CHARACTERISING HISTORIC LAND USE AND LAND COVER CHANGE USING LANDSAT EARTH OBSERVATION DATA IN THE WATERBERG BIOSPHERE RESERVE

By

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DECLARATION

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

Signature ………………………………………………. Date……27/05/2019………………………...…

ABSTRACT

Information about Land use and land cover (LULC) is important for making a better decision, planning, and management of human activities and natural resources in protected, conserved and unprotected areas such as river catchment area and biosphere reserve.

The study was conducted in the Waterberg region to characterize and compare historical landscape modification within the Waterberg Biosphere Reserve (WBR) and the surrounding river catchments, both prior to and after its promulgation with United Nation Education Scientific and Cultural Organization's Man and Biosphere Programme in 2001. The research objectives of this study were to map the LULC classes from 1984 to 2016 in successive five years interval using the Landsat 4-5, 7 and 8 images, quantify LULC changes within and outside the WBR (River catchment areas) and lastly, quantify the impact of the WBR on urban and agriculture. Information about LULC was derived using Support Vector Machine (SVM) algorithm with 140 reference data for each LULC class (70% as training data and the remaining 30% as validation data). The Normalized Difference Vegetation Index (NDVI) and statistical testing (paired t-test) were computed and performed, respectively.

The overall accuracies range from 80.29% to 90.12%, User's accuracies (50.65 to 100%), producer's accuracies (45.24% to 100% and kappa indices (0.78 to 0.81) Landscape has insignificantly modified over the analysis period ($P > 0.05$) on both sides of the study whilst the NDVI shows significant change ($P<0.05$). Cultivated land decreased on both sides of the WBR as land covered by this LULC type was 8.41% (Inside) and 7.52% (Outside) in 1984 and decreased to 4.04% and 4.90% inside and outside the WBR respectively, in 2016. Built up area increased outside the WBR as it was 1.04% in 1984 and 1.59% in 2016. However, built up area decreased from 0.79% in 1984 to 0.69% in 2016 outside the WBR. Mines occur outside the periphery of the WBR and increased from 0.04 %(1984) to 0.13% (2016). Waterbody also increased from 0.10% inside and 0.01% outside the WBR in 1984 to 0.13% and 0.04% respectively, in 2016.

The area is experienced rapid urban and mine growth which raise concern on the quality of water, aquatic species and ecosystem functionality as the WBR did not halt these developments within the region as it holds the potential coalfields to supply coal for fossil energy generation. The conversion of cropland to game farming caused revegetation which could influence the ecological functioning of both aquatic and terrestrial ecosystems. Proper planning and management of both human activities and natural resources are recommended to conserve the biodiversity while promoting local community involvement in sustainable development structures.

DEDICATIONS

In lovely memory of my mother and grandmother: Ms Mashudu Ratshitaka and Mrs Mukatshelwa Singo. The dedication also goes to my siblings: Vhutshilo Mundalamo, Masha Mundalamo, and Seani Mundalamo.

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ABBREVIATIONS AND ACRONYMS

ANN	Artificial Neural Networks
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
AVHRR	Advanced Very High-Resolution Radiometer
BIC	Bushveld Igneous Complex
BR	Biosphere Reserve
DEA	Department of Environmental Affairs
DEAT	Department of Environmental Affairs and Tourism
DRDLR	Department of Rural Development and Land Reform
DMR	Department of Mineral Resources
DWS	Department of Water and Sanitation
ENVI	Environment for Visualising Images
ETM+	Enhanced Thematic Mapper Plus
FLAASH	Fast Line of Sight Atmospheric Analysis of Hyperspectral Cubes
GCP	Ground Control Points
GDP	Gross Domestic Product
GIS	Geographic Information Systems
GPS	Global Positioning System
K2C	Kruger to Canyon
LULC	Land use and land cover
MAB	Man and Biosphere
MODIS	Moderate Resolution Imaging Spectroradiometer
MSS	Multi-spectral scanner
NGI	National Geospatial Information
OLI	Operational Land Imager
PCA	Principal Component Analysis
RDP	Reconstruction and Development Programme
RMSE	Root Mean Square Error
RS	Remote Sensing
SANLC	South African National Land Cover
SPOT	Satellite Pour l'Observation de la Terre
SVM	Support Vector Machine
TIRS	Thermal Infrared Sensor

TM	Thematic Mapper
UNESCO	United Nations Education, Scientific and Cultural Organization
USGS	United States Geological Survey
UTM	Universal Transverse Mercator
VBR	Vhembe Biosphere Reserve
WGS	World Geodetic System
WBR	Waterberg Biosphere Reserve

Contents

CHAPTER ONE: INTRODUCTION

1.1. General introduction

Headwater streams provide ecosystem services, such as the drinking water purification, aquatic habitat and the rapid processing and nutrients uptake, which can limit the accumulation of Phosphorus and Nitrogen to the downstream aquatic and riparian ecosystems (Wigington *et al.*, 2001; Lowe and Ikens, 2005; Freeman *et al*., 2007). Additionally, headwater streams are also important for water provision for human consumption and industry, regulation of water quality thorough biological mitigation of sedimentation and salinization, as well as indirect economic benefits, tourism and educational activities associated with intact headwater environments (Brauman *et al.*, 2007). These services will be preserved only if headwater streams are properly conserved.

However, these streams are impacted by natural and anthropogenic processes (Giri, 2012), while the latter such as agricultural activities, mining, and urban development is increasingly recognized as a dominant force in landscape modification. These streams are vulnerable to land use impact than larger, higher-order streams due to their abundance and small size (Meyer and Wallace, 2001; Hamza and Lyela, 2012; Burdon *et al*., 2013). Conventional agriculture, urban development, and mining activities are among the threats to headwater streams (Meyer *et al*., 2007; De Klerk, 2016). These human activities involve channelization, filling and piping of small water streams, which are accompanied by habitat modification, increased flood risk, stream metabolism modification, impact on processing of organic matter, affected food supply for organisms, increased Nitrogen and Phosphorus loading and reduced nutrient retention, the eutrophication and hypoxia of distant downstream ecosystems (Meyer and Wallace, 2001; Winter, 2007; Alexander et al., 2007; Freeman et al., 2007; Elmore and Kaushal, 2008; Clapcott and Barmutta, 2010). Mining activities has severely impacted the Upper Oliphant River in Mpumalanga due to poor decision making, planning and policy making (De Klerk, 2016). The modification of headwater streams can have an impact on the ecological integrity of freshwater and coastal ecosystems.

Information about Land use and land cover (LULC) has been used for better decision making, planning, managing and policy-making for natural resources (Prakasam, 2010; Yadav *et al.*, 2010; Mani and Krishman, 2013). This information is important for understanding the relationship between natural phenomena and human and also their interaction (Lu *et al*., 2004) and it has been captured through traditional field-based approaches. These approaches, however, are costly, time-consuming and inaccurate geometry in inaccessible areas (Abdullar and Lalit, 2013; Mani and Krishman, 2013). Remote Sensing (RS) and Geographical Information Systems (GIS) techniques outplayed the traditional field-based approaches in landscape assessment as they are time efficient, cost-effective, good accuracy and capable in inaccessible regions (Chena *et al*., 2009; Abdullar and Lalit, 2013).

The RS and GIS techniques have been successfully used in mapping and detecting LULC changes in Nyazvidzi river catchment in Zimbabwe (Gumindoga *et al*., 2018), Northern Keiskamma river catchment in South Africa (Dyosi *et al*., 2018), Luvuvhu River Catchment in South Africa (Singo, 2018).

The Waterberg is a subtropical savanna ecoregion with significant biodiversity values and a home to the Waterberg Biosphere Reserve which was promulgated under the United Nations Education, Scientific and Cultural Organization (UNESCO) Man and Biosphere (MaB) programme in 2001. The region has, together with numerous headwaters in the notoriously water scarce province, four rivers namely: The Lephalala, Mokolo, Matlabas and Mogalakwena Rivers which are already modified and increasingly vulnerable to change from agriculture intensification, peri-urban spread, mining activities and atmospheric deposition from fossil fuel-based power generation (RHP, 2006; Ashton *et al*., 2008; CSIR, 2012). However, a study by De Klerk and De Klerk (2011) found that Waterberg's main rivers are still in reasonably good condition as far as water quality and the aquatic ecosystem. The region has experienced a conversion of cropland to game farming (Baber and Abram, 2013), expansion and establishment of mines and power stations as it holds the remaining coalfield that will supply South Africa for fossil energy-based generation (DMR, 2009).

The studies on LULC changes have been conducted at different biosphere reserves within the Republic of South Africa. A study by Coetzer *et al* (2010) showed remarkable land cover changes in the Kruger to Canyons (K2C) biosphere reserve (1993-2006). The study by Evans (2017) shows LULC changes from 1990 to 2014 in Vhembe Biosphere Reserve (VBR). The quantification of LULC changes within the WBR and surrounding River Catchment Areas (RCA) is not yet done. This study attempted to analyze the impact of WBR on the landscape within WBR and surrounding RCA from 1984 to 2016 using Landsat datasets. The study findings are important to assess the efficacy of the WBR in ecosystems conservation and for better decision making, proper planning and management of the WBR and water resources within the region.

1.2. Problem statement

The Waterberg region is one of the remaining unexploited regions with high biodiversity and human presence stretches back to the Middle Stone Age. The Waterberg region is less populated because of its remoteness, inaccessibility and soil conditions (Van der Ryst, 1998). However, land modification has been occurring, of which subsistence and commercial crop farming is the dominant land use practice, especially along river banks (De Klerk, 2003). In particular, some of the headwater streams of these river catchments (Mokolo, Mogalakwena) originated outside the biosphere reserve.

Cropland has considerably decreased due to its weather conditions, poor-nutrient soils, and government subsidiaries removal. These caused the rise of eco-tourism and the foreigners in acquiring/purchasing land for wildlife industries (De Klerk, 2003).

The region is experienced with pressure from economic development (tourist destination, mining, and agriculture) (De Klerk, 2003). As a response, the WBR was introduced in 2001 to ensure the conservation of biodiversity by promoting local community involvement in conservation structures and sustainable development initiatives. Today, both cropland and game farming, built up expansion, population growth, mining establishment and expansion, power station establishment and expansion are among the land use activities threating headwater streams within the Waterberg region (Aurecon, 2010). These activities are accompanied by landscape changing, habitat destruction, biological invasion, and increased water resource stressed (Baber and Abram, 2013). Headwater streams of Mokolo and Mogalakwena are vulnerable to land degradation, before flowing into the biosphere reserve as they are originated from outside the biosphere reserve.

In South Africa, the studies on LULC change were done in Northern Keiskamma River Catchment (Dyosi *et al*., 2018) and Luvuvhu River Catchment in South Africa (Singo, 2018). And, studies were also done per biosphere reserve at K2C Biosphere Reserve (Coetzer *et al*., 2010) and VBR (Evans, 2017). This study attempted to assess LULC changes within WBR and the surrounding river catchments using the advanced image classification algorithm. The study findings are important to assess the efficacy of the WBR in ecosystems conservation and for better decision making, proper planning and management of the WBR and water resources within the region.

1.3. Research objectives

1.3.1. Aim

The aim of the study is to characterize and compare historical landscape modification inside and outside of the WBR, both prior to and after promulgation in 2001 over successive five-year periods (1984, 1990, 1996, 2001, 2006, 2011 and 2016).

1.3.2. Research objectives

i. To map the LULC classes from 1984 to 2016 using the multispectral Landsat data.
ii. To quantify and analyze LULC changes inside and outside the WBR from 1984 and 2016.
iii. To quantify the impact of WBR on urban areas and agriculture.

1.3.3. Research questions

i. What LULC changes have occurred within and outside biosphere reserve from 1984 to 2016?
ii. Has urban or agricultural development accelerated or decelerated inside and outside the WBR since 2001?

CHAPTER TWO: LITERATURE REVIEW

2.1. Biosphere Reserve

Biosphere reserves are sites identified either on marine or terrestrial ecosystems (or both) that are internationally recognized under the framework of UNESCO's Man and Biosphere (MaB) programme (Batisse, 1982). The aim of the biosphere reserve is to promote sustainable development while conserving natural resources within the area (Pool-Stanvliet, 2013).

The biosphere reserve has three functions: Development, conservation, and logistic, where the latter is essentially the development, encouragement, and facilitation of education, learning and training, including skills training. The biosphere reserve is divided into three interrelated zones to fulfil the above-mentioned functions (Pool-Stanvliet, 2013). The core zones are protected sites for biodiversity conservation, development with minimally ecosystem disturbance and non-destructive research and other low impact land use. The buffer zones are sites of low-intensity land use activities and usually protect the core zones from the impacts of activities within transition zones and vice versa. Diversity of sustainable activities are contained within transition zones (Pool-Stanvliet, 2013). Today, World Network of Biosphere Reserves of the MaB programme composed of 686 biosphere reserves in 122 different countries worldwide with 20 transboundary areas included. 79 biosphere reserves proclaimed in 28 African countries with South Africa leading in terms of number of biosphere reserves (UNESCO, 2019).

South Africa has ten biosphere reserves, namely: Gouritz-Cluster Biosphere Reserve, Kogelberg Biosphere Reserve, Cape West Coast Biosphere Reserve, Cape Winelands Biosphere Reserve, Garden Route Biosphere Reserve, all in the Western Cape Province, Waterberg Biosphere Reserve, Vhembe Biosphere Reserve, Kruger to Canyons Biosphere Reserve, all in the Limpopo Province, Magaliesburg Biosphere Reserve in the North West and Gauteng provinces and recently proclaimed in 2018 is the Marico Biosphere reserve in the North West Province (UNESCO, 2019). However, despite the growing number of biosphere reserves in South Africa, little is documented about the biosphere reserve and receives limited fund support from the national government (Pool-Stanvliet, 2013).

2.2. GIS and remote sensing of land use and land cover changes in biosphere reserves

Land use and land cover (LULC) are the two interrelated concepts which are used for observing the earth's surface (Duhamel, 2011). Land use refers to the human activity on a piece of land, whereas land cover is defined as the natural material and artificial infrastructure covering the earth's surface and subsurface (Turner *et al.*, 1995; Meyer, 1995; Lambin *et al.*, 2003; Pellikka, 2008; Sohl *et al*, 2010; Duhamel, 2011). Single land cover can support multiple land uses.

For example, natural forest cover can be used for hunting and gathering, fuelwood collection, recreation and wildlife preservation (Briassoulis, 2011; Verheye, 2011). LULC change refers to a conversion/alteration of one land use/cover category to a new land use/cover category or within one land use/cover type (Meyer and Turner, 1992; Lambin and Geist, 2003.). LULC changes are caused by both natural processes and human activities such as floods, drought, agriculture, urban development and recreations (Meyer and Turner, 1992; Turner *et al.*, 1995).

