

Multi-temporal mapping and projection of urban Land-Use-Land-Cover

Change: Implication on urban green spaces

By

Otunga, Charles Onyango

212558378

Supervisor: Dr. John Odindi

Co-supervisor: Prof. Onesimo Mutanga

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Pietermaritzburg Campus

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Declaration

I hereby declare that;

1. The research reported in this dissertation, except where otherwise pointed out, is my original work.
2. This dissertation has not been submitted for any degree or examination at any other institution of higher learning.
3. The dissertation does not contain other persons' data, equations, pictures, graphs or other information, unless specifically cited.
4. This dissertation does not contain other persons' writings, unless specifically acknowledged as being sourced from other researchers by properly referencing.

Signed:

Charles Otunga

Signed:

Dr. John Odindi

(Supervisor)

Signed:

Professor Onesimo Mutanga

(Co-Supervisor)

Dedication

Dedicated to all the young aspiring research scientists in space science and technology education for the betterment of the global environment.

Acknowledgement

To the Almighty Father, I am humbled for your mercies throughout the entire master's programme. I would like to sincerely thank my two able supervisors Prof. Onesimo Mutanga and Dr. John Odindi, for their wonderful scholarly advice, suggestions, corrections, guidance, constructive criticisms, patience and understanding throughout this master's program. To my mentors, Prof. Deogratious Jaganyi, Dr. Saha, Dr. Mironga, Mr. Oyugi, Mr. George Owoko, Mr. Agik Suji (late), Mr. Patrick Ochieng (Ujamaa Center Mombasa), Mr. Chrispine Owalla (CIAG-K), Mr. John Nyambare, Mr. Semeyi Som, Mrs. Wanyandeh, Ms. Joan Mumia, Mr. Octavian Mwandoto, Mrs. Florence Obwaka (late), Ms. Jenipher Agola, Mrs. Christine Akinyi, Mr. Matiko Akedi, Mr. Martin Muguda (late), Mr. Vitalis Okello, and Mr. Kenneth Alando among others, words cannot express my appreciation for your support, prayers and encouragements throughout my period of study. To my family, you have done me proud always, thank you for your unyielding support. I would also like to extend my heartfelt appreciation to all my colleagues and staff in the Department for their invaluable insights and moral support. To the Kenyan Community in Pietermaritzburg (KCP) members, thank you so much for making me feel at home away from home. I do wish to thank the UKZN's College of Agriculture, Engineering and Science for the scholarship/bursary offered to me to pursue my MSc. Similarly, appreciations go to the South African National Space Agency (SANSA) and the eThekweni municipality Environmental Planning and Climate change Protection Department (EPCPD) for providing the SPOT images, aerial photographs and other GIS data.

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Abbreviations

EMA:	eThekwini Municipality Area
EPCPD:	eThekwini Municipality Environment and Climate Protection Department
LULC:	Land-Use-Land-Cover
SANBI:	South African National Biodiversity Institute
LCM:	Land Change Modeler
RMSE:	Root Mean Square Error
D'MOSS:	Durban Metropolitan Open Space System
KZNSS:	KwaZulu-Natal Sandstone Sour Veldt
WGS:	World Geodetic Coordinate System
EOSAT:	Earth Observation Satellite
SPOT:	Systeme' Probatoire d'Observation de la Terre
ASTER:	Terra Advance Space bone Thermal Emission and Reflection Radiometer
MODIS:	Moderate-Resolution Imaging Spectrometer
NOAA:	National Oceanic and Atmospheric Administration
AVHRR:	Advanced Very High Radiometer Resolution
DOS:	Dark Object Subtraction
GCS:	Geographic/geodetic Coordinate System
GCP:	Ground Control Point
ENVI:	Environment for Visualising Images

Abstract

This study determines and predicts multi-temporal Land-Use-Land-Cover Change (LULC) in a peripheral urban landscape over a 22 year period in relation to the study area's greenery. A change detection analysis using post classification Maximum Likelihood algorithm on three multispectral SPOT-4 images was used to determine land-cover transformation. To predict future land coverage, a Land-Cover Change Modeler (LCM) and a Markov Chain were used. Results show that between the year 2000-2006, 2006-2011 and 2000-2011 the study area experienced varied changes in the different LULCs. Built-up areas increased by 10.08%, 3.15% and 13.23% in 2000-2006, 2006-2011, and 2000-2011 respectively. Areas covered by thicket decreased by 0.59% in 2000-2006 but increased by 0.56%, 0.07% in 2006-2011 and 2000-2011 respectively. Forest land-cover increased by 2.59% in 2000-2006, 2.82% in 2006-2011, and 5.41% in 2000-2011. Grassland declined by 8.46% and 2.64% in 2000-2006 and 2000-2011 respectively while degraded grassland declined by 3.62%, 12.45% and 16.07% in 2000-2006, 2006-2011, and 2000-2011 respectively. Projection results indicate a consistent pattern of growth or decline to those experienced between 2000-2011. This study provides insight into LULC patterns within the eThekweni metro area and offers invaluable understanding of the transformation of the urban green spaces.

Key words: Land-Use-Land-Cover Change, Change detection, Land-Cover Change Modeler, Markov Chain Process, Land-Cover Change Prediction.

Chapter 1: Introduction

1.1 General Introduction

Global population has increased significantly since mid-20th century. Accompanying this growth has been increased urbanization. By the end of the last decade for instance, the world's urban population had reached 2.9 billion which accounts for 40% of the world's total population (Van Zyl *et al.* 1997; Palmer and Ainslie 2005; Martindale 2008). In sub-Saharan Africa, urban population is expected to double to more than 4.9 billion, an equivalent of 52%-60% of its total population by 2030 (Keiser *et al.* 2004; Odindi *et al.* 2012).

The rapid urban population growth has led to significant urban landscape transformation (Jensen 1996b; Oluseyi 2006; Odindi *et al.* 2012). In sub-Saharan Africa for instance, constant development of physical infrastructure, deforestation, urban agriculture and other man-made and natural processes have strained the local ecosystem's ability to produce basic ecological goods and services (Prol-Ledesma *et al.* 2002; Alberti 2005; Mundia and Aniya 2005). According to Shao *et al.* (2006) the effects of these transformations may include deterioration of land and water quality, loss of urban green spaces, change of urban hydrology, air and water pollution. The conversion of green environment to impervious and built-up areas that characterise growing urban landscapes further impact on the albedo which considerably impact on local and regional land-atmosphere energy exchange (Palmer and Ainslie 2005).

In South Africa, the onset of urban landscape transformation has been associated with the period immediately after the country's independence (Collinson *et al.* 2007; Odindi *et al.* 2012; Christopher 2001). Kok and Collinson (2006) for instance note that urban areas grew by 4.3% between 1996 and 2001. This influx has been attributed to, among other factors, the abolishment of restrictive urban movement laws such as the Prevention of Illegal Squatters Act (PISA) of 1951 and myriad urban-pull and the rural-push factors. These include a search for better living conditions, employment, education, and better healthcare (Desanker *et al.* 1997; Naude and Kregell 2003; Van Vuuren *et al.* 2011).

Recent concerns on urban environmental quality, emerging problems associated with climate change and the increasing quest for sustainable green living have increased the value of urban green spaces. A number of studies (Anderson *et al.* 1996; Miller 1997; Gao 1999; Thompson 2002; Conner 2005; Yu *et al.* 2006; Mahdih Abkar *et al.* 2010) note that these spaces contribute immensely to the provision of different critical functions that include upholding biodiversity, averting soil erosion, engrossing rain water and contaminants, mitigating the effects caused by urban heat island, screening of wind and noise, mitigating effects of storm water management, as well as air and water purification.

Current, medium and long-term planning for urban environmental landscapes and mitigation of existing and future adverse environmental effects require knowledge on the implication of existing and projected urban Land-Use-Land-Cover (LULC) Changes on urban green environments. Traditionally, this information has been derived from field surveys and aerial photo interpretation. The use of these techniques is however time consuming, labour-intensive, and often costly (Liverman 1998; Islam and Ahmed 2011; Peerbhay *et al.* 2013), and thus not considered ideal for quantification and analysis of LULC patterns (Liverman 1998; Coppin *et al.* 2004; Kavzoglu and Colkesen 2009). In the recent past, remotely sensed multi-temporal datasets in concert with geographic information system (GIS) techniques have proved to be more useful for studying LULC changes (Huang *et al.* 2002; Liu and Zhou 2004; Abd El-Kawy 2011). The value of remote sensing in LULC mapping has particularly been driven by advances in sensor technology and therefore data quality, establishment of standardised remote sensing methods and its wide adoption in research applications and increased software availability (Rogan and Chen 2004; Johnson 2009; Kavzoglu and Colkesen 2009).

Multi-temporal LULC mapping is particularly critical to environmental stakeholders in making informed ecosystem planning and management decisions for sustainable supply of ecosystem goods and services (Liu *et al.* 2003; Liu *et al.* 2008). Critically, quantifying rates of LULC changes is a vital step in understanding and prioritising the threats facing urban green spaces (Slater *et al.* 1987; Gitelson 1992). In this regard, LULC monitoring and evaluation that involve

quantification of LULC characteristics, multi-temporal change and prediction of future trends are critical to natural resource management decisions (Bangamwabo 2010; Mhangara *et al.* 2012). A number of researchers (Abbott and Douglas 2003; Mundia and Aniya 2005; Deng *et al.* 2008; Dewan and Yamaguchi 2009), have studied urban LULC change. Whereas these studies provide invaluable information on urban LULC dynamics and their implication on urban green environment, such studies are commonly based on an entire urban landscape that often include central urban nodes that are commonly already saturated by built-up impervious surfaces. Green spaces within such built-up nodal areas are commonly under active protection by relevant stakeholders. Consequently, such green spaces are often stable and may not be readily vulnerable to external pressure. Typically, the highest rate of urban LULC transformation takes place at the urban fringes commonly characterised by peripheral urban growth (Steffens *et al.* 2008). As urban areas expand, green spaces at the periphery are assimilated into the impervious and built-up landscape. According to Jensen and Cowen (2011), LULC transformation and densification on the urban fringes has led to fragmentation and change of urban green spaces which may compromise their ability to provide ecosystem goods and services. This study sought to determine, and predict LULC transformation in Ward 7 (Shongweni), an urban fringe of the eThekweni Metropolitan area, KwaZulu-Natal, South Africa.

1.2 The Study Aim, Objectives and Research questions

The primary aim of this study was to detect and assess the trends of Land-Use-Land-Cover Change within Shongweni area (Ward 7) of eThekweni Municipality in KwaZulu-Natal province. To achieve this, the two major objectives and associated research questions were pursued:

Objectives of the Study

- a) To map and assess rates of change in LULC in the study area and its implications on urban green spaces for the period between 2000 and 2011.
- b) To predict future patterns of LULC Change in the study area.

Research questions

- What were the rates of change in LULC between 2000 and 2006, between 2006 and 2011 and between 2000 and 2011?
- During these specific periods, which LULC were more transformed and to what LULC types were they converted/changed to?
- From the identified ecosystem transformation trends in the study area, what is the spatial coverage of LULC types in the next eleven years?

Chapter 2: Literature review

2.1 Introduction

Urban expansion and the increasing urban population in most of South Africa's metros have placed increasing demands on the urban open green spaces. Due to the internal urban saturation, commonly, most urban areas have grown on the peripheral areas and existing open spaces. These areas are particularly critical for the provision of ecosystem goods and services. Sustainable ecosystem planning, development, management and conservation requires an up-to date LULC change baseline mapping. Such local baseline information may provide an insight on the urban areas drivers to ecological processes and patterns. This chapter provides a survey of the literature and highlights on the issues related to the objectives set in chapter one.

2.2 Climate change impacts: an overview

Climate change has been linked to severe effects such as the European heat waves of 1998 and 2003 (Beniston and Diaz 2004; Patz *et al.* 2005), increased incidences and severity of wildfires across the Mediterranean and the American West (Pinol *et al.* 1998; Amelung *et al.* 2007) and recent increases in the frequency of intense hurricanes across the southeastern United States and the Caribbean (Bell *et al.* 2000; Dale *et al.* 2001; Hultman 2006; Pielke Jr *et al.* 2008). Consequently, in the recent past, climate change has been widely recognized by among others politicians, academics, scientists and policy makers across the globe as a key threat to social and environmental systems (Houghton *et al.* 2001; Vincent 2004). Globally, climate change has had serious impacts on the realisation of the seventh millennium development (King and Hutchinson 1976; McCarthy *et al.* 2001; Beniston 2004; Solomon 2007).

Global climate change is largely influenced by human activities (Romme and Turner 1991; Kareiva *et al.* 1993; Klein *et al.* 2005; Metzger *et al.* 2005; Amelung *et al.* 2007; Riahi *et al.* 2007). Some of the noted causes of climatic changes include; increases in greenhouse gases, deforestation, industrial air pollution, urban growth and development, and overpopulation (Turner *et al.* 1993; Davis *et al.* 2008).

