FACULTY OF SCIENCE

DEPARTMENT OF ENVIRONMENTAL SCIENCE

GEOSPATIAL ASSESSMENT OF LAND DEGRADATION: A CASE STUDY OF SELEBI PHIKWE AND MMADINARE AREA, BOTSWANA

A dissertation presented to the Faculty of Science in partial fulfilment of the requirements for the award of the degree of Master of Science in Environmental Science

BY

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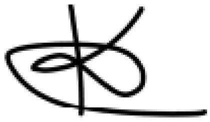
STATEMENT OF ORIGINALITY

The work contained in this thesis was conducted by the author at the University of Botswana. It is an original work except where due reference is made and neither has been nor will be submitted for the award of any other University.



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PLAGIARISM DECLARATION

I confirm that this research project is my work, is not copied from any other person's work (published or unpublished) and has not been previously submitted for assessment elsewhere.

DEDICATION

This work is dedicated to my late father Itsiseng Bulayani, my mother, my husband, my children, and the rest of my family. Above all, I dedicate this work to God who guided me.

ACKNOWLEDGEMENT

I would like to thank God for his ever-sufficient grace throughout this project. He has blessed me richly by giving me the invaluable gift of life and great wisdom and for that, I give all the glory unto Him.

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List of Acronyms

ALDEP	Arable Lands Development Program
ARAP	Accelerated Rainfed Arable Programme
AVHRR	Advanced Very High-Resolution Radiometer
BCA	Botswana College of Agriculture
CA	Cellular Automata
CBNRM	Community Based Natural Resource Management
CM	Cellular Models
CSO	Central Statistics Office
DEM	Digital Elevation Model
DNs	Digital Numbers
DPSIR	Drivers Pressure State Impact and Response
EA	Environmental Assessment
EIA	Environmental Impact Assessment
ENSO	El Nino-Southern Oscillation
ERDAS	Earth Resources Data Analysis System
ETM+	Enhanced Thematic Mapper Plus
FAO	Food and Agriculture Organisation
FPAR	Fraction of Photosynthetically Active Radiation
GIS	Geographic Information Systems
GNSS	Global Navigation Satellite Systems
GPS	Global Positioning Systems
IFPRI	International Food Policy Research Institute
IPCC	Intergovernmental Panel on Climate Change
ISPAAD	Integrated Support Programme for Arable Agriculture Development
LAI	Leaf Area Index
LCM	Land Change Modeller
LD	Land Degradation
LULC	Land Use Land Cover
LULCC	Land Use Land Cover Changes
MDGs	Millennium Development Goals
MLP	Multi-Layer Perceptron
MSS	Multi-Spectral Scanner
NAP	National Action Programme
NDVI	Normalised Difference Vegetation Index
NLB	Ngwato Land Board
NOAA	National Oceanic Atmospheric Administration

NPP	Net Primary Productivity
NSP	National Settlement Policy
OLI	Operational Land Imager
PRA	Participatory Rural Appraisal
PRRA	Participatory Rapid Rural Appraisal
RRA	Rapid Rural Appraisal
RS	Remote Sensing
SAVI	Soil Adjusted Vegetation Index
SPSS	Statistical Package for the Social Sciences
SPTC	Selebi Phikwe Town Council
TCMA	Twin Cities Metropolitan Area
TM	Thematic Mapper
TRRA	Topical Rapid Rural Appraisal
TVI	Transformed Vegetation Index
UN	United Nations
UNCBD	United Nations Convention for the Conservation of Biodiversity
UNCCD	United Nations Conventions to Combat Desertification
UNCED	United Nations Conference on Environment and Development
UNEP	United Nations Environment Programme
UNESCO	United Nations Education, Scientific and Cultural Organization
UNFCCC	United Nations Framework Convention on Climate Change
USGS	United States Geological Survey
WCED	World Commission on Environment and Development
WMO	World Meteorological Organization

ABSTRACT

Botswana is one of Sub-Saharan Africa drylands that are prone to land degradation. Land degradation is among others linked to pressure from conflicting land uses and cyclical droughts. This study aimed to assess land degradation in Bobirwa sub-district in the Selebi Phikwe and Mmadinare area that has been noted to experience resource depletion. The study assessed the spatial and temporal dimensions of land degradation and its drivers over a period of 48 years (1971 to 2019), applied decrease in vegetation cover as the main indicator in addition to others such as bush encroachment. Evidence was gathered using geospatial information technology, social and biophysical surveys and from secondary data. Image classification, vegetation indices and thermal radiation were applied to detect and map land degradation as appropriate using 1971 Air photographs, 1990 Landsat Thematic Mapper (TM), 2010 Landsat 7 Enhanced Thematic Mapper Plus (ETM+) and 2019 Landsat 8 Operational Land Imager (OLI) imagery. The established evidence was integrated using Geographical Information Systems (GIS) and related to rainfall, livestock rearing, human population, and land-use pressure, especially mining activity. Four levels of degradation according to severity were established; highly degraded; moderately degraded; slightly degraded and non-degraded. Results showed that by 1971 the study was dominated by the non-degraded level of degradation but in subsequent years the area remained predominantly under moderately degraded. Highly degraded areas were confined to drainage systems and the vicinity of settled areas. These results formed the basis for modelling the likely status of land degradation by 2030. The study concluded that mining and resulting land-use pressure, especially overgrazing and deforestation intensified land degradation during periods of below-average rainfall. These findings will contribute further to the discussions on the role of human and climatic factors on the process of land degradation in semi-arid lands and the need to put in place appropriate management systems.

Keywords: *Geospatial Information Technology, Land Degradation, Climate Variability, Land Cover Land Use, Selebi Phikwe, Mmadinare, Botswana.*

1. INTRODUCTION

Land degradation is a globally experienced phenomenon that has detrimental effects on society and the environment. Pulido and Bocco (2014) and Peprah (2015) highlighted that land degradation is a composite feature activated by the interaction of environmental, economic and social factors. It has been estimated that over 1.5 billion people are affected by land degradation and this includes large numbers of the rural poor (Bai et al., 2008). It is noted that in many parts of the world more than 20% of all cultivated areas, 30% of forests and 10% of grasslands are undergoing degradation and millions of hectares of land per year are being degraded in all climatic regions (Kapalanga, 2008). Land degradation is a major problem in drylands of Africa, particularly the Sahel region and parts of Southern Africa. An estimated 65% of Africa's agricultural land is subjected to erosion, chemical and physical degradation (Kapalanga, 2008). Africa is especially vulnerable to land degradation due to extreme droughts, floods, storms, poverty and poor land management systems (UNESCO, 2007).

Land degradation has a wide range of definitions that describe circumstances of reduced biological productivity of the land. From the agricultural perspective, land degradation is a condition whereby the ability of soil to yield food for humans and livestock is lessened while from the ecological viewpoint, land degradation is when the healthy functioning of land-based ecosystems is impaired (WMO, 2005; Bai et al., 2008; Moghanm and Baroudy, 2014; Gupta, 2019; Vågen and Winowiecki, 2019; Mahala,2020). However, this study adopted the ecological perspective of land degradation. The existence of uncontrolled land degradation could eventually lead to desertification over the long term (UNESCO, 2007). Desertification, as defined by United Nations Environment Programme (UNEP) in 1992 and adopted by United Nations Convention to Combat Desertification (UNCCD), is 'land degradation in arid, semi-arid and dry sub-humid areas resulting from various factors, including climatic variations and human activities’ (Ajai et al., 2009). However, desertification is not only the advance of the desert onto arable land. It also occurs when dry-land ecosystems are persistently degraded by unsustainable land management, such as intensive farming, mining, over-grazing and clear-cutting of land (Mair, 2014). It is envisaged that in Africa climate change is set to increase the area prone to drought, land degradation and desertification (UNESCO, 2007).

Drought is a hazard that is defined from many angles: meteorological, agricultural, socio-economic, and hydrological. The meteorological drought is the first sign of drought conditions, marked by periods with high temperatures, wind intensification and rainfall deficit (Armaş et al., 2016; Brema, 2019). Meteorological drought is the focus of this study as it relates to climate variability which has a major role in land degradation.

The reduced biological productivity of land is due to an intricate mixture of biophysical and socioeconomic factors interacting and exerting influences disproportionally over space and time (Mambo and Archer, 2007). For example, population increase leads to increased pressure on the use of land resources resulting in deforestation and forest degradation. These in turn contribute to climate variability and poverty increasing pressure on land resources with feedback on further degradation of land resources (UNESCO, 2007; Pulido and Bocco, 2014).

Studies that have addressed the most significant causes and consequences of land degradation from a socio-environmental perspective have identified some of the main proximate drivers and underlying factors of change which lead to the risk of desertification (Lambin and Geist, 2006; Lal and Stewart, 2013; Belay et al., 2014; Pingali et al., 2014; Salvati et al., 2016). Proximate drivers are those that have a direct effect on the terrestrial ecosystem. These include climatic conditions, topography, unsuitable land uses and inappropriate land management practices (such as deforestation, overgrazing). Conversely, the underlying drivers of land degradation include land tenure, poverty, population density, weak policy, and regulatory environment in the agricultural and environmental sectors (Lambin and Geist, 2006; Kiage, 2013; Kirui and Mirzabaev, 2015; Gupta, 2019).

The increasing pressure from various human activities and the threat of climate variability that is enhanced by anthropogenic climate change pose serious challenges to environmental and livelihood sustainability resulting in land degradation (Ringrose and Chanda, 2000; Gupta, 2019; Vågen and Winowiecki, 2019; Orimoloye et at., 2020). Land degradation manifests itself on the ground by spreading from centres of high-pressure points and lessen as one moves away from the centre (Pickup and Chewings, 1994; Dube and Pickup, 2001).

An environmental indicator is a variable that describes the state of the environment and its impact on human beings, ecosystems, materials, the pressures on the environment, the driving forces, and the responses steering that system (Kosmas et al., 2013). Indicators of land degradation may be of social, biological, physical and chemical (Pulido and Bocco, 2014). The social indicators are due to the pressures from the anthropogenic activities, while the biophysical indicators are due to extreme climatic events such as drought (FAO, 2003). The examples of social indicators are migration, distance to field, poverty, distance to drinking water. The biophysical indicators are; low rainfall, decreased vegetation cover, bush encroachment, declining crop yields, the decline in livestock productivity, increase in patches of bare soil, change in soil surface characteristics (nutrient status and water holding capacity), progressive drying up of surface water resources, wind erosion, and dune formation, decrease in grass density as well as the change in some grass species and landscape fragmentation (Kinlund, 1996; Dube and Pickup, 2001; Southworth et al., 2004; UNESCO, 2007; Mambo and Archer, 2007).

Land degradation has been linked to food insecurity (Barbier and Hochard, 2016; Gupta, 2019). Reed et al. (2015) posit that future problems of global food and energy security and water availability will be exacerbated by land degradation. Considering the above discussions, sustainable land management is key to addressing the land degradation problem. Sustainable land management is based on the concept of sustainable development which is defined in the Brundtland Report as the ‘development that meets the demands of the current without conceding the capability of future generations to meet their own needs’ (WCED, 1987).

Success in combating land degradation requires an improved understanding of its causes, impact and its interactions with climate, soil, water, land cover and socio-economic factors (Kapalanga, 2008). Several approaches have been applied to assess land degradation including the use of earth observation data to determine changes in land properties, ecological methods to assess soil and vegetation and socio-economic surveys that may employ expert opinions and interviews (Stringer and Reed, 2007). Geographical Information Systems (GIS) modelling method has become a trend for assessing land degradation because of its ability to aid with managing integrating and manipulating large amounts of spatial data (Yuan, 2008).

1.1 The Case of Land Degradation in Botswana

Botswana is one of Sub-Saharan Africa drylands that are prone to land degradation, affecting mostly the rangelands (Stringer and Reed, 2007). Land degradation in Botswana is due to the combined effects of increasing pressure from conflicting land uses, for instance, intensive grazing, wood harvesting, veld products gathering, crop production, urbanization and expansion of rural settlements, occurring amid cyclical disturbances such as droughts (Darkoh, 2000; Dube and Pickup, 2001). Within these many factors’ livestock rearing has been recognized to have a major role in depleting rangeland resources (Albertson, 1998; Mulale, 2008). Recent satellite imagery reveals that there has been substantial unrestrained development of cattle-posts in areas put aside for wildlife management. This leads to the emergence of land-use conflicts and widespread degradation of the tree savanna (Darkoh, 2000).

Although cattle numbers in Botswana fluctuate due to incidents of drought and disease epidemics, numbers remain mostly high as they quickly build up during wet years. The highest number of cattle was recorded in 2002 at 3. 060 million and the lowest numbers were recorded in 2015 at 1. 744 million (Figure 1-1). These decline in cattle numbers was due to that the 2015 Agricultural Census was conducted during a drought year (CSO, 2016). High cattle numbers, especially in communal-grazing systems increase the risk of over-grazing during drought years. This is partly due to the dual grazing rights of the Tribal Grazing Land Policy farmers as they graze their cattle in the communal rangeland, and when conditions deteriorate, they move their cattle into their farms where they have exclusive rights (Mulale, 2008).

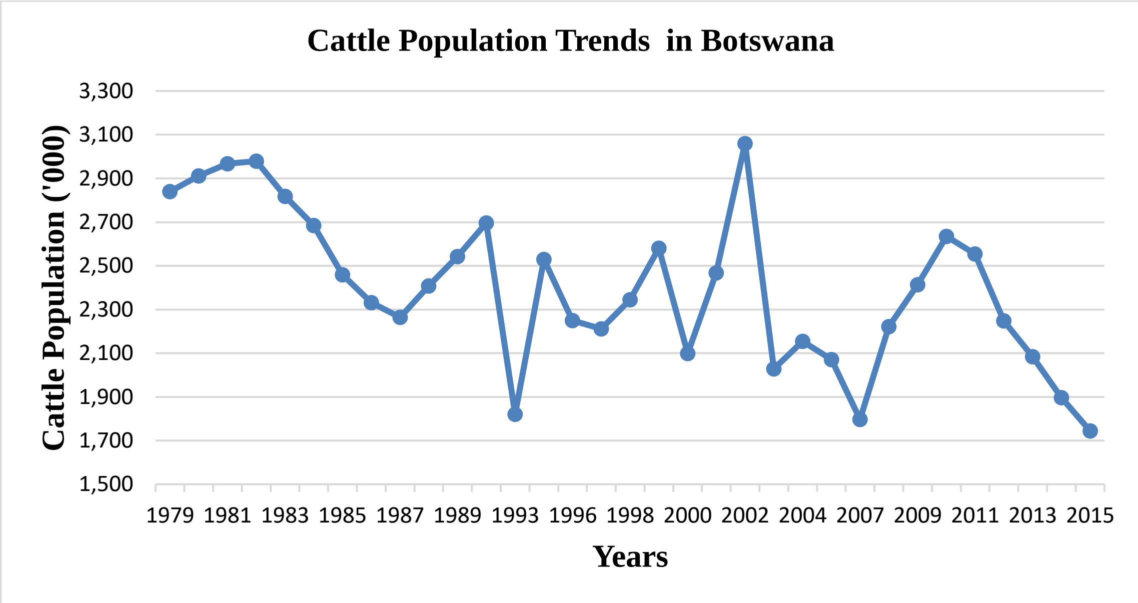


Figure 1-1: Cattle Population Trend ('000) from 1979 to 2015
Source :(CSO, 2013; CSO, 2016; CSO,2017)

In addition to livestock rearing in the past decades, pressure on land resources has been driven by mining activities which gave rise to urbanization (Giuliani et al., 2020). Mining activities have increased rapidly over the country since the first mine in the 1960s in Selebi Phikwe, with new mines such as Ghagho, Lerala and Karowe diamond mines and Khoemacau Copper Mining established in the past 10 years.

Selebi Phikwe was established as a mining town after the discovery of copper and nickel. Following this, diamond mining towns, Orapa in 1972 and Jwaneng in 1982 were established. The Sowa township was established in 1991 with the beginning of mining of Soda Ash and Salt. Mining accelerated Botswana’s urbanization due to migration to mining towns, particularly Selebi Phikwe and Jwaneng. People relocated from rural localities to mining centres for employment opportunities (Gwebu, 2012) hence putting pressure on natural resources in the surrounding areas and increasing vulnerability to land degradation (Giuliani et al., 2020. The urban population of Botswana increased from 5.9% in 1968 to 58% in 2017 growing at an average annual rate of 4.87% (Knoema, 2018).

The government continues to promote mineral exploitation on a large-scale, pointing to the need to assess the effect of these activities on land resources (Asare and Darkoh, 2001). For example, Gupta and Gorai (2007) indicated that opencast mining causes land degradation, land fragmentation, soil disruption, soil contamination, erosion and soil quality degradation.

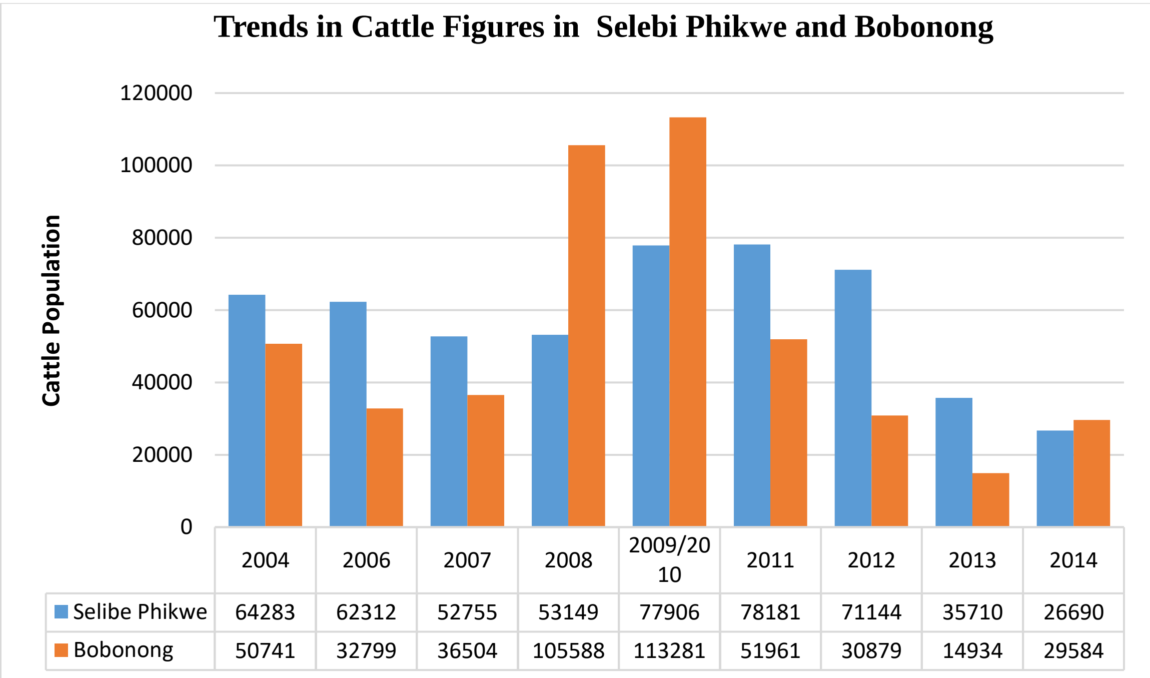
1.2 Land Degradation in Bobirwa Sub - District

Bobirwa is one of the driest parts of eastern Botswana that over the years has shown a substantial reduction in vegetation cover, which becomes prominent during drought years when large areas remain bare, exposing productive topsoil to erosion (Botswana College of Agriculture, 2004). During the 1980s drought that affected the whole of Botswana, Bobirwa sub-district was one of the areas most affected. The impacts of this drought led to wildlife and livestock mortality and migration; lack of water for animals; low water levels in dams and other surface water sources; degradation of soil by the heat of the sun, wind and water when rains returned (CSO, 2015).

In Bobonong village, variation in vegetation cover is a result of changes in relief, soils, availability of water and human activities such as overstocking of the veld resulting in range degradation (McLeod, 1992). The more valuable-perennial grasses are overgrazed by livestock thus resulting in the appearance of areas of bare soil, which are then invaded, by less edible and perennial species, annual grasses and weeds, leading to bush encroachment (McLeod, 1992; de Klerk, 2004; Zimmermann et al., 2008).

The annual percentage human population growth rate of the Bobirwa sub-district has been steadily increasing, registering, 1.4%, 2.3% and 7.4% for the period 1981 -1991, 1991-2001 and 2001-2011 respectively (CSO, 2010; CSO, 2013).

In addition, cattle numbers have been increasing despite fluctuations as is the case countrywide (Figure 1-1). By 2009/2010 the major village and city in the District, Bobonong and Selebi Phikwe respectively, had a total of 191187 cattle in contrast to 115024 by 2004, although the cattle numbers declined thereafter (Figure 1-2). Mugari et al. (2018) highlighted that the Bobirwa Sub-district has been heavily degraded by agricultural activities.



	2004	2006	2007	2008	2009/2010	2011	2012	2013	2014
Selibe Phikwe	64283	62312	52755	53149	77906	78181	71144	35710	26690
Bobonong	50741	32799	36504	105588	113281	51961	30879	14934	29584

Figure 1-2: Trends in Cattle Figures in Selebi Phikwe and Bobonong
Source: CSO, 2008; CSO, 2011a; CSO, 2015; CSO, 2016).
***Note:** There was no survey conducted in 2005

Bobirwa sub-district has experienced changes in land use since mid-20th Century, from the traditional hunting and harvesting of veld products such as *Mopane* worms to livestock keeping and crop production in a rural setting to include urban lifestyles linked to the Copper-Nickel mining, at Selebi Phikwe (Markus et al., 1988; Maundeni, 2008).

The Selebi Phikwe population grew tenfold due to migration into the area from 4480 in 1971 to 48411 in 2011 (CSO, 2011b). Population influx began to spill over to neighbouring villages such as Mmadinare. This lead to heightened demand for land for grazing livestock, arable agriculture and harvesting of firewood and other veld products thus putting pressure on land resources in an area of high climate variability. For example, commercialization of mopane worms' results in over-harvesting of the worms, which ultimately leads to the reduction of the worms in the field (Lucas, 2010). As a result, Selebi Phikwe and Mmadinare area used herein as case studies, have undergone land cover land-use changes that may have led to land degradation.

1.3 Statement of the Problem

Resource depletion largely ascribed to land-use pressure especially during drought periods is a major problem in the semi-arid lands of Botswana. BCA (2004) noted that over 1 million ha in Eastern Botswana had grassland, shrubs, and forest in 1971 but by 2000 half of the land had been cleared for human activities. The depletion of resources is linked to mismanagement of land resources concomitant with population increase and in recent years has also increasingly been linked to urbanization resulting partly from the growing mining activities (Kayombo et al., 2005). Urbanization increases demand and commercialisation of land resources. However, studies on land degradation in the country are insufficient, considering the significance of the problem also in the light of climate change. More up to date work integrating earth observation and socio-economic data is needed to assess the driving forces and extent of land degradation on the eastern, hardveld land systems part of Botswana dominated by loamy soils that are susceptible to soil erosion. The hardveld is the most suitable part of the country for arable agriculture and supports higher population density and infrastructure development than the rest of the country. This study used geospatial tools and socio-economic data to assess the extent of land degradation and model the future dimensions of the phenomenon in Bobirwa, focusing on Selebi-Phikwe and Mmadinare area in the hardveld.

1.4 Aim and purpose of the Study

This study aimed to assess, with the aid of geospatial information technology, land degradation in the Selebi Phikwe and Mmadinare area with respect to land cover land use dynamics and climate variability, over a period of 48 years, from 1971 to 2019. The purpose of the study was to advance the understanding of land degradation in Botswana, using Selebi Phikwe and Mmadinare as a case study.

1.5 Research Objectives and Key Research Questions

Table 1-1: Objectives of the study and Associated Research Questions

Research Objectives	Key Research Questions
1. To assess the spatial extent and temporal trends in land degradation in Selebi Phikwe and Mmadinare area from 1971 to 2019.	i. What indicators of land degradation are prevalent in Selebi Phikwe and Mmadinare area? ii. How widespread (over space and time) is land degradation in the Selebi Phikwe and Mmadinare area?
2. To investigate the role of climate variability and land-use pressure on land degradation in Selebi Phikwe and Mmadinare area.	iii. How is climate variability and land use linked to the spread of land degradation? iv. How has mining contributed to land-use pressure?
3. To model land degradation in Selebi Phikwe and Mmadinare area.	v. How widespread will land degradation be in 2030?

1.6 Significance of the Study

Currently, there are on-going global efforts to combat land degradation and desertification. International agreements of which Botswana is a party to such as UNCCD, United Nations Convention for the Conservation of Biodiversity (UNCBD) and United Nations Framework Convention on Climate Change (UNFCCC) are among others aimed at mitigating or reversing the socio-economic impact of land degradation and desertification (Kutter, 2004). Botswana ascribes to Sustainable Development Goals, Agenda 2030. Of reference in Agenda 2030 is the Planet goal which aims to protect the planet for present and future generations; promote sustainable consumption and production; manage natural resources and take actions on climate change. Nationally, Botswana has set herself Vision 2036 that commits to Sustainable Environment that; by 2036, *sustainable and optimal use of our natural resources will have transformed our economy and uplifted our people's livelihoods.* By focusing on understanding the spatial extent of land degradation in Selebi Phikwe and Mmadinare area, this study contributes to a realisation of that goal and the broader international goals noted above.

1.7 Scope of the Study

This study focused on trends in land degradation, using key informants' interviews, secondary and physical data to map and assess degraded areas over a 48-year period (1971 -2019) in the area around Selebi Phikwe and Mmadinare. The study focused on drivers and indicators of land degradation to help understand the process of degradation. The year 1971 has been chosen as the commencement date because this was when the BCL Limited mining activity, originally founded as Bamangwato Concessions Limited started in Selebi Phikwe, leading to significant change on land use in the area. Subsequent years were selected to provide for sufficient time to assess the land cover land-use changes that could have occurred thereafter contributing to the degradation of the land. This study further modelled land degradation to appreciate how widespread land degradation will be in 2030, ten years from now.

This study did not cover the effects of air pollution from BCL mine on vegetation productivity. The socio-economic effects of land degradation were also not part of this study.

1.7.1 Choice of Study Area

The study area is in the eastern part of Botswana in Bobirwa Sub-District, in one of the major ecological zones the hardveld region that accounts for 20% of the land surface of the country. The hardveld is known for its unique landscape, relatively fertile soils with generally higher population density than the sandveld formed by the Kalahari aeolian sands system that constitutes the remaining 80% of the country (Kayombo et al., 2005). The study area, focused on Selebi Phikwe and Mmadinare, was chosen partly because of its slightly hilly landscape and a drier climate compared to the rest of the hardveld, plus proximity to the BCL mine, which together makes it susceptible to land degradation where the management of land use is lacking.

2. THE STUDY AREA

2.1 Physical Environment

2.1.1 Location

The study area falls under one of the country's largest district, the Central District (Figure 2-2) in the Bobirwa sub-District, focused on Selebi Phikwe and Mmadinare area. Selebi Phikwe is located at 21° 58′ 33″ S and 27° 50′ 24″ E while Mmadinare is at 21° 52′ 28.56″ S and 27° 44′ 58.56″ E, 15 km from Selebi Phikwe (Maplandia.com, 2016).

2.1.1 Climate

Selebi Phikwe and Mmadinare fall under a semi-arid climate formed by the distinct dry and wet season, with lowest and highest recorded temperature ranging from 18° C to 35° C. The highest temperatures are recorded midway between September and April during the wet season and regularly exceed 30°C (Figure 2-1). The period from May to August is the cooler months and temperatures can drop below 10° C but can rise to 26°C by midday (Figure 2-1) (Department of Meteorological Services, 2019).

