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Title: Satellite Imagery for land use change and ecosystem services assessment in the Greater Limpopo Trans frontier Region.

We accept this report as conforming to the required standard

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DATE: 10 January 2020
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DEDICATION

I dedicate this work to all the young black girls that are motivated by the will to change lives in a sustainable manner. All the girls that look to education for answers and a way forward to better our communities and future. To all the young girls that lack resources to study and look to God for answers. To all the abused girls that strive to make their lives better through education. Finally, to all the girls and women in universities killed by perpetrators this one is for you.

I say, soldier on, the universe is only the beginning.
ABSTRACT

Land use change can result in variations in ecosystem services (ESs) and their relationships. Understanding the spatiotemporal changes in land use and land cover change helps understand ESs management. Studying the temporal dynamics of ESs and their relationships can support scenario analyses that provide the theoretical basis for policy decisions and regional ecosystem management in any context. This can be achieved by utilizing remote sensing techniques which are an efficient tool in conducting spatio-temporal analysis of phenomena on earth, in particular in data scarce regions of southern Africa. Consequently, this study is aimed at using Landsat imagery to assess land use land cover change dynamics from 2007 to 2018 in the Greater Limpopo Trans-frontier Region, as well as assess its impacts on ecosystem services during the stipulated time. Furthermore, to assess the drivers of land cover change in the study area over time. The specific objectives are as follows; (i) to spatially map the change in land cover within the given period, (ii) to assess performance of random forest classification scheme, and (iii) to use InVEST Carbon Model to quantify the amount of carbon storage in the study area, (iv) to use Scenario-based model to model future projections of carbon sequestration and vegetation change and (v) to utilize the carbon sequestration and vegetation change data to inform planning for ecosystem services. Landsat imagery acquired in 2007 and 2018 was used to derive land cover classes. The derived maps (classified) were compared graphically and statistically. To achieve this, the study spatially mapped the change in land cover using the Random Forest Classification Scheme with an overall accuracy of 76%. Results of the quantified spatial changes showed that in 2007, Agricultural areas occupied 2% of the total area, Bareland 29%, built up area 25%, dense vegetation 6%, grassland 22%, water 3% and shrubland a total of 7%. While in 2018, Agricultural areas occupied 3% of the area, bareland 13%, built up area 24%, dense vegetation 5%, water at 1% and shrubland a total of 13%. Overall, results showed a slight decrease in built-up areas and an increase in agricultural land over time. Drivers of land cover change in the area were identified mainly as migration, climatic conditions, agricultural drivers and deforestation. Carbon storage also shows that there was a decrease in carbon storage from 2007 to 2018. With the scenario-based model, the results showed an increase in agricultural areas and corresponding carbon storage. The results were used to inform policy and recommend effective land use management practices.

Keywords: land cover, land use, Ecosystem Services, Remote Sensing, InVEST
<table>
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<tr>
<th>ACRONYM</th>
<th>DESCRIPTION</th>
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<td>GLTR</td>
<td>Greater Limpopo Trans-Frontier Region</td>
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<td>ESs</td>
<td>Ecosystem Services</td>
</tr>
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<td>GIS</td>
<td>Geographic Information Systems</td>
</tr>
<tr>
<td>LULC</td>
<td>Land Use Land Cover Change</td>
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<tr>
<td>IPCC</td>
<td>Intergovernmental Panel on Climate Change</td>
</tr>
<tr>
<td>REDD+</td>
<td>Reducing of Emissions from Deforestation and Forest Degradation</td>
</tr>
<tr>
<td>NDVI</td>
<td>Normalised Difference Vegetation Index</td>
</tr>
<tr>
<td>InVEST</td>
<td>Investments in Natural Capital Project</td>
</tr>
<tr>
<td>FAO</td>
<td>Food And Agriculture Organisation</td>
</tr>
<tr>
<td>SDGs</td>
<td>Sustainable Development Goals</td>
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<tr>
<td>ECJRC</td>
<td>European Commission’s Joint Research Center</td>
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<tr>
<td>ANN</td>
<td>Artificial Neural Networks</td>
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<tr>
<td>NASA</td>
<td>National American Space Agency</td>
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<tr>
<td>SAR</td>
<td>Synthetic Aperture Radar</td>
</tr>
<tr>
<td>AGB</td>
<td>Above Ground Biomass</td>
</tr>
<tr>
<td>BG</td>
<td>Below Ground</td>
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<tr>
<td>DS</td>
<td>Dead Soil</td>
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<tr>
<td>LUP</td>
<td>Land Use Plan</td>
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<td>PPPs</td>
<td>Plans. Policy. Programs</td>
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<td>Carbon Dioxide</td>
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<td>Red Green Blue</td>
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CHAPTER 1: INTRODUCTION

1.1 BACKGROUND

International political borders rarely tally with natural ecological margins. Because neighboring countries often share ecosystems and diverse species, they also share ecosystem services. Forests are important at both global and local scales as they take part in the regulation of the global climate and the provision of shelter for wildlife for example. These forests provide food and drinking water for people, regulate ecological processes, contribute to the mitigation of climate change all which is commonly known as ecosystem services (Kindu et al, 2016; Diaz et al, 2019). However, the fact that these forests are often transboundary is one of the reasons why they are worldwide under heavy pressure. Immediate conservation with accurate monitoring is of utmost importance to secure the deliverance of ecological services that are so important for the survival of both the people and the species surviving there. The use of remote sensing as a monitoring and assessment tool for conservation of such extensive areas seems therefore promising for active conservation and combating of the pressures of the loss of ecosystem services (Hegazy et al, 2012; Haaren et al, 2019). To counteract these pressures, it is important to apply an assessment system that provides quick and reliable information within a shortest possible time span.

According to Betru et al, (2019) Land Use Land Cover change (LULC) is the modification of the natural landscape on the earth’s surface to a different structure, this is a natural phenomenon however, it is commonly caused by humans. Land use/cover change or transformation poses as one of the greatest threats to local and global biodiversity and considering extensive land cover change, protected areas (PAs) are often viewed as important for conservation, (Bellefontaine et al, 2000; Xu et al, 2019). Studies also show that there’s only a few landscapes on Earth and particularly in South Africa, that remain in a natural state (Food and Agriculture Organisation (FAO); 2003; Lindquist et al, 2012). Due to both anthropogenic and natural phenomena, the earth’s surface is being significantly altered. Man, and his use of land has had a profound effect on the environment thus resulting into an observable pattern in the land use over time (Lesoli et al, 2013; Betru et al, 2019). Vegetation change detection using Geographic Information Systems (GIS) and remote sensing techniques provides an observable and detectable way of controlling the rate at which the vegetation rate is deteriorating (Tekle and Hedlund, 2000; Xu et al, 2019). In general, urban areas are dominated by built up land with impervious surfaces. Furthermore, urban landscape is exemplified by the large concentration of population and expansion of the urban zones which lead to the alteration in the land use and land cover configuration that consequently impacts on the landscape (Mohammed, 2012).
Semi-arid forests provide a wide variety of Ecosystem Services (ESs such as carbon storage, absorption of pollutants from the atmosphere, wildlife habitat, and acts as a source of energy (Kindu et al, 2016; Mograbi et al, 2015; Zhang et al, 2018). In many developing countries, semi-arid forests and their ecosystem services are a vital source of food, timber and non-timber products, at the household and national levels (O’Conner, 2014; Mograbi et al, 2015; Zhang et al, 2018). Ecosystem services are mainly recognised as vital for alleviating poverty and achieving the global Sustainable Development Goals (SDGs) (Fortnam et al, 2018). According to Fortnam et al, (2018), there is a difference between knowing what the objectives of the SDGs and the environment are. As such, knowing the impact of ecosystem services in relation to environmental degradation is as vital as understanding its impacts on human health and the people involved.

In essence, vegetation is one of the most important characteristics of ecosystems services offered in semi-arid forests. The earth’s natural environment is covered by 30% practicable vegetation which is essential for the world’s population (FAO, 2018; Lindquist et al, 2012). Thus, vegetation diversity is an essential component of the biosphere contributing to social development worldwide and equitable ecosystems services (FAO, 2010; Kindu et al, 2016). According to the United Nations Millenium Ecosystem Assessment (MEA); (2005), vegetation supports all terrestrial ecosystems, providing necessary life support systems for other forms of biodiversity and humankind. Furthermore, vegetation contributes to the maintenance of good water quality by trapping or filtering water pollutants as well as minimising soil erosion and land degradation protection by mitigating flash water flows that cause erosion downstream (FAO, 2010).

1.2 GLOBAL LAND COVER PERSPECTIVE

Earth's lithosphere is divided into several inflexible tectonic plates that drift across the surface over periods of millions of years. Approximately 71% of Earth's surface is covered with water, consisting mostly of oceans (FAO, 2012; Wang et al, 2019). The remaining 29% is land comprising of continents and islands that when put together have many lakes, rivers and other sources of water that contribute to the hydrosphere (FAO, 2012; Wang et al, 2019). Most of the Earth’s polar regions are covered in ice, including the Antarctic ice sheet and the sea ice of the Arctic ice pack (Mohamed, 2012). Earth’s interior remains active with a solid iron inner core, a liquid outer core that generates the Earth's magnetic field, and a mantle that drives plate tectonics (Hegazy, 2012).

Total surface area of the Earth is about 510 million km² (FAO, 2014; Hu et al, 2019). Of this, 70.8%, is below sea level and covered by ocean water (FAO, 2014; Hu et al, 2019). Below the ocean's surface are much of the continental shelf, mountains, volcanoes, oceanic trenches, submarine canyons, oceanic plateaus,
abyssal plains, and a globe-spanning mid-ocean ridge system. The remaining 29.2%, not covered by water has a topography that varies greatly from place to place and consists of mountains, deserts, plains, plateaus, and other landforms (Hegazy, 2012). Earth has properties that have been overused by humans. Those are termed non-renewable resources, such as fossil fuels, that are only renewable over geological timescales. In 1980, 50.53 million km² of Earth’s land surface comprised of forest and woodlands, 67.88 million km² was grasslands and pasture, and 15.01 million km² was cultivated as croplands (Hegazy, 2012). The estimated amount of irrigated land in 1993 was 2,481,250 km² (Hegazy, 2012). Humans also live on the land by using building materials to construct shelters.

According to (FAO, 2014; Hu et al, 2019), 0.6% of Earth’s land surface is defined as ‘artificial surfaces’. Artificial surfaces include any area that has an artificial cover due to human activities such as construction (cities, towns, transportation), extraction (open mines and pits) or waste disposal. This figure gives us an estimate of roughly 900,000 km² of human-covered land worldwide (FAO, 2014). However, even non-urban areas contain roads, train tracks, farms and other marks of human domination. The (FAO GLC SHARE, 2014) data shows that 12.6% of land is categorised as cropland. In 2009, the European Commission’s Joint Research Center (ECJRC) published a map in the World Bank’s World Development report, presentation the fact that 95% of the world’s population is concentrated in just 10% of the land surface. However, only 10% of land on Earth is considered remote and habitable (ECJRC, 2009). In addition, it could be said that from these results that 10% of Earth is inhabited by humans, and only about 3% comprises of protected areas (Hegazy, 2012).

1.3 MAPPING LAND COVER CHANGE

Timely, the availability of data is of great importance for urban planners and decision makers since it guides informed decision making in the development of urban areas and the protection of natural environments (Odindi and Mhangara, 2011; Carreiras et al, 2019). Mapping of a protected area is important for urban planners to detect and monitor any changes in the urban and natural environment. Spatial and temporal maps provide landscape data about the location of features (Odindi and Mhangara, 2011; Yudong et al, 2011; Chen et al, 2018). Furthermore, mapping land cover types and changes is an important tool to plan and control sustainable manipulation of environmental resources, more especially of protected areas (Maselli, 2001; Zhang et al, 2014). In addition, availability of such information enables identification of areas that need infrastructural development and urban sustainability.

One method of mapping and monitoring land cover change is using remote sensing techniques. These techniques are cost effective means of quantifying both natural and manmade features due to broad
spatial coverage (Chen et al, 2000; Che et al, 2018). Remote sensing methods include a variety of aerial photo clarification and satellite data analyses. The increased availability and improved quality of multi-resolution and multi-temporal remote sensing data makes it possible to monitor change in urban ecosystems in a timely and cost-effective manner (Mohammed, 2012).

Machine learning, artificial neural networks (ANN) and geobios has been used in the past to understand the dynamics of Earth systems (Lieb et al, 2016). These tools have enabled a better understanding of the current land cover land use (LULC) maps. In China, these tools were used by Ran et al (2010) in Global Vegetation Monitoring Unit of the European Commission Joint Research Centre researching on the use of machine learning in determining the accuracies of land cover mapping. Tucker et al, (2004; Zhang et al, 2007; Zhang et al, 2014) concluded that the National Space Agency (NASA) has recently used orthorectified machine learning tools to improve the accuracies of global land cover maps through the use of new satellites and Synthetic Aperture Radar (SAR) datasets.

### 1.4 QUANTIFYING ECOSYSTEM SERVICES

Savannas cover 40% of the land in Africa (FAO, 2015; Higgins et al, 2016), and millions of people depend on the provisional and regulating ecosystem services of the Savanna biomes for their livelihoods (Higgins et al, 2016). A predictive knowledge of the relationships between land-use practices, the composition, structure and function of vegetation, and the supply of ecosystem services is required (Higgins et al, 2016).

In these Savannas, agricultural is one of the most dominant sources of subsistence on a day to day basis (Higgins et al, 2016). With the deterioration trends in landscape and biodiversity in Southern Africa and most of the Sub-Saharan Africa region (Kori et al, 2012; Droogers, Seckler, & Makin, 2001; Nnyaladzi, 2009), agricultural production is most likely to decline, raising concerns about issues of food security (Kori et al, 2012) and ecosystem management. According to the 2004 report of the Food and Agriculture Organization (FAO), the state of food insecurity in the world is now at its prime more than ever before. More than 814 million people in developing countries are undernourished (FAO, 2004; Gericke et al, 2011). Of these, 204 million live in countries of sub-Saharan Africa including South Africa (Kori et al, 2012).

As a result of decades of dispossession and racist land laws, land distribution in South Africa is among the most highly skewed in the world, with large capital-intensive farms dominating much of the rural areas (Department of Agriculture and Forestry, 2016). The result is that only 28 % of South Africa’s rural population which comprises of a large proportion of people whom are farm workers and their dependents, live on 88 % of the agricultural land (DoAF, 2016; Simbi, 2012). Thus, the remaining 12 % of agricultural land supports 72 % of the rural population in the overcrowded former homelands which lack
the infrastructure for successful agriculture. The demand for agricultural services, such as food, fiber, and water, strongly increases all over the world. In Zimbabwe, policy governs agricultural practices and who has access to it (WWF, 2016). Thus, the capacity of ecosystems to provide services is determined by many different direct and indirect driving forces operating at the local to global levels (Alcamo et al, 2016). Agriculture is one such service that is affected by changes in the landscape. Therefore, Land use change can result in variations in ecosystem services (ESs) and their relationships over time (Yang et al, 2018; Kindu et al, 2015; Alcamo et al, 2016).

The ecosystem service concept has become popular since the United Nations' Millennium Ecosystem Assessment 2005 (MEA, 2005). To achieve sustainable ecosystems services (Apitz et al, 2006), an integrative approach can be implemented (Euliss Jr et al, 2011). This approach unifies quantitative studies (Yang et al, 2018; Fu et al, 2013) and allows scenarios to be drawn for effective decision making (Euliss Jr et al, 2011). Integrated ES research gives weight to the development of efficient and sustainable ecosystems (Apitz et al., 2006; Yang et al, 2018). Furthermore, using an integrative ES approach allows policy makers to make informed decisions on food production and consumption (Fu et al., 2013; Yang et al, 2018). The use of models to calculate and predict ES drivers and impacts as well as tradeoffs in this region is limited and therefore the need to is observed. Careful management of ecosystems within our modern and highly diverse landscapes is important for intergenerational sustainability of ecosystems (Euliss Jr et al, 2011). Understanding how land use changes affects multiple and simultaneous ecosystem services helps researchers appreciate processes of regulating them in an integrative manner.

Furthermore, the development of cost effective (Euliss Jr et al, 2011), integrated (Fu et al, 2013) and adaptative (Reyers et al, 2012) modelling of ecosystems services for sustainable development helps evaluate and assess ESs and landscape changes on a bigger scale. For example, a study carried out by (Euliss Jr et al, 2011) used a frame-based model approach to quantify ESs derived from landscape changes. The authors focused on the ecologically diverse Lower Mississippi Valley. Furthermore, the model showed that different land uses led to different quantities of ESs in the area and to quantify them using a frame by frame approach was best. This model (Euliss Jr et al, 2011) shows that with the correct conditions set (economic, policy and management), landowners, policy makers and stakeholders can evaluate the area for ecological trade-offs involved in complex landscapes. Constructing future scenarios of ES changes and impacts will help with the achievement of the SDGs in South Africa. Due to policy of separate development (DoA, 2012; Van Riet, 2017) intensive farming is found on the northern side of the Greater Limpopo Trans-
frontier Region (GLTR) and communities are found on mountainous regions south of the area. This is turn leads to lack of land for producing and for ES values delivering for the people.

1.5 PROBLEM STATEMENT

The Great Limpopo Trans-frontier Region (GLTR) is a region which is comprised of three different countries (Zimbabwe, South Africa and Mozambique) which interact together to strengthen the ties of conservation and sustainability within Southern Africa. This region has been combined to form the Great Limpopo Trans frontier Park which is considered to be the largest animal kingdom in Africa, spanning an enormous area of 37,572 km² (GLTFCA, 2016). This Region consists of community, state owned and private owned land joining together some of the most prominent wildlife conservation areas in southern Africa which include Kruger National Park in South Africa, Gonarezhou National Park in Zimbabwe and Limpopo National Park in Mozambique.