2.3 Urbanisation and climate change

Climate change on the continent is largely driven by urban growth (Turner *et al.* 1993). On the continent, issues related to climate are increasingly becoming a concern as Africa's urban areas have recently become focal points for economic growth, innovation, and employment (Dauskardt 1993; Chen *et al.* 2001; Cohen 2006). Through conversion of the landscape greenery into impervious urban surfaces, increased growth has potential to significantly transform urban biogeophysical environment (Martindale 2008; Batra 2010).

In sub-Saharan Africa, constant urban development, population increase, urban agriculture, and other natural processes have strained the local ecosystem's ability to produce basic ecological goods and services (Prol-Ledesma *et al.* 2002; Alberti 2005; Mundia and Aniya 2005). In South Africa for example, it has been noted that negative transformation in most of the urban areas was aggravated during the period immediately after the country's independence (Collinson *et al.* 2007; Odindi *et al.* 2012). Exponential population growth in most of the South Africa's urban areas during the democratic transition led to significant LULC changes. For instance, there was a 4.3% increase in the level of urbanization in South Africa between 1996 and 2001 (Kok and Collinson 2006). This influx has been particularly linked to the abolishment of restrictive urban movement laws implemented during the apartheid era (Meyer and Turner 1992; Desanker *et al.* 1997; Van Vuuren *et al.* 2011; Lu *et al.* 2012). Other factors like search for better living conditions, employment, education, and better healthcare have also influenced urban growth (Naude and Kregell 2003).

2.4 Urbanization and climate change in Africa

Currently, urban centers around the globe serve as local, national, regional, and global nodes of socio-economic growth (Bond *et al.* 2003; Wittenberg 2003; Un-Habitat 2010). Urbanization on the African continent is commonly characterized by rural-urban migration, geographic expansion through annexations and the transformation of urban fringes into small urban settlements (Coquery-Vidrovitch 1991; Hope 1998; Habitat 2003; Cohen 2006; Vongsy 2007). Currently, majority of these urban centers are undergoing rapid expansions which in turn affect

the composition, structure, and functional elements of the ecosystem (Winkler 2003; Corresponding *et al.* 2004; Warner 2005). However, our knowledge on urban landscapes and therefore our ability to effectively manage these landscape remains limited (Kaufmann and Seto 2001; Wittenberg 2003).

2.5 Urban Land-Use-Land-Cover Change

As urban and metropolitan areas continue to expand, new areas become engulfed into the urban landscape. This extends into open spaces which once provided basic ecological goods and services (Streutker 2003; Paul and Meyer 2008; Pickett *et al.* 2008). Typically, the growth of urban areas has led to drastic changes which in turn have contributed to urban green spaces transformations. These transformations compromise the ability of such spaces to provide the much needed ecosystem goods and services. Since LULC Change influences biodiversity, water and radiation budgets, carbon sequestration and human livelihoods, understanding of changes in LULC is critical in ecosystem management (Martin and Howarth 1989; Turner and Meyer 1994).

Land-Use-Land-Cover Changes in urban environments can be modeled through observation of the past and projections of the future (Kriebel 1978; Gao 1996). These models can be used to understand LULC Change dynamics that are required for informed environmental management decisions. Critically, quantifying rates of LULC Changes is a vital step in understanding and prioritising the threats facing different ecosystems (Slater *et al.* 1987; Gitelson 1992).

Studies towards mapping and monitoring changes in LULC using remotely sensed data have in the recent past become popular, see Table 1 below among others.

Table 1: A summary of the state-of-the-art Land-Use-Land-Cover Change detection using remotely sensed data.

Authors	Study objective	Journal published
Gong <i>et al.</i> 1992	Mapping and modeling urban sprawl of the Ajmer city, India using SPOT HVR data.	Remote Sensing of Environment.
Chen <i>et al.</i> 2003	Documenting the growth and related changes in Ilorin township, Nigeria using Landsat data.	Remote Sensing and Spatial Information Sciences.
Streutker 2003	Quantification of wetlands and other land-cover types in Georgia using Landsat Thematic Mapper data.	Remote Sensing of Environment.
Mundia and Aniya 2005	Mapping the spatial dynamics of LULC changes in Nairobi city, Kenya by using Landsat data.	International Journal of Remote Sensing.
Yuan <i>et al.</i> 2005	Mapping and monitoring LULC change using multi-temporal Landsat TM data in the Metropolitan Area of Minnesota.	Remote Sensing of Environment.
Fitzpatrick <i>et al.</i> 2008	Determine LULCs in Alaska using Landsat MSS data.	Global change biology.
Pillay and Sebake 2008	LULC change analysis on Landsat imagery of Cape town, South Africa.	Sustainable energy futures, CSIR Conference 2008.
Tiwari and Saxena 2011	Produce LULC maps of Mandideep and obedullaganj areas in India using TM, Landsat 5 & LISSIII, PAN IRS ID data.	International Journal of Technology And Engineering System.
Odindi <i>et al.</i> 2012	Monitoring LULC changes in the city of Port Elizabeth, South Africa using Landsat TM data.	South African Journal of Science.

The basic premise of employing remote sensing in change detection is that changes in LULC can frequently be determined and is cost effective (Mas 1999; Longley 2002). In the recent past, advancement in remote sensing and GIS tools and methods have made it possible for researchers to map, assess, model, and predict changes in LULC more efficiently and cost effectively than using traditional methods (Kamusoko and Aniya 2007; Bangamwabo 2010).

2.6 The value of change detection

Land-Use/Land-Cover is often dynamic and critical in understanding the interaction of anthropogenic activities with the environment (Mahdavi 2010). Commonly, managers, scientists and government agencies require timely and accurate information on existing LULC for a variety of applications such as natural resource management (Foody and Mathur 2004), environmental monitoring (Chen and Stow 2003) and monitoring of vegetation communities (Pal and Mather 2004).

Change detection is the process of identifying differences in the state of an object, area or phenomenon by observing it at different periods (Singh 1989; Coppin *et al.* 2004). In this regard, LULC Change detection process is aimed at comparing multi-date spatial representation to detect and monitor changes brought about by both environmental conditions and man's activities (Singh 1989; Green *et al.* 1994). The procedure requires images of the area/phenomena under study from two or more dates. Consequently, the process involves data assimilated by the same sensor, similar spatial resolution, viewing geometry, spectral bands, radiometric resolution, and acquired at the same time of day (Barnsley 1999; Lillesand *et al.* 2004). It is also desirable to use centennial date images in order to limit the differences linked with sun angle and periodic variations. Similarly, accurate spatial recording of images, between a quarter and half a pixel is required for operative results (Paolini *et al.* 2006 ; Arsanjani 2012)

By employing remote sensing and GIS techniques, LULC Change detection monitoring and projections can effectively be carried out through the use of multi-spectral and multi-temporal satellite images to evaluate LULC Changes. Change detection is used for a number of functions

which may include forest and vegetation change (Adelabu *et al.* 2012), deforestation, forest management, wetland changes, forest fires and urban landscape and environmental changes (Macleod and Congalton 1998). Mapping LULC Change is particularly critical in monitoring and managing ecosystem resources since it makes it possible to quantitatively analyse the spatial distribution of different LULC Changes (Zubair 2006). Typically, a change detection process requires that changes which have occurred in a landscape be detected, the nature of LULC Change that is taking place in an area identified, the extent of the changes be determined, and an assessment of the spatial patterns of change carried out (Macleod and Congalton 1998; Zubair 2006; Kamusoko and Aniya 2007).

Land-Use-Land-Cover Change detection can be done by employing pre-classification or post-classification methods (Yuan and Elvidge 1998). Even though the pre-classification change detection methods have been successful in establishing LULC Changes, they may not offer details on the nature of changes (Singh 1989; Ridd and Liu 1998). Some of the commonly used LULC Change detection techniques include: Image differencing (Jensen 1981; Ridd and Liu 1998; Mas 1999; Sohl 1999), Image Ratios (Dale *et al.* 1994; Jensen 1996a), post-classification comparison change detection (Toll *et al.* 1980; Jensen 1981; Mas 1999; Sohl 1999), normalized difference vegetation index (NDVI), principal component analysis (Toll *et al.* 1980; Fung *et al.* 1987; Fung 1990; Li and Yeh 1998), and change vector analysis (Jensen 1981; Lambin and Strahlers 1994; Johnson and Kasischke 1998; Sohl 1999). See Singh (1989), and Coppin *et al.* (2004) for an in-depth review of the commonly used change detection techniques.

2.7 Land-Use-Land-Cover Projection

Land-Use-Land-Cover Change is regarded as a major driver to local, regional and global environmental change. In this regard projecting these changes is critical for the assessment and monitoring of environmental impacts (Lambin 1997; Tian *et al.* 2009; Mubea *et al.* 2011). Such assessment is invaluable in making sustainable environmental decisions and initiating appropriate conservation strategies. Typically, LULC Change projection involves computing the transition probability matrix of LULC Change from year one to year two, which is then

considered to be the basis upon which to assign a later time period (Li and Reynolds 1997; Urban 2005; Sang *et al.* 2011). These projections mostly highlight how much of each LULC category will change and where that change is likely to occur (Pontius Jr *et al.* 2004; Liu and Zhou 2005). LULC change models are used to predict the future state of LULC patterns of which various physical and socioeconomic elements need to be considered (Bangamwabo 2010; Mhangara *et al.* 2012). An analysis of different scenarios of LULC Change projections is critical in the identification of future ecosystem change locations which helps in understanding LULC dynamics and contributes to informed ecosystem management decisions (Martin and Howarth 1989).

2.8 Value of open green space

Urban green spaces can be defined as outdoor places with significant amounts of vegetation which often exist as semi-natural areas (Chen *et al.* 2007; Baycan-Levent and Nijkamp 2009). These spaces may include all the significant outdoor spaces which fall under the influence of an urban area (Anderson *et al.* 1996; Miller 1997). These green spaces contribute immensely to the provision of different goods and services within an urban set-up (Maller *et al.* 2006; Mahdieh Abkar *et al.* 2010). Other functions performed by open spaces include upholding biodiversity, averting soil erosion, engrossing rain water and contaminants, and mitigating urban heat island effects (Smith *et al.* 1986; Gao 1999; Thompson 2002; Yu *et al.* 2006). Generally, the aforementioned functions can be categorised as:

- Environmental and ecological functions:

Climatic amelioration, providing habitats for wild plants and animals, wind and noise screening, hydrological cycles and storm water management and air and water purification (Anderson *et al.* 1996; Miller 1997; Chiesura 2004). Urban vegetation can further help in;

- Moderating the often harsh urban climates:

This can be achieved by the urban green vegetation shading, reduction of wind speed impacts and minimisation of pollution. Water resources can also be protected by reduced storm water runoff, and soil erosion control (Konijnendijk *et al.* 2000; Konijnendijk 2003).

- Social and societal including psychological functions:

People tend to prefer outdoor leisure occasions close to their homes, open urban green spaces have become more popular open-air entertainment spaces. Consequently, these green spaces may impact positively on the physical and mental health of urban dwellers and visitors, through the provision of areas for bodily exercise and traditional and divine practices (Bo 2002; Hansmann *et al.* 2007; Seeland *et al.* 2009). These influence human physical and psychological health and well-being, facilitate social contact and communication, provide relief from the often stressful metropolitan life, provide space for cultural and commercial activities and provide space and facilities for leisure and recreation (Burgess *et al.* 1988; Miller 1997; Chiesura 2004; Hansmann *et al.* 2007).

Different green space transformations can be quantified through evaluating the LULC Changes that have occurred within a particular area over a specified time period. Such transformations may be experienced in the existing LULCs within the area of interest. Detecting, mapping, and monitoring the spatial changes and conversions in the LULC offer an opportunity for computing different trends in urban landscape transformation (Chavez 1996). This is vital in the identification of factors that may trigger trends and the extent of urban green space changes which may have serious implications on urban green space management (Conese and Maselli 1993; Chander and Markham 2003).

2.9 Summary

This review has highlighted the main issues in the literature on LULC Change detection and projection. It has been emphasized that, LULCs are critical variables that provide a link between human and the physical environments. Thus the information on LULC Change including how the land resource can be utilized sustainably is critical for the selection, planning and implementation of conservation programs locally, regionally and even nationally. Consequently any changes in LULC attributed to man's presence on the earth including the utilization of the earth resources would therefore have a significant effect on the different ecosystem processes of a given area. Even though local information on the types and rates of LULC Changes are still limited, an understanding on the importance of LULC Change through mapping, monitoring and

predicting the LULC Change effects is vital. Therefore with the advent of remote sensing and GIS techniques, the ability to detect, map, monitor and predict LULC Changes has become increasingly practical. In this chapter, several LULC Change detection techniques which have been frequently used have been pointed out. This chapter concludes by identifying the major aspects highlighted in literature on LULC Change detection and projection using remotely sensed data set and gaps that need potential investigation.