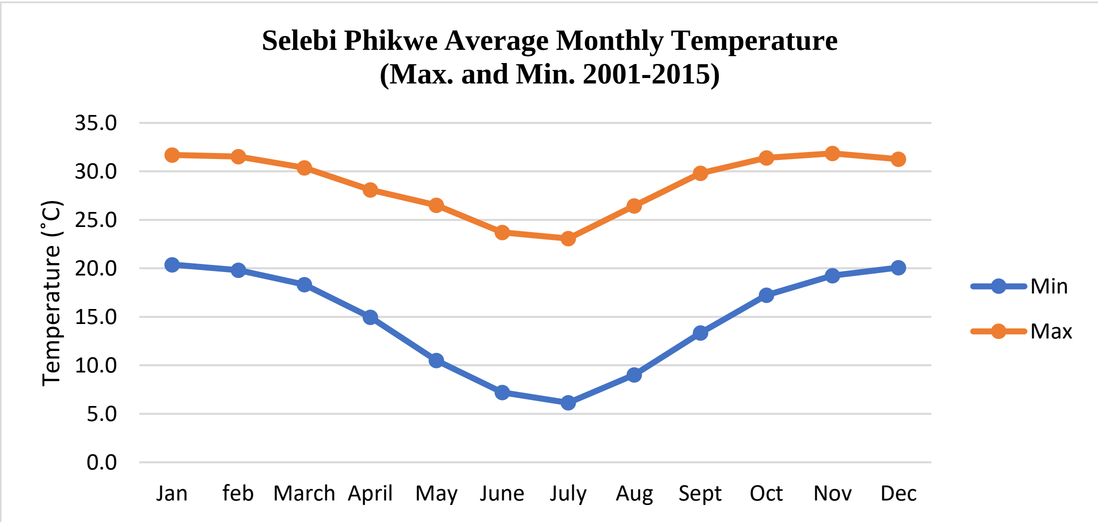


Figure 2-1: Monthly Average Temperature for Selebi Phikwe
(Source: Department of Meteorological Services, 2019)

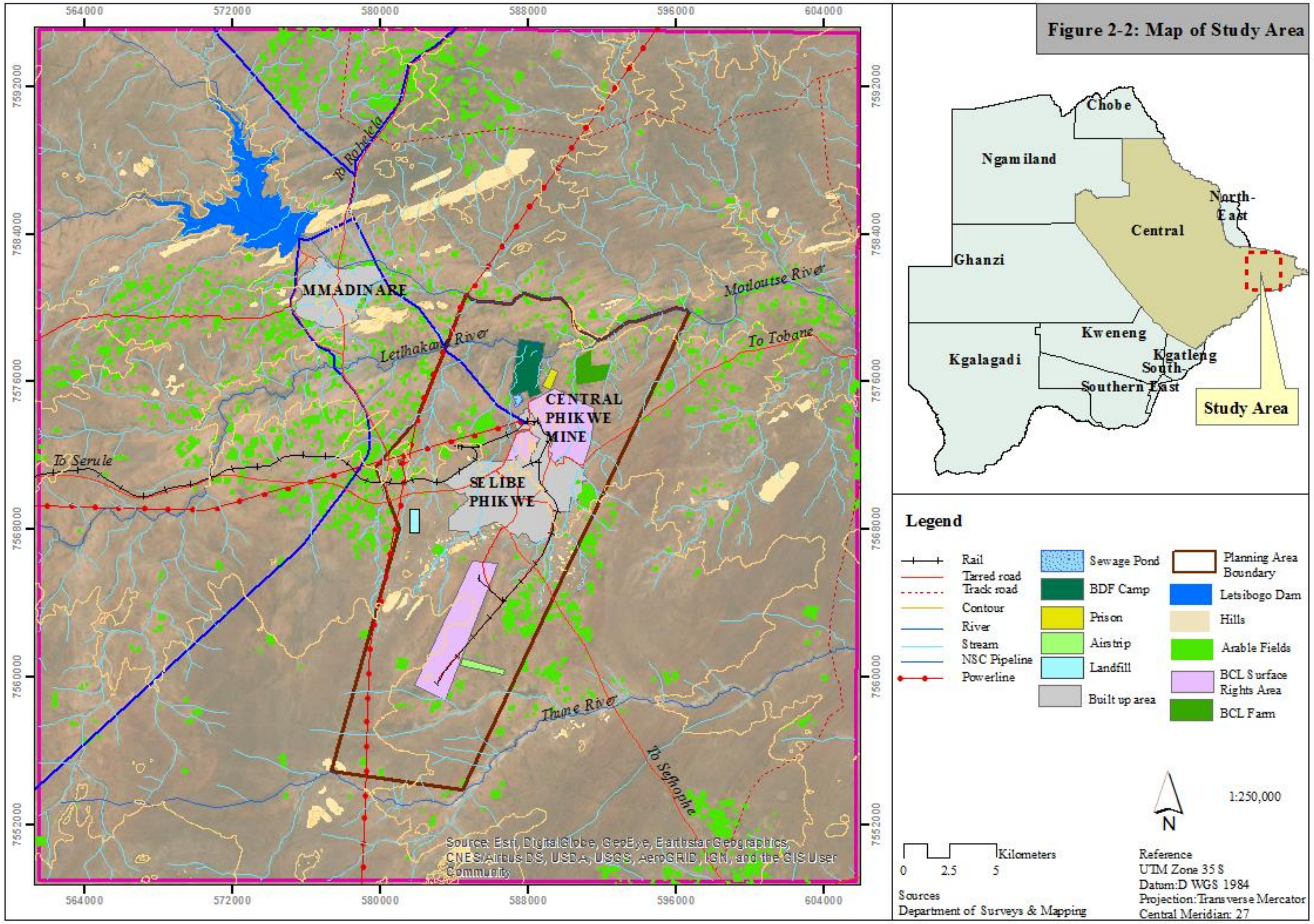


Figure 2-2: Map of Study Area

Source: (Department of Surveys and Mapping, 2012)

The long-term annual rainfall for Selebi Phikwe and Mmadinare area averages to 361.23 mm which is below the national annual rainfall average of 475 mm. Mean monthly precipitation in the study area for the period 1998 to 2016 ranged from 0.33 mm to 77.05 mm with the least rainfall occurring in July while January was the wettest month (Figure 2-3). Over 90% of the annual rainfall is received during the summer months of October to April (Department of Meteorological Services, 2019).

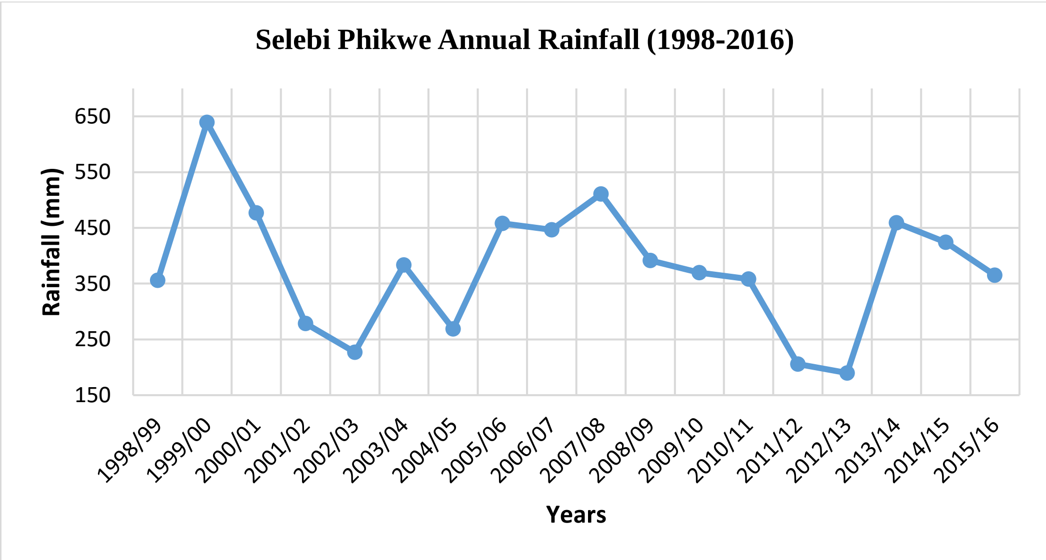


Figure 2-3: Annual Rainfall for Selebi - Phikwe (1998-2016)
(Source: Department of Meteorological Services, Selebi – Phikwe, 2019)

2.1.2 Geology Setting

The geology around Selebi Phikwe Township and Mmadinare is predominantly of high grade metamorphic gneisses which are banded due to a series of tectonic deformations of the Limpopo Mobile Belt (Geoflux, 2012). The Selebi Phikwe mine lies on the amphibolites, which form the primary host of the sulphide ore mined, which form sharp concordant layers within the quartzofeldspathic gneisses up to 100 m thickness (Geoflux, 2009). Hence Selebi Phikwe mine and the Township, as well as the area around, have different geological setting.

2.1.3 Topography and Drainage

The topography in the Selebi Phikwe and Mmadinare area, like the rest of eastern Botswana, is generally flat and characterized by small granitic hills and network of ephemeral rivers and streams. The topography of the area controlled and influenced the presence of the Motloutse River and its tributaries. The drainage is towards the Motloutse River, which in turn flows eastwards into the Limpopo River (Geoflux, 2012).

2.1.4 Soils

Land degradation involves deterioration in soil properties related to crop production, infrastructure maintenance and natural resource quality (Chalise et al., 2019). In general, the soils in the study area are derived from granitic gneiss parent material, alluvial system, basalt and sandstone (Geoflux, 2012). The Selebi Phikwe and Mmadinare soils have been classified into; Regosols, Lixisols and Luvisols respectively (Figure 2-4). Regosols are weakly developed soils that lack a noticeable B horizon (i.e. B horizon is less than 5 cm thick). The Regosols originate from sloping landforms and in Selebi Phikwe and Mmadinare. They are found on gentle slopes of the Letlhakane river catchment in the north and north-western part of Motloutse river catchment and rock outcrops. Lixisols are soils with a subsurface accumulation of low activity clays and high base saturation. The Lixisols are associated with gentle slopes to undulating topography. They range from west to south-west of the Selebi Phikwe Planning Area Boundary. Soils that are widely distributed in the Selebi Phikwe and Mmadinare area are the Luvisols, which are the most fertile and cultivated among the soils found in the study area (FAO, 1990; Geoflux, 2012). The Luvisols span from the northern and southeastern portions of the Motloutse catchment to the western plains of the Letlhakane river catchment (FAO, 1990).

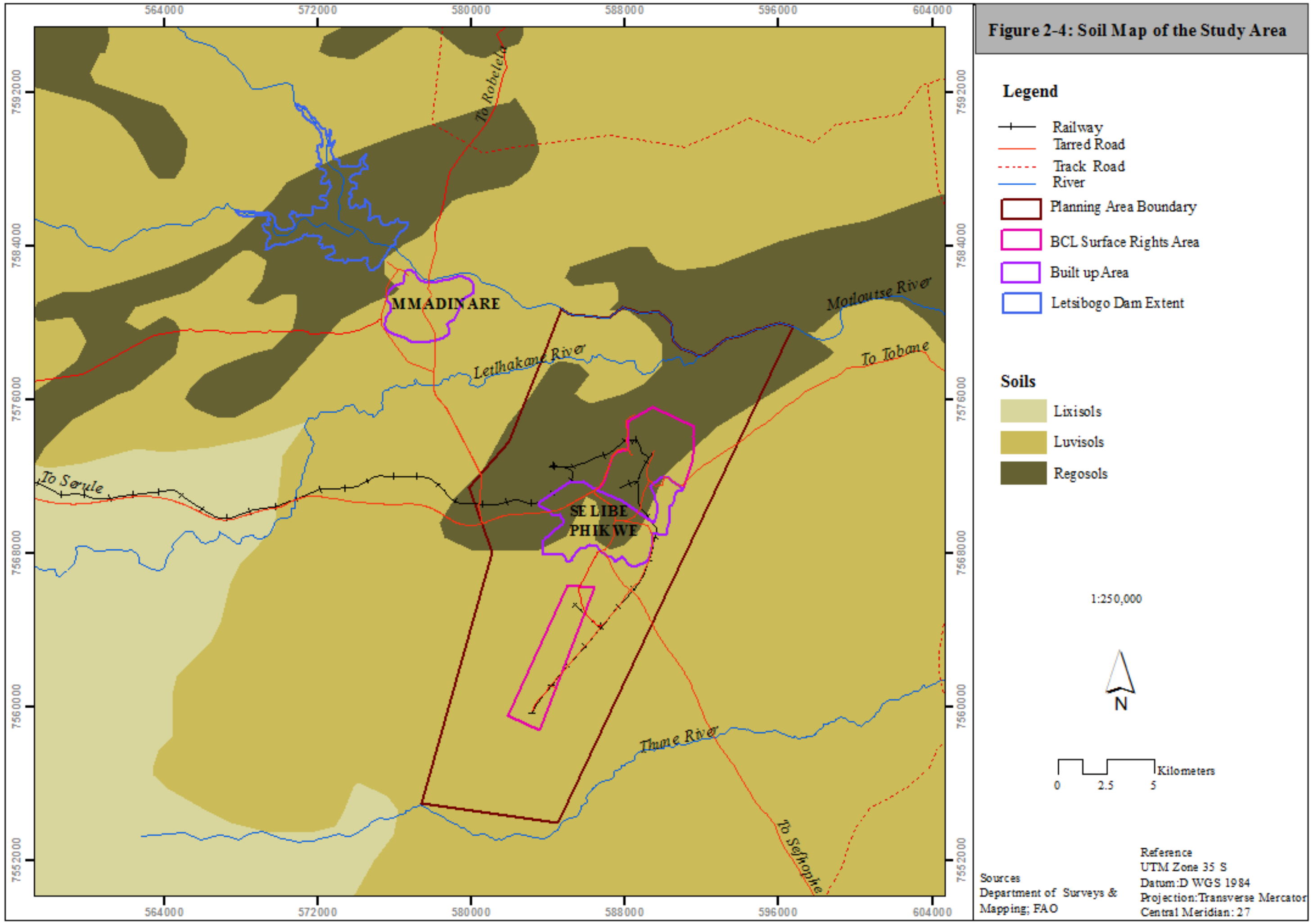


Figure 2-4: Soil Map of the Study Area

(Source: Department Surveys and Mapping; Food and Agriculture Organisation, 1990)

2.1.5 Vegetation

Selebi Phikwe and Mmadinare area flora is predominantly *Colophospermum mopane* with associations of other species thus forming either mixed communities or near pure stands of *C. mopane*. In mixed communities, flora occurs with mixtures of *Sclerocarya birrea subsp*. Caffra, Commiphora species, Combretum species, Dichrostachys species, Acacia species, and wild berry-producing species of the Grewia and Ximenia families and in an association of Boscia, Euclea and *Ziziphus mucronata (*Table 2-1). Along the watercourses, the *C. mopane* monotony is broken by the emergence of other species, especially of the Acacia family. Three physiognomic levels occur; low shrub, high shrub (thicket) and woodland and the former two being prevalent in the area (McLeod, 1992; Aqualogic, 2010). In some places, pastureland is marginal due to the domination of *C. mopane* (Molosiwa, 2013). The grass condition and diversity improve in mixed communities where other species colonized the area before the invasion by *C. mopane* (Aqualogic, 2010).

Table 2-1: List of Tree Species in the Study Area

Scientific name	**Common name**	**Setswana name**
Dichrostacys cineria	Sickle bush	Moselesele
Ziziphus mucronata	Buffalo thorn	Mokgalo
Acacia mellifera	Blackthorn	Mongana
Boscia albtrunca	Shepherd tree	Motopi
Acacia karoo	Sweet thorn	Mooka
Acacia tortilis	Umbrella thorn	Mosu
Grewia flava	Raisin bush	Moretlwa
Terminelia prunioides	Purple Pod	Motsiara
Colosphermum mopane	Mopane	Mophane
Acacia nigrescens	Knob thorn	Mokoba
Commiphora spp	Corkwood	Seroka
Terminelia sericea	Silver Cluster Leaf	Mogonono
Combretum imberbe	Lead wood	Motswere
Kirkia acuminata	White syringe	Modumela

Source: (McLeod, 1992; Aqualogic, 2010)

2.1.6 Wildlife

The Selebi Phikwe area is relatively low in mega-fauna species and most of the wildlife is concentrated in the privately-owned game farms and reserves located in the Tuli Block area. However, a significant number can still be found in the Motloutse and Limpopo rivers, such as Kudu (*Tragelaphus strepsiceros*), Zebra (*Equus burchelli*) and Wildebeest (*Connochaetes taurinus*) (Table 2-2). The open range of the Tuli area allows for unrestricted wildlife movement. Some species such as Hippopotamus (*Hippopotamus amphibius*) and elephant (*Loxodanta Africana*) are influenced in distribution by permanent water bodies in the region i.e. the Limpopo River and the Letsibogo Dam. As such various species of ungulates are found in remnants of habitats across the region (Table 2-2).

Table 2-2: List of known Wildlife in the Study Area

Scientific name	Common name	Setswana name
Tragelaphus strepsiceros	Kudu	Tholo
Alcelaphus bucelaphus	Hartebeest	Kgama
Aepyceros melampus	Impala	Phala
Phacochoerus aethiopicus	Warthog	Kolobeyanaga
Connochaetes taurinus	Wildebeest	Kgokong
Raphicerus campestris	Steenbok	Phuduhudu
Equus burchelli	Zebra	Pitse-Ya-Naga
Taurotrogus oryx	Eland	Kgama
Giraffe camelopardalis	Giraffe	Thutwa
Tragelaphus scriptus	Bushbuck	Serolobotlhoko
Kobus ellpsiprymnus	Waterbuck	Letimoga
Hippopotamus amphibius	Hippopotamus	Kubu
Loxodanta Africana	Elephant	Tlou

*Source(s): (*Geoflux, 2009; Aqualogic, 2010)

Motloutse and Limpopo River basin is a birdlife rich area coming third after the Okavango and the Chobe Regions. The area hosts a sizeable number of bird species and these include; Lappet-faced vulture (*Torgos tracheliotos*), Kingfisher species, Eagle species, Bee-eaters, Storks, Hornbills, Bustards, Meyer's parrot and Rollers (Aqualogic (2010).

2.2 Human Environment

2.2.1 Population and Administrative Framework

The study area comprises of two land tenure systems. Mmadinare is under Tribal land while all land in Selebi-Phikwe Township is state land, falling under the Planning Area (Figure 2-2). Tribal land is administered by the Ngwato Land Board whilst State land is administered by the Department of Lands (Geoflux, 2009). The Selebi Phikwe Township has a fully-fledged Urban Council – Selebi Phikwe Town Council (SPTC) as a locally elected representative body. The SPTC's authority is confined to the township area of the Planning Area and subject to the Township Act. The rest of the Planning Area (beyond the township boundary) is governed by the Tribal Land Act. The village of Mmadinare is located in the Bobirwa sub-district whose administrative centre is based in Bobonong (Geoflux, 2009). Tribal administration in Mmadinare village is the custodian of the traditional and cultural fabric of the local communities, headed by the Chief. Land administration in the Mmadinare village is under the responsibility of the Mmadinare Land Board (Geoflux, 2009).

Table 2-3 indicates that the study area experienced an increased population growth which could be attributed to the mining activities, and government departments which created employment opportunities. These attracted people to the area, hence more demand for land resources making the land susceptible to land degradation.

Table 2-3: Selebi Phikwe and Mmadinare Population Change from 1971 to 2011

NAME	1971	1981	1991	2001	2011
Selebi Phikwe	4480	19034	39772	48848	48411
Mmadinare	2879	5234	8901	10918	12086

Source: (CSO, 2011b)

2.2.2 Land Use

The land uses found in the study area comprises, rural settlements and urban built areas, mining, agricultural including cattle keeping and arable cultivation. A significant portion of the study area is used for subsistence agriculture in the form of arable fields around Mmadinare and Selebi-Phikwe. There is also a sizable concentration of arable fields along the Motloutse and Letlhakane rivers and a BCL farm located east of the Selebi-Phikwe Township. Further from the arable fields are communal grazing areas and rangeland (Figure 2-2).

In addition to agriculture, communities harvest a variety of veld products such as mopane worms (*Gonimbrasia belina*), morula fruit (*Sclerocarya birrea*) and mokolwane tree (*Hyphaene petersiana*) for basket weaving (Aqualogic, 2010). The seasonal mopane worm has for a long time formed part of the subsistence and economic activity of the Bobirwa region (Molosiwa, 2013).

3. Literature Review and Conceptual Framework

3.1 Overview of Land Degradation

According to UNCCD (2013), global assessments indicate that the percentage of total land area that is highly degraded has increased from 15% in 1991 to 25% by 2011. International Food Policy analysis Institute (IFPRI) (2012) indicated that if this situation of land degradation continues over successive twenty-five years, it is going to scale back international food production, from what it would be, by as much as 12% ensuing in global food prices as much as 30% higher for some supplies.

Land degradation and desertification reflect a loss of biological and economic productivity. They differ in that desertification is attributed to drylands only and is considered an extreme case of degradation whilst land degradation occurs in all the world regions (Safriel, 2009). Ecosystem degradation arises from the long-lasting loss of vegetation cover and biomass productivity over time and in space, because of a combination of natural and socio-economic drivers (Ivits et al., 2013).

Unsustainable use of natural resources, weak economic development and policy inaction are some of the drivers of land degradation and point to the complex relationship between local ecological conditions, socioeconomic dynamics, and policy action (Bisaro et al., 2013). Hence the proximate and underlying drivers of land degradation (Lambin, 2003). The proximate drivers of land degradation include both the natural and anthropogenic causes. On the other hand, underlying drivers are those that indirectly affect the proximate causes of land degradation; the policies and socio-economic factors (Kirui and Mirzabaev, 2015).

In a study of land use land cover changes and their impact on the lake ecosystem of the Central Rift Valley of Ethiopia, it was found out that both proximate and underlying driving forces caused the observed changes in land cover in the study area. The proximate causes were the immediate actions of local people such as agricultural expansion since the coverage of total cultivated land increased overtime. Furthermore, the study found out that, the underlying factors push the proximate causes into immediate effect. In the Central Rift Valley area, population pressure was found as one of the major underlying causes of land use land cover changes which contribute more to resources degradation through shrub/tree cutting for fuel consumption and charcoal production (Elias et. al., 2018).

The Intergovernmental Panel on Climate Change (IPCC) (2003) noted that ecosystems are subject to many pressures (for example; land-use change, resource demands, and population changes) as a result their extent and pattern of distribution are changing, and landscapes are becoming more fragmented.

According to the World Meteorological Organization (WMO) (2005) meteorological drought is characterized by a shortage of rainfall that results in water shortage and like land degradation, occurs throughout the world including in the humid regions. Indicators of land degradation have become increasingly important for communicating information to policymakers and the general public, as well as for assessing the environmental performance and the progress made to mitigate land degradation and desertification (Kosmas et al., 2013). In Ghana during fieldwork, Peprah (2015), selected specific indicators for the diagnosis and monitoring of forest land degradation. These indicators were categorised as follows; *Biological indicators;* - diminishing size of farm produce, absence of some wildlife species, reduced tree cover/adverse changes in vegetation, crops that used to grow faster than weeds but now the opposite is true. *Physical indicator;* - dry riverbeds, crusting, burrow pits, rate of soil loss. *Socio-economic indicator;* -

reduced f*arm produce, abandonment of land, risks of the forest fire.* While for Sub-Saharan Africa Symeonakis and Drake (2004), developed a desertification monitoring system that uses four indicators; vegetation cover, rain use efficiency (RUE), surface run-off and soil erosion. The four indicators were combined to highlight the areas with the greatest degradation susceptibility.

3.2 Land Degradation in Africa

UNESCO (2007) highlighted that two-thirds of Africa are categorized as deserts or drylands and these areas are found mostly in the Sahelian region, the Horn of Africa, and the Kalahari in the south and these form areas most susceptible to land degradation. Sub-Saharan Africa has the highest rate of land degradation, and the per capita food production continues to decrease. It is estimated that losses in productivity of cropping land in Sub-Saharan Africa are in the order of 0.5-1% annually, suggesting productivity loss of at least 20% over the last 40 years (Scherr, 1999). Overexploitation of the natural environment has led to widespread deforestation and land degradation. More than four million hectares of forest are lost every year in Africa, double the rate at which deforestation occurs in the world (UNEP, 2008).

Vegetation production in arid and semi-arid regions is closely related to the long-term average and inter-annual rainfall variability especially in Southern Africa which is strongly affected by the El Nino-Southern Oscillation (ENSO) phenomenon (Wessels et al., 2007). Therefore, short-term variability in primary production makes it exceptionally difficult to differentiate long-term change because of human-induced land degradation from the effects of periodic droughts (Wessels et al., 2007; Batisani and Yarnal, 2010). However, the use of the grazing gradient approach to studying land degradation address this difficulty as the method assumes that grazing effects decrease with distance from water and that temporary grazing impacts largely disappear as vegetation responds to major rainfalls and those areas where vegetation does not recover indicate long term damage (Pickup and Chewings, 1994).

3.3 Land Degradation in Botswana

The Botswana Country Report (2013) noted that some of the major environmental problems are degradation of rangeland, depletion of wood resources and over-exploitation of veldt products. The indicators of land degradation identified in Botswana are soil erosion, soil salinization, water stress, forest fires, a retreat of grass cover and perennial grasses, bush encroachment, reactivation of dunes (Vanderpost et al., 2011; Mashame and Akinyemi, 2016). Furthermore, Vanderpost et al. (2011) used Landsat imagery to determine long-term potential range degradation over natural rangelands in semi-arid Botswana through 1984-2000. The study revealed that range degradation was most widespread during the 1980s drought when 25% of the country was affected, decreased to 6.5% in 1994 and increased to 9.8% in 2000. These studies focused on range condition change mapping throughout Botswana over time, hence the study findings were generalised.

In Boteti, north-central Botswana land degradation, particularly in the southernmost densely populated part of the area, has been on-going for some time. Land degradation manifested mostly in the form of increased soil erosion, change in species during 1984-1993 period and reductions in vegetation cover density and long-term water supplies (Ringrose et al., 1996; Kayombo et al., 2005; Sebego et al., 2019).

Most people in Botswana depend on livestock for their livelihoods and when range resources decline, it becomes increasingly difficult to support livestock (Reed, 2005; Mugari et al., 2018). Approximately 76 % of the total land surface area is used for grazing in the country. The sustainability of communal rangelands is threatened by over-grazing resulting in the spread of inedible and annual herbaceous plant species and encroachment by shrub vegetation. The pressure exerted on the communal land manifests itself through moderate to severe incidents of land degradation (Kgosikoma, 2012: Sebego et al., 2019).

Apart from agricultural activities, in particular, livestock rearing other land uses such as mining also have a role in land degradation in Botswana. Engleton (2010) noted that diamond mining and its related activities in Boteti have intensified land degradation and impacted negatively on the environment and livelihoods of the local communities. This study did not ascertain whether degradation in Boteti is exclusively due to climatic variations, anthropogenic factors, or both. However, findings on the role of mining in driving land degradation were established in Selebi Phikwe by Asare and Darkoh, (2001).

To address the land degradation problem, Botswana put some measures in place and is a signatory to the world's major agreement on land degradation, the UNCCD. Botswana has developed a National Action Programme (NAP) that outlines the major causes of degradation and propose approaches to address national challenges of desertification and drought (Reed et al., 2015). The NAP describes several priority areas for averting and remedying land degradation; (i) poverty alleviation and community empowerment; (ii) partnership and capacity building amongst stakeholders and researchers; (iii) sustainable natural resource management; and (iv) developing mechanisms to fund and resource these activities (Government of Botswana, 2006).

In Bobirwa sub-district the community is involved in the Community Based Natural Resource Management (CBNRM), a government initiative that ensures communities cautiously use forest resources sustainably. There is the encouragement of traditional coping mechanisms such as shifting to other agricultural activities during poor yield years, minimum farming methods for conservation of soil, water, and carbon. Some farmers relocate their livestock to areas that have been least affected by the drought. Locals also fence arable fields to prevent arable farming-livestock conflicts and crop attacks by wildlife as well as allow restoration of grazing resources in fields after the harvest (Kinlund, 1996; SADC, 2011). However, there is a need to improve monitoring and evaluation methods for the efficient management of land degradation in the country (Symeonakis and Drake, 2004).

3.4 Approaches Used to Assess Land Degradation

Numerous studies have been conducted at various levels across the globe on land degradation and on how geospatial tools and socio-economic methods have been used to assess land degradation. Moghanm and Baroudy (2014) noted that between direct field observation and satellite remote sensing the latter is more cost-effective and time-efficient to use to investigate land degradation due to its repetitive data acquisition capabilities and large area coverage. However, for a more holistic approach remote sensing-based land degradation studies need to be integrated with other variables such as climate variability and socio-economic information. (Mugari et al., 2018).

3.4.1 Socio-economic Methods

There are several socio-economic methods for data collection. The participatory landscape-based sampling approach combines participatory field point sampling for estimating land-use trends with remote sensing and GIS, household, and key informant interviews for obtaining socio-economic data and discussing policy issues (Sandewall et al., 2015). Sandewall et al. (2015) used participatory landscape-based sampling approach to analyse trends in plantation forestry including driving forces and impacts to environment, climate, economic growth, and livelihoods in China, Ethiopia, and Vietnam. This was done by combining regional, national, and local scale analyses of which the participatory field point sampling approach was applied in the local scale analyses. The approach was found to be flexible and feasible for addressing a range of policy issues by combining different techniques and involving local stakeholders, to establish information on tropical land use and forest change for strategic planning.

Another socio-economic approach to data collection is Topical Rapid Rural Appraisal (TRRA), which answers precise questions on a subject and makes use of the usual Rapid Rural Appraisal techniques of secondary data review, semi-structured interviewing, direct observation, and workshop formation (McCracken, 1988). Kayombo et al., (2005) used TRRA to carry out a study in three villages in Bobirwa Sub-district to identify factors constraining crop and livestock productivity and other human activities associated with the rate of land degradation. The multi-disciplinary team consulted and discussed with local leaders, groups, individuals' farmers as well as support institutions that promote agricultural development in the areas. The study found out that the key graze and browse species have reduced in abundance.

3.4.2 Sampling Techniques

Several sampling techniques are applied to establish field data for both social surveys and biophysical data. These include transects, quadrats, Braun-Blanquet method, stratified random sampling, systematic and purposive sampling.

Transects and quadrats are two ecological tools that help to quantify the relative abundance of organisms in an area (Marutirao, 2016). To track changes over time, it is important to be able to quantify changes in abundance (Marutirao, 2016). A transect is a defined strip of land within which data will be collected and is usually a straight line. A belt transect is a rectangular area, centered on this straight line (Nichols, 1930). A quadrat may be a frame that is set right down to bound a space of the community to be sampled. Inside the quadrat frame, the frequency of plants is recorded using the correct measure of abundance. Quadrats may be square, rectangular, or circular and they may be of any appropriate size (Baxter, 2014).

The Braun-Blanquet method that was devised in 1927, has been widely used in the field for vegetation classification into units based on floristic composition and the identification of characteristic species (Enright and Nunez, 2013). It is used to survey large areas very rapidly. The scale method consists of a plus sign and a series of numbers from 1 to 5 signifying both the numbers of species and the proportion of the area covered by that species, ranging from + (sparse and covering a small area) to 5 (covering more than 75% of the area). The Braun Blanquet scale also includes a five-point scale to express the degree of presence of a plant. For example, 5 = constantly present in 75-100% of the areas; 1 = rare in 1-20% of the areas (Campbell, 1974; Botany Dictionary, 2003).

In contrast to the Braun-Blanquet method, stratified random sampling can be applied for both ecological and social surveys. In stratified random sampling, the sampling frame is divided into sub-groups or strata, and each stratum is then sampled using the simple random sampling method (Stehman,1996). The first step in stratified sampling is usually to divide the population into subgroups based on mutually exclusive criteria (Westfall, 2009). Random samples are taken from every subgroup. Simple random sampling is a fair sampling technique, where each member of the population has an equal likelihood and probability of being selected (Taherdoost, 2016). Compared to random sampling, systematic sampling involves selecting sample elements at regular intervals. Systematic sampling has certain aspects of randomness and at the same time has some non-probability characters. It is defined for social science as obtaining a collection of elements by selecting every tenth person from a prearranged list of them (Jawale, 2012).

Purposive sampling is another approach used for social survey and is a strategy in which settings of persons or events are selected intentionally to provide important information that cannot be obtained from other choices (Maxwell, 1996). Snowballing also used mainly in social surveys is known as chain referral sampling and is considered a type of purposive sampling. In this technique, participants, or informants with whom contact has already been created use their social networks to refer the investigator to other people who might probably form part of the sample (Jawale, 2012; Etikan et al., 2016). However, the risks with this method are that respondents often suggest others who share similar characteristics. It is also mandatory on the researcher to ensure that the original set of respondents is adequately varied so that the sample is not skewed excessively in any one particular direction (Etikan et al., 2016).

In a study for land degradation in Tanzania focusing on perception from the village, stratified and random sampling methods were employed to collect principal data on the major ecological and socio-economic causes of land degradation (Dejene et al., 1997).

