrt{2\left(1 - e^{-\alpha}\right)} \tag{4.3}$$

Where *i* and *j* = the two classes being compared

C_i = the covariance matrix of signature *i*

μ_i = the mean vector of signature *i*

ln = the natural logarithm function

$|C_i|$ = the determinant of C_i (matrix algebra)

4.4.3. *Classification*

For this study, three popular and commonly used supervised classification algorithms, namely Parallelepiped, Minimum Distance to Means and Maximum Likelihood, were examined. The reasoning for comparing the different classification algorithms is due to the 'no-free-lunch' theorem proposed by Wolpert and Macready (1997). This theorem states that there is no one perfect algorithm for any given situation, with each classifier having its own advantages and disadvantages.

Porter-Bolland *et al.* (2007) used the parallelepiped classifier to derive LUCC maps, with an accuracy of 87%, in order to understand the land-use changes occurring in the La Montaña region of Mexico. In their study on the role of land abandonment in landscape dynamics in Central Spain between 1984 and 1999, Romero-Calcerrada and Perry (2004) used the parallelepiped algorithm to classify images of their study area. However, in contrast to the previous case study the authors used a maximum likelihood decision rule to assign a class to those pixels which fell in the overlap region between two classes. The accuracy of each of the land cover maps derived by Romero-Calcerrada and Perry (2004) varied between the years considered in the study, 1984 had an accuracy of 77.53%, 1991 had 78.95% and 1999 showed the highest accuracy with a percentage of 82.47%.

The Minimum Distance to Means classification algorithm was used by Chen *et al.* (2003) who developed a new method for determining change type by combining single image classification with minimum distance categorization, based on the cosines of change vectors. The authors achieved a very high overall accuracy of 96.3% with a Kappa coefficient of 0.87. Schneider *et al.* (2009) found the Maximum Distance to Means classifier to be a better alternative to the Maximum Likelihood classifier, in their study on land cover classification of tundra environments in the Arctic Lena Delta, due to the limited number of training sites. Their accuracy assessment indicated a reasonable overall accuracy of 77.8%.

In their study on urban expansion and land-use change in Shijiazhuang, China from 1987 to 2001, Xiao *et al*. (2006) employed the Maximum Likelihood classifier to detect land cover types present in the study area. The land-use maps produced from the classification had accuracies of above 80% and Kappa coefficients greater than 0.8. Shalaby and Tateishi (2007) conducted a similar study in Egypt where they used remote sensing and GIS to map and monitor land cover and land-use changes in the Northwestern coastal zone. The Maximum Likelihood classifier was once again used to classify the different land cover types and the authors achieved very high accuracies for the two years considered in their study, i.e. 1987 (91%) and 2001 (92.3%).

The classifiers considered in this study are described in greater statistical detail below.

4.4.3.1. Parallelepiped

In comparison to other classification algorithms, the parallelepiped classifier (also known as the box classifier) is methodologically straightforward and computationally fast (Aronoff, 2005; Richards and Jia, 2006; Schowengerdt, 2007). This decision rule classifier is based on simple Boolean ‘and/or’ logic and uses the threshold of each class signature to determine whether or not a pixel belongs to a particular class (Jensen, 2005; Teodoro *et al.*, 2009). In order to perform a classification, the parallelepiped classifier uses training data to define a class as an *n*-dimensional parallelepiped, where *n* is the number of spectral bands in the image (Albert, 2002; Jensen, 2005). The *n*-dimensional parallelepiped is constructed for a class using the class mean and standard deviation, the parallelepiped algorithm assigns pixel X to a class only if the following equation is satisfied (Jensen, 2005):

$$\mu_{ck} - \sigma_{ck} \le X \le \mu_{ck} + \sigma_{ck} \quad (4.4)$$

Where c = number of classes

k = number of bands

μ= the mean value of the training data

σ = the standard deviation of the training data

Therefore if the high (H) and low (L) boundaries of the box are defined as

$$L_{ck} = \mu_{ck} - \sigma_{ck} \quad (4.5)$$

$$H_{ck} = \mu_{ck} + \sigma_{ck} \quad (4.6)$$

The parallelepiped algorithm then becomes

$$L_{ck} \le X \le H_{ck} \quad (4.7)$$

Pixels which fall above the low threshold and below the high threshold of a specific class parallelepiped are assigned to that class. If a pixel does not fall within any class parallelepiped, it is left as unclassified. In some cases, a pixel may fall in the overlap area between two or more parallelepiped. When this occurs, the pixel will be assigned to the first class for which it satisfies all criteria (Jensen, 2005; Schowengerdt, 2007; Teodoro *et al.*, 2009). Despite the relative simplicity and efficiency of the parallelepiped classifier, it does have a few disadvantages. When the thresholds of a class are too small, many pixels will be left as unclassified, and when they are too large, pixels which fall within the overlap regions will either be arbitrarily placed in a class or regarded as unclassified (Albert, 2002; Aronoff, 2005; Jensen, 2005; Lillesand and Kiefer, 2000).

4.4.3.2. Minimum Distance to Means

Similar to the parallelepiped classifier, the widely used Minimum Distance to Means (MDM) classification algorithm is non-parametric and relatively easy to compute (Acharya and Ray, 2005; Lu *et al.*, 2004). Although the Minimum Distance to Means classifier is very simple, when it is used correctly it can still result in classification accuracies similar to other more computationally intensive classifiers such as the Maximum Likelihood (ML) algorithm. The

Minimum Distance to Means classifier functions by first calculating the mean of each class and thereafter the Euclidean distance of each pixel from the mean. A pixel is assigned to that class whose distance is nearest to the mean (i.e. the distance between the pixel and the mean is minimum). If a pixel is further than a user-defined distance from any class mean, it is regarded as unclassified (Aronoff, 2005; Lillesand and Kiefer, 2000; Joseph, 2005). The computation of the Euclidean distance from an unknown pixel (X) to the mean of a class is calculated using the following equation (Jensen, 2005):

$$Dist = \sqrt{\left(X_k - \mu_{ck}\right)^2 + \left(X_l - \mu_{cl}\right)^2} \qquad (4.8)$$

Where μ_{ck} = mean for class c measured in band k

μ_{cl} = mean for class c measured in band l

The main drawback of the Minimum Distance to Means classifier is that it does not take into account that some features have a wider range of spectral values than others thus leading to some misclassification of pixels (Aronoff, 2005; Lillesand and Kiefer, 200). However, in spite of this disadvantage, the Minimum Distance to Means algorithm is very useful for classifying large images as it is very fast and uncomplicated (Aronoff, 2005).

4.4.3.3. Maximum Likelihood

Unlike the parallelepiped and Minimum Distance to Means classifiers, the Maximum Likelihood classification algorithm uses probabilities to overcome the limitations associated with the parallelepiped and Minimum Distance to Means classifiers (Aronoff, 2005). This parametric classifier is one of the most commonly used supervised classification algorithms and is often the method of choice for many users as it does not require an extended training process (Jensen, 2005; Pal and Mather, 2003). When classifying an image the Maximum Likelihood classifier, which pixel-based, evaluates both the variance and covariance of the training class pixels (Lillesand and Kiefer, 2000). Classification is carried out by first calculating the probability of a pixel belonging to a set of predefined classes and then assigning each pixel to the class for which the probability is the highest (Keuchel *et al.*, 2003; Jensen, 2005). This algorithm is based on the assumption that the training data statistics for each class in each band follow a Gaussian (normal) distribution (Keuchel *et al.*, 2003; Jensen, 2005; Pal and Mather, 2003). The Maximum Likelihood classifier is defined by the following equations as suggested by Nag and Kudrat (1998):

$$g(x) = \log \rho(w_i).\rho(x \mid w_i) \tag{4.9}$$

Where $g(x)$ = probability density

$\rho(w_i)$ = a priori probability

$\rho(x|w_i)$ = probability of x for falling in class i

$i = 1, 2, 3, \ldots n$

For equal a priori probability with Gaussian distribution:

$$g_i(x) = -\log|\Sigma_i| - \frac{1}{2}\log\left[(x-\mu_i)^t\,\Sigma^{-1}(x-\mu_i)\right] \tag{4.10}$$

Where $|\sum_i|$ = determinant of variance-covariance matrix of class i

$\sum^{-1}$ = inverse of variance-covariance matrix

x = measurement vector, i.e. DN values of any pixel for all the channels

μ_i = mean vector for i^{th} class

t = transpose

A pixel is classified into the i^{th} class only if:

$$g_i(x) \geq g_j(x) \text{ for all } i \neq j \tag{4.11}$$

The disadvantage of this classifier is that since it requires a large number of computations to classify each pixel, it has slower processing time than the parallelepiped and Minimum Distance to Means algorithms (Lillesand and Kiefer, 2000). However, Aronoff (2005) states that despite the complex and lengthy computations of the Maximum Likelihood classifier, it is still advantageous to use it for all but the very large images.

4.3.4. *Post classification*

4.4.4.1. Filtering

After implementing the various classifiers the next step of the classification process was to apply a filter to the classified images. Classification results often contain scattered pixels of one class surrounded by a larger area of another class. As such, filtering functions are thematic generalization processes which identify minor features and amalgamate them into the surrounding classes (Gao, 2009). This process is usually conducted in the spatial domain and has a number of advantages, such as fine tuning of the classified images to make them more reasonable and thereby improving their aesthetic appearance and communication effectiveness (Gao, 2009). In this study the clumping and sieving filtering techniques were implemented because clumping maintains the spatial coherency of classified images by removing any unclassified black pixels while sieving removes isolated classified pixels using blob grouping (Gautam *et al.*, 2003).