Transboundary ecosystems are connected and linked to one another regardless of the political boundaries that separate the countries. This study focuses on the Limpopo basin semi-arid ecosystem that is mainly shared by South Africa and Zimbabwe. An increase or decrease in the vegetation dynamics due to problems that affect any of the countries listed above affect the vegetation quality, carbon storage and ecosystem services that provide livelihoods and habitats for wildlife and human life in both countries. Understanding the dynamics of vegetation loss and gains assists in helping manage the semi-arid forest that is found there as well as quantify the mitigation strategies that may be used to protect the area. As noted, vegetation is one of the biggest contributors of carbon sequestration in any ecosystem and therefore knowing the amount to which is contributed by vegetation is of utmost importance.

The use of remote sensing as a monitoring tool for conservation of such an extensive area seems promising for active conservation and combating of the pressures of ecosystem services and its benefits. However, there is limited or non-existent information regarding the status of the quantity of vegetation found, as well as a lack of studies applying remote sensing technology, in the study area. In addition, there is a lack of knowledge on the spatial extent of vegetation types found in the area. Specifically, the utility of Landsat imagery in assessing vegetation dynamics, correlating it to ecosystem services in the study area is unknown. Furthermore, there is limited to no available information which shows the rate of carbon sequestration recorded as opposed to vegetation change in relation to other vegetation cover types in the study area, therefore, the intention of this study is to assess transboundary ecosystem services in correlation to ecosystem services over the Greater Limpopo Trans-frontier Region.
The use of models to calculate carbon storage and scenario-based carbon storage in African context is seldom performed. This is mostly due to lack of data. The use of InVEST Natural Capital Project in quantifying carbon within the GLTR has not been done yet.

The following questions emerge;

1. What is the spatial extent of changes from 2007 to 2018 in the study area?
2. Can satellite imagery provide enough information to characterize land cover change?
3. Can the InVEST model quantify carbon storage in the study area?
4. Can the Scenario-Based Model project future land cover change and carbon storage?
5. What are the possible planning recommendations that can be considered?

1.6 AIM AND OBJECTIVES

The main aim of this study is to assess the dynamics of land cover/vegetation change using a time series analysis technique over a period of 11 years (2007-2018). The specific objectives of the study are as follows:

1. To spatially map the change in land-cover between 2007 and 2018
2. Assess performance of Landsat Satellite in mapping land cover change
3. Using InVEST Carbon Model to quantify the amount of carbon storage in the study area
4. To use a scenario-based model to model future projections of carbon sequestration and land cover change
5. To utilize the carbon sequestration and land cover change data to inform planning for ecosystem services

1.7 STUDY AREA

The Great Limpopo Trans-frontier region is a region which is comprised of three different countries (Zimbabwe, South Africa and Mozambique) which interact together to strengthen the ties of conservation and sustainability within Southern Africa. This region has been combined to form the Great Limpopo Transfrontier Park which is considered to be the largest animal kingdom in the world spanning an enormous area of 37,572 km², (GLTFCA, 2016). This Region consist of community, state owned and private owned land joining together some of the most prominent wildlife conservation areas in southern Africa which include Kruger National Park in South Africa, Gonarezhou National Park in Zimbabwe and Limpopo National Park in Mozambique.
1.8 METHODOLOGY
This research used a spatial design research method. Through this method quantitative data was accumulated as results. The research made use of both secondary and primary sources of information. Field and remote sensing data was collected and classified. Land cover maps were derived as well as the change maps of the consecutive dates. Carbon storage was calculated using the Carbon model on the InVEST software and the scenario-based model will be used to quantify future carbon storage as well as future land cover change. A detailed methodology is presented in chapter 3.

1.9 POTENTIAL SIGNIFICANCE OF RESEARCH
There are a number of benefits that can be expected from the outcome of this study. The main significance of the study is the development of a database on land cover distribution of the GLTR. This database is useful for efficient decision-making by allowing town planners and the local government/municipality to integrate spatial information into sustainable urban expansion efforts and ecosystem protection. Such a database can also be crucial in the management of the GLTR’s environmental variables such as land degradation and soil erosion. In this regard, the database can be used by governmental and non-
governmental organizations to assess the extent of urban expansion as well as the effect it has on the environment on the protected area.

The result of this assessment is an important input in the design of strategies to help in the growth of environmentally friendly urban areas that provide protection to natural habitats. This research will also help in the realization of global resources within a changing natural environment that is influenced by human beings. The availability of such studies will help in the progress of other studies aimed at assessing the extent to which protected areas are populated and occupied as well as preserved. This study will also evaluate the significance of carbon within the vegetated areas for effective land use management. The study has a potential to serve as baseline information for further investigation and vegetation monitoring. Moreover, it can be used as an input to long time series analysis of land cover dynamics in the area and the surrounding areas too.

1.10 ORGANIZATION OF THESIS
The thesis consists of six chapters. Chapter One (this chapter) deals with the introduction, which covers overview of landuse and ESS assessment, definition of the problem and the objectives of study. Chapter Two presents the literature review and focuses on research related to this specific study. Chapter Three introduces the study area by focusing on the physical and environmental characteristics. This chapter then provides details of the research methods used in the study. Presentation of results is given in Chapter Four. Chapter Five presents the Discussion, and chapter six presents Conclusions and recommendations of the study.
CHAPTER 2: LITERATURE REVIEW

2.1 INTRODUCTION
Vegetation patterns are generally dictated by climatic variables, primarily precipitation and temperature (Bucini, 2010). In addition to climate, other factors such as soil characteristics, natural fire, herbivory and human activities are important forces in the development and control of vegetation structure (Young, 1992; Timberlake, 2000; Zeng and Neelin, 2000; Yao et al, 2010). One aspect of vegetation structure is the dynamics in composition of vegetation types over time. Forests are important at both global and local scales as they take part in the regulation of the global climate and the provision of shelter for wildlife, (O’ Conner, 2014). These forests provide food and drinking water for people, regulate ecological processes, and contribute to the mitigation of climate change all which is commonly known as ecosystem services. Immediate conservation with accurate monitoring is of utmost importance to secure the deliverance of ecological services that are important for the survival of both the people and the species surviving in ecosystems.

Understanding the spatio-temporal characteristics of such dynamics is a vital component of monitoring and managing the vegetation and the environment in ecosystems and any given area. This literature review presents the works of selected researchers that are in line with the current study. A brief description of what semi-arid forests are is presented first. This is followed by a description of vegetation dynamics within the context of semi-arid forests. Furthermore, a description of ecosystem services is presented next. The effects of vegetation dynamics on biodiversity is presented next, followed by a highlighting of the importance of monitoring vegetation dynamics in ecosystems. Ecosystems services and their drivers are then presented, followed by carbon storage and studies that have quantified it. The final component will present applications of remote sensing techniques in monitoring vegetation dynamics and their change.

2.2 DESCRIPTION OF A SEMI-ARID FORESTS
Semi-arid forests consist mostly of woody vegetation (Bao et al, 2014). The height and growth form of woody species is commonly used to separate herbaceous plants from trees, however, the distinction is rather random (Bucher, 1987; Zhu et al, 2014; Zinnert et al, 2011). This is based on the principle that woody plants can grow to greater heights than herbaceous plants. In Asia, the climate comprises of rainy season rainfalls and long dry seasons. These climatic conditions contribute to the development of different woody vegetation structures (Bellefontaine et al, 2000, Zhu et al, 2011). The climate leads to dry deciduous forests which have a closed forest formation with no substantial opening in the crown cover.
(Bao et al, 2014). The dry deciduous forests are approximately 20 m high and trees lose their leaves during the year (Powell et al, 2013). In the dry and semi-arid regions of India there are dry thorny forests ranging from forests to desert steppe (Bellefontaine et al, 2000; Wigley et al, 2009; Wigley et al, 2010). In parts of Cambodia and Thailand woodlands can occur with crowns almost continuous leaving little space for light to penetrate to the understory (Bao et al, 2014).

Drivers of large-scale vegetation patterns in semi-arid regions are well known, such as differences in topography, substrate, soil resources, or disturbances (Aguia and Sala, 1999; Greig-Smith, 1979; Rietkerk and van de Koppel, 2008; Wetzel, 2002). Spatial heterogeneity in limiting resources creates local species filters and therefore differentially assembled communities of vegetation leading to non-random vegetation patterns (Macek et al, 2009; Seabloom et al, 2005; Tirado and Pugnaire, 2005; Ward et al, 2014). Because water is essential for plants, its directional supply may result in non-random community structure and pronounced changes in species composition (Stanton et al., 2013). In arid regions, the positive effect of some shrub species on the herbaceous understory has often been linked to amelioration of soil conditions (Moro et al., 1997; Maestre et al., 2003; Prieto et al., 2011; Pugnaire et al., 2004, 2011). Consistent with these and other studies, van Zonneveld et al. (2012) suggested that shrubs could have a facilitative effect on woody seedlings of semi-arid forest species. Shrub-driven amelioration of soil conditions, including increased soil moisture through fog interception, can provide a relevant mechanism to stimulate tree regeneration, a process that could eventually give rise to new forest patches in dry environments (Pugnaire et al, 2004; Yang et al, 2010, 2018).

Africa is categorised into Sudanian, Sahelian, Zambezian and Madagascar types of semi-arid to dryland areas that are filled with different types of vegetation (Bellefontaine et al, 2000; Betru et al, 2019). The Sudanian region, mostly in West Africa, typically comprises of high floristic composition forest which lose their leaves in the dry season (Abate et al, 2012; Betru et al, 2019). The dense understory is made of shrubs which can reach a height of 5 m (Knauer et al, 2014). In addition, there are open woodlands comprising of a number of plant profiles with herbaceous formations and maximum height ranging from 12 to 18 m (Gamo et al, 2013; Ward et al, 2014). In the Sahelian zone the woody vegetation is characterised by steppes and shrub savanna with open tree layers surrounded by grasslands (Sop and Oldeland, 2013).

In the Zambezian biome, found in Southern Africa hardwood deciduous shrubs (1 to 2 m high) are surrounded by grass cover (Timberlake, 2000; Wigley et al, 2009, 2010). The Zambezian biome is largely characterised by evergreen forest, mesic woodlands and drought adapted woodlands (mopane and
acacia) (Timberlake, 2000; Wigley et al, 2009, 2010). Most of the vegetation found in the Zambezian biome comprises of short shrubs and tall trees. Dry and semi-arid vegetation contributed by the rainfall and the lack thereof within the area.

2.3 VEGETATION DYNAMICS IN SEMI-ARID REGIONS

The spatial pattern of plants has attracted interest presumed, but rarely proven, outcome of regulatory mechanisms within the plant community (Kenkel 1988; Hughes 1988; Nguyen et al, 2019). Regular spacing of even-sized individuals of the same species has been interpreted as a result of density-dependent mortality caused by intraspecific competition for an evenly distributed resource (Phillips & MacMahon 1981; Nguyen et al, 2019). Aggregated patterns have been explained in terms of regeneration ecology, e.g. regeneration close to seed sources, vegetative regeneration or the occurrence of ‘safe sites’ (Harper 1977; Beatty 1984; Augspurger 1984; Soto et al, 2019). Savannas are characterized by a continuous grassy layer and, in most cases, a discontinuous cover of shrubs and/or trees (Bourlière & Hadley 1983; Thompson, 1999; Zhang et al, 2019). In humid and sub-humid savannas trees are prevented from forming closed stands by human disturbances, including fire and herbivory, and/or by soil conditions (Medina 1987; Nguyen et al, 2019). In arid and semi-arid savannas competition for soil moisture is the main determinant of the woody component (Walker & Noy-Meir 1982; Nguyen et al, 2019).

In Australia, land managers use perennial fodder shrubs such as saltbush species to broaden existing perennial stands of native woody vegetation which lack understorey components to restore habitat and ecosystem function (Collard and Fisher, 2010). In addition, between 1999 and 2006, 7 000 ha of saltbush species were planted across Australia (Fisher and Collard, 2010). In the riverine woodlands and herb-rich woodlands of Victoria, Australia, woody vegetation increased by 18 730 ha between 1989 and 2005 (Lunt et al, 2010).

The abundance of native woody plants such as oaks and ponderosa pine have increased within their historic geographic ranges of North America, Arizona (Asner et al, 2003). Some woody plants that were introduced in North America are now well established and found in widespread areas, whereas others are quite localised (Asner et al, 2003). Resin woody plants that was introduced to North America from South Africa in the 1930s spread, growing on hillsides in the semiarid grasslands, resulting in decline of native plants (Van Auker, 2000). However, some of the woody plants which are indigenous species have increased in density or cover because of changes in local biotic or abiotic conditions (Archer et al, 2009). In the United States of America, the increase of (mesquite and creosote) woody plants resulted in the
conversion of former black grama grassland into dense woodlands; this process has accelerated since the 1900s (Eldridge et al., 2011).

A study of local perception on woody dynamics in the sub-Saharan region of Burkina Faso revealed that more than 90% of the woody species have declined since the 1950s, (Sop and Oldeland, 2013). Indigenous invasive woody species of the Borana rangelands of southern Ethiopia have increased in the past four decades, replacing the grassland (Terefe et al., 2011). In southern Africa, woody plant dominance has been traced back from the late 19th century with the rate of change −0.131 to 1.275% per year (O'Connor et al., 2014). A study of woody vegetation dynamics in the southern Africa region by (Pricope et al., 2015) indicates that woody vegetation in these semi-arid environments is responsive to climatic fluctuations and the long-term trend is one of increased heterogeneous vegetation cover with reduced herbaceous plants.

Woody plants have been dominant on the savanna grassland in South African biomes which has been noted over the last half century (Bond and Khavhagali, 2008; Akiyemi et al., 2019). A study conducted in the South African savanna environment of Hluhluwe Game Reserve to quantify changes in woody vegetation cover from 1937 to 2004, showed an increase in woody plants from 14% to 58% (Wigley et al., 2010). Woody plants dominance has been experienced in small protected areas, intermediate under commercial tenure, and slowest under communal tenure and natural environments (O'Connor et al., 2014). Wigley et al. (2010) study in South Africa shows that land-use practice had enormous impacts on the process of woody plant dominance. Communal areas experienced a decrease of 21% in grass, an increase of tree cover by 5% and an increase in shrub cover by 13%. In commercial farm areas, there was a considerable decrease in grass cover (46%) and moderate increase in shrub cover (10%) and a massive increase in tree cover (36%) between 1937 and 2000.

### 2.3 DRIVERS OF WOODY VEGETATION DYNAMICS

The replacement of grass by woody plants brings about fundamental changes to any ecosystem (Andela et al., 2013). It is therefore critical to understand the main factors that determine the dynamics and expansion of woody plants. Some of the notable potential aspects which play a role in the increases in woody plants include fire regimes, climate, browsing and grazing, increase in atmospheric CO2, and anthropogenic activities.
2.3.1 FIRE REGIMES

The effect of fire on woody vegetation generally depends upon the interacting elements defining the fire regime as well as frequency and intensity of the fire. However, the resilience of woody vegetation to fire is due to the fact that woody plants are conditioned to re-sprout from root stocks (Smit et al, 2010). Fire has negative impacts on the survival, growth and seedling regeneration of woody plants. Less fire disturbances result in drier environments being dominated by woody plants (O’Conner et al, 2014). However, fire generally slows woody vegetation development, destroys seedlings and causes changes in species composition (Yang and Prince, 2000). Furthermore, fire can affect forest regeneration directly by killing stem tissues of seedlings and by heating the soil sufficiently to sterilise seeds and damage roots near the soil surface (Balch et al, 2013).

Fire exclusion has an ambiguous influence on the increase of woody vegetation; fire can cause high seed mortality (O’Conner et al, 2014). Grasslands in savanna areas have high fuel loads hence frequent fire would prevent fire tolerant woody plants from gaining dominance (Archer, 2009). Heavy grazing reduces fuel abundance leading to reduced frequency and intensity of fires (Balch et al, 2013). This leads to suppression of woody plants (Wessels et al, 2011).

Impact of fire on woody structure is highly dependent on the fire regime, frequency, and intensity. Fire regime, especially when burning is conducted as an annual or biennial event, in particular, late dry season fires may be more intense than early dry season fires because of the drier state of the vegetation (Diouf et al, 2012). Repeated fire in summer seasons of the savanna can negatively affect woody plants. The seedlings of many shrubs and other woody plants of the semiarid grasslands are sensitive to fire. Some will not resprout while others replenish if their tops are destroyed (Van Auken, 2000; Archer, 2009).

2.3.2 PRECIPITATION

Changes in precipitation intensity can affect the balance between grass and woody plants (Yang and Prince, 2000). Increases in precipitation intensity does push soil water deeper into the ground resulting in increased woody plants and less grassland. Woody plants with deeper root system will competitively suppress grass growth by accessing water from near the water table (Kulmatiski and Beard, 2013). However, availability of shallow water due to sporadic precipitation in the semi-arid areas benefits grass more than deep rooted woody plants (Kulmatiski and Beard, 2013). Precipitation effects at local levels are influenced by soil depth and texture; woody plants replenish comparatively better in relatively deep and well drained soils than grass (Archer et al, 2009). Severe drought degrades perennial grass which in turn
promotes woody seedling establishment during the following wet period, particularly in the semi-arid environments (O’Connor et al, 2014).

### 2.3.3 INCREASE IN ATMOSPHERIC CO2

Woody plant expansion can be linked to increases in atmospheric CO2 that have occurred over a number of years (Idso, 1992; Polley et al, 1997; Lee et al, 2019). Increased atmospheric CO2 levels have been hypothesised to spearhead woody plants domination in savannas due to the reduced transpiration rate, increased water percolation and reduced seedling mortality (Polley et al, 1997; Lee et al, 2019). Higher atmospheric CO2 levels result in a higher root biomass which ensures rapid regrowth of woody plants lost due to fire (O’Connor et al, 2004). An increase in CO2 levels favour woody plants which have the C3 photosynthetic pathway over grass with the C4 photosynthetic pathways (Archer et al, 2009; Ward et al, 2014). Woody plants have mechanisms to compensate for and overcome drawbacks that may be related to their photosynthetic pathway (Polley et al, 1997). Elevated atmospheric CO2 levels can also increase the water-use efficiency of plants, thereby increasing levels of soil moisture and reducing water stress (Ward et al, 2014). Differential responses of photosynthetic pathways to atmospheric CO2 fertilization cannot explain increases in woody plant abundance especially in temperate regions where both grasses and shrubs possess the C3 photosynthetic pathway (Idso, 1992; Lee et al, 2019).