The use of remotely sensed images for the extraction of LULC attributes has an extensive history, prior to the launch of the Earth Resources Technology Satellite (ERTS) now Landsat 1 (Sohl *et al.*, 2010). The recent remote sensing technology offers capturing and data analysis with linkages to Global Positioning System (GPS) data. GPS and GIS integrated with RS provide the information useful for planning, decision making, and management cost-effectively (Franklin *et al.*, 2000). GIS and RS techniques are of most value in cases of inaccessible regions in obtaining the required data for mapping on time and cost-effective basis (Steininger, 1996; Adeyemi, 2017).

GIS models the available data and uses statistical and analytical functions to measure the trends in LULC changes (Lu *et al.*, 2004; Giri, 2012; Abdullar and Lalit, 2013). The choice of the selection of RS data on ecological application depends on the variety of factors as different images have a different spectral resolution, temporal resolution, spatial resolution and radiometric resolution (Daudze, 2004). And based on spatial resolution, sources range from high resolution (Rapideye, IKONOS, and QuickBird) to medium resolution (Landsat and SPOT) and thus with a lower spatial resolution (MODIS) (Ellis, 2014).

Landsat has the longest historical coverage of the earth and four sets of generation. The first generation was equipped with Multi-Spectral Scanner and includes Landsat 1, 2 and 3, the second generation is Landsat 4-5 and they are Thematic Mapper (TM), third includes Landsat 7 and equipped with Enhanced Thematic Mapper Plus (ETM+) sensor. The latest generation includes the Landsat 8, which is equipped with Operational Land Imager (OLI) sensor and Thermal Infrared Sensor (TIRS). (Daudze, 2004; Mas, 2009).

Remote sensing has the shortcoming of separating phenomena (Green root and green vegetation) with similar spectral reflectance (Fonji and Fark, 2014) and this could led to a generalization of the landscape features. However, continuous temporal, radiometric and spatial resolution advancements can provide valuable assistance in the LULC mapping (Jensen, 1983). The problem of generalization of the features can also be solved by the application of the hyperspectral data. However, these datasets have challenges in terms of availability, cost, and processing (Dalponte *et al.*, 2009; Omer *et al.*, 2015).

The RS and GIS techniques have been successfully used in different biosphere reserves around the world. Hogdon *et al* (2015) applied RS and GIS techniques to quantify deforestation rate at the largest biosphere reserve in Central America (Maya biosphere reserve) in fourteen years period. The results show a deforestation rate of 1.2 % annually, from 2000 to 2014. Another study by Saranya and Reddy (2012) shows deforestation in Simillipal Biosphere Reserve (1930-2012) in India. A study conducted by Parsa *et al* (2016) shows a downward trend in forestland at the expense of increasing agriculture and barren land in Arasharan Biosphere reserve in Iran.

In Africa, studies about LULC change using RS and GIS have been conducted successfully. These include the study by Adeyeni (2017) in Omo biosphere reserve from 2000 to 2015. This study shows a significant reduction of natural forest with expanding plantation forest and settlement. The study by Houessou *et al* (2013) shows the conversion of woodland and savanna to crop cultivated land.

Although little is known about BR in the Republic of South African, studies have been conducted successfully in mapping and quantifying LULC at different biosphere reserves. These include studies at K2C Biosphere Reserve (Coetzer *et al*., 2010) and VBR (Evans, 2017). The former study shows settlement and agricultural expansion with decreasing of mining and forest by 6.3 % and 7.1 % respectively (1993-2006). There have been no attempts to map and quantify the LULC change in WBR and its surroundings with population growth, development and agricultural intensification taking places. Therefore, this study attempted to assess LULC change inside and outside the WBR using the advanced image classification algorithm.

CHAPTER THREE: MATERIALS AND METHODS

3.1. Study area

The study area is the Waterberg Biosphere Reserve (WBR) and the surrounding river catchment areas, which lies in the South West of Limpopo Province, South Africa and forms part of the savanna biome of Southern Africa (Low and Roberto, 1996). The WBR was registered with UNESCO's MaB programme in 2001 and lies between latitude 27^{o} 30'00" S and 28^{o} 40' 00" S and longitude 23^{o} 10'00" E and 24^{o} 40'00" E and shares its northern boundary with the Vhembe Biosphere Reserve (VBR) (Figure 1).

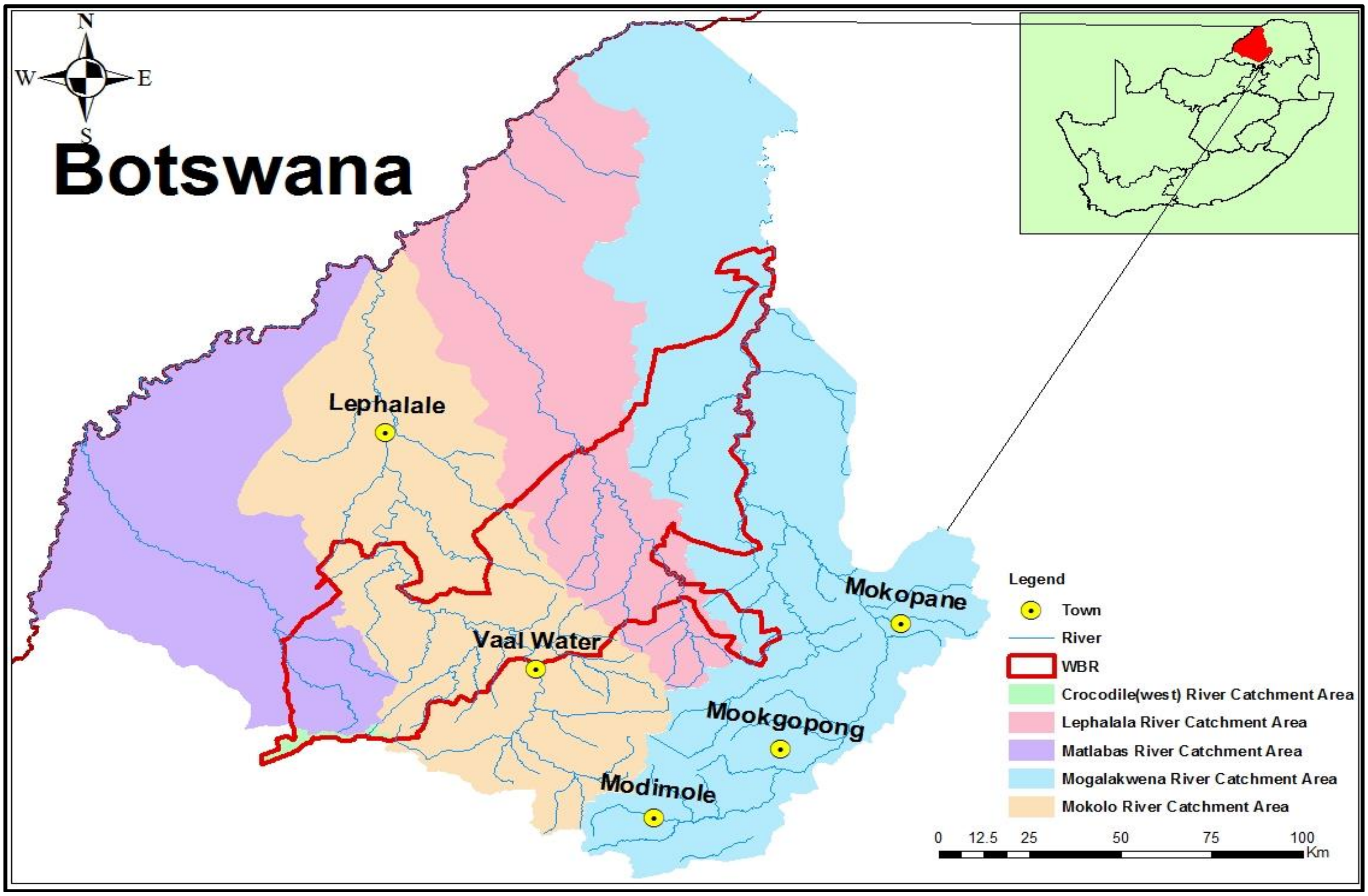


Figure 1: Locality Map (Source: DWS and DEA)

The study area includes protected areas of Masebe Natural Reserves, Moepel farms, Marakele National Park, Lepalala Wilderness, Touchstone Game Ranch, and Welgevonden Game Reserve. The WBR covers an area of 417406 hectares (ha) and delimited into a core zone, buffer zone and transition zone of 121 249 ha, 146 157 ha, and ±150000 ha respectively. However, the proposed plan to expand the WBR submitted to UNESCO to ensure that the BR promotes environmental conservation and sustainable development. Currently, the WBR cannot encourage conservation and sustainable development as important biodiversity hotspots are outside the periphery of the WBR.

Four main rivers exist, namely the Mokolo, Lephalala, Mogalakwena and Matlabas Rivers. These rivers, together with tributaries, are part of the Limpopo Water Management Area (LWMA) and drain into internationally shared Limpopo River Basin, including Botswana, South Africa, Mozambique, and Zimbabwe. The climatic condition is temperate and semi-arid with mean annual rainfall ranges between 300mm to 700mm. Rainfall is seasonal, mainly occurring in October to March with thundershowers and becomes dry in July and August.

The geology is sedimentary rocks (Waterberg Supergroup) as eroded from the Bushveld Igneous Complex (BIC) (Truswell, 1977; SACS, 1980). BIC is rich in Platinum Group Metals, wherein Waterberg Coalfield is confined within Waterberg Supergroup (DEAT, 1997a). Waterberg mountain range varies from 807.7 meters (m) (De Klerk and Loubser, 1989) and 2100 m (Van Stadew, 2002). The vegetation of the region classified as Savanna biomes (Rutherford and Westfall, 1989; Low and Rebelo, 1996).

The region has experienced population growth from 218 981 in 1980 to approximately 600 000 people in 2011 (Stats SA, 2011). Mining is the current primary contributor to the Gross Domestic Product (GDP) followed by agriculture (IDP, 2017). In addition, numerous mineral explorations are taking place especially at Waterberg Coalfield. Development of towns, roads, and villages is not extensive as mining, game farming, tourism and irrigation (De Klerk, 2003).

3.2. Materials and methods

3.2.1. Remote sensing data

Datasets obtained from different sources were used to increase the accuracy of the results. These include Landsat images from the Earthexplorer website (https://earthexplorer.usgs.gov), South African National Land Cover (SANLC) maps, aerial photos, topographical maps and Google Earth images. The SANLC maps and both topographical maps and aerial photos were sourced from the South African National Biodiversity Institute website (https://sanbi.org.za) and Department of Rural Development and Land Reform under Chief Directorate: National Geospatial Information, respectively. Biosphere reserve and river catchment area shapefiles sourced from the Department of Environment Affairs and Department of Water and Sanitation (DWS) respectively, were used for delineation of the study area. Details of the satellites used are shown in table 1. Figure 2 illustrates the methodology followed for this study.

Table 1: Satellite/sensor properties

Date	Sensor and spectral range		Spatial resolution	Temporal resolution
19841024 19841019 19900927 19900820 19900801 19960911 19960902 19960801 20060923 20060914 20111015 20111022	**Landsat 4-5 TM** 1 (Blue) 2 (Green) 3 (Red) 4 (Near Infrared) 5 (Short Wave Infrared) 6 (Thermal Infrared) 7 (Short wave Infrared)	 0.45-0.52 0.52-0.60 0.60-0.69 0.76-0.90 1.55-1,75 10.4-12.50 2.08-2.35	30 m	16 Days
20010917 20010823	**Landsat 7-ETM+ (SLC on)** 1 (Blue) 2 (Green) 3 (Red) 4 (Near Infrared) 5 (Short Wave Infrared-1) 6 (Thermal Infrared) 7 (Short wave Infrared-2) 8 (Panchromatic)	 0.45- 0.52 0.52- 0.60 0.63- 0.69 0.77- 0.90 1.55- 1.75 10.40- 12.50 2.09- 2.35 0.52- 0.90	30m	16 Days
20160902 20160909	**Landsat 8-OLI/TIRS** 1 Coastal/Aerosol 2 Blue 3 Green 4 Red 5 Near Infrared 6 Shortwave Infrared-1) 7 (Shortwave Infrared-2) 8 (Panchromatic) 9 (Cirrus) 10 (Thermal Infrared-1) 11(Thermal Infrared-2)	 0.43 - 0.45 0.45 - 0.51 0.53 - 0.59 0.64 - 0.67 0.85 - 0.88 1.57 - 1.65 2.11 - 2.29 0.50 - 068 1.36 - 1.38 10.60 - 11.19 11.50 - 12.51	30m	16 Days

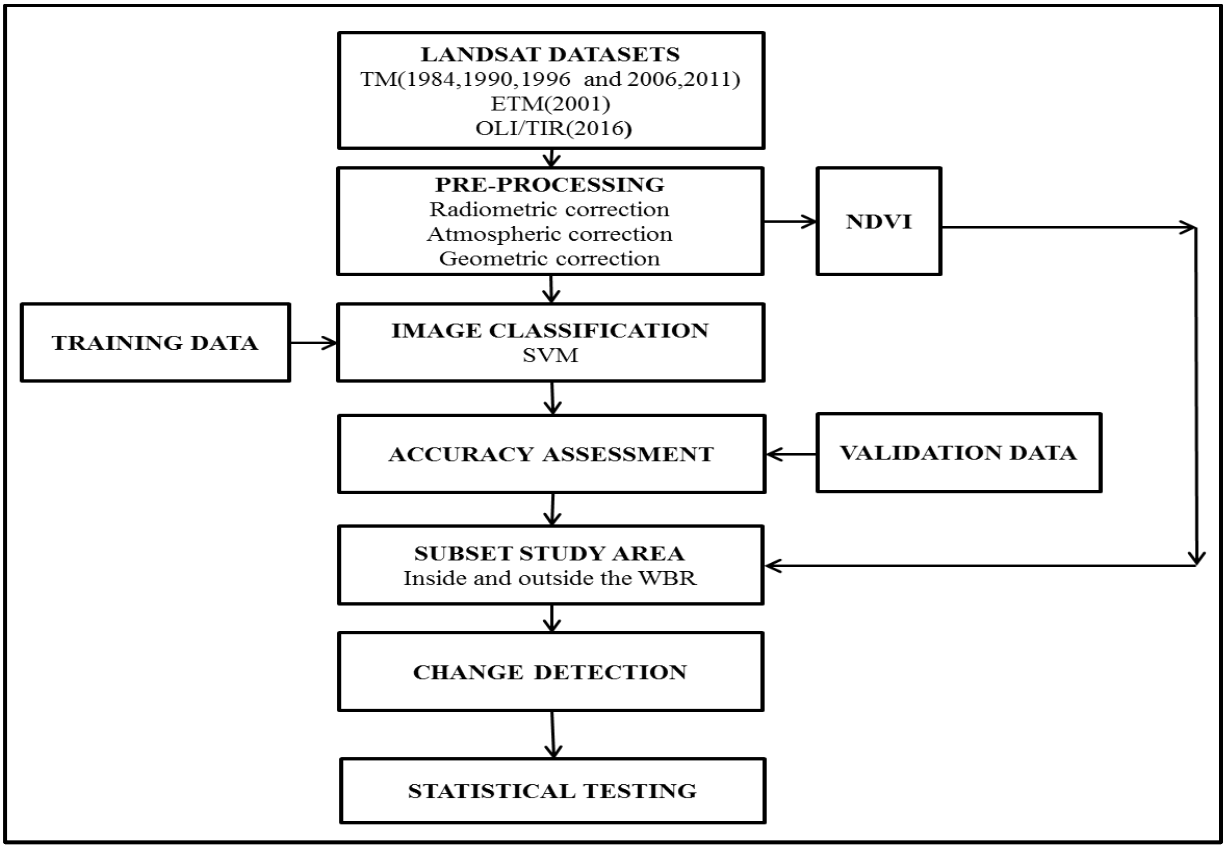


Figure 2: Methodology Flow chart

The 1984 and 1990 Landsat images used deviate from the planned five-year interval due to cloud cover and unavailability of some images on the Earthexplorer (Table 1). The 1990 Landsat images had better quality compared to the 1991 images (Cloud cover) and 1985 image is unavailable.