4.4.4.2. Accuracy Assessments

In remote sensing, the term accuracy is typically used to express the degree to which a classification can be regarded as correct. Evaluating the accuracy of classified images is particularly important for change detection studies because errors in classification may obscure substantial change or act to exaggerate change (Foody, 2010). It is for these reasons that accuracy assessments are considered fundamental and an integral component of the post classification process (Varshney and Arora, 2004; Foody, 2010; Congalton, 1991). In this study, the accuracy of the 2008 Landsat 5 TM image was assessed utilizing a total of 150 GPS points (i.e. test dataset) that were collected during the field visit (see section 4.1.2). Accuracy assessments were conducted by comparing the classes from the test dataset to the classes provided by the final classification map. The data was summarized using an error matrix and various statistics such as overall accuracy, producer's accuracy, user's accuracy and the kappa coefficient were then computed.

According to Congalton (1991), an error matrix is a square array of numbers set out in columns and rows which represent the number of sample units assigned to a particular class relative to the actual class on the ground. The columns of the matrix represent the test data while the rows represent the classified data. Overall Accuracy (OA) is used to determine the accuracy of the entire classification process and is calculated by dividing the number of correctly classified pixels by the total number of pixels in the test dataset (Congalton, 1991; Varshney and Arora, 2004). Producer's Accuracy (PA) is the ratio of correctly classified samples of a class to the total number of testing samples of that class in the test dataset (Varshney and Arora, 2004). User's Accuracy (UA), on the other hand, refers to the probability that a sample from the classification map represents an actual class on the ground (Varshney and Arora, 2004). The kappa coefficient of agreement, unlike the other accuracy measures, considers and accounts for the agreement between the classified image and the test dataset arising due to chance (Varshney and Arora, 2004; Foody, 2002). Kappa is a widely used measure of accuracy as it considers all elements of the error matrix (Mas, 1999). The accuracy assessments were carried out in ENVI 4.7 (ITT, 2009), and the error matrix with the corresponding accuracy measurements were then reported. The classifier that produced highest kappa coefficient and classification accuracy was subsequently used to classify the other two images considered in this study.

4.4.5. *Change Detection*

Analysis of LUCC for this particular study was carried out using ENVI 4.7. The software utilizes the image differencing technique when performing change detection. Image differencing is one of the most popular and widely used change detection algorithms and entails the subtraction of two coregistered images acquired at different dates (Coppin *et al.*, 2004; Jensen, 2005; Sader *et al.*, 2003). The process typically involves the cell-by-cell subtraction of one image from another, both of which have been accurately registered first (Sader *et al.*, 2003). Simply put, it subtracts the first-date image, pixel by pixel, from the second-date image to generate a third image. This resultant image is composed of the numerical differences between the pairs of pixels (Lu *et al.*, 2004; Moser *et al.*, 2003; Ridd and Liu, 1998). Areas on the image which display no change will have values which are very small, i.e. approaching zero, whilst those areas which display some form of change will have larger positive or negative values (Jensen, 2005; Lillesand and Kiefer, 2000). Low costs and the potential for massive data processing are two of the main advantages associated with image differencing (Lunetta, 1999). Although it does not provide a detailed change matrix like some of the other change detection methods, image differencing is a simple and straightforward method and produces results which are easy to interpret (Lu *et al.*, 2004).

4.4.6 *Markov Chain Model*

Understanding the interaction between LUCC and their associated driving factors is very complex and region-dependant, and thus a widely used approach to predicting future LUCC is based on stochastic models (Geist, 2006). These models, which mainly consist of transition probability models such as Markov chains, stochastically describe LUCC processes that move in a sequence of steps through a set of set of states. States in this case refers to the land cover class for which a given parcel of land can belong to at a particular moment in time (Lambin, 2004; Munthali and Murayama, 2011). Simply put, Markov chain models use observed LUCC to estimate the probability of future changes based on the current land cover at a location (Geist, 2006). A more detailed explanation is provided by (Zhang *et al.*, 2011). The authors describe Markov chains as a set of states, $S = \{s_0, s_1, s_{2,} \ldots s_n\}$ with the LUCC process starting in one of these states and then moving successively from one state to another.

Each move is called a step. If the chain is currently in state s_i, then it moves to state s_j at the next step with a probability of p_{ij}. This probability of moving from one state to another is called a transition probability and does not depend on which states the chain was in before the current state (Munthali and Murayama, 2011; Zhang *et al.*, 2011). Transition probabilities can be represented in the form of a transition probability matrix, whose elements are non-negative (Munthali and Murayama, 2011). The matrix provides a description of the basic behavior of the system and defines the pattern of movement as elements change from state to state (Lein, 2003). Each row reflects the proportion of the original land cover class which changed into other land cover classes by the end of the specified period (Pena *et al.*, 2007). An example of a simple three state transition probability matrix is given below:

$$P = \begin{array}{c} \\ S_1 \\ S_2 \\ S_3 \end{array} \begin{array}{c} \begin{array}{ccc} S_1 & S_2 & S_3 \end{array} \\ \begin{bmatrix} P_{11} & P_{12} & P_{13} \\ P_{21} & P_{22} & P_{23} \\ P_{31} & P_{32} & P_{33} \end{bmatrix} \end{array}$$

Markov models are based on three assumptions. Firstly, they assume that LUCC is a first-order process, meaning that the conditional probability of a land cover class at any time, given all previous uses/covers at earlier times, depends solely on the most recent use/cover and not on any earlier ones (Lambin, 2004). Secondly, it is assumed that the Marko chain is stochastic (Weng, 2002; Zhang *et al.*, 2011). Lastly, these models rely on the assumption that transition probabilities are stationary, i.e. temporally homogeneous (Wu *et al.*, 2006; Zhang *et al.*, 2011). The main advantage of using Markov chain models stems from the last assumption, whereby the stationarity of the transition probability matrix allows for it to be used to calculate the probability of land cover change of one class to another (van Schrojenstein Lantman *et al.*, 2011). It should also be noted that in comparison to other LUCC models, the Markov chain model is mathematically and operationally simple, with current land cover information as the only data requirement (Lambin, 2004). For this study, the Markov chain model was used to predict changes in land cover classes in the year 2016. The 2008 image was used as the final state image and the 2000 image was used as the initial state image.

4.5. Summary

This chapter summarized the data and methodology employed during the course of this research. In terms of the data used, the Landsat 5 TM images were both readily available and appropriate for the purposes of this research. Eight land cover classes, i.e. Waterbodies, Wetlands, Cultivated Land, Plantation, Forest and Woodlands, Bushveld, Clearfelled and Settlements, were identified using a combination of remotely sensed images, aerial photographs and field observations. With regards to the methodology, various classifications methods were considered and described, with specific attention paid to their advantages and disadvantages in relation to the objectives of this research. Thereafter an explanation of the accuracy assessment was provided, followed by a description of the image differencing change detection method and Markov Chain model.