Mengesha et al., (2014) used purposive sampling techniques to collect primary data and informant selection to conduct a study on land use, land cover and climate change impacts on the bird community in and around Lake Zeway in Ethiopia. The purposive sampling technique allowed for the selection of individuals who had lived for a long time in the area and had in-depth knowledge and experience of conditions of their environment and could provide long-term information.

In a study on perceptions of ecosystem services provision performance in the face of climate change among communities in Bobirwa, key informants were purposively conducted with personnel and experts from various departments. These departments were specifically chosen as they either managed the actual ecosystem services or the areas providing ecosystem services.

The interviews provided more insight about the study area as well as expert opinion on the availability, use, management, distribution and trends in critical ecosystem services under their jurisdiction (Mugari et al., (2018).

3.4.3 Geo-Spatial Information Technologies

Geospatial refers to all the technology used to acquire, manipulate, and store geographic information (Dempsey, 2014). Geospatial data identifies the geographic location and characteristics of natural and constructed features and boundaries on Earth (Folger, 2009). Furthermore, geospatial analysis is the gathering, display, and manipulation of imagery, use of Global Positioning Systems (GPS), satellite photography and historical data, described clearly in terms of geographic coordinates (American Association for the Advancement of Science, 2019).

Remote sensing (RS) and GIS are effective information technology tools used to generate land cover land-use change data. Integrating GIS and remote sensing provide valuable information on the nature of land cover changes especially the area and spatial distribution of different land cover changes (Shalaby and Tateishi, 2007).

Remote sensing has been outlined as a "science and - art of getting obtaining data regarding an object, area, or phenomenon through the analysis of data acquired by a tool that is not in contact with the item, area, or phenomenon under scrutiny" (Lillesand et al., 2004). The availability of remotely sensed data from different sensors of various platforms with a wide range of spatial, temporal, radiometric and spectral resolutions has made remote sensing the best source of data for different applications (Melesse et al., 2007; AbdelRahmana et al., 2019; Brema, 2019; Orimoloye et al., 2020). Accessibility of temporal data from satellite imagery allows for monitoring of land cover change (Giuliani et al., 2020). In particular, remote sensing facilitates the assessment of vegetation, soil and water, which are three critical biophysical components of land degradation (Lillesand et al., 2004). The assessment of changes in the type or condition of surface features is enabled by multi-temporal imaging. Change detection commonly used in monitoring land degradation is one of the most important of all analyses in remote sensing (Salih et al., 2017). The large size of areas affected, and the variability characteristics of semi-arid areas make satellite monitoring the most appropriate method for surveying land degradation (Dube, 2000). Hence, land cover information as the driver of land degradation can be deduced from remote sensing.

There are several definitions of GIS; Burrough (1986) defined GIS as a collection of tools for assembling, storing, retrieving at will, transforming, and displaying spatial data from the actual world for a set of purposes. GIS integrates hardware, software, and data for capturing, managing, analyzing, and displaying all types of geographically referenced information (ESRI, 1990). Further, a practical instance of a GIS combines software with hardware, data, a user, to solve an issue, support a choice, and help to plan (Goodchild,1997).

Rashid et al. (2011) in a study to assess land degradation in Kashmir Himalaya, India, indicated that remote sensing and GIS are helpful in identification, assessment, monitoring, and mapping degraded lands. NDVI and slope of the region were determined using Landsat-Enhanced Thematic Mapper Plus (ETM+) data, advanced space-borne thermal emission and reflection radiometer, and digital elevation model together with secondary information were analysed to produce varied thematic maps. The vegetation condition, elevation and land use land cover information of the area were integrated to assess the land degradation situation in the area by means of the ArcGIS ‘Spatial Analyst Module’. The resultant composite coverage was classified into four classes: non-degraded, slightly degraded, moderately degraded, and highly degraded.

In some instances, historical air photos are used to depict the land cover land use that was in an area at a certain time. Historical conditions lay the foundation for present management options and can help direct restoration goals. Aerial photographs have been routinely collected since the 1930s in many parts of the world and have aided land management for over 75 years (Morgan et al., 2017).

3.4.4 Image classification

Various methods of detecting and mapping land degradation using remote sensing are used. Image classification is one such approach, whereby images are classified into land cover categories that facilitate detection of the extent of degradation (Munyati and Ratshibvumo, 2011). However, before image classification, there was a need to normalize the multiple images so that the images can be relatively compared.

Relative radiometric normalization to eliminate sensor effects, solar and atmospheric variation from at-sensor radiance values is usually necessary for effective detection of temporal change. In using pseudo-invariant features for radiometric normalization, two images which cover the area of interest, taken at different dates and in some cases captured by different sensors (e.g. Landsat 7 ETM+ and Landsat 8 OLI) are used and have to be Normalised . The image with less radiometric distortions (Yang and Lo, 2000) shown by the normality of its histogram is chosen as the reference image to which the other image known as overpass image is co-registered (Hall, 1991; Yuan, 1996).

Traditionally, pseudo-invariant features are chosen subjectively, whereas an analyst manually chooses known objects, often man-made, that should not change over time (Bao et al., 2012). Ground features that are recognized as having low temporal variability are used as Pseudo - invariant targets and the most commonly used Pseudo - invariant targets are large bright concrete and asphalt surfaces (bright objects), as well as dark asphalt and water targets (dark objects) (Themistocleous et al., 2012). To select appropriate Pseudo - invariant targets, Karpouzli and Malthus (2003) recommended that initial spectral measurements are made before the final selection of the targets to reduce extrapolation beyond the calibration data. Cited in De Carvalho et al., (2013), Schott et al., 1988; Caselles et al., 1989; Eckhardt 1990 argued that it is essential to consider that the elevation is approximately identical over the realm on which radiometric control points are to be selected; the vegetation is minimal due to its susceptibility to temporal changes and that the brightness range is large enough. This increases the reliability of the regression model and the co-efficient thereof. However, this method has shortcomings which include the fact that moisture changes in pseudo-invariant features can influence the accuracy of the approach and the accuracy of isolating the pseudo-invariant features depends on the user's ability and knowledge (Chen et al., 2005).

There are two approaches to multispectral classification, being unsupervised and supervised (Sabins, 1987). The objective of the image classification process is to automatically classify all pixels in an image into land cover categories or themes (Lillesand and Kiefer, 1994). Unsupervised image classification is a technique in which the image interpreting software separates the pixels in an image-based upon their reflectance values into classes with no direction from the analyst. The image analyst then determines the land cover type for each class based on image interpretation, ground truth information, or secondary data and allocate each class to a specified category (Sabins, 1987; Nyamugama et al., 2008).

Supervised classification is whereby the image analyst will outline a training site, being a small defined area on the image which is characteristic of every landscape class found in that image (Nyamugama et al., 2008). The decision space in every class defined is based on the spectral values. The delineation of training areas representative of a cover type is most effective when an image analyst has knowledge of the geography of a region and familiarity with the spectral properties of the cover classes. Once the signatures for each land cover category have been defined, the software then uses those signatures to classify the remaining pixels (Sabins, 1987; Shalaby and Tateishi, 2007; Nyamugama et al., 2008).

Shalaby and Tateishi (2007) in their study to map and monitor land cover and land use changes using remote sensing and GIS in the North-western coastal zone of Egypt applied maximum likelihood supervised classification and post-classification change detection techniques to Landsat images acquired in 1987 and 2001 respectively. Supervised classification was conducted with the aid of ground truth data information collected between 1998 and 2002. This study concluded that agricultural and tourism development projects gave rise to severe land cover change, that led to vegetation degradation and waterlogging in part of the study area.

In their study to evaluate long-term land use and land cover change in a highland watershed in the Blue Nile basin of Ethiopia, Bewket and Abebe (2013) used panchromatic aerial photographs (1957 and 1982) which are taken using visible radiation and a Landsat Thematic Mapper image (2001) as the main input data from which three land use and land cover maps were created using geospatial techniques.

To assess the impact of seasonal land use and land cover variation on land degradation in Palapye region in Central District, Botswana, Mashame and Akinyemi (2016) utilized maximum likelihood supervised classification method to sort Landsat 8 image pixels. The method was able to identify that about 985 km² (22%) of the study area is susceptible to land degradation by water.

In a study to characterise land cover over time in Eastern Botswana, Bobirwa sub-district Botswana College of Agriculture (2004) made use of images from three Landsat sensors *viz*:

(Multi-Spectral Scanner (MSS), Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM+)). These images were classified using supervised classification. The classes developed were bare or lack of grass or tree cover, agricultural (cultivated and grazing), human settlement and forest. The results of this study depicted that there has been an increase in the land occupied by human activities from about 320 000 ha in 1971 and to 800 000ha in 2000. In 1971 over a 1 000 000 ha were mostly devoted to grassland, shrubs, and forest, while by 2000 about half of this area had been cleared for human activities.

3.4.5 Vegetation Indices

Vegetation indices are quite simple and effective algorithms for quantitative and qualitative assessments of vegetation cover, vigour, and growth dynamics (Xue and Su, 2017). Vegetation indices derived from satellite data are one of the main sources of information for monitoring and assessment of the Earth's vegetative cover (Yengoh et al., 2014). They use bands in the visible and infrared wavelengths of the remotely sensed data (Yengoh et al., 2014). Hence, vegetation indices are used to measure the change in vegetation cover, either short- or long-term changes, including monitoring its dynamics (Mambo and Archer, 2007; Munyati and Ratshibvumo, 2011). To enhance the vegetation signal in remotely sensed data and provide an estimated measure of live green vegetation, several spectral vegetation indices have been developed to approximate biophysical parameters of vegetation (Ahmad, 2012).

Some of the vegetation indices are as follows; Normalised Difference Vegetation Index (NDVI), which is a measure of the balance between energy received and energy emitted by objects on Earth. When applied to plant communities, this NDVI establishes a value for the chlorophyll content, that is, the quantity of vegetation present in each area and its state of health or vigour of growth (Meneses-Tovar, 2011). Other vegetation indices were developed to address the shortcomings of the NDVI. For example, one of the earliest attempts at separating green vegetation from the soil background using the NIR/Red ratio was carried out by Pearson and Miller (1972). Since then, many and various vegetation indices have been developed, tested, modified, and used for vegetation-related studies worldwide (Yengoh et al., 2014). Some of these indices are the Transformed Vegetation Index (TVI) proposed by Deering et al., (1975) aimed at eliminating negative values and transforming NDVI histograms into a normal distribution.

The Leaf Area Index (LAI) is the per cent vegetation cover, green leaf biomass, fraction of absorbed photosynthetically active radiation, photosynthetic capacity, and carbon dioxide fluxes (Yengoh et al., 2014). Even though these indices appear to be more reliable and less noisy than the NDVI, they are not widely used except in hypothetical studies. The NDVI seems still to be the leading index in remote sensing applications (Ahmad, 2012).

3.4.5.1 Normalised Difference Vegetation Index

Normalised Difference Vegetation Index (NDVI) is one of the easiest to calculate, most commonly available and has been proven to be an effective tool for monitoring vegetative changes across a wide range of global ecosystems (Shoopala, 2008; Hogrefe et al., 2017). The index is a simple ratio calculation of the red and near-infrared (NIR) reflectance bands that are sensitive to the reflected photosynthetically active radiation of plants (Hogrefe et al., 2017; Brema, 2019; Meng et al., 2). It has also been used to estimate vegetation change, either as an index or as one input to dynamic vegetation models (Bai et al., 2008). Meneses-Tovar (2011) elaborated that NDVI is a dimensionless index, its values range from –1 to +1. The higher values are indicators of high photosynthetic activity linked to shrubland, temperate forest, rain forest and agricultural activity while the low values are indicators of water bodies and bare ground.

There is a good relationship between rainfall variations and NDVI on seasonal and inter-annual time scales for areas where mean annual rainfall ranges from approximately 200 to 1200mm (Nicholson et al., 1990). Temporal variations in the NDVI may be symbolic of the vegetation's response to climatic variability (Vicente-Serrano, 2007). Hence the index can be used to assess the condition of the vegetation cover in relation to rainfall.

However, there is still some uncertainty as to what the NDVI means on the ground in terms of woody cover species types and tree: grass ratio, (Arnberg and Ringrose, 2002). To overcome this uncertainty (Ringrose et al., 1989; Ringrose and Matheson, 1991; and Matheson and Ringrose, 1994), determined that the NDVI was mostly useful in semi-arid areas after the rains by indicating the extent of woody vegetation re-growth and (green) grass cover. In terms of the normal dry season and frequent drought conditions, the NDVI has limited value over Botswana. This is because it can imply a bare soil condition resulting in low NDVI when thinly dispersed to dense, microphyllous leafed woody plants are predominant on the ground (Ringrose et al., 1998).

Nicholson and Farrar (1994) demonstrated that the productivity of woody vegetation is also linked to previous rainfall events, that is, it might not be the current season rainfall that accounts for the vegetation re-growth and resulting high NDVI, but wetness in the previous years, leading to accumulated moisture in the soil that wood vegetation with long roots can draw from and remain productive.

Jafari et al. (2008) in their study of an image-based diversity index for assessing land degradation in an arid environment in South Australia revealed that most of the widely used vegetation indices such as the NDVI are less effective in arid and semi-arid environments where perennial woody vegetation dominates. Due to NDVI limitations especially in arid and semi-arid environments, other indices have been developed such as SAVI, which was developed to improve the estimation of vegetation by minimizing soil brightness influences from spectral vegetation indices involving red and near-infrared (NIR) wavelengths (Huete, 1988).

Nonetheless, satellite-derived vegetation indices, such as the NDVI, have proven their value in the field of large-scale monitoring of vegetation cover and dynamics for land degradation and desertification studies (Ivits et al., 2013; Brema, 2019). Furthermore, NDVI derived from the AVHRR has shown to be capable of systematic, repeatable, and spatially extensive monitoring of vegetation productivity to assess desertification (Wessels et al., 2007). Therefore, this study by using NDVI for 20-year intervals for wet and dry seasons found out the relationship between NDVI, rainfall patterns and land degradation in the studied years.

3.4.6 Thermal Band Data

In a study of improved land use, land cover classification of semi-arid deciduous forest landscape using thermal remote sensing Sinha et al. (2015) used Landsat-7 satellite data. The study targeted the improvement of classification accuracy with the combined use of thermal and spectral information from satellite imagery. The study noted that land surface temperature is sensitive to land surface features and hence can be used to extract information on LULC features. Panah et al. (2001) evaluated the capability of Thematic Mapper (TM) thermal band in land cover land use mapping in Iran, in the Ardakan region, an area of desert with severe salinity conditions, and the Mook region, an area of mountains, forests, dry farming and orchards. The results of image classifications showed that TM band 6 improved the accuracy of classification in Ardakan. In other words, in climatic and geographic conditions represented by dry surface and sparse vegetation, thermal band data may prove to be more useful.

In an attempt to indicate temperature differences in urban areas and compare the relationships between urban surface temperatures and land cover types in Vietnam, Van (2012) extracted land surface temperature from the thermal band of Landsat 7 ETM+. He highlighted that thermal energy responses of different landforms in the study area indicated the variation in the surface temperature of different surface patterns. Analysis indicated that the industrial, residential areas had the highest surface temperature relative to vegetation and water exhibiting lower temperature.

3.4.7 Approaches to Validation and Accuracy Assessment

Recently, there is an increased interest in positioning techniques based on Global Navigation Satellite Systems (GNSS) such as Global Positioning System (GPS), cellular network infrastructure or on the integration of the two technologies for a widespread of applications such as tracking systems, navigation, and precise positioning (Choy, 2016). A GPS is used to ascertain the precise location of the area and features that can be used to assess the accuracy of for instance remote sensing products. For applications that require precision such as geo-referencing of satellite images the GPS should be accurate to less than ½ an image pixel (Copenhaver and Mueller, 2011)

Hatfield Consultants (2008) explained that in planning a field data survey there is need to consult the available maps and satellite imagery to identify areas of interest or uncertainty about information and land cover types in the satellite image. In a study to detect land degradation, mapping and monitoring in the Lake Naivasha Basin, Kenya, Torrion (2002) subdivided the field survey and data collection into phases. These were familiarization and reconnaissance survey and sample area survey, observation, and data collection. The exploratory field survey was conducted to get familiarized with the general conditions in the area. Reconnaissance survey focused on areas affected by land degradation identifying sites for detailed study, which were used for sampling and collection of field data.

Training samples are usually collected from fieldwork, or fine spatial resolution aerial photographs and satellite images. Different collection approaches, such as single-pixel, seed, and polygon, may be used (Lu and Weng, 2007). Some studies have used unsupervised classification to stratify the image for sampling areas to be visited during field data collection.

Boakye et al. (2008) used unsupervised classification method to classify the images into the various land cover categories. The method is self-organizing in that the image data are first classified by being aggregated into natural spectral groupings present in the scene. The classified areas are then visited during the field data collection period, to verify the location and collect GPS points for the various classified areas.

Bastin et al. (1993); Dube and Pickup (2001) revealed that it has not been possible to undertake rangeland monitoring using ground-based methods because of the lack of precise and repeatable methods capable of separating grazing impact from both seasonal variability and natural landscape heterogeneity. However, these problems can be overcome by analyzing the entire grazed landscape using remotely sensed data and 'grazing gradient' method which separate grazing effects from natural variation. After a period of grazing, vegetation cover typically decreases as one moves closer to the water point producing a spatial pattern known as a grazing gradient (Bastin et al., 1993; Dube and Pickup, 2001). In the simplest case of an isolated watering point in one uniform rangeland type, a gradient of utilisation pressure develops which is greatest near the watering point and decreases as a function of distance from it (Thrash and Derry, 1999).

Data for accuracy assessment can be established from a field survey and secondary sources i.e. maps or even sometimes from higher spatial resolution satellite data i.e. Landsat ETM+ could be used to validate MODIS data without fieldwork. Validation ensures that what is shown in remotely sensed products is the same feature found on the ground at a given location. Accuracy assessments are used to determine the quality of the classification (Millard and Richardson, 2015).

Congalton (1991), noted that the use of the error matrix for accuracy assessment of classification products has been recommended by many researchers. Copenhaver and Mueller (2011) noted that there are many ways to measure image accuracy, producer's accuracy, users' accuracy, and Kappa statistics.

The errors of omission (producer's accuracy) indicate the probability of a reference pixel being correctly classified and the producer of the classification is interested in how well a certain area can be classified. The errors of commission (users' accuracy) are indicative of the probability that a pixel classified on the map or image represents that category on the ground (Congalton, 1991; FAO (2016). Kappa statistics is a measure of actual agreement of in the error matrix for the remotely sensed classification and the reference data (Torrion, 2002; Rashid et al., 2011).

Namdar et al. (2014) chose 410 reference sampling locations from the image using a stratified random sampling procedure to encompass the full variety of land cover land use classes in semi-arid regions with knowledge of the locality. An error matrix was generated to compare land cover and land use from image classification with the ground-based land cover land use reference classes established the same month of the image capture. The extent to which these two classifications agreed was measured by map producer's, user's accuracies and by the kappa coefficient.

In a study to carry out accuracy assessment, Shalaby and Tateishi (2007) used 200 points, 150 points from field data and 50 points from existing topographic maps dated 1983 and land cover map dated 1987. The location of the 200 points on the land cover land use classification was chosen using a random stratified method to represent different land cover classes of the area.

Mashame and Akinyemi (2016) validated the Landsat 8 imagery of seasonal land use land cover maps, using stratified sampling points for land use land cover maps for 2014 dry and rainy seasons for Palapye area. They generated 202 and 204 points for dry and rainy season land use land cover maps, respectively.

3.5 Spatial Modelling of Land Degradation

Modellers project future land cover, by accounting for driving forces of land cover change from local to global and the interaction of those driving forces over space and time (Sohl and Sleeter, 2012; Mienmany, 2018). Land use land cover change models are used to improve and/or a better understanding of the modification of land use that is brought about by human activities (Brown, 2004; Joseph et al., 2020).

Remote sensing and GIS are powerful tools in change analysis and simulation of land use land cover. Continuous data from Landsat imagery also provides valuable information that can be used as input for prediction studies (Hamad et al., 2018). In conceptualizing and developing models for problems of spatial nature, GIS has become most valuable. GIS tools go a further step from processing, analyzing, and combining spatial data, to consolidate and assimilate spatial processes into larger systems that model the actual world (Schaller and Mattos 2009; Khawaldah et al., 2020). Some of the methods for land cover and land-use change modelling include Markov Chain and Land Change Modeller (LCM).

When changes and processes in the landscape are difficult to describe, Markov chain analysis is one of the methods used to predict land use land cover changes (Estmen, 1995; Hamad et al., 2018; Liping et al., 2018). Markov Chains is a stochastic process model that describes the probability of change from one state to another, according to state space, which is from one land-use type to another, using a transition probability matrix. The transition chance would be the possibility that a land cover type (pixels) at the time t_0 shifts to a different land cover type in the time t_1. Hence, changes in land use between the dates are used to develop a probability transition matrix and then predict land uses for a future time (Mishra et al., 2014; Vázquez-Quintero et al., 2016; Liping et al., 2018; Nath et al., 2020). The Markov model is a good model for this study as the Markovian model estimates the quantity of change and is suitable to be implemented to predict the future changes for 2030 (Hamad et al., 2018).

In a study to detect land use land cover changes (1985–2007) and to forecast the changes in the future (2021) using multi-temporal satellite imagery in the semiarid area in western Iran, Fathizad et al. (2015) used Markov chain model. The classified images of 1985, 2000, and 2007 were applied as land cover maps to make transition matrix for simulation land-use changes in 2021. The training data was sampled in 2014. Therefore, the temporal map of a 7-year cycle was chosen for prediction. By using land cover maps obtained for each period, the transition matrix of land cover classes between two periods was calculated.

Mirkatouli et al. (2015) used the proximity to and the amount of agricultural and forestland in the analysis and modelling of the land-use changes. The probability of the conversion of agricultural and forestland to built-up areas were modelled using the Markov chain. The study concluded that without attention to planning for protective procedures, the trend toward changing agricultural and forestland to built-up areas will continue and have adverse effects on the regional environment.

However, Markov chains are essentially projection models, they are not policy-sensitive and cannot easily incorporate the range of policy variables that might be of interest in predicting the impacts of various land-use policies (Iacono et al., 2012; Hamad et al., 2018). Therefore, this study considered this during data analysis.

The Land Change Modeller (LCM) for Ecological Sustainability is designed to address the problem of accelerated land conversion and the very specific analytical needs of biodiversity conservation. LCM is integrated within the IDRISI system and available as an extension to ESRI's ArcGIS. LCM provides tools for the assessment and projection of land cover change, and the implications for species habitat and biodiversity (ClarkLabs, 2009; Näschen et al., 2019). In LCM, land cover change prediction utilizes two land cover maps from two different dates (time 1 and time 2) to predict what the land cover will be in the future (time 3) (ClarkLabs, 2009; Vázquez-Quintero et al., 2016; Näschen et al., 2019).

In a study to predict and analyse the present and future growth of Muzaffarpur city and it's surrounding in Bihar (India), change prediction map of the year 2025 and 2035 were produced using the Landsat satellite images of 1988 and 2010 using LCM. The transitions and exchanges that took place between the various land use and land cover categories during the years were obtained both in a map and graphical form (Mishra et al., 2014).

3.6 Conceptual Framework

According to the DPSIR framework, "there is a chain of causal links starting with 'driving forces' (economic sectors, human activities) through 'pressures' (emissions, waste) to 'states' (physical, chemical and biological) and 'impacts' on ecosystems, human health and functions, eventually leading to political 'responses' (prioritisation, target setting, indicators)" (Kristensen, 2004).

Darkoh and Mbaiwa (2014) made use of the DPSIR framework in their study of the environmental threats facing the Okavango Delta, in Botswana. The framework assisted in organising the study, identifying, and describing the stresses and key environmental threats. The framework depicted that the ecosystem is rapidly transformed by both physical factors such as climatic variability, climate change, tectonic activities and human activities. The human activies are, overgrazing of rangelands, arable farming, hunting of wild animals, over-harvesting of veld products, deforestation and bushfires.

This study through the application of the DPSIR framework (Figure3-1) aimed at assessing the driving forces of land degradation and if there has been an expansion in its extent between the 1971 to 2019 period over different land systems of Selebi Phikwe and Mmadinare area. The driving forces of land degradation were found to be both natural and anthropogenic (Ringrose and Chanda, 2000; Kiage, 2013).

This model (Figure3-1) allows the evaluation of the impact of the human socio-economic pressures on the environment. The ‘drivers’(causes) are the social, demographic and economic development in the world. The factors such as urbanization, unemployment (Giuliani et al., 2020) and mining and climate variability drive the activities which have a direct impact on the environment. The ‘pressure’ also known as ‘pollutants’ are the ever-changing stress on the human and environmental systems. These are deforestation, over-grazing and increased human population which lead to increased demand for land for developments.

The ‘state’ is the quality of land in an area at a given point in time, e.g. reduction in vegetation cover, degree of land degradation and rate of land degradation. However, the quality of land depends on the resilience of the land and its ability to recover after dry periods or after the pressures are removed or reduced from the area (Engleton, 2010). The ‘impact’ is the indicators of land degradation such as loss of water resources, loss of productive land and bush encroachment. The ‘response’ to land degradation involves the formulation and adoption of policies to manage environmental problems and employing pro-active measures such as data assimilation. All these measures could lead to attaining sustainable development goals through the promotion of sustainable production, consumption and managing natural resources.

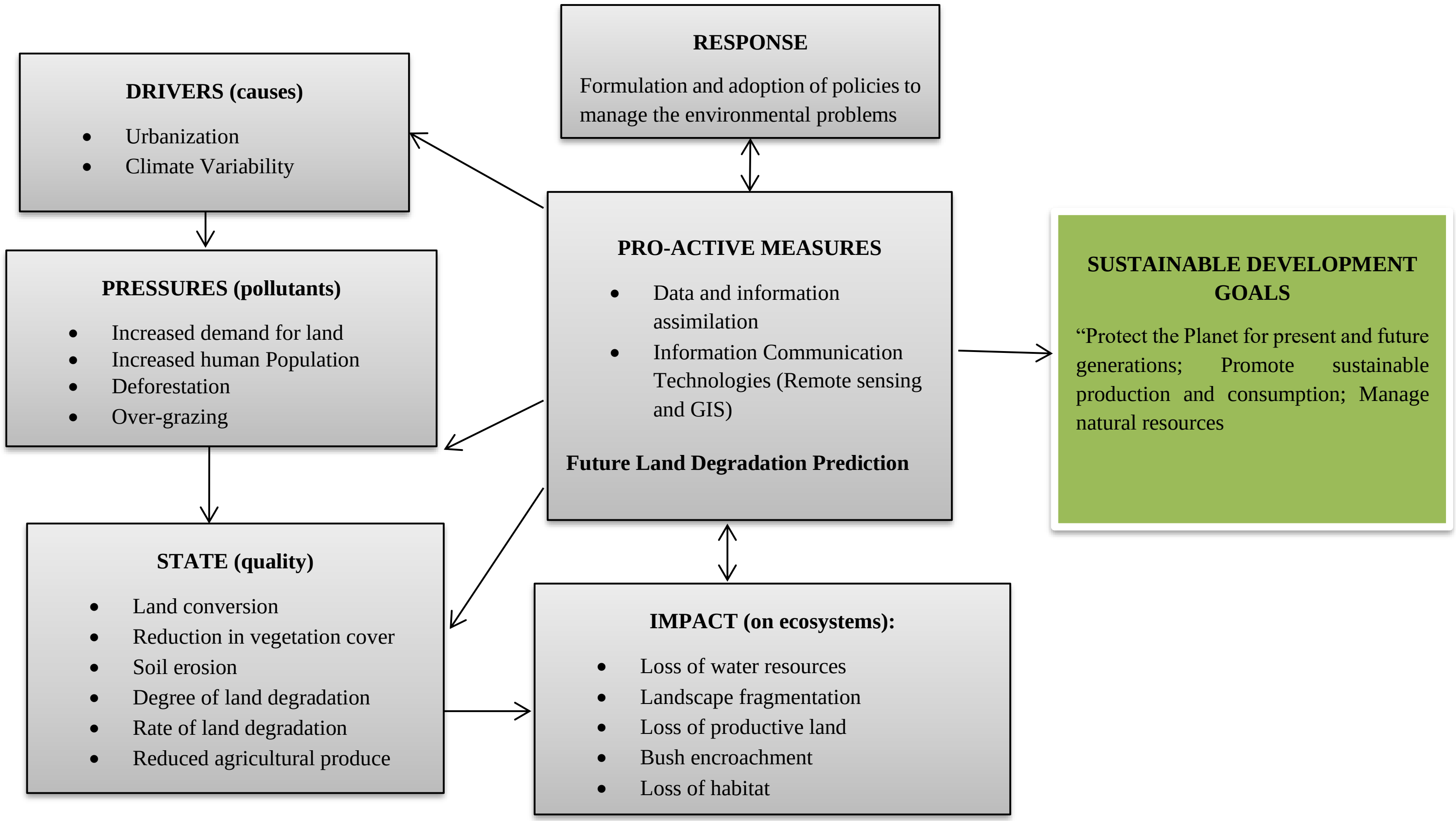


Figure 3-1: Modified DPSIR Framework
Source: *(Kristensen, 2004)*

4. RESEARCH METHODOLOGY

4.1 Overall Approach

This chapter is focused on the data collection methods; secondary, primary and geospatial based data, to address the objectives 1 and 2. The objectives *assess the spatial extent and temporal trends in land degradation in Selebi Phikwe and Mmadinare area from 1971 to 2019 and investigate the role of climate variability and land-use pressure on land degradation in Selebi Phikwe and Mmadinare area.* The chapter describes methods used to gather biophysical field data and socio-economic data and the process that was applied to identify land-use pressure points to assess patterns of land degradation. In addition, measures used to process, extract information from secondary data, socio-economic data, air photos and satellite images and analyse the outputs are reported. The accuracy assessment of the satellite products is also presented. Furthermore, the chapter describes spatial modelling of land degradation using Markov chain to address the objective 3 on; *to model land degradation in Selebi Phikwe and Mmadinare area.*

Socio-economic data, air photos and satellite images were employed to assess land degradation of Selebi-Phikwe and Mmadinare area. The study employed qualitative and quantitative methods to foster a multi-dimensional approach to investigating land degradation. The flow chart below shows how the different data sets were linked and used to establish the data for assessing and predicting land degradation (Figure 4-1).