### 2.3.4 GRAZING AND BROWSING

Excessive grazing by livestock or wildlife can promote the woody vegetation increase by reducing the fuel load or by reducing grass competition to woody plants (O’Connor et al, 2014). When heavy grazing takes place the available soil moisture is utilised by woody species leading to woody vegetation dominance (Skarpe, 1991; Ward et al, 2014). The removal of grass by livestock and wild animals results in reduced fuel loads and consequently less frequent and intense fires (Russell and Ward, 2014). This reduces the effectiveness of fire in the control of woody vegetation, leading to altered competitive interactions between the woody and herbaceous layers due to the removal of grass (Britz and Ward, 2007; van Langevelde et al, 2019).

Browsing animals usually keep shrubs and trees from establishing or from reaching high densities; thus the absence of such animals leads to expansion of woody vegetation (O’Connor et al, 2014). For example, elephants reduced woodland cover in the Serengeti by 5% between 1962 and 1972 (Van Auken, 2000; O’Connor et al, 2014). Herbivory can alter grassland composition at high density and frequency by changing the grassland to shrubland or woodland (Archer, 1990). Herbivores alter plants and the ability
of plants to obtain resources or selectively eliminate plants as competitors, thereby influencing the outcome of species interactions by damaging plant parts (Van Auken, 2000; van Langevelde et al, 2019). However, to some extent, herbivores may also be effective agents of seed dispersal leading to woody vegetation expansion (O’Connor et al, 2014).

2.3.5 ANTHROPOGENIC ACTIVITIES

Humans play a significant role in the dynamics of woody vegetation in most parts of the world. Natural woodlands are rapidly being transformed for subsistence cultivation around growing human settlements (Ward et al, 2014). For example, pastoralists in rural communities in Ethiopia depend on woody plants for various uses including medicine, food, and local construction (Abate et al, 2012). Heavy utilisation of woody plants for fuel purposes in an unsustainable manner leads to the reduction in woody plants (Wessels et al, 2011). The sustainability of ecosystem services under such circumstances, particularly in impoverished rural areas, is under pressure (Yang and Prince, 2000; Wessels et al, 2011). This is seen in the alteration of the landscape in North Africa (Zerboni et al, 2019). The Anthropocene has led to a change in global biodiversity and has negatively altered ecosystems around the world (Branquinho et al, 2019).

2.4 EFFECTS OF WOODY VEGETATION DYNAMICS ON BIODIVERSITY

Ecological changes and increases in the population densities of woody plants in many rangelands, grasslands and savanna ecosystems result in decreased herbaceous production and diversity (Bond and Khavhagali, 2008). Decreased herbaceous production can have an impact on effective resource management and utilisation strategies (Roques et al, 2001; Lesoli et al, 2013). Large scale changes of savanna habitats that are mostly characterized by grassland communities may also compromise wildlife habitat and contribute to the decline of biodiversity (Bucini, 2010).

2.4.1 EFFECTS OF WOODY VEGETATION DYNAMICS ON FLORA

Woody vegetation dynamics influence the flora of an area in various positive and negative ways (Wessels et al, 2011). Woody plants compete for resources with other plants, particularly in the establishment phase when saplings are shaded by grass (Bond and Khavhagali, 2008). Woody plants often have the ability to out-compete indigenous species and grass in any given area, resulting in habitats dominated by encroaching woody species (Bond and Midgley, 2000). An increase in woody plants on pasture lands contribute to increased competition for nutrients, thereby reducing the availability of grazing lands for livestock (Tobler et al, 2003). Such a loss of grazing land leads to a decline in livestock production (Van
Auken, 2000). Environmentally, decreased grass cover causes increased runoff and erosion leading to land degradation (Van Auken, 2000).

Deep-rooted plants benefit the understory vegetation by transporting water from deeper soil layers to drier surface soils through hydraulic lift, particularly in dry periods (Sagar et al., 2008). The canopies of woody plants provide a more stable microhabitat for the understory (Van Auken, 2000). Woody plants protect the understory against irradiance and overheating through direct solar radiation, which increases potential for moisture stress, resulting in reduced species richness (Sagar et al., 2008).

### 2.4.2 EFFECTS OF WOODY VEGETATION DYNAMICS ON FAUNA

The spread of woody plants, in a previously grass dominated environment, leads to changes in the structure and quality of the habitat (Seamster, 2005). In some cases, woody plants form clusters that grow over time with greater diversity of microhabitats than grasslands (Archer, 1990). An increase in woody plant cover in the savanna ecosystem can reduce the quality of the local habitat for both domesticated and wild animal populations (Seamster, 2005; Tobler et al., 2003). A study by Yang and Price (2000) showed a decline in the abundance and density of a variety of organisms including insects, rodents, and carnivores in areas affected by woody plant expansion. In more open habitats, carnivores such as cheetahs tend to locate their territories in areas that contain woody plant cover (Tobler et al., 2003). Furthermore, woody plants affect the safety and health of livestock and wild animals by influencing pest environments and predator-prey relationships (Rose, 2012).

### 2.4.3 IMPORTANCE OF MONITORING VEGETATION DYNAMICS IN SEMI-ARID REGIONS

Assessing vegetation dynamics is important since vegetation dynamics influence ecosystems as well as the local human population (Mitchard et al., 2009). Furthermore, monitoring of vegetation dynamics helps establish whether biodiversity set objectives are being met (Rose, 2012). Knowledge of change is important in designing an appropriate management strategy that is suitable to the given locality (Tobler et al., 2003). From a functional point of view, land users do not regard plant domination as a problem; rather they consider it as an improvement in terms of availability resources for various uses (Wigley et al., 2009). For example, wood is the primary source of fuel for cooking and fencing of communal areas in sub-Saharan Africa (O’Conner et al., 2014).

### 2.5 APPLICATIONS OF REMOTE SENSING IN MONITORING LULC DYNAMICS

Traditional methods of assessing woody vegetation in the earth’s environment largely make use of field data analysis (Van Auken, 2000; Hu et al., 2019). Monitoring dynamics usually involves repeated
observations of usually the targeted features to assess changes in composition, structure and condition over time (Bellefontaine et al, 2000; Hu et al, 2019). Although field-based monitoring is considered accurate, it is generally inefficient since it is unable to cover large spatial area (Lesoli et al, 2013). In addition, field-based monitoring requires longer time periods, large personnel and is relatively expensive. In contrast, remote sensing techniques provide information in a short period of time and allow for analysing data over complex landscapes at significantly lower cost (Hellesen and Matikainen, 2013).

Remote sensing is the science of collecting information about objects without direct physical contact with the objects (Lillesand et al, 2008; Xu et al, 2019). Remote sensing specifically senses and records electromagnetic radiation that is reflected from different objects such as plants, buildings, water bodies or clouds in the atmosphere (Lillesand et al, 2008; Yudong et al, 2011; Chen et al, 2018). The above-mentioned objects show characteristic patterns of reflectance across the spectrum of electromagnetic radiation allowing for determination of specific types of objects (Schröter et al, 2009). As such, objects are discriminated based on differences in their spectral reflectance behaviours (Schröter et al, 2009; Chen et al, 2018).

Evidence of land cover changes delivered by repeated satellite images greatly contributes to planning appropriate management strategies of available resources, particularly in developing countries where baseline data are often lacking (Kebrom and Hedlund, 2000; Li et al, 2010). Remote sensing satellite imagery prove to be of great importance when assessing large spatial areas because of the relatively wide swath of the image for example Landsat imagery. As a result, numerous studies have applied remote sensing techniques to characterise woody vegetation communities, for example (Maggi et al, 2007; Wigley et al, 2010; Zinnert et al, 2011; Hellesen and Matikainen, 2013; Zhu and Liu, 2014; Vannier and Hubert-Moy, 2014).

Multispectral Landsat images were used for change detection analysis of woody vegetation dynamics on the border between France and Italy (Maggi et al, 2007; Che et al, 2018). A separability analysis based on the Jeffries Matusita (JM) distance was conducted to spectrally distinguish classes (shrubs, herbaceous plants, forest and bare land). A nomenclature classification scheme was used in this study. An accuracy assessment was measured using both field survey and high-resolution aerial images. Error matrices and accuracy indices were generated to assess commission and omission errors of the classified maps. The results of the study showed an increase of woody vegetation by 4% between 1984 and 2000 with overall classification accuracy of 90%.
Gray scale images from 1937, 1960 and 2004 were used to compare woody vegetation increase on commercial farms, conservation and communal rangeland (Wigley et al, 2010). The study was conducted in Hlabisa, KwaZulu-Natal. Manual classification was conducted in the study and classified images were subtracted from each other using a raster calculator. Manually classified results were found to be highly convergent with much higher agreement than for computer generated classification. Total woody vegetation cover increased from 3% to 50% in all sites over the study period. The study achieved an overall classification accuracy of 96%. The study by Wigley et al (2010) used manual and automated classification in the analysis and archived high accuracy results compared to the study by (Maggi et al, 2007) which used nomenclature automated classification.

Zinnert et al (2011) assessed woody vegetation cover dynamics in response to climate change on the Hog Islands, United States of America (USA). The main aim of the study was to examine the conversion rate of grassland to woodland over time relative to climate change. Objectives of the study were to quantify woody expansion and relate the rate of woody expansion to shoreline migration and changes in climatic variables. The study used Landsat imagery obtained between 1984, 1988, 1994, and 2010, and Light Detection and Ranging (LiDAR) data. From 2010 the NDVI utility was used to evaluate woody vegetation. Field survey and high-resolution image were used to select area of interest in performing maximum likelihood classification. Woody vegetation accounted for 8% of total land area in 1984, 13% in 1988, 20% in 1994 and increased to 31% by 2010. Overall classification accuracy of 99% was achieved.

Hellesen and Matikainen (2013) performed a study in Denmark using an object based approach for mapping woodland using LiDAR and Colour-infrared (CIR) Orthoimages. The objective of the study was to investigate the potential of classifying woody cover in the study area using aerial CIR images and LiDAR height data for 2010. Object- based image analysis was applied in combination with a CART classifier function (eCognition software for image analysis). The LiDAR classification result improved significantly when the normalised Digital Surface Model (nDSM) was included, from 82% to 97%. The producer’s and user’s accuracies improved from 81% and 53% to 94% and 90% with LiDAR data, respectively. Results of the study show that nDSM gives better definition for image enhancement in classification. The study by Hellesen and Matikainen (2013) used nDSM information extracted by LiDAR data in classification compared to the study by Zinnert et al (2011) which used the LiDAR Digital Elevation Model (DEM) information, and the NDVI utility in measuring vegetation density.

Zhu and Liu (2014) carried out a time-series analysis of forest area cover in Vinton county Ohio, USA. Landsat images acquired in March, September, October and November of 2011, as well as in April and
July of 2012, were used in the study. The study implemented a hierarchical classification to improve the discrimination between classes. The overall accuracy of the classification was 91%, while adding DEM information (landscape height above sea level used to distinguish vegetated mountainous areas in classification) improved the accuracy slightly to 93%.

Vannier and Hubert-Moy (2014) conducted a multiscale comparison of remote sensed data for woody vegetation mapping. The study was conducted in France using different remote sensed data spanning a wide range of resolutions, 0.3 m LiDAR data to 23 m Indian Remote Sensing Satellite (IRS) from 2002 to 2009. Segmentation was applied in all images during analysis as well as object-oriented classification. Classification results showed 85%, 97%, and 98% for Satellite Pour l’Observation de la Terre (SPOT 5), Korean Multi-purpose Satellite (KOMPSAT II), and LiDAR data respectively. Vannier and Hubert-Moy (2014) used many remote sensing datasets, using segmentation and object-oriented classification, unlike Zhu and Liu (2014) who used DEM data and a hierarchical classification in the analysis applying Landsat data only.

2.9 ECOSYSTEM SERVICES

“Ecosystem services” is a phrase with many meanings, yet very few studies have primarily focused on comparing different definitions of the term. Ecosystem services are now generally used in identifying an appropriately wide range of environmental variables for policy and management as well as better understanding the benefits provided by those aspects of the environment. A review of the dominant definitions of ecosystem services reveals the term is “comprehensive in its scope and requires further specification for most purposes. Analysis further reveals that there are four main categories of conceptual definitions” (Bruins et al, 2017).

While the MEA defines ESs as “the benefits people obtain from ecosystems” (Millenium Ecosystem Assessment, 2005, p. V) the term ESs scarcely provides specificity or clarity for how to approach environmental science or what aspects of the environment are important for study. Assuming agreement on what ESs are from a definition as elegant as the MEA definition obscures a wide variety of uses and meanings of the term. Bruins et al, (2017) present a review of different ESs definitions, but the focus of their analysis is on which authors consider ESs to be benefits of nature and those which consider ESs to be processes and physical features that create benefits instead of an in-depth review of those definitions.

The capacity of ecosystems to provide services is determined by many different direct and indirect driving forces operating at the local to global levels (MEA, 2005; Alcamo et al, 2016). Ecosystem services as identified in literature ranges from four types that are namely; provisioning, (food, fibre and timber),
(Alcamo et al, 2016), regulating, {Carbon sequestration and Habitat Quality} (Yang et al, 2018), cultural, {aesthetic, music and art}, (National Wildlife Federation, 2016) and supporting services {photosynthesis, nutrient cycles} (Chivian et al, 2008). Managing ecosystem services requires the knowledge of the dynamic systems of landscapes and all its changes over time (Li et al, 2016), as well as its connections to the interactions between services, structures and functions (Chivian et al, 2008). With this framework of different ecosystem relationships and service flows, ESs can be conceptualized as the interlinking of these four identified components of services as a whole. The debate about how to define ES centers around a variety of approaches to three interlinking and overlapping concepts:

a) the physical components of the ecosystem (structure),
b) the functioning of and interaction between those components (process or function), and
c) the resulting contribution to human welfare from the ecosystem (benefit or benefit-providing service).

The emphasis in this definition of ESs is on the natural processes and conditions producing benefits to humans (Jiang et al, 2016). The regulatory functions of ecosystems as well as the intangible benefits reaped directly from nature’s processes are included in ESs, while ESs can also be the background processes that “maintain biodiversity and the production of ecosystem goods” (Jiang et al, 2016; Apitz, 2006). This definition of ecosystem services incorporates the self-sustaining aspects of ecosystems as well as the beneficial impacts ecosystems have on humanity. This interpretation argues the processes of nature are necessary for human welfare since the processes of nature, ESs, make human life possible. This is seen through the outlining of the Sustainable Development Goals (SDGs) and the timeline that was set to achieve these goals. Most studies (Yang et al, 2018; Kindu et al, 2016, Liu et al, 2012) show how the concept of ESs has help the United Nations (MEA) to define and achieve SDGs within the ESs context.

Furthermore, agreements on ESs classification and organizational structure are not uniform in character, as evidenced by the recent IPBES framework that suggests a need for revised thinking of ESs not as the results of natural or semi-natural ecosystems, but instead as the results of coproduction of social-ecological systems (Diaz et al., 2015). International agreements, frameworks, and policy initiatives concerning ESs represent important cooperation and collaboration, but they have not settled the issue of how to identify a specific aspect of the natural world as an ESs for all purposes. ESs represents a desire for improving human interactions with nature as much as it represents a way to identify aspects of the natural world for science and policy.
In addition, environmental valuation (Fuller et al, 2018) has emerged as an independent discipline, aiming at valuing and balancing these various goods and services when planning the exploitation of natural resources. A strong challenge for this thinking is its practical applications: qualification and quantification of single and jointly produced ecosystem services as input to management and planning (Wang et al, 2018). Experiences in rating and valuing the values of “hard” ecosystem services such as flood control, CO2-sequestration, denitrification, filter effects and to some extent recreation have been gained in recent decades.

The ecosystem service concept has become popular since the United Nations' Millennium Ecosystem Assessment 2005 (further referred to as MEA, 2005). To achieve sustainable ecosystems services (Apitz et al, 2006), an integrative approach can be implemented (Euliss Jr et al, 2011). This approach unifies quantitative studies (Yang et al, 2018; Fu et al, 2013) and allows scenarios to be drawn for effective decision making (Euliss Jr et al, 2011). Careful management of ecosystems within our modern and highly diverse landscapes is important for intergenerational sustainability of ecosystems (Euliss Jr et al, 2011). Understanding how land use changes affects multiple and simultaneous ecosystem services helps researchers appreciate processes of regulating them in an integrative manner. The development of cost effective (Euliss Jr et al, 2011), integrated (Fu et al, 2013) and adaptative (Reyers et al, 2012) modelling of ecosystems services for sustainable development helps evaluate and assess ESs and landscape changes on a bigger scale. For example, a study carried out by (Euliss Jr et al, 2011) used a frame-based model approach to quantify ESs derived from landscape changes. The authors focused on the ecologically diverse Lower Mississippi Valley. Furthermore, the model showed that different land uses led to different quantities of ESs in the area and to quantify them using a frame by frame approach was best. This model, (Euliss Jr et al, 2011) shows that with the correct conditions set (economic, policy and management), landowners, policy makers and stakeholders can evaluate the area for ecological trade-offs involved in complex landscapes.

The provision of ecosystem services is directly linked to the condition of ecosystems (Kindu et al, 2016), e.g. land use/land cover (LULC) types, in a given area (Kindu et al, 2016; Lu et al, 2014; Olyver et al, 2010). Dynamics of LULC can cause changes in the values of ecosystem services (Kreuter et al., 2001; Lu et al., 2014; Polasky et al., 2011). Cai et al (2018) outlined that one of the fundamental issues that cause land use changes are landscape fragmentation which in essence changes the structure and pattern of ecosystems, (Yang et al, 2018) and decreases the function of the ecosystems, (Cai et al, 2018). The identification and measurement of varying ecosystem services linked to changing landscapes and its uses
helps quantify (Yang et al, 2018) the environmental cost-benefit (Cai et al, 2016) and different land planning decisions allowing decision makers to better understand different trade-offs (Alcamo et al, 2011) for efficient ecosystems services management. The Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) model is one such tool that can be used to quantify land use changes and simultaneously spatially estimate ESS quantities (Nelson et al, 2009; Yang et al, 2018). For example, (Yang et al, 2018) used InVest to quantify five regulating ESS for observed land use changes in the Loess Plateau in China. Van et al (2017) used InVest to assess ecosystem services on conserved properties in Sonoma County, California.