Chapter 3: Methodology

3.1 Introduction

The objectives of this study were to detect and assess the trends of different LULC Changes within Ward 7 area in eThekweni Municipality, identify the effects of the detected changes on the urban green spaces and to predict urban green spaces and associated LULC Changes within the area. Consequently, in this chapter, the study area is described and the methods used to achieve the study objectives are discussed.

3.2 Study Area

This study was conducted in Shongweni area in eThekweni Municipality, KwaZulu-Natal Province, South Africa. It lies between the latitudes of 29° 55' 23.46" and 29° 47' 33.64" South, and longitudes of 30° 37' 39.07" and 30° 47' 30.45" East (Figure 1).

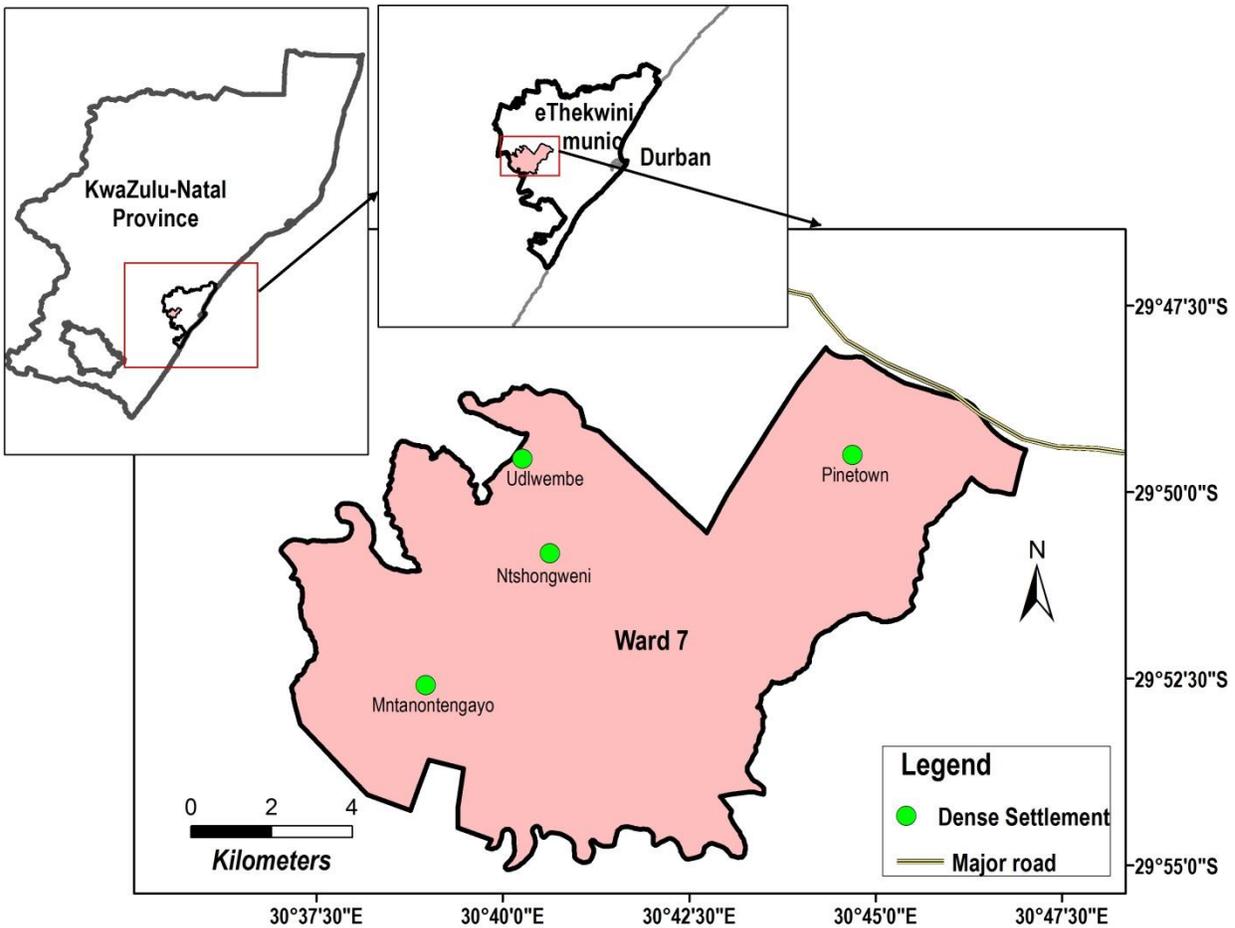


Figure 1: Location of the study area.

The most dominant vegetation types in this area are; the Eastern Valley Bushveld and the Ngongoni Veldt (also known as the dry coastal hinterland Ngongoni veldt) - (Mucina *et al.* 2006; Mucina and Rutherford 2006). The choice of this study site was motivated by the classification of the veldt type (Ngongoni) as ‘threatened’ within the eThekweni Metro (Scott-Shaw *et al.* 1996; Scott-Shaw 1999; Flats and Ridge 2006). This veldt type is comprised of woody plant vegetation communities and mostly occupies the dry valleys of lower elevation in the Metro (Ellis and Porter-Bolland 2008; Tian *et al.* 2009; Byerly 2010). The area is generally classified as a summer rainfall region. The altitude ranges from sea level to over 300 m. Precipitation in the area varies considerably, from 500 mm to over 2000 mm per annum (CAMP 1997; Gumede

2003). Areas within the Metro have a humid subtropical climate with approximately 1000 mm of rain per year; warm summers and mild winters. The area experiences a significant range of temperatures with summer months (November to March) temperatures ranging from 20° C to 35° C (Scott-Shaw *et al.* 1996) and Winter temperatures between 12° C to 25° C. Humidity often range between 50% and 70%. Prevailing winds blow mainly parallel to the coast with south-westerly and north-easterly winds roughly balanced in frequency, which makes for high wind variability (CAMP 1997; Gumede 2003). The area falls within the metro's fringe zones and was considered a good case study for the effects of urbanisation on the metro's open green spaces and possible implication on climate change.

The study area falls within the jurisdiction of the eThekweni Municipality's Ward 7 (Figure 1). A large portion of this area falls within the eThekweni Metropolitan Open Space System. The area therefore represents an urban/rural transition landscape that is subject to rapid LULC transformations influenced by human activities (Guillén 2001; Robinson 2007). The metro's rapid expansion and urban sprawl, has the potential implication on the area's green spaces. These could be through increased poaching and 'muthi' (medicinal plants) collection, loss of grasslands, increased erosion due to increased storm water run-off, human settlements, and the invasion of alien woody plant vegetation (Baddeley and Van Lieshout 1993; Ethekeeni 2003)

3.3 Image acquisition

Three sets of multi-temporal SPOT-4 imagery acquired on 14th March 2000, 7th March 2006 and 29th March 2011, sourced from the South African Space Agency (SANSA), and detailed in table 1 were used for this study. The images covered the study area and comprised four multispectral bands with spatial resolution of 20 m. The spectral ranges of the four bands are Band 1 (Green) 0.50~0.59µm, Band 2 (Red) 0.61~0.68µm, Band 3 (Near infrared) 0.78~0.89µm, and Band 4 (Short wave infrared) 1.58~1.75µm wavelengths. As pointed out by Quarmby and Cushnie (1989), Paolini *et al.* (2006) and Deng *et al.* (2008), these images met common sensor, radiometric and spatial resolution essentially required for change detection analysis. The pre-conditions are aimed at eliminating discrepancies arising from seasonal variations, sun

inclination and phenological differences. In addition to the aforementioned, the images were chosen because they were cloud free, were of centennial dates, were available in the image provider's archives, and they covered the focus study area. Whereas a uniform six year difference between the images could have been ideal, the six (2000-2006), and five (2006-2011) year difference were used because the 2012 image that fit the aforementioned characteristics was unavailable. According to and El Hajj *et al.* (2008), Davranche *et al.* (2010), the image's 20 meter spatial resolution makes them ideal for temporal and multi-temporal LULC mapping, change detection and standing green biomass estimation. In addition to the satellite imagery, Ground Control Points (GCPs), field observations, expert knowledge, existing land cover maps and the SPOT image's associated aerial photographs were used for analysis and ground validation.

Table 2: Image acquisition dates and characteristics.

Image	Path/Row	Image centre	Incidence angle	Acquisition		Resolution	
				Date	Time	Spatial	Spectral
2000	141/409	-29 ⁰ 43' 12"/30 58' 12"	-29.27 ⁰	14 th March	7:49:06	20 m	4 bands
2006	141/408	-29 ⁰ 57' 36"/31 01' 48"	-28.25 ⁰	7 th March	7:48:18	20 m	4 bands
2011	141/410	-29 ⁰ 57' 36"/30 54' 00"	-29.65 ⁰	29 th March	7:23:28	20 m	4 bands

3.4 Image pre-processing

Image pre-processing allows for conformity of comparative spatial or locational aspects within multi-temporal images (Chen *et al.* 2001; Rhoads 2006; El Hajj *et al.* 2008). According to Pitas (2000), and Richards (2012), pre-processing ensures that miscalculations that may arise from influences like image brightness are reduced. Image pre-processing is particularly critical in multi-temporal landscape analysis that require spatial quantification (Chavez 1988; Chavez 1996). In this study, the three sets of images were georectified and radiometrically corrected. Given that the three image sets were from the same sensor, image to image registration using the

2011 which was already georeferenced was performed. The other two images (the 2000 and 2006 set of images), were resampled using nearest neighbor interpolation method and an accuracy of less than half a pixel Root Mean Squares Error (RMSE) achieved. This ensured that each pixel in the three multi-temporal images represented similar ground location.

To ensure comparability of the multi-temporal imagery, atmospheric normalisation using the relative dark object subtraction (DOS) approach was adopted based on the radiometric information that were inherent in the three images (Du *et al.* 2002; El Hajj *et al.* 2008). The DOS atmospheric correction method progresses under the notion that the relationship between the top of the atmosphere radiances noted at two different times from regions of constant reflectance is spatially identical and can be approximated by an undeviating function (Chavez 1996; Canty *et al.* 2004). The normalization process can then be reduced to a linear regression calculation for each spectral band (Furby and Campbell 2001; Du *et al.* 2002; D'Elia *et al.* 2003; Canty *et al.* 2004). This kind of atmospheric correction method assumes that within a satellite image there exist invariant features like tarmac road, dense forest, parking lots, shadows due to topography, rooftops and deep water among other features that have close to zero percent reflectance over time. Consequently, there are pixels within each band of a multispectral image that have very low or no reflectance. The difference between the brightness value of these pixels and zero is therefore regarded to be due to haze and are removed (Chavez 1988; Chavez 1996; Furby and Campbell 2001). In the current study, tarmac road and/or places within the image where pixels seemed completely dark in color (table 3), were identified and used for the correction as explained by (Chavez 1996). This technique is strictly image-based, thus simple and relatively easy-to- use. The method also normalizes and removes the atmospheric additive scattering component which is accredited to path radiance. The normalisation process is valuable in multi-temporal image analysis as it compensates for the discrepancies in the solar output as per the time of year and sun elevation angle (Eastman 2006; Mutanga *et al.* 2012). After pre-processing, sub images for the study area were extracted for analysis.

Table 3: Average brightness (Digital Number) of pixels from selected tarmac roads and/or places that appeared completely dark.

Image	Digital Numbers (DN)		
	2000	2006	2011
Band 1 (Green)	16	21	20
Band 2 (Red)	78	47	55
Band 3 (Near infrared)	96	61	82
Band 4 (Short wave infrared)	16	17	15
Average Digital Numbers (DN)	52	37	43

3.5 Field data collection

Based on the multi-temporal imagery and associated orthorectified aerial photos of 0.3 m resolution, the 2000 national LULC map, the 2005 provincial LULC map, and on-site visits data (fieldwork that was conducted in June 2012) for verification and/or as a set of reference data to guarantee classification consistency and accuracy, five major LULC types; Built-up, Degraded grassland, Forest, Grassland, and Thicket were identified (Table 4). The field work carried out in June, 2012 entailed the collection of ground truth data for enhanced analysis of remote sensing data where different locations were collected through a Garmin eTrex GPS device. The device was used to collect the locational coordinates and attributes of different Land-Use-Land-Cover in the study area recorded. A total of 66 locations within the study area were captured.