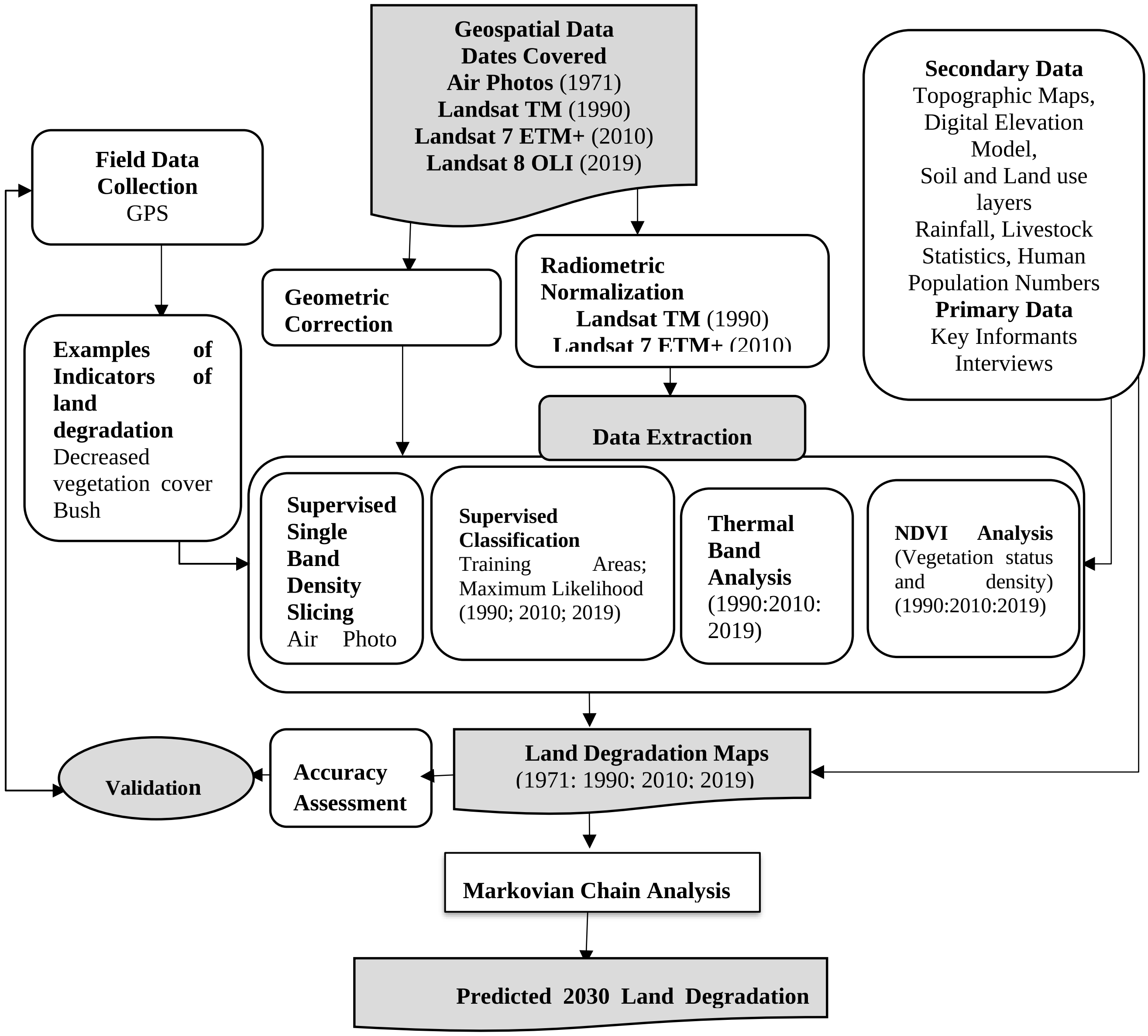


Figure 4-1: Flow Diagram for Establishing Information for Assessing and Predicting Land Degradation

4.2 Data Collection Methods

4.2.1 Secondary Data

Secondary data was used to address objective on *"To investigate the role of climate variability and land-use pressure on land degradation in Selebi Phikwe and Mmadinare area*.

Topographic Maps for the study area were secured from the Department of Surveys and Mapping. The type of land degradation at any time and place depends on the susceptibility of the soil to degradation, therefore, soil data was a key input and was secured at 1:250,000 from the Ministry of Agriculture (FAO, 1990).

Rainfall data that covers the years (1990, 2010 and 2019) was established from the Department of Meteorological Services. This data was used to select satellite image dates; 1990 Landsat Thematic Mapper (TM) coinciding with an annual rainfall of 338.5mm, 2010 Landsat 7 Enhanced Thematic Mapper Plus (ETM+) was for annual rainfall of 358.5mm, and 2019 Landsat 8 Operational Land Imager (OLI) a drought year where rainfall levels were 273.5mm. The use of rainfall data to select images ensured both above and below-average rainfall seasons were considered to adequately assess the land degradation process.

The recorded livestock data from 2004 to 2015 for the Selebi Phikwe and Bobonong area that was surveyed annually by the Ministry of Agriculture was collected from the Central Statistics Office. The livestock data was used to substantiate the results of the study in terms of the number of cattle in the study area which are also linked to over-grazing and subsequently land degradation. The human population for 1971-2011 censal periods, was used in this study to assess the pressure brought onto the environment by the mining activities in the study area.

4.2.2 Primary Data Collection

4.2.2.1 Key Informants

Open-ended interviews (Appendix 1) were administered to the key informants to gather Qualitative information. The major data categories collected were on demographics and length of stay of key informants, different land uses in the area in the 1970s, the rainfall patterns over the years and the causes and indicators of land degradation. Key informants included experts in relevant technical departments and selected members of the public in the study area, who included elderly persons. The respondents were interviewed about the historical changes in land cover land use that took place and the changes observed about climate variability. Key informants' interview data was related to analysis from remotely sensed data and field investigations to find out any relationship between the two data that could explain the land degradation that took place. The interview instrument was divided into two sections, demographic characteristics, and land cover land-use changes. This method addressed objective on*: "To investigate the role of climate variability and land-use pressure on land degradation in Selebi Phikwe and Mmadinare area".*

4.2.2.2 Sampling Technique for Key Informants

Ten experts from Physical Planning at the Selebi Phikwe Town Council, Technical Officers from Mmadinare Sub Land Board and Department of Surveys and Mapping were purposively selected based on their expertise (Maxwell, 1996). The selection was based on the premise that they have been involved in the planning of the study area, and they will provide contemporary data for the study.

Purposive sampling was also applied for the selection of members of the public who have lived in the study area since the 1970s or earlier and as a result were considered eligible to provide historical information on land cover land-use changes in the area. The members of the public were selected through a snowballing sampling procedure, as the members of the public know each other and they referred the interviewer to the next respondent (Jawale, 2012; Etikan et al., 2016). The starting point was the Chief given his knowledge of the people he presides on.

The number of people to be interviewed was guided by the responses received, and after interviewing thirty members of the public, there was no significant new information, the interview process was ended. The data gathered was considered representative of the targeted key informants.

4.2.3 Geospatial based Data

4.2.3.1 Land Cover / Land Use Data Collection

Remote sensing was used to address objectives 1 and 2: "*To assess the spatial extent and temporal trends in land degradation in Selebi Phikwe and Mmadinare area from 1971 to 2019"* and *"To investigate the role of climate variability and land-use pressure on land degradation in Selebi Phikwe and Mmadinare area".* The results obtained from Remote sensing were the basis for achieving the objective on: *to model land degradation in Selebi Phikwe and Mmadinare area.*

Remote sensing allows for the provision of spatial and temporal information on land cover and land use for understanding these processes and hence, providing for the ability to model and make projections (Yuan et al., 2005).

Above-average rainfall years (1990 and 2010) were used to assess the potential of recovery, which was an indication that the area has not lost productivity potential after droughts such as that of the 1980s. The 1980 year cannot be used to assess the potential of recovery as assessing land degradation during a drought year could confuse the temporary effects of drought with long term change. However, the year 2019 was an exception as it was the most recent year for the study.

The baseline data creation for this study required images for the year 1971, however, satellite imagery system had not been operational at the time. To ameliorate this, this study relied on panchromatic Aerial Photographs which are available for the year in question. The panchromatic films cover mostly the visible portions of the spectrum and produce black and white images (Bewket and Abebe, 2013). The March 1971 air photos (Figure 4-2) were secured from the University of Botswana, Department of Environmental Science archives.

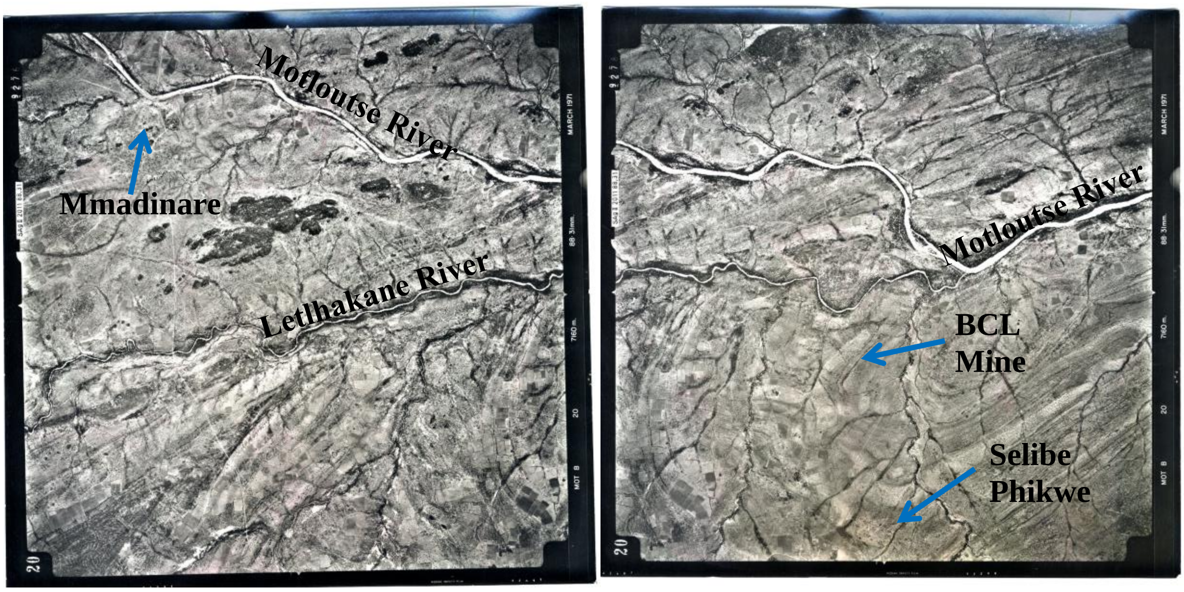


Figure 4-2: March 1971 Air Photos
Figure 4-2 Explanatory Note: Aerial photos cover Mmadinare and Selibe Phikwe before the mine was established (now located on an aerial photo on the right). A very dark coarse area on hills and along streams are very dense vegetation, in some areas grey and medium grey is dense vegetation. Fields occur as some light tone and other dark-grey to grey.

Images used in the study were acquired from various sources including Worldview and United States Geological Survey (USGS) web site (Table 4-1). All the images were acquired at UTM -WGS 84 map projection. In addition to above-average rainfall as a basis of selecting image dates, the 1990 Landsat Thematic Mapper (TM) and 2010 Landsat 7 Enhanced Thematic

Mapper Plus (ETM+) dates allowed for assessment of land degradation over a 20-year period, which is an adequate period for observing land cover land-use changes (Burnharm, 1973). While the 2019 Landsat 8 Operational Land Imager (OLI) imagery was used as the basis for accuracy assessment because it is the most recent date, which can be matched with ground data.

Table 4-1: Spatial and Spectral Resolution of Landsat Satellite Sensors data used in the Study

Resolution	Landsat 4-5 TM	Landsat 7 ETM+	Landsat 8 OLI
Spatial (m)	**30**	**30**	**30**
Spectral (μm)			
Band 1	0.45-0.52 (Blue)	0.45-0.52 (Blue)	0.43-0.45 (Coastal Aerosol)
Band 2	0.52-0.60 (Green)	0.53-0.61 (Green)	0.45-0.51 (Blue)
Band 3	0.63-0.69 (Red)	0.63-0.69 (Red)	0.53-0.59 (Green)
Band 4	0.76-0.90 (NIR)	0.75-0.90 (NIR)	0.64-0.67 (Red)
Band 5	1.55-1.75 (SWIR)	1.55-1.75 (SWIR)	0.88-0.85 (NIR)
Band 6	10.40-12.50 (TIR)-120 m	10.40-12.50 (TIR) - 60 m	1.57-1.65 (SWIR 1)
Band 7	2.08-2.35 (SWIR)	2.1-2.35 (SWIR)	2.11-2.29 (SWIR 2)
Band 8		0.52 - 0.90 (PAN) -15m	0.50-0.68 (PAN) - 15m
Band 9			1.36-1.38 (Citrus)
Band 10			10.60-11.19 (TIRS 1) - 100m
Band 11			11.5-12.51 (TIRS 2) - 100m

***NB*:** IR: Infrared, NIR: Near-Infrared, SWIR: Short-Wavelength Infrared, TIR: Thermal Infrared, TIRS: Thermal Infrared Sensor, PAN: Panchromatic*
Source: https://www.usgs.gov/land-resources/nli/landsat

Further attempts were made to ensure images of the same season taken over the same months are secured to reduce illumination differences and atmospheric effects (Appendix 2). A wet and dry image was secured for each studied date including the 2019 date. The months of April (wet season) and September (dry season) respectively (Figure 2-3), were adopted for the 1990 Landsat TM, 2010 Landsat 7 ETM+ and 2019 Landsat 8 OLI imagery to allow for assessment of land degradation. Land degradation was assessed on the images with the aid of image classification, vegetation indices and thermal bands (Figure 4-3).

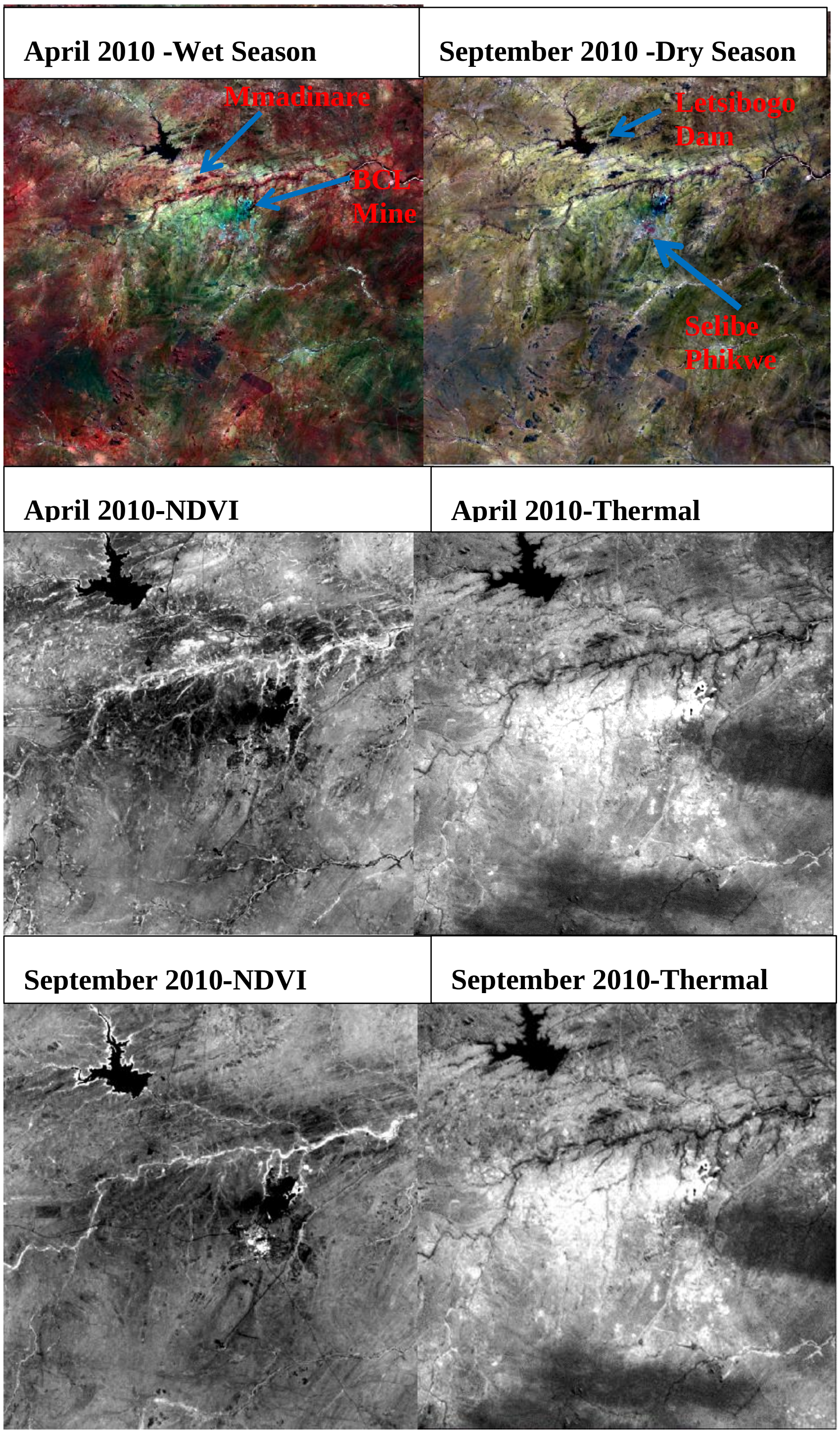


Figure 4-3: 2010 Landsat ETM+ Raw Images, Normalised Difference Vegetation Index (NDVI) Images and Thermal Band

Figure 4-3 Explanatory Note: The first pair are raw false colour images where vegetation is shown in red colour during the wet season, Letsibogo dam comes out dark with BCL mine and township shown in cyan-greenish colour while Mmadinare village shares nearly the same colour as bare areas shown in shades of light green. The second pair are NDVI image where white tone indicated dense vegetated cover, and the darker tone designated bare soils and other non-vegetated features e.g. water bodies. On the thermal band, bare bright soils and the built-up area appeared white due to high temperature associated with high thermal radiation emitted by these surfaces, whilst water bodies and vegetated areas appeared darker because they are cooler and as a result emitted less energy.

4.3 Biophysical Field Data Collection

All satellite-based assessment requires validation which can be achieved using field data, secondary information from available maps or evidence established through key informant interviews. Biophysical field data was collected to establish cover types and indicators of land degradation, establish cover types to carry out a semi-automated image classification and its validation and establishing the accuracy of satellite-based information for the latest date. This was to help provide some indication on the potential accuracy of information from the historical dates used. A Global Positioning System (GPS) and topographic maps were used in the field for orientation and establishing the location of sampling points and observed features of relevancy.

Preliminary land cover maps were produced before going to the field, for both wet and dry season images of the respective image dates, using unsupervised classification (Sabins, 1987; Nyamugama et al., 2008) (Figure 4-4, Table 4-2 and Appendix 3). These preliminary maps provided the base for the ground sampling transects. The NDVI images and thermal bands of April (wet) and September (dry) months for each studied date were overlaid with the preliminary classification to ascertain the land cover types in the study area and establishing where to locate ground transects for sampling biophysical data (Nichols, 1930) (Figure 4-3, Figure 4-4, Table 4-2 and Appendix 4).

The field data collection exercise enabled the systematic recording of information on indicators of land degradation over the 40km x 40km study area. Sampling relied on eight belt transects located using a GPS and formed by a 2km wide rectangular area, centred on a line drawn from the western side of Selibe Phikwe built-up area, though not a land use pressure point but was treated as the centre of the study area (Nichols, 1930). This allowed the assessment of land degradation from different cover types.

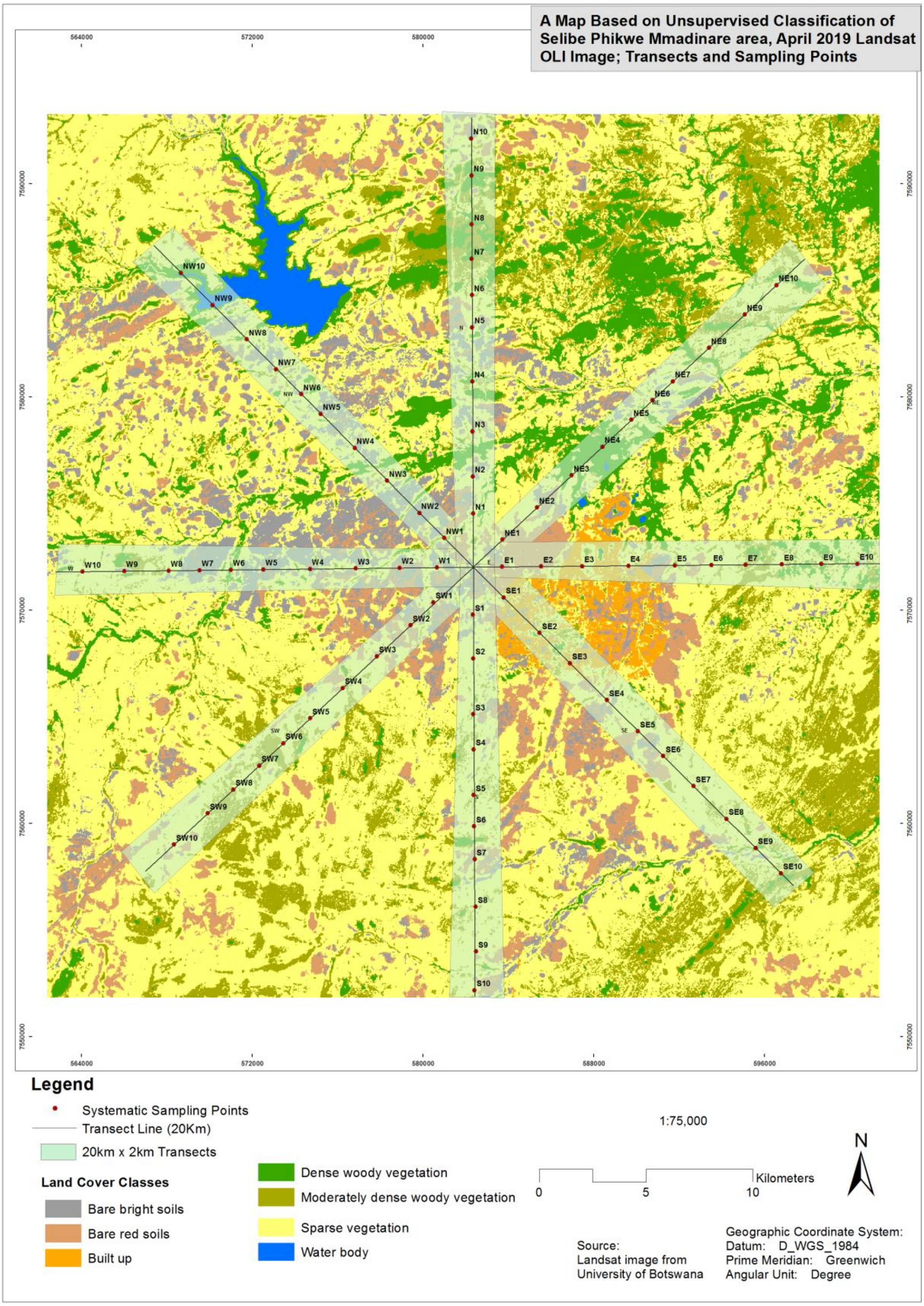


Figure 4-4: Preliminary Land Cover Map of Selibe Phikwe Mmadinare area, April 2019 Landsat OLI Image with Field Transects and Sampling Points

Figure 4-4 Explanatory Note: Transects were centred on a line drawn from the western side of Selibe Phikwe built-up area, though not a land-use pressure point but was treated as the centre of the study area

Table 4-2: General Description of Preliminary Land Cover Land Use Classes

Land Cover Land Use Class	General Description
Dense woody vegetation	Areas covered with 60-100% dense woodland vegetation and shrubs forming closed canopies, also found on hilltops and along river channels
Moderately dense woody vegetation	Areas with 40-60% vegetation and grass cover
Sparse vegetation	Areas with up to 40% vegetation and grass cover
Bare Soils	Areas of exposed soil surface as influenced by human impacts and/or natural causes, as well as areas with active excavation
Built-up area	Includes areas with human settlements, for example, town, or village
Arable fields	Well-demarcated cultivated areas and abandoned arable fields
Mining area	These include the areas where mining activities are taking place
Waterbody	Areas of open water, for example, dams, ponds, streams, and rivers,

The transects extended over a distance of 20km to the boundary of the study area, going either side of the eight cardinal directions (North-N; South-S; East-E; West-W; NE, SE, SW; NW) (Figure 4-4). Transects were used to sample biophysical data because they allowed for quantification of the relative abundance of plants in the study area (Marutirao, 2016).

Systematic random sampling was achieved by determining the distance between sampling points along the transect (Jawale, 2012). Systematic random sampling was applied because it reduced the potential for bias in the data as the selection method was at a fixed distance between each sample. To delineate sample plots within the 20km x 2km belt transects, sampling points were placed on the centre line along the transect to treat the centre of the transect as the centre line of the quadrat. This allowed estimating the area of a quadrat that is covered by land cover type (Baxter, 2014). These translated into 10 samples per transect. In total there were 80 samples from different cover types in the study area. A 40m x 40m quadrat was established on the ground at each 2km interval and therefore slightly larger than the pixel size of the satellite data, 30m x 30m to allow for potential location errors on the image. A GPS was used to establish coordinates of each quadrat in the field in line with their position on the image. Quadrats were numbered corresponding to the transect label.

In each quadrat, the following major data categories were collected, landform and drainage systems, major land uses, soils, and vegetation. A biophysical field data sheet (Appendix 5) was used to systematically collect information within a quadrat based on observations. Vegetation cover was collected in the field with the aid of the Braun-Blanquet scale method (Campbell, 1974; Botany Dictionary, 2003; Enright and Nunez, 2013). Braun-Blanquet scale method was applied as the system provides a reasonably accurate and uniform approach to vegetation classification (Campbell, 1974). GPS was used for picking the coordinates of indicators of land degradation which were compared with the classified Land Cover Land Use maps to produce land degradation maps.

To establish cover types from the quadrat to the transect level, vegetation cover-abundance within the quadrats was visually interpreted based on thresholds provided by Braun-Blanquet cover-abundance scale. The proportion of land under woody and the herbaceous cover was expressed as a percentage. This was carried out separately for woody and herbaceous species. Woody species identification was also carried out per quadrat where all species occurring within each quadrat were recorded. Proportions of woody and herbaceous cover for all quadrats within a specific transect were averaged to represent the entire transect.

4.4 Data Processing

4.4.1 Processing of Key Informants and Secondary Data

The primary data on key informants (Table 4-3) and secondary data on livestock statistics, human population and rainfall data were coded, cleaned, captured, processed, and analysed using the Statistical Package for Social Scientists (SPSS). Tables, pie charts and graphs (that displays multiple variables simultaneous for comparison or analytic purposes) were used to display trends in rainfall data, livestock, and human population. These facilitated comparisons and analysis of land degradation variables over time.

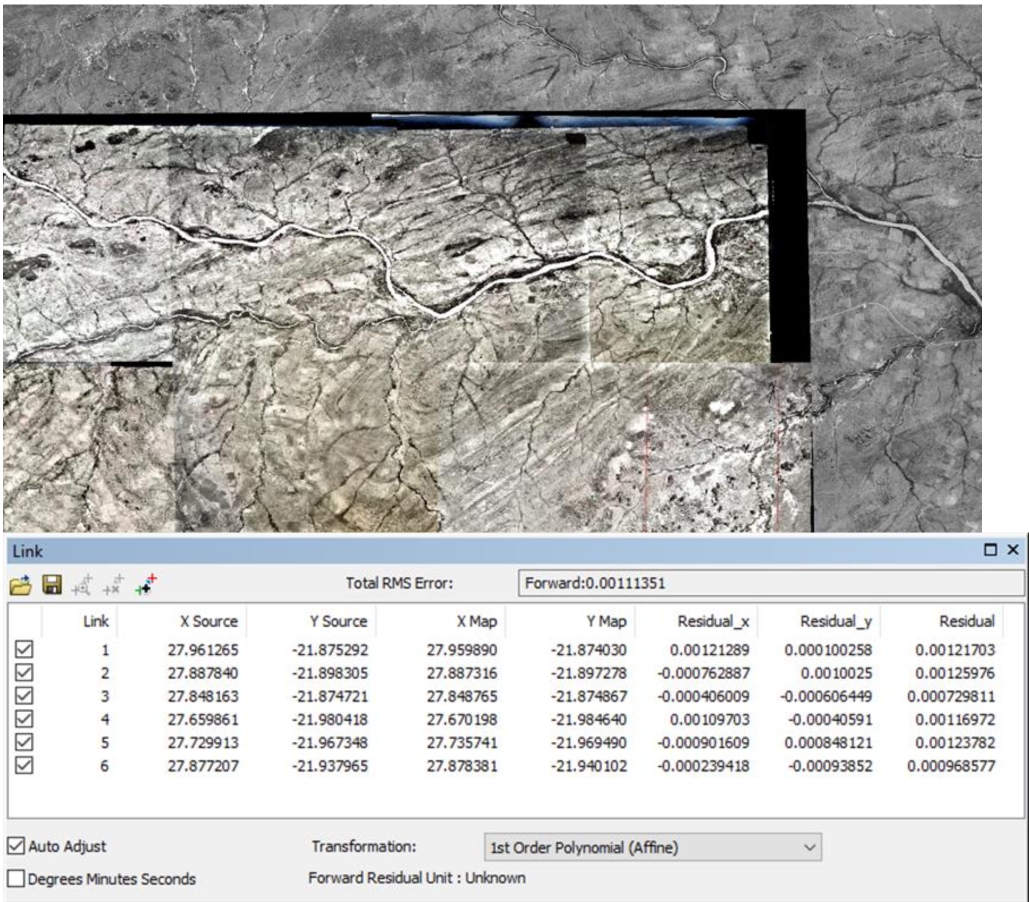
Table 4-3: Categories of Key Informants and their respective Codes Ranges

Code	**Organisation**
KI-1 – KI-4	Selebi Phikwe Town Council
KI-5 – KI-8	Mmadinare Sub Land Board
KI-9 – KI-10	Department of Surveys and Mapping
KI-11 – KI-40	Member of the Public (10 from Selibe Phikwe and 20 from Mmadinare)

4.4.2 Processing of Geospatial Data

The March 1971 air photos were scanned and ortho-rectified to normalise scale before data manipulation and overlaying with other data sets to establish the land cover land use that was present in the study area. To rectify the air photos, the 2002 Orthophoto maps for the study area, acquired from the Department of Surveys and Mapping were used (Figure 4-5).