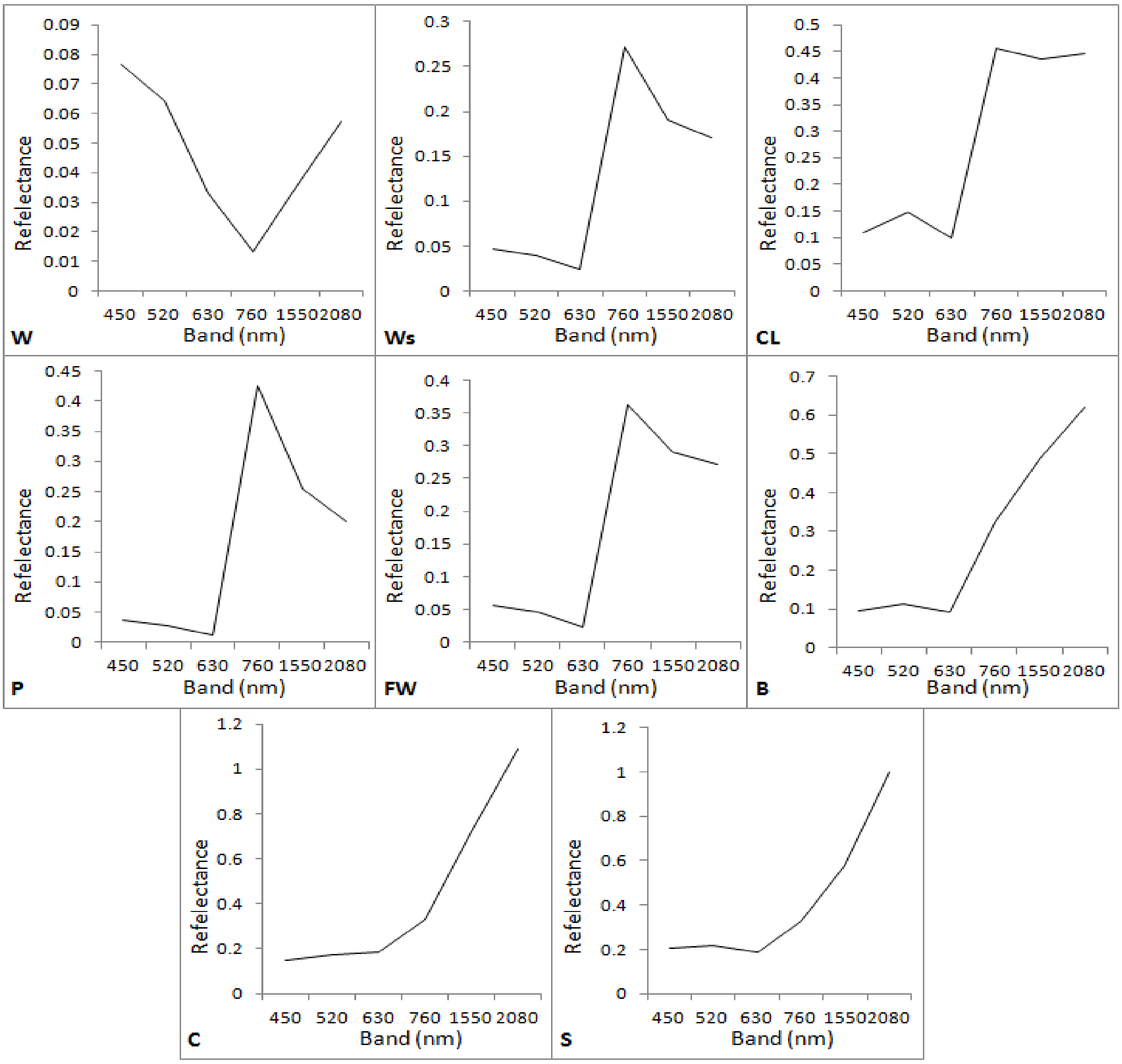
CHAPTER 5: RESULTS

5.1. Introduction

The aim of this chapter is to provide a detailed description, in the form of statistical graphs and maps, of the results and outcomes achieved in the study. Firstly, it addresses the signature separability between the individual land cover classes by presenting each classes' spectral plot and J-M value. Thereafter, the results of the three classification algorithms are illustrated and, based on the accuracies (i.e. OA, PA and UA) the most appropriate algorithm is chosen. The rest of this chapter is dedicated to describing the findings produced by the change detection process as well as the Markov model predictions.

5.2. Signature separability

The use of spectral properties to distinguish individual land covers and develop unique spectral signatures is a common procedure in land cover mapping and change detection studies (Lu *et al*., 2004; Schulz *et al*., 2010; Siren and Brondizio, 2009). In this study, the spectral signature for a particular feature is described in the form of a spectral reflectance curve (Figure 5.1) that indicates the reflectance values of a particular class across the electromagnetic spectrum. By plotting the spectral response curves of the nine land cover classes, it was possible to identify specific portions of the electromagnetic spectrum where the reflectance values for the classes varied.



*W – Water, Ws – Wetlands, CL – Cultivated Land, P – Plantation, FW – Forest and Woodlands, B – Bushveld, C – Clearfelled, S – Settlements

Figure 5.1: Spectral reflectance plots for individual land cover classes.

From Figure 5.1, it is evident that the Waterbodies, Clearfelled and Settlement classes all display significantly different spectral reflectance curves and as such can be readily distinguished. The reflectance of water is generally low, with maximum reflectance occurring in band 1 (450 nm). As the wavelength increases, the reflectance of water decreases, so that in the NIR band the reflectance of deep water is virtually zero. In comparison, the reflectance of Clearfelled land increases with increasing wavelength. The Clearfelled class is essentially bare soil and as such the reflectance in the visible bands is affected by the presence of organic matter and soil moisture content. In the case of the Settlements class, there is a gradual increase in reflectance as wavelength increases. This class has no distinct peak, most probably due to the fact that settlement areas comprise of a mixture of classes, such as vegetation. The vegetation classes, Cultivated Land, Plantations, Forest and Woodlands, and Bushveld, have essentially the same spectral pattern. They all display extremely low reflectance in the visible portion (450 to 630 nm) of the electromagnetic spectrum with reflectance increasing dramatically thereafter and peaking in band 4 (760 nm). The reason for low reflectance of vegetation in the visible bands is because chlorophyll strongly absorbs energy in these bands, whilst high reflectance in band 4 is attributed to the internal cell structure of a plant leaf (Lillesand and Kiefer, 2000; Mather and Koch, 2011). Subsequent to the sharp increase in reflectance in the NIR band, reflectance starts to decrease albeit at varying levels for the individual vegetation classes. Despite the similar spectral reflectance curves of these vegetation classes, it is still possible to distinguish between them as demonstrated by the J-M values shown in Table 5.1.

Table 5.1: Jeffries-Matusita values for each of the eight classes

	W	**Ws**	**CL**	**P**	**FW**	**B**	**C**	**S**
W								
Ws	2.000							
CL	2.000	1.999						
P	1.999	1.964	1.992					
FW	2.000	1.939	1.982	1.450				
B	2.000	1.999	1.855	1.992	1.963			
C	2.000	2.000	1.999	2.000	2.000	1.911		
S	1.999	1.999	1.978	1.999	1.998	1.811	1.913	

*W – Water, Ws – Wetlands, CL – Cultivated Land, P – Plantation, FW – Forest and Woodlands, B – Bushveld, C – Clearfelled, S – Settlements

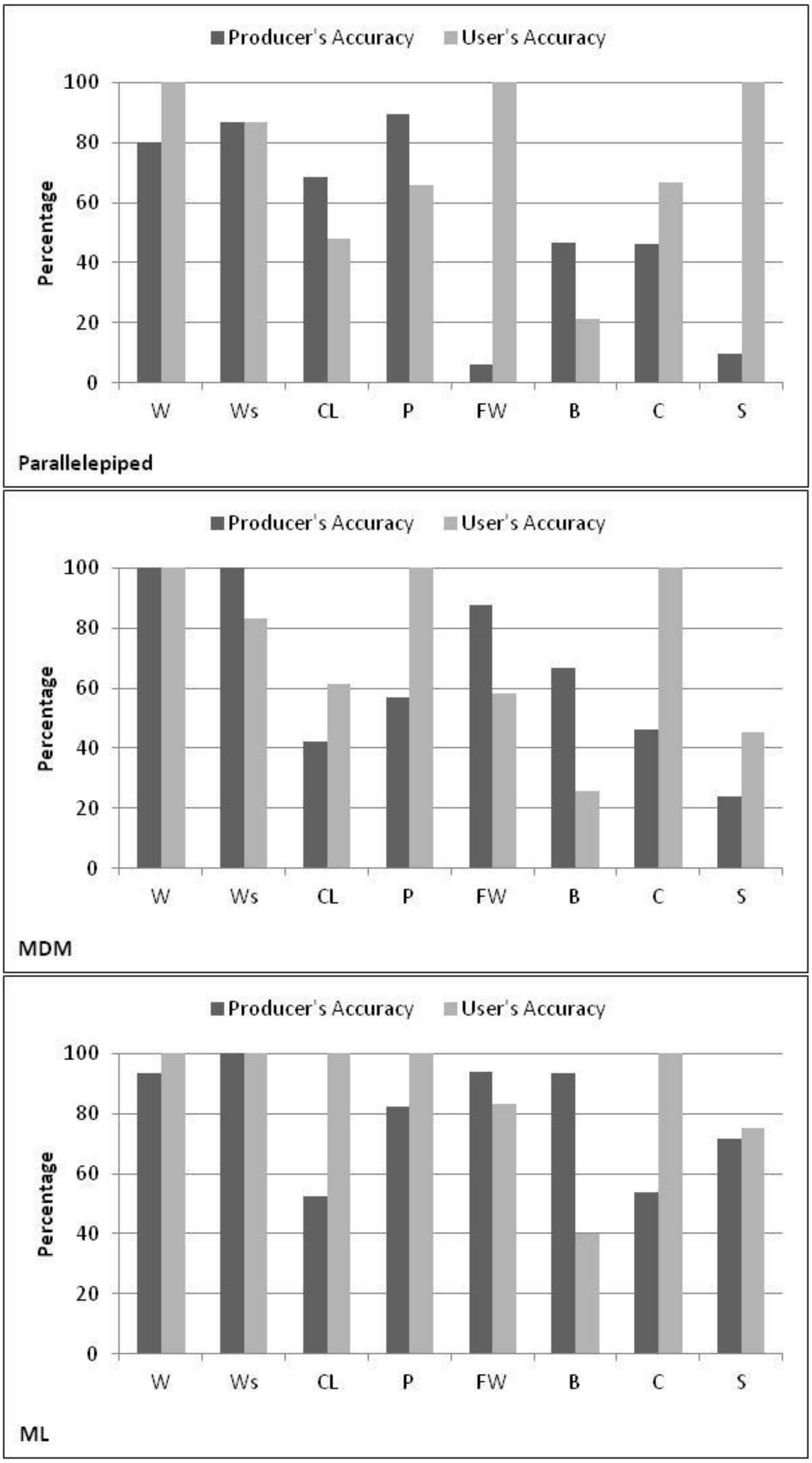
As discussed in section 4.3.1, the J-M separability index is used to statistically determine the spectral separation between each of the land cover classes (Paolini *et al.*, 2002). Table 5.1 depicts the degree of spectral differences for all possible class combinations. The J-M values range between 0 and 2, with values approaching 2 indicating that the classes are completely separable, while those close to 0 indicate a low degree of separability. The higher the spectral separation between classes and thus J-M values greater than 1.6 reduce the probability of classification error (Paolini *et al*, 2002; Marpu, 2009). It is apparent from Table 5.1 that most of the class combinations have J-M values greater than 1.8, indicating that these classes can be easily distinguished from one another. The class combination which is the least separable is Plantation (P) and Forest and Woodlands (FW). This class combination has a comparatively low J-M value of 1.450. However, this is not surprising because both these classes comprise of commercial tree species which have similar spectral signatures. The relatively high spectral differentiations between the eight land cover classes chosen also indicates that they were appropriate in relation to identifying main land-uses in the area that were significantly different from each other.