Generally, regulating services tend to increase and the provisioning services decrease with the input of human wellbeing or needs into the equation (Yang et al, 2018; Redhead et al, 2017; Seppelt et al, 2013). Since the most common tradeoffs in ESs happen between regulating and provisional services. To fully understand landscape restoration and land degradation management (Olver, 2012) conflicts are bound to arise. Having the ability to see across such scenarios (Seppelt et al 2013) gives rise to the possibility of land use change management strategies, inform policy as well as ESs management (Yang et al, 2018). Mapping ESs grounded on multiple land use land cover change scenarios can expose all the changes in ESs given diverse future land use patterns in order to inform land use decisions and planning (O’Farrell and Anderson, 2010; Raudsepphearn et al., 2010; Maes et al., 2012; Yang et al, 2018). Most studies (Yang et al, 2018; Nelson et al, 2009; Thompson et al, 2016) focus on the different scenarios that are informed by policy in ESs assessment. These studies are useful in assisting policy making and achieving sustainable development (Thompson, 2016), moreover, quantifying ESs based on scenarios also provides data for future studies. The need for knowledge about ES management in an African context is big (Polasky et al, 2011). Adding on to knowledge production, policy makers can use scenarios developed to improve poor peoples’ wellbeing that live in similar conditions.

2.9.1 PROVISIONING SERVICES
Forests provide a large and diverse array of goods and services for humans to use and consume and, as we previously noted, these are primarily provisioning services (Lu et al, 2012) and include energy, fiber, food, genetic resources, and water (Polasky et al, 2011). Wood is the most obvious and common product generated by forested ecosystems. Wood has a variety of uses and, in many cases, represents the basic building material for residential homes and businesses. Wood can be found in the flooring, walls, ceilings, and roofs of many structures (Apitz, 2006). Doors and window frames are also commonly made from wood. Wood is frequently used in the manufacture of furniture for homes and offices, such as bed frames,
chairs, chests, dressers, shelves, and tables (Jiang et al, 2012; Apitz, 2006). Tool handles are typically made from wood; these include axes, chisels, hammers, knives, rakes, shovels, and wheelbarrows. Other items made from wood include bowls, cups, napkin holders, plates, and utensils.

Another set of important wood product are paper products derived from wood fiber, which include books, copy paper, magazines, newspapers, and writing tablets, as well as softer products such as hygiene products, napkins, paper towels, tissue paper, and toilet paper (Apitz, 2006). Since the moment that fire was discovered to be of value to humans, wood from forested ecosystems has been used for heating and cooking purposes (Apitz, 2006; Jiang, 2012). More recently, technologies have been developed to transform wood into pellet form, which is easier to transport but can only be safely used indoors in specially designed stoves.

Other provisioning services generated by forested ecosystems are the wild foods and medicines that can be derived from plants and animals found there. Another provisioning service facilitated by forested ecosystems is the water resource that arises from forested areas (Su et al, 2013). Water regulation and supply are suggested to account for nearly 7% of the value of ecosystem services, and many of the world’s largest cities partly rely on water derived from forests (Su et al, 2013).

2.9.2 REGULATING SERVICES

Forested ecosystems provide a number of regulating functions or services that can be viewed as services for human civilization and for the Earth’s biosphere or, more generally, as benefits obtained from other processes (Su et al, 2013). These services include carbon sequestration, climate regulation, disease regulation, erosion control, flood regulation, and water purification. Carbon storage, flood control, and water filtration are considered the most important ecosystem services in Canadian boreal forests (Su et al, 2013). Thompson et al, (2016) describe regulating services as intermediate ecosystem services that relate more directly to the continued existence and maintenance of ecosystem processes. Regulating services are also important for human security (or personal safety), resource access, and disaster mitigation. These services are linked to the basic needs of most living creatures for food, shelter, and access to goods. These services can also influence human health indirectly by promoting strength and positive feelings and directly by providing access to clean air and water.

An important regulating service provided by ecosystems is species redundancy. It has been postulated that ecosystems have many different species that perform the same or similar sets of functions. Species redundancy could lead to greater ecosystem resiliency from natural disturbance processes (Polasky et al,
Further, an ecosystem that has high species diversity (more species) may have stable ecosystem processes and regulating functions if the species that perform similar functions have different levels of environmental sensitivity (Polasky et al., 2011). An ecosystem that has too few species or species with similar functionality may be more vulnerable if the removal of one of these species from the ecosystem has an important impact on the function of the ecosystem (Fonseca and Ganade, 2001). Numerous actors or events can affect the regulating services provided by forested ecosystems. For example, one actor involves changes in local land use and land cover, which can have enormous impacts on the regulating functions of an ecosystem. Climate change is a sixth potential actor that might affect the regulating functions of ecosystems (Fonseca and Ganade, 2001). Although increased concentrations of carbon dioxide in the atmosphere may stimulate plant growth the increase over time could lead to changes in the distribution of particular plant communities.

2.9.3 CULTURAL SERVICES

Cultural services are a key set of values that forested ecosystems provide or facilitate. Cultural services include nonmaterial benefits to humans; these relate to changes in human welfare (Smart 2010) and are highly dependent on the other ecosystem services. The cultural services that humans derive from forested ecosystems generally include cognitive development, recreation, reflection, spiritual enrichment, and other values gained by viewing aesthetically pleasing vistas. The cultural services (i.e., recreational and tourism opportunities) facilitated by tropical forests of the Tapanti’ National Park in Costa Rica provide one set of examples (Bernard et al. 2009). The Millennium Ecosystem Assessment (2005) refines the idea of cultural services to more Forested ecosystems are, therefore, important for providing cultural heritage to local communities. Cultural heritage is obviously linked to cultural identity and is developed over both space and time. Cultural heritage can influence how people learn to manage the forested ecosystems around them.

Another cultural service that ecosystems provide relates to the heritage and knowledge of local communities. Local knowledge systems are dependent on human interaction with local forested environments and are developed over several human generations. The high level of indigenous knowledge developed over time not only connects local inhabitants with forests and natural resources but also leads to effective management and an understanding of how a particular ecosystem function. This knowledge loss can also slow the process of identifying new chemicals and compounds that may be useful in the development of new medicines. Aesthetic values, recreational opportunities, and ecotourism are other cultural services that forested ecosystems can provide or facilitate. Other cultural services facilitated by
forests include recreational opportunities and ecotourism experiences. Forest-based tourism or ecotourism opportunities can be developed to positively benefit the social and environmental aspects of local communities.

2.9.4 SUPPORTING SERVICES
The final key ecosystem service provided or facilitated by forests and related communities are the supporting services. Smart et al. (2010) describe supporting services as “intermediate ecosystem services that are necessary for the production of all other ecosystem services.” The Millennium Ecosystem Assessment (2005) describes these services as being more clearly indirect than the regulating services. Supporting services within an ecosystem are essential for the continuation of all other ecosystem services, and include processes such as primary production, photosynthesis, soil formation, nutrient cycling, and water cycling. Primary production is the energy accumulated in plants (Smart, 2010), and radiant (electromagnetic) energy is one of the main inputs into a forested ecosystem. This energy is critical for the maintenance of plant health and reproduction. The productivity of ecosystems is highly dependent on local and regional rainfall levels and temperature regimes. From a primary production standpoint, tropical forest ecosystems are typically more productive than are forests located in boreal regions. The variation in ecosystem productivity around the world is further illustrated by the quantity of biomass stored in those ecosystems.

2.10 CARBON SEQUESTRATION
Forest vegetation and soils constitute a major terrestrial carbon pool with the potential to absorb and store carbon dioxide (CO2) from the atmosphere. The CO2 source and sink dynamics as trees grow, die, and decay are subjected to disturbance and forest management (Kaul et al, 2010). Evidence of climate change linked to human-induced increase in greenhouse gas (GHG) concentrations is well-documented in international studies (BernsteinIPCC, 2007). To contribute to reduction of GHG emissions, and to partly offset deforestation, the Kyoto protocol (KP) explicitly considered reforestation and afforestation activities for carbon sequestration accounting (Bernsein, IPCC, 2007). The recognized importance of forests in mitigating climate change has led countries to study their forest carbon budgets and initiate the assessment of enhancing and maintaining carbon sequestration of their forests resource. The total global potential for afforestation and reforestation activities for the period 1995–2050 is estimated to be between 1.1 and 1.6 Pg C (1 Pg = Peta gram, 1015 g) per year, of which 70% could occur in the tropics (IPCC 2000). Afforestation and reforestation are seen as potentially attractive mitigation strategies, as wood production and carbon (C) storage can be combined. Several carbon budget models of different
complexity have been developed and used to account for forest carbon dynamics (e.g. Parton et al. 1987; Kurz et al. 1992; Kimmins et al. 1999; Price et al. 1999; Karjalainen et al. 2002; Peng et al. 2002; Seely et al. 2002; Masera et al. 2003). Some of these studies not only account for the carbon in the forest ecosystem but also for the carbon contained in the harvested wood products (Burshel et al. 1993; Karjalainen et al. 1994, 2002, 2003; Harmon et al. 1996; Pingoud et al. 2001; Skog and Nicholson 1998; Winjum et al. 1998; Masera et al. 2003).

United Nations Framework Convention on Climate Change (UNFCCC) has recognized the importance of plantation forestry as a greenhouse gas mitigation option, as well as the need to monitor, preserve and enhance terrestrial carbon stocks (Updegraff et al. 2004). In addition, production from plantation forests may relieve pressure on timber extraction from natural forests, and thus contribute to forest conservation. Globally, the annual planting rate is 4.5 million ha, with Asia and South America accounting for 89% (Fang et al. 2007). Large parts of India offer good growing conditions, good rainfall and water resources, a tropical climate and ample sunshine, so that trees may grow fast (Kaul et al., 2010; Updegraff et al., 2004). Forest plantations constitute a very important part of the forest resources as a large proportion of wood produced in India comes from tree plantations established both within and outside the forest reserves.

In general, previous studies (Kaul et al., 2010; Fang et al., 2007; Yang et al., 2018) find that the costs of carbon sequestration in forests are comparable to, and in some cases lower than, costs of alternative mitigation and abatement approaches. However, these analyses are focused solely on the opportunity costs of agricultural production. An important issue not considered in these studies is the impact of the resulting land use changes on biodiversity. Although agricultural land is generally regarded as purely an anthropogenic habitat, it is, in fact, a significant resource for a variety of species of conservation interest (Herkert, 1994, Vickery et al., 1994).

In many parts of the developing world, specifically in sub-Saharan Africa, the accurate quantification of AGB, although still a challenge, is important for national carbon accounting, REDD+ project payments, sustainable forest management and strategic policy-making. The 11th Conference of Parties of the United Nations Framework Convention on Climate Change (UNFCCC) under the Kyoto Protocol initiated the Reducing Emissions from Deforestation and Forest Degradation (REDD+) project in developing countries (Agrawal et al. 2011). The main aim of the REDD+ project was to highlight the need for possible climate change mitigation measures through sound forest conservation actions in developing countries (Agrawal et al. 2011; Chinembiri et al. 2013). In sub-Saharan Africa thus far, few countries, have fully embraced the
aims and objectives highlighted by the Kyoto Protocol, which advocate sustainable forest (i.e. both indigenous and emerging plantation forests namely, Pinus, Eucalyptus and Acacia spp.) management and assessing their contributions to biosphere-atmospheric carbon cycles, as potential carbon sinks. Studies conducted elsewhere in the world (e.g. South America) demonstrate that forest plantations occupy a significant spatial extent and are capable of storing meaningful amounts of atmospheric carbon content (le Maire et al. 2011).

**2.10.1 MAPPING CARBON STORAGE**

The recognition of forests as a potential sink of atmospheric carbon content has resulted in many AGB quantification methods (i.e. direct and indirect methods) being developed (Chinembiri et al. 2013; Dube et al. 2016; Henry et al. 2011; Singh et al. 2011; Phachavo. 2014; Loboda et al, 2018). Direct AGB estimation methods are broadly classified into (1) Tier-1: basic methods, based on generalized equations; (2) Tier-2: intermediate approaches, based on volume equations and wood gravity; and (3) Tier-3: complexity methods, based on biomass equations (Henry et al. 2011). However, the lack of suitable parameters is one of the major issues and challenges associated with direct methods of estimating and mapping AGB or carbon in places such as sub-Saharan Africa and southeast Asia. In sub-Saharan Africa, numerous studies have utilised traditional methods (i.e. direct methods) to estimate AGB (Dovey 2009; Henry et al. 2011; Schönau & Boden 1982). Most parameters for estimating biomass (i.e. allometric equations, wood density values, yield tables and biomass expansion factors) have, however, been derived from studies performed outside Africa, in countries, such as Costa Rica, Brazil and Mexico (Henry et al. 2011). Since most allometric equations were developed outside sub-Saharan Africa, the major challenge is finding ways to implement these parameters in Africa with limited uncertainties. Consequently, very few published sources exist for forest types in sub-Saharan Africa (Henry et al. 2011). In addition, besides the scarcity of suitable and key parameters, traditional methods are environmentally destructive and impractical for large-scale implementation. Moreover, these methods require intensive field work and large volumes of ancillary data for analysis, which are labor-intensive, costly and time-consuming (Henry et al. 2011).

Moreover, when using traditional methods, site access in protected areas is poor, due to complex terrain and organizational restrictions (Jonckheere et al. 2005). By using remotely sensed data, these limitations may be addressed in a range of scales and remote sensing technology offers a suitable means for the independent verification of the forest carbon pool estimates (Muuukonen & Heiskanen 2005). Remote sensing, unlike traditional approaches, provides spatial and temporal data that are useful in mapping AGB.
at different spatial scales in a more robust, quick and efficient manner (Boyd et al. 1999; Carreiras et al. 2012). It allows for repeated image acquisitions over the same locations, which are necessary for the detection of temporal changes in carbon stocks. In addition, remotely sensed data are stored in digital format so that they can be easily integrated with ancillary data in a Geographic Information System (GIS) for further analysis. In the light of these advantages, researchers have used optical sensors (Boyd et al. 1998, 1999; Foody & Boyd 2002) and active sensors (Carreiras et al. 2012; Colgan et al. 2013; Mitchard et al. 2009, 2011, 2012, 2013) to estimate AGB in sub-Saharan Africa, with varying degrees of accuracy. Therefore, the utility of remote sensing in estimating AGB necessitates a review of the extent to which the technology has been utilized within the African context. This information is important for sustainable forest management and the identification of readily available datasets for the accurate estimation of AGB on a regional scale. The current prevailing economic situation in most countries in sub-Saharan Africa requires cost-effective and accurate methods for quick, accurate and efficient AGB estimation, particularly on a national or regional scale (Dube et al. 2014).

Although studies (Carreiras et al. 2012, 2013; Mitchard et al. 2013) have successfully attempted to estimate AGB in different parts of sub-Saharan Africa, using lidar and radar datasets, their main limitation is that all of them were implemented at a local or small scale. AGB (figure 2) estimates are currently required at regional or global scale, because “wall-to-wall” estimates are more effective in providing a comprehensive understanding of the global carbon pool than local scale. Unlike other parts of the world (i.e. the developed world), the application of these datasets on a regional or global scale remains one of the major challenges in sub-Saharan Africa. The main reasons for this limitation is the cost, the scarcity of data for operational applications and limited image pre-processing technical expertise, amongst others.
Literature demonstrates that there is a decline in the number of studies using conventional methods to estimate AGB, compared to remote sensing methods (Thimothy et al, 2016). Conventional methods, although accurate, are time-consuming, too costly and practically impossible to apply on a broader scale. Although active sensors, such as lidar and radar, provide higher and more reliable AGB estimates than coarse multispectral data, they are still not operational in the African environments, due to the cost of their acquisition (Timothy et al, 2016). Given the poor economic situation of most sub-Saharan African countries, multispectral data remain relevant for AGB quantification, regardless of saturation problems in densely closed canopies, the occurrence of mixed pixels and a huge mismatch between the size of field measurements and the image pixel size (Timothy et al, 2016). Previous work outside sub-Saharan Africa shows that AGB estimates can be greatly improved by the use of multi-date multispectral datasets, the integration of remotely sensed data with ancillary data and spectral decomposition. Therefore, there is a need for further investigations into the applicability of the above approaches in quantifying AGB in sub-Saharan Africa, using new generation sensors and software such as Clarklabs and the Natural Capital InVEST. Additionally, there is a need to identify efficient and robust predictive models that can help improve AGB estimates from these datasets (Timothy et al, 2016).

2.11 SUMMARY
Studies show that the dominance of woody vegetation result in a decrease in grassland cover. The continued expansion by LULC has been central to many vegetation monitoring studies and traditional methods have been developed to analyze LULC dynamics. However, remote sensing has recently been...
used as a tool to monitor and assess LULC dynamics replacing most traditional methods. InVEST software has been used to calculate carbon storage. Although remote sensing techniques have been used in the past, they have been deemed ineffective, hence the use of the Investment Natural Capital Project. This chapter presented the description of ecosystem services, drivers for and effects of ESS dynamics. The chapter also presented selected studies that utilized remote sensing techniques to assess vegetation dynamics in different parts of the world. Furthermore, the chapter presented literature on carbon sequestration and how to quantify carbon storage using remote sensing. The chapter also presented the limitations of doing so in an African context. The next chapter will provide details of the methods used to conduct the study presented in this dissertation.
CHAPTER 3: RESEARCH METHODOLOGY

3.1 INTRODUCTION
Remote sensing techniques have become a powerful tool to assess land cover dynamics at local, regional and global levels. This study applied these techniques to assess the dynamics of land cover change in the study area. This chapter presents the methodology followed to achieve the objectives of the study which are to; To spatially map the change in land-cover between 2007 and 2018, Asses performance of Landsat Satellite in mapping land cover change, Use InVEST Carbon Model to quantify the amount of carbon storage in the study area, To use Scenario-based model to model future projections of carbon sequestration and land cover change and To utilize the carbon sequestration and land cover change data to inform planning for ecosystem services. An overall description of the study area is provided in the first section and followed by descriptions of remotely-sensed data. The last section presents in detail analysis of remotely-sensed data.