All the satellite imagery used were acquired at UTM -WGS 84 map projection, hence, the air photos and all the other study maps are at this map projection. Though attempts were made to secure images of the same month over the different dates, the images represented different seasons and hence different solar illumination and atmospheric conditions in addition to sensor related differences resulting in radiometric distortion that needed to be rectified before the data is used. As a result, invariant targets identified on the images were used to normalize (Appendix 6) the data for trend analysis to be performed (Karpouzli and Malthus, 2003; Themistocleous et al., 2012; Bao et al., 2012). Invariant targets such as hilltops, river sands which have remained spectrally stable over the study dates were used to normalize the images (Chen et al., 2005; Bao et al., 2012). Landsat 8 OLI is less prone to scattering as it has an aerosol band (Band1) which corrects for atmospheric scattering was used as a reference image to which the other studied image dates known as overpass images were co-registered (Hall, 1991; Yuan, 1996).



Link	X Source	Y Source	X Map	Y Map	Residual_x	Residual_y	Residual
1	27.961265	-21.875292	27.959890	-21.874030	0.00121289	0.000100258	0.00121703
2	27.887840	-21.898305	27.887316	-21.897278	-0.000762887	0.0010025	0.00125976
3	27.848163	-21.874721	27.848765	-21.874867	-0.000406009	-0.000606449	0.000729811
4	27.659861	-21.980418	27.670198	-21.984640	0.00109703	-0.00040591	0.00116972
5	27.729913	-21.967348	27.735741	-21.969490	-0.000901609	0.000848121	0.00123782
6	27.877207	-21.937965	27.878381	-21.940102	-0.000239418	-0.00093852	0.000968577

Figure 4-5: Rectification of 1971 Air photos

Figure 4-5 Explanatory Note: The 1971 air photo overlain on the 2002 orthophoto maps during the rectification process and the georeferencing link table.

Earth Resources Data Analysis System (ERDAS) Imagine, a remote sensing software package was used for image processing, while ArcGIS 10.5 was used for producing thematic maps from the classified images, location analysis, overlay analysis and presentation of map outputs. GIS was used to enhance the classified map outputs using remote sensing by overlaying the different image dates to establish the changes that occurred over time (Reed et al., 2011). These software's are readily available in the Department of Environmental Science at the University of Botswana.

4.5 Information Extraction

4.5.1 Information Extraction from Key Informants and Secondary Data

Sub-themes (indicators and the drivers of land degradation, spatial and temporal trends in land degradation) were developed from the research objectives and used to aggregate, analyze and interpret the key informant’s data. Statistical data from rainfall, livestock numbers and the human population were employed to explain the trends in land degradation.

4.5.2 Information Based on Air Photographs

The scanned and geo-referenced panchromatic air photographs of March 1971 were classified to establish land cover land use classes. The density slicing supervised classification based on spectral characteristics of earth features in the visible radiation was applied since this was a single band one-dimensional data (Table 4-4) The brightness values of the air photos that are expressed in grey tones were partitioned into defined intervals that were related to land cover land use classes. The output was refined using visual on-screen digitizing in ArcMap.

Table 4-4: Land Cover Land Use Class-Specific Identity Characteristics, 1971 Air Photo

Name of Land Cover Land Use	Description of Land Cover Land Use	Value	Tone	Histogram	Specific Identity Characteristics
Dense vegetation	Very dark coarse areas on hills and along streams and in some areas grey and medium grey	0		3928409	Medium grey to dark tone
		64		19080	
Arable fields	Well-demarcated cultivated areas	128		75590	Light tone and other dark-grey to grey
		191		93285	
Built-up area	Areas with human settlements, with a circular shape	255		68116	Slight to medium grey tone

4.5.3 Information Established from Satellite Images

Data was established from satellite images through classification and undertaking accuracy assessment. The satellite data was complemented with information from NDVI and thermal radiation images.

4.5.3.1 Information Extraction from Image Classification

Information required to address objective No. 1: "*To assess the spatial extent and temporal trends in land degradation in Selebi Phikwe and Mmadinare area from 1990 to 2019"* was established through the application of supervised classification as with the air Photographs. However, in this case, supervised classification using the maximum likelihood was performed to produce maps of different types and severity of land degradation and other cover types in each image date (Shalaby and Tateishi, 2007). The Maximum likelihood classifier was used because of its demonstrated ability to perform better in areas with a range of different cover types (Bolstad and Lillesand, 1991). Training areas were delineated based on the spectral patterns and knowledge of the land cover types found in the study area (Nyamugama et al., 2008) (Appendix 7). Information on cover types was derived among others, from the assessment of the 1971 photographs, preliminary unsupervised classification outputs, the 2020 fieldwork and secondary sources such as the Google Earth maps and complemented by the information gathered from past maps and key informants' interviews (Table 4-2 and Table 4-4).

To detect change over time, the March (wet) season air photos and satellite images April (wet) and September (dry) months were first classified to show land cover land use data for each studied date (Table 4-2 and Table 4-4). However, these land cover land use classes differ across studied years, for example by 1971 and 1990 the Letsibogo dam was not yet constructed. The land degradation classes were extracted in ArcMap from these land cover land use classes using indicators, such as the spatial expansion of settlement, decreased vegetation cover, increase in patches of bare soils to produce land degradation maps for the respective image dates.

4.5.3.2 Accuracy Assessment

One of the first steps in making classification products useful is to assess its quality (Elias et. al., 2018). For this study different accuracy assessments, approaches had to be applied due to the different data types and dates used in the study. For the Air photo-based 1971 map that was used as the baseline for assessing land degradation, relative verification was conducted using past maps and information gathered through interviews of key informants. Similarly, for the 1990 and 2010 satellite imagery classification results, relative validation was achieved using the 1971 Air Photos, historical imagery in Google Earth maps, key informant interviews and past maps. However, these data sets were not of the same dates as the historical imagery (Figure 4-6), hence accuracy assessment of the most recent image, 2019 also served to provide confidence on the likely accuracy of information established from the historical dates.

Figure 4-6: Historical Imagery from Google Earth (December 1990 and December 2010)
Figure 4-7 Explanatory Note: Built-up and mine areas and Letsibogo dam visible on the 2010 imagery. By 1990 the dam was not yet constructed.

The performance of the latest image date, April 2019 classification was verified using field data collected in March 2020 (Table 4-5). To verify the classification an error matrix which cross-tabulates the land cover classes was prepared to establish the overall accuracy, the user’s and producer’s accuracy (Congalton, 1991; Lillesand et al. 2014; FAO, 2016). However, the error matrix indicates how well the statistics extracted from sampled classes can be used to categories the same classes. It does not indicate how the classifier performs elsewhere in the image (Lillesand et al. 2004). To overcome these limitations, the Kappa Coefficient was applied to provide a measure of agreement between the field data and the results of the classification that is adjusted for chance agreement (Torrion, 2002; Rashid et al., 2011; Lillesand et al. 2014; Elias et. al., 2018). The Kappa coefficient was calculated as:

$$K = \frac{\sum_{i=1}^{r} X\,ii - \sum_{i=1}^{r} (x_{i+} * x_{+i})}{N^2 - \sum_{i=1}^{r} (x_{i+1} * x_{+i})} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..equation\ 1$$

Where **N** is the total number of observed pixels in the matrix; in this study, this was constituted by the land cover classes for both classified data and field data for the 2019 image.

r is the number of rows in the error matrix, in which in this study this was constituted by the land cover classes from the classified data.

X*ii* is the number of sites in row *i*, and column *i*, in which in this study this was constituted by, land cover classes verified during the field survey and are correctly classified.

x+i is the total of sites in column *i*, in which in this study this was constituted by the total land cover classes captured from field survey.

Elias et. al. (2018) indicated that the value greater than 0.80 signifies good classification, that there is better agreement between field data and classification than by chance; the value between 0.40 and 0.80 means moderate classification results while less than 0.40 denotes poor classification. Therefore, the overall accuracy and kappa coefficient for this study was 73.33% and 0.69, respectively signifying from the Kappa value that moderate classification accuracy was established (Elias et. al., 2018) (Table 4-5)

Table 4-5: Accuracy Assessment for April 2019 OLI Image Analysis

Land Cover Land Use Class	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy
Dense Woody Vegetation	30	29	27	90%	93.1%
Moderately Dense Woody Vegetation	30	48	18	60%	37.5%
Sparse Vegetation	30	20	10	33.3%	50%
Bare Bright Soils	30	38	24	80%	63.2%
Water body	30	30	30	100%	100%
Mining area	30	27	27	90%	100%
Built-up area	30	18	18	60%	100%
Totals	210	210	154		

Overall Classification Accuracy = 73.33%; Overall Kappa Statistics = 0.6889

4.5.3.3 Normalised Difference Vegetation Index

The Normalised Difference Vegetation Index (NDVI) was used together with the results of the classification to establish the spatial and temporal extent of land degradation (Shoopala, 2008; Hogrefe et al., 2017). NDVI values are positively related to living vegetation cover and as a result can help in the identification of areas that are probably degraded (Mambo and Archer, 2007).

The NDVI images of April (wet) and September (dry) months for each studied year were assessed to find out the status and density of vegetation. The wet and dry NDVI allowed for assessments of the ability of vegetation to recover even after dry periods which has been used by others to establish if an area is degraded or not (Vicente-Serrano, 2007).

The use of the dry season NDVI images also allowed for the possibility to detect perennial vegetation which paved the way to detecting ephemeral vegetation cover during the wet season as a potential indicator of land degradation (Cui et al., 2013). The evidence from the classification and NDVI complemented each other in detecting degraded areas and helped to cross-check the accuracy of each method.

4.5.3.4 Thermal Band Data

The spatial and temporal extent of land degradation established from image classification and the use of the NDVI were further cross-checked using thermal radiation images. Thermal radiation measured by a satellite sensor is related to temperature and emissivity of cover types on the ground, for example, the bare areas are expected to emit highly due to elevated temperature associated with high albedo. Other cover types such as vegetated areas and water bodies have low temperatures and hence emit less energy resulting in low Thermal Infrared radiation values (Van, 2012; Sinha et al., 2015).

4.5.3.5 Process of Defining Land Degradation Classes

Preliminary land cover land use maps, Normalised Vegetation Difference, and thermal infrared emissions for satellite imagery at Selibe-Phikwe and Mmadinare were assessed to establish patterns of degradation in the study area. Land degradation classes were derived based on NDVI categories for different vegetation covers as recommended by (Parmar et al., 2019) and further augmented by thermal emissions for the land cover (Table 4-6 and Appendix 8).

Table 4-6: NDVI, Land Cover Type and Land Degradation Class

NDVI Range	Land Cover Type	Land Degradation class
-1.0-0.0	Bare Bright Soils	Highly degraded
0.0-0.5	Moderately Dense Woody Vegetation	Moderately degraded
0.5-0.7	Sparse Vegetation Cover	Slightly degraded
0.7-1.0	Dense Woody Vegetation	Non-degraded
-0.2-0.2	Bult-up area	-
-0.17-0.056	Mining area	-
0.006-0.467	Arable fields	-
-0.332-0.011	Water body	-

(Adapted from Parmar et al., 2019) *Note: areas marked with a dash are land cover classes

4.6 Spatial Modelling of Land Degradation

The spatial modelling of land degradation was based on the temporal data on land cover land use maps of 1990 and 2010.

4.6.1 The Markov Chain and Land Degradation Prediction

The temporal land cover data from the studied years was subjected to the Markov analysis to address objective 3: *"To model land degradation in Selebi Phikwe and Mmadinare area"*. The Markov chain models are premised on several assumptions. One basic assumption is to regard land cover land-use change as a stochastic process and different categories of land cover are treated as states in a chain (Arsanjani et al., 2013; Mishra et al., 2014; Vázquez-Quintero et al., 2016; Nath et al., 2020). At the same time, a chain is defined as a stochastic process having the property that the value of a process at time *t*, X*t*, depends only on its value at time *t*-1, X*t*-1. This process does not depend on the sequence of values X*t*-2, X*t*-3…. Xo that the process passed through in arriving at X*t*-1 (Arsanjani et al., 2013; Mishra et al., 2014; Vázquez-Quintero et al., 2016; Nath et al., 2020). Therefore, given changes in a particular land cover land use map over a historical time frame, it is then possible to estimate the probability of shifts from each state of land cover to other states (Burnharm, 1973). The model consists of two major components: the *transition matrix* and the *transition probability matrix*.

4.6.1.1 The transition matrix (T) and the transition probability matrix (P)

The transition matrix defines a shift from a specified land cover land use group to another, between two observed points in time. The land cover land use classification results of different dates were used to determine the transition matrix (Burnharm, 1973; Hamad et al., 2018)

A transition probability matrix defines the probability of land shifting from one land cover land use to another over a given period (Burnharm, 1973; Hamad et al., 2018). Burnharm (1973) derived the formula as follows:

$P_{ij} = {}^{t}{}_{ij}$ ……………………………………………..equation 2

L_1^{1990} to calculate the transition probability matrix for the land uses, where: P_{ij} denotes the probability of acreage in land cover land use *i* shifting to land cover land use *j* over a given period of study, in the case of this study, a 20-year period, that is 1990-2010, and, ${}^{t}{}_{ij}$ is the observed acreage shift from land cover land use *i* to land cover land use *j* between in the same period of study. (Cells of the [T]) and L_i^{1990} equals total hectares devoted to land use *i* in 1990 (row total of the [T]).

4.6.1.2 Simulating Land Degradation for the year 2030

The time interval between projection points in the Markov framework is fully determined by the temporal relationship or interval between the two observed points (Burnharm, 1973; Hamad et al., 2018). For this study, the temporal interval is 20 years. Hence, the projection was for the year 2030. The simulation runs projected land cover land use shift between 1990, 2010 and 2030 as these dates allowed a 20-year time interval needed between projection points (Burnharm, 1973). For projecting the 2030 land-use scenario, the following formula was used:

$t_{ij}^{X+1990} = L_j^{X}.\, Pij$……………………………………………..equation 3

Where t_{ij}^{X+1990} denotes the projected acreage shifting *i* to land cover land use type *j* over the 20 years; Pij is the probability of acreage in land cover land use type *i* shifting to land cover land use type *j* over the 20 years. Subsequently, via matrix manipulation, the projected [T] collapses to a projected land use vector $[L]^{X+1990}$

$$\sum_{i=1}^{6} t_{ij}^{X+1990} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.. \text{equation } 4$$

$[L]^{X+1990} = \quad = [L]^{X}.[P]$ ………………………………………..equation 5

Where; $[L]^{X}$ is a row vector that specifies total hectares in each land cover land use type group during the base period and [P] is the transition probability matrix. The matrix process then involved the manipulation of each column in the projected [T] resulting in the projected 2030 land cover land use configuration. The degraded classes were extracted from the modelled land cover land use map to produce a 2030 land degradation map.

4.6.1.3 Model Validation

Model validation is an important step in the process of model prediction (Liping et al., 2018). The 2030 land degradation map was validated by testing the efficacy of the Markov Chain model. This was achieved by predicting the 2010 land degradation map, from the year 1990, as this provided the 20-year temporal interval. The predicted 2010 land degradation map was then compared with the actual classified 2010 land degradation map. Hence the modelled 2010 land degradation map results served to provide confidence on the likely accuracy of information established from the predicted 2030 map to be realistic.

4.7 Data Analysis

The 1971 land degradation map was analysed as the baseline data to determine the degraded areas before mining occurred in the area.

The degraded area coverages for 1971 air photo, 1990 Landsat TM, 2010 Landsat ETM+ and 2019 Landsat 8 OLI classified land degradation maps were calculated and populated in tables for each respective image date. These separate land degradation classes were then overlaid to assess trends over time. The classified land degradation maps were checked for alignment in terms of land degradation classes with the thermal radiation images and NDVI for the respective years. The information from the topographic map and soil maps for the study area complemented the data from field surveys to determine the landforms, drainage systems and soil conditions. Furthermore, the data from the key informant interviews were analysed statistically to explain the trends in land degradation.

Reclassify tool in ArcGIS was applied to discern the land degradation classes and assess the level of degradation in each studied date. The spatial statistical tool such as 'calculate geometry' within ArcMap was applied to generate figures and percentages of change over time. The obtained figures were compared in table form and presented in percentages for ease of appreciation of the spatial and temporal changes in land degradation.

The modelled results were analysed to find out how widespread land degradation will be in 2030. The degraded classes were extracted from the modelled land degradation map and related to the 1990-2019 land degradation data and the potential future trends of land degradation were assessed.

4.8 Limitations of the Study

Limitations, according to Patton (2014), are potential weaknesses or challenges in a study which are beyond the control of the researcher. This study was based on the use of secondary data, key informants, field survey and geospatial data to assess the extent of land degradation and model the future dimensions of the phenomenon in Selebi-Phikwe and Mmadinare area. The researcher established the land degradation that took place over the studied years and predicted how widespread the phenomenon will be in 2030. However, one of the major limitations was non-availability of remotely sensed data for the study area in the 1970s, to adequately analyse the area before mining activities that attracted more people into the area. Therefore, 1971 aerial photographs were employed, and key informant interviews were conducted to complement the results from these aerial photos. There were restrictions on undertaking an accuracy assessment of historical dates (1990 and 2010). To achieve some level of precision, historical imagery in Google Earth was employed, and the images were not of the same dates, hence, key informant interviews and past maps were used to complement the results from the Google Earth historical imagery. Furthermore, there were limitations to validate the 2030 land degradation map. Therefore, to establish that the predicted 2030 land degradation is accurate, the predicted 2010 land degradation map, was validated with the actual classified 2010 land degradation map and was used a the basis to measure the effectiveness of the model.

The other restraint was lack of available secondary data over time; hence, it was difficult to sufficiently study the linkages. For example, the livestock statistics, rainfall, and temperature data were not available for most of the past dates. However, these inadequacies were overcome by multiple uses of data to analyse the land degradation, e.g. use of NDVI, thermal data, field surveys and key informant's data to complement results from the classification outputs.

The study aimed to interview elders to reflect on the historical changes but some of the members of the public did not fit the category of elders and some their length of stay in the study area was not adequate to reflect on historical changes, however, these inadequacies were complemented by data from secondary sources.

The fieldwork schedule fell into a period when the world was hit by the Coronavirus (COVID-19) pandemic, which brought the world to a standstill. The fieldwork exercise was interrupted by the national lockdown rules and regulation enforced by the Botswana government to curb the spread of the virus. Thus, only field surveys were conducted during the first field visit in late March 2020. The key informants' interviews could not be conducted as it was not possible to have physical consultations during this time. However, another trip to the study area was made after the government had eased the national lockdown rules, to interview the key informants. This situation impacted on the study completion and the fieldwork exercise was costly.

4.9 Research ethics

4.9.1 Ethical Considerations

Creswell (2014) recommends that all codes of ethics should be given adequate consideration by the researcher at the beginning of the research study. Hence, ethical issues were observed and the research permit was obtained through the University of Botswana, Office of Research and Development and approved by the Government of Botswana through the Ministry of Land Management, Water and Sanitation Services (Appendix 9).

4.9.2 Dissemination of Results

The copies of the dissertation will be deposited to the University of Botswana Library, Department of Environmental Science (University of Botswana), through the School of Graduate Studies.

4.9.3 Validity

According to Golafshani (2003) validity refers to the accuracy to which research outcomes or results are, that is whether the research truly measures that which it was intended to measure. To ensure validity, biophysical field data was collected for image classification, validation and establishing the accuracy of 2019 satellite images. The key informant's questionnaires were piloted on a few samples to check if they captured what was intended. The instruments were then revised to improve their precision in capturing the required data.

4.9.4 Reliability

Reliability refers to the extent to which results are consistent over time and an accurate representation of the total population under study (Golafshani, 2003). The study employed multiple data analysis methods to complement each other as well as ensuring consistency of results generated. Biophysical field data collection and key informants' questionnaires pre-test also improved on the reliability of the results of the study.

5. RESULTS

This chapter presents the key informant's demographics, indicators of land degradation, the spatial and temporal dimensions of land degradation and its drivers from 1971 to 2019 based on air photography and satellite imagery. The assessment of land degradation using the DPSIR framework and the likely status of land degradation by 2030 are also presented. Hence, the key findings of this study address the three study objectives: *assessing the spatial extent and temporal trends in land degradation in Selebi Phikwe and Mmadinare area from 1971 to 2019; investigating the role of climate variability and land-use pressure on land degradation in Selebi Phikwe and Mmadinare area, and modelling land degradation in Selebi Phikwe and Mmadinare area.*

5.1 Key Informants Demographics

A total of 30 members of the public were interviewed and 10 experts as noted in section 4.4.1 (Table 4-3). About 52.5% (N=40) of the respondents were aged between 45 and 65 years while 27.5% were aged above 65 years (Table 5-1). About 60% of respondents were females while 40% (N=40) were males (Table 5-1) and 90% of participants were engaged in informal employment especially drought relief programmes.

Only 30% (N=40) of respondent lived in the study area more than 40 years and therefore could provide data on the historical land cover land use for the period during the 1970s while 24.5% resided for 30-40 years and elaborated on the land cover land uses for the years 1990 and 2010. The rest lived in the area for less than 30 years (Table 5-1).

In general members of the public above 65 years were considered to have the most reliable information on past changes, but their views were complemented by the other 52.5% group and the 10 experts.

Table 5-1: Age, Gender and Length of Stay established from key informants, March 2020

Age Category	**Percentage (%) of Key Informants**
18-29 years	0
30-45 years	20
45-65 years	52.5
65 years and above	27.5
Gender	
Male	40
Female	60
Length of stay	
Less than 10 years	11
10-20 years	17
20-30 years	17.5
30-40 years	24.5
More than 40 years	30

5.2 Indicators of Land Degradation

This section provides results on indicators of land degradation established in Selibe Phikwe and Mmadinare from social and biophysical surveys that were conducted in March and May 2020.

5.2.1 Indicators of Land Degradation from Key Informants

Information from Key informants was employed to assess the incidence and extent of land degradation in Selibe Phikwe and Mmadinare. About 26% of the 40 respondents indicated that there is land degradation in Selibe-Phikwe and Mmadinare in contrast to 14% who said there is no degradation (Figure 5-1). The rest were undecided.

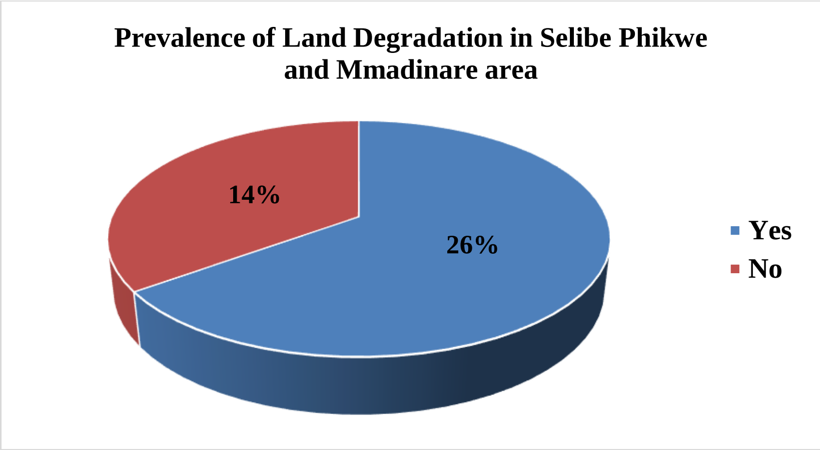


Figure 5-1: Prevalence of Land Degradation in Selibe Phikwe Mmadinare area established from key informants, March 2020

All the respondents who indicated the presence of land degradation in the area reported evidence of indicators of degradation such as decreasing vegetation cover, bush encroachment, increase in patches of bare soil, progressive drying of surface water, decrease in grass density and long dry spells and erosion of soils (Figure 5-2). Five of the respondents over 65 years who had lived in the area for over 40 years indicated that the water drawing points that they used in the 1970s have dried up and those that remain have reduced in size. Some 22.5% of the respondents showed that there is a decrease in vegetation cover in the study area (Figure 5-2).

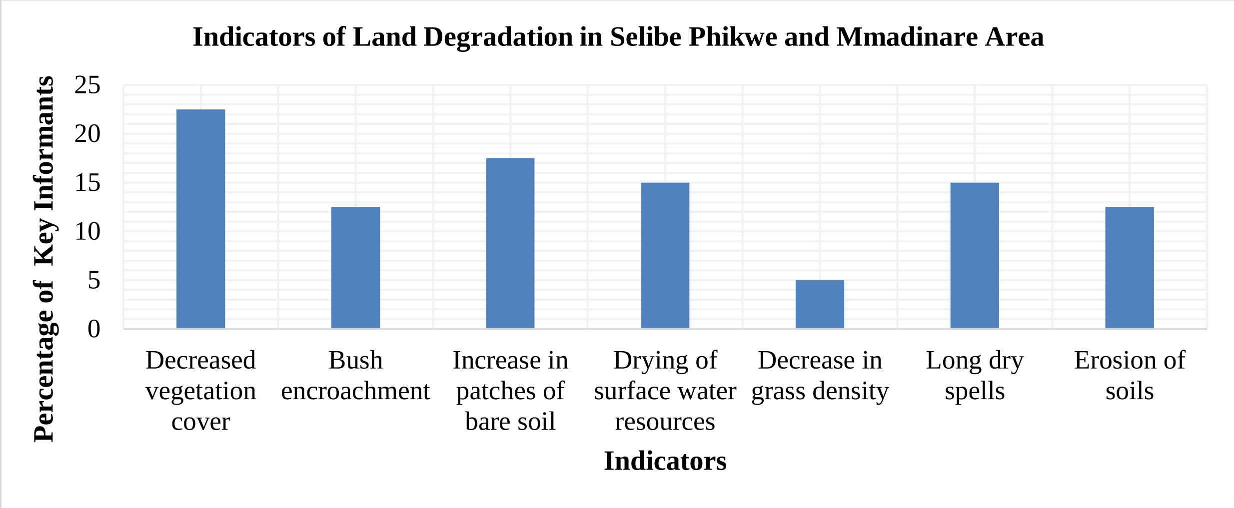


Figure 5-2: Indicators of Land Degradation in Selibe Phikwe Mmadinare Area as perceived by key informants, March 2020

Figure 5-2 Explanatory Note: The Y-axis is the percentage of the key informants (N=40) who noted the indicators

5.2.2 Indicators of Land Degradation Established from Biophysical Field Survey

Results of the field survey conducted in March 2020 showed that major landforms identified during fieldwork were similar to those noted from secondary information and on-air photos and imagery and included river systems and rock outcrops (Figure 2-2 and Table 5-2). In addition, bright and red soils covered most of the study area with limited clay deposits as noted in Figure 2-4 in Chapter 2. Major land-uses matched the land cover land use classes identified in Table 4-2 and included built-up areas, arable fields, mining areas and water body .

It was also established from field survey that vegetation species found in the area were mainly as noted from secondary information in Chapter 2 constituted by *Colosphermum mopane* (Mophane woodland) and A*cacia totillis* (Mosu) (Table 2-1). Other species composition included *Sclerocarya birrea* (Morula), *Adansonia digitata* (Mowana) and *Kirkia acuminata* (Modumela) (Table 2-1 and Table 5-2)

Table 5-2: Landforms and soils, Land cover, Plant Species and Land uses in the Study Area established from March 2020 Field Survey

Transect	Landforms and soils	Land cover	Plant species	Land uses
N	Rivers (dry) Bright, fine-grained soils	Fields and Dense woody vegetation	75% A*cacia totillis* (Mosu), 25% *Colosphermum mopane* (Mophane woodland)	Arable agriculture and grazing
NE	Hills and rocky surfaces, Rivers Bright sandy soils,	Fields and Dense woody vegetation	60% A*cacia totillis* (Mosu) and 40% *Colosphermum mopane* (Mophane woodland)	Arable agriculture, mining
E	Rock outcrops, Red soils	Sparse woody vegetation	10% *Sclerocarya birrea* (Morula), 70% A*cacia totillis* (Mosu) and 20% *Colosphermum mopane* (Mophane woodland)	Built-up area, mining, grazing
SE	Rock outcrop, river Red soils with clay deposits	Fields and Moderate woody vegetation	50% A*cacia totillis* (Mosu), 5% Mowana and 45% *Colosphermum mopane* (Mophane woodland)	Grazing, arable agriculture, built-up area, mining, mogobe (well),
S	Rock outcrop Bright sandy soils, red soils	Moderate woody vegetation	5% *Sclerocarya birrea* (Morula), 5% *Adansonia digitata* (Mowana), 45% A*cacia totillis* (Mosu), and 45% *Colosphermum mopane* (Mophane woodland)	Mining, grazing
SW	Rocky surfaces and Red soils	Fields and Moderate woody vegetation	100% A*cacia totillis* (Mosu)	Arable agriculture, Built-up area, Mining
W	River Red soils,	Fields and Sparse woody vegetation	100% Short woody A*cacia totillis* (Mosu)	Cemetry, Arable agriculture, built-up area and mining area, grazing
NW	Hills, River, Bright sands, red soils,	Sparse woody vegetation	100% *Colosphermum mopane* (Mophane woodland)	Grazing, Built-up area, Dam, powerline, water Pipeline,

Analysis of vegetation cover from the 8 transect and 80 quadrats sampled across the study using the Braun-Blanquet cover-abundance scale showed that vegetation cover-abundance increased from the western side of Selibe Phikwe which was covered by woody vegetation in all directions of the transects (Figure 5-4 and Figure 5-4).