5.3. Selecting the best classification algorithm

In order to decide which supervised classification algorithms was best suited for the purpose of this study, the latest image (2008) was classified using all of the algorithms. Since field data as well as the latest aerial photographs and land-use maps were available for 2008, the 2008 Landsat image was an ideal choice for calculating the overall accuracy and kappa coefficients for each of the classification algorithms. Figure 5.2 and Table 5.2 display the UA, PA, OA percentages as well as the kappa coefficient values for the Parallelepiped, Minimum Distance to Means and Maximum Likelihood algorithms, whilst Figures 5.3 and 5.4 depict the classified images of the study area using each classifier.

Table 5.2: Overall Accuracy percentages and kappa coefficient values for each algorithm

	Parallelepiped	**Minimum Distance to Means**	**Maximum Likelihood**
OA	55.63%	62.68%	**79.58%**
Kappa	0.49	0.57	**0.77**



*W – Water, Ws – Wetlands, CL – Cultivated Land, P – Plantation, FW – Forest and Woodlands, B – Bushveld, C – Clearfelled, S – Settlements

Figure 5.2: User's and Producer's Accuracy percentages for each of the nine classes and three algorithms

From Table 5.2, it is evident that the least accurate classification algorithm was Parallelepiped, with a low OA percentage of 55.63% and kappa coefficient of 0.49. Unlike the other algorithms, this classifier resulted in a total of 21 1269 of pixels being left unclassified (as indicated in black in Figure 5.3(a)). Except for Water (PA = 80% and UA = 100%), Wetlands (PA = 86.7% and UA = 86.7%) and Plantation (PA = 82.1% and UA = 76.7%), other classes classified using the parallelepiped algorithm displayed relatively low PA and UA percentages (refer to Figure 5.2), with Forest and Woodlands and Settlements having PA's of just 6.25% and 9.52%, respectively. Cultivated Land appeared to be the most dominant land cover class, covering approximately 22.8% of the study area (shown in yellow in Figure 5.3(a)).

With regards to the Minimum Distance to Means classifier, this algorithm proved to be more accurate than the parallelepiped classifier with an OA of 62.68% and kappa coefficient of 0.57. Some classes classified using the Minimum Distance to Means algorithm also exhibited relatively low UA and PA percentages with Settlements having the lowest PA (23.81%) and Bushveld the lowest UA (25.64%). Conversely, Waterbodies and Wetlands displayed very high UA (100% and 83.3%) and PA (100% and 100%) values. In Figure 5.3(b), Bushveld is the most dominant class (shown in the color brown) whilst there are very fewer areas classified as Settlement. Although the field assessment and aerial photographs prove Settlements to be one of the more dominant land cover classes in the study area, the parallelepiped and Minimum Distance to Means algorithms fail to accurately classify the Settlements class with Figure 5.3(a) and (b) and Figure 5.4 (d) portraying the settlement class to be the least dominant class of the nine land cover classes considered in this study.

The ML classifier is the most accurate classification algorithm with an OA of 79.58% and kappa coefficient of 0.77. Additionally, all but one of the classes (i.e. Bushveld) have UA and PA values greater than 50%, with the majority of classes having UA and PA values greater than 90%. These high values, especially with regards to UA, indicate that the classified image provides a reliable interpretation of the study area and can be used to predict future LUCC. It is for these reasons that the Maximum Likelihood classification algorithm was selected to classify the 1992 and 2000 Landsat images (Figure 5.5).

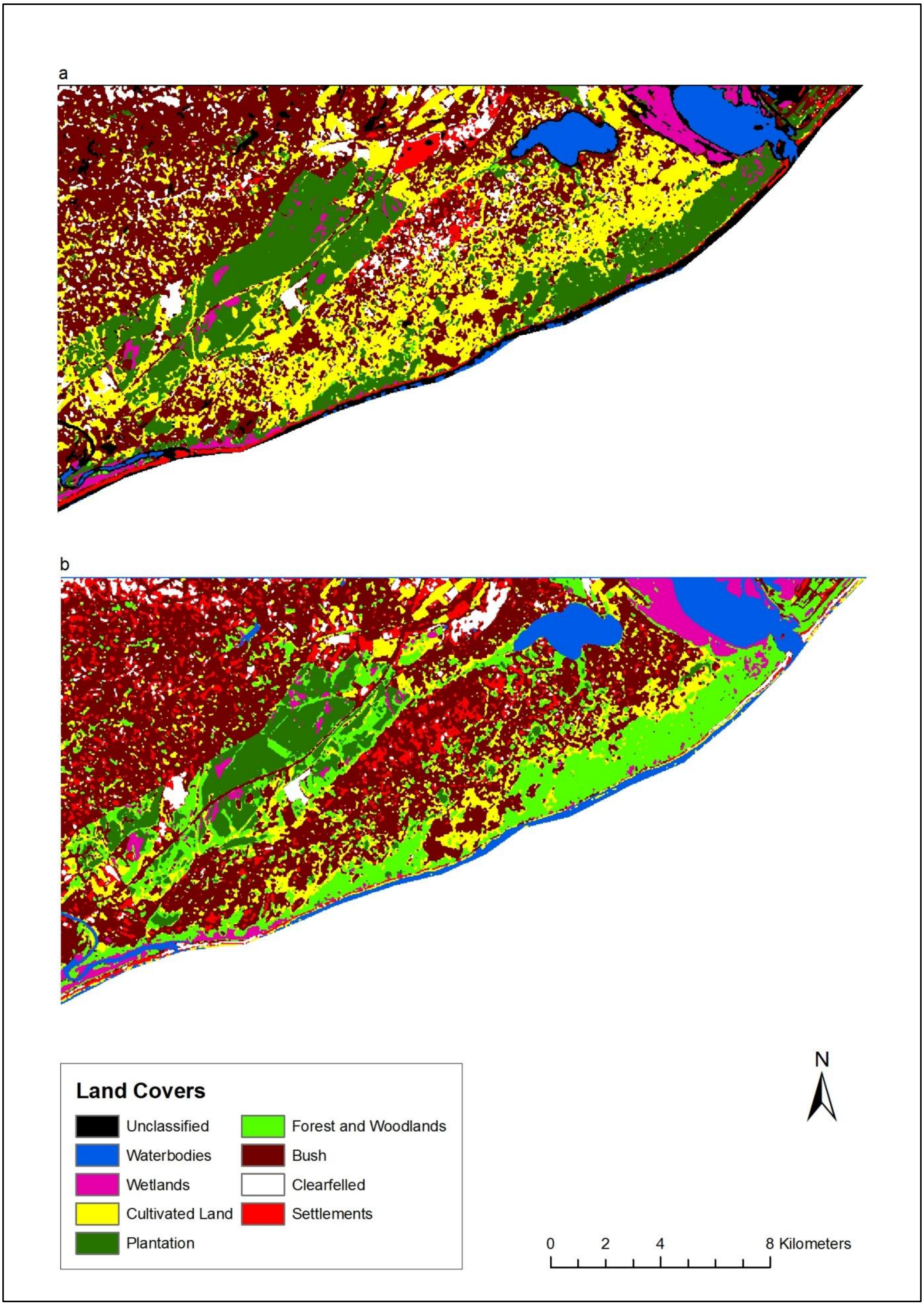


Figure 5.3: Classified images of study area in 2008 using the (a) Parallelepiped and (b) Minimum Distance to Means classification algorithms