3.2 STUDY AREA
The Great Limpopo Trans-frontier region is a region which is comprised of three different countries (Zimbabwe, South Africa and Mozambique).

![Figure 3: location of the Greater Limpopo Trans-frontier Region, South Africa and Zimbabwe](image_url)

This region has been combined to form the Great Limpopo Trans frontier Park with an area of 37,572 km², (GLTFCA, 2016). The region comprises a vast area of the lowland savannah biome and semi-arid
ecosystems. Geographically the GLTP features two spectacular Cliff landscapes in Chilojo Cliffs in Gonarezhou National Park and Shingwedzi Cliffs in Limpopo National Park. There are five major types of vegetation, namely Mopane woodlands and shrub veld in the northern portions, mixed bushveld in the southern half, sand veld in the south eastern areas of Mozambique, riverine woodlands mostly in Kruger and Gonarezhou, and seasonally flooded and dry grasslands in and around Banhine National Park. This transboundary ecosystem is necessary to study due to the recently noted changes in the landscape coupled with the anthropogenic activities that have been emerging from the same area.

The region comprises a vast area of the lowland savannah ecosystem and semi-arid ecosystems, not only in the trans-frontier Park itself, but also in the conservation area. Geographically the GLTP features two spectacular Cliff landscapes in Chilojo Cliffs in Gonarezhou National Park and Shingwedzi Cliffs in Limpopo National Park. There are five major types of vegetation, namely Mopane woodlands and shrubveld in the northern portions, mixed bushveld in the southern half, sandveld in the south eastern areas of Mozambique, riverine woodlands mostly in Kruger and Gonarezhou, and seasonally flooded and dry grasslands in and around Banhine National Park.

Extreme harsh weather conditions have been experienced within the area with specific reference to the cyclone Eline which resulted in the breaking of the Rundebridge which crossed the Lundi river linking the Gonarezhou National Park and the local communities (Masvingo Bureau 2006). Since this area is situated in the lowveld, the Limpopo basin area provides vast river tributaries which pour into the main river (Limpopo River) providing communities and National Parks with water for both plants and animals through irrigation and games water reservoirs.

Different communities which make up the region include Vhembe, Phalaborwa, Hoedspruit and Giyani in South Africa, Mahenye, Chilonga, Save and Malilangwe in Zimbabwe as well as Mapai, Makuya Park and Madimbo Corridor in Mozambique. These communities include different tribal groups which reflect diverse ethnicity within all three countries. For the purposes of this study, only South Africa and Zimbabwe will be explored.

3.3 CLIMATE

Climate data was obtained from the Polokwane Weather Station (Limpopo) for South African weather and Buffalo Range Weather Station (Chiredzi) for Zimbabwe weather which was the nearest weather stations to the Greater Limpopo Trans frontier Region. The data showed that for the past 11 years (2007 to 2018) the average yearly maximum temperature varies between 27°C and 31°C. The highest temperatures were
recorded between 2009 and 2018 at temperatures greater than 28 °C (Figure 4). Average yearly minimum temperature varied between 28°C and 27°C. The lowest temperatures were recorded between 2007 and 2013 at temperatures less than 28°C (Figure 4).

Average annual rainfall (Figure 5) over the past 11 years varied between 14mm and 17mm. Most of the rain fell between 2011 and 2016 and varied between 16mm and 17mm. The lowest rain fell between 2007 and 2018. The mm recorded were 13mm and 14mm.
3.4 VEGETATION

There are four generic vegetation biomes that were found in the study area, the savanna biome, grassland biome, a forest and the arizonal biome. The savanna biome constitutes most of the vegetation in the study area while the grassland biome constitutes a relatively smaller portion, the forests are found within the grassland biome and they occupy a relatively large amount of the biome. Finally, arizonal biome is only found in the northern parts of the study area. Savanna biome refers to herbaceous vegetation of relatively short and simple structure dominated by graminoids and the rainfall is usually seasonal, mostly in the summer season (Mucina and Rutherford, 2011). Grassland biomes are large, regular terrains of grasses, flowers and herbs. A grassland is a region where the average annual precipitation is excessive enough to support grasses, and in some areas a few trees. (Mucina and Rutherford, 2011). A forest is a region filled with tall woodlands and dense vegetation, while the arizonal biome is filled with dense shrublands. Figure 6 illustrates the two different biomes that are found within the study area.

3.5 TOPOGRAPHY

Elevation of the study area varies between 2046 metres to 769 metres above mean seal level (Figure 7). The average height above sea level for the study area is approximately 1400 metres. The study area is surrounded by mountains, hills and low-lying areas. The high lying areas of the study area are found in the moutaineous range of the Gonarezhou National Park on the northern side of the study area in Zimbabwe. The Southern side which covers Kruger National Park is mostly flatland and this is the South African side.
3.6 RESEARCH DESIGN AND METHODOLOGY

The research followed a hybrid explorative spatial design method. This was done so that Land use cover changed can be effectively mapped and quantify. The methodology of this study is a mixed quantitative and spatial method. This was done to effectively measure the effects of LULC change on ESSs. Figure 8 shows a schematic of the methodology followed in the study. To begin, Landsat images were acquired from the USGS website. Then after, they were mosaiced to fit the study area. An atmospheric correction was performed then training samples were done on the images to obtain areas of different classes. The random forest classification scheme was used for the land cover maps. From the same maps, carbon maps were also calculated. NDVI was derived from the corrected images using a false colour (RGB) composite. Statistics of land cover change were derived from the change maps that were calculated from the random forest classification scheme. The following section discusses this in detail.

Figure 7: elevation of the study area

Figure 8: methodology of the remotely sensed data
3.6.1 DATASETS
A typical remote sensing of land use / land cover assessment involves analysis of remotely sensed data supported by information acquired using field observation. Field observations are useful to either evaluate remote sensing interpretation or to train remotely sensed data for a digital classification. In the absence of field observation or to reduce the cost of field surveys, high resolution imagery or aerial photography can be used. Landsat images for this study were obtained from the United States Geological Survey (USGS) website (http://earthexplorer.usgs.gov/).

3.6.2 FIELD DATA
The process of ground sampling is highly dependent upon the design of the sampling scheme (Muzein, 2006). The area was first classified as a natural environment in a transboundary region. As time went by, evidence of human built-up areas was sighted in the study area from 2007 to 2018. 100 samples were obtained and were all randomly dispersed on the study area with no equal number of samples given to a specific class (Figure 9). In addition to randomness, various factors such as accessibility and nearness to the water source and walkable paths around the area were considered in the selection of samples. The filed work was carried out on the 21st of May 2019 to the 23rd of May 2019 and again on the 20th of July 2019 till the 21st of July 2019. This data was collected with a time period of 2 months apart, therefore the precision of the ground truth data is highly accurate.

Figure 9: sampling method used in fieldwork
A Global Positioning System (GPS); (Juno handheld Trimble, GPS pathfinder) was used to locate the sample points. In instances where the sample points were considered incorrect due to inaccessibility, they were replaced by points near the original points through spatial interpolation. A 5 plots of 30m radius centred at each sample point was established to make clear observations. This size is approximately equivalent to four-pixel sizes of a Landsat image. Having more than one pixel was necessary in this case to minimize locational and spectral error. In each plot, visual observations of features were made to relate to the land cover classifications of the study. Observations in the natural area included identification of generic vegetation type, visual estimation of dominant vegetation cover and observation of overall vegetation cover both wet and dry were made. The classes observed in the natural area were identified as bare land, water, grassland and dense vegetation, sparse vegetation, dense shrubs, sparse shrubs, woodland and agricultural area. While the impervious surfaces were identified as built-up area.

In both natural and built up manmade areas, the classes were approximated according to Thompson (1996) that standardised land cover types for interpreting remotely sensed data. (Table 1) presents the class definitions used for this study. These observations were then populated in the attribute table of each sample point using ArcGIS software.
### Table 1: Classification scheme according to (Thompson, 1996)

<table>
<thead>
<tr>
<th>Category</th>
<th>Description</th>
</tr>
</thead>
</table>
| Grassland     | • All areas of grassland with less than 10% tree Unimproved Essentially indigenous species, growing under natural or and or shrub canopy cover, and greater than grassland semi-natural conditions. Typically associated with the 0.1 % total vegetation cover.  
• Grass-like, non-woody, rooted herbaceous plants. Typically associated with the Grassland and Savanna biomes. |
| Dense Shrubs  | • dominated by low, woody, self-Shrubland Typically broad-leaved or bushes, frequently deciduous.  
• A low fynbos supporting, multi-stemmed plants branching at typical example would be vegetation from the Karoo  
• near the ground, between 0.2-2 m in height. biomes. Category also includes dwarf succulent shrub.  
Total tree cover >1.0%. |
| Sparse Shrubs | • Low shrublands and heathlands typically small-leaved.  
• near the ground, between 0.2-2 m in height. biomes. Category also includes dwarf succulent shrubs that is scattered  
Total tree cover <1.0%. |
| Dense vegetation | • composed of tall, woody, Thicket Areas of densely interlaced trees (often May subdivide category on project or user specific parameters as self-supporting, single and or multi-stemmed forming an impenetrable community).  
• plants with in multi-stemmed plants with no clearly definable structure  
• no Clearly definable structure. Total or layers, with> 70% cover.  
• canopy cover> 10%, with canopy height Valley Bushveld. |
| Sparse vegetation | • Scattered islands of not too tall or not too short vegetation (i.e. < 70% cover). |
| Woodland      | • wooded areas with greater than 10% tree Forest Tree canopy cover> 70%.  
• Woodland Tree canopy cover between 40-70%.  
• growing under natural or semi-nat-canopy community, typically consisting of a single tree grove forest  
• Excludes planted forests (and woodlots).  
Type- Wooded Tree canopy cover between 10-40%. |
| Agricultural area | • Permanent crops  
• Temporary crops |
| Bare-land     | • Non-vegetated areas, or areas of very little vegetation cover (excluding agricultural fields with no crop cover, and opencast mines and quarries), where the substrate or soil exposure is clearly apparent. |
| Built-up area | • Impervious Surfaces |
| Water         | • Areas of (generally permanent) open water. The category includes natural and man-made water bodies, which are either static or flowing, and fresh, brackish and saltwater conditions. |
3.6.3 REMOTELY SENSED DATA

Change detection and monitoring encompass the use of multi-temporal images to evaluate differences in land cover due to environmental conditions and human actions between the acquisition dates of images (Mundia and Aniya, 2005). It is highly recommended that images acquired using the same sensor or sensors with similar characteristics are used in change detection analysis to eliminate error that would result from different types of images, (Mundia and Aniya, 2005; Yang et al, 2018). Sources of errors may be as a result of combining different images from different sensors, for example Landsat and SPOT as this can result in the variation of spectral characteristics. Landsat satellite imagery was chosen for this study for a number of reasons:

I. The imagery has a long history with uninterrupted data available since 1972 this is useful to undertake long-term time series analysis.

II. The spatial resolution of the imagery is relatively good for most landscape level assessments, (30M).

III. Landsat is freely available and can readily be downloaded from the internet and takes relatively a short time to request and acquire.

IV. Landsat imagery has several bands in the visible and near-infrared regions of the electromagnetic spectrum. These bands have been used for numerous land use / land cover assessments.

A transitory chronology of Landsat series that were used in this study is described in the following section. Landsat 5 was launched in March 1984 near polar orbit with the height of 705 – 900 km above ground. The images are taken after every 16 days. The Landsat 5 satellite has an on-board sensor called the
Thematic Mapper (TM). The TM sensor records the surface reflectance of electromagnetic (EM) radiation from the sun in seven discrete bands (Lillesand et al, 2008).

Landsat 8 was launched in February 2013 into orbit 705 km above ground. Landsat 8’s Operational Land Imager (OLI) sensor improves on past Landsat sensors; OLI collects data from nine spectral bands. Seven of the nine bands are consistent with the Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM+) sensors found on earlier Landsat satellites. Two new 30 metres bands include a new coastal/aerosol band for coastal zone observations and aerosol estimation (Lillesand et al, 2008).

Spectral properties of all Landsat images used in the study are presented in Table 2. The OLI has the greatest number of bands of all sensors, followed by ETM+, TM and MSS. The reflectance behaviour of objects varies along the range of electromagnetic spectrum (Lillesand et al, 2008). For example, characteristics of water bodies and soil are observed with high accuracy at 0.45 - 0.52 μm range (blue band) ~ Band 1 of TM and ETM+ and at 0.8 – 1.1 μm range near-infrared ~ Band 4 MSS (Lillesand et al, 2008). Several indices, which attempt to quantify vegetation attributes, primarily use the following ranges: 0.63 - 0.69 μm (red band) and 0.70 - 1.3 μm (near-infrared band), due to the contrasting reflectance behaviour of plants (Lillesand et al, 2008).

Table 2: spectral properties of the Landsat Satellites

<table>
<thead>
<tr>
<th>Band</th>
<th>MSS band width (μm)</th>
<th>TM band width (μm)</th>
<th>ETM+ band width (μm)</th>
<th>OLI band width (μm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.5 - 0.6</td>
<td>0.45 - 0.52</td>
<td>0.45 - 0.52</td>
<td>-</td>
</tr>
<tr>
<td>2</td>
<td>0.6 - 0.7</td>
<td>0.52 - 0.60</td>
<td>0.52 - 0.60</td>
<td>0.45 - 0.51</td>
</tr>
<tr>
<td>3</td>
<td>0.7 - 0.8</td>
<td>0.63 - 0.69</td>
<td>0.63 - 0.69</td>
<td>0.53 - 0.59</td>
</tr>
<tr>
<td>4</td>
<td>0.8 - 1.1</td>
<td>0.76 - 0.90</td>
<td>0.77 - 0.90</td>
<td>0.64 - 0.67</td>
</tr>
<tr>
<td>5</td>
<td>-</td>
<td>1.55 - 1.75</td>
<td>1.55 - 1.75</td>
<td>0.85 - 0.88</td>
</tr>
<tr>
<td>6</td>
<td>-</td>
<td>10.40 - 12.50</td>
<td>10.40 - 12.50</td>
<td>1.57 - 1.65</td>
</tr>
<tr>
<td>7</td>
<td>-</td>
<td>2.08 - 2.35</td>
<td>2.09 - 2.35</td>
<td>2.11 - 2.29</td>
</tr>
<tr>
<td>8</td>
<td>-</td>
<td>-</td>
<td>0.50 - 0.68</td>
<td>-</td>
</tr>
<tr>
<td>9</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

Landsat images for this study were obtained from the United States Geological Survey (USGS) website (http://earthexplorer.usgs.gov/). The path and row of the Landsat scenes covering the study area were 169 and 076, 169/076, 170/075 respectively. All the images acquired had to be mosaiced together to fit the study area as different regions and trans boundaries follow different paths and rows. All the historical images (2007 and 2018) were downloaded from the Global Land Survey (GLS) collection of the USGS website. The GLS selects and documents images at certain time intervals (periods) that enable monitoring of long-term land cover dynamics. Images in this collection are cloud free and therefore did not need atmospheric correction to remove cloud cover, however a radiometric calibration was done to reduce the
error from the mosaic. In addition, the collection contains images that as much as possible show the maximum vegetation and landscape changes of any area.

Table 3: Remotely-Sensed data acquired for the study

<table>
<thead>
<tr>
<th>Year</th>
<th>Sensor</th>
<th>Path/Row</th>
<th>DOA</th>
<th>Resolution (M)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2007</td>
<td>Landsat 4-5 (TM)</td>
<td>169/075</td>
<td>2007/03/17</td>
<td>30</td>
</tr>
<tr>
<td>2007</td>
<td>Landsat 4-5 (TM)</td>
<td>169/075</td>
<td>2007/03/03</td>
<td>30</td>
</tr>
<tr>
<td>2007</td>
<td>Landsat 4-5 (TM)</td>
<td>169/076</td>
<td>2007/04/17</td>
<td>30</td>
</tr>
<tr>
<td>2007</td>
<td>Landsat 4-5 (TM)</td>
<td>170/075</td>
<td>2007/04/21</td>
<td>30</td>
</tr>
<tr>
<td>2007</td>
<td>Landsat 4-5 (TM)</td>
<td>170/075</td>
<td>2007/04/17</td>
<td>30</td>
</tr>
<tr>
<td>2018</td>
<td>Landsat 8 (OLI)</td>
<td>169/075</td>
<td>2018/03/17</td>
<td>30</td>
</tr>
<tr>
<td>2018</td>
<td>Landsat 8 (OLI)</td>
<td>169/075</td>
<td>2018/04/20</td>
<td>30</td>
</tr>
<tr>
<td>2018</td>
<td>Landsat 8 (OLI)</td>
<td>169/076</td>
<td>2018/03/17</td>
<td>30</td>
</tr>
<tr>
<td>2018</td>
<td>Landsat 8 (OLI)</td>
<td>170/075</td>
<td>2018/04/11</td>
<td>30</td>
</tr>
<tr>
<td>2018</td>
<td>Landsat 8 (OLI)</td>
<td>170/076</td>
<td>2018/04/11</td>
<td>30</td>
</tr>
</tbody>
</table>

(Table 3) summarises specifications of Landsat imagery used in the study. The imagery dates varied between the summer months of the years selected. These months are representative of the summer rainy season in the study area, therefore, capturing the vegetation variance and phenology as well as other landscape changes of the area.

### 3.7 PRE-PROCESSING OF LANDSAT IMAGE

All Landsat images were orthorectified though georeferencing on ArcMap Version 10.5 and projected to the local coordinate system (WGS_UTM_ZONE_35S). Two analyses were carried out on the extracted images to achieve the objectives of the study. The first analysis is classifying the composite image of each date and subsequently comparing the difference in classes among the dates. This analysis addresses the first two objectives of the study. The second analysis focused on exploring the potential of NDVI to assess the presence and absence of vegetation in the study area.
### 3.8 IMAGE CLASSIFICATION

Land cover classes are characteristically mapped from remotely sensed data through digital image classification and interpretation. The overall objective of the image classification procedure is to inevitably categorize all pixels in an image into land cover classes or themes (Lillesand et al, 2008). For this study, a supervised classification approach was adopted because it allows spectral clusters to be identified with a reasonable amount of independence through creating training samples of areas with already known values. The classification was done in ArcGIS using the supervised classification algorithm and signature files. In this software, there are combinations of interactive supervised classification and maximum likelihood classification tools, (ArcMap, 2019).