The Landsat images were used in this study due to its fairly coarse pixel resolution (30m) when compared with other satellite imagery (Worldview, IKONOS), spatial extent, has the historical records for spatiotemporal analysis and its accessibility at no cost. The Landsat images were collected from August to October as it is dry months (No rain) and seasonal rivers are dried up during this season. The software used for this study is Environment for Visualizing Images (ENVI 5.4), ArcMap 10.5, and Rstudio.

3.3. Land use and land cover mapping

3.3.1. Image pre-processing

All Landsat images used for this study were pre-processed as they were acquired at different times using different satellite sensors. This is highlighted by Lu *et al.* (2004) that historical and current Landsat images differ in atmospheric correctness, radiometric and geometric precision. Pre-processing is comprised of atmospheric correction, radiometric calibration and geometric correction (Şatır and Berberoğlu, 2012; Iqbal and Khan, 2014). Additionally, a topographic correction may be necessary for rugged or mountainous study areas (Lu *et al*. 2004). The corrections of these irregularities improve LULC mapping results.

In this study, each tile's digital number values were radiometrically corrected using the *Radiometric Calibration* function in ENVI 5.4. The radiometrically corrected images were then atmospherically corrected with the use of *Fast Line-Of-Sight Atmospheric Analysis of Hyperspectral Cubes* (FLAASH) model. The model is a physics-based algorithm used for atmospheric corrections of the visible to infrared spectrum. The parameters used for FLAASH model were rural for the aerosol model as the rural area has the greatest share of the land, the aerosol retrieval of 2-Band (K-T) and 20-40 km was chosen for the initial visibility based on the quality of Landsat images acquired.

The precise spatial registration of multi-temporal imagery is vital for accurate change detection as misregistration leads to largely spurious results of change detection (Stow, 1999). Image registration is defined as overlaying of more than one image of the same scene acquired from different viewpoints, by different sensors and/or at different times. It geometrically aligns the reference and new images (Zitova and Flusser, 2003). The difference between the location of a Ground Control Points on the reference image and the transformed image is Root Mean Square Error (RMSE) and it must be less than or equal to 0.5 according to Jensen (1996). All Landsat images came georeferenced, then the image to image registration was performed to align all images (1984, 1990, 1996, 2001, 2006 and 2011) to 2016 images (better geometric accuracy than imagery from other Landsat images) using the *Image to Image Registration* function in ENVI 5.4 classic and the RSMEs of all registrations were less than 0.5.

In mosaicking, two or more images are combined into one big image that covers the whole study area. The *Seamless Mosaic* function in ENVI 5.4 was used to mosaic the all registered images to form one big image that covers the study area and projected to the Universal Transversal Mercator (WGS 1984 Datum). These mosaicked images were the input images for the subsequent analysis and were clipped to the study area.

3.3.2. Reference data and image classification

The LULC classes were defined based on what constitutes the study area and on the South African land cover classification scheme for remote sensing (Table 2) (Thompson, 1996).

Table 2: LULC classes

CLASS	DESCRIPTION
Waterbody	All areas covered with water
Natural Vegetation	An area that includes thicket, bushland, low shrubland, and grassland
Cultivated Land	Large-scale are with soil tilled for agricultural purposes
Barren Land	Non-Vegetated land (excluding agricultural fields and open cast mines)
Built-up land	An area where there are buildings and other man-made structures and activities excluding mine infrastructures
Mines and quarries	Post mined area or mining areas including surface infrastructures, mine dumps associated with underground mining
Shadows	Surfaces at which true LULC type could not be captured due to sunlight obstructed by the opaque surrounding

Source: Thompson (1996)

For every image in the series (1984 to 2016), the in-situ data were not available, therefore Google Earth images, aerial photos, topographical maps, and SANLC maps used for reference data (Jensen, 2005). 70% of the total reference dataset was used for training the classifier whereas the remaining 30% was used for validation (Table 3).

Table 3: Reference datasets for the LULC

Class	Training data	Validation data	Total
Waterbody	98	42	140
Natural Vegetation	98	42	140
Cultivated Land	98	42	140
Barren Land	98	42	140
Built-up land	98	42	140
Mines and Quarries	98	42	140
Shadows	98	42	140

Image classification is a process of grouping all reflectance in an image or raw remote sensing data to get a set of labels (Lillesand and Keifer, 1994) and it is the most common approach used to derive LULC information routinely and cost-effectively (Huang *et al*., 2002; Marthur and Food, 2008). Image classification methods are broadly grouped into unsupervised and supervised classification. These two classification methods can be combined into hybrid methodologies (Richard and Jia, 2006). Training sites on the images are defined by the analyst on supervised classification methods.

The acquisition of Landsat 1 in the early 1970s led numerous supervised classification algorithms (Townshend, 1992). These include new and improved Maximum Likelihood Classifier, Artificial Neural Network, and Decision Tree classifiers which are considered as popular classifiers over the few decades (Huang *et al*., 2002). Recently, new classifiers such as Random Forest, Support Vector Machines (SVM), Relevance Vector Machines and Incremental Import Vector Machines have been developed (Pal, 2012; Roscher *et al*., 2012; Tiggers *et al*., 2013; Adelabu *et al*., 2014).

The SVM was used for this study and it has been successfully applied in classifying the remotely sensed data (Huang *et al*., 2002; Pal and Mather, 2004; Dixon and Candade, 2007; Schuster *et al*., 2012; Adam *et al*., 2014; Adelabu *et al*., 2014; Abdikan *et al*., 2015; Schuster *et al*., 2015; Gegana, 2016; Jombo, 2016). Jombo (2016) derived the LULC information using the SVM. The SVM provides good classification results with high accuracy compared to other classification methods such as Artificial Neural Network and Maximum Likelihood Classification (Candade and Dixon, 2004; Foody and Mathur, 2004).

The SVM is a non-parametric algorithm which was originally aimed at binary classification by determining optimal boundaries between two classes (Cortes and Vapnik, 1995; Huang *et al*., 2002). The SVM makes no assumption normality in classifying the images and it performs well even with limited training samples. The SVM classifier differentiates and divides the classes by determining the boundaries in feature space and maximizes the margins between the classes (Vapnik, 1995). The margin is created between two classes and middle of the margin is the optimal separating hyperplane. The SVM includes penalty parameters that allow a certain degree of misclassification which is important for non-separate training datasets (Vapnik, 1995; Cortes and Vapnik, 1995; Huang *et al*., 2002). The optimal hyperplane is determined using training samples and its accuracy is assessed by validation samples.

The success of the classification accuracies of the SVM depends on the kernel used, the method used to produce SVM, tune parameters to fit the kernel, and how well the training was conducted (Huang *et al.*, 2002; Otukei and Blascke, 2010). There are several kernels to choose, namely: Polynomial, Linear, and Radial Basic Function. The Radial Basic Function was a preferable choice over others because it provides optimal results and literature proved it to be the most popular kernel (Pal, 2005; Hsu *et al.*, 2010; Liu *et al*., 2014).

SVM within ENVI 5.4 was used for classification analysis on each of the multi-date Landsat images acquired for the study area. The SVM classification method was used with RBF (The kernel type), 0.143 for gamma in the kernel function, 120 for penalty parameter and 0.05 for classification probability threshold.

3.3.3. Accuracy assessment

The use of historic images in LULC analysis is affected by the unavailability of the ground reference information (Jensen, 2005). The confusion (Error) matrix is a common tool for accuracy assessment. This is a comparison of pixels between classified image and reference data (Jensen, 2005). The user's accuracies, producer's accuracies, overall accuracies, and kappa coefficients measure the accuracy of the classified images.

The overall accuracy of the classified image is the comparison of how each of the pixels is classified against the actual land use and land cover conditions sourced from their corresponding validation data. The overall accuracy is the quotient of correctly classified pixels and the total number of pixel in the dataset (Varshney and Arora, 2004).

Producer's accuracy, measures error of omission, is the ratio 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 measures errors of commission, which represents the likelihood of a classified pixel matching the land cover type of its corresponding real-world location (Congalton, 1991; Jensen, 2005; Campbell, 2007).

Kappa coefficient of agreement measures the agreement between the validation data and the classified image arising to change (Foody, 2002; Varshney and Arora, 2004). The Kappa coefficient lies between the value of 0 and 1. The value of 1 shows perfect agreement between validation data and classified image whereas a value of 0 shows disagreement between validation and classified image (Dorn *et al.*, 2015).

In this study, the accuracy assessment of the SVM classification was done using the validation dataset (30% of the total dataset). The confusion matrix function within ENVI 5.4 was used for the construction of a confusion matrix to calculate the user's accuracies, producer's accuracies, overall accuracies and kappa coefficients.

3.4. Normalized Difference Vegetation Index

NDVI was also used and it is related to the green biomass of the vegetation (Mas, 1999). NDVI is calculated using the standard formula (Rouse *et al.*, 1974) as: **NDVI=** $\boldsymbol{\frac{NIR-R}{NIR+R}}$**,**

Where NIR is the Near Infrared and R is the Red band

NDVI maps were derived from images from Landsat 5, 7 and 8 over the analysis period (1984-2016) using the *Image Analysis* function in ArcMap

3.5. Change detection

Change detection is a process of analyzing the multi-temporal remotely sensed data to identify differences over different times (Singh 1989). Change detection uses the multi-temporal datasets to quantitatively assess the temporal effects of the phenomenon (Lu *et al.*, 2004). Numerous change detection methods are available and their selections depend on user's knowledge about the methods, remote sensing data handling skills, the type of datasets used and study area characteristics. Additionally, the outcome of the change detection method is also essential when choosing change detection method as some change detection techniques can only provide limited change information, while other techniques can provide a detailed change (Lu *et al.*, 2004). Image differencing, image rationing, Principal Component Analysis (PCA) and post-classification comparison are among the change detection methods successfully used in RS applications (Singh, 1989).

The post-classification method was used for detecting LULC change. This is the most commonly used change detection technique and requires the comparison of independently classified images of different epochs (Singh, 1989). This technique provides a detailed change attributes and limits different atmospheric and environmental impacts between the two or more datasets acquired at a different time (Lu *et al.*, 2004). Before change detection was performed, the classified images were subsetted into inside and outside the WBR. The method was used for detecting LULC change from 1984 to 2016 inside and outside the WBR.

The LULC changes inside and outside the WBR were quantified as 1984-1990; 1990-1996, 1996-2001; 2001-2006; 2006-2011 and 2011-2016. The LULC changes between 1984 and 2001 images indicate changes before the WBR and those from 2001 to 2016 show the impact of the WBR on the landscape.

Time series analysis was performed on the multi-temporal NDVI using random points generated over the study area. The NDVI values were then extracted from NDVI maps (Inside and outside the WBR). Post classification comparison was also done in NDVI. Statistical analysis was, in both LULC and NDVI, to test if LULC changes significantly differ between outside and inside the WBR using the paired t-test method. The following hypotheses were formulated for a statistical test of the LULC and NDVI changes between consecutive study years at a significant level of 0.95.

H_0: There is insignificant LULC change
H_A: There is significant LULC change

H_0: There is insignificant NDVI change
H_A: There is significant NDVI change

Where $P < 0.05$, the null hypothesis was rejected and the alternative hypothesis accepted.

CHAPTER FOUR: RESULTS

4.1. Spatial distribution of land use and land cover over the study area

The land use and land cover (LULC) classes were presented in distribution maps, histograms and tables. Additionally, the Normalized Difference Vegetation Index (NDVI) maps, time series, and values are presented.

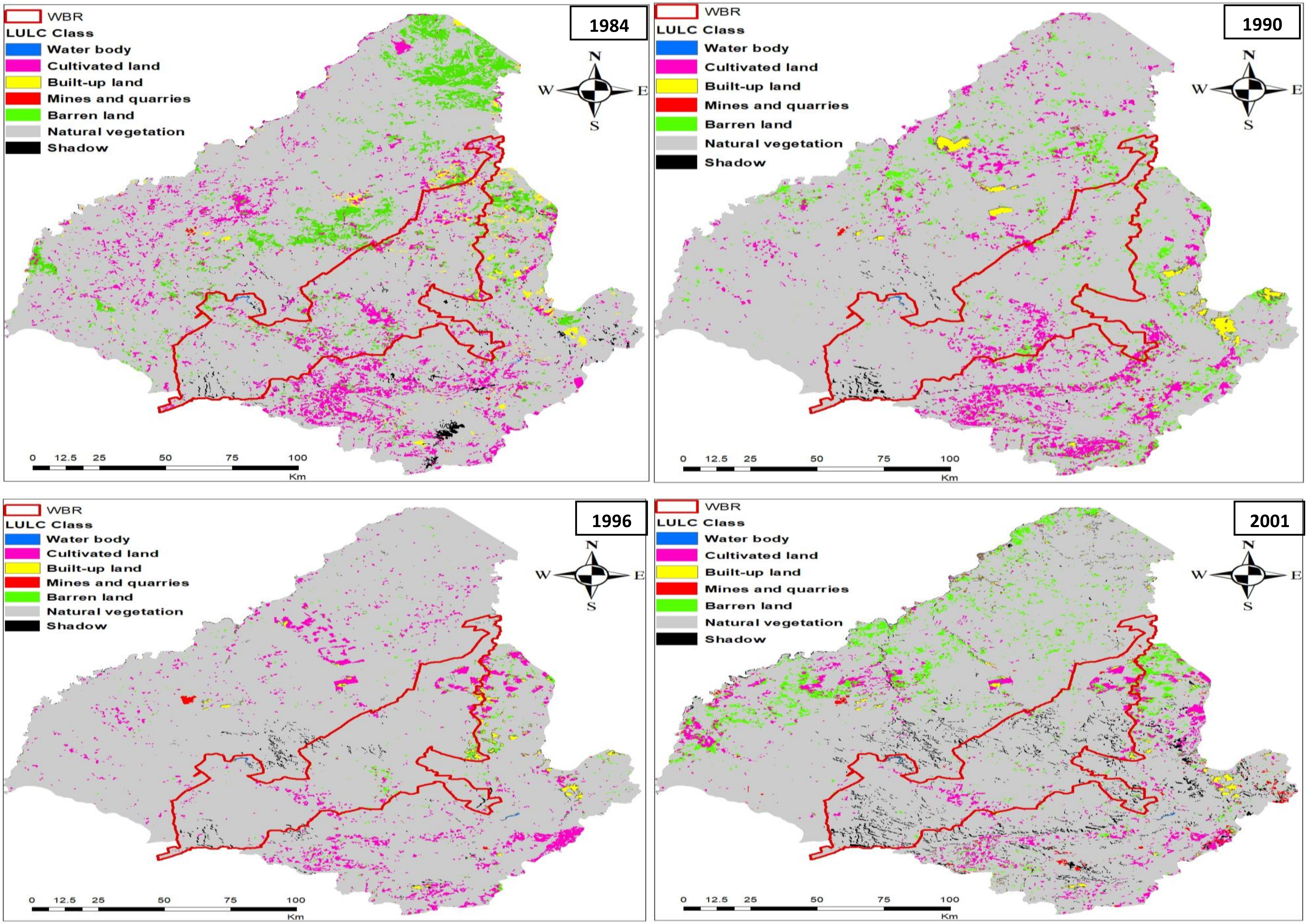
4.1.1. Land use and land cover maps over the entire study area

Over the time period from 1984 to 2016, natural vegetation was the dominant LULC class in the study area as it occupied 81.85% in 1984, 88.11% in 1990, 92.45% in 1996, 90.70% in 2001, 87.13% in 2006, 85.58% in 2011 and 89.21% in 2016. This followed by cultivated land, bare land, built up area, mines and water bodies (Figure 3 and 4 and table 4).