3.6 Image Classification

A hybrid classification using unsupervised and supervised classification were performed on the image scenes (Chavez 1988; Chavez 1996; Song *et al.* 2001). Firstly, the unsupervised classification scheme was performed on the image datasets to provide a multi-temporal overview of the different clusters in the study area. Based on fine generalization level, this process was achieved using both the CLUSTER and ISOCLUST modules in IDRISI Andes. Typically, these algorithms aggregate image pixels based on naturally associated clusters (Mas *et al.* 2004; IDRISI 2006). Based on the unsupervised naturally occurring clusters, the spectral signatures of

known categories of LULC were developed and the identity of LULC types determined (Yuan and D. Elvidge 1998; Seto *et al.* 2002; Frauman and Wolff 2005). Using the training developed using unsupervised classification results; supervised classes were generated using Maximum Likelihood Classification and LULC labels assigned. A combination of these two techniques is commonly adopted to improve the accuracy of LULC classes (Weng 2002; Xiuwan 2002; Frauman and Wolff 2005).

Due to the multi-temporal image's inherent spectral variability encountered during the classification process, classification results in this study showed isolated (stray) pixels. Consequently, to re-assign the isolated pixels thereby eliminating the speckled appearance after classification, the classified images were smoothed (using post-classification smoothing operation) in ERDAS Imagine and ArcGIS softwares. This served to group together the LULC classes created after the classification process so as to characterise each of the information classes (Eastman 2006; IDRISI 2006; ESRI 2007). As recommended by Lillesand *et al.* (2004), in the current study, a majority filter of a 5 by 5 kernel was applied on the three classification outputs.

3.7 Classification accuracy assessment

Evaluation of map accuracy is critical as it indicates the quality of the LULC map output and its suitability for a particular purpose (Foody 2002; Foody 2004). Consequently, an accuracy assessment to verify and evaluate the reliability of the LULC classification results was performed on the three classified images based on the field survey and the validation datasets (Congalton 1991; Jensen 1996a; Brand *et al.* 2008). The assessment was done as an error evaluation for quality assurance to check the accuracy of the LULC classifications (Dormaar *et al.* 1989; Palmer and Ainslie 2006; Brand *et al.* 2010). According to Foody (2004), and Foody (2002), evaluation of map accuracy is vital as it indicates the quality of the LULC map output and its suitability for a particular purpose (Foody 2002; Foody 2004).

As recommended by Congalton (1991), Lu *et al.* (2003), and McCann *et al.* (2007), in this study a stratified random sampling method, where the validation points are stratified according to the

distribution of Land-Cover categories on the classified images and as verified from the associated aerial photographs, the 2000 National Land-Cover (NLC) & the 2005 Provincial Land-Cover maps, as well as data collected in the field during ground-truthing were used to assess the classification accuracy. Using ERDAS Imagine 2011 software and a random point generator tool, the Hawth's analysis tool for ArcGIS 9.3 software were used to generate 200 random points on each of the three classified land cover maps of the study area for validation (Beyer 2004; Gómez Gutiérrez *et al.* 2009; Mutanga *et al.* 2012).

Classification accuracy assessment that include; the Overall Classification Accuracy (the fraction of LULC classes that are properly assigned), Kappa Statistics (used to check if the classification results obtained were better/different than those that could have been achieved by chance), Producer's Accuracy= Error of commission, and User's Accuracy=Error of omission (Bishop *et al.* 1975; Rosenfield and Fitzpatrick-Lins 1986; Hardin and Shumway 1997; Congalton 2001) achieved based on the fieldwork survey and the validation datasets will be presented.

3.8 Land-Use-Land-Cover Change Detection and Prediction

Firstly, the unsupervised classification scheme was performed on the image datasets to provide a multi-temporal overview of the different clusters in the study area. Typically, unsupervised classification algorithms aggregate image pixels based on naturally associated clusters (Mas *et al.* 2004; IDRISI 2006). Based on the unsupervised clusters, the spectral signatures of known categories of LULC were developed and LULC labels determined based on Maximum Likelihood Classification results.

To achieve the aforementioned objectives, a 'from-to' post- classification comparison change detection procedure using Land Change Modeller (LCM) and Markov chain process were employed. This technique relies on separate multi-temporal image classification and subsequent image comparison (Deng *et al.* 2008; Odindi *et al.* 2012). As aforementioned, the LULC Change detection analysis in this study was achieved using the LCM for Ecological Sustainability module in IDRISI Andes software. According to Eastman (2006) and Bangamwabo (2010), the LCM is suited for analysis and prediction of LULC types and evaluation of implications of the changes on the entire ecosystem. Based on Markov Chain or any other external change

prediction model, the LCM can then be used in detailing spatial increase and loss, net change, net change drivers, tendencies of change and landscape prediction (IDRISI 2006; Mhangara 2011).

The Markov chain projection model was implemented on the 2000, 2006, and 2011 classified images. The process involves computing the transition probability matrix of LULC change from time one to time two, which is then considered to be the basis upon which to apportion a later time period (Li and Reynolds 1997; Pontius Jr and Malanson 2005; Zubair 2006; Kamusoko *et al.* 2009). A transition probability matrix indicates the probability of inter-class transitions among different LULC types, while a transition area matrix shows the quantity of LULC that is expected to transform from one class to another over a specified time period (Veldkamp and Lambin 2001; Eastman 2006; IDRISI 2006). Consequently, a transition area matrix depicts the approximate area measure (number of pixels) of homogenous LULC that is expected to change from one cover type to the other within the projected time period (Li and Reynolds 1997; Zubair 2006; Kamusoko *et al.* 2009). This is represented by the rows and columns respectively in the transition areas matrix recorded as a text file (Urban and Wallin 2002; Eastman 2006; IDRISI 2006). Furthermore, conditional probability images present the likelihood of the existence of a specific LULC category over the predicted period of time.

In the recent past, the Markov model has been found to be useful in the analysis of one or more pairs of LULC images which provide outputs of transition probability matrices, transition area matrices and a set of conditional probability images (Bangamwabo 2010; Mhangara 2011). Markov chain processes are technically sound and generally provide reliable results with experimental data such as LULC Change (Li and Reynolds 1997; Winkler 2006). Consequently, in this study, the LULC transition probability results served as an indicator of the course and extent of LULC Change processes. Generally, prediction processes using Markov chain does not require deep understanding of the system of dynamic change and can assist in specifying areas where such an understanding would be important; this can be used as a guide for future LULC Change research (Petit *et al.* 2001; Mubea *et al.* 2011). Furthermore, the computational requirements of Markov processes are modest and can easily be met by small desktop computers (Islam and Ahmed 2011; Mubea *et al.* 2011). One of the limitations of applying a Markov chain

analysis for predicting LULC Change is that landscape patterns resulting from complex interactions of biophysical, socio-economic, and political factors make its prediction uncertain in landscapes where such levels of interaction exist (Bangamwabo 2010; Mhangara 2011).

Lambin *et al.* (1999), and Petit *et al.* (2001), note that LULC Change is considered to be temporally persistent over 10-15 year intervals, thus an eleven year period (2011-2022) illustrated in this study is within the required range. The 2000 / 2006, 2006/2011, and 2000 / 2011 classified image maps were used as the earlier and later land-cover images respectively. The predictions were thus purely based on the state of land-cover in 2000, 2006, and 2011. Boolean images were similarly generated for each of the three LULC maps to highlight multi-temporal transformation of open green spaces between the years 2000, 2006, and 2011. A future LULC Change map for the year 2022 was similarly created based on the 2000-2011 LULC Change trends.

3.9 Summary

This chapter has presented the different methods that were employed in the study to detect, map, monitor, predict and assess the trends of different LULC and their effect on urban green spaces within the study area. Firstly, three cloud free multi-spectral SPOT-4 images were acquired, processed and classified using a hybrid classification procedure. Secondly, transformations within the three classified images were determined. Thirdly, classification accuracy assessment was performed on the classified images and lastly the Markov chain analysis was used to project the different LULC Changes.

Chapter 4: Results

4.1 Introduction

This chapter presents the results achieved from the LULC Change detection and projections. The detection and projection specifically presents a summary of LULC classification statistics for the 2000, 2006, and 2011, the rates of change between 2000-2006, 2006-2011, and 2000-2011 and the future predictions based on markov chain analysis.

4.2 LULC classification

Based on a hybrid image classification, five major LULCs (Table 4) were identified and verified using associated aerial photographs, field visits/work data, the 2000 national and the 2005 KwaZulu-Natal Province LULC maps. The supervised classification results for the 2000, 2006, and 2011 images are hence presented in Figure 2.

Table 4: Description of major Land-Use-Land-Cover classes identified in the study area.

Land-Cover Category	Description
Built-up	Permanent man-made structures, buildings, tarred roads, towns/urban, formal township and residential areas and rural villages.
Degraded grassland	Eroded grassland areas with less than 10% tree and/or shrub canopy cover.
Forest	Wooded area, tree communities with interspersed mixtures composed of canopy, sub-canopy, shrub and herb layers.
Grassland	Non-woody, rooted herbaceous plants, areas utilised for grazing.
Thicket	Evergreen heathlands and shrub lands, fine-leafed low shrubs and leafless tufted grass, alien exotic species, clumps/high fynbos.

During the study period (2000 to 2006, 2006 to 2011, and 2000 to 2011) the study area experienced changes in the different LULCs (Table 5). Built-up areas increased by 10.08%, 3.15% and 13.23% in 2000-2006, 2006-2011, and 2000-2011 respectively. Areas covered by Thicket decreased by 0.59% in 2000-2006 but increased by 0.56% and 0.07% in 2006-2011 and 2000-2011 respectively. Forest land-cover experienced increases of 2.59% in 2000-2006, 2.82% in 2006-2011, and 5.41% in 2000-2011 periods. The area covered by Grassland declined by 8.46% and 2.64% in 2000-2006 and 2000-2011 periods respectively while Degraded grassland declined by 3.62%, 12.45% and 16.07% in 2000-2006, 2006-2011 and 2000-2011 respectively.

Results in Table 5 indicate that the predominant LULC categories in 2000 were Degraded grassland, Grassland and Thicket covering 27.86% (3135.36ha.), 26.35% (2964.88ha.) and 20.58% (2315.56ha.) respectively. The rest of the area's landscape was covered by Forest 15.29% (1720.52ha.), and Built-up 9.92% (1116.2ha.). The most visually dominant changes from 2000 to 2011 were an increase in Built-up (13.23%) and Forest (5.41%), and a decrease in Degraded grassland (16.07%) and Grassland (2.64%). By 2011, Degraded grassland covered only 11.79% (1326.88ha.) of the area, while Grassland covered 23.71% (2323.6ha.), a decrease of 16.07% and 2.64% respectively. Many of the 2000 Degraded grassland and Grassland areas changed to either Built-up, Forest or Thicket by 2011. To highlight multi-temporal transformation of open green spaces between the years 2000, 2006, and 2011, Boolean images were generated for each of the three periods (Figure 3).

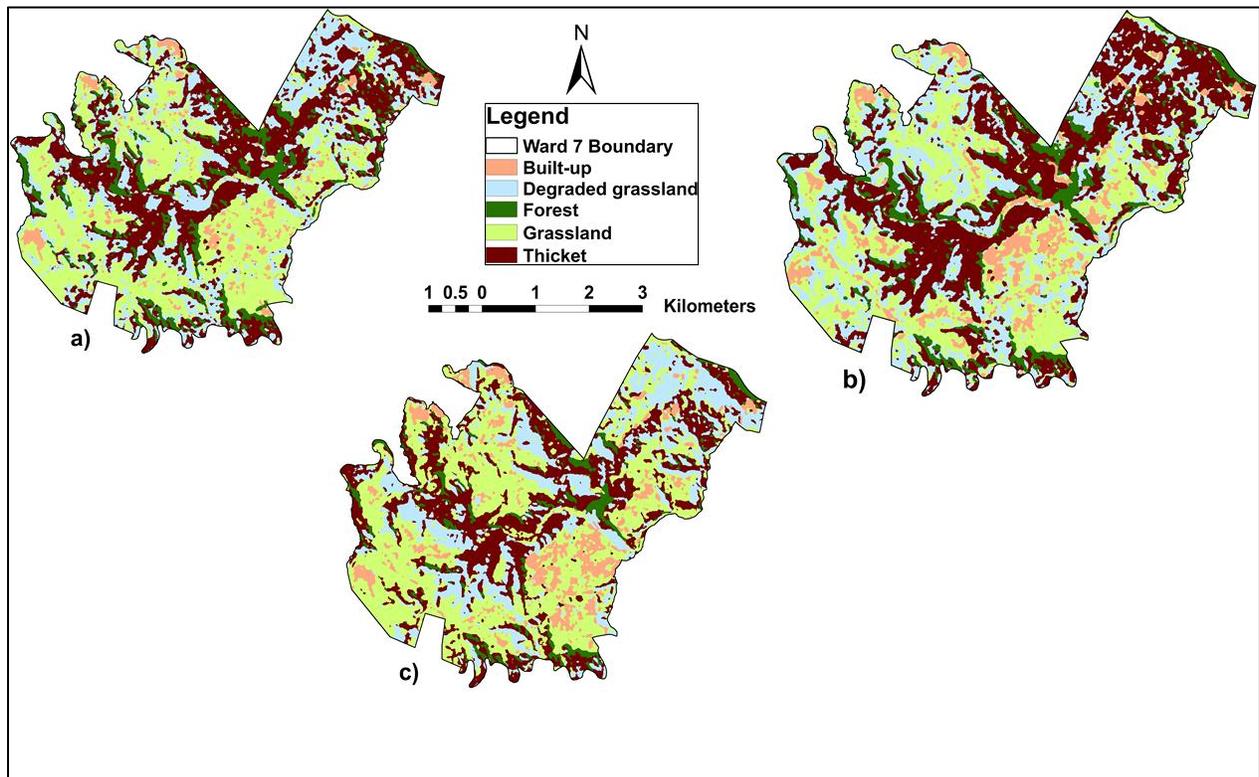


Figure 2: The LULCs - 2000- a, 2006 - b, and 2011 - c.