Table 4: training signature from 2007

<table>
<thead>
<tr>
<th>FID</th>
<th>Shape</th>
<th>Classname</th>
<th>Classvalue</th>
<th>RED</th>
<th>GREEN</th>
<th>BLUE</th>
<th>Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>Polygon</td>
<td>Agricultural Area</td>
<td>1</td>
<td>6</td>
<td>72</td>
<td>235</td>
<td>1730</td>
</tr>
<tr>
<td>1</td>
<td>Polygon</td>
<td>Water</td>
<td>19</td>
<td>237</td>
<td>16</td>
<td>26</td>
<td>4488</td>
</tr>
<tr>
<td>2</td>
<td>Polygon</td>
<td>Bareland</td>
<td>52</td>
<td>91</td>
<td>173</td>
<td>22</td>
<td>31951</td>
</tr>
<tr>
<td>3</td>
<td>Polygon</td>
<td>Dense Vegetation</td>
<td>63</td>
<td>33</td>
<td>188</td>
<td>233</td>
<td>71599</td>
</tr>
<tr>
<td>4</td>
<td>Polygon</td>
<td>Grassland</td>
<td>80</td>
<td>116</td>
<td>76</td>
<td>113</td>
<td>18059</td>
</tr>
<tr>
<td>5</td>
<td>Polygon</td>
<td>Built Up Area</td>
<td>93</td>
<td>77</td>
<td>198</td>
<td>150</td>
<td>1687</td>
</tr>
<tr>
<td>6</td>
<td>Polygon</td>
<td>Dense Shrub</td>
<td>100</td>
<td>160</td>
<td>39</td>
<td>204</td>
<td>3787</td>
</tr>
<tr>
<td>7</td>
<td>Polygon</td>
<td>Sparse Shrub</td>
<td>105</td>
<td>113</td>
<td>138</td>
<td>67</td>
<td>664</td>
</tr>
<tr>
<td>8</td>
<td>Polygon</td>
<td>Sparse Vegetation</td>
<td>107</td>
<td>197</td>
<td>66</td>
<td>173</td>
<td>86</td>
</tr>
<tr>
<td>9</td>
<td>Polygon</td>
<td>Woodland</td>
<td>109</td>
<td>133</td>
<td>42</td>
<td>247</td>
<td>58</td>
</tr>
</tbody>
</table>

Table 5: training signature from 2018

<table>
<thead>
<tr>
<th>FID</th>
<th>Shape</th>
<th>Classname</th>
<th>Classvalue</th>
<th>RED</th>
<th>GREEN</th>
<th>BLUE</th>
<th>Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>Polygon</td>
<td>water</td>
<td>1</td>
<td>115</td>
<td>223</td>
<td>255</td>
<td>4103</td>
</tr>
<tr>
<td>1</td>
<td>Polygon</td>
<td>Dense Vegetation</td>
<td>33</td>
<td>38</td>
<td>115</td>
<td>0</td>
<td>2763</td>
</tr>
<tr>
<td>2</td>
<td>Polygon</td>
<td>Grassland</td>
<td>42</td>
<td>255</td>
<td>235</td>
<td>175</td>
<td>7437</td>
</tr>
<tr>
<td>3</td>
<td>Polygon</td>
<td>Dense Shrubs</td>
<td>54</td>
<td>168</td>
<td>168</td>
<td>0</td>
<td>11432</td>
</tr>
<tr>
<td>4</td>
<td>Polygon</td>
<td>Built Up Area</td>
<td>59</td>
<td>255</td>
<td>0</td>
<td>0</td>
<td>6059</td>
</tr>
<tr>
<td>5</td>
<td>Polygon</td>
<td>Sparse Shrub</td>
<td>79</td>
<td>170</td>
<td>255</td>
<td>0</td>
<td>3726</td>
</tr>
<tr>
<td>6</td>
<td>Polygon</td>
<td>Sparse Vegetation</td>
<td>100</td>
<td>0</td>
<td>230</td>
<td>169</td>
<td>3996</td>
</tr>
<tr>
<td>7</td>
<td>Polygon</td>
<td>Woodland</td>
<td>111</td>
<td>255</td>
<td>255</td>
<td>0</td>
<td>1995</td>
</tr>
<tr>
<td>8</td>
<td>Polygon</td>
<td>Agricultural Area</td>
<td>119</td>
<td>76</td>
<td>230</td>
<td>0</td>
<td>2623</td>
</tr>
<tr>
<td>9</td>
<td>Polygon</td>
<td>Bareland</td>
<td>152</td>
<td>137</td>
<td>90</td>
<td>68</td>
<td>15495</td>
</tr>
</tbody>
</table>
The Landsat imagery for the years 2007 and 2018 was first mosaiced to obtain a full scene of the study area. After the mosaic, image correction and radiometric calibration was performed to reduce the noise on the Landsat scenes. The images were then classified into ten classes following the number of classes specified by the visual observations on reference data. These classes were then interpreted using the definitions given in (Table 1). Different band combinations such as true colour and false colour combinations of the image were used in the interpretation of the classes. The specific band combination that was used in this case is the Near InfraRed (NIR) band (5,4,3) for Landsat 8 OLI and Near InfraRed (NIR) band (4,3,2) for Landsat 4-5 TM. The classes were subsequently assessed using reference data (fieldwork) with the objective of validating the effectiveness of Landsat sensors for this study. The assessment focussed on 30m radius plots due to the small size of the study area.

3.9 ACCURACY ASSESSMENT

An accuracy assessment of the different values of the classification scheme was conducted in this study. In many instances, an accuracy assessment requires clear reference data or ground truthing or even through physical appearance in the study site. In cases where the study site is not visited due to expenses or other unforeseen circumstances, high-resolution images that are of recent years are used as reference data for an accuracy assessment. This study used field data as reference data. A random sampling method was used on the ground to obtain ground truth data.

The total process was done by comparing the classified image with the reference data collected from the field. Random sampling was adopted to calculate the classification accuracy of each land cover image. The logic to use this sampling method is each land cover class found the equal probability to be observed per class. A total of 87 random points were used for accuracy assessment of one classified image obtained in 2018. This was done solely because it was the most recent image of the whole dataset that had been classified, also, the filed data was highly reliable as it is first-hand observed data. The data was summarized and quantified by using an error matrix.

An error matrix is a square array of numbers organized in rows and columns that express the number of sample units assigned to a particular category relative to the actual category as indicated by the reference data. The columns typically represent the reference data and the rows indicate the map generated from the remotely sensed data (Congalton, 2004). The diagonal entries represent correct classifications or agreement between the map and the groundtruthed data, and the off-diagonal entries represent misclassifications, or lack of spatial agreement between the map and the data (Stehman & Czaplewski,
Therefore, the error matrix of this project summarizes results comparing the groundtruthed data to the classified Landsat satellite image.

Accuracy parameters derived from the error matrix include overall accuracy, producer’s accuracy, user’s accuracy, and the kappa coefficient. The overall accuracy is computed by dividing the total correct by the total number of pixels in the error matrix, (Congalton, 2004). The quotient of the total number of correct pixels in a class by the total number of pixels of that category from the groundtruth data is termed the ‘producer’s accuracy’, (Congalton, 2004). On the other hand, if the total number of correct sample units in a category is divided by the total number of sample units that were classified into that category on the map, then this result is a measure of commission error. This measure is called user’s accuracy (Story & Congalton, 1986).

Another measure of map accuracy is the kappa coefficient, which is a measure of the proportional (or percentage) improvement by the classifier over a purely random assignment to classes. It shows the extent to which the correct values of an error matrix are due to true versus chance agreement. Alternatively, the kappa coefficient is a measure of agreement that compares the observed agreement to agreement expected by chance if the observer ratings were independent. It also expresses the proportionate reduction in error generated by a classification process, compared with the error of a completely random classification (Cohen, 1960; Munoz & Bangdiwala, 1997). The kappa coefficient is computed by the following equation (Jensen, 1996; Sim & Wright, 2005):

Equation 1: showing the Kappa Coefficient

\[
\hat{k} = \frac{\text{Observed Agreement} - \text{Chance Agreement}}{1 - \text{Chance Agreement}}
\]

According to (Landis & Koch, 1977; Munoz & Bangdiwala, 1997; Viera & Garrett, 2005), the kappa can be interpreted as being poor (<0), slight (0.01–0.20), fair (0.21–0.40), moderate (0.41–0.60), substantial (0.61–0.80), and almost perfect (0.81–1.0).

**3.10 NORMALISED DIFFERENCE VEGETATION INDEX (NDVI)**

The normalised difference vegetation index uses the principle that healthy vegetation absorbs most of the visible light that strikes it and reflects a large portion of the near-infrared light (Jiang et al, 2016; Holme et al, 1987). In contrast, unhealthy or sparse vegetation reflects more visible light and less near-infrared light (Holme et al, 1987). The index thus exploits information contained in these two bands and is
computed using Equation 1. The NDVI image was classified using the same random forest classification method conducted on the Landsat image. The multispectral band combinations using different colour combinations (true colour and false colour) were used as reference in interpreting the resultant classes. In addition to that, interpretation of NDVI derived classes was also tested using a general guideline given in Table 6 as reference. Other sources provide similar guidelines with slight variations (Jiang et al, 2016; Rouse, 1973; Holme et al, 1987; Roderick et al, 1996).

Equation 2: showing the NDVI

\[
\frac{\text{NIR} - \text{RED}}{\text{NIR} + \text{RED}}
\]

Table 6: NDVI values and class categories according to Holme et al, 1987

<table>
<thead>
<tr>
<th>Class</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Water</td>
<td>-1 to -0.2</td>
</tr>
<tr>
<td>Bareland</td>
<td>-0.1 to 0.1</td>
</tr>
<tr>
<td>Grassland</td>
<td>0.2 to 0.6</td>
</tr>
<tr>
<td>Woodland</td>
<td>0.7 to 1</td>
</tr>
</tbody>
</table>

3.11 QUANTIFYING CARBON SEQUESTRATION

The Carbon Model was used to evaluate CS. Carbon storage on a land parcel largely depends on the sizes of four carbon pools: aboveground biomass, belowground biomass, soil, and dead organic matter. The InVEST Carbon Storage and Sequestration model aggregates the amount of carbon stored in these pools according to land use maps and classifications provided by the first objective (InVEST, 2018). The LULC maps required for the model were obtained from the first objective. The carbon sink data used in the present study were taken from the standardized African IPCC carbon stock table, at (http://www.ipcc-nggip.iges.or.jp/public/2006gl/pdf/4_Volume4/V4_02_Ch2_Generic.pdf, IPCC 2006). These pool tables were then further contextualised to an African ecological landscape and tailored to the study’s different land cover classes.
The scenario-based model on InVEST was used to model future LULC to the year 2030 and to quantify the estimated carbon storage in the future. The proximity-based scenario generator creates a set of contrasting land use change maps that convert habitat in different spatial patterns (InVEST, 2018). The user determines which habitat can be converted and what they are converted to, as well as type of pattern, based on proximity to the edge of a focal habitat. In this manner, an array of land-use change patterns can be generated, including pasture encroaching into forest from the forest edge, agriculture expanding from currently cropped areas, forest fragmentation (InVEST, 2018). The resulting land-use or other models for biodiversity or ecosystem services that are responsive to land use change and future LULC.

### 3.12 SUMMARY

This chapter presented the methodology followed in the study. The first part provided site characterisation of the study area. This was followed by a description of the reference and remotely sensed data, namely Landsat imagery. Data analysis was presented next. The study applied random forest classification on different Landsat products including multispectral imagery and NDVI derived images. This was followed by accuracy assessment that compared the effectiveness of Landsat products in discriminating vegetation and other classes. Finally, a strategy to quantify carbon storage presently and in the future was presented. The following chapter presents the results of data analysis.

<table>
<thead>
<tr>
<th>lucode</th>
<th>LULC_name</th>
<th>C_above</th>
<th>C_below</th>
<th>C_soil</th>
<th>C_dead</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>Water</td>
<td>1</td>
<td>1</td>
<td>10</td>
<td>0</td>
</tr>
<tr>
<td>1</td>
<td>Dense Vegetation</td>
<td>1643</td>
<td>1031</td>
<td>1096</td>
<td>505.5</td>
</tr>
<tr>
<td>2</td>
<td>Built Up Area</td>
<td>22</td>
<td>14</td>
<td>135</td>
<td>1</td>
</tr>
<tr>
<td>3</td>
<td>Agricultural Area</td>
<td>47</td>
<td>28</td>
<td>218</td>
<td>2</td>
</tr>
<tr>
<td>4</td>
<td>Bareland</td>
<td>10</td>
<td>20</td>
<td>10</td>
<td>5</td>
</tr>
<tr>
<td>5</td>
<td>Grassland</td>
<td>29</td>
<td>23</td>
<td>128</td>
<td>4</td>
</tr>
<tr>
<td>6</td>
<td>Woodland</td>
<td>548</td>
<td>228</td>
<td>410</td>
<td>92</td>
</tr>
<tr>
<td>7</td>
<td>Sparse Shrubs</td>
<td>75</td>
<td>8</td>
<td>50</td>
<td>11</td>
</tr>
<tr>
<td>8</td>
<td>Dense Shrubs</td>
<td>115</td>
<td>31</td>
<td>165</td>
<td>53</td>
</tr>
<tr>
<td>9</td>
<td>Sparse Vegetation</td>
<td>285</td>
<td>120</td>
<td>250</td>
<td>23</td>
</tr>
</tbody>
</table>
CHAPTER 4: RESULTS

4.1 INTRODUCTION

Results of the analyses of the data sets using the methods outlined in the chapter three are presented here. Results relating to comparison of field observations that was obtained during field work in 2019 and a classified map of 2018 are presented first. This is followed by the accuracy of the random forest classification scheme. The presentation of classification results of both dates and their comparisons are then presented next. The results on the NDVI analysis are then presented next. The final section provides results of carbon sequestration of all dates and their comparisons.

4.2 COMPARISON OF REFERENCE DATA AND LANDSAT DERIVED LAND COVER CLASSES

A comparison was made between reference data that was obtained in 2019 and land cover classes derived from a Landsat image that was acquired in 2018. The 2018 imagery was classified and subsequently interpreted using both false and natural (true) colour band combinations of the original 2018 image. These band combinations enabled relatively easy identification of features as illustrated in (Figure 12). The figure shows examples of areas that are dominated by the water and dense vegetation.

Fourteen samples were allocated from the built-up stratum and thirteen samples from the vegetation stratum were used for assessing the accuracy of the classification. The comparison showed that ten sample points in the built-up stratum were correctly classified by the interpretation of Landsat image as shown in whereas only ten of the fifteen samples were correctly classified for dense vegetation (Table 8).
Five points were allocated for the grassland stratum and only three were correct. Three samples were allocated to the bareland stratum and two were correctly classified. Agricultural Areas were allocated twelve points and only ten were correct. Water had six points and seven were correctly classified. Sparse vegetation had seven points and six were correctly classified. Sparse shrubs had only a single point allocated to it and it was entirely correct. Finally, dense shrubs had ten points allocated to it, and nine were correct.

Table 9 shows the overall classification accuracy showed that; of the 3 signatures that were trained for bare land, only 2 were accurate, producing a producer’s accuracy of 67% and a user’s accuracy of 40%. A total of 14 signatures were trained for built up area however only 10 were accurate constructing a producer’s accuracy of 71% and a user accuracy of 83%. Within the dense vegetation class, a total of 13 signatures were trained with only 10 that were accurate, that tallied a producer’s accuracy of 77% and a user accuracy of 71%. 12 signatures were trained for the agricultural area class and only 10 were accurate computing 83% of producer’s accuracy and 77% user accuracy. 10 random signatures were trained to the dense shrubs class and 9 were accurate, this produced a producer’s accuracy of 90% and 50% user accuracy. 7 predictions were made for water and only 6 were accurate, this resulted in a producer’s accuracy of 86% and a user’s accuracy of 86%. Woodland received 17 signatures and only 10 were accurate, noting a 59% producer accuracy and a 91% user accuracy. Sparse vegetation had only 1 training.
sample that was accurate, producing a 100% user and producer accuracy. In total, 89 signatures were trained were made, and a total of 65 were accurate, and this gave an overall 76% accuracy assessment for the random forest classification scheme.

Kappa = 0.645—The overall Kappa coefficient was 0.65, meaning that the accuracy is above average.

Table 9: Error Matrix accuracy assessment

<table>
<thead>
<tr>
<th>Error Matrix</th>
<th>Agricultural Area</th>
<th>Built up area</th>
<th>Dense Shrubs</th>
<th>Dense Vegetation</th>
<th>Grassland</th>
<th>Sparse Shrubs</th>
<th>Sparse Vegetation</th>
<th>Water</th>
<th>Woodland</th>
<th>Total Predictions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agricultural Area</td>
<td>10 0 0 0</td>
<td>0 0 0 0</td>
<td>2 0 0 0</td>
<td>0 0 0 0</td>
<td>0 0 0 0</td>
<td>0 0 0 12</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Built up area</td>
<td>0 2 1 0</td>
<td>0 0 0 0</td>
<td>0 0 0 0</td>
<td>0 0 0 0</td>
<td>0 1 0 3</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dense Shrubs</td>
<td>0 0 0 0</td>
<td>3 1 0 0</td>
<td>0 0 0 0</td>
<td>0 0 0 0</td>
<td>0 0 0 10</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dense Vegetation</td>
<td>0 0 0 2</td>
<td>10 0 0 0</td>
<td>0 0 0 0</td>
<td>0 0 0 1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Grassland</td>
<td>2 0 0 0</td>
<td>0 0 0 0</td>
<td>2 0 0 0</td>
<td>0 0 0 5</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sparse Shrubs</td>
<td>0 0 0 0</td>
<td>0 0 0 0</td>
<td>1 0 0 0</td>
<td>0 0 0 1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sparse Vegetation</td>
<td>1 0 0 0</td>
<td>0 0 0 0</td>
<td>1 0 0 0</td>
<td>0 0 0 7</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Water</td>
<td>0 0 1 0</td>
<td>0 0 0 0</td>
<td>0 0 0 6</td>
<td>0 0 0 7</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Woodland</td>
<td>0 0 0 0</td>
<td>7 0 0 0</td>
<td>0 0 0 10</td>
<td>0 0 17</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>13 5 7 2</td>
<td>12 5 7 6</td>
<td>1 0 0 1</td>
<td>5 7 11</td>
<td>85</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>UA_%</td>
<td>83 67 71</td>
<td>80 77 69</td>
<td>100 71 86</td>
<td>100 86 91</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>OA_%</td>
<td>77 40 83</td>
<td>50 71 56</td>
<td>100 100 86</td>
<td>91</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
ha in 2007 and increased to 312200 ha in 2018. In 2007, built up area classification decreased from 246603 ha to 127838 ha in the year 2018. Water decreased from 2007 to 2018 from 66437 ha to 49833 ha.