The cultivated land decreased over the time period 1984 to 2001 as it was 7.4% in 1984,6.64% in 1990, 4.63% in 1996 and 3.97% in 2001 then increased from 3.97% in 2001 to 4.09 % in 2006, 4.48% in 2011 and decreased to 4.44% in 2016 (Figure 3 and 4 and table 4).

Water bodies covered the smallest portion of the land (figure 3 and 4 and table 4) and land occupied by this LULC class was 0.03 % in 1984, 0.05 % in 1990, 0.07 % in 1996, 0.17% in 2001, 0.09% in 2006, 0.09% in 2006 and 0.06 % in 2016.

There are multiple mining activities taking place within the Waterberg region. Table 4 shows that 0.03% in 1984, 0.05% in 1990, 0.12 % in 1996, 0.09% in 2001, 0.11% in 2006, 0.11% in 2011and 0.17% in 2016 of land was covered by mining activities and occur close to Lephalale and Mokopane (Figure 3). The coverage and distribution of built-up land over the study area (Figure 3 and 4). Table 4 also shows an increment on the built-up land from 1984 to 2016 as it was 0.99% in 1984, 1.05% in 1990, 1.06% in 1996, 1.09% in 2001, 1.13% in 2006, 1.25 % in 2011 and 1.41 % in 2016. Figure 5 and 6 show NDVI spatial distribution and time series, respectively, from the year 1984 to 2016. The NDVI shows different values from 1984 to 2016 as it was 0.30 in 1984, 0.28 in 1990, 0.30 in 1996, 0.27 in 2001, 0.28 in 2006, 0.28 in 2011 and 0.26 in 2016 (Table 5).


1984
WBR
LULC Class
Water body
Cultivated land
Built-up land
Mines and quarries
Barren land
Natural vegetation
Shadow
N
W
E
S
0 12.5 25 50 75 100
Km
1990
WBR
LULC Class
Water body
Cultivated land
Built-up land
Mines and quarries
Barren land
Natural vegetation
Shadow
N
W
E
S
0 12.5 25 50 75 100
Km
1996
WBR
LULC Class
Water body
Cultivated land
Built-up land
Mines and quarries
Barren land
Natural vegetation
Shadow
N
W
E
S
0 12.5 25 50 75 100
Km
2001
WBR
LULC Class
Water body
Cultivated land
Built-up land
Mines and quarries
Barren land
Natural vegetation
Shadow
N
W
E
S
0 12.5 25 50 75 100
Km

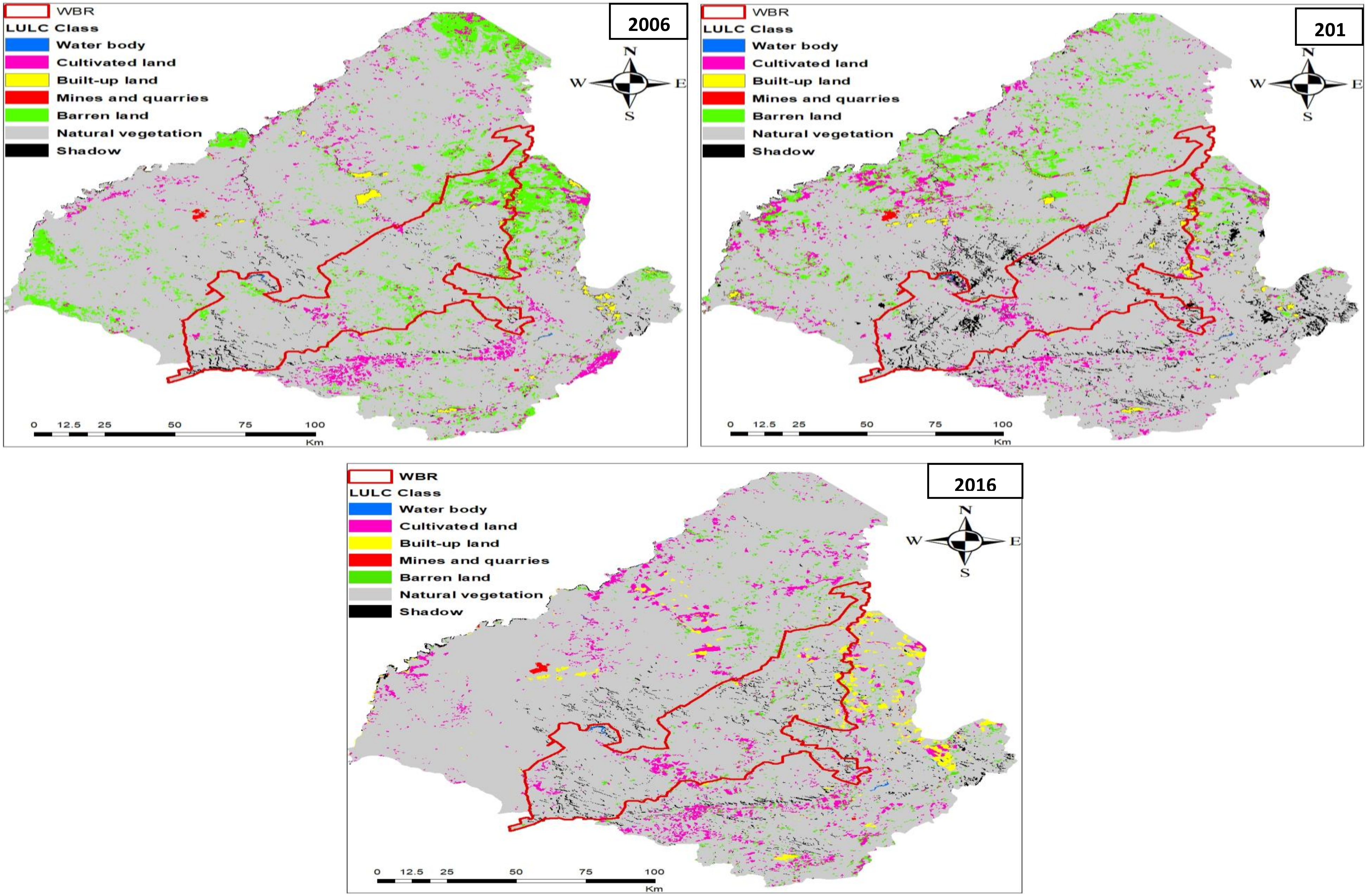
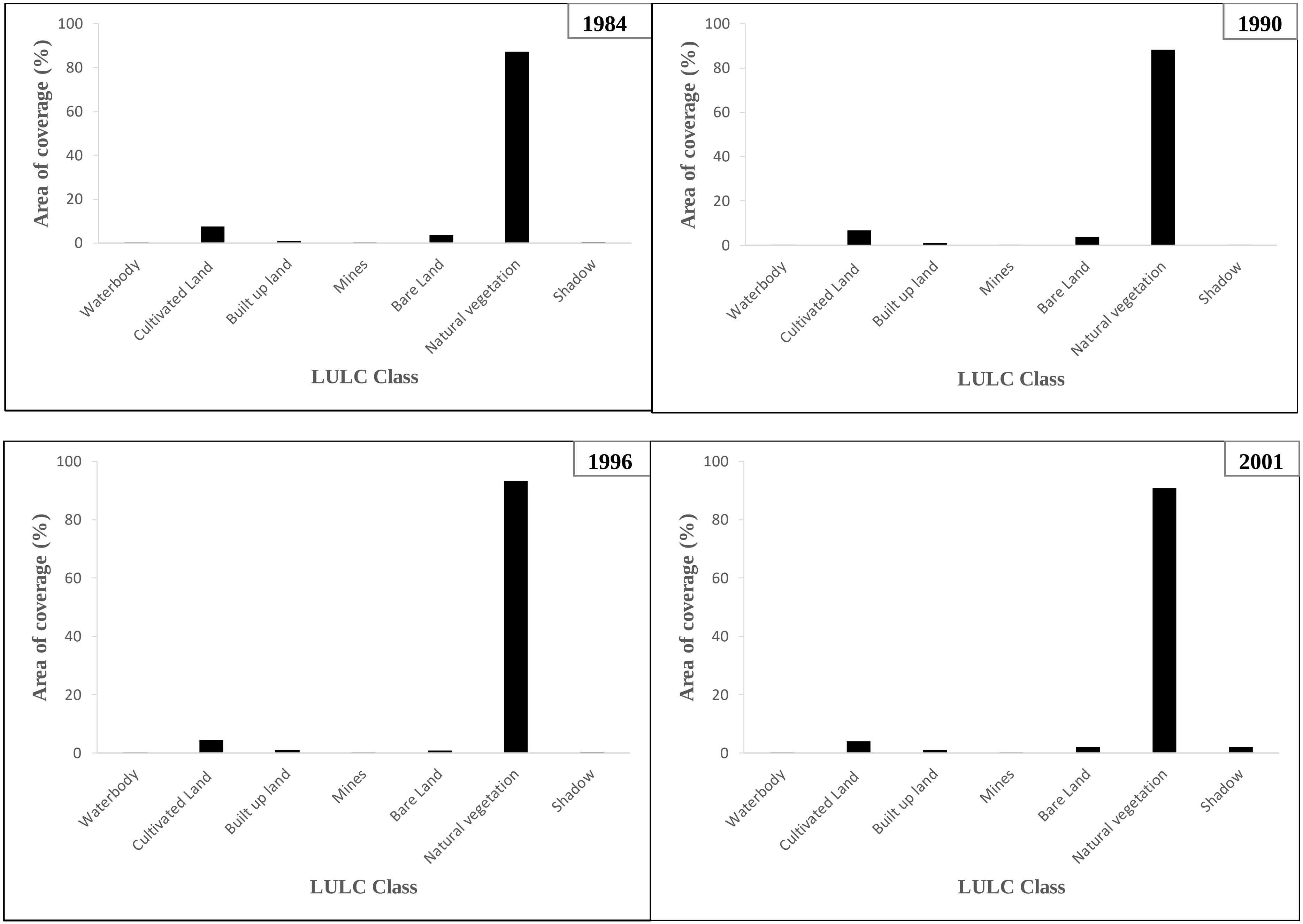


Figure 3: LULC map of WBR in 1984, 1990, 1996, 2001, 2006, 2011 and 2016


1984
1990
1996
2001
Area of coverage (%)
100
80
60
40
20
0
Waterbody
Cultivated Land
Built up land
Mines
Bare Land
Natural vegetation
Shadow
LULC Class