Table 5: Summary of LULC classification area statistics for the 2000, 2006, and 2011 images.

Land-cover class	2000		2006		2011		Percentage change		
	Area (ha.)	%	Area (ha.)	%	Area (ha.)	%	2000-2006	2006-2011	2000-2011
Built-up	1116.2	9.92	2250.68	20	2605.44	23.15	10.08	3.15	13.23
Degraded grassland	3135.36	27.86	2727.48	24.24	1326.88	11.79	-3.62	-12.45	-16.07
Forest	1720.52	15.29	2012.44	17.88	2329.12	20.7	2.59	2.82	5.41
Grassland	2964.88	26.35	2012.52	17.89	2667.48	23.71	-8.46	5.82	-2.64
Thicket	2315.56	20.58	2249.4	19.99	2323.6	20.65	-0.59	0.56	0.07
Total	11252.52	100	11252.52	100	11252.52	100			

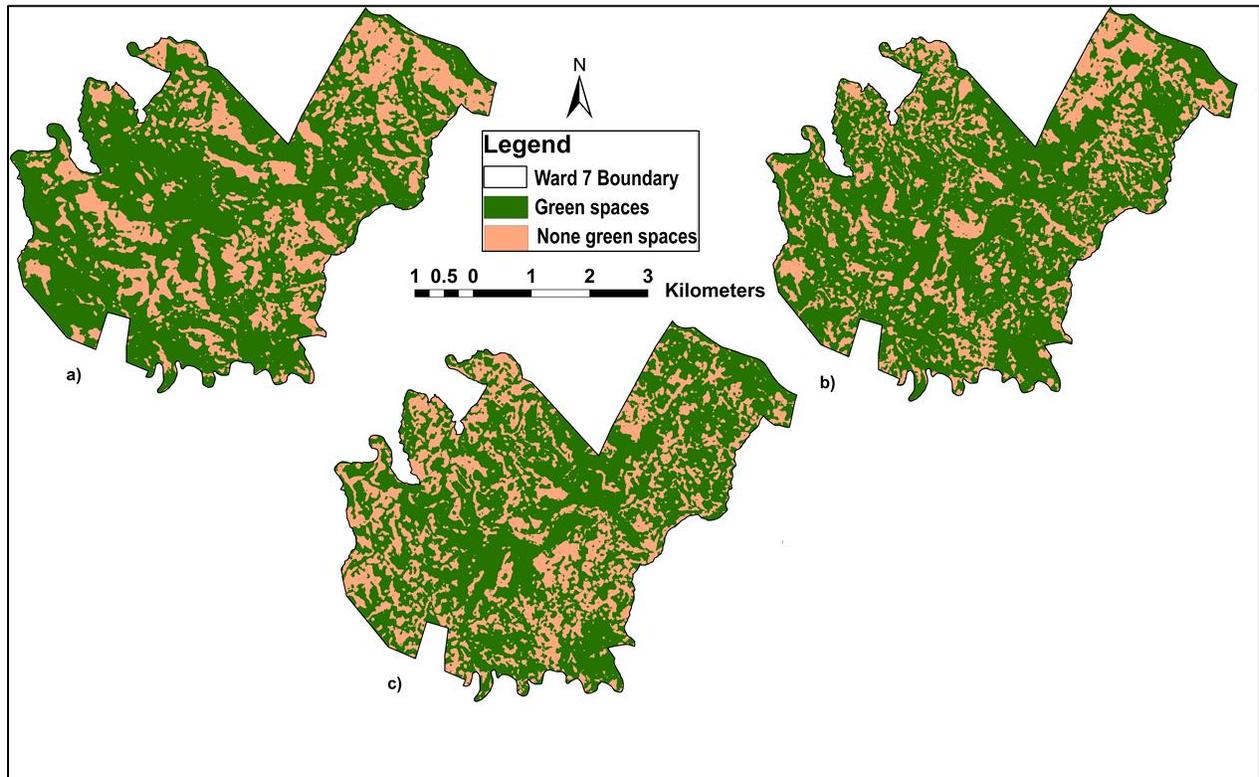


Figure 3: Boolean images generated for green space land-covers in 2000 - a, 2006 - b, and 2011- c from reclassification of the 2000, 2006, and 2011 classified images, respectively.

The overall accuracy and Kappa index for the LULC classes were; 91.00% and 0.8875 for the 2000 image, 86.50% and 0.8315 for the 2006 image, 89.00% and 0.8625 for the 2011 image respectively (Table 6 a, b, c).

Table 6: Classification accuracy assessment report for the 2000 - a, 2006 - b, and 2011 - c classified images.

a)	Reference Data					Accuracy (%)		Conditional Kappa	
Classified Data	Forest	Thicket	Degraded grassland	Grassland	Built-up	Row total	producer's	User's	for each LULC
Forest	37*	1	0	2	0	40	92.50%	92.50%	0.9063
Thicket	2	36*	2	0	0	40	92.31%	90.00%	0.8758
Degraded grassland	1	0	36*	2	1	40	87.80%	90.00%	0.8742
Grassland	0	2	0	38*	0	40	86.36%	95.00%	0.9359
Built-up	0	0	3	2	35*	40	97.22%	87.50%	0.8476
Column total	40	39	41	44	36	200			
Overall accuracy =	91.00%		Overall Kappa = 0.8875		Correctly classified pixels are shown with *				
b)	Reference Data					Accuracy (%)		Conditional Kappa	
Classified Data	Forest	Thicket	Degraded grassland	Grassland	Built-up	Row total	producer's	User's	for each LULC
Forest	36*	2	1	1	0	40	92.31%	90.00%	0.8758
Thicket	0	39*	1	0	0	40	79.59%	97.50%	0.9669
Degraded grassland	3	4	27*	2	4	40	87.10%	67.50%	0.6154
Grassland	0	2	2	36*	0	40	87.50%	87.50%	0.8438
Built-up	1	2	0	1	36*	40	90.00%	90.00%	0.875
Column total	40	49	31	40	40	200			
Overall Accuracy =	86.50%		Overall Kappa = 0.8315		Correctly classified pixels are shown with *				
c)	Reference Data					Accuracy (%)		Conditional Kappa	
Classified Data	Forest	Thicket	Degraded grassland	Grassland	Built-up	row total	producer's	User's	for each LULC
Forest	37*	1	1	1	0	40	92.50%	92.50%	0.9063
Thicket	1	35*	1	1	2	40	94.59%	87.50%	0.8466
Degraded grassland	1	1	35*	2	1	40	87.50%	87.50%	0.8438
Grassland	1	0	0	38*	1	40	82.61%	95.00%	0.9351
Built-up	0	0	3	4	33*	40	89.19%	82.50%	0.7853
Column total	40	37	40	46	37	200			
Overall Accuracy =	89.00%		Overall Kappa = 0.8625		Correctly classified pixels are shown with *				

4.3 LULC change detection analysis using land change modeler (LCM)

Land-use/land-cover change was done by evaluating the gains and losses experienced by the different LULC categories. Multi-temporal gains and losses (Figure 4), net changes (Figure 5), and contributions to net changes experienced by Forest, Grassland, and Thicket (Figures 6, 7, & 8) during the study period were determined. Net changes show the quantity of LULC that occurred for each LULC category between 2000-2006, 2006-2011, and 2000-2011 year periods. The results of the net changes in the current study were calculated by summation of the gains and differencing the losses of the earlier LULC areas. These changes signify the difference between LULC in the earlier date together with gains and losses incurred. Furthermore, they highlight the quantity of LULC changes that took place for each category between the periods under investigation. Consequently, the types of LULC categories that contributed to net change experienced by Forest Grassland, and Thicket categories are presented (Figures 6, 7, and 8).

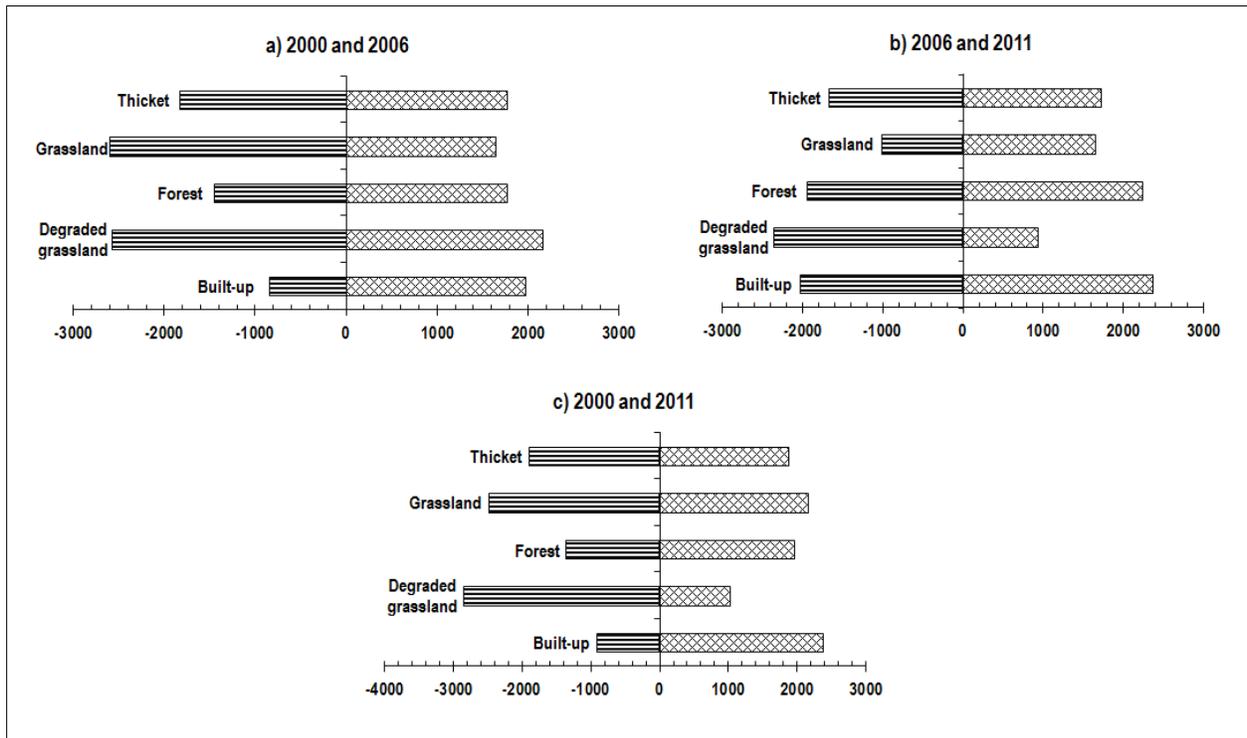


Figure 4: Gains and losses experienced by various LULC categories between the study periods. Positive values indicate gains while negative values indicate losses.

During the 2000-2006 period, Built-up and Forest categories had a net gain of 1134 ha, and 292 ha respectively. This shows that Grassland transformed to Built-up, Thicket, and Forest (Figure 5). Consequently, during this period, Degraded grassland was transformed to Built-up, Grassland, Thicket, and Forest (Figure 5).