Table 10 area coverage in hectares and percentages in 2007 and 2018.

<table>
<thead>
<tr>
<th>CLASS</th>
<th>2007</th>
<th>2018</th>
<th>Chang_ha</th>
<th>change_%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agricultural Area</td>
<td>202441</td>
<td>249851</td>
<td>47410</td>
<td>19</td>
</tr>
<tr>
<td>Bareland</td>
<td>261142</td>
<td>476433</td>
<td>215291</td>
<td>45</td>
</tr>
<tr>
<td>Built Up Area</td>
<td>227945</td>
<td>184278</td>
<td>-43667</td>
<td>-24</td>
</tr>
<tr>
<td>Dense Shrub</td>
<td>215095</td>
<td>312200</td>
<td>97105</td>
<td>31</td>
</tr>
<tr>
<td>Dense Vegetation</td>
<td>66437</td>
<td>49833</td>
<td>-16604</td>
<td>-33</td>
</tr>
<tr>
<td>Grassland</td>
<td>366973</td>
<td>323511</td>
<td>-43462</td>
<td>-13</td>
</tr>
<tr>
<td>Sparse Shrub</td>
<td>246603</td>
<td>127838</td>
<td>-118765</td>
<td>-93</td>
</tr>
<tr>
<td>Sparse Vegetation</td>
<td>203272</td>
<td>108581</td>
<td>-94691</td>
<td>-87</td>
</tr>
<tr>
<td>Water</td>
<td>29738</td>
<td>27067</td>
<td>-2671</td>
<td>-10</td>
</tr>
<tr>
<td>Woodland</td>
<td>101793</td>
<td>61850</td>
<td>-39943</td>
<td>-65</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>1921439</td>
<td>1921442</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figure 13: maps showing 2007 and 2018 classification schemes
Table 10 shows the percentage change of all the classes that were derived from the supervised classification. The changes are reported per class type in the two dates that the study focuses on. A positive percentage indicates an increase in coverage within the area while a negative percentage or no value indicates a decrease or no increase or decrease in coverage. Water, for example, decreased in the 11 years by 33% this is seen by a 2% coverage in the study area in 2007 to 1% in 2018. Dense Vegetation increased by 31% in 2018. Grassland decreased by 87% from 2007 to 2018, Bare land increased by more than 50% resulting to 16% increase in area coverage. There was a 93% decrease in built up areas, while both sparse and dense shrubs decreased by 24% and increased by 10% respectively. Woodland decreased by 10%. Moreover, agricultural areas showed a 13% decrease throughout the years.

In hectares, (Figure 14) show change that is quantifiable in a sense that visible change can be noted. The grassland class for example, drastically decreased from 203272 ha in 2007 to 108581 ha in 2018 meaning that it decreased by 94691 ha. Bare land increased sharply from 261142 ha in 2007 to 476433 ha in 2018 meaning that it increased by 215291 ha. Dense vegetation covered 215095 ha in 2007 and increased to 312200 ha in 2018 meaning that it increased by 97105 ha. In 2007, built up area classification decreased from 246603 ha to 127838 ha in the year 2018 meaning that it decreased by 118765 ha. Water decreased from 2007 to 2018 from 66437 ha to 49833 ha meaning that it decreased by 16604 ha.

To spatially assess the amount of changes that have occurred with time within the study area from 2007 to 2018, a change map was developed. According to (Congalton, 2004) a change map spatially and visually shows the changes through time in a time series analysis. In this case, a change map was derived using
Terrset software on Clarklabs and a set of two maps were processed as results. To understand these maps, a coding system was derived for the different classes that were made. This coding system has characters from -9 to 9, where the negative values indicate a bad change towards the environment and class whereas a positive value indicates good change. A value where there is 0 indicates that there has been no change at all. The numbers on the legend indicate a code of all the classes derived from the observed study area. Class 1 is grassland, 2 equals to dense vegetation, 3 is sparse vegetation, 4 water, 5 is built up areas, 6 is sparse vegetation, 7 is bareland, 8 is agricultural areas, 9 is dense shrubs and 0 woodland.

Figure 15: map showing change from 2007 to 2018
For a clearer indication, figure 16 shows areas that have drastic change and areas that do not have change at all. As indicated in the legend, positive values from 2 to 14 show areas that have positive change, for example, these are areas that gained most vegetation or had classes that upgraded from grassland to shrubs or from woodland to dense vegetation. Negative values from -1 to -14 indicate changed that are not reasonably good for the study area. This for example -6 to -3 shows classes that lost to other stronger classes, for example, water lost to bareland, dense vegetation lost to sparse vegetation, agricultural areas lost to bareland and agricultural areas also lost to bareland.

![Change Map](image)

Figure 16: map showing areas affected by change in the study area

Table 11 shows a cross tabulation series of changes within the study area and these are grouped according to class. The table is arranged with a Boolean expression where 1 shows the class that gained and 0 shows the class that did not gain area coverage in the study area. According to the table, results show that Agricultural class lost to bareland, Bareland lost its class to built-up area, grassland, sparse shrubs and sparse vegetation. Built-up area lost only to bareland and dense shrubs lost to agricultural areas. Dense vegetation lost to built-up areas and dense shrubs while grassland lost to bareland, sparse shrubs and sparse vegetation. Sparse shrubs lost to bareland and built-up area while sparse vegetation lost to
bareland, built-up area, dense shrubs, grassland and sparse shrubs. Water class lost to bareland and finally woodland did not lose or gain from any class.

Table 11: cross tabulation of 2007 to 2018

<table>
<thead>
<tr>
<th></th>
<th>Agricultural Area</th>
<th>Bareland</th>
<th>Built up area</th>
<th>Dense Shrubs</th>
<th>Dense Vegetation</th>
<th>Grassland</th>
<th>Sparse Shrubs</th>
<th>Sparse Vegetation</th>
<th>Water</th>
<th>Woodland</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agricultural Area</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Bareland</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Built up area</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Dense Shrubs</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Dense Vegetation</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Grassland</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Sparse Shrubs</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Sparse Vegetation</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Water</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Woodland</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

A cross tabulation method was also used to measure the accuracy of the pixel-based signatures derived from the error matrix. This was performed so see the accuracy of the change map and to determine which class positively or negatively gained. This is illustrated in (Table 12). According to the table, the cross proportional table has significant levels of accuracy from 0.01 to 0.9 and ultimately 1 regarding the classes identified in table 1.

Table 12: Kappa Coefficient for different classes

<table>
<thead>
<tr>
<th>Category</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.0054</td>
<td>0.0073</td>
<td>0.0007</td>
<td>0.0012</td>
<td>0.0001</td>
<td>0.0121</td>
<td>0.0991</td>
<td>0.0003</td>
<td>0.0003</td>
<td>0.001</td>
<td>0.0149</td>
</tr>
<tr>
<td>2</td>
<td>0.0026</td>
<td>0.6628</td>
<td>0.0081</td>
<td>0.0006</td>
<td>0.0037</td>
<td>0.0002</td>
<td>0.0005</td>
<td>0.0005</td>
<td>0.0005</td>
<td>0.0001</td>
<td>0.6792</td>
</tr>
<tr>
<td>3</td>
<td>0.0013</td>
<td>0.0064</td>
<td>0.0068</td>
<td>0.0094</td>
<td>0.0033</td>
<td>0.0018</td>
<td>0.0006</td>
<td>0.0006</td>
<td>0.0006</td>
<td>0.0006</td>
<td>0.0006</td>
</tr>
<tr>
<td>4</td>
<td>0.0002</td>
<td>0.0010</td>
<td>0.0054</td>
<td>0.0034</td>
<td>0.0234</td>
<td>0.0085</td>
<td>0.0045</td>
<td>0.0045</td>
<td>0.0045</td>
<td>0.0045</td>
<td>0.0045</td>
</tr>
<tr>
<td>5</td>
<td>0.0001</td>
<td>0.0007</td>
<td>0.0017</td>
<td>0.0069</td>
<td>0.0127</td>
<td>0.0019</td>
<td>0.0096</td>
<td>0.0096</td>
<td>0.0096</td>
<td>0.0096</td>
<td>0.0096</td>
</tr>
<tr>
<td>6</td>
<td>0.0000</td>
<td>0.0002</td>
<td>0.0004</td>
<td>0.0038</td>
<td>0.0027</td>
<td>0.0061</td>
<td>0.0083</td>
<td>0.0083</td>
<td>0.0083</td>
<td>0.0083</td>
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</tr>
<tr>
<td>7</td>
<td>0.0000</td>
<td>0.0002</td>
<td>0.0002</td>
<td>0.0021</td>
<td>0.0026</td>
<td>0.0132</td>
<td>0.0075</td>
<td>0.0188</td>
<td>0.0047</td>
<td>0.0001</td>
<td>0.0048</td>
</tr>
<tr>
<td>8</td>
<td>0.0000</td>
<td>0.0001</td>
<td>0.0001</td>
<td>0.0022</td>
<td>0.0006</td>
<td>0.0038</td>
<td>0.0038</td>
<td>0.0019</td>
<td>0.0126</td>
<td>0.0008</td>
<td>0.0402</td>
</tr>
<tr>
<td>9</td>
<td>0.0000</td>
<td>0.0001</td>
<td>0.0001</td>
<td>0.0022</td>
<td>0.0006</td>
<td>0.0038</td>
<td>0.0038</td>
<td>0.0019</td>
<td>0.0126</td>
<td>0.0008</td>
<td>0.0402</td>
</tr>
<tr>
<td>10</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0004</td>
<td>0.0001</td>
<td>0.0007</td>
<td>0.0015</td>
<td>0.0015</td>
<td>0.0015</td>
<td>0.0015</td>
<td>0.0015</td>
</tr>
<tr>
<td>Total</td>
<td>0.0097</td>
<td>0.6792</td>
<td>0.0243</td>
<td>0.0341</td>
<td>0.0149</td>
<td>0.0590</td>
<td>0.0402</td>
<td>0.0359</td>
<td>0.0382</td>
<td>0.0094</td>
<td>1.0000</td>
</tr>
</tbody>
</table>

According to the table, categories 1 to 10 are the different classes as derived by the classification scheme found in chapter 3. Category 1 represents agricultural areas, 2 is bareland, 3 is built up area, 4 is dense shrubs, 5 is dense vegetation, 6 is grassland, 7 is sparse shrubs, 8 is sparse vegetation, 9 is water and 10 is woodland. These categories that make up the codes used for the Kappa coefficient accuracy assessment.

Kappa = 0.72 The overall Kappa coefficient was 0.72, meaning that the accuracy is moderately good.
4.4 NORMALISED DIFFERENCE VEGETATION INDEX (NDVI)

NDVI values were computed to illustrate the vegetated areas as compared to the non-vegetated areas from 2007 to 2018. NDVI values fall within -1.0 and 1.0. (Table 13) shows NDVI values for the sampled areas. Positive values show areas that are vegetated while negative values show areas that are not vegetated. Figure 6 shows a visual illustration of the NDVI values were the colour black shows high NDVI values and white shows low NDVI values.

![Figure 17: Maps showing NDVI](image)

Table 13: NDVI ranges from 2007 to 2018

<table>
<thead>
<tr>
<th>Year</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>2007</td>
<td>-0.51 to 0.4</td>
</tr>
<tr>
<td>2018</td>
<td>-0.36 to 0.35</td>
</tr>
</tbody>
</table>

NDVI was used to show the vegetation dynamics of the study area from 2007 to 2018. (Figure 17) shows NDVI maps derived from the Landsat images of 2007 and 2018. In the year 2007 the NDVI high was 0.89 and the low was -0.51. In 2018, the lowest recorded value was -1 and the highest value was 0.15. Typically, extreme negative values represent water; values around 0 represent impervious surface and NDVI values close to 1 represent dense green vegetation on all maps.
4.5 QUANTIFYING CARBON

(Figures 19, 20, 21, 22) show all the maps that were produced from the carbon pools table. Carbon stored in aboveground biomass estimates for natural and plantation forest types (Ruesch & Gibbs, 2008). For LULC categories dominated by woody biomass, belowground biomass can be estimated roughly with the “root to shoot” ratio of belowground to aboveground biomass (InVEST, 2018). Above stored soil and future stored soil ranged from 0.09m/p to 147mg/p. Below ground biomass ranged 0.05mg/p to 92mg/p. Carbon stored in the soil currently and in the future ranged from 0 to 98mg/p and 0 to 45mg/p respectively. Current carbon and future carbon storage in the study area.

Figure 18: Maps showing carbon pools storage, current above carbon, unit storage is in mg/pixel
Figure 21: maps showing below current and future carbon pools in mg/pixel

Figure 20: maps showing dead current and future carbon pools in mg/pixel
Figure 22: Maps showing current and future soil carbon pools.
Table 14 shows carbon pools carbon storage where the red frames represents below carbon storage, the yellow frames represent the above carbon storage, the green frame represents the dead carbon storage and the blue frames represent the soil carbon storage. The measurements are acquired in milligrams per pixel.

Table 14: carbon pools carbon storage where the red frames represents below carbon storage, the yellow frames represent the above carbon storage, the green frame represents the dead carbon storage and the blue frames represent the soil carbon storage. The measurements are acquired in milligrams per pixel:

<table>
<thead>
<tr>
<th>Carbon</th>
<th>Units (mg/pixel)</th>
</tr>
</thead>
<tbody>
<tr>
<td>C_above_cur</td>
<td>0.09 – 147</td>
</tr>
<tr>
<td>C_above_fut</td>
<td>0.09 – 147.8</td>
</tr>
<tr>
<td>C_below_cur</td>
<td>0.09 – 92</td>
</tr>
<tr>
<td>C_below_fut</td>
<td>0.09 – 92</td>
</tr>
<tr>
<td>C_dead_cur</td>
<td>0 – 45</td>
</tr>
<tr>
<td>C_dead_fut</td>
<td>0 – 45</td>
</tr>
<tr>
<td>C_soil_cur</td>
<td>0.9 – 98</td>
</tr>
<tr>
<td>C_soil_dead</td>
<td>0.9 – 98</td>
</tr>
</tbody>
</table>

The current carbon storage year was calculated using the year 2018 (figure 23). The range of the carbon stored in the study area currently is from 1.04 to 384mg per pixel. Carbon Storage according to figure seems to be dominating in the Southern parts of the study area and the north eastern parts of the GLTR.

Figure 23: map showing current carbon storage
The scenario-based model was used to predict the amount of carbon that could occur in the future based on the agricultural expansion predicted by 2030. Figure 24 shows the map that was generated from the model to calculate projected carbon in the study area.

Figure 24: Map Showing Scenario based land cover change

The future carbon storage was projected to the year 2030 (figure 25). The range of the carbon stored in the study area currently is from 1.04 to 384mg per pixel. The range of the future carbon storage ranges from 1mg to 384mg per pixel, dominating on the southern most parts of the study area.

Figure 25: Map showing future carbon storage in mg/pixel
Aggregate Results (figure 26) show that total currently stored carbon in the study area is 852464751.45 mgC. The total future stored carbon is 737391204.12 mgC. The total Redd+ carbon estimate is 852464751.66 mgC. The total change in carbon from 2017 to 2039 is -115090731.66 which shows a decrease in carbon storage within the 13 years.

Table 26: Aggregate results showing carbon units in the study area

<table>
<thead>
<tr>
<th>Description</th>
<th>Value</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total cur</td>
<td>852464751.45</td>
<td>Mg of C</td>
</tr>
<tr>
<td>Total fut</td>
<td>737391204.12</td>
<td>Mg of C</td>
</tr>
<tr>
<td>Total redd</td>
<td>852464751.45</td>
<td>Mg of C</td>
</tr>
<tr>
<td>Change in C for fut</td>
<td>-115090731.66</td>
<td>Mg of C</td>
</tr>
<tr>
<td>Change in C for redd</td>
<td>0.00</td>
<td>Mg of C</td>
</tr>
</tbody>
</table>

Figure 26: Aggregate results showing carbon units in the study area

Figure 26 shows the difference in carbon stored between the future/REDD landscape and the current landscape. The values are in Mg per pixel. In this map some values may be negative and some positive. Positive values indicate sequestered carbon, negative values indicate carbon that was lost.