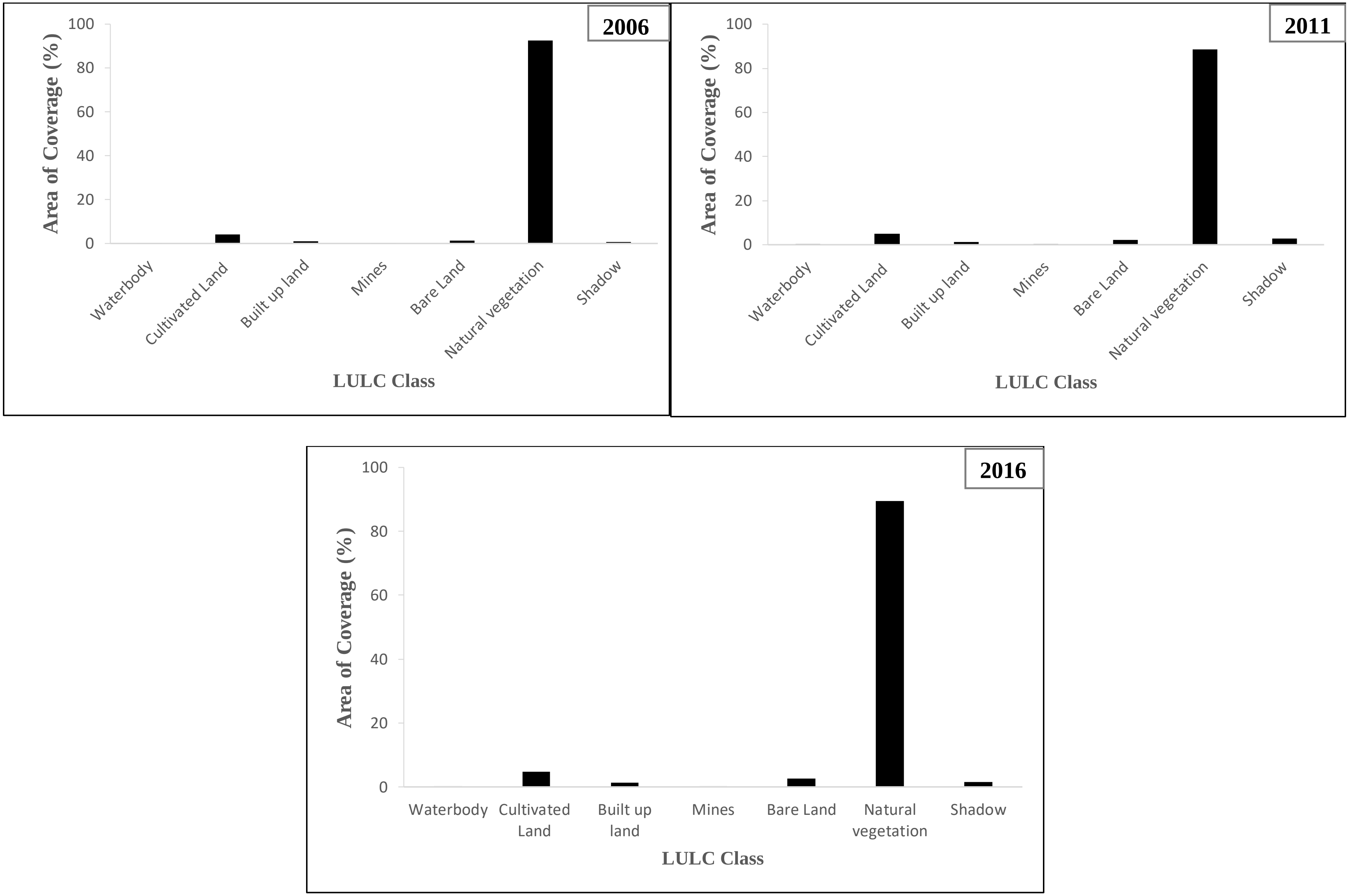
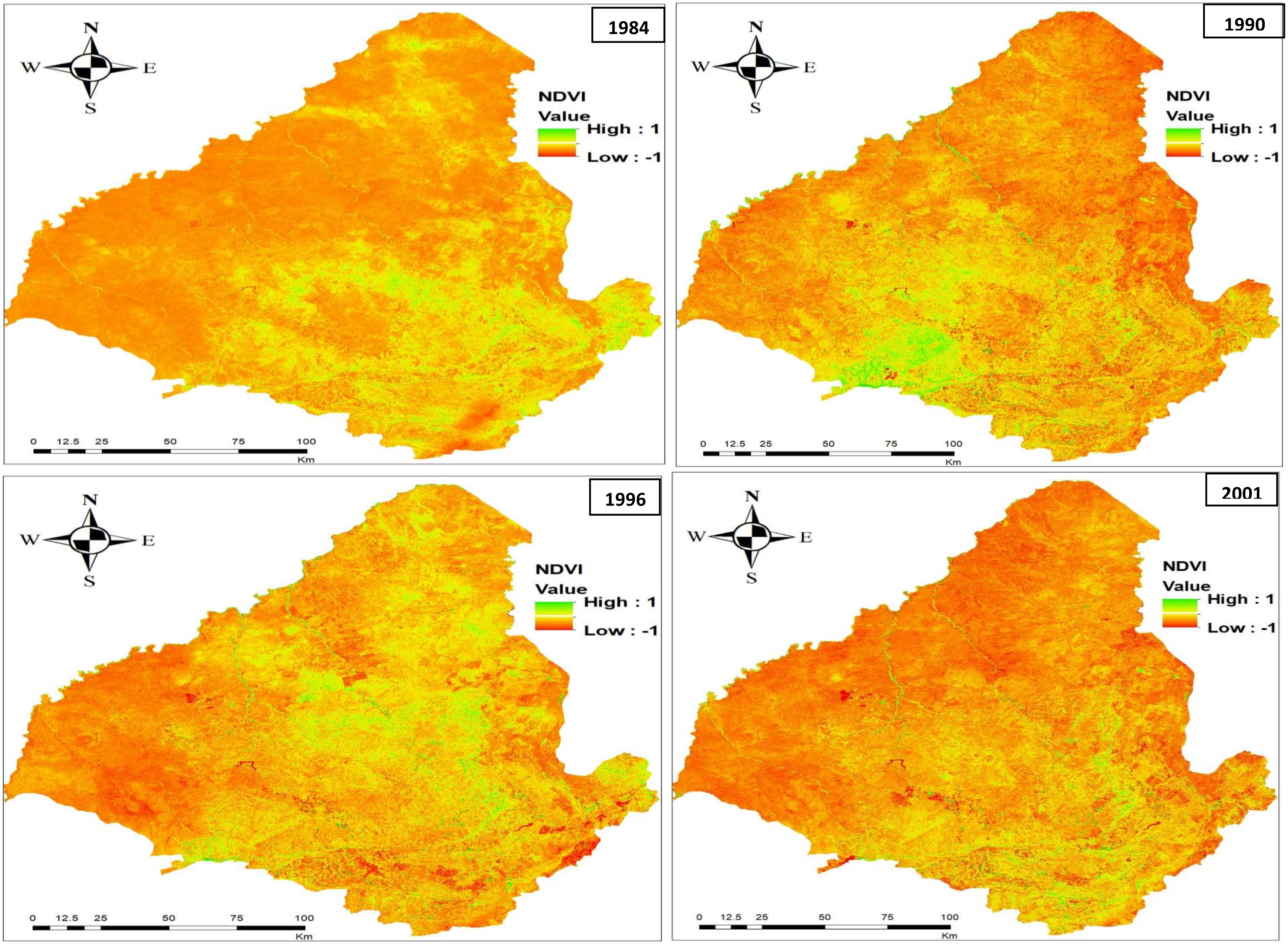


Figure 4: LULC coverage (%) for 1984, 1990, 1996, 2001, 2006, 2011,and 2016

Table 4: LULC coverage of the study area for the years 1984, 1990,1996,2001,2011 and 2016

	1984		**1990**		**1996**		**2001**		**2006**		**2011**		**2016**	
LULC	**ha**	**%**	**ha**	**%**	**ha**	**%**	**ha**	**%**	**ha**	**%**	**ha**	**%**	**ha**	**%**
Water body	968.85	0.03	1590.93	0.05	2277.9	0.07	5484.24	0.17	3221.82	0.10	3079.53	0.09	1971.63	0.06
Cultivated Land	243967.2	7.69	219121.7	6.64	143927.5	4.36	130869.5	3.97	137432.7	4.17	166994	5.06	156088.1	4.73
Built up land	31307.67	0.99	34594.92	1.05	34836.21	1.06	35876.7	1.09	37393.2	1.13	41182.92	1.25	46617.3	1.41
Mines	1102.77	0.03	1593.54	0.05	2483.37	0.08	2877.66	0.09	2449.71	0.07	3292.56	0.10	3528.09	0.11
Bare Land	117936	3.72	127867.4	3.87	24310.53	0.74	63762.57	1.93	40040.28	1.21	68487.21	2.08	87978.87	2.67
Natural vegetation	2764748	87.09	2909743	88.12	3079293	93.34	2992671	90.70	3052296	92.54	2921750	88.61	2953400	89.48
Shadow	14376.78	0.45	7683.21	0.23	11877.3	0.36	67988.79	2.06	25575.21	0.78	92453.13	2.80	50949.99	1.54


1984
N
W
E
S
NDVI
Value
High : 1
Low : -1
0 12.5 25 50 75 100
Km
1990
N
W
E
S
NDVI
Value
High : 1
Low : -1
0 12.5 25 50 75 100
Km
1996
N
W
E
S
NDVI
Value
High : 1
Low : -1
0 12.5 25 50 75 100
Km
2001
N
W
E
S
NDVI
Value
High : 1
Low : -1
0 12.5 25 50 75 100
Km

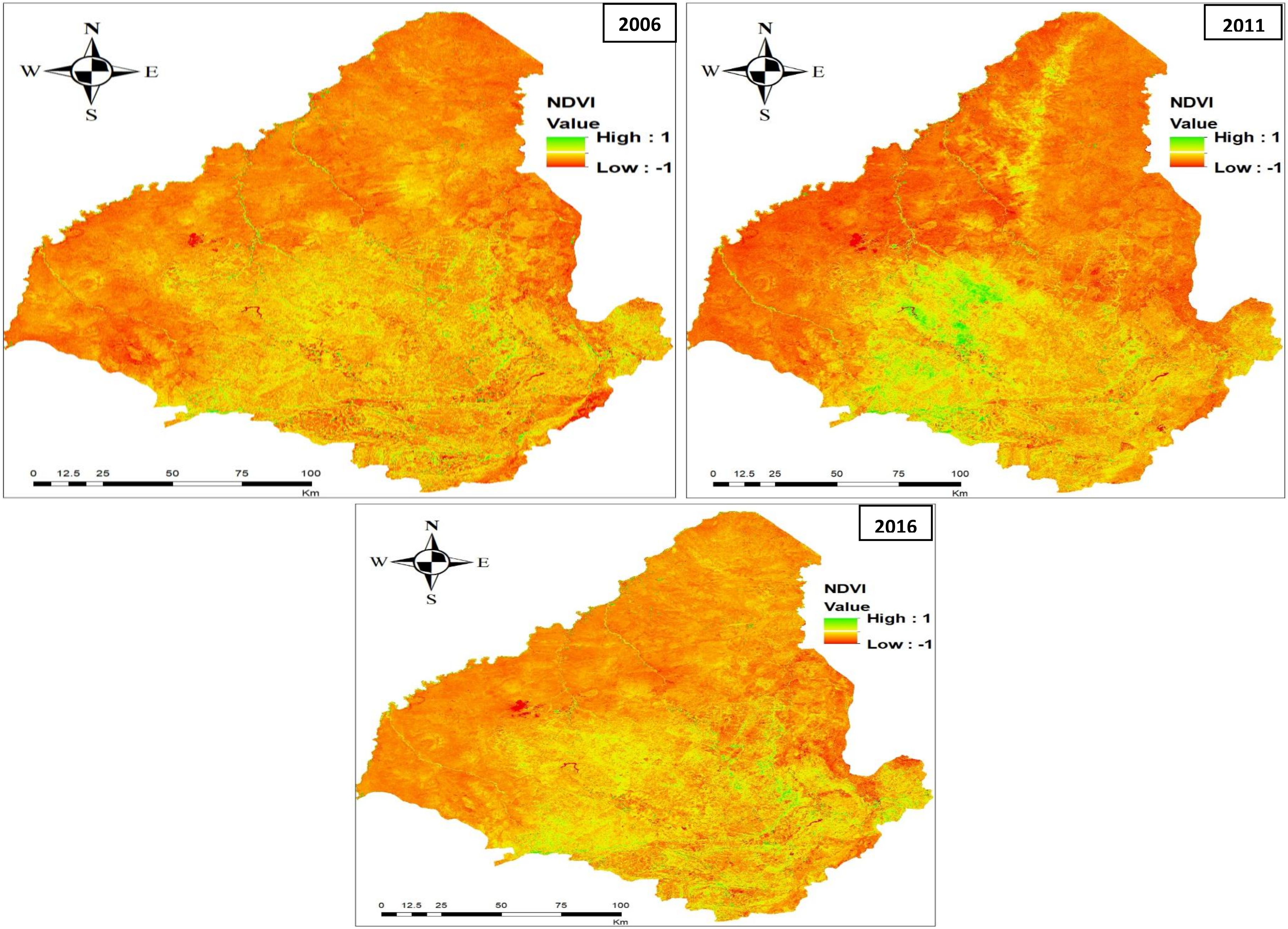


Figure 5: NDVI maps for the year 1984, 1990, 1996, 2001, 2006, 2011 and 2016

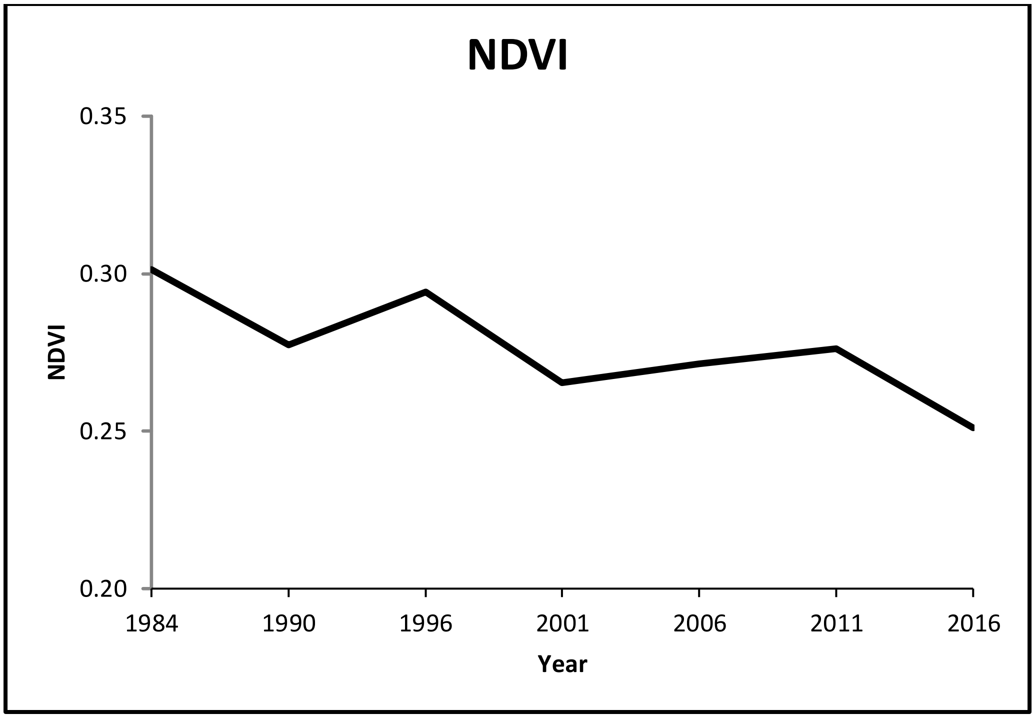


Figure 6: NDVI trend from 1984 to 2016

Table 5: NDVI values from 1984 to 2016

Year	1984	1990	1996	2001	2006	2011	2016
NDVI	0.31	0.28	0.30	0.27	0.28	0.28	0.26

4.1.2. Land use and land cover coverage in WBR and surroundings

Comparative analysis of LULC coverage between inside and outside the WBR was undertaken to determine the impact of the WBR on the landscape of the study area. Paired t-tests were performed to test the statistical difference between LULC coverage inside and outside the WBR. The differences in LULC and NDVI between inside and outside the WBR are illustrated in Table 6 and figure 7 and 8).

Natural vegetation has the greatest share on both sides (Inside and outside the WBR) of the study area from 1984 to 2016. The natural vegetation occupied 86.51% and 87.23% in 1984 , 91.32% and 87.32% in 1990, 94.47% and 93.06% in 1996 , 91.06 % and 90.61 % in 2001, 94.45 % and 92.07 % in 2006, 88.79% and 88.57% in 2011 and 90.23% and 89.30% in 2016 of the land inside and outside the WBR, respectively (Table 6 and figure 7).

Cultivated land shows a decreasing trend in both sides of the study area (Table 6 and figure 7). The land covered by this LULC class inside and outside WBR was 8.41 % and 7.52% in 1984, 5.03% and 7.04% in 1990, 2.74% and 4.76% in 1996, 3.02% and 4.20% in 2001, 2.18% and 4.66% in 2006, 3.92% and 5.35% in 2011 and 4.04 and 4.90%, respectively.