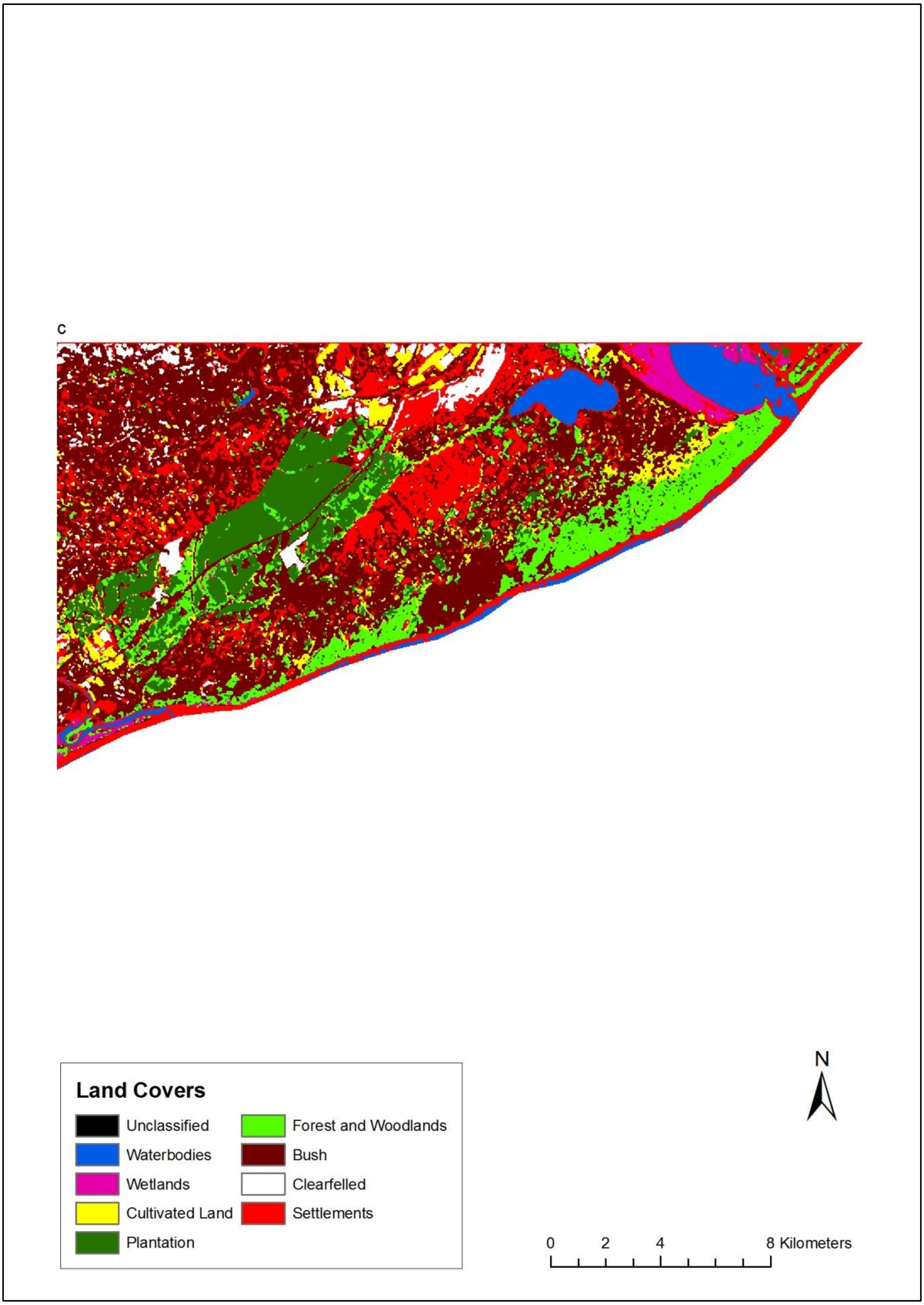


Figure 5.4: Classified image of study area in 2008 using the (c) Maximum Likelihood classification algorithm

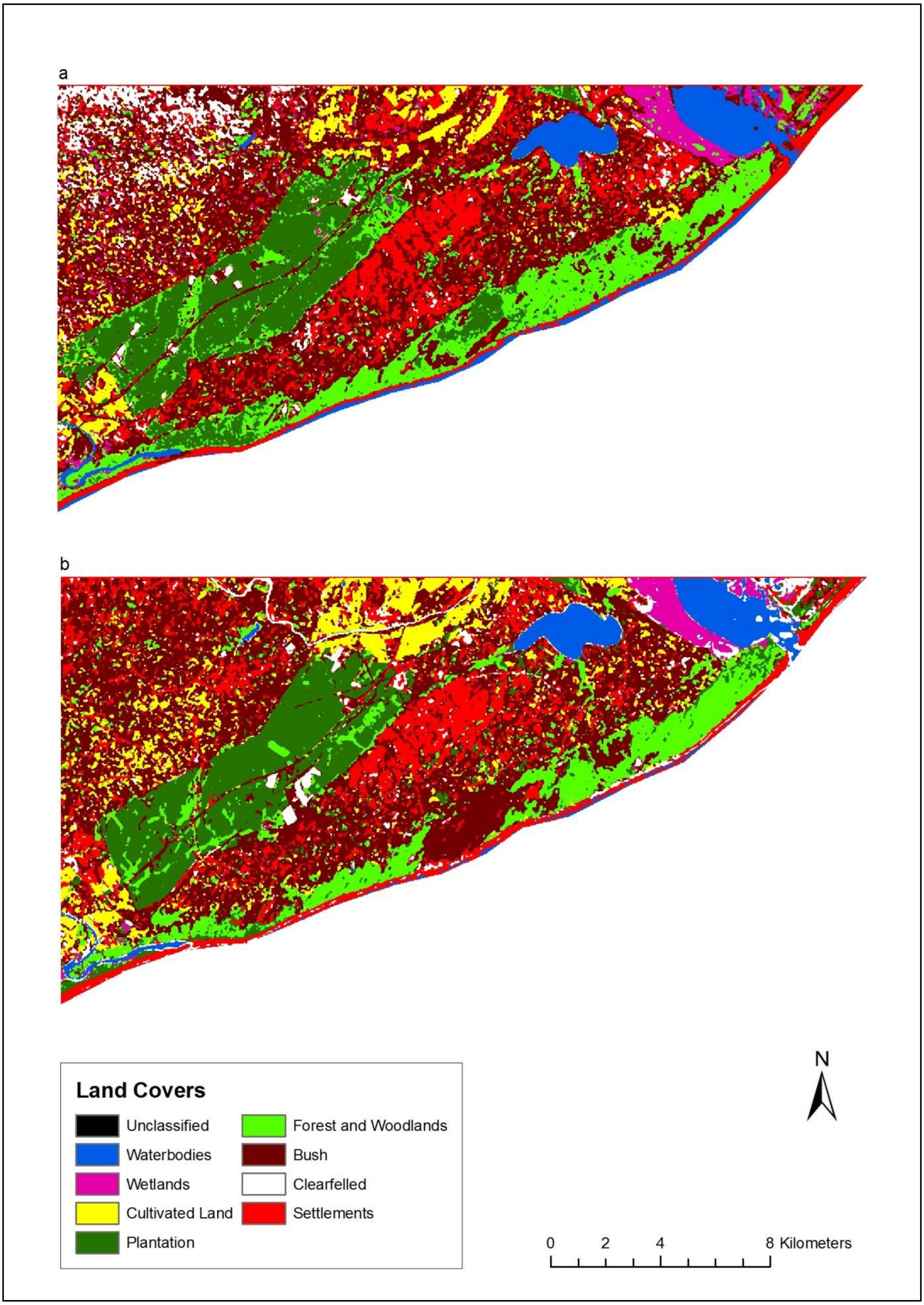


Figure 5.5: Classified images of study area in (a) 1992 and (b) 2000 using the Maximum Likelihood classification algorithm

5.4. Change Detection Analysis

The spatial distribution of the land cover classes for each of the three years (1992, 2000 and 2008) is depicted in Figure 5.5 (a) and (b) and Figure 5.4 (c). Initial visual interpretation of these classified images indicated that there have been significant changes in the land cover from 1992 to 2008. Specifically, the growth in Settlements with a concomitant decrease in land cover classes such as Wetlands and Forest and Woodlands is clearly discernible. This deduction is further verified by the land cover class change analysis presented in Table 5.3 and Table 5.4.

Table 5.3: Percentage change in each class over a 16 year period from 1992 to 2008

		Initial State							
		W	**Ws**	**CL**	**P**	**FW**	**B**	**C**	**S**
Final State	**W**	**83.2**	1.4	0.0	0.0	0.4	0.5	0.0	0.2
	Ws	0.5	**37.7**	0.1	0.7	2.6	0.3	0.0	0.0
	CL	0.0	0.5	**19.5**	2.9	3.4	7.1	3.4	1.0
	P	0.2	2.9	1.0	**52.6**	12.0	2.4	3.0	0.2
	FW	0.1	5.9	1.7	15.3	**45.4**	6.5	1.2	0.3
	B	0.3	19.9	43.4	22.4	27.8	**58.7**	71.0	8.8
	C	0.0	0.9	16.4	3.8	0.7	3.3	**14.8**	0.5
	S	15.6	30.8	18.0	2.4	7.8	21.1	6.6	**89.0**
	Class Change	16.8	62.3	80.5	47.4	54.6	41.3	85.2	11.0
	Image Difference	-8.2	-41.6	-6.9	-24.8	-17.5	12.8	-20.3	5.2

*W – Water, Ws – Wetlands, CL – Cultivated Land, P – Plantation, FW – Forest and Woodlands, B – Bushveld, C – Clearfelled, S – Settlements

Table 5.3 provides a detailed description of the change observed in each class from the initial state (1992) to the final state (2008). The class change values indicate the total percentage of pixels that have changed classes while the individual class rows (i.e. W, Ws etc) indicate how these changes have occurred in relation to the other classes considered in the study. The image difference row values provide information as to whether the overall class size has increased or decreased, as signified by a positive or negative value, respectively. The land cover classes which exhibited the largest class change values are Clearfelled (85.2%), Cultivated Land (80.5%) and Wetlands (62.3%). In terms of image difference, most classes had negative values indicating that these classes decreased in size from 1992 to 2008. Although this decrease was relatively small in most cases, the Wetlands class showed a significant decline with an image difference value of -41.6. The fact that both Bushveld (12.8%) and Settlements (5.2%) had positive image difference values implies that the majority of the areas previously covered by each of these classes have not changed or transformed to other land cover classes, but instead expanded in size.

Table 5.4: Summarized Class Change and Image Difference values for each class from 1992 to 2000 and from 2000 to 2008

			Initial State							
			W	**Ws**	**CL**	**P**	**FW**	**B**	**C**	**S**
Final State	**1992 – 2000**	**Class Change**	22.0	58.7	58.3	36.4	55.5	44.0	97.6	11.4
		Image Difference	-15.9	-43.5	48.2	-1.4	-21.2	4.2	-18.3	2.2
	2000 – 2008	**Class Change**	8.6	30.7	27.3	82.6	44.3	42.0	92.8	10.7
		Image Difference	9.1	8.3	3.4	-37.2	-23.7	4.6	-2.5	2.9

*W – Water, Ws – Wetlands, CL – Cultivated Land, P – Plantation, FW – Forest and Woodlands, B – Bushveld, C – Clearfelled, S – Settlements

Table 5.4 provides a brief description of the net changes experienced by each land cover class during the eight year periods from 1992 to 2000 and from 2000 to 2008. With regards to the first set of changes, it appears that with the exception of Waterbodies and Settlements, all other land cover classes had comparatively high class change values, especially the Clearfelled class which had the highest class change (97.6%). Wetlands, Plantation, and Forest and Woodlands also showed changes of more than 50%. In comparison, the image difference values were relatively lower, although Wetlands (-43.5%) did show a marked decrease in class size whilst Cultivated Land increased by 48.2% during this period.