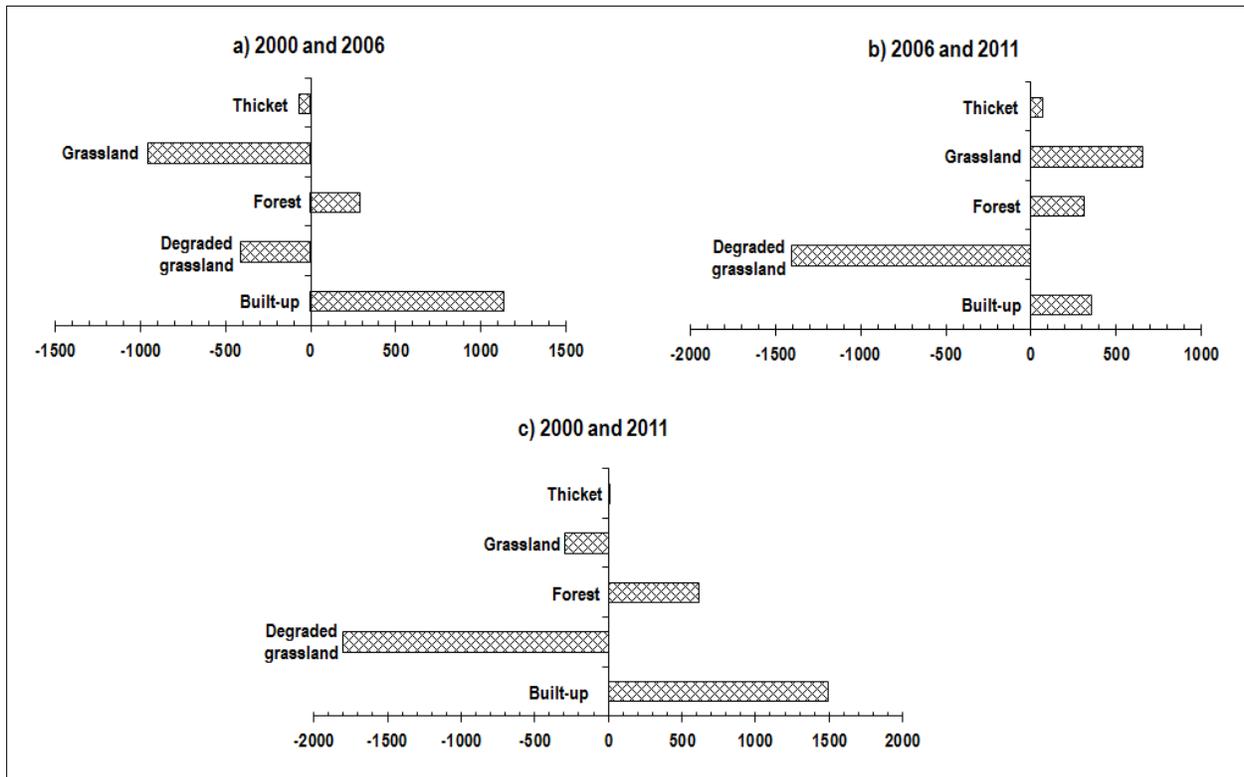


Figure 5: Net changes experienced by various LULC categories between the study periods.

In the 2006-2011 period, Grassland, Built-up, and Thicket had a net gain of 655 ha, and 354 ha, respectively. Between 2000-2011 period, Built-up and Forest had a net gain of 1489 ha, and 609 ha respectively.

During the 2000-2006 period, it can be observed that Grassland was transformed to Built-up, Degraded grassland, Thicket, and Forest (Figure 6).

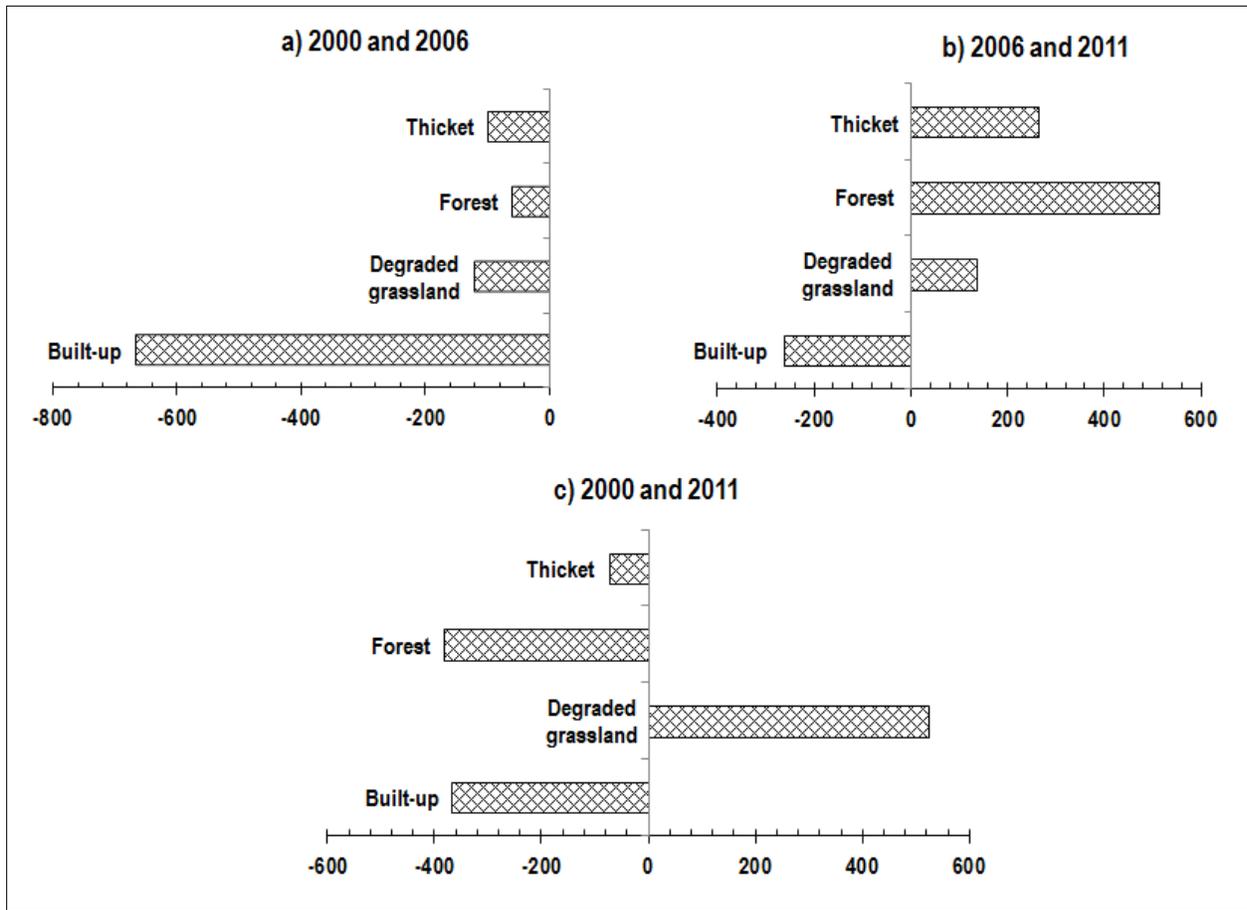


Figure 6: Contributions to net changes experienced by Grassland category.

Negative values highlight areas in hectares of the LULCs that contributed to the reduction in grassland category; while positive values show the number of hectares of different LULC categories which gave rise to the observed increases in the other LULCs.

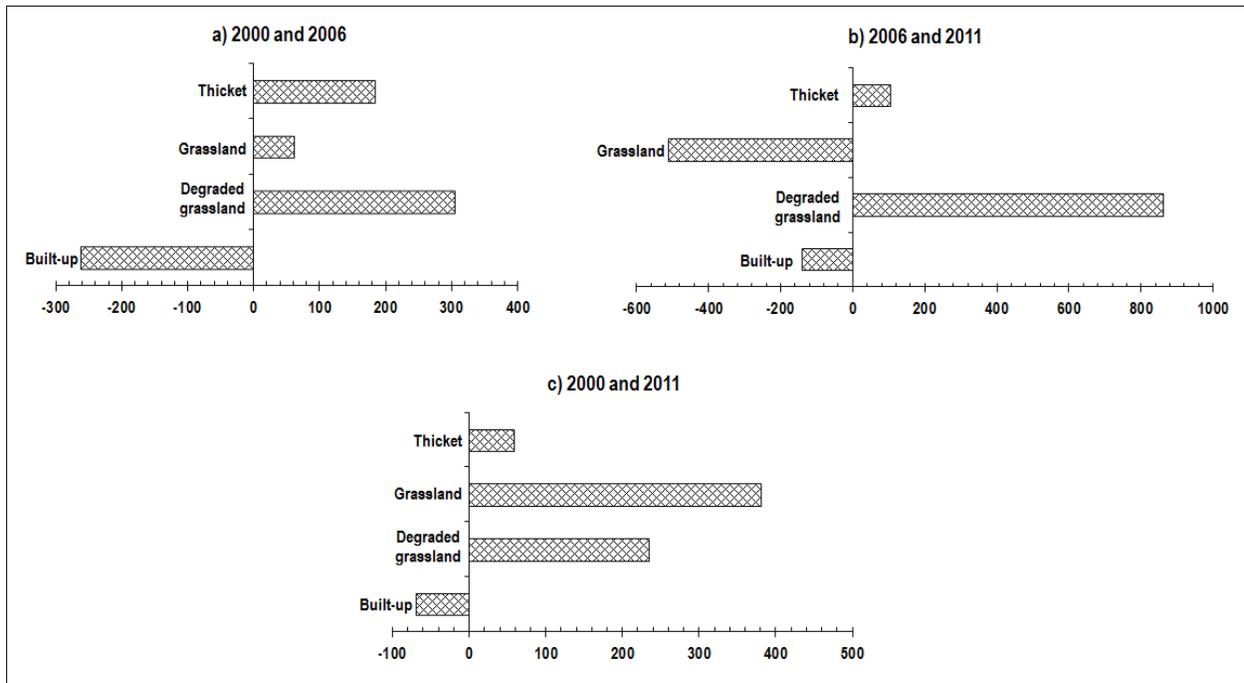


Figure 7: Contributions to net changes experienced by Forest category.

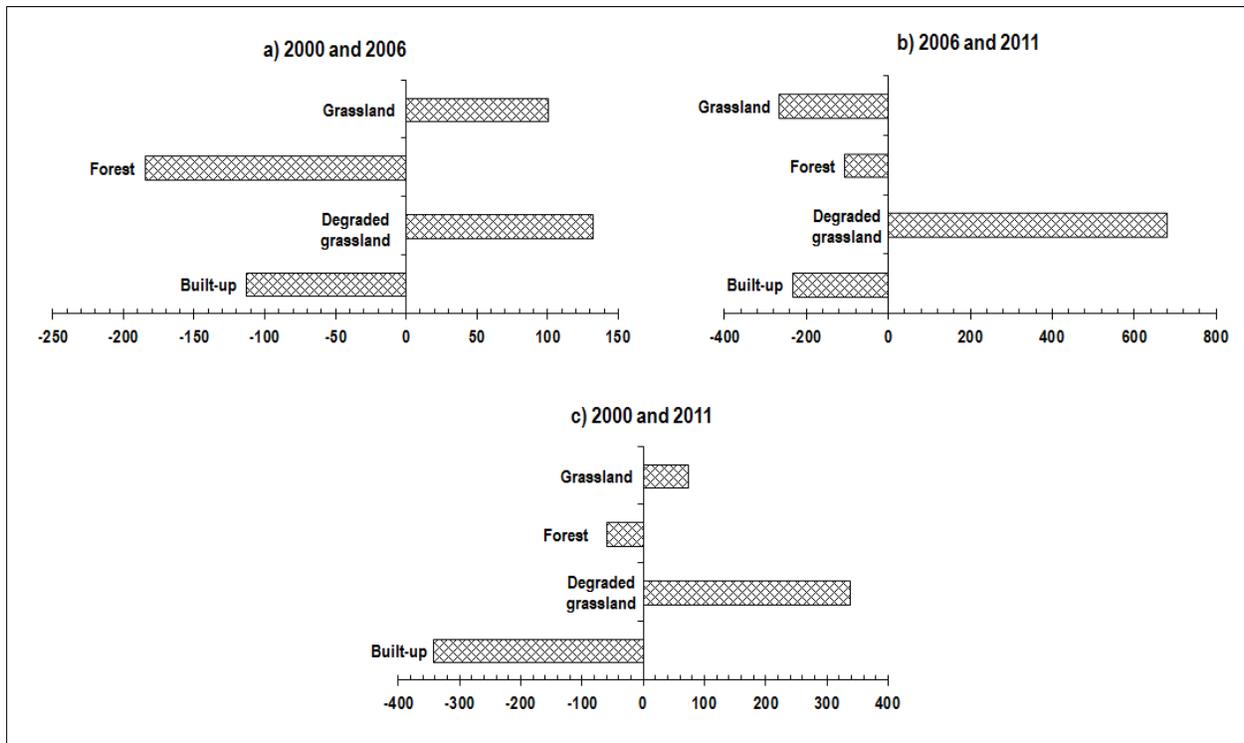


Figure 8: Contributions to net changes experienced by Thicket category.