Water bodies class has the smallest share of the land on both sides of the study area and its coverage outside the WBR is less compared to water bodies coverage inside the WBR. Table 6 and figure 7 illustrate that land covered by water was 0.10 % in 1984, 0.15% in 1990, 0.17% in 1996, 0.22% in 2001, 0.19% in 2006,0.19% in 2011 and 0.13% in 2016 (Outside the WBR) whereas it covered 0.01%, 0.02%, 0.04%, 0.15%, 0.08%, 0.07% and 0.04% outside the WBR over the same time period.

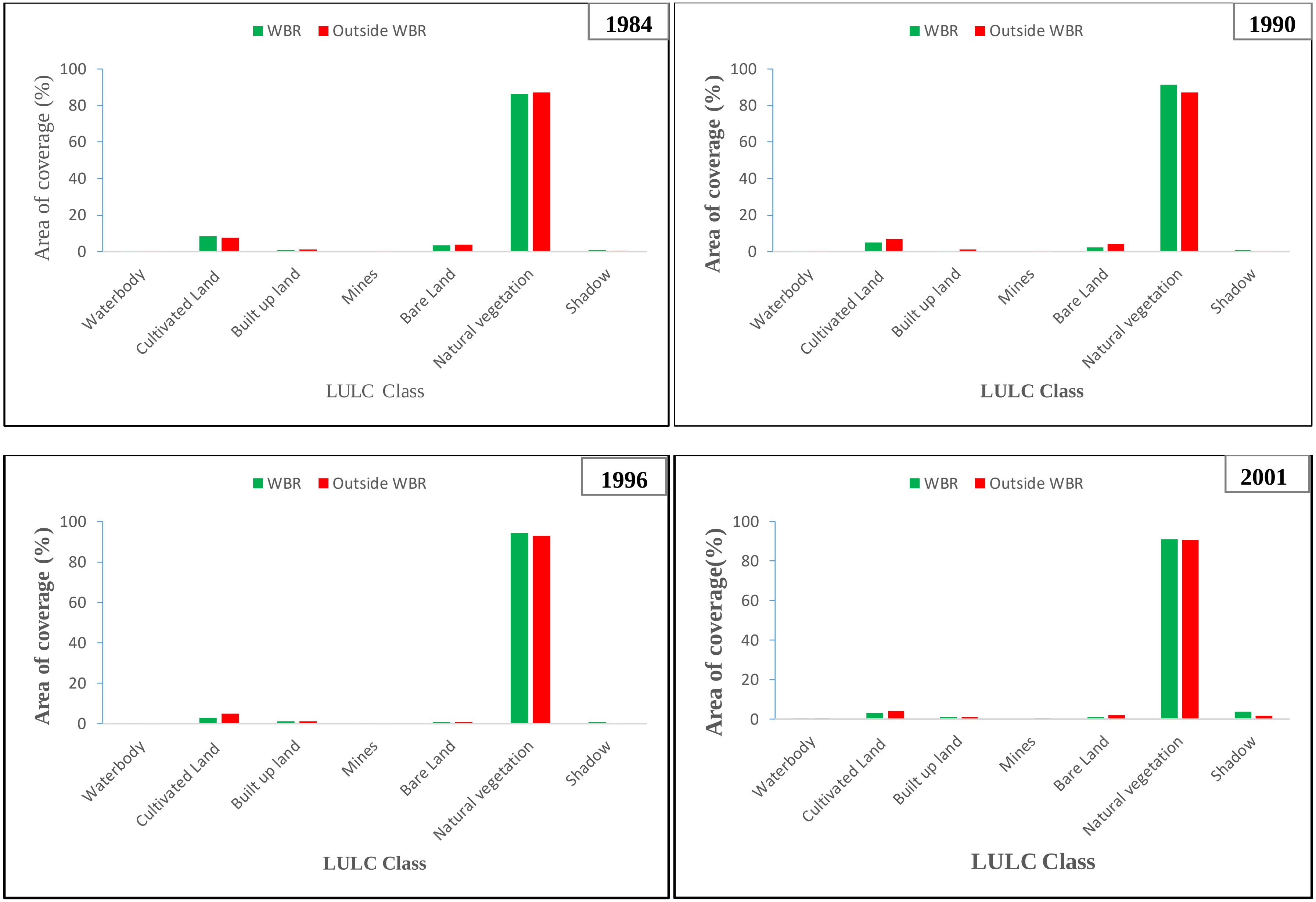
Mining activities are taking place within the region, however, these activities are outside the periphery of the WBR. The land occupied by mines increased from 1984 to 2016 as it was 0.04% in 1984, 0.06% in 1990, 0.09% in 1996, 0.11% in 2001, 0.09% in 2006, 0.12% in 2011 and 0.13% in 2016 outside the WBR.

Table 7 shows the difference in land covered by built-up land between inside and outside the WBR. The land covered by built up was 0.79% in 1984, 0.30% in 1990, 1.04% in 1996, 0.95% in 2001, 0.80 in 2006,1.25% in 2011 and 0.69 in 2016 and differed to 1.04% ,1.22%, 1.06%, 1.12%, 1.22%, 1.25% and 1.59% (Inside) of land covered by same LULC class outside the WBR over the same analysis period.

The NDVI inside the WBR is different from NDVI outside the WBR. Figure 8 shows higher NDVI values inside the WBR compared to NDVI outside the Biosphere Reserve.

Table 6: LULC coverage within and outside the WBR from 1984 to 2016

	1984		1990		1996		2001		2006		2011		2016	
LULC Classes	**WBR**	**Outside WBR**	**WBR**	**Outside WBR**	**WBR**	**Outside WBR**	**WBR**	**Outside WBR**	**WBR**	**Outside WBR**	**WBR**	**Outside WBR**	**WBR**	**Outside WBR**
	%	**%**		**%**	**%**	**%**	**%**	**%**	**%**	**%**	**%**	**%**	**%**	**%**
W	0.10	0.01	0.15	0.02	0.17	0.04	0.22	0.15	0.19	0.08	0.19	0.07	0.13	0.04
CL	8.41	7.52	5.03	7.04	2.74	4.76	3.02	4.20	2.18	4.66	3.92	5.35	4.04	4.90
BUL	0.79	1.04	0.30	1.22	1.04	1.06	0.95	1.12	0.80	1.22	1.25	1.25	0.69	1.59
M	0.00	0.04	0.00	0.06	0.00	0.09	0.00	0.11	0.00	0.09	0.00	0.12	0.01	0.13
BL	3.55	3.76	2.43	4.23	0.89	0.70	1.12	2.13	0.63	1.36	0.80	2.39	2.35	2.74
NV	86.51	87.23	91.32	87.32	94.47	93.06	91.06	90.61	94.45	92.07	88.79	88.57	90.23	89.30
S	0.65	0.41	0.77	0.10	0.69	0.28	3.63	1.67	1.75	0.54	5.06	2.25	2.55	1.30


1984
WBR
Outside WBR
Area of coverage (%)
100
80
60
40
20
0
Waterbody
Cultivated Land
Built up land
Mines
Bare Land
Natural vegetation
Shadow
LULC Class
1990
WBR
Outside WBR
Area of coverage (%)
100
80
60
40
20
0
Waterbody
Cultivated Land
Built up land
Mines
Bare Land
Natural vegetation
Shadow
LULC Class
1996
WBR
Outside WBR
Area of coverage (%)
100
80
60
40
20
0
Waterbody
Cultivated Land
Built up land
Mines
Bare Land
Natural vegetation
Shadow
LULC Class
2001
WBR
Outside WBR
Area of coverage(%)
100
80
60
40
20
0
Waterbody
Cultivated Land
Built up land
Mines
Bare Land
Natural vegetation
Shadow
LULC Class

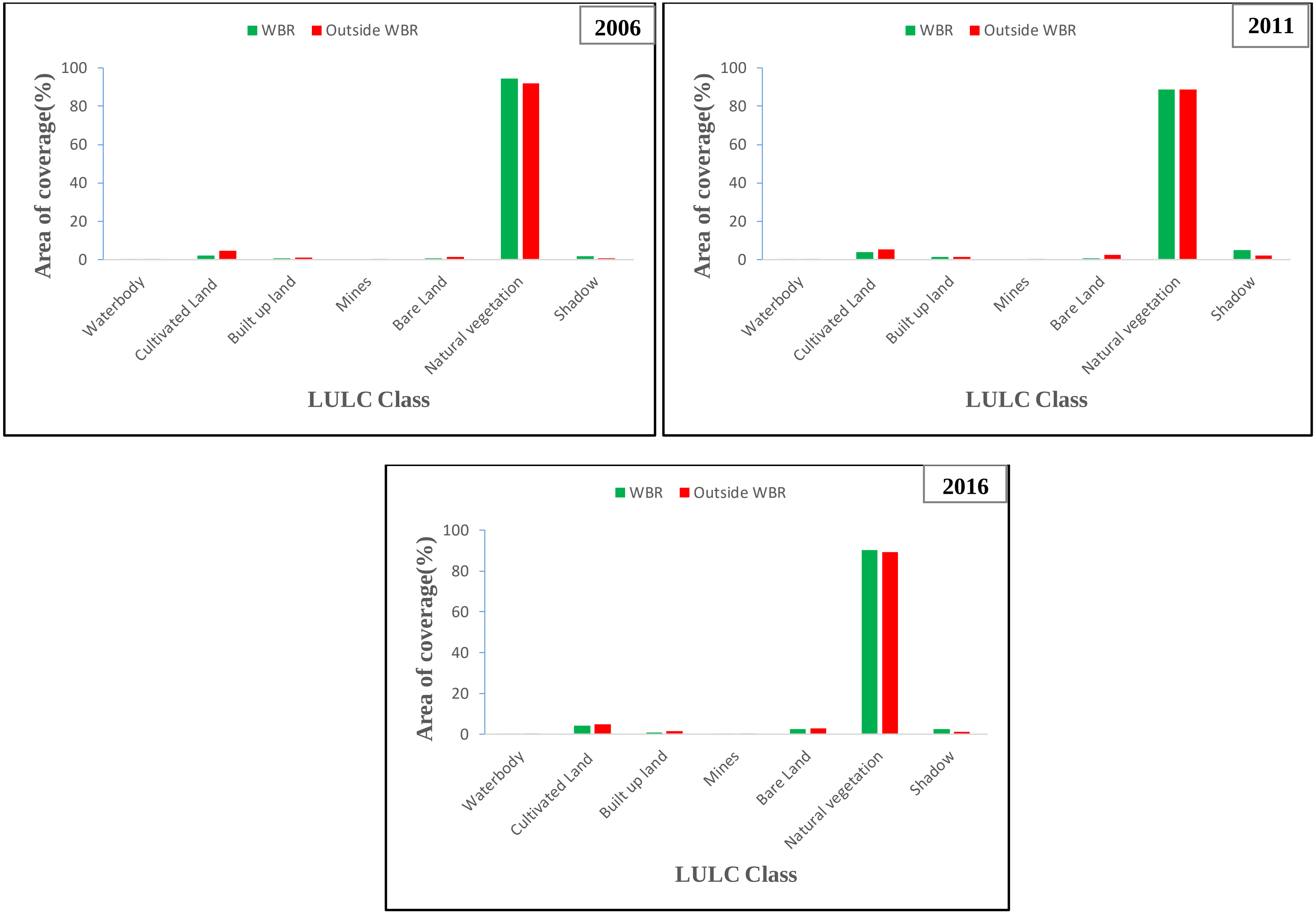


Figure 7: LULC coverage (%) inside and outside WBR for 1984, 1990, 1996, 2001, 2006, 2011 and 2016

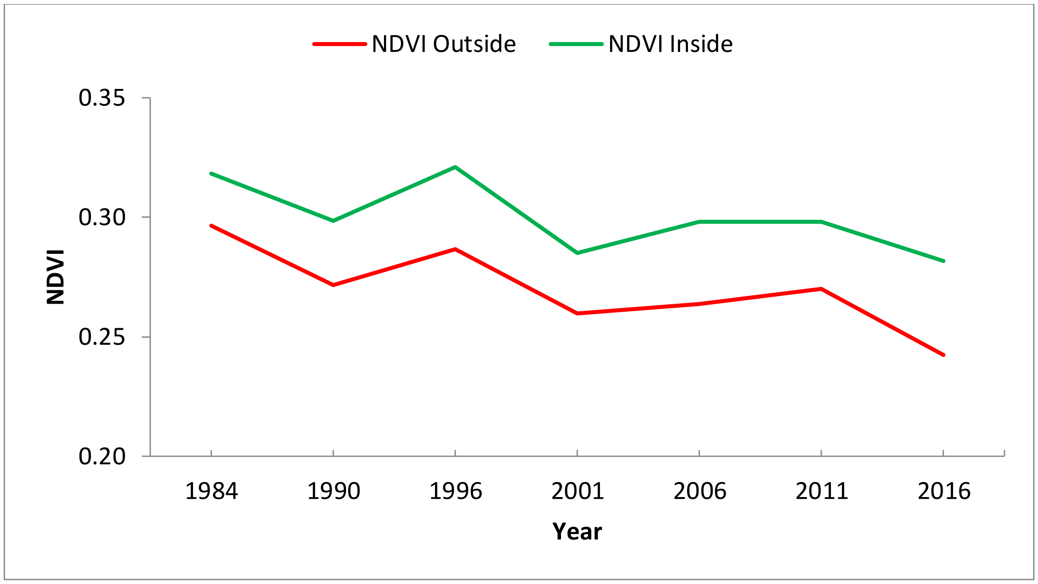


Figure 8: NDVI comparison between inside and outside the WBR

4.2. Accuracy assessment

Accuracy assessments of all images that were individually classified by SVM were performed using the confusion matrices within ENVI 5.4. The remaining 30% of the reference data was used for the construction of the confusion matrices. The validation datasets were digitized from topographical maps and aerial photographs for the years 1984, 1990, 1996, and 2001 and for the years 2006, 2011 and 2016 were derived from Google Earth imagery. The user's accuracies, producer's accuracies, overall accuracies, and Kappa coefficients are presented on the tables 7-13.