The land cover changes which took place from 2000 to 2008 displayed a somewhat similar pattern to the 1992 to 2000 changes. The Clearfelled class again experienced the greatest amount of change with a class change value of 92.8%. This was closely followed by Plantation, with a value of 82.6%. Aside from Plantation and Forest and Woodlands, all other land cover classes had image difference values below 10%. Both of the aforementioned classes decreased in size from 2000 to 2008, Plantation by -37.2% and Forest and Woodlands by 23.7%.

5.5. Markov Chain Model

The results of the Markov chain model are indicated in the transition probability matrix below. This matrix is a result of the cross-tabulation of the 2000 and 2008 images, adjusted by the proportional error of 0.15. The reasoning behind the use of these two images for the model is that since there is an eight year difference between the 2000 image and the more recent 2008 image, they would be ideal for predicting land cover changes for the year 2016. Table 5.5 depicts the percentage of pixels expected to change from each land cover type to each other land cover type in 2016. The rows in the matrix represent the older land cover classes and the columns represent the newer classes.

Table 5.5: Transition probability matrix

		Probability of changing into							
		W	**Ws**	**CL**	**P**	**FW**	**B**	**C**	**S**
Given	**W**	80.32	0.68	0.03	0	0.14	0	0	18.83
	Ws	15.11	34.71	1.33	2.5	7.42	4.36	1.35	33.18
	CL	0.01	0.01	13.87	0.47	6.3	38.3	13.33	25.04
	P	0.01	1.11	2.94	45.87	31.98	9.62	6.03	2.12
	FW	0.02	0.25	7.18	7.54	50.63	25.52	3.48	5.12
	B	0	0.04	9.21	1.23	12.08	50.55	13.87	12.7
	C	0.05	3.18	5.26	16.12	29.11	24.7	9.75	11.2
	S	4.34	0.26	6.6	0.72	5.44	20.1	15.8	46.39

*W – Water, Ws – Wetlands, CL – Cultivated Land, P – Plantation, FW – Forest and Woodlands, B – Bushveld, C – Clearfelled, S – Settlements

Before the Markov results are described in detail, it is important to realize that these values do not necessarily represent realistic changes in the study area but are rather direct equivalents of the land cover changes that have occurred between the time period of 2000 and 2008, and thus it is due to their new mutual independence that they may be compared directly (Muller and Middleton, 1994). From Table 5.5, it is evident that many of the predicted changes for 2016 appear to be relatively minor, except in the case of Settlements, Bushveld, Clearfelled and Forest and Woodlands. The significance of the Settlements class is that although only 46.39% of the class will remain intact, a percentage of every other land cover class will be converted into settlements, with Wetlands (33.18%) and Cultivated Land (25.04%) displaying the largest change over and Plantation (2.12) and Forest and Woodlands (5.12) displaying the lowest. A possible explanation for the low transition probability percentage of Forest and Woodlands and Plantations to Settlements is the fact that settlement growth in the area appears to be confined to specific localities, mainly expansion in existing natural resource areas. The western parts of the study area consist mainly of private-owned plantation and therefore community expansion outside of traditional areas is highly unlikely.

Waterbodies (80.32%), Forest and Woodlands (50.63%) and Bushveld (50.55%) displayed high transition probability percentages for remaining in the same position in 2016. On the other hand, Cultivated Land (13.87%) and Clearfelled (9.75%) were two land cover classes which had the lowest probability percentages and it is thus most likely that the areas currently occupied by these classes will soon be replaced with other land covers. With regards to Cultivated Land, Bushveld (38.3%) and Settlements (25.04%) show the highest probabilities of replacing this class, whilst Clearfelled will mostly be replaced by Plantation (16.12%) and Forest and Woodlands (29.11%).

5.6. Summary

This chapter summarized the main findings emanating from the study. In terms of signature separability, the results for the J-M index for all pair-wise class combinations revealed that all but one are totally separable from each other. The choice of the Maximum Likelihood classifier as the most appropriate classification algorithm was entirely dependent on the accuracy results presented in Table 5.2 and Figure 5.2. This classifier proved to have the best OA, PA and UA and was thus selected to classify all three images for change detection analysis. With regards to the change detection statistics, many of the land cover classes changed significantly during the sixteen year period from 1992 to 2008, with all but Bushveld and Settlements actually decreasing in size. The Markov model predicted a similar trend in 2016, as most classes displayed a relatively low probability of remaining unchanged. The significance of the abovementioned findings will be discussed in greater detail in the next chapter.

CHAPTER 6: DISCUSSION

6.1. Introduction

The first part of this chapter briefly discusses the selection of the Maximum Likelihood classifier as the algorithm of choice. The rest of the chapter focuses on describing the observed and predicted trends in land cover change as well as their associated implications. The most relevant land cover classes, i.e. Waterbodies, Wetlands, Cultivated Land, Plantation, Forest and Woodlands and Settlements, are discussed separately in different subsections. The significant results for each class are highlighted and the consequences of both past and future changes are discussed in accordance with the relevant literature. A short overall summary of the main findings is provided at the end of the chapter.

6.2. Selection of the best classification algorithm

The ML classifier is the most accurate classification algorithm of the three, with an OA of 79.58% and kappa coefficient of 0.77. Although many researchers such as Brown *et al*. (2000), Ge *et al*. (2007), Lucas *et al*. (1989) and Treitz and Rogan (2004) set a minimum acceptable accuracy target of 85% for land cover maps derived from remote sensing data, Foody (2008) argues that such a target may be overly harsh and extremely difficult to achieve. Furthermore, Foody (2008) states that often the approaches used to evaluate the accuracy of image classification are sometimes harsh and misleading and are commonly pessimistically biased. Thus, it is recommended that realistic accuracy targets are set while at the same time ensuring that land cover maps of low quality are not viewed as acceptable (Foody, 2008). It is for these very reasons that the OA of the Maximum Likelihood classifier can be regarded as relatively high and appropriate for the scope of this study. Additionally, the UA and PA of most of the individual land cover classes are extremely high, ranging between 80% and 100%. These high values, especially with regards to UA, indicate that the classified image provides a reliable interpretation of the study area and can be used to predict future LUCC. This does not imply that the other two classifiers considered for this study are weak or inefficient but rather that they did not meet the needs of this particular research. Each of the other classifiers has in fact been used with great success by other researchers as per the case studies mentioned in Chapter 4.

6.3. Land cover trends and implications

According to Meyer and Turner (1992) and Jansen and Di Gregorio (2002), land cover changes can take one of two forms, namely conversion or modification. In this study however, only conversion from one class to another is discernible. Modifications within classes were not detectable as a broad classification scheme was used which did not allow for these subtle changes to be distinguished. The conversions from one class to another and the potential implications of such changes are described in greater detail below.

6.3.1. *Waterbodies*

The Waterbodies land cover class is one of two classes in the uMhlathuze municipality which has not undergone significant change between 1992 and 2008, displaying a low class change value of just 16.8%. Furthermore, in comparison to the other classes, Waterbodies are not expected to change drastically by 2016, with the Markov chain model predicting that 80.32% of the class will remain intact. The relative stability of this class is in line with other studies which have also showed that Waterbodies do not exhibit large changes during short periods of time. One such study is that of Long *et al*. (2007) which investigated the socioeconomic driving forces of land-use change in Kunshan, China. The authors found that of all the classes, natural lakes and rivers displayed the least amount of change during the period from 1987 to 2000.

The observed changes in waterbodies are difficult to interpret as they may well be attributed to both seasonal and anthropogenic factors. In this study, Table 5.3 shows that Waterbodies has actually been replaced by the Settlements class. The same pattern is expected in 2016 where 18.83% of the Waterbodies class will be replaced by Settlements. The increase in the Settlements class will result in a greater demand of water, a fact not taken into account by the Markov chain model. The impacts of such land cover changes on Waterbodies and the hydrological cycle has been discussed in broad detail in section 2.4.2.

It should be emphasized, that these comparatively subtle changes in Waterbodies are of serious concern as the availability of water in South Africa is severely hampered by the fact that the country is both part of a semi-arid region, with an annual rainfall that is little more than half of the world average, and susceptible to droughts and floods (Department of Water Affairs and Forestry - DWAF, 2004). Consequently, water availability has emerged as the dominant factor inhibiting development of the country as a whole and is the closely linked to the prevalence of disease, hunger and poverty (Turpie *et al*., 2008). Other than their impact on water availability, Haas *et al*. (2011) note that changes in Waterbodies can also serve as ecological indicators for short-term ecohydrological changes. In a study conducted in sub-Saharan Western Africa, the authors proved that there was a link between vegetation cover, rainfall and surface water extent. Waterbodies can thus serve as good indicators of year-to-year rainfall availability, for water availability during the dry season, and for the state of an ecosystem (Haas *et al*., 2011). An unfortunate disadvantage of this study is that it did not examine water quality, which could be undermined given the increase in Settlements, as highlighted by Foley *et al*. (2005) and Chen (2002) in Chapter 2.