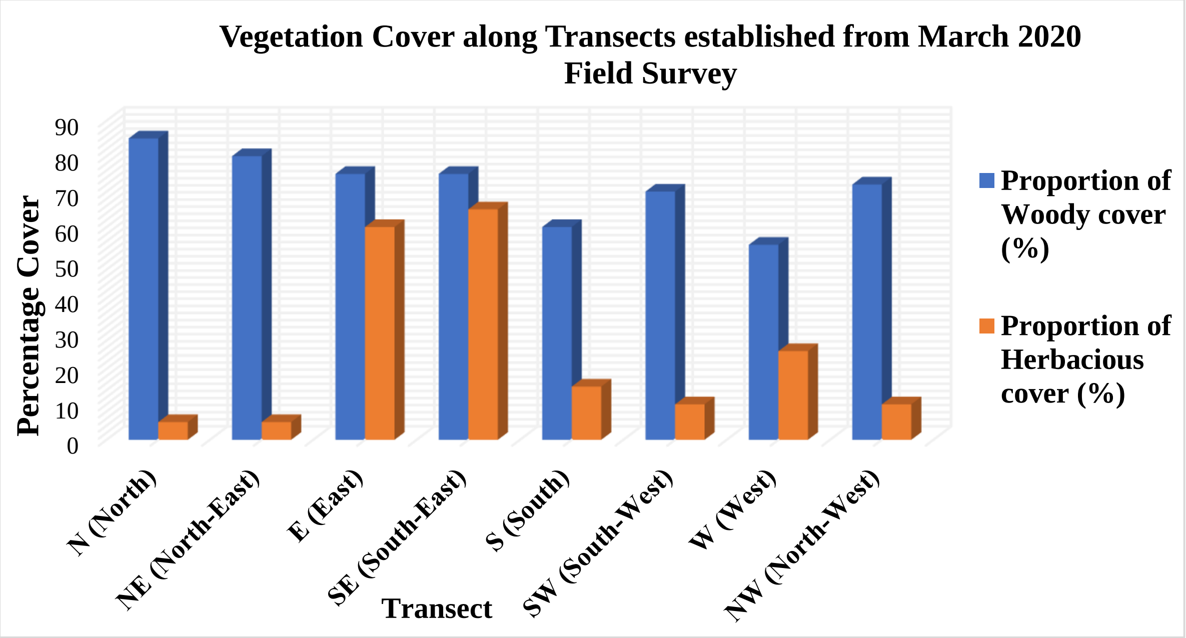


Figure 5-3: Vegetation Cover along Transects established from March 2020 Field Survey

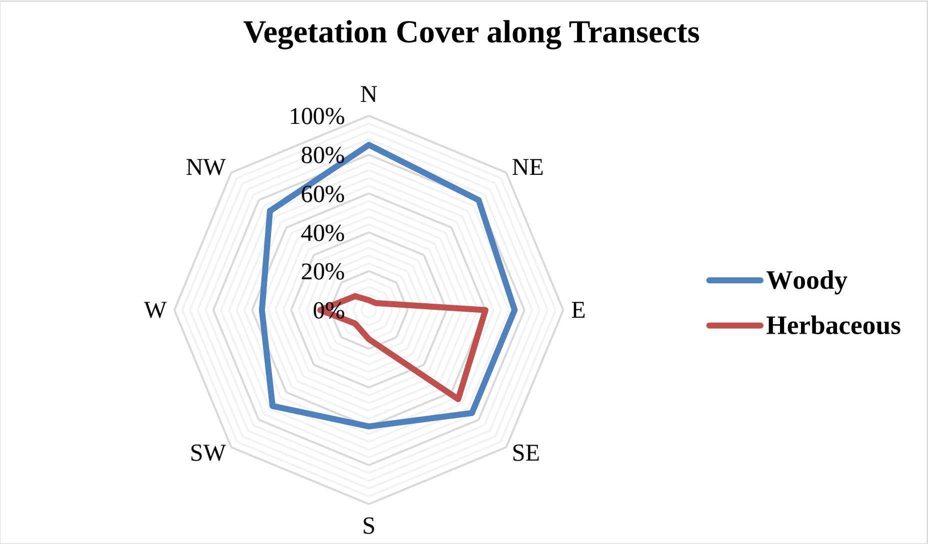


Figure 5-4: Vegetation Cover along Transects established from March 2020 Field Survey

Figure 5-4 Explanatory note: Alphabets are the transects labels based on the 8 cardinal points e.g. North (N), South east (SE). Woody and the herbaceous cover measured on a 0 to 100% scale; the proportion of land cover was expressed as a percentage of the entire transect. For example, 50% cover explains that woody or herbaceous cover accounted for only 50% of transect land area.

5.3 Spatial and Temporal Trends in Land Degradation:1971 to 2019

This section presents spatial and temporal trends in land degradation established from assessing the 1971 aerial photographs and subsequent years using satellite imagery. The assessment is based on the land degradation classes that were derived from a combination of information from different sources including from the social and biophysical surveys, secondary data sources and linked to air photos and imagery data (Table 4-6).

5.4.2 Trends in Land Degradation Established from 1971-2019

The 1971 aerial photo was employed as baseline data to establish land degradation in the study area (Figure 5-6). Although the Selibe Phikwe and Mmadinare area showed fluctuating patterns of degradation between 1971 and 2019 (Figure 5-6 and Figure 5-7), the area remained predominant moderately degraded from 1990 to 2019. Highly degraded areas were elevated mostly over the 1990 dry season registering an amount of 14.10% of the total area while the 2010 dry season registered the lowest area of highly degraded (Figure 5-5 and Appendix 10). The slightly degraded area was lowest in 1990 wet and dry season with 14.60% and 14.10% respectively but generally increased slightly from 2010 for both wet and dry season (Figure 5-5 and Appendix 10). The non-degraded areas changed over the years registering the highest in 1971 with 88.1% of the land area but, declining significantly for subsequent years and reaching the lowest over the dry seasons of 2010 and 2019 (Figure 5-5and Figure 5-7). However, the non-degraded area remained always higher than the highly degraded area but lower than the slightly degraded class.

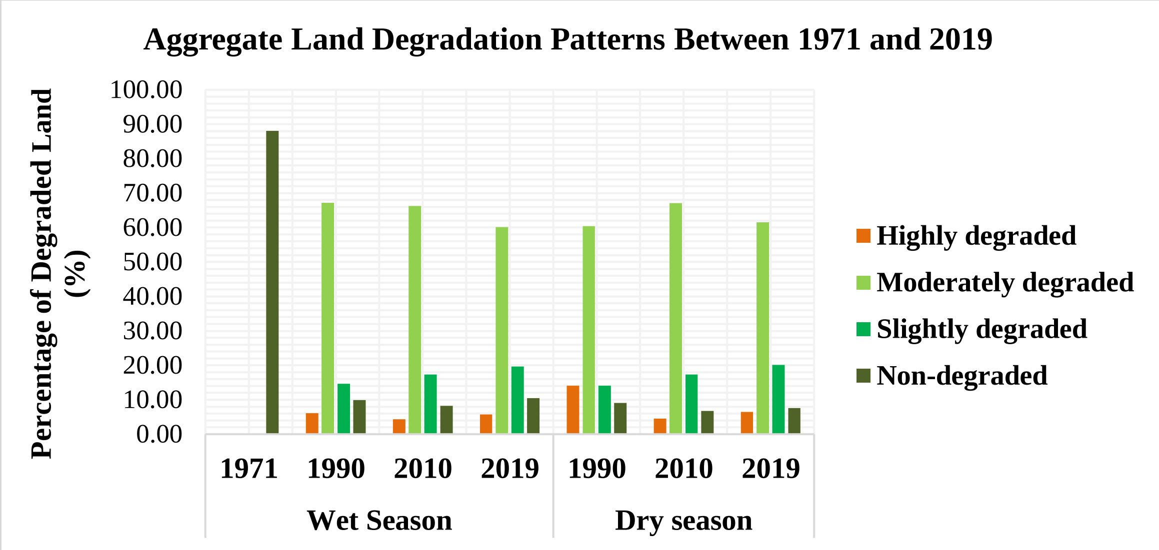


Figure 5-5: Aggregate Land Degradation Patterns Between 1971 and 2019

The study further revealed the locations of the levels of degradation classes. Highly degraded areas appear along river streams and in the north-western parts of the study area (Figure 5-7), where luvisols are found and these are the most fertile and cultivated soils in the study area (Figure 2-4). Moderately degraded areas appear uniformly across all section of Selibe-Phikwe and Mmadinare. Slightly degraded areas appear randomly located across the study area but associated with non-degraded areas which appear mostly in the north, north-eastern and south-eastern part of the study.

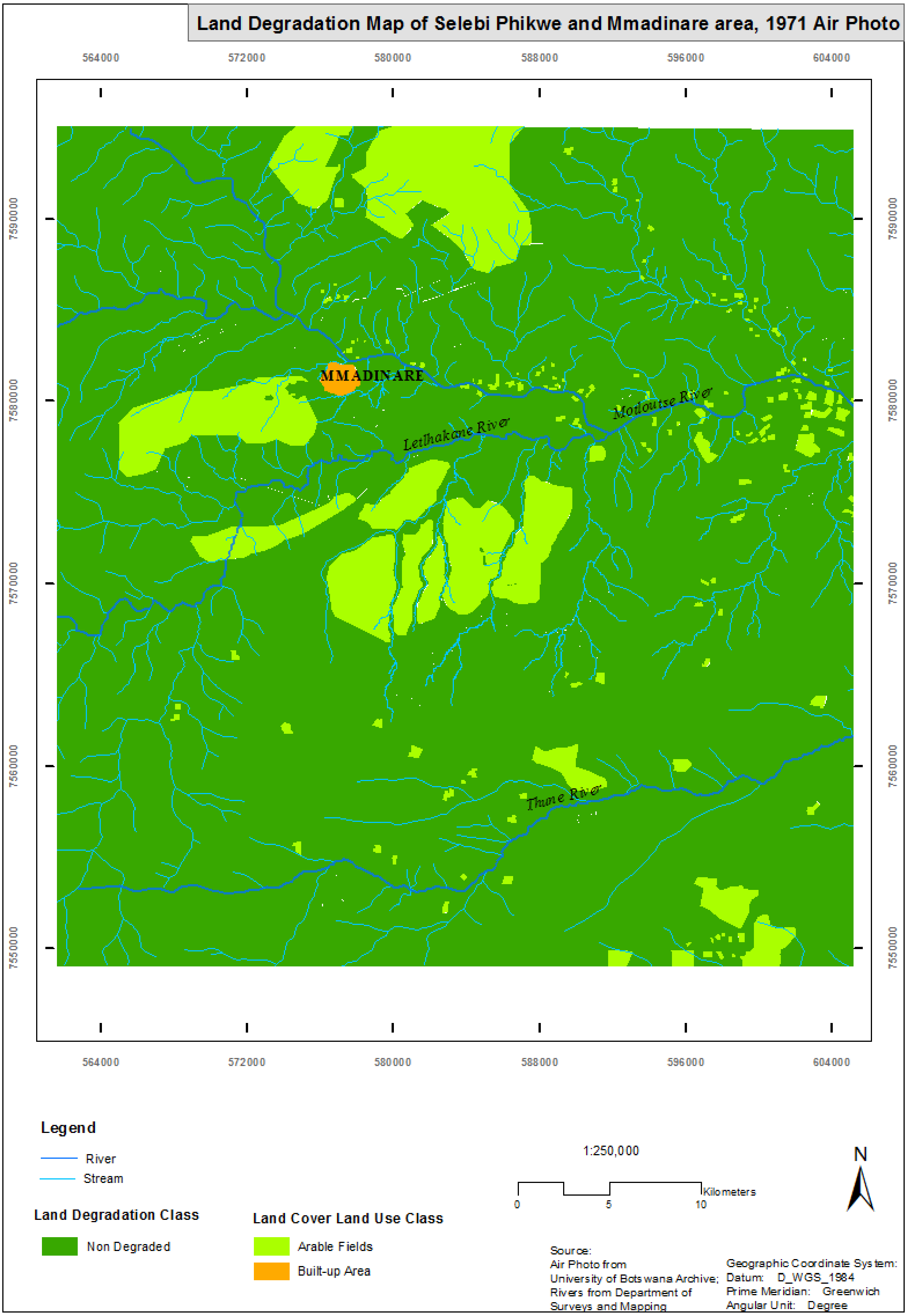


Figure 5-6: Land Degradation Map of Selebi Phikwe and Mmadinare Area, 1971 Air Photo

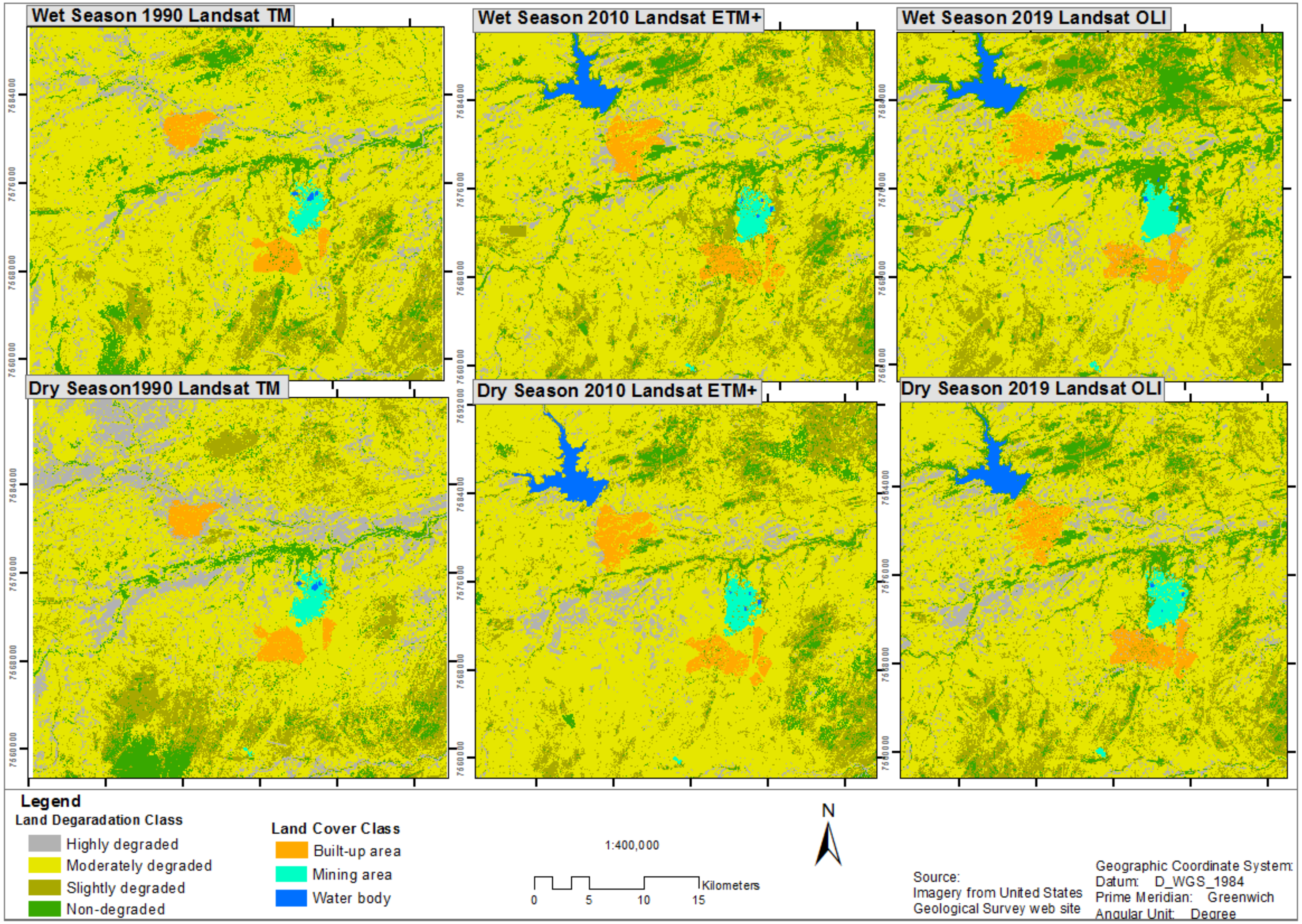


Figure 5-7: Land Degradation Map for Selebi Phikwe and Mmadinare area based on Satellite Images of 1990, 2010 and 2019

5.4 Drivers of Land Degradation in Selibe Phikwe and Mmadinare

The drivers of land degradation in Selibe Phikwe and Mmadinare were established from secondary data sources and field survey. Information from the social survey shows that majority of respondents, 47.5% (N=40), from members of the public aged 65 years and above who have resided in the study area for more than 40 years attributed land degradation to low and unreliable rainfall in the study area (Figure 5-8). Four respondents aged over 65 years who have resided in the study area for over 40 years indicated that rainfall patterns changed over the years and they had to undertake unsustainable farming practices" (Darkoh, 2009; Yengoh et al., 2014). Rainfall trends showed a significant decline between the 1990s and the year 2000 (Figure 2-3). Rainfall amounts fluctuated between the years 2002 and 2016 with an increase of 269.4mm over the 2013/14 season and declined between the 2013/14 and 2015/16 seasons (Figure 2-3).

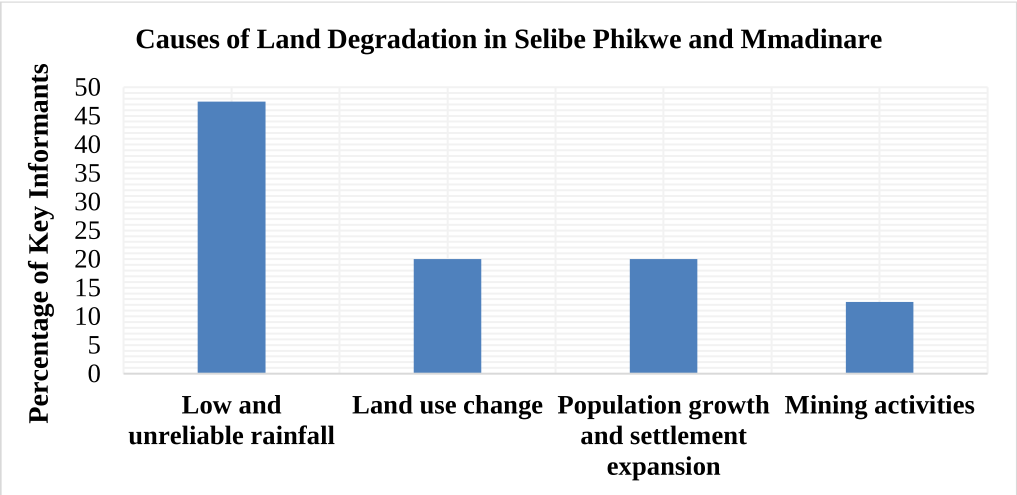


Figure 5-8: Causes of Land Degradation in Selibe Phikwe and Mmadinare established from March 2020 Field social Survey

However, about 20% (N=40) of respondents from both the members of the public and technical experts attributed population growth and settlement expansion to the occurrence of land degradation in the study area (Figure 5-8Figure 5-8). The study participants from members of the public in Selebi Phikwe and Mmadinare aged 65 years and above who have resided in the study area for more than 40 years indicated that land-uses in the study area before 1971 were defined by residential and arable uses (Figure 5-6). The respondents further indicated that the land area was previously owned by Mmadinare people. As noted by three of the respondents aged 65 years and above who had resided in the study area for over 40 years, the area was "*known then as Boswelakgomo and Thakadiawa fields*" (Figure 5-6). The population of Selebi Phikwe increased from 4480 in 1971 to 48411 in 2011 (CSO, 2011b). During this period population in Mmadinare increased from 2879 to 12086 (CSO, 2011b).

The three respondents (KI-12, KI-22, and KI-37) aged 65 years and above and had resided in the study area for over 40 years) indicated that cattle numbers varied over the years mainly due to occurrences of drought and diseases, but during the years of good rains, the numbers increased. In 2004, Bobonong and Selebi Phikwe had a total of 115024 cattle, which increased to 191187 by 2009/2010 and cattle numbers declined to 56274 by 2014 (CSO, 2008; CSO, 2011a; CSO, 2016). On the other hand, only 12.5% of respondents attributed land degradation to mining activities (Figure 5-8) and most of these respondents resided in Mmadinare and had a period of stay in the area of more than 40 years. KI-4, KI-6 and KI-9 respondents who were technical experts from Selebi Phikwe Town Council, Mmadinare Sub Land Board and Department of Surveys and Mapping and are involved in the planning of the study area explained that the movement of people to the mining town changed the landscape of the area, as more pressure was put on natural resources to meet the demand for land for settlement, infrastructural developments, livestock and arable farming.

5.5 Assessment of Land Degradation Using DPSIR Framework

The DPSIR framework was used to assess land degradation from 1971 to 2019 in Selebi Phikwe and Mmadinare area. The results from the studied images, key informants data and field surveys were placed in the context of the DPSIR framework as a dais for the explanation.

Through DPSIR, land resources found within Selebi Phikwe and Mmadinare area rapidly changed due to the drivers (causes), that is, climate variability; establishment of settlements, farming practises and mining activities (Darkoh and Mbaiwa, 2014). KI-2, KI-3 and KI-8 who were technical experts from Selebi Phikwe Town Council and Department of Surveys and Mapping stated that employment opportunities from the mining activities attracted the human population, which put pressure on the land resources. The population increase of 43 931 and 9 207 between 1971 and 2011 for Selibe-Phikwe and Mmadinare respectively is identified as a contributing cause of land cover land-use changes which contributed to resource degradation as the land was cleared for development initiatives (Elias et. al., 2018).

The need for land resulted in the acquisition of most suitable agricultural lands for development, hence arable fields and cattle posts were relocated further away in an endeavour to separate the land uses. This posed a challenge for farmers amid the threat of climate variability (Ringrose and Chanda, 2000; Gupta, 2019; Vågen and Winowiecki, 2019).

As illustrated on Figure 5-6 and Figure 5-7 the state of land changed over the years, mainly due to increasing human footprint as the land was converted from natural habitat and agricultural use to built-up areas, mining areas, construction of Letsibogo Dam, roads and other infrastructural developments. Furthermore, it was observed during the field survey, that natural balance of woody plants and grass cover had shifted, as bush encroachment was evident as *Colosphermum mopane* (Mophane woodland) and A*cacia totillis* (Mosu) were predominant within the study area (Molosiwa, 2013).

The overall framework reveals that there is a need for the formulation and adoption of policies to manage the land degradation problem. This entails undertaking pro-active measures such as data integration and further application of remote sensing and GIS technologies to understand this phenomenon.

5.6 Land Degradation in Selebi Phikwe and Mmadinare Area by the Year 2030

The future trend of land degradation was based on the temporal data on land cover land use maps of 1990 and 2010 which was subjected to the Markov analysis. The degraded classes were extracted from the predicted land cover land use map to generate a 2030 land degradation map. The data was prepared and analysed in terms of area, and the frequency ratio model was calculated in Excel. This involved calculating prediction rate values and using these values to recalculate to the dataset to produce predicted trends. The modelled data was assigned *probable* to *very probable* based on the extent of change in land degradation classes between the studied years to assign the expression that best described the likelihood of a change to occur.

The interval time for the prediction of 2030 land degradation map was 20 years, hence 1990 and 2010 land degradation classes for both seasons were the basis for prediction. The resultant predictions (Table 5-3 and Figure 5-9) shows that it is very probable for the extent of the highly degraded area to remain almost the same (4.47%) by 2030 during the wet season and there could probably be a slight increase from 4.55% in 2010 to 4.69% by 2030 during the dry season. Furthermore, there could probably be a slight increase in moderately degraded areas during the dry season by 2030. The predicted results indicate that it is very probable for slightly degraded and non-degraded areas to remain at almost the same extent by 2030, accounting for 18.22% and 8.50% respectively when compared to 17.29% and 8.23% in 2010 respectively during the wet season.

Table 5-3: Predicted Land Degradation in Selebi Phikwe and Mmadinare for Wet and Dry Seasons 2030

	2030 Wet Season area (Ha)	%	2030 Dry Season area (Ha)	%
Land Degradation class				
Highly degraded	6016	4.47	6019	4.69
Moderately degraded	92698	68.81	88586	68.98
Slightly degraded	24539	18.22	24585	19.14
Non-degraded	11449	8.50	9237	7.19

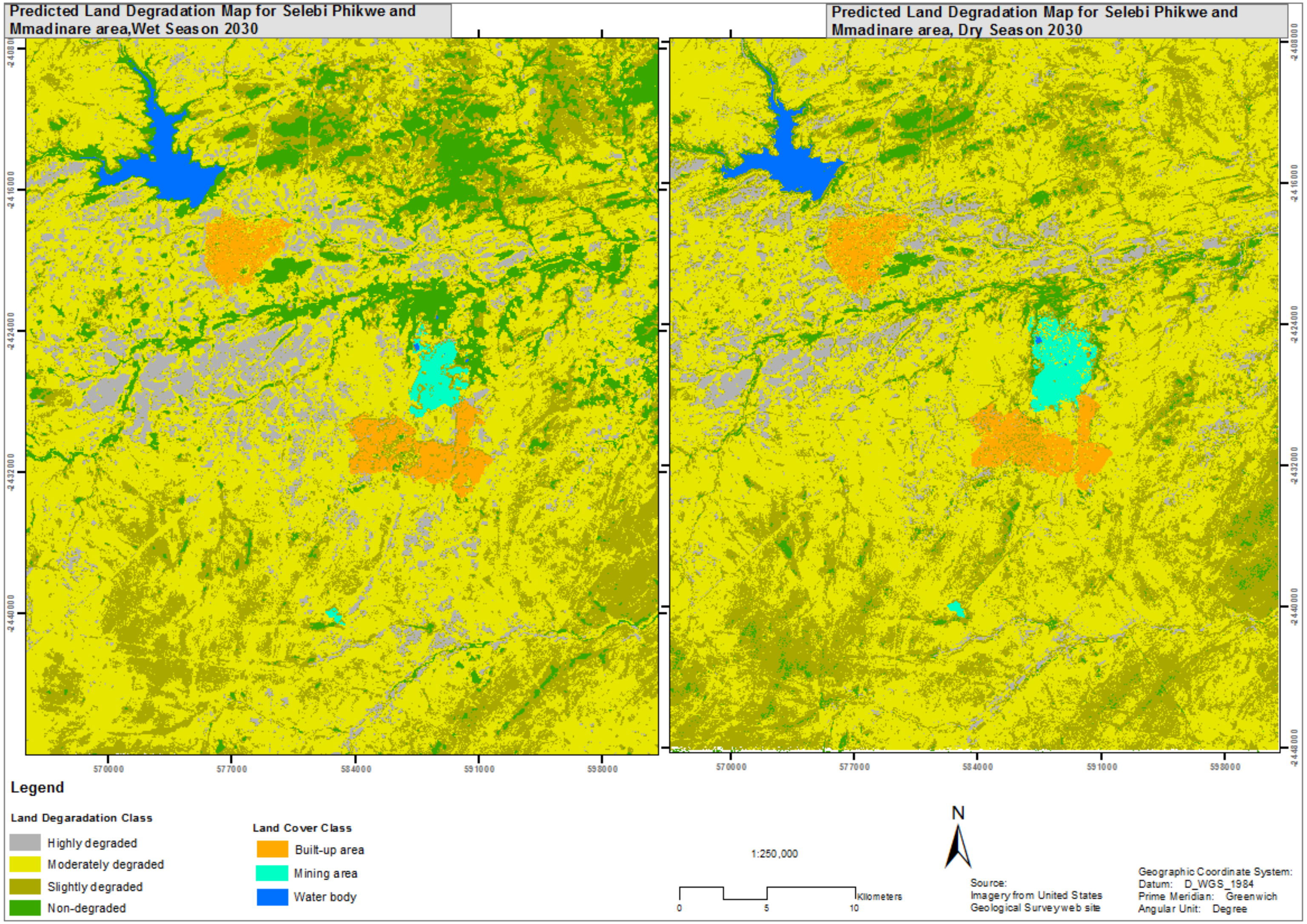


Figure 5-9: Predicted Land Degradation Map for Selebi Phikwe and Mmadinare area, Wet and Dry Season 2030

6. DISCUSSION

This chapter discusses the key findings that emerged from the results with respect to the objectives of the study.

The field observation results, secondary data and key informant’s data suggest that erratic rainfall, population growth, settlement expansion and the predominance of woody *Colosphermum mopane* (Mophane) and A*cacia totillis* (Mosu) (Figure 6-1) and (Appendix 11) accounted for incidence and changing patterns of land degradation in Selibe Phikwe and Mmadinare.

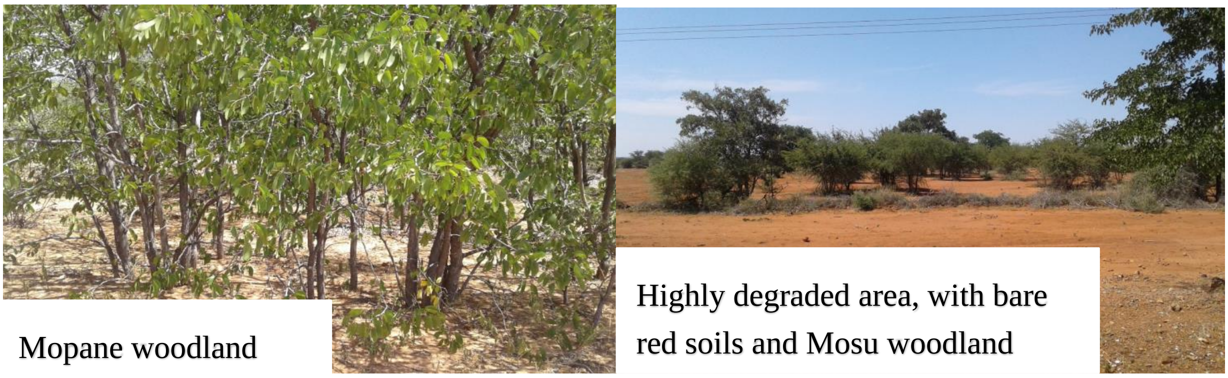


Figure 6-1: *Colosphermum mopane* (Mophane) and A*cacia totillis* (Mosu)
Figure 6-1 Explanatory Note: *Colosphermum mopane* (Mophane) on the western parts of the study area and A*cacia totillis* (Mosu) along Selibe Phikwe Mmadinare road, eastern and northern parts of the study area, March 2020 Field Survey

The increase in human population in the study area since the start of BCL mine put pressure on the landscape already affected by the changing rainfall seasons. The rapid population growth and settlement expansion (Figure 5-6 and Figure 5-7) led to the loss of natural habitat and cultivated land (Darkoh, 2009). Furthermore, members of the public aged 65 years and above pointed out that with the discovery of BCL mine, and establishment of Selebi Phikwe as a town, their lifestyles changed to encompass the urban life (Markus et al., 1988; Maundeni, 2008), which further put more pressure on the land resources in an area of high climate variability.