Table 7: The confusion matrix for the 1984 classified image

	Reference Data									
	LULC Classes	**W**	**CL**	**BUL**	**M**	**BL**	**NV**	**S**	**Totals**	**User's Accuracy (%)**
Classification Data	**W**	**36**	0	0	0	0	0	0	100	100
	CL	0	**34**	1	0	1	1	1	38	89.47
	BUL	0	0	**37**	0	0	1	0	38	97.37
	M	0	0	0	**40**	0	0	0	39	100
	BL	0	3	3	0	**41**	1	0	48	85.42
	NV	2	5	1	3	0	**39**	6	56	69.64
	S	0	0	0	0	0	0	**35**	35	100
	Totals	42	42	42	42	42	42	42	**294**	
	Producer's Accuracy (%)	95.24	80.95	88.10	92.86	97.62	92.86	83.33		
	Kappa Index=0.81, Overall Accuracy=90.14									

W=Water body, CL=Cultivated Land, BUL=Built up Land, M=Mines, BL=Bare Land, NV=Natural Vegetation and S=Shadow

Table 8: The confusion matrix for the 1990 classified image

	Reference Data									
Classification Data	**LULC Classes**	**W**	**CL**	**BUL**	**M**	**BL**	**NV**	**S**	**Totals**	**User's Accuracy (%)**
	W	**31**	0	0	0	0	0	0	31	100
	CL	1	**35**	0	0	3	0	0	39	89.74
	BUL	0	5	**40**	0	8	0	0	53	75.47
	M	0	0	0	**41**	0	0	0	41	100
	BL	0	0	1	0	**19**	0	0	20	95
	NV	10	2	1	1	12	**42**	12	80	52.50
	S	0	0	0	0	0	0	**30**	30	100
	Totals	42	42	42	42	42	42	42		
	Producer's Accuracy (%)	73.81	83.33	95.24	97.62	45.24	100	95.24		
	Kappa Index=0.78, Overall Accuracy=80.95									

W=Water body, CL=Cultivated Land, BUL=Built up Land, M=Mines, BL=Bare Land, NV=Natural Vegetation and S=Shadow

Table 9: The confusion matrix for the 1996 classified image

	Reference Data									
Classification Data	**LULC Classes**	**W**	**CL**	**BUL**	**M**	**BL**	**NV**	**S**	**Totals**	**User's Accuracy (%)**
	W	**40**	0	0	0	0	0	0	100	100
	CL	0	**34**	1	0	1	1	1	38	89.47
	BUL	0	0	**37**	0	0	1	0	38	97.37
	M	0	0	0	**39**	0	0	0	39	100
	BL	0	3	3	0	**41**	1	0	48	85.42
	NV	2	5	1	3	0	**39**	6	56	69.64
	S	0	0	0	0	0	0	**35**	35	100
	Totals	42	42	42	42	42	42	42	**294**	
	Producer's Accuracy (%)	95.24	80.95	88.10	92.86	97.62	92.86	83.33		
	Kappa Index=0.81, Overall Accuracy=90.14									

W=Water body, CL=Cultivated Land, BUL=Built up Land, M=Mines, BL=Bare Land, NV=Natural Vegetation and S=Shadow

Table 10: The confusion matrix for the 2001 classified image

	Reference Data									
	LULC Classes	**W**	**CL**	**BUL**	**M**	**BL**	**NV**	**S**	**Totals**	**User's Accuracy (%)**
Classification Data	**W**	**41**	0	0	0		0	0	41	100
	CL	0	**27**	0	0	7	0	0	34	79.41
	BUL	0	0	**41**	0	3	0	0	44	93.18
	M	0	0	0	**42**	3	0	0	45	85.42
	BL	0	0	0	0	**23**	0	0	23	100
	NV	1	14	1	0	6	**41**	1	64	64.06
	S	0	1	0	0	0	1	**41**	43	95.34
	Totals	42	42	42	42	42	42	42	**294**	
	Producer's Accuracy (%)	97.62	64.29	97.62	100	54.76	97.62	97.62		
	Kappa Index=0.81, Overall Accuracy=87.07									

W=Water body, CL=Cultivated Land, BUL=Built up Land, M=Mines, BL=Bare Land, NV=Natural Vegetation and S=Shadow

Table 2: The confusion matrix for the 2006 classified image

	Reference Data									
	LULC Classes	**W**	**CL**	**BUL**	**M**	**BL**	**NV**	**S**	**Totals**	**User's Accuracy (%)**
Classification Data	**W**	**41**	0	0	0	0	0	2	43	95.35
	CL	0	**38**		0	6	0	0	44	86.36
	BUL	0	0	**37**	4	0	0	0	41	90.24
	M	0	0	0	**32**	0	0	0	32	100.00
	BL	0	2	3	0	**29**	0	0	33	76.32
	NV	1	2	2	6	7	**36**	3	57	63.16
	S	0	0	0	0	0	6	**37**	43	95.24
	Totals	42	42	42	42	42	42	42	294	
	Producer's Accuracy (%)	97.62	90.48	88.10	76.19	69.05	85.71	88.10		
	Kappa Index=0.81, Overall Accuracy=85.03									

W=Water body, CL=Cultivated Land, BUL=Built up Land, M=Mines, BL=Bare Land, NV=Natural Vegetation and S=Shadow

Table 3: The confusion matrix for the 2011 classified image

	Reference Data									
Classification Data	**LULC Classes**	**W**	**CL**	**BUL**	**M**	**BL**	**NV**	**S**	**Totals**	**User's Accuracy (%)**
	W	**38**	0	0	0	0	0	0	38	100
	CL	2	**34**	0	0	4	2	0	42	80.95
	BUL	0	2	**38**	0	0	0	0	40	95
	M	0	0	0	**37**	0	0	0	37	100
	BL	0	0	1	0	**23**	1	0	25	92
	NV	2	6	3	4	15	**39**	2	72	54.17
	S	0	0	0	0	0	0	**40**	40	100
	Totals	42	42	42	42	42	42	42		
	Producer's Accuracy (%)	90.48	80.95	90.48	88.10	57.76	92.86	95.24		
	Kappa Index=0.81, Overall Accuracy=84.69									

W=Water body, CL=Cultivated Land, BUL=Built up Land, M=Mines, BL=Bare Land, NV=Natural Vegetation and S=Shadow

Table 13: The confusion matrix for the 2016 classified image

	Reference Data									
Classification Data	**LULC Classes**	**W**	**CL**	**BUL**	**M**	**BL**	**NV**	**S**	**Totals**	**User's Accuracy (%)**
	W	**39**	0	0	0	0	0	0	39	100
	CL	0	**28**	0	0	0	0	0	28	100
	BUL	0	1	**41**	0	0	0	0	42	97.62
	M	0	0	0	**37**	0	3	0	40	97.37
	BL	0	2	0	0	**24**	0	0	29	92.31
	NV	1	11	1	5	18	**39**	2	77	50.65
	S	2	0	0	0	0	0	**40**	42	95.24
	Totals	42	42	42	42	42	42	42		
	Producer's Accuracy (%)	88.10	66.67	97.62	88.10	57.14	92.86	95.24		
	Kappa Index=0.81, Overall Accuracy=84.35									

W=Water body, CL=Cultivated Land, BUL=Built up Land, M=Mines, BL=Bare Land, NV=Natural Vegetation and S=Shadow

The overall accuracies for seven classified images range from 80.95% to 90.14%. The bare land has the lowest producer's accuracy of 45.24% in 1990 (Table 7). The user's accuracy for natural vegetation was the lowest in 2016 with a value of 50.65% (Table 13). The low values in bare land indicate that the class is sharing spectral reflectance with other classes such as cultivated lands.

On the other hand, a low value in natural vegetation also indicates difficulty in spectral separation between two or more classes such as bare land as the area is going through conversion from conventional farming to game farming. Kappa coefficient indices ranged from 0.78 to 0.81 which is “substantial” (0.61-0.80) and “almost perfect” (0.81-1.00) (Landis and Koch, 1977).

4.3. Change detection

The study area’s LULC classes insignificantly changed from 1984 to 2016. The LULC and NDVI changes occurred within and outside are compared in table 14 and 15. In table 14 and 15, positive and negative signs indicate an increase and decrease of LULC class and NDVI between different epochs.

4.3.1. Comparative analysis of WBR and its surroundings

A comparative analysis was undertaken to determine the overall impact of the WBR on the LULC of the study area, as well as the differences between the WBR and its surrounding area. All LULC classes did not change significantly within and outside the WBR from 1984 to 2016 (Table 14). The NDVI outside follows the same trend with NDVI inside the WBR over the analysis period and changed significantly over some analysis periods (Table 15).

The land covered by natural vegetation shows similar change pattern within and outside the WBR. the natural vegetation gained on both sides of the study area during 1984-1990,1990-1996, 2001-2006 and 2011-2016 analysis periods by 4.82% and 0.10%, 3.15% and 5.74%, 5.52% and 3.97%, and 1.44% and 0.73% inside and outside respectively. However, natural vegetation decreased in time periods 1996-2001 (3.55% inside and 4.96% outside) and 2006-2011 (5.66% inside and 3.50% outside) (Table 14). The change in natural vegetation land was insignificant ($P>0.05$).

Cultivated land insignificantly decreased inside and outside the WBR ($P>0.05$). Table 15 shows that cultivated land decreased by 3.42% and 0.47% (1984-1990) and 2.25% and 2.28% (1990-1996) inside and outside respectively. In 1996-2001, 2001-2006 and 2011-2016 analysis periods, the insignificant difference was observed between cultivated land changes inside and outside as cultivated land decreased by 0.18% outside and increased by 0.42% inside the WBR (1996-2001). A similar trend was observed in time period 2011-2016 where cultivated land increased (0.12%) inside and decreased (0.45%) outside the WBR. However, cultivated land decreased inside the WBR by 0.98% and increased by 0.07% outside the WBR (2001-2006). In 2006-2011, cultivated land increased on both sides of the study (1.74% inside and 0.69%) (Table 14).

Table 14 shows that mines increased from 1984 to 2016 outside the periphery of the WBR. Mines increased by 0.02% in 1984-1990, 0.03% in 1990-1996, 0.07% in 1996-2001, 0.03% in 2006-2011 and 0, 01% in 2011-2016 analysis periods outside the WBR. However, mines decreased by 0.07% between 2001 and 2006 outside the WBR. Water bodies show similar change trends between inside and outside of the WBR except between the year 2006 and 2011, where it decreased by 0.01% and unchanged (0.00%) outside and inside respectively.

Water bodies increased from both sides of the study area in 1984-1990 (0.05% inside and 0.01% outside), 1990-1996 (0.02% both sides) and 1996-2001 (0.05% inside and 0.11% outside) and decreased by 0.03% inside and 0.08% outside (2001-2006) and 0.06% inside and 0.03% outside (2011-2016) the WBR.

The built land insignificantly changed from 1984 to 2016($P>0.05$), a similar trend in built-up land change between inside and outside was only observed between 2006 and 2011. Over this analysis period, inside and outside the WBR increased by 0.44% and 0.03% respectively. In analysis period 1984-1990, 1996-2001 and 2011-2016, built up land decreased inside while increasing outside the WBR (Table 14). The built-up land decreased by 0.42%,0.36% and 0.56% inside whereas increasing outside the WBR by 0.18%,0.16% and 0.34% over the aforementioned time period. An increase and decrease of the built-up land inside and outside of the WBR were observed over analysis periods 1990-1996 and 2001-2006. The built-up land increased by 0.67% (1990-1996) and 0.12% (2001-2006) inside the WBR while decreasing by 0.16% and 0.01% outside the BR respectively.

NDVI significantly decreased ($T=3.58$, $df =151$, $P<0.05$) in 1984-1990 outside the WBR by the value of 0.02 inside whereas insignificantly decreased by the same value inside the WBR (Table 15). The NDVI significantly increased (Inside=-2.71, $df = 43$, $P<0.05$ and outside=-4.77, $df = 151$, $P < 0.05$) and then decreased (Inside=-3.33, $df = 43$, $P < 0.05$ and outside = 1.62, $df = 151$, $P < 0.05$) in 1990-1996 and 1996-2001, respectively. The NDVI insignificantly increased in the time period 2001-2006 by 0.01 and <0.01 inside and outside the WBR respectively. Over time period 2006-2011, the NDVI change was insignificant inside the WBR and outside the WBR. NDVI did not change significantly within the WBR, but significantly declined ($T = 10.64$, $df = 151$, $P<0.05$) by 0.02 outside the WBR.

Table 14: LULC changes (%) within and outside WBR from 1984 to 2016

(W=Water bodies, CL=Cultivated Land, BUL=Built up Land, M=Mines, BL=Bare Land, NV=Natural Vegetation, S=Shadow, WBR=Waterberg Biosphere Reserve and OWBR=Outside Waterberg Biosphere Reserve)

	1984-1990		***1990-1996***		***1996-2001***		***2001-2006***		***2006-2011***		***2011-2016***	
LULC	***WBR***	***OWBR***	***WBR***	***OWBR***	***WBR***	***OWBR***	***WBR***	***OWBR***	***WBR***	***OWBR***	***WBR***	***OWBR***
W	*0.05*	*0.01*	*0.02*	*0.02*	*0.05*	*0.11*	*-0.03*	*-0.08*	*0.00*	*-0.01*	*-0.06*	*-0.03*
CL	*-3.42*	*-0.47*	*-2.25*	*-2.28*	*0.42*	*-0.18*	*-0.98*	*0.07*	*1.74*	*0.69*	*0.12*	*-0.45*
BUL	*-0.42*	*0.18*	*0.67*	*-0.16*	*-0.36*	*0.16*	*0.12*	*-0.01*	*0.44*	*0.03*	*-0.56*	*0.34*
M	*0.00*	*0.02*	*0.00*	*0.03*	*0.00*	*0.07*	*0.00*	*-0.07*	*0.00*	*0.03*	*0.01*	*0.01*
BL	*-1.15*	*0.47*	*-1.52*	*-3.53*	*0.49*	*3.42*	*-0.75*	*-2.76*	*0.77*	*1.03*	*1.15*	*0.35*
NV	*4.82*	*0.10*	*3.15*	*5.74*	*-3.55*	*-4.96*	*5.52*	*3.97*	*-5.66*	*-3.50*	*1.44*	*0.73*

Table 15: NDVI Changes and Statistical testing

	1984-1990				**1990-1996**				**1996-2001**				**2001-2006**				**2006-2011**				**2011-2016**			
	Change value	**t-statistic**	**DF**	**p-value**	**Change value**	**t-statistic**	**DF**	**p-value**	**Change value**	**t-statistic**	**DF**	**p-value**	**Change value**	**t-statistic**	**DF**	**P-value**	**Change value**	**t-statistic**	**DF**	**P-value**	**Change value**	**t-statistic**	**DF**	**P-value**
NDVI (Inside)	-0.02	1.76	43	0.08	0.02	-2.71	43	<0.01	-0.03	6.88	43	<0.01	<0.01	-3.33	43	0.2	0.01	0.02	43	0.98	-0.03	1.86	43	0.07
NDVI (Outside)	-0.02	3.5835	151	<0.01	0.02	-4.77	151	<0.01	-0.04	8.07	151	<0.01	0.01	-1.61	151	0.11	-0.00	-1.914	151	0.07	-0.02	10.63	151	<0.01

NDVI=Normalized Difference Vegetation Index and DF=Degree of Freedom

CHAPTER FIVE: DISCUSSION

5.1. Land use and land cover mapping and change analysis

This section is divided into the mapping of land use and land cover (LULC), LULC change analysis from 1984 to 2016 and its implications for the landscape of the WBR are explored.

5.1.1. Mapping land use and land cover distribution using multispectral Landsat data

LULC types in the Waterberg region were successfully mapped using Geographical Information System (GIS) and Remote Sensing (RS) techniques. This concurs with the experiences of Parsa *et al* (2016), Bassa (2012), Coetzer *et al* (2016) and Evans (2017) in their respective study areas. Coetzer *et al* (2016) used GIS and RS techniques to map LULC classes for detecting LULC changes in Kruger to Canyon biosphere reserve and Evans (2014) used South African Land cover maps to map LULC changes within Vhembe biosphere reverse.