6.3.2. *Wetlands*

The Wetlands land cover class has undergone a considerable amount of change from 1992 to 2008, with a class change value of 62.3% and image difference value of -41.6%, the highest from all other land cover classes. Unlike in the case of Waterbodies, only 34.71% of this class is expected to remain the same in 2016, with the rest of Wetlands being converted to Settlements (33.18%). The impact of rapid urban land expansion on the Wetlands class is not only prevalent in this study area but is consistent with observations from around the world. For example, Dewan and Yamaguchi (2009) analyzed land-use and land cover change in Great Dhaka, Bangladesh and found that substantial growth of built-up areas have led to a significant decrease in wetlands. The authors observed that property development had increased from 1975 to 2003 and property developers continue to develop wetlands regardless of the environmental cost.

In this study, the change from Wetlands to Settlements will have serious implications for the hydrological cycle and other ecosystem services provided by wetlands. In terms of the hydrological cycle, wetlands in South Africa play a vital role in the provision of water. For example, in grassland catchment areas, much of the summer rainfall is caught by seepage wetlands which function as sponges by slowly releasing infiltrated water and thereby maintaining base flows in the catchments during the dry season (Turpie *et al*., 2008). Wetlands are also effective at flood mitigation, minimizing sediment loss, purifying surface water, controlling run-off volume, and enhancing aquifer recharge (Baker *et al*., 2006). Dahlberg and Burlando (2009) note that the coastal plain of KwaZulu-Natal is made-up of mostly sandy soils and thus, the scattered wetlands provide areas of productive soil essential for local agriculture. This provision of flat, fertile land with a ready supply of water means that many of the local communities living in southern African countries can utilize wetlands for fishing, cultivation and livestock production (Aldekola and Mitchell, 2011; Dixon, 2008; McCartney *et al.*, 2011). Wetlands are therefore important contributors to livelihoods, food security and poverty alleviation (Aldekola and Mitchell, 2011; McCartney *et al.*, 2011). In a study conducted by Rebelo *et al.* (2010) in Tanzania, the contribution of wetlands to the livelihoods of people living in rural areas is further emphasized. The authors found that rural communities rely heavily on wetlands to meet their basic needs for household survival. The wetlands in the study area provide natural resources and are utilized for agriculture, thereby contributing greatly to food security, household income and welfare (Rebelo *et al*., 2010). These assertions are also relevant in Dube and Esikhawini as indicated by Bassa (2010).

The aforementioned case studies serve to underscore the importance of preserving wetlands both for the sake of the ecosystem services they provide and their vital contribution to rural livelihoods. Thus, the wetlands in the current study area have and are still being affected by land cover change. This is a matter of concern, especially as past experiences of wetland management in Africa have, as stated by Dixon (2008) and McCartney and Houghton-Carr (2009), shown that unsuitable agricultural development in wetlands can negatively affect sustainability and have severe economic and social impacts for the rural communities dependent on the ecosystem services provided by these wetlands. Furthermore, it undermines ecological integrity and have serious environmental impacts given the roles that wetlands play (Gleick *et al*., 2009).

6.3.3. *Cultivated Land*

During the sixteen year period from 1992 to 2008, Cultivated Land has changed considerably as indicated by the 80.5% class change value. The Markov chain model results revealed that only 13.87% of this class will remain unchanged in 2016. The majority of this class will be replaced with the Settlements class (25.04%). Many authors have shown that Cultivated Land is increasingly being replaced with Settlements. Seto and Fragkias's (2005) study on quantification of spatiotemporal patterns of urban land-use change in four cities of China with time series landscape metrics showed that in southern China, most of the areas surrounding these cities is used for agriculture and thus, urban sprawl often occurs at the expense of cultivated land. The literature review revealed that a major concern in terms of long-term impacts of land cover change is linked to food production and therefore food security. It is clear that in this study area the loss of Cultivated Land means that there is a decline in agricultural activities at the commercial level. Bassa's (2010) study also found that subsistence agriculture in the area has also been on the decrease. The consequences of changes in the Cultivated Land class are thus likely to affect food security at both regional and household levels.

Aside from urban expansion, another possible reason for the decline in agriculture in the study areas is livelihood diversification. During the last two decades of the 20th century, the economies of South Africa and other sub-Saharan countries underwent drastic changes and rural populations began to move away from an agricultural dominated lifestyle to becoming more dependent on non-agricultural income-generating activities (Bryceson, 2000; 2002). In a study conducted in five Eastern and Southern African countries, Jayne *et al*. (2010) list a few of the main challenges faced by subsistence farmers and are thus responsible for the decrease in agricultural activities in many rural areas. These challenges are as follows: "(1) declining land/labor ratios and high inequality of landholding distribution within smallholder sectors; (2) high concentration of marketed maize and other crops; (3) most rural households being purchasers of maize rather than sellers; (4) rapid urbanization based on a pushing of labor out of rural areas; and (5) changing urban consumption patterns" (Jayne *et al*., 2010: 1385). Whilst it is impossible to ascertain given the scope of this study which of the aforementioned challenges is responsible for the negative change in Cultivated Land in the present study area, the literature review and background to the case study reveal that some of the challenges raised by Jayne *et al*. (2010) are discernible in the area under study.

6.3.4. *Plantation*

While the Plantation class has exhibited a rather high class change value (59.3%) between 1992 and 2008, it has a very low image difference value (-1.3%) which shows that in sixteen years this class has only decreased by 1.3%. The Markov model predicts that 45.87% of the Plantation class will remain as is in 2016 with Forest and Woodlands expected to replace 31.98% of Plantation. This conversion to Forest and Woodlands is not of particular concern as these two classes have very similar spectral signatures and as such the predicted change may be attributed more to errors of misclassification than a likely occurrence.

The current and expected trend in forest plantation change is not surprising considering the fact that areas for plantation forestry are limited within South Africa and the number of new areas chosen for afforestation has decreased significantly in recent years. In light of this, forest productivity maximization within existing planted areas is of crucial importance to forestry managers. Forest plantations, consisting of various exotic species such as *Pinus spp*., *Eucalyptus spp*. and *Acacia spp*., cover approximately 1.37 million ha of the country and over 80% percent of them are located in KwaZulu-Natal, Mpumalanga and the Eastern Cape (DWAF, 2005). Although commercial forest plantations only cover 1.1% of the total area of South Africa, they contribute significantly (R22 billion) to the Gross Domestic Product and produce more than 22 million m^3 of round-wood which is worth approximately R5.1 billion annually (Department of Agriculture, Forestry and Fisheries - DAFF, 2009; DWAF, 2005). Presently, the forestry sector just meets the timber demands of the country, however, should this demand increase in the next few years, the sector will have to either rely on timber imports or consider expanding the existing plantation estate (DAFF, 2009). In order to ensure that South Africa's forestry sector remains self sufficient and continues to contribute to foreign exchange earnings, the DAFF has developed the Forest Sector Transformation and Growth Charter tool which will, in the long run, explore opportunities for new afforestation over an area up to 100 000 ha, mostly in the Easter Cape (DAFF, 2009). Of concern in rural areas is that this expansion could undermine existing livelihoods and natural resources that poorer communities tend to rely on. It is therefore imperative that plantation forestry expansion should consider community based forestry and ascertain mechanisms to ensure that rural households have adequate access to resources.

6.3.5. *Forest and Woodlands*

From 1992 to 2008, Forest and Woodlands have changed by 50.6% and 50.63% of this class will remain in 2016. Although these changes appear to be comparatively less than those of other classes, they are nonetheless significant to the people living in this study area. Many of the people who live in the traditional area Dube do not have access to electricity and are therefore highly dependent on indigenous forests for fuelwood. Fuelwood still remains the area's primary energy source for domestic purposes. Other than the provision of fuelwood, Forest and Woodlands provide many other goods and services. The following statistics provided by DAFF (2009), albeit at a national level, highlight the undeniable value of this natural resource, especially in relation to poverty alleviation: (a) 27 million people rely on medicinal plants for healthcare and over 65% of these plants are forest and woodland species; (b) between 9 and 12 million people use fuelwood, wooden utensils and wild fruits acquired from forest and woodlands; (c) an average rural household uses 5.3 tons of firewood, 104 kg of wild fruits, 185 large poles for fences and construction, and 58 kg of wild spinaches each year, most of which are obtained from forest and woodlands; (d) access to this natural resource contributes roughly 25% of total livelihood accruals; (e) approximately 800 000 people work in the craft industry which is heavily dependent on forest and woodland resources; and (f) about a 100 000 households in the country engage in small-scale trade in forest products from forest and woodlands. Shackelton *et al*. (2007) add that while forest and woodlands and their associated products contribute greatly to the well-being and survival of the rural poor, these benefits are also extended to urban communities where forest products are widely used and marketed.

In light of the statistics listed above, it is apparent that the changes observed in the Forest and Woodlands class have a two-fold impact on rural communities in that the depletion of this resource will negatively impact on their livelihoods and quality of life but the continued rate of usage will only lead to a further decrease in the availability of this natural resource. The impacts of land cover change on forestry resources were examined in the literature review and reinforce the importance of forestry resources to rural livelihoods as discussed above.

6.3.6. *Settlements*

In relation to the other classes, Settlements has exhibited the least amount of change with a class change value of 13.5% and an image difference of 1.5%. The results indicate that although only 46.39% of the class is to remain intact in 2016, urban expansion has resulted in the considerable reduction of the other classes, especially in regards to Wetlands and Cultivated Land. The increasing population size coupled with the dominance of the historical township dynamic in the study area continues to negatively impact other land cover classes. This is of concern as townships generally consist of mainly poorer households who depend heavily on natural resources. This dependence by poverty stricken people together with rising demand for land for urban and agricultural use threatens biodiversity, water resources and food security (Turpie *et al*., 2008). Bassa (2010) illustrated that as long as poor people remain poor and the current resource use is continued, the natural resource base of this particular study area will continue to be depleted.