Negative values highlight areas in hectares of the LULCs that contributed to the reduction in different land-covers. On the other hand, positive values show number of hectares of different LULC categories which gave rise to the observed increases in the other LULCs. During the 2000-2006 period (Figure 7), Grassland was transformed to Built-up, Thicket, Forest, and Degraded grassland. Built-up category experienced an increasing trend over the 2000-2006, 2006-2011, and 2000-2011 period. Within the study period, Degraded grassland land-covers declined at 3.62%, 12.45%, and 16.07% between 2000-2006, 2006-2011, and 2000-2011 period respectively. Figure 9 is a graphical representation of net changes that occurred over the three year period between the five LULC categories. Negative values in the graph represent the amount of areas loss experienced by the respective Land-Cover types.

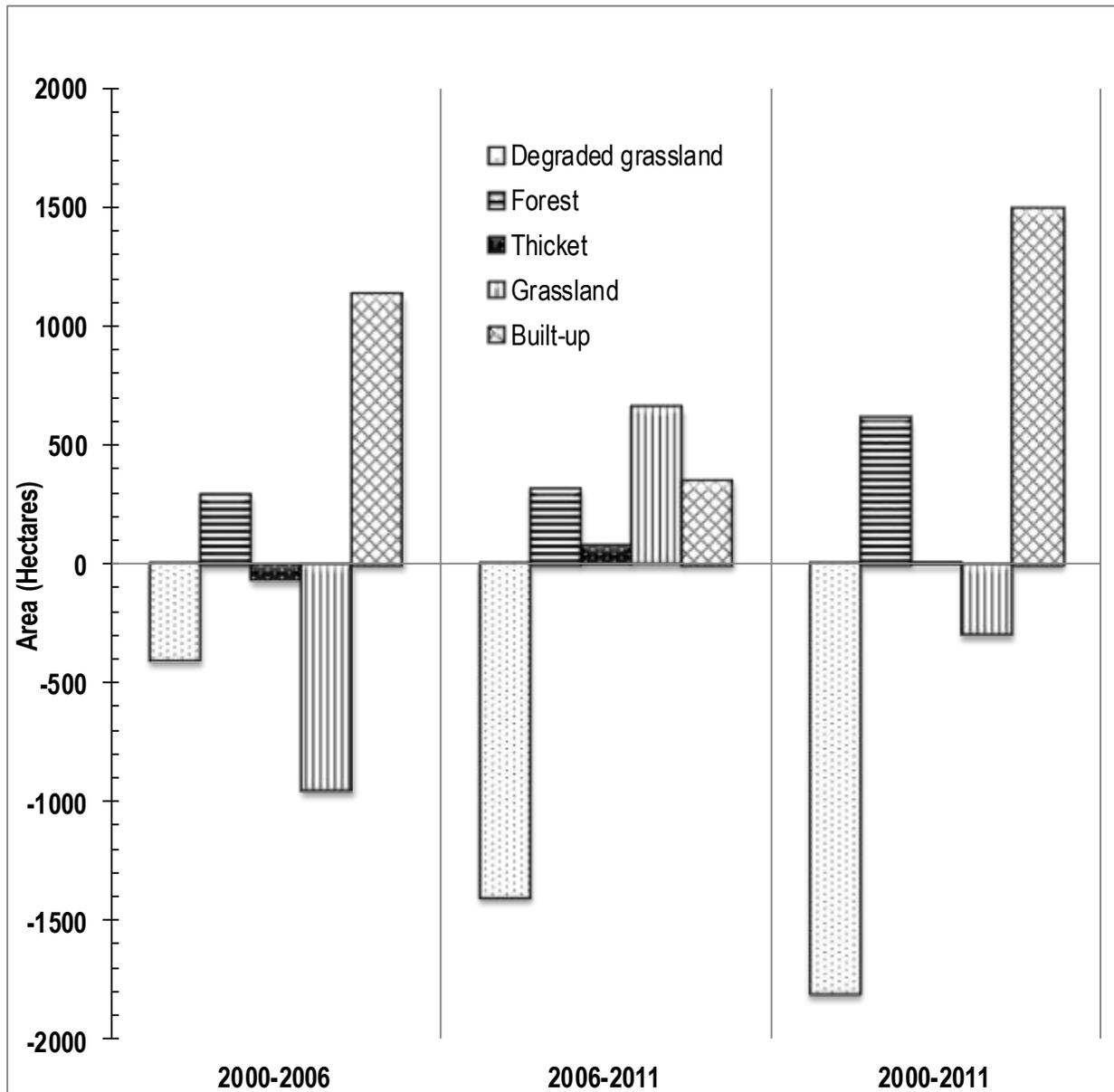


Figure 9: Net changes in LULCs between 2000-2006, 2006-2011, and 2000-2011.

A detailed change transitions between the five LULCs during the periods 2000-2006, 2006-2011, and 2000-2011 is presented in Table 7.

Table 7: 2000 to 2006, 2006 to 2011, and 2000 to 2011 LULC change transition areas.

LULC changing		Transition Area (ha.)		
From	To	2000 to 2006	2006 to 2011	2000 to 2011
Grassland	Built-up	744.56	433.24	565.32
Thicket	Built-up	381.68	645.32	638.20
Forest	Built-up	405.08	960.64	372.52
Degraded grassland	Built-up	447.12	333.16	818.24
Built-up	Grassland	75.88	172.80	197.36
Thicket	Grassland	456.48	553.80	614.00
Forest	Grassland	329.68	688.16	399.08
Degraded grassland	Grassland	784.40	249.88	957.08
Built-up	Thicket	268.96	412.84	295.16
Grassland	Thicket	556.40	287.92	687.16
Forest	Thicket	313.72	210.40	334.08
Degraded grassland	Thicket	630.52	824.48	573.76
Built-up	Forest	143.76	820.72	303.08
Grassland	Forest	391.56	176.00	780.84
Thicket	Forest	498.76	316.72	394.48
Degraded grassland	Forest	711.80	936.92	489.64
Built-up	Degraded grassland	355.36	611.24	109.44
Grassland	Degraded grassland	906.28	112.52	431.60
Thicket	Degraded grassland	498.84	145.60	235.44
Forest	Degraded grassland	405.48	74.48	253.76

The areas covered by Forest, Grassland, and Thicket categories were transformed by 1531.32 ha, 2039.2ha, and 1576.04ha to Built-up land-covers in 2000-2006, 2006-2011, and 2000-2011, respectively. During the aforementioned periods, 1810.6ha of Forest, 332.6ha of Grassland, and 920.8ha of Thicket land-covers were transformed to Degraded grassland.

4.4 Land-use and land-cover change prediction

The Markov chain analysis was employed to project the different LULC changes that will occur in the study area by 2022. The 2000 and 2006, 2006 and 2011, and 2000 and 2011 classified image pairs were used to generate the Markov chain matrices which included a transition probability matrix, a transition area matrix and a set of conditional probability maps showing the chance of the presence of particular LULC classes over the study period. The set of these conditional likelihood images are calculated as time-based forecasts in concert with the earlier and later input LULCs. The transition probability matrix thus indicates the likelihood of the transitions occurring within the mapped LULC categories. These likely LULC images are calculated as time-based predictions based on the 2000, 2006, and 2011 input LULC images.

Table 8 below highlights the probabilities of the five LULC categories changing by the years 2011, 2016 and 2022, using the 2000 to 2006, 2006 to 2011 and 2000 to 2011 transitions. The main diagonal values, represent the chances of the different LULC categories remaining the same whereas off diagonal values depict the likelihood that the categories will transform to different LULCs. Table 8 highlights the transition area matrices showing the number of pixels which are expected to transform from each LULC category to the other LULC type over the study period. In both the transition probability matrix and the area matrix tables, the rows indicate the earlier LULC classes and the columns denote the newer LULCs. The 2000 and 2006, 2006 and 2011, 2000 and 2011 were used as the earlier and later input LULC in the Markov projection. In Table 7 a, b, c and Table 8 a, b, c below; row categories represent LULC classes in 2000, 2006, and 2011 while column categories represent land-cover categories of 2011, 2016, and 2022.

From the Markov chain model predictions presented in Table 8 and 9, the probabilities are 24.19%, 25.64%, and 17.13 % of Forest, Grassland, and Thicket surfaces respectively changing to Built-up in 2011. During this same period, the likelihood of Forest, Grassland, and Thicket land-covers transforming to Degraded grassland are 24.22%, 31.21%, and 22.39% respectively (Table 7a). In the 2006-2011 transitions, the probabilities are 22.51%, 19.65%, and 28.51% for Forest, Grassland, and Thicket surfaces respectively changing to Built-up in 2016. The chances

of Forest, Grassland, and Thicket surfaces changing to Degraded grassland in 2016 are 15.34%, 15%, and 10.52% respectively (Table 8b).

Furthermore, the 2000-2011 transition depicts that the likelihood of Forest, Grassland, and Thicket LULCs transforming into Built-up in 2022 are 48.03%, 24.73%, and 30.21% respectively. During this period, the chances that Forest, Grassland, and Thicket surfaces will transform into Degraded grassland are 3.72%, 6.42%, and 6.82% respectively (Table 8c).

Figure 10 represents the projected LULC in 2011, 2016, and 2022. Furthermore, the projected LULC maps for 2011, 2016, and 2022 were reclassified into green spaces and non-green spaces so as to present the LULC types that were regarded as green spaces. The reclassification produced three Boolean images which highlighted multi-temporal transformation of the green spaces in the study area between the years 2000- 2022 (see Figure 11).

Table 8: Markov transition probabilities generated from LULC maps of 2000 and 2006 - a, 2006 and 2011 - b, 2000 and 2011 - c.

a)					
Given: 2000 & 2006:	Probability of changing to: in 2011:				
	Built-up	Degraded grassland	Forest	Grassland	Thicket
Built-up	0.2073	0.3338	0.1350	0.0713	0.2526
Degraded grassland	0.1473	0.1522	0.2345	0.2584	0.2077
Forest	0.2419	0.2422	0.1317	0.1969	0.1874
Grassland	0.2564	0.3121	0.1349	0.1050	0.1916
Thicket	0.1713	0.2239	0.2238	0.2049	0.1761
b)					
Given: 2006 & 2011:	Probability of changing to: in 2016:				
	Built-up	Degraded grassland	Forest	Grassland	Thicket
Built-up	0.1608	0.1015	0.2810	0.1830	0.2737
Degraded grassland	0.2651	0.0804	0.1586	0.3100	0.1859
Forest	0.2251	0.1534	0.1784	0.2412	0.2019
Grassland	0.1965	0.1500	0.2714	0.1433	0.2388
Thicket	0.2851	0.1052	0.1762	0.2743	0.1591
c)					
Given: 2000 & 2011:	Probability of changing to: in 2022:				
	Built-up	Degraded grassland	Forest	Grassland	Thicket
Built-up	0.0880	0.2763	0.3710	0.0781	0.1866
Degraded grassland	0.1251	0.1194	0.3519	0.0939	0.3097
Forest	0.4803	0.0372	0.0333	0.3440	0.1052
Grassland	0.2473	0.0642	0.1005	0.4236	0.1644
Thicket	0.3021	0.0682	0.1483	0.2593	0.2222

Table 9: Markov transition areas (ha) generated from LULC maps of 2000 & 2006 - a, 2006 & 2011 - b, 2000 & 2011 - c.

a)						
Cells: in 2000 & 2006:	Expected to transition to: in 2011:					
	Built-up	Degraded grassland	Forest	Grassland	Thicket	Total
Built-up	11665	4010	14214	7598	18780	56267
Degraded grassland	12902	5280	9641	6785	15704	50312
Forest	9633	11521	9904	12588	12590	56236
Grassland	12171	9906	9426	6625	12183	50311
Thicket	10042	17617	14161	15987	10380	68187
Total	56413	48334	57346	49583	69637	281313
b)						
Cells in: 2006 & 2011:	Expected to transition to: in 2016:					
	Built-up	Degraded grassland	Forest	Grassland	Thicket	Total
Built-up	10474	6610	18305	11920	17827	65136
Degraded grassland	8793	2668	5262	10285	6166	33174
Forest	13110	8930	10387	14044	11757	58228
Grassland	13102	10003	18097	9558	15926	66686
Thicket	16563	6110	10238	15935	9243	58089
Total	62042	34321	62289	61742	60919	281315
c)						
Cells in: 2000 & 2011:	Expected to transition to: in 2022:					
	Built-up	Degraded grassland	Forest	Grassland	Thicket	Total
Built-up	5734	17996	24164	5088	12155	65137
Degraded grassland	4151	3960	11674	3114	10273	33172
Forest	27965	2168	1937	20033	6125	58228
Grassland	16495	4284	6701	28246	10962	66688
Thicket	17550	3960	8613	15061	12906	58090
Total	71895	32368	53089	71542	52421	281313

Projected LULC maps for the years 2011, 2016, and 2022 based on 2000-2006, 2006-2011, and 2000-2011 transitions are presented in Figure 10. Consequently, a summary of the predicted LULC area statistics for the year 2016 and 2022 are presented in Table 10.