Four respondents (KI-5, KI-6, KI-7 and KI-8), who have lived in the area for over 40 years highlighted that overgrazing occurs along rivers mostly, where bush encroachment has not yet occurred and this deteriorates vegetation conditions closer to these water sources (Pickup and Chewings, 1994; Dube and Pickup, 2001) (Figure 5-7). The temporal increase in highly degraded areas between wet and dry seasons in 1990 could be attributed to the presence of ephemerals that then disappeared in the dry season. Furthermore, the temporal increase in highly degraded areas by 1990 could be attributed to overgrazing from increased cattle numbers in 1990 after the effect of the 1980's drought (Figure 1-1).

The reduction in non-degraded land from 1971 to 2019 could be attributed to arable production intensification influenced by government policies and subsidies to promote crop and animal production. Post-1980's the government of Botswana implemented the Arable Lands Development Program (ALDEP); the Accelerated Rainfed Arable Programme (ARAP) and the Integrated Support Programme for Arable Agriculture Development (ISPAAD) to promote national agricultural output. The programmes stimulated large scale land clearing and the increase in farming area (Seleka, 1999). Over the years, rainfall periods have varied impacting heavily on arable farming, hence, majority of the arable fields have remained unproductive and appear bare during the dry season hence contributing to the wider spread of degraded areas at the study area.

The BCL mine closed its operations in October 2016 (Botswana Chamber of Mines, 2020), however, the results of this study suggest that mining activities that took place in the study area contributed to land-use pressure that led to degraded lands in some parts of the study area. About 26.8% from the members of the public aged 65 years and above who have resided in the study area for over 40 years indicated that before the inception of BCL mine, the study area was predominantly used for arable and livestock farming (Asare and Darkoh, 2001). The fields were taken, and the owners were compensated by the then Bamangwato Concessions Limited (BCL). The Selebi Phikwe Planning Area boundary was then demarcated and Selebi Phikwe was established as a mining town in the 1960s, and people started to relocate to the mining town for employment opportunities (Gwebu, 2012). About 22.5% from the members of the public aged 65 years and above who have lived in the study area for over 40 years pointed out that as years passed, they started travelling long distances to fetch firewood, as the areas they used to collect firewood from, had been cleared for developments. This vegetation clearing in some areas exposed the land to agents of soil erosion, consequently, leading to land degradation (Elias et. al., 2018).

The field survey and data from key informant interviews revealed that the mining activities brought changes to the land resource which used to support animal and vegetation life. Similarly, Asare and Darkoh, (2001); Geoflux, (2009) found that the effluent from the BCL mine activities polluted the river water as it was discharged into the Motloutse River. Hence, the water is no longer good for livestock watering and horticulture farming which is widely practised along the Motloutse River (Asare and Darkoh, 2001). Furthermore, during the field survey, it was discovered that aquatic life in Motloutse River has been disturbed as vegetation has grown within the riverbed, due to overharvesting of river sand for smelting process at BCL mine (Figure 6-2 and Appendix 11).

Figure 6-2: Plant species within Motloutse riverbed, Selibe Phikwe Mmadinare area, March 2020

The modelled results indicate that the predicted trend of land degradation (Figure 5-9) is due to population growth and human pressure on land cover land uses (Fathizad et al., 2015; Joseph et al., 2020). If population growth rate would be the same as in period 2001-2011, the human population in Selebi Phikwe and Mmadinare is likely to increase in future. The projected population in 2021 would be 49020 and 13244 (CSO, 2011b) respectively. Hence, there is a likelihood that the predicted results could be actualised as people will need more land to erect homesteads and other development initiatives (Mirkatouli et al., 2015; Hua, 2017).

The measures and policies that would have been put in place to avert the land degradation process could influence the results shown in (Table 5-3 and Figure 5-9). However, the Markov chains are forecast models and they are not policy sensitive (Iacono et al., 2012; Hamad et al., 2018), hence measures put in place would not have an input in the predicted map. The predicted results demonstrate continued minimal change in land degradation status for the coming years, hence, the results provide suggestions and a basis for development planning and conservation strategies (Mirkatouli et al., 2015) to be put in place in Selebi Phikwe and Mmadinare area.

7. Conclusion and Recommendations

7.1 Conclusion

The study assessed the spatial extent and temporal trends in land degradation from 1971 to 2019 and interrogated the role of climate variability and land-use pressure on land degradation in the area and further projected future land degradation. The field data results showed that the study area was dominated by *Colosphermum mopane* (Mophane) and A*cacia totillis* (Mosu) woodland. Therefore, the reduced perennial grasses due to this bush encroachment is a threat to cattle production as is the decline in water resources.

The importance of integrating geospatial tools, secondary data, key informant data and biophysical field data to validate research findings has been highlighted. Assessment of land degradation, based on the 1971 aerial photographs and Landsat temporal images of the year 1990, 2010 and 2019 was achieved. The results indicate that land degradation has taken place with the area falling mostly under moderately degraded class for over 30 years in contrast to 1971 when it was predominantly non-degraded. The study further predicted how land degradation will have manifested by the year 2030.

The findings show that climatic variations, mining and resulting land-use pressure, especially overgrazing and deforestation intensified land degradation and have had some detrimental impacts on the environment.

The overall result of land degradation suggests the need for land conservation and management strategies. Based on the 2030 predicted land degradation results, a perspective measure must be taken, and future research work is required to evade the loss of remaining land resources.

7.2 Recommendations

In line with the above conclusion, this study makes the following recommendations

1. The community should be encouraged to be involved in community-based natural resources management for sustainable use of the *Mopane* woodlands and other sources of livelihoods in the area.
2. Encourage the community of Selebi Phikwe and Mmadinare to plant trees in the vicinity of settlements as a way of reducing the prevailing bare areas on the ground. However, there should be a consideration of the plant species considering climatic variations and soil types.
3. Additional studies could advance on the findings of this study by assessing biomass productivity, that is the limits or thresholds of acceptable change in the study area.
4. Further research should be undertaken by the year 2030, to ascertain the extent of land degradation in the study area and compare the results with the modelled output from this study. The results will also be used to assess the capability of the Markov chain as a modelling tool
5. Further research is needed to assess trends in woody vegetation relative to grass cover, change in species composition and water resource availability
6. Further research should be conducted to assess the effects of air pollution from BCL mine on vegetation productivity
7. Further research could be conducted to assess the socio-economic effects of land degradation in the study area

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APPENDICES

Appendix 1: Interview Instrument

UNIVERSITY of BOTSWANA

Department of Environmental Science Interview No:

<u>KEY INFORMANT INTERVIEWS (Technical Experts and Members of the Public in the Study Area)</u>

Introduction

Thank you in advance for your time and contribution in this survey. My name is Kenewang Keagakae. I am a Master of Science student under Department of Environmental Science at the University of Botswana. As per the requirements of the programme, I am collecting data for my thesis; Geospatial Assessment of Land Degradation: A Case Study of Selebi Phikwe and Mmadinare Area, Botswana

This study aims to assess, land degradation in the Selebi Phikwe and Mmadinare area with respect to land cover land use dynamics and climate variability, over 49 years, from 1971 to 2019.

The information you share will only be used for academic purposes. The information will **NOT** be used against you at any time and it will be kept confidential. For the members of the public, questions will be read out to them in Setswana and responses will be noted in English.

Thank you for your time.

Date of interview___________________

Name of interviewee___________________________________

Profession____

Employer_____________________________________

Area/Ward_____________________________________

A. DEMOGRAPHICS DATA

1. Gender □ Male □ Female

2. Age □ 18 – 29 years □ 30 -45 years
□ 45-65 years □ 65 and above

3. What is your level of education?

Primary level	
Junior Secondary	
Senior Secondary Level	
Tertiary	
Other (Specify)	

4. How long have you lived in the Selebi Phikwe and Mmadinare area?

Less than 10 years □ 10-20 years □

20-30 years □ More than 30 years □

B. Land Degradation

The respondents will be interviewed about the direct historical changes in land cover land use that took place and the changes observed regarding climate variability.

1. What was the different land uses in the area in the 1970s in the Selebi Phikwe and Mmadinare area?
____
____
____
____

2. Who previously owned the land before all these changes took place?
____
____
____
____

3. What are the major environmental challenges and problems faced in Selebi Phikwe and Mmadinare?
____
____
____
__

4. What effects have the changes in land use had on the environment?
____
____
____
____

Definition of land degradation: Land degradation has a wide range of definitions that describe circumstances of reduced biological productivity of the land. This study adopted that, land degradation is when the healthy functioning of land-based ecosystems is impaired (WMO, 2005; Bai et al., 2008; Moghanm and Baroudy, 2014).

5. With respect to the given definition of land degradation; Is there land degradation in Selebi Phikwe and Mmadinare?

____
____
____
____

6. The following have been noted as indicators of land degradation; decreased vegetation cover, bush encroachment, increase in patches of bare soil and progressive drying up of surface water resources and decrease in grass density. Have these indicators been evident in this area and are there any other indicators you have observed?

____
____
____
____
____

7. What do you think causes land degradation?

____
____
____
____
____

8. Have rainfall patterns changed over the years, if so how?

____
____
____
____
____

9. Which land uses are currently dominant in the area?

____
____
____
____
____

10. How has land degradation affected you?

____
____
____
____

11. What is your input/role in reducing land degradation?

____
____

____
____

12. Do you think your efforts are making a difference, if not why?
____
____
____
____

13. What can be done to stop land degradation?
____
____
____
____

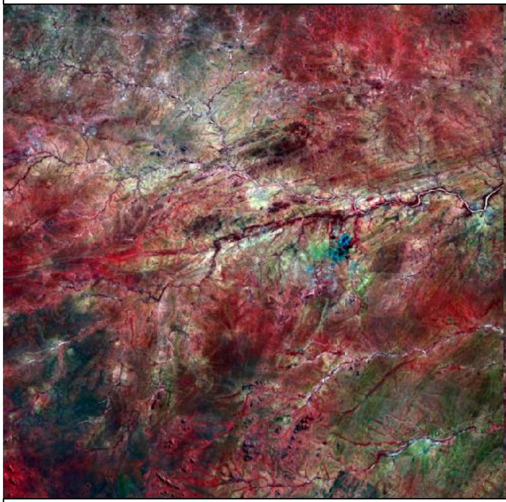
14. What can be done to rehabilitate degraded areas?
____
____
____
____

Thank you for your time.

Ending Time: ___________________

Appendix 2: Raw Images (1990 Landsat TM; 2010 Landsat ETM+ and 2019 Landsat OLI)

April 1990 -Wet Season

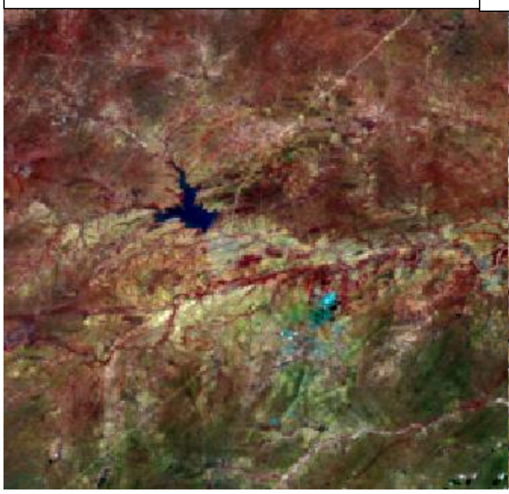


September 1990 -Dry Season

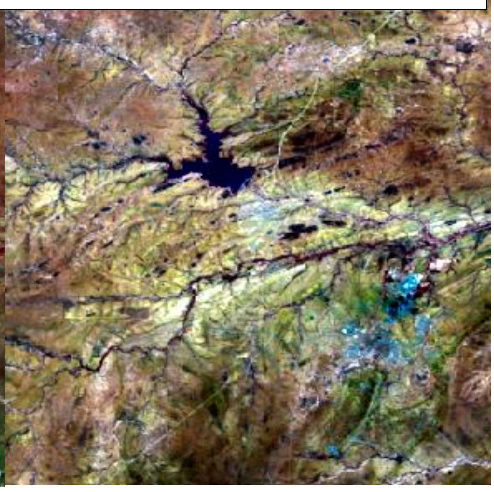
April 2010 -Wet Season

September 2010 -Dry Season

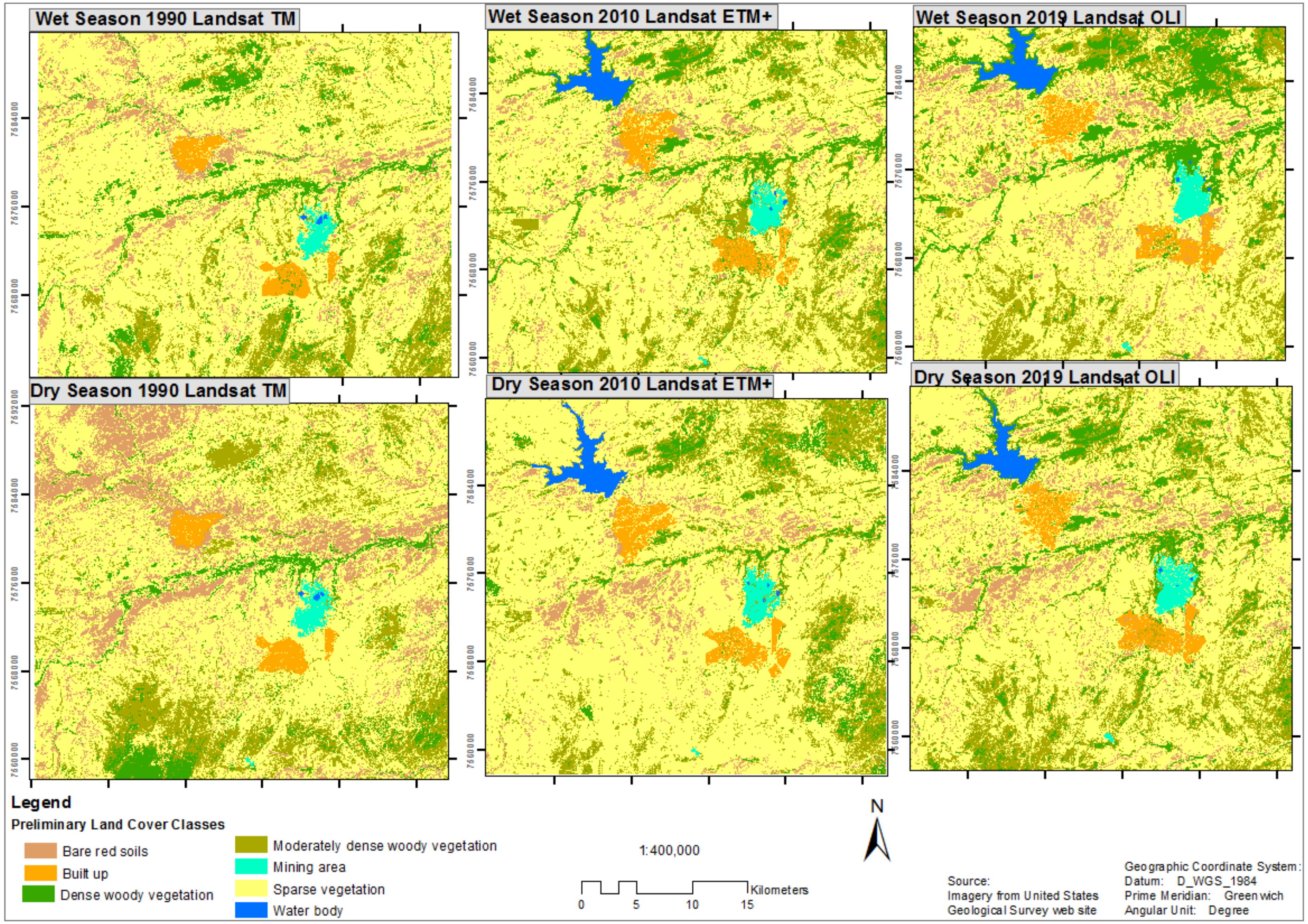
April 2019 -Wet Season



September 2019 -Dry Season

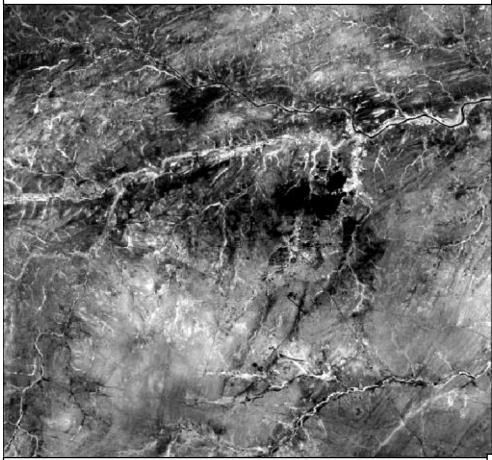


Appendix 3:Preliminary Land Cover Land Use Maps (Wet and Dry Seasons: 1990, 2010 and 2019)

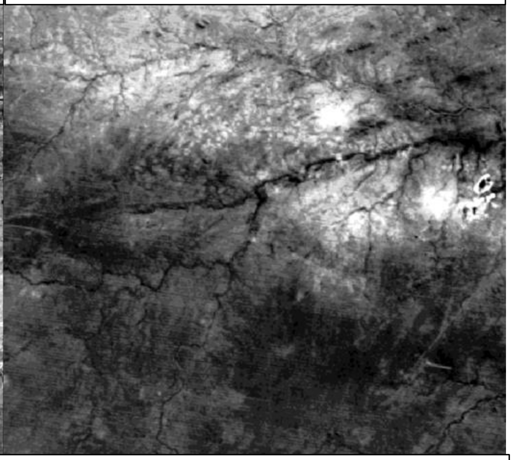


Appendix 4: NDVI Images and Thermal Bands (1990 Landsat TM; 2010 Landsat ETM+ and 2019 Landsat OLI)

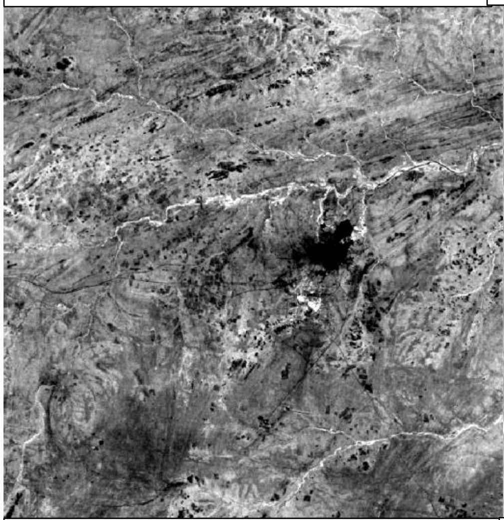
April 1990-NDVI



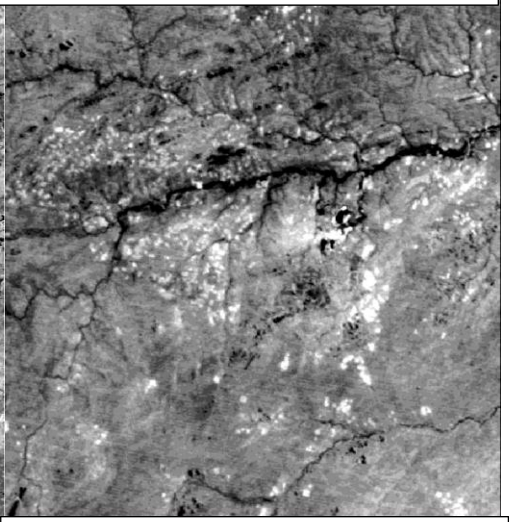
April 1990-Thermal



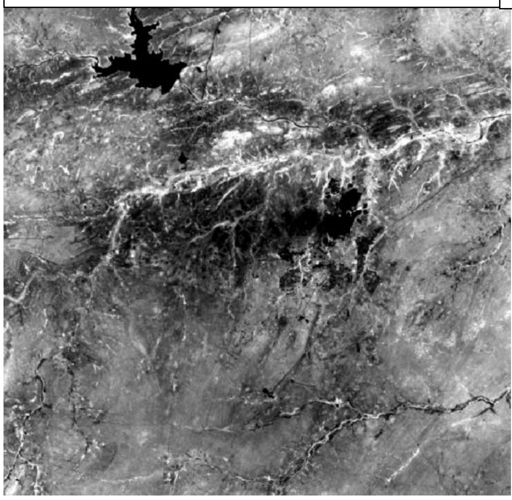
September 1990-NDVI



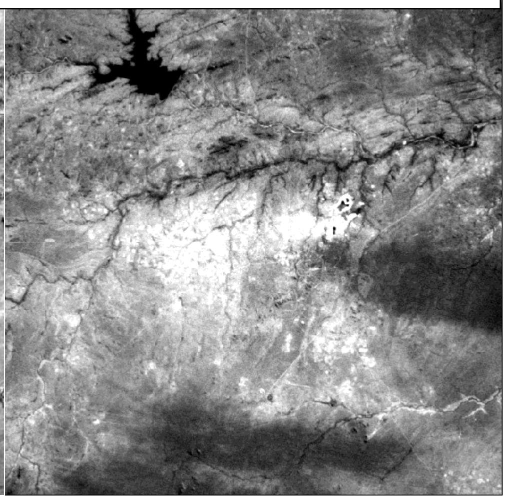
September 1990-Thermal

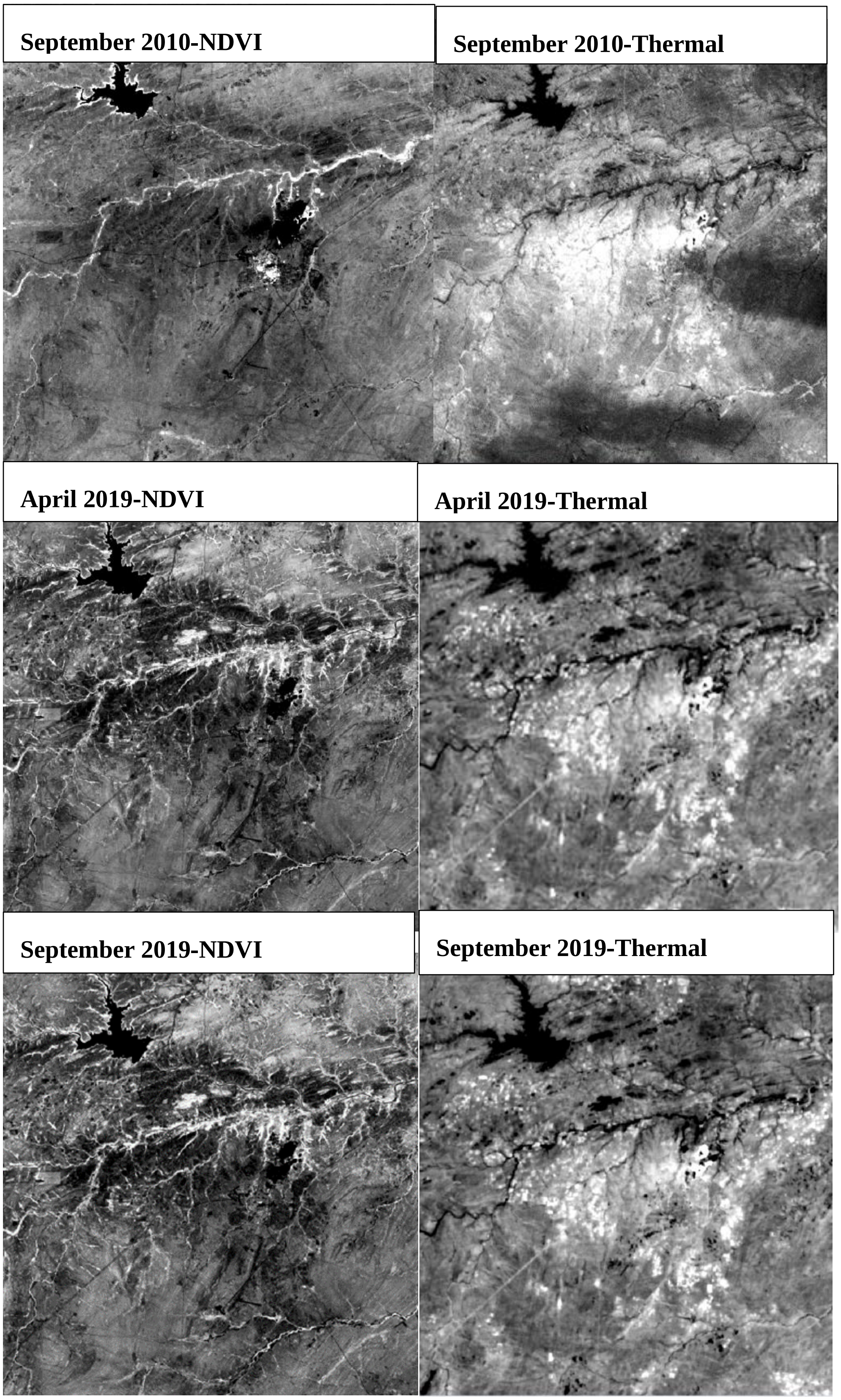


April 2010-NDVI



April 2010-Thermal




September 2010-NDVI
September 2010-Thermal
April 2019-NDVI
April 2019-Thermal
September 2019-NDVI
September 2019-Thermal

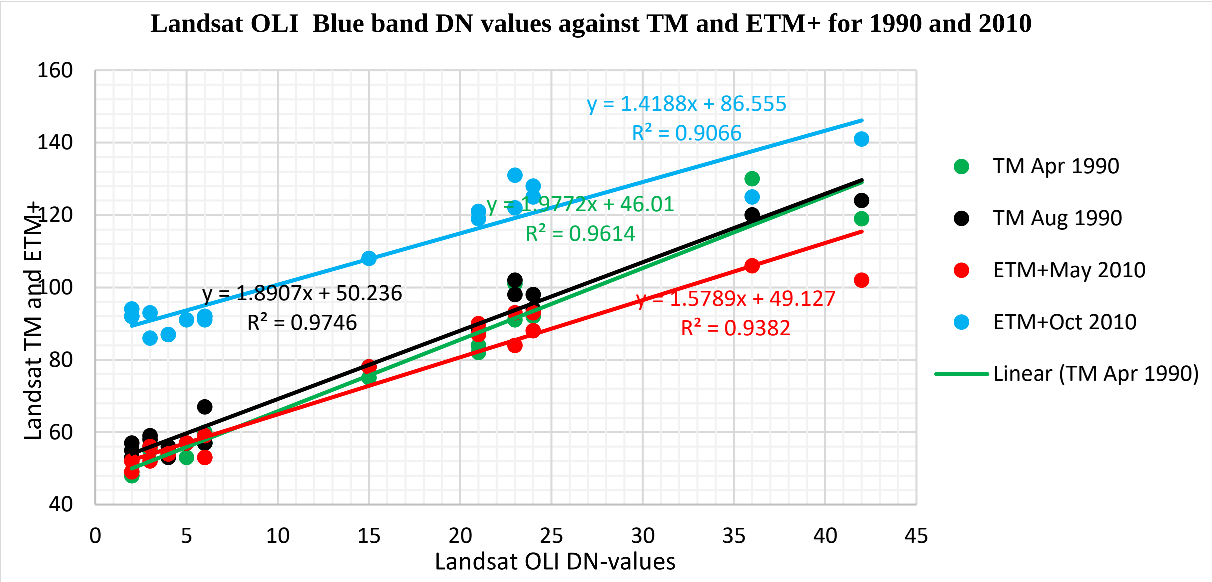
Appendix 5:Biophysical Field data Sheet

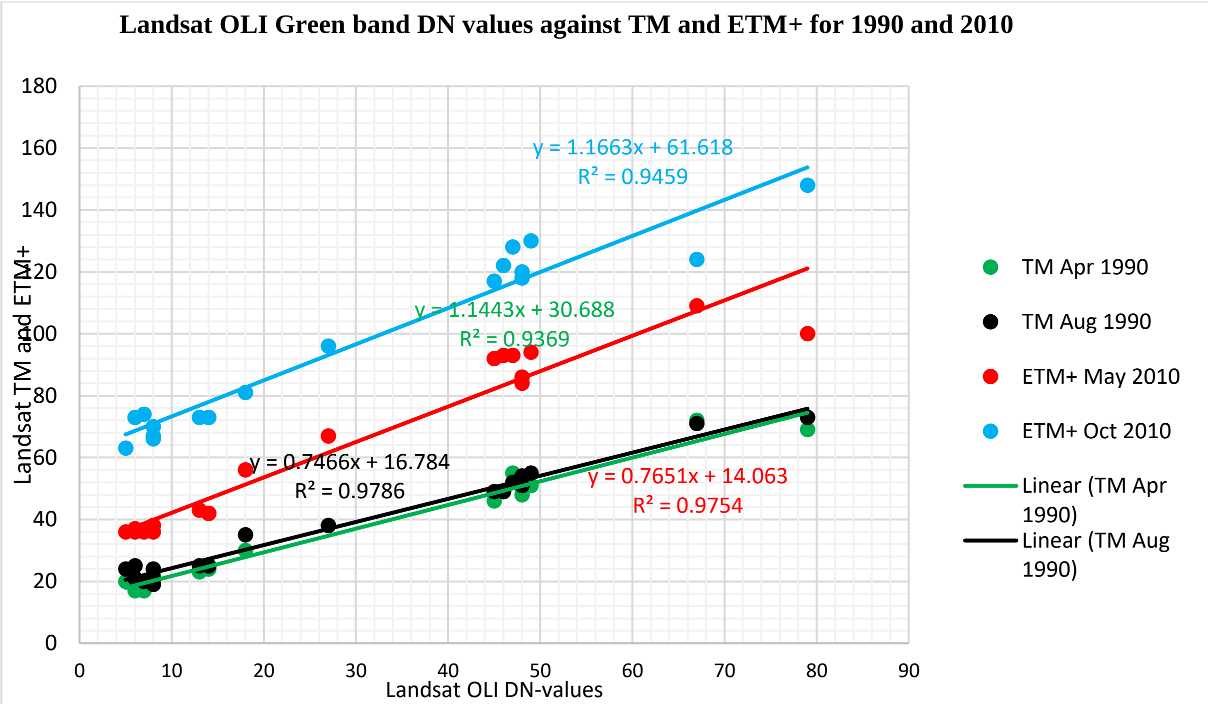
Name of Recorder: _______________**Date:** ________**Transect No**: ___________