According to Pauchard *et al*. (2006) much of the research on urban sprawl has focused on developed countries and it is important to note that the effects of this phenomenon are different for developing countries. In contrast to developed countries, where urbanization is responsible for fragmenting large areas, urban growth in developing countries is concentrated around urban cores and generally involves the replacement of adjacent land-uses such as agriculture and other natural vegetation (Pauchard *et al*, 2006). Other examples of countries displaying a similar trend include a study conducted by Lopez *et al*. (2001) in Puerto Rico. This study aimed to link population growth, socioeconomic changes and land-use patterns to losses of agricultural land in the country. The authors found that urban areas increase by 27.4% during the 17 year period of interest and urban growth on land suitable for agriculture increased by 41.6% (Pauchard *et al*, 2006). Pauchard *et al*. (2006) concluded that Puerto Rico lost a total of 6% of potential agricultural land and this pattern of urban sprawl into potential farmlands is still continuing. These findings are clearly evident in the present study area where, as mentioned before, Cultivated Land and Wetlands have and will continue to be replaced by Settlements.

6.4. Summary

This chapter discussed the implications of the main findings of the study and through the use of literary sources offered several explanations for current and future land cover change trends. Human settlement increase emerged as a key driver of change in the study area and given the rural context of the study area, the increased demand on natural resources (both Wetlands and Forest and Woodlands) in the area is likely to have severe environmental impacts which will in turn affect rural livelihoods.

CHAPTER 7: CONCLUSION AND RECOMMENDATIONS

7.1. Introduction

The observed land cover change pattern in Dube and Esikhawini is influenced greatly by the increase of the Settlements class. The results show that the spread of this class has led to a decline in the spatial extent of the other classes and, should the current land cover change trend continue, Settlements will emerge as the future dominant land cover class in the area.

The determinants of land cover change, mentioned in the literature review, continue to influence land cover dynamics in the study area and this study has served to quantify the relationship between land cover change and key driving forces. Whilst the role of social and cultural factors have begun to diminish as important drivers of change in the study are, technological and more importantly economic factors still play a vital role. Although this study did not focus on the policies, many of the main governmental policies, for example, the Growth, Employment and Redistribution policy, are centered around development and promoting of the economic agenda. More often than not, however, these policies do not take into consideration the long term impact of economic activities, such as mining in the case of this study, on the natural environment. Therefore, as Brink and Eva (2009) assert, it is critical that land cover changes and their impacts are understood before appropriate land management practices and policies are developed and implemented.

With regards to demographic factors, the importance of this factor as a driver of land cover change, especially in developing countries, has been repeatedly emphasized by the literature. The one drawback of this study is that the model chosen to predict future changes did not take into account demographic factors and as such any predictions made by the Markov chain model are most probably very conservative. The expected land cover change by 2016 and their likely impacts on this area would have been considerably different had increasing population size been factored into the model.

7.2. Summary of key findings in relation to the objectives

This study revealed that remote sensing can play a significant role in contributing towards examining land cover changes and potential impacts on the natural resource base. In this section the objectives of the study presented in Chapter 1 are reviewed to evaluate how they were achieved.

7.2.1. *To determine the dominant land cover changes that have occurred during the 16 year period*

Eight major land cover classes were identified in the study area, namely Waterbodies, Wetlands, Cultivated Land, Plantation, Forest and Woodlands, Bushveld, Clearfelled and Settlements. Three classification algorithms were used to classify the study area in accordance with the aforementioned land cover classes. Based on the results of the accuracy assessment, the Maximum Likelihood classifier was deemed the most appropriate algorithm for the study. In order to determine the dominant land cover changes that have occurred from 1992 to 2008, an image differencing change detection technique was employed. The change detection technique results revealed that whilst Waterbodies, Plantation, Bushveld and Settlements had class change (Table 5.3) values below 50%, the rest of the classes had significantly higher values, indicating that these land cover classes changed considerably during the sixteen year period.

7.2.2. *To evaluate the extent of these changes*

In terms of the extent of the land cover changes in the area, settlement expansion (i.e. an increase in the Settlements class) emerged as a key driver of change. Thus, it is of no surprise that the Settlements class displayed the lowest class change and image difference values of just 11% and 5.2%, respectively. The only other class with an extremely low class change value was Waterbodies (16.8%). This land cover class decreased from 1992 to 2008, with 15.6% changing to Settlements. In the case of Wetlands, Cultivated Land and Clearfelled, the results showed that these three classes had undergone extensive changes and in comparison to the other classes the class change values for Wetlands (62.3%), Cultivated Land (80.5%) and Clearfelled (85.2%) were significantly higher. Although Plantation (47.4%), Forest and Woodlands (54.6%) and Bushveld (41.3%) did not have class change values as high as the aforementioned classes, these three land covers did change considerably with both Plantation and Forest and Woodlands decreasing (image difference values of -24.8% and 17.5%, respectively) and Bushveld increasing (image difference values of 12.8%).

7.2.3. *To predict the extent of future changes*

In order to predict the extent of land cover changes in 2016, a Markov Chain model was used. The model results were in line with those of the change detection analysis which showed settlement expansion to be the main driver of change in the study area. Although the model revealed that only 46.39% of Settlements is to remain the same in 2016, a portion of every other land cover class will change to this class, with Wetlands (33.18%) and Settlements (25.04%) displaying the largest conversion percentages. Waterbodies, Plantation, Forest and Woodlands and Bushveld displayed relatively high transition probability percentages for remaining in the same position in 2016. Despite the fact that some of these results were debatable, the Markov Chain model proved to be a useful scenario building tool as it highlighted the fact that unattended settlement expansion in rural areas, such as this study area, is a serious problem especially in terms of sustainable development.

7.2.4. *To examine potential impacts of these changes on the natural resource base*

As per the previous chapter, it is evident that rural livelihoods are linked extensively to access to natural resources. As such, the predicted increase in the Settlements class coupled with the decrease in the other land cover classes, specifically Wetlands, raises serious questions about environmental stability in the area. Furthermore, the literature cautions that continued depletion of access to and availability of natural resources are likely to undermine rural livelihoods and contribute to increased poverty among vulnerable groups.

7.3. Recommendations

The study has shown that there is a need to document land cover changes occurring in the area at periodic intervals, in order to better manage existing natural resources and ensure that the people who depend on them have a secure livelihood. From the summary of the objectives above, it is clear that attaining sustainability is critical to ensure livelihoods for the poor. It is also important that population pressures associated with settlement expansion in particular, which this study reveals as a key driver of land cover change in the area, need to be addressed. As stated by McCartney and Houghton-Carr (2009), the role of natural resource management in sub-Saharan Africa needs to be strengthened since this widely perceived to be the key to sustainability, and central to overcoming both developmental and environmental problems.

This section provides several recommendations for future research studies that will hopefully lead to improved land cover change assessments. Firstly, although the methodology utilized in the study could not be used to examine modifications within land cover classes, this needs to be addressed further as during the fieldwork it was evident that agricultural practices were changing, for example, sugarcane plantations were being replaced by pineapples. Secondly, while the present study does indeed exhibit satisfactory results, misclassification does exist to some degree, possibly due to one of many factors, such as the spatial, temporal or spectral properties of the images used or the classification method chosen.

The images used in this study were of multispectral origin which, while adequate for meeting the aims and objectives of this particular research, cannot compare to the advantages provided by hyperspectral images. Hyperspectral images are of a higher spatial resolution and made up of hundreds of narrow bands thereby allowing for higher classification accuracies to be achieved (Chan and Paelinckx, 2008). It is thus recommended that future studies consider the use of hyperspectral datasets as they are effective for addressing land cover problems at higher-order thematic levels where spatial resolutions of 5 m or greater are needed (Rogan and Chen, 2004).

There are various factors which influence land cover change that were not taken into account by this study. For example, climatic factors, such as rainfall patterns, were neglected and it is important that future studies, particularly those conducted in coastal areas, factor these variables in as they play a role in climate change prediction. Demographic factors, as mentioned before, have also not been considered during this research and it is again emphasized that they be a part of future research, especially when predicting future land cover changes.

The last and perhaps most important recommendation for future research is the need to consider stakeholder perceptions. This study has not looked at the relevant stakeholders and how they perceive the changes which have taken place given the focus of the study. Stakeholder perceptions should form an essential component of future land cover change studies, particularly in cases where the information derived is used to inform policy and planning.

7.4. Concluding Remarks

This study has successfully examined the issues raised as being important when undertaking land cover change research. The three classification algorithms used during the course of this research indicate that there are several potential methods suitable to examine land cover change. Each situation needs to be assessed and the objectives of the study need to be taken into account when choosing a classification algorithm. In this study the Maximum Likelihood classifier was deemed to be the most appropriate. The land cover maps derived during this study have many uses, for example, they can be used to identify spatial patterns of physical quantities such as vegetation cover or land-use. In addition, this study has shown the degree and extent, both temporally and spatially, of land cover changes taking place in the area. It has managed to identify, albeit in a limited way, the major consequences of these changes and the key drivers that are informing future land cover change trends. Furthermore, given the prominence of economic activities such as commercial forestry and agriculture in the area, an improved form of the methodology used in this study can be applied at a regional scale. This study emphasizes the importance of considering sustainability imperatives (socioeconomic and environmental aspects) when examining results of LUCC studies. It further demonstrates the importance of these types of studies in rural contexts to explore impacts.

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