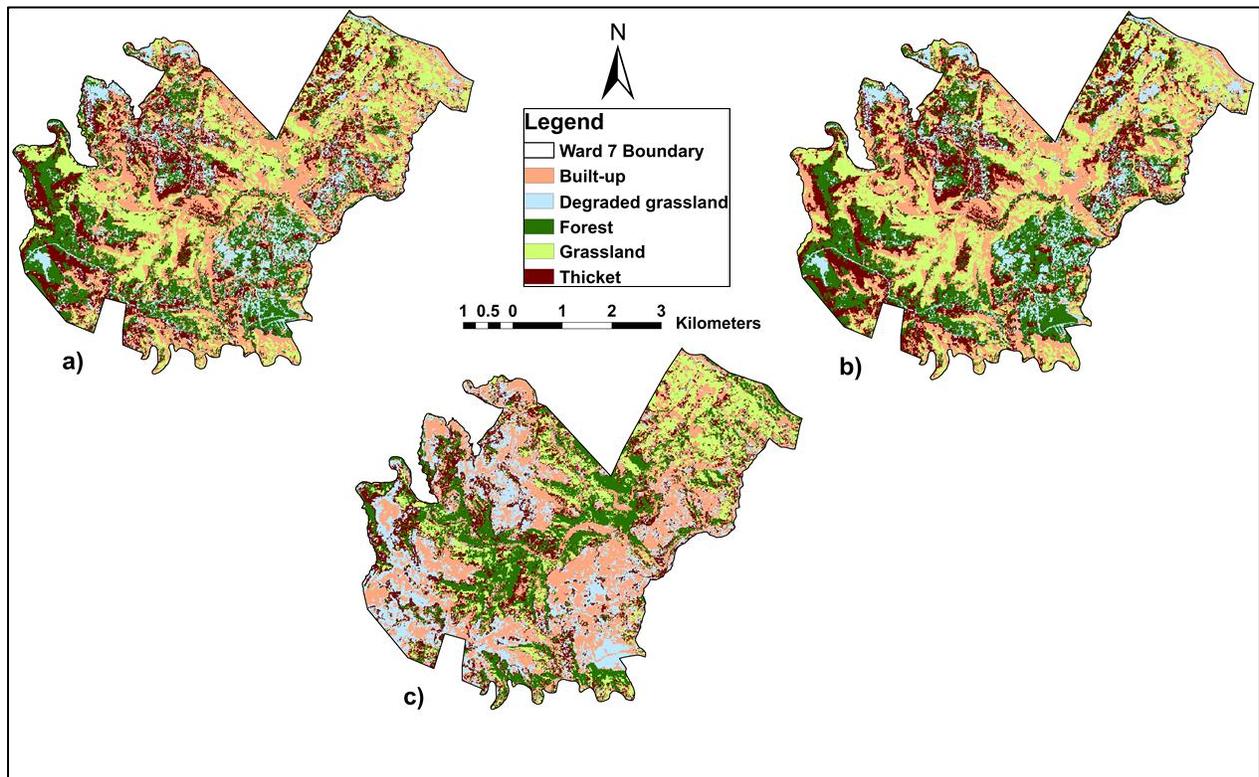


Figure 10: Projected LULC maps for 2011 - a, 2016 - b, and 2022 - c.

Table 10: Predicted LULC area statistics.

Land-cover class	2016		2022		Percentage change		
	Areas (ha.)	%	Areas (ha.)	%	2011-2016	2016-2022	2011-2022
Built-up	2481.68	22.05	2875.8	25.56	2.00	3.50	5.50
Degraded grassland	1372.84	12.20	1294.72	11.51	-4.98	-0.69	-5.68
Forest	2491.56	22.14	2123.56	18.87	1.76	-3.27	-1.51
Grassland	2469.68	21.93	2861.68	25.43	4.32	3.48	7.81
Thicket	2436.76	21.66	2096.84	18.63	-3.10	-3.02	-6.12
Total	11253	100	11253	100			

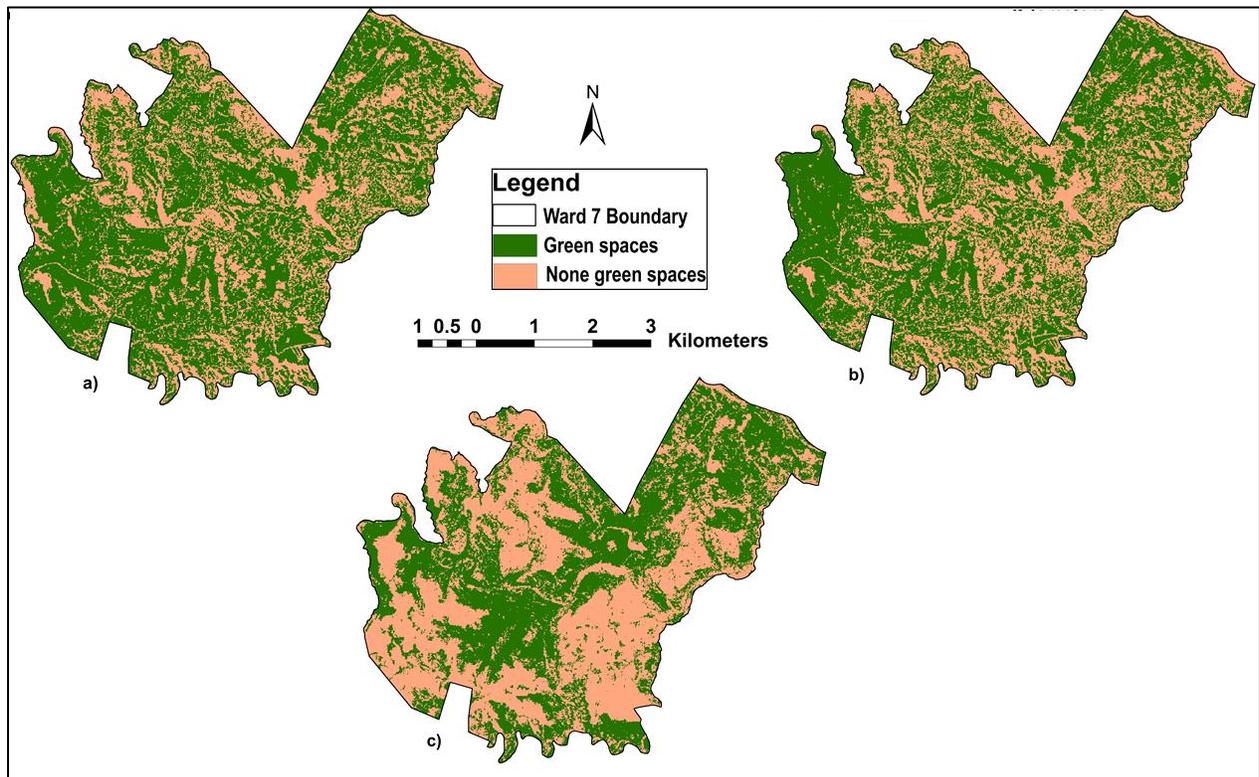


Figure 11: Boolean images generated for the green space land-cover projections of 2011 - a, 2016 - b, and 2022 - c.

4.5 Summary

The chapter has presented the main findings obtained during the study. In the chapter, the results of LULC change attained at each of the three time intervals (2000-2006, 2006-2011, and 2000-2011) to show where LULC Change is occurring and the relative rate at which this is taking place over time has been presented. Furthermore, the predicted changes to occur in 2016 and 2022 have also been shown.

Chapter 5: Discussion and conclusions

5.1 Introduction

In this chapter, the study results presented in chapter four as per the study aim and objectives are discussed. The chapter further discusses the value of LULC Change mapping and prediction on sustainable management of urban green spaces and critically examines the implications of other LULC types on the open green spaces in the study area. Specific emphasis is laid on the determination of change between the stated periods and the future LULC Change projections based on markov chain analysis. A number of recommendations are also highlighted.

5.2 LULC classification and change detection

In this study, LULC classification and change detection analyses were achieved using post classification comparisons and the LCM for Ecological Sustainability module. From the supervised classification results achieved, the overall classification accuracies depicted reliable kappa coefficient index between 0.83 and 0.89 (Table 4). These values are within Congalton and Green (1999) recommendation. Based on the LULC categories identified in the study area (Table 3 and Figure 2), it is apparent that changes occurred in the five land-cover categories during the study period. The expansion of Built-up and a reduction in degraded grassland and grassland land-cover visible in this study (Table 3) are consistent with literature on South Africa's urban growth (Sihlongonyane 2003; Pillay and Sebake 2008). These declines can be attributed to increasing Built-up and Thicket land-covers between the time periods. The decrease in the Degraded grassland and Grassland can be attributed to an increase in Built-up, Forest and Thicket land-covers. According to Sihlongonyane (2003) and Odindi *et al.* (2012), the transformation of vegetation into Built-up cover types seen in this study depicts a typical conversion of most of South Africa's urban fringes from urban greenery to impervious surfaces. Furthermore, results in this study are consistent with literature which note a significant decline in green spaces in the eThekweni municipality's urban fringe (Ethekewini 2003; SANBI 2009; Pillay 2010).

Generally, in this study, the green spaces transformation can be attributed to the sustained expansion of Built-up areas. This accounts for the projected 3.5% and 5.5% between 2016-2022 and 2011-2022 respectively (Table 9). The transformation of the green spaces can similarly be attributed to injudicious land-use practices (Coquery-Vidrovitch 1991; Abbott and Douglas 2003; Collinson *et al.* 2007; Odindi and Mhangara 2012).

5.3 Land-Use-Land-Cover Predictions

According to Jensen and Cowen (2011), LULC Changes on urban periphery have led to fragmentation and change of open green spaces. Such transformation compromise the ability of the green spaces to provide vital urban ecosystem goods and services. In this regard, multi-temporal mapping and projection of urban landscape is critical in understanding urban landscape processes. Understanding multi-temporal transformation of urban green spaces is particularly important for designing strategies to mitigate adverse negative urban environmental effects.

In this study, the markov chain prediction model was used to compute LULC transition probabilities from the multi-temporal LULC maps (Figure 2). The LULC transition probabilities and transition area matrices for the 2000–2006, 2006-2011, and 2000–2011 periods, calculated on the basis of the frequency distribution of the observations, are shown in Tables 7 and 8. The probabilities of green spaces changing to other land-cover categories in 2016 and 2022 is higher, indicating that there is a persistent decline compared to those experienced between 2000-2011. The high chance of the green spaces transforming in future is as a result of the losses to Built-up and Degraded grassland and reflects a continuous transformation of these critical greeneries at the urban fringes. From 2000-2006 probability matrix, it is evident that the chance of Grassland remaining unchanged is lower than the likelihood of this category changing to other land-cover categories. This represents instability in the green spaces as the probability of changing to Built-up is higher. This finding is consistent with the SANBI biodiversity survey report that projected future decline in Ethekwini's greenery (Ethekwini 2003; SANBI 2009). This finding is also consistent with Steffens *et al.* (2008) and Jensen and Cowen (2011) who note that continued expansion of built-urban landscapes leads to a fragmentation and reduction of the urban green environment.

The LULC Changes experienced in the study area typifies African urban areas, particularly South African metros peripheral growth (Steffens *et al.* 2008). This trend can, in part be attributed to the country's new dispensation and therefore free movement and the government's urban housing initiatives under the Reconstruction and Development Programme (RDP) (Naude and Kregell 2003; Collinson *et al.* 2007; Odindi and Mhangara 2012).

In conclusion this study has successfully determined multi-temporal and projected LULC trends in eThekweni's Ward 7. The findings show that there has been a persistent reduction of the green spaces in the study area which constitutes the municipality's periphery. Based on these findings, it can therefore be concluded that most of the greeneries are lost due to the urban area's peripheral growth. This can particularly be attributed to the municipality's densification of the urban cores and the spillage of new settlements to the urban periphery. The transformation of green spaces to other impervious surfaces can further be attributed to settlement related infrastructural development like roads and retail services.

Urban greeneries play a critical role in urban socio-ecological balance. Consequently, the transformation experienced in this study highlights the challenges faced by the eThekweni municipality in maintaining urban greenery and mitigating climate change. This study particularly highlights the value of remotely sensed data set in concert with GIS applications in understanding the transformation of urban landscapes. Understanding this transformation is invaluable to current and future decision making processes and in formulation of effective land-use policies. The use of the LCM and markov chain provide an important green spaces change determination and projection that can be used for planning and mitigation of current and future negative impacts.

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