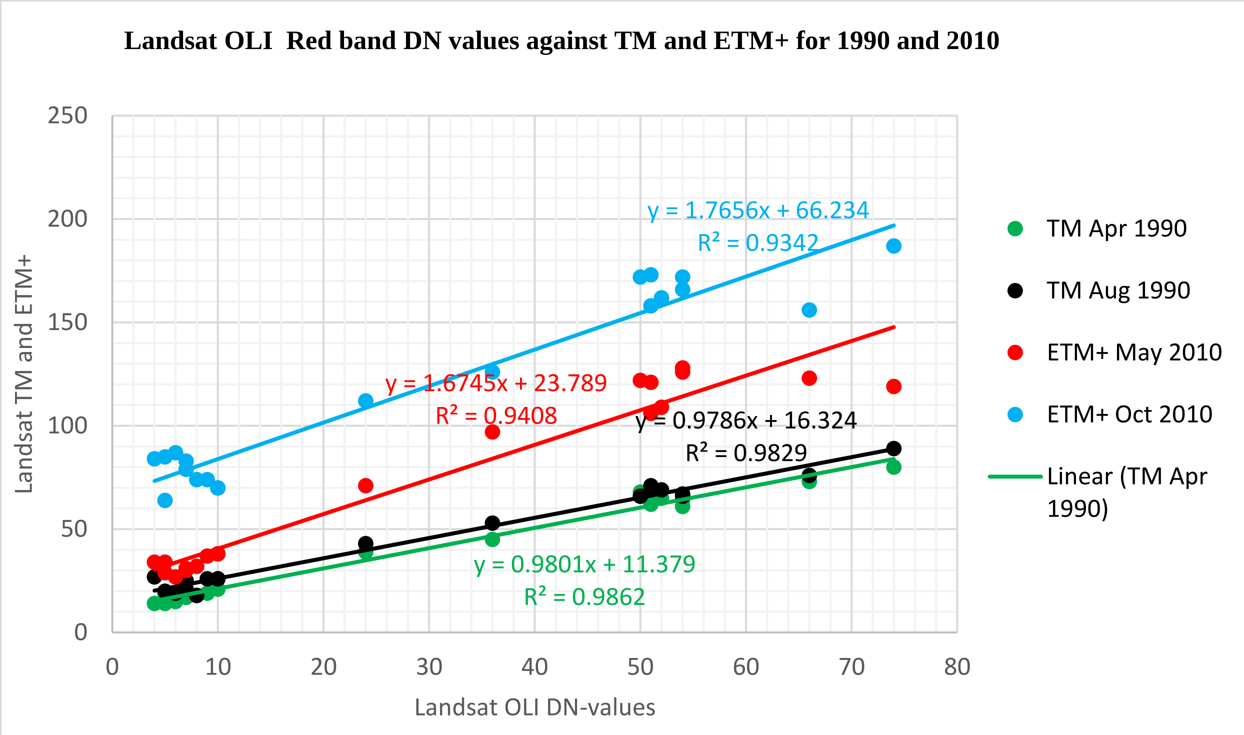
Direction of Transect: ______________ **Quadrat No**: _________**GPS Point:** ________

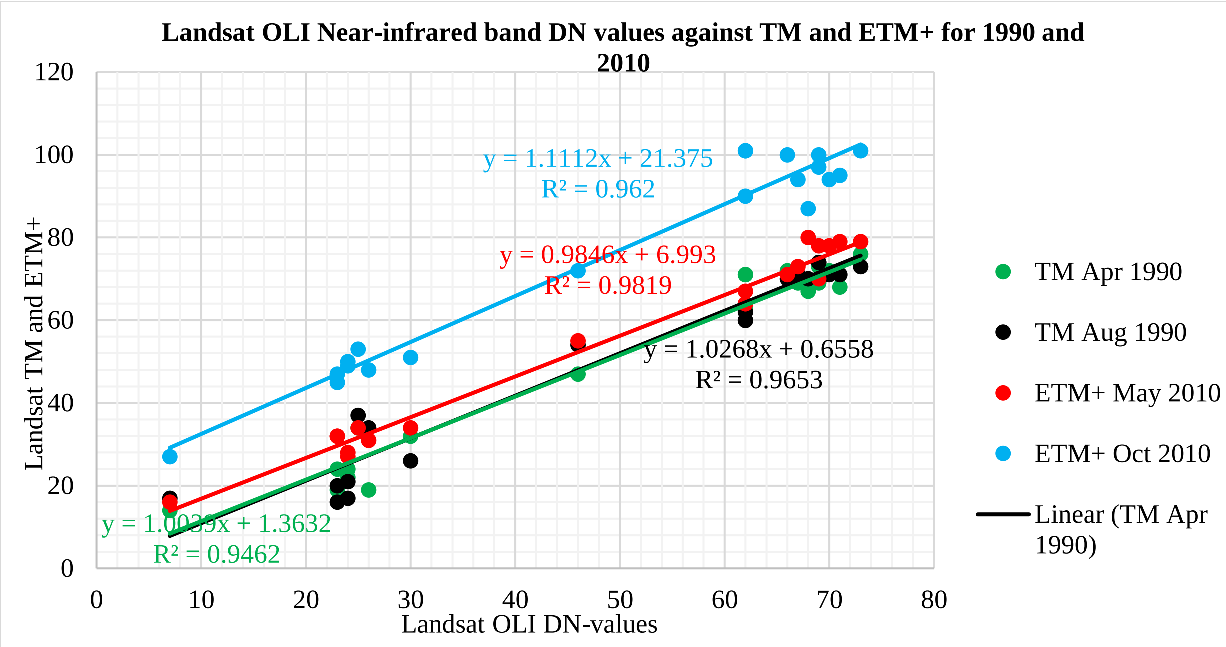
LANDFORM AND DRAINAGE SYSTEMS	
Landform type	
Status of open water sources	
SOILS	
Soil type	
Soil Colour	
Erosion Features	
Erosion Agents	
Erosion Intensity	
% Cover for eroded areas	
MAJOR LAND USES	
Type of Land use	
The distance of fields from settlements/built-up area	
VEGETATION	
Patterns of distribution of vegetation cover	
Existence of bush encroachment	
Proportions of grass cover vs woody plants/shrubs	
Proportions of perennials vs ephemerals or herbaceous cover	
Height of major vegetation types e.g. grasses, shrubs, and trees	
% Cover of bare ground	
PLANT TYPE COVER	
Plant Type	**% Cover**

Appendix 6: Radiometric Normalization Using Invariant Targets






Landsat OLI Red band DN values against TM and ETM+ for 1990 and 2010
Landsat TM and ETM+
Landsat OLI DN-values
y = 1.7656x + 66.234
R² = 0.9342
y = 1.6745x + 23.789
R² = 0.9408
y = 0.9786x + 16.324
R² = 0.9829
y = 0.9801x + 11.379
R² = 0.9862
TM Apr 1990
TM Aug 1990
ETM+ May 2010
ETM+ Oct 2010
Linear (TM Apr 1990)


Landsat OLI Near-infrared band DN values against TM and ETM+ for 1990 and 2010
Landsat TM and ETM+
Landsat OLI DN-values
y = 1.1112x + 21.375
R² = 0.962
y = 0.9846x + 6.993
R² = 0.9819
y = 1.0268x + 0.6558
R² = 0.9653
y = 1.0039x + 1.3632
R² = 0.9462
TM Apr 1990
TM Aug 1990
ETM+ May 2010
ETM+ Oct 2010
Linear (TM Apr 1990)

Appendix 7: Training Area Summary Statistics (1990 Landsat TM; 2010 Landsat ETM+:2019 Landsat OLI)

April 1990 Landsat TM						September 1990 Landsat TM					
Bare Soils						**Bare Soils**					
		Minimum	Maximum	Mean	Std.Dev			Minimum	Maximum	Mean	Std.Dev
BAND	1	180	235	202.16	14.722	BAND	1	188	229	207.887	8.849
	2	42	55	47.759	3.144		2	44	56	51.744	1.728
	3	52	81	71.326	4.617		3	60	87	79.125	3.17
	4	59	79	71.688	3.112		4	54	77	70.442	2.832
Sparse Vegetation						**Sparse Vegetation**					
		Minimum	Maximum	Mean	Std.Dev			Minimum	Maximum	Mean	Std.Dev
BAND	1	158	188	172.811	6.975	BAND	1	169	195	181.338	5.435
	2	35	42	38.932	1.982		2	40	45	42.239	1.127
	3	39	58	50.689	5.189		3	57	67	62.141	2.35
	4	57	70	65.662	3.612		4	55	65	59.761	2.446
Moderately Dense Woody Vegetation						**Moderately Dense Woody Vegetation**					
		Minimum	Maximum	Mean	Std.Dev			Minimum	Maximum	Mean	Std.Dev
BAND	1	144	158	151.459	3.123	BAND	1	158	173	164.248	3.331
	2	30	33	31.412	0.849		2	35	39	36.51	0.785
	3	28	36	32.388	2.144		3	40	53	47.537	1.937
	4	52	58	54.471	1.452		4	39	50	44.282	2.354
Dense Woody Vegetation						**Dense Woody Vegetation**					
		Minimum	Maximum	Mean	Std.Dev			Minimum	Maximum	Mean	Std.Dev
BAND	1	142	176	151.908	4.733	BAND	1	148	186	157.615	3.743
	2	29	38	31.312	1.331		2	32	44	34.148	1.288
	3	27	46	31.339	2.976		3	34	60	38.619	2.875
	4	52	62	56.303	1.912		4	32	55	37.73	3.061
Built-up area						**Built-up area**					
		Minimum	Maximum	Mean	Std.Dev			Minimum	Maximum	Mean	Std.Dev
BAND	1	164	255	199.205	14.502	BAND	1	180	255	200.837	13.286
	2	35	53	42.984	2.951		2	42	55	47.256	2.697
	3	40	68	55.115	6.852		3	58	79	67.093	4.644
	4	35	66	52.074	7.928		4	46	69	55.523	4.639
Mining area						**Mining area**					
		Minimum	Maximum	Mean	Std.Dev			Minimum	Maximum	Mean	Std.Dev
BAND	1	178	216	196.385	8.262	BAND	1	173	220	188.956	14.877
	2	36	47	39.872	2.051		2	38	51	43.176	4.194
	3	37	57	43.761	3.361		3	45	64	53.659	6.076
	4	24	47	30.752	4.128		4	24	44	34.495	5.549
Water body						**Water body**					
		Minimum	Maximum	Mean	Std.Dev			Minimum	Maximum	Mean	Std.Dev
BAND	1	138	160	146.739	6.797	BAND	1	139	173	148.209	6.881
	2	26	33	28.986	2.12		2	30	39	31.935	2.302
	3	25	36	28.775	1.759		3	33	52	38.444	2.645
	4	9	44	17.188	7.2		4	9	41	16.248	7.129

April 2010 Landsat ETM+						September 2010 Landsat ETM+					
Bare Soils						**Bare Soils**					
		Minimum	Maximum	Mean	Std.Dev			Minimum	Maximum	Mean	Std.Dev
BAND	1	153	208	168.935	7.681	**BAND**	1	103	126	111.787	4.395
	2	109	153	120.833	6.2		2	99	124	109.922	4.32
	3	164	255	203.512	13.231		3	131	177	156.286	5.989
	4	74	88	79.917	2.299		4	79	100	91.313	2.823
Sparse Vegetation						**Sparse Vegetation**					
		Minimum	Maximum	Mean	Std.Dev			Minimum	Maximum	Mean	Std.Dev
BAND	1	139	151	145.14	2.847	**BAND**	1	91	107	100	2.1
	2	90	103	95.368	3.654		2	85	94	89.551	1.844
	3	120	172	144.514	13.931		3	114	132	123.07	3.337
	4	67	81	73.205	2.946		4	73	81	77.302	1.526
Moderately Dense Woody Vegetation						**Moderately Dense Woody Vegetation**					
		Minimum	Maximum	Mean	Std.Dev			Minimum	Maximum	Mean	Std.Dev
BAND	1	131	143	134.543	1.894	**BAND**	1	89	99	93.305	1.72
	2	75	83	78.994	1.985		2	72	80	75.746	1.784
	3	79	97	86.513	4.103		3	87	100	93.928	2.868
	4	57	67	61.407	2.258		4	58	65	60.968	1.596
Dense Woody Vegetation						**Dense Woody Vegetation**					
		Minimum	Maximum	Mean	Std.Dev			Minimum	Maximum	Mean	Std.Dev
BAND	1	129	142	132.707	1.974	**BAND**	1	87	96	90.918	1.423
	2	73	84	76.165	1.459		2	69	84	72.48	1.892
	3	70	94	78.491	3.512		3	71	105	80.975	4.886
Built-up area						**Built-up area**					
		Minimum	Maximum	Mean	Std.Dev			Minimum	Maximum	Mean	Std.Dev
BAND	1	151	186	166.059	6.569	**BAND**	1	97	116	104.967	3.515
	2	95	118	105.825	4.784		2	85	109	94.399	3.958
	3	129	174	152.805	9.453		3	106	137	119.761	5.108
	4	50	65	56.77	3.994		4	61	78	68.38	3.113
Mining area						**Mining area**					
		Minimum	Maximum	Mean	Std.Dev			Minimum	Maximum	Mean	Std.Dev
BAND	1	143	181	163.847	7.231	**BAND**	1	92	116	101.275	3.783
	2	87	119	99.208	5.911		2	72	97	82.154	3.882
	3	102	164	127.671	11.82		3	76	111	88.278	6.414
	4	29	46	36.329	4.119		4	33	52	40.645	3.789
Waterbody						**Waterbody**					
		Minimum	Maximum	Mean	Std.Dev			Minimum	Maximum	Mean	Std.Dev
BAND	1	129	142	134.287	1.849	**BAND**	1	81	90	85.246	1.351
	2	69	78	75.187	1.488		2	58	70	61.526	1.382
	3	63	80	69.788	2.224		3	45	69	51.455	2.842
	4	14	24	16.454	0.764		4	17	54	20.857	5.588

April 2019 Landsat OLI					
Bare Soils					
		Minimum	Maximum	Mean	Std.Dev
Band	1	14	32	22.289	4.067
	2	11	26	18.558	2.79
	3	26	55	40.898	4.003
	4	32	63	47.454	4.231
Sparse Vegetation					
		Minimum	Maximum	Mean	Std.Dev
Band	1	6	12	8.216	1.58
	2	5	10	7.165	1.366
	3	14	27	19.235	3.226
	4	14	39	24.509	5.365
Moderately Dense Woody Vegetation					
		Minimum	Maximum	Mean	Std.Dev
Band	1	3	8	3.977	0.847
	2	2	8	3.408	0.741
	3	7	21	9.934	1.68
	4	4	26	8.597	2.908
Dense Woody Vegetation					
		Minimum	Maximum	Mean	Std.Dev
Band	1	2	7	3.937	0.81
	2	2	5	3.232	0.652
	3	6	14	8.491	1.24
	4	3	15	5.848	1.536
Built-up area					
		Minimum	Maximum	Mean	Std.Dev
Band	1	10	26	16.14	2.671
	2	8	20	12.825	1.97
	3	18	38	26.331	2.952
	4	21	37	28.531	2.883
Mining area					
		Minimum	Maximum	Mean	Std.Dev
Band	1	9	25	13.753	2.149
	2	7	19	11.235	1.721
	3	18	44	27.395	3.665
	4	19	40	27.692	2.778
Water body					
		Minimum	Maximum	Mean	Std.Dev
Band	1	7	11	9.652	0.672
	2	6	10	8.274	0.713
	3	13	20	17.728	1.089
	4	6	14	9.047	1.362

September 2019 Landsat OLI					
Bare Soils					
		Minimum	Maximum	Mean	Std.Dev
Band	1	29	182	57.405	28.329
	2	38	202	68.838	32.364
	3	53	240	92.507	37.11
	4	76	255	125.309	35.604
Sparse Vegetation					
		Minimum	Maximum	Mean	Std.Dev
Band	1	16	34	21.923	2.178
	2	20	40	27.242	2.491
	3	30	57	40.727	4.471
	4	54	91	71.594	7.235
Moderately Dense Woody Vegetation					
		Minimum	Maximum	Mean	Std.Dev
Band	1	9	17	11.7	1.867
	2	11	22	14.824	2.448
	3	17	33	22.236	3.383
	4	37	58	45.045	4.665
Dense Woody Vegetation					
		Minimum	Maximum	Mean	Std.Dev
Band	1	6	17	9.969	1.838
	2	8	21	12.878	2.177
	3	13	30	19.609	2.62
	4	19	50	30.857	4.933
Built-up area					
		Minimum	Maximum	Mean	Std.Dev
Band	1	20	52	33.311	5.298
	2	24	58	38.692	5.42
	3	37	71	52.072	5.151
	4	57	89	73.063	5.369
Mining area					
		Minimum	Maximum	Mean	Std.Dev
Band	1	14	36	21.365	2.819
	2	18	41	26.027	3.17
	3	28	61	41.528	5.773
	4	42	78	56.346	6.216
Water body					
		Minimum	Maximum	Mean	Std.Dev
Band	1	16	26	20.756	1.274
	2	20	30	25.444	1.489
	3	25	36	30.939	1.55
	4	12	29	16.865	2.94

Appendix 8: Thermal Emissions and NDVI Values from Study Images

April 1990 Landsat TM					
Land Cover	**Thermal Emission**				
	Pixel 1	Pixel 2	Pixel 3	Pixel 4	Average
Dense woody vegetation	131	132	131	132	131.5
Sparse vegetation	132	132	132	132	132
Moderately dense woody vegetation	138	136	136	136	136.5
Bare Soils	138	137	139	139	138.25
Built-up	140	139	140	140	139.75
Mining area	144	143	142	149	144.5
Water Body	130	128	130	129	129.25

April 2010 Landsat ETM+					
Land Cover	**Thermal Emission**				
	Pixel 1	Pixel 2	Pixel 3	Pixel 4	Average
Dense woody vegetation	129	128	129	128	128.5
Sparse vegetation	136	136	135	136	135.75
Moderately dense woody vegetation	140	139	141	139	139.75
Bare Soils	143	141	145	145	143.5
Built-up	139	138	140	140	139.25
Mining area	148	159	160	154	155.25
Water Body	127	127	128	127	127.25

September 1990 Landsat TM					
Land Cover	**Thermal Emission**				
	Pixel 1	Pixel 2	Pixel 3	Pixel 4	Average
Dense woody vegetation	127	124	125	128	126
Sparse vegetation	133	132	132	132	132.25
Moderately dense woody vegetation	135	133	134	135	134.25
Bare Soils	140	139	140	138	139.25
Built-up	133	137	132	133	133.75
Mining area	145	147	142	145	144.75
Water Body	116	120	119	121	119

September 2010 Landsat ETM+					
Land Cover	**Thermal Emission**				
	Pixel 1	Pixel 2	Pixel 3	Pixel 4	Average
Dense woody vegetation	156	157	159	156	157
Sparse vegetation	165	165	165	166	165.25
Moderately dense woody vegetation	169	169	168	167	168.25
Bare Soils	174	172	174	173	173.25
Built-up	167	167	168	168	167.5
Mining area	182	180	186	184	183
Water Body	129	128	130	131	129.5

April 2019 Landsat OLI					
Land Cover	**Thermal Emission**				
	Pixel 1	Pixel 2	Pixel 3	Pixel 4	Average
Dense woody vegetation	121	112	115	113	115.25
Sparse vegetation	144	142	144	145	143.75
Moderately dense woody vegetation	162	157	171	161	162.75
Bare Soils	185	181	183	186	183.75
Built-up	155	160	158	159	158
Mining area	204	189	193	201	196.75
Water Body	66	68	67	64	66.25

September 2019 Landsat OLI					
Land Cover	**Thermal Emission**				
	Pixel 1	Pixel 2	Pixel 3	Pixel 4	Average
Dense woody vegetation	125	118	126	122	122.75
Sparse vegetation	150	149	147	150	149
Moderately dense woody vegetation	173	175	171	173	173
Bare Soils	209	217	213	205	211
Built-up	163	166	170	166	166.25
Mining area	241	215	220	234	227.5
Water Body	3	8	23	7	10.25

April 1990 Landsat TM					
Land Cover	NDVI				
	Pixel 1	Pixel 2	Pixel 3	Pixel 4	Average
Dense woody vegetation	0.318	0.277	0.326	0.3	0.30525
Sparse vegetation	0.2	0.264	0.258	0.21	0.233
Moderately dense woody vegetation	0.16	0.131	0.122	0.106	0.12975
Bare Soils	0.018	0.017	0.062	0.046	0.03575
Built-up	0.01	-0.012	-0.011	0.01	-0.00075
Mining area	-0.213	-0.194	-0.184	-0.265	-0.214
Water Body	-0.463	-0.487	-0.375	-0.364	-0.42225

September 1990 Landsat TM					
Land Cover	NDVI				
	Pixel 1	Pixel 2	Pixel 3	Pixel 4	Average
Dense woody vegetation	0.113	0.053	0.079	0.063	0.077
Sparse vegetation	0.065	0.077	0.039	0.064	0.06125
Moderately dense woody vegetation	0.06	0.034	0.027	0.054	0.04375
Bare Soils	0.03	0.037	0.048	0.045	0.04
Built-up	-0.101	-0.094	-0.096	-0.094	-0.0963
Mining area	-0.134	-0.169	-0.179	-0.182	-0.166
Water Body	-0.545	-0.542	-0.532	-0.529	-0.537

April 2010 Landsat ETM+					
Land Cover	NDVI				
	Pixel 1	Pixel 2	Pixel 3	Pixel 4	Average
Dense woody vegetation	0.315	0.38	0.273	0.253	0.30525
Sparse vegetation	0.219	0.245	0.21	0.211	0.22125
Moderately dense woody vegetation	0.151	0.161	0.146	0.164	0.1555
Bare Soils	-0.441	-0.442	-0.452	-0.438	-0.44325
Built-up	-0.498	-0.454	-0.434	-0.426	-0.453
Mining area	-0.567	-0.569	-0.558	-0.547	-0.56025
Water Body	-0.626	-0.621	-0.621	-0.638	-0.6265

September 2010 Landsat ETM+					
Land Cover	NDVI				
	Pixel 1	Pixel 2	Pixel 3	Pixel 4	Average
Dense woody vegetation	0.254	0.26	0.242	0.263	0.25475
Sparse vegetation	0.235	0.245	0.246	0.247	0.24325
Moderately dense woody vegetation	0.228	0.213	0.226	0.227	0.2235
Bare Soils	0.172	0.149	0.168	0.103	0.148
Built-up	-0.274	-0.27	-0.237	-0.259	-0.26
Mining area	-0.349	-0.302	-0.324	-0.359	-0.3335
Water Body	-0.388	-0.396	-0.413	-0.421	-0.4045

April 2019 Landsat OLI					
Land Cover	**NDVI**				
	Pixel 1	Pixel 2	Pixel 3	Pixel 4	Average
Dense woody vegetation	0.741	0.689	0.714	0.709	0.71325
Sparse vegetation	0.509	0.527	0.519	0.481	0.509
Moderately dense woody vegetation	0.308	0.342	0.37	0.364	0.346
Bare Soils	0.158	0.176	0.162	0.176	0.168
Built-up	0.185	0.159	0.178	0.171	0.17325
Mining area	0.022	0.062	0.018	0.014	0.029
Water Body	-0.429	-0.6	-0.4	-0.5	-0.48225

September 2019 Landsat OLI					
Land Cover	**NDVI**				
	Pixel 1	Pixel 2	Pixel 3	Pixel 4	Average
Dense woody vegetation	0.218	0.211	0.226	0.22	0.21875
Sparse vegetation	0.153	0.163	0.166	0.17	0.163
Moderately dense woody vegetation	0.14	0.141	0.144	0.139	0.141
Bare Soils	0.113	0.112	0.116	0.113	0.1135
Built-up	0.083	0.084	0.077	0.095	0.08475
Mining area	0.026	0.07	0.041	0.03	0.04175
Water Body	-0.122	-0.121	-0.12	-0.117	-0.12

Appendix 9: Research Permit

Office of the Deputy Vice Chancellor (Academic Affairs)

Office of Research and Development

Corner of Notwane and Mobuto Road, Gaborone, Botswana
Pvt Bag 00708 Gaborone Botswana
Tel: [267] 355 2900
Fax: [267] 395 7573
E-mail: research@mopipi.ub.bw

UNIVERSITY of BOTSWANA

UBR/RES/IRB/SOC/GRAD/260

20th February 2020

The Permanent Secretary
Ministry of Land Management, Water and Sanitation Services
Private Bag BO199
Gaborone

RE: REQUEST FOR EXPEDITED REVIEW OF A RESEARCH PROPOSAL

TITLE: "Geospatial Assessment of Land Degradation; A Case Study of Selibe Phikwe and Mmadinare area, Botswana."

RESEARCHER(S): Kenewang Keagakae

Since it is a requirement that everyone undertaking research in Botswana should obtain a Research Permit from the relevant arm of Government, The Office of Research and Development at the University of Botswana has been tasked with the responsibility of overseeing research at UB including facilitating the issuance of Research Permits for all UB Researchers inclusive of students and staff.

I am writing this letter in support of an application for a research permit by the above-mentioned Principal Investigator who is pursuing a Degree of Master of Science (Environmental Science, Geospatial) in the Faculty of Sciences, University of Botswana. The main objective of this study is to assess, with aid of geo-spatial information technology, land degradation in the Selibe Phikwe and Mmadinare with respect to land cover land use dynamics and climate variability, over a period of 49 years, from 1970 to 2019. It is hoped that the findings from this study will advance understanding of land degradation in Botswana and further provide a platform for further discussion on the role of human and climate factors on process of land degradation in semi-arid lands.

The Office of Research and Development is satisfied with the process for data collection, analysis and the intended utilization of findings from this research and is confident that the project will be conducted effectively and in accordance with local and international ethical norms and guidelines.

Your kind and timely consideration of this application will be highly appreciated and we thank you for your usual cooperation and assistance.

Sincerely,

UNIVERSITY OF BOTSWANA Office of Research & Development
2020 -02- 20
P/BAG UB 00708 GABORONE TEL: 3552900/2902 FAX: +267 3957573 email: research@mopipi.ub.bw

The Secretariat, University of Botswana Institutional Review Board
Office of Research and Development

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Republic of Botswana

MINISTRY OF LAND MANAGEMENT, WATER & SANITATION SERVICES

CMLWS 1/ 17 /4 IV (40)

17th March, 2020

Mrs Kenewang Keagakae
P.O. Box 3864
Gaborone

(Attention: Ms Keagakae)

RE: APPLICATION FOR RESEARCH PERMIT BY KENEWANG KEAGAKAE ON GEOSPATIAL ASSESSMENT OF LAND DEGRADTION: A CASE STUDY OF SELIBE PHIKWE AND MMADINARE AREA, BOTSWANA

The above subject matter refers.

- Permission is being granted to conduct research titled **"Geospatial Assessment of Land Degradation: A case study of Selibe Phikwe and Mmadinare Area, Botswana**
- We trust the research programme will be conducted in accordance with local and international ethical norms and as per research guidelines of July 2004 issued by the Office of the President attached herewith.
- We request an oral presentation on the findings to the Senior Management

Vision: Sustainable Human Settlements
Mission: Management of land and water resources for socio-economic development

BOTSWANA

and the final copy to be submitted to the ministry.

- The focal person for the ministry for this research is Mr. Khawulani Ace Bachobeli.
- The following personnel will be involved in the research:

    i. Mrs Kenewang Keagakae (Principal Investigator)
    ii. Dr. O.P. Dube (Supervisor)

- Any changes on the research personnel should be communicated to this Ministry.

- The research will be undertaken in the following areas:

    i. **Selibe Phikwe and Mmadinare**

The research permit will last for a period of **Seven Months (7)**, commencing from **17 March 2020** to **26 October 2020.**

Yours Faithfully,

Khawulani Ace Bachobeli
Principal Research Officer I
+267 71576661/3904823

Vision: Sustainable Human Settlements
Mission: Management of land and water resources for socio-economic development

Appendix 10: Land Degradation Patterns Between 1971 and 2019 (1971 Air Photo, 1990 Landsat TM; 2010 Landsat ETM+ and 2019 Landsat OLI)

Land Degradation in Selebi Phikwe and Mmadinare area in 1971		
	Area (Ha)	% Cover
Land Degradation Class		
Non- degraded	179536	88.1
Land Cover Class		
Built-up area	294	0.14
Arable fields	21285	10.44

Land Degradation in Selebi Phikwe and Mmadinare for Wet and Dry Seasons in 1990				
	1990 Wet Season Area (Ha)	%	1990 Dry Season Area (Ha)	%
Land Degradation Class				
Highly degraded	8534	6.13	19142	14.10
Moderately degraded	93634	67.22	82016	60.40
Slightly degraded	20338	14.60	19151	14.10
Non-degraded	13783	9.90	12313	9.07
Land Cover Class				
Water	65	0.05	59	0.04
Mining area	790	0.57	968	0.71
Built-up area	2142	1.54	2148	1.58

Land Degradation in Selebi Phikwe and Mmadinare for Wet and Dry Seasons in 2010				
	2010 Wet season area (Ha)	%	2010 Dry season area (Ha)	%
Land Degradation Class				
Highly degraded	6031	4.35	6254	4.55
Moderately degraded	91838	66.23	92186	67.05
Slightly degraded	23977	17.29	23820	17.33
Non-degraded	11418	8.23	9308	6.77
Land Cover Class				
Water body	1484	1.07	1785	1.30
Mining area	989	0.71	1077	0.78
Built-up area	2922	2.11	3056	2.22

Land Degradation in Selebi Phikwe and Mmadinare for Wet and Dry Seasons in 2019				
	2019 Wet Season area (Ha)	%	2019 Dry Season area (Ha)	%
Land Degradation class				
Highly degraded	8207	5.72	8652	6.47
Moderately degraded	86307	60.14	82186	61.51
Slightly degraded	28232	19.67	26914	20.14
Non-degraded	14968	10.43	10076	7.54
Land Cover Class				
Water	1561	1.09	1409	1.05
Mining area	1142	0.80	1227	0.92
Built-up area	3088	2.15	3158	2.36

Appendix 11: Field Survey Photos

Motloutse Riversand has been overharvested for mine smelting process

Plant species within Motloutse riverbed

Highly degraded area, adjacent to a water source, in study area

Highly degraded area, outskirts of Mmadinare village

Uncultivated arable field towards Mmadinare

Slightly degraded area around Letsibogo Dam

Colosphermum mopane (Mophane) woodland western parts of the study area

Highly degraded area, with bare red soils and *Acacia totillis* (Mosu) woodland along Selibe Phikwe Mmadinare road