The greatest share of the land in the Waterberg region was covered by the natural vegetation, followed agriculture, bare land, built up land, water bodies and mines (1984 to 2016). Natural vegetation in the Waterberg area is well conserved and forms the basis for the ecological management of tourism destinations (Bredenkamp and Brown, 2001) and Walker and Bothma (2005) considered the area as rich in wilderness quality. The high diversity of natural vegetation within the area is primarily due to historical conservation initiatives which became common in the Waterberg region in the 1980s with the first private nature reserve being initiated in 1960s (Snijders, 2012). The Lephalala Wilderness, Welgevonden Game Reserve and numerous private and public nature reserves are results of the conservation initiatives (Marcatelli, 2015).

The conservation development led to the initiation of eco-tourism which today contributes to the local economy, Game farming income increased to R303 millions in 2010 from R9 millions in 1991, South African president Cyril Ramaphosa bought an R19.5 million buffalo cow in Waterberg district in 2012 and Keta Game reserve gained R25 millions in May 2014 (Snijders, 2012; Farmers weekly, 2012; Marcatelli, 2015). However, this type of agricultural practice offers fewer job opportunities contrasted to conventional farming (Snijders; 2012, Spierenburg and Brooks, 2014).

In 1970, farmers also began converting crop farming into game farming, which accelerated in 1994 (Van der Ryst, 1998; DWAF, 2004; Marcatelli, 2015) due to the elimination of government subsidies favoring livestock production in the commercial farming sector, poor nutrient soils and water scarcity problem (Kruger, 2001).

This gives the region a low population density and wilderness character (Walker and Bothma, 2005; Seaman *et al.*, 2013; Marcatelli, 2015). The study by Baber and Abram (2013) indicated that all animal species that were killed by European hunters in the WMC were successfully reintroduced.

Agriculture is another dominant LULC type within the Waterberg region where commercial and subsistence crop farming activities currently occur on alluvial soils close to the Mokolo, Mogalakwena, Matlabas and Lephalala rivers. These activities are mainly distributed in the Mokolo River catchment as it has the largest surface water compared to the other three catchments (DWAF 2004; Seaman *et al.*, 2013).

The maize, tobacco, sorghum, citrus and tropical fruits, and vegetables are among the agricultural products within the region and significantly contribute to the agricultural GDP of the Limpopo Province with Vaalwater town being among the major tobacco growing region in South Africa (DWA, 2012; Seaman *et al.*, 2013). However, crop farming decreased due to farm conversion (Walker and Bothma, 2005; Seaman *et al.*, 2013; Marcatelli, 2015). Bryceson (2000, 2002) stated that people moved from an agricultural dominated lifestyle to non- agricultural income generating activities in Southern Africa.

The Waterberg region has significant mineral zones as it also holds the remaining coalfield to supply coal for fossil fuel based electricity generation for South African and neighboring countries (DMR, 2009; Wardley, 2012). Mining is the currently largest contributor to the Gross Domestic Product in the region (IDP, 2017). However, an increase in mining industry raises concern on the ecological function as well water quality as mining activities at the depleted Highveld coalfield had impacts on the water quality and riparian ecosystem, for example, Acid Mine Drainage (AMD) deteriorates water quality (De Klerk, 2016) but the study by Alphane and Vermeulen (2015) found low chance of AMD occurrence in the region due to limited rainfall, low groundwater recharge, and high evapotranspiration rate. However, proper planning and management of these activities should be prioritized to avoid the consequences of mining within the Waterberg area. An increase in mining activities also raised a new concern in an acute water shortage region which led to water transfer project from Crocodile (West) River into Mokolo River (Van Niekerk and Du Plessis, 2013).

The Waterberg region is a water scarce region with four river catchments namely: Matlabas, Mogalakwena, Lephalala and Mokolo Rivers. Mokolo River has the largest surface water capacity and it is where agricultural (87% water of Mokolo River) and mining activities are mainly located and farmers are opting to convert their crop farming to game farming (DWAF, 2004; Seaman *et al.*, 2013) due to acute water shortage for irrigation. The limited water is also consumed in Grootegeluk Colliery, Matimba Power station, Medupi Power station, and Lephalale municipality residents.

The supply for these activities was not enough, however, water is now being transferred from the Crocodile (West) River to the Mokolo River to address the problem (Van Niekerk and Du Plessis, 2013) as it is supported by Marcatelli (2015) that water supplies in Vaalwater were interrupted to the point where it did not meet the minimum standards for basic water provision.

The Waterberg region contains sparse human settlement, due to large households and numerous villages, and it appears the conversion of traditional farming to game farming contributed to human migration from private farms to informal settlements, rural villages and other provinces. O'Laughlin *et al* (2012) reported that 1.7 million farm dwellers and workers were removed from farms between the year 1984 and 2004. In addition, some of farm workers/dwellers moved to Leseding Township (Marcatelli, 2015).

5.1.2. Land use and land cover changes within and outside biosphere reserve from 1984 to 2016

The LULC insignificantly changed within and outside the WBR over the study years. NDVI shows that changes are significant within the WBR in 1996-2001 ($T=-2.71$, $df = 43$, $P < 0.05$) and 2006-2001 ($T = 6.88$, $df = 43$, $P < 0.05$) and outside the WBR in 1984-1990 ($T=3.58$, $df=151$, $P<0.05$), 1990-1996 ($T=-4.77$, $df=151$, $P<0.05$), 1996-2001 ($T=8.07$, $df = 151$, $P < 0.05$) and 2011-2016 ($T=10.64$, $df = 151$, $P < 0.05$).

Over the time period, 1984 to 1996, water body and natural vegetation increased on both side of the study area whilst cultivated land decreased. The decrease in cultivated land on both sides of the study area could be due to the conversion of the conventional farming to game farming (Atkinson, 2007; Seaman *et al.*, 2013; Marcatelli, 2015). The conversion was influenced by the limited water availability, poor nutrients soils and state subsidies removal on crop products (Marcatelli, 2015). According to Marcatelli (2015), conservation initiatives became common in the Waterberg region in the 1980s with intention to bring the region back to its original ecosystem composition and had led to the development of the Lepalala Wilderness and Welgevonden Game Reserve in 1981 and 1987, respectively, through purchasing of farms from landowners in financial crisis, whilst, first private natural reserve was initiated in the 1960s (Baber and Abram, 2013; Marcatelli, 2015).

The built-up land increased and decreased inside and outside the WBR over the analysis period (1984 to 1996) and this might be due to natural hazards such as floods, removal of fences and other infrastructure (Li, 2009; Hall *et al.*, 2013). People relocated from farms due to loss of jobs, reduced income and seeking for better lives as wildlife industries offer fewer job opportunities compared to crop farming (Langholz and Kerley, 2006; Snijders, 2012). O'Laughlin *et al* (2013) reported that 1.7 million farm dwellers and workers removed from farms between time period 1984 and 2004. Built-up land also increased as results of the government subsidies houses erected through Reconstruction Development Programme (RDP) from 1994.

Leseding Township near Vaalwater town was established during the period through the government subsidies houses (Marcatelli, 2015).

The land covered by mines only increased outside the WBR as the valuable mining minerals are outside the periphery of the WBR (Wardley, 2012). The increase is not surprising as the Waterberg region is considered a replacement for the depleting Highveld coalfield supplier for electricity supply to the rest of South Africa (DMR, 2009).

An increase in cultivated land between years 2001 to 2016 could be the result of land redistribution process as some local communities within WBR and its surroundings do not understand the importance of natural resources conservation and ecotourism promotion returned to crop farming through the South African land reform programme (Baber and Abram, 2013). However, these farms usually became abandoned land due to lack of skills in the farming industry (Moabelo, 2007)

The decrease in water bodies over the time period could be due to the 2005/2006 and 2015/2016 droughts as the area is comprised of farm dams that are isolated from rivers. The drought resulted in reduced grazing land and water for livestock and irrigation. These predicted trends are supported by studies of the FAO (2004), LBPTC (2010) and WMO (2012), that Limpopo River Basin experienced some of the most damaging droughts. The study by Zhu and Ringler (2012) found that in Limpopo Province, water resources are stressed under today's climate conditions. LBPTC (2010) reported that 72,500 hectares of cultivated cropland damaged by the 2005/2006 drought in Botswana and resulted in economic losses and Limpopo River Basin is subjected to increasing temperature and extreme event such as drought.

The statistical tests show the LULC changes that had occurred inside and outside the WBR from 1984 to 2016 are insignificant. However, NDVI shows a significant difference between consecutive years. This could be the continued farm conversion, urban growth, expansion of Grootegeluk Colliery, Matimba power station and establishment of the Medupi power station, the mines and power stations (Baber and Abram, 2013; Marcatelli, 2015).

5.1.3. Impacts of WBR on urban and agricultural development since 2001

The impacts of WBR on urban and agriculture development were assessed by looking on the two LULC changes from 2001 to 2016 as the WBR was proclaimed in 2001.

The land covered by built-up area increased over time periods 2001-2006 and 2006- 2011 then decreased over analysis period 2011-2016. The urban growth is experienced in the region since 2001 with Lephalale town being one of the rapidly growing towns in South Africa. This is supported by population growth and developments in the region since 2001 (StatsSA, 2011).

However, the decrease of the LULC classes could be due to the removal of fences and other infrastructure as the result of the conversion of crop farming to game ranching.

The cultivated land only decreased over the time periods 2001-2006 and then increased in 2006-2011 and 2011-2016. The decrease in agriculture could be due to continuous conversion of farming types that had begun in the 1980s (Marcatelli, 2015) and drought experienced within the acute water shortage region in the year 2005/2006 and 2015/2016. This is supported by the RESILIM (2017) that the 2015/2016 drought reduced grazing land and water for livestock and irrigation in Limpopo Basin. The increase in cultivated land could be due to challenges of employment which forced people to cultivate the land through South Africa's Land Restitution Process (Baber and Abram, 2013).

The proclamation of the WBR influenced the conservation of the environment while allowing the region to develop economically (primarily ecotourism activities), which is the aim of the biosphere reserve concept. Snijders (2012) found that revenue in game farming increased from R9 million in 1991 to R303 millions in 2010 within Waterberg district with The Keta Game reserve making a profit of R25 millions in May 2014 (Marcatelli, 2015). However, wildlife farming offers fewer job opportunities compared to crop farming which resulted in jobs losses, reduced incomes and migration of farm workers and dwellers from farms to the informal settlements and other provinces for better lives (Snijders, 2012; Spierenburg and Brooks, 2014).

Urban and agriculture development did not decrease since 2001. This concurs with the study Pool-Stanvliet (2014) that the impacts of WBR and its international designation are not notable. This could due to how the WBR zones were delineated as they were based on government departments, private landowners and rural community's knowledge. The zoning systems did not consider the importance of either important ecosystems, or habitats, biodiversity or river catchment areas. The formally protected state land and private land belonging to WMC members became core zone and buffer zone respectively. The remaining land became a transition zone (Marcatelli, 2015). The WBR committee, however, submitted an application for expansion of the WBR with a management plan to UNESCO in 2013 to protect the environment and solve socio-economic challenges.

5.2. Limitations

Though the study managed to detect LULC changes at WBR and its surroundings, challenges were faced. The use of free Landsat data in the study was very effective but also has limitations due to the low spatial resolution. In contrast, the use of fine resolution satellite images such as WorldView and Geoeye would have greatly increased the accuracy of the results as they have high spatial resolutions. In addition, the unavailability of certain Landsat images necessitated the use of inconsistent time periods.

Unavailability of historic aerial photos that fully cover the entire study area from several years to collect reference datasets (Training and validation data) limited the visual interpretation and classification process as most historic aerial photos covered towns or areas experienced rapid development.

CHAPTER SIX: CONCLUSIONS AND RECOMMENDATIONS

6.1. Conclusions

The LULC changes in Waterberg area from 1984 to 2016 were quantified using Remote Sensing and using Geographical Information System techniques. The images from Landsat 5,7 and 8 were analyzed for LULC change detection from the aforementioned period in five years interval. The study area was divided into inside and outside the Waterberg biosphere reserve to quantify the impacts of WBR on the landscape. The study revealed the usefulness of the GIS and RS techniques in LULC change analysis at effective time and cost.

The following conclusions are drawn from this study:

The LULC changes occurred on both sides of the study are insignificantly difference ($P>0.05$) and these included land covered by agriculture which decreased as a result of the conversion of the conventional farming to wildlife farming. This conversion was influenced by state subsidies on crop products, water shortage, and poor nutrients soil. However, Local residents are forced to return back to their crop farming through the Land Reform process (Cultivated land increased between 2006 and 2016). Wildlife farming practice contributes to the local economy of the region through auctions and eco-tourism, whilst job losses to the farm workers occurring.

The region has mineral zones and mining activities increased as the Waterberg coalfield is considered a replacement for the declining Mpumalanga Highveld coalfield for the supply of fossil-fuel based power generation. The increase in mining industries raises the concern over its negative impacts on the natural resources to the water scarcity area (Van Niekerk and Du Plessis, 2013).

An area covered by built-up also increased over the analysis period due to the expansion of towns, informal settlements and power stations. Leseding Township and Medupi Power station were established over this analysis period and Matimba power station was expanded.

The decrease and increase in water bodies over the analysis period were difficult to interpret as water bodies changes are associated with natural and human activities. The decrease in water bodies in 2005 and 2006 is likely the result of drought across Limpopo Province (2005/2006 drought).

The proclamation of WBR did not halt urban and agriculture development within the Waterberg region, this could be due the scientific based procedures were not followed during zoning of the WBR. However, a new management plan was submitted in 2011 to UNESCO to enlarge the existing WBR so it can cover the important biodiversity hotspots.

The LULC information gathered through this study is useful to the BR management committees in better decision making, planning, and management of the land use activities and natural resources to ensure that developments are at appropriate locations without harming the surrounding environment.

6.2. Recommendations

The results presented in this study shed some light on the LULC changes in the Waterberg area. The comparison between the WBR and its surroundings shows that LULC changes continued between both assessed sides. To make a well-functioning biosphere reserve that will provide protection of the natural resources and address various socio-economic challenges, habitant ecosystems, river catchment, and biodiversity hotspots must be included in the zoning of the WBR. The expansion of the WBR is recommended with adequate and scientific knowledge.

The LULC maps produced in this study can be used by the WBR committee to understand the LULC distribution and trends within the WBR and its surroundings so they can have a better decision, effective planning and management of land use activities without harming the surrounding environment.

The need for continuous and updated information about the WBR and their practices is essential in determining the WBR current status as well as future planning and management of the land use activities. It is recommended that remote sensing data integrated with GIS techniques, which is cost and time effective in determining and monitoring of LULC changes related to BR, could be used to keep up with changes. The mapping of LULC in WBR and its surroundings using fine resolution satellite images such as WorldView and Geoeye is recommended to increase the results accuracy as the datasets have fine spatial resolutions.

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