4.5 SUMMARY
This chapter presented the results of ESS assessment in relation to other land cover classes using remote sensing techniques. The results compared reference data with classes derived from multispectral and NDVI products. LULC results have shown that there were changes in all the classes from 2007 to 2018 (Table 10). The grassland class for example, drastically decreased from 203272 ha to 108581 ha from 2007 to 2018. Bare land increased sharply from 261142 ha in 2007 to 476433 ha in 2018. Dense vegetation covered 215095 ha in 2007 and increased to 312200 ha in 2018. In 2007, built up area classification decreased from 246603 ha to 127838 ha in the year 2018. Water decreased from 2007 to 2018 from 66437 ha to 49833 ha. Results of the accuracy assessment were also presented here. Results showed that overall accuracy assessment of the classification was 75% with a kappa of 0.65 for and a kappa of 0.72 for individual class accuracy. Carbon storage results were also presented in this chapter. Aggregate Results (figure 23) show that total currently stored carbon in the study area is 852464751.45 mgC. The total future stored carbon is 737391204.12 mgC. The total Redd+ carbon estimate is 852464751.66 mgC. The total change in carbon from 2017 to 2039 is -115090731.66 The next chapter discusses the drivers of LULC in detail.
CHAPTER 5: DRIVERS OF CHANGE

5.1 INTRODUCTION
Discussion of the analyses of the data sets using the methods outlined in Chapter Three is presented here. Discussion relating to the results compiled in chapter four is also presented here. The underlying drivers of ecosystems services related to this study are presented as well as the observed changes in land cover changes. The comparison between carbon storage and land use changes is also discussed in this chapter. Possible drivers and causes of landscape changes and the corresponding statistical evidence is also discussed in this chapter.

5.2 DRIVERS OF CHANGE

5.2.1 AGRICULTURAL DRIVERS
Agricultural drivers were one of the most important drivers affecting land cover change in the study area. The agricultural practices around the study area are mainly for commercial use and subsistence livelihoods. This therefore shows the impact that the driver has on the economy. Generally, economic models show that the demand of a certain factor within the ecosystem ensures its supply, (Martinez, 2013). Therefore, the demand for agricultural practices within the study area shows the drive for its supply, hence the demise of an ecosystem. With the data analysed, the results showed that the agricultural practices decreased by more than 3000ha. However, when compared to combined classes, the numbers show that it increased by more than 20000ha. In practise, this a very large area that covers agricultural grounds with a very high chance of altering the ecosystem. The reasons behind the increase in agricultural practices can be attributed to the increase in the population and productivity within the study area. This is validated by the Boolean cross tabulation (Table 11) where it is noted that the agricultural area lost its area to bareland however other vegetation classes lost to it. According to the ministry of Agricultural and Forestry (2018), agricultural practices in South Africa contributed about 20% towards the national GDP.

Additionally, since the study area is in the semi-arid region of South Africa and Zimbabwe, the climatic conditions allow for crop production at a very large scale. Furthermore, the increase in the agricultural production in this area can be attributed to the subsistence livelihoods that the surrounding people live by. The fact that most people that live around the study area survive by subsistence farming, a percentage of the increase in agriculture may be attributed to their consistency in farming practices and expansion in farming knowledge systems inherited from indigenous knowledge systems.
5.2.2 CARBON SEQUESTRATION

Aggregate Results of carbon sequestration show that total currently stored carbon in the study area is 852464751.45mgC. The total future stored carbon is 737391204.12mgC. The total Redd+ carbon estimate is 852464751.66mgC. The total change in carbon from 2017 to 2039 is -115090731.66 which shows a decrease in carbon storage within the 13 years. These results may be explained by the prevalence and abundance of cropland in the area. Interestingly, the presence of settlements contributed a small amount of the carbon as illustrated in the carbon maps. Therefore, the need to assess the trade-offs between carbon and crop production is seen.

<table>
<thead>
<tr>
<th>Description</th>
<th>Value</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total cur</td>
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</tr>
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<td>Total fut</td>
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<td>Mg of C</td>
</tr>
<tr>
<td>Total redd</td>
<td>852464751.45</td>
<td>Mg of C</td>
</tr>
<tr>
<td>Change in C for fut</td>
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<td>Mg of C</td>
</tr>
<tr>
<td>Change in C for redd</td>
<td>0.00</td>
<td>Mg of C</td>
</tr>
</tbody>
</table>

Figure 27: carbon aggregate results

The scenario-based model was used to predict the amount of carbon that could occur in the future based on the agricultural expansion predicted by 2030. The results showed that most of the study area may be covered by dense vegetation and agricultural practices that contribute a significant amount of carbon within this area. Coupled with the climatic changes depicted in this study, drought resistant crops and other highly economic crops are being planted in this transboundary area, (figure 27). This is to support the people’s livelihoods on the South African side as well as to support the economic situation in Zimbabwe.

The quantification and expression of ESs values and their trade-offs can predict environmental change and provide scientific backing for land use policies decisioning (Yang et al, 2018). The different research objectives covered in this study may require different quantification and expression methods. Some studies have demonstrated that trade-offs occur between regulating and provisioning services, while synergies are more likely to be generated by regulating services (Jia et al., 2014; Zheng et al., 2014; Lin et al., 2018). This study showed that with the increase or decrease in vegetation and with change in the land
use and land cover types, this affects the amount of carbon that is stored in the study area. This phenomenon suggests an ecosystem trade-off.

Figure 24 shows maps that illustrate current carbon storage and future carbon storage projected to the year 2030. The current carbon storage shows that most of the carbon is stored in both zones of the study area. The carbon is mostly stored where there are croplands and agricultural areas, whether substantial or commercial agriculture. To the contrary, the least carbon is stored where the settlements are located. This may be due to the regional ecosystems that are found in the area. Since the area is a semi-arid dryland area, the chances of agricultural practices to be present are high. The fact that both countries are still developing means that they mainly rely on agriculture to sustain the country’s GDP and the peoples’ livelihoods. Furthermore, the study area is surrounded by two very big national parks. This is the Gonarezhou National Park and the Kruger National Park. These nature reserves preserve woodlands, forested areas and deep agriculture. This could be another explanation of the high concentration of carbon within these areas. The future predicted carbon storage shows that most of the carbon will be stored in the South African side of the study area. This may be explained by the lack of economic sustainability in Zimbabwe to maintain people’s livelihoods and the environment when it comes to agriculture. Although the GDP of the South African economy is gradually dropping, the increase in carbon may be attributed to the agricultural practices around the area.

5.2.3 DEFORESTATION

The study area is in a dryland region and most of the vegetation that grows can be used for furniture or other wood related items. The results show a drastic decrease in bareland from 2007 to 2018, (Table 7) from 552361ha to 245233ha in 2018. This is can be explained using the corresponding increase in agricultural areas and vegetation. Although the decrease in bareland may appear as a good aspect of landscape changes, in this case it is not good. The vegetation class was clustered from dense shrubs, dense vegetation, sparse shrubs, sparse vegetation, woodland and grassland to one big vegetation cluster, (see Table 15). This was done to see the trend in the deforestation as a driver of the landscape changes within the ecosystem. Cumulatively, results showed that of the total land cover, vegetation covered 839389ha in 2007 and 1202382ha in 2018. This shows an increase in the overall vegetation cover in the landscape. Furthermore, when separated into different types of vegetation classes, it is observed that the grassland and sparse shrubs classes increased significantly.
As observed in table 1, the bareland class decreased significantly as the vegetation class increased. As previously mentioned, that this does not necessarily mean that it is a good thing as table 11 showed the different classes that are increasing in area. The cross-tabulation (table 7) confirms that the bareland class lost to built-up areas and vegetation. However, the type of vegetation increase found is shrunken sparse shrubs and grassland. This phenomenon shows a series of desertification naturally and intentionally.

5.2.4 MIGRATION

Since the study area lies between a transboundary region between a middle-income country and a low-income country, the decrease in built up areas may be attributed to the migration trend from 2007 to 2018. According to StatsSA, 2018, more than 1.2 million Zimbabweans migrated to rural South Africa between 2008 and 2018. In most cases, Zimbabweans have migrated to South Africa and Mozambique due to their economic struggles in their home country. This is proven by the built-up area that decreased by 23430ha from 2007 to 2018 (table 11), in the northern part of the study area as seen on the maps. That is a very huge and significant level of decrease in a class especially a class that is attributed to human wellbeing. Other factors that might have influenced the decrease in built up areas is the lack of agricultural resources within the study area.

The northern part of the study area houses Zimbabwe and observations show a decrease in built up areas in that part of the study area. As a result of economic degradation, the lack of housing and homes in the area may be attributed to agricultural resources and their lack thereof. This is proven by the corresponding decrease in agricultural practices in the area. The lack of subsistence drives human beings away from an area as well as promotes ghost towns and villages. On the southernmost part of the study area, a decrease in built-up areas may be attributed to rural-urban migration. STATSSA. 2018 noted that over 1 million people migrate to Johannesburg and other big cities in search for employment and better living conditions. This could explain the 10% decrease in built up components in the study area.

<table>
<thead>
<tr>
<th>Class</th>
<th>2007</th>
<th>2018</th>
<th>Loss_ha</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bareland</td>
<td>552361.77</td>
<td>245233</td>
<td>-307129</td>
</tr>
<tr>
<td>Built up area</td>
<td>478261.35</td>
<td>454831</td>
<td>-23430</td>
</tr>
<tr>
<td>Vegetation</td>
<td>839389.59</td>
<td>1202382</td>
<td>362993</td>
</tr>
<tr>
<td>Water</td>
<td>51425.91</td>
<td>18996</td>
<td>-32430</td>
</tr>
</tbody>
</table>

Table 15: table showing categorized change
5.2.5 CLIMATIC CONDITIONS

Changes in climatic conditions are one of the largest contributors to ecosystem changes and its dynamics. Although 11 years is not enough time scale to consider climatic variables, it is however an effective indicator of the different climatic conditions that are dominating the study area. Climatic changes in the study area includes the drying up of fresh water sources. This is evident by the decrease of the water class from 51425 ha in 2007 to 18996 ha in 2018. This is a drastic decrease in water sources promoting drought, poor living conditions and poor health conditions within the study area. The study area houses the Limpopo river and through visual observation over time, the river has been decreasing. This in turn affects other ecosystem services like agricultural production, water availability for both people and the wildlife as well as vegetation sustenance. The decrease of water in the Limpopo river can be attributed to the low rainfall and the increase in temperatures over the years. Weather data from the South African Weather Services, 2019 and the Zimbabwean Weather services show an increase in temperatures and a corresponding decrease in rainfall (figure 28).

The decrease in the area coverage of water could be one of the reasons why there is a decrease in built-up areas as the climatic and the weather conditions in the area do not support human survival over long periods of time. The lack of water over the years impacted negatively on the natural environment in the study area. As observed, there was a decrease in dense vegetation and dense shrublands in the area. This gave rise to sparse shrubs and sparse vegetation. This trend shows that the vegetation in the area is no longer thriving. The levels of degradation are high, and the vegetation types are changing due to different climatic conditions. This negatively affects the natural environment and the services rendered by it. It may
be said that the increase in vegetation within the area is a good impact of climatic conditions in an ecosystem, however the vegetation degradation and the type that is contributing to the increase in vegetation is a strong indicator of landscape changes perpetuated by climate change.

As it stands, the study area is dominated by grasslands and sparse shrubs. As observed using remote sensing data, the dense vegetation class drastically changed within 11 years of drought and dry seasons, the chances of the grassland turning to bareland or bare rock in the coming 20 years are more than 30%. These climatic conditions alter the natural landscape of the ecosystems therefore affecting the services. This gives a rise to migration, inequality, reduced farming activities, poor living conditions and a high mortality rate.

5.3 PLANNING

Using the results that were obtained from this study, it is clear that planning systems are a product of the development of the society and can therefore be very different from country to country. Land use planning is understood as partially integrating and sector-overlapping planning. Plans for using land resources are made everywhere. For example, farmers and livestock owners decide which products they want to have in what areas whether to increase or reduce the size of their herds and whether to fence off pasture land or to keep meadows for growing food only. Enormous organizations managing wood and energy just as specialists worried about street building or preservation of the nature additionally choose which zones they wish to use for their motivation. Also, there are endless other individual plans by different individuals, gatherings and associations at various levels with respect to land use in country territories.

At higher administrative levels (national and regional) heterogeneous systems are characterised by modern planning instruments, following the example of former colonial powers and other industrialised nations. Different regulating mechanisms may work at the lower level. Important city regions are often the exception. Therefore, the following integrative planning system can be suggested for the study area’s future land use planning mechanism. Figure explains the process in detail such as:

Table 16: process entailed in a planning framework

<table>
<thead>
<tr>
<th>Planning process</th>
<th>Key question</th>
<th>Objective</th>
</tr>
</thead>
<tbody>
<tr>
<td>Land Use Planning</td>
<td>What is a certain area of land suitable for and what demands to use it exist?</td>
<td>Optimisation of land use in an area in terms of • sustainability which is adapted to the area, • meeting needs for long term conservation of land resources and • the settlement of conflicts between interest groups</td>
</tr>
</tbody>
</table>
Figure 29 shows guidelines that can be used as a further step in developing an approach to land use planning (LUP) within the framework of development co-operation.

5.4 SUMMARY
This chapter presented the observed and the perceived reasons behind the results obtained in chapter 4. Drivers of ecosystem services which included climatic conditions, agricultural drivers, migration, deforestation and carbon sequestration. The possible climatic changes and the scenario-based land use and land cover changes were also discussed in this chapter and results showed that most of the study area in 2030 will be covered by dense vegetation and agricultural areas. Carbon results were also discussed, and the projected carbon storage showed how carbon storage will most likely decrease. A planning framework that shows proposed guidelines towards an integrated land use planning was also discussed here. The next chapter presents the objectives achieved, the limitations of the study as well as the recommendations for future studies and the final conclusions.
CHAPTER 6: SUMMARY AND CONCLUSIONS

6.1 INTRODUCTION

Transboundary ecosystems are connected and linked to one another regardless of the political boundaries that separate the countries. This study focused on the Greater Limpopo Trans-Frontier Region that is shared by South Africa, Mozambique and Zimbabwe. An increase or decrease in the vegetation dynamics due to problems that affect any of the countries listed above affect the vegetation quality, carbon storage and ecosystem services that provide livelihoods and habitats for wildlife and human life. Understanding the amount of vegetation loss and gains assists in managing the semi-arid forest that is found there as well as quantify the mitigation strategies that may be used to protect the area.

6.2 SUMMARY OF STUDY

The study set to quantify the land use land cover changes in the study from 2007 to 2018. This was achieved through the use of the random forest classification on Landsat 4&5 TM and Landsat 8 OLI images that were obtained in the summer months of the two years listed above. Field work was also conducted to sample the study area of the different land cover types that are found there. The study also set to quantify the amount of carbon that is stored in the study area in 2018 and in 2030. This was achieved through the use of the InVEST and SOARES software by model building.

Two approaches were used to assess the dynamics of land cover change for the years of 2007 and 2018 in the Greater Limpopo Trans-frontier Region. In the first approach, a Landsat image of each date was classified using a random forest classification scheme and they were interpreted as water, dense vegetation, grassland, bare land, dense shrubs, sparse shrubs, woodland, sparse vegetation, dense shrubs and built-up areas. A random sampling method was used. Subsequently, the interpreted classes of the different years were compared against each other and an error matrix was produced. The accuracy of the random forest classification showed a total of 89 signatures were trained were made, and a total of 65 were accurate, and this gave an overall 76% accuracy assessment and a kappa coefficient of 0.65 for the random forest classification scheme. Overall, the results of the land use land cover showed a decrease in built-up areas and an increase in the vegetation, decrease in bareland and water class from 2007 to 2018. Classes such as the sparse shrubs showed a steady increase as time went by. This was attributed to increase in unmonitored grassland growth in the area. Such alteration has a negative effect on the natural biodiversity of the area.
The second approach utilised NDVI to assess land cover dynamics between the two dates that were considered in the study. The NDVI demonstrated its effectiveness in discriminating the different land use / land cover types and the difference between vegetated areas and non-vegetated areas. The results showed a prominent increase in sparse vegetation and decrease in bareland and the data corresponds with the classified images of 2007 and 2018.

Over the past 11 years, the study area has experienced drastic land use changes. The phenomenon is described as drastic because the changes happened at an abnormally fast rate. The main goal of the study was to use Landsat imagery to assess land use land cover change dynamics from 2007 to 2018 in the Greater Limpopo Trans-frontier Region, as well as assess its impacts on ecosystem services during the stipulated time. Furthermore, to assess the drivers of land cover change in the study area over time. A supervised classification was used and produced an overall accuracy of 75%. Drivers of land cover change as identified in the study area are migration, climatic conditions, agricultural drivers and deforestation. Some of the factors that contributed to land cover change were deemed to be proportional and obvious, however the trend at which the dynamics were changing as well as their rate was alarming.

Other factors such as economic transformations in transboundary dryland regions were underlying contributing factors of landscape changes in the study area. The drivers of ecosystem changes as identified in the study may well be avoidable if sustainable solutions can be implemented. This will promote an ecosystem that supports the climate, environment and livelihoods within the transboundary region. Since transboundary natural regions rely on each other for change, policy makers need to look closely into the drivers of the ecosystems that negatively affect the environment and more especially people’s lives.

The Carbon Model was used to evaluate CS. Carbon storage on a land parcel largely depends on the sizes of four carbon pools: aboveground biomass, belowground biomass, soil, and dead organic matter. The InVEST Carbon Storage and Sequestration model aggregates the amount of carbon stored in these pools according to land use maps and classifications provided by the first objective (InVEST, 2018). Results showed that above stored soil and future stored soil ranged from 0.09m/p to 147mg/p. Below ground biomass ranged 0.05mg/p to 92mg/p. Carbon stored in the soil currently and in the future ranged from 0 to 98mg/p and 0 to 45mg/p respectively. current carbon and future carbon storage in the study area. Aggregate Results how that total currently stored carbon in the study area is 852464751.45mgC. The total future stored carbon is 737391204.12mgC. The total Redd+ carbon estimate is 852464751.66mgC. The total change in carbon from 2017 to 2039 is -115090731.66 which shows a decrease in carbon storage within the 13 years. Which can be attributed to the abundance of agricultural areas in the study area.
The scenario-based model in InVEST was used to predict the amount of carbon that could occur in the future based on the agricultural expansion predicted by 2030. The results showed that most of the study area may be covered by dense vegetation and agricultural practices that contribute a significant amount of carbon within this area. And finally, an integrative approach was suggested for future land use planning in the study area.

6.3 OBJECTIVES REVISED

The main aim of this study was to assess the dynamics of land cover/vegetation change using a time series analysis technique over a period of 11 years (2007-2018). The specific objectives of the study were to:

1. To spatially map the change in landcover between 2007 and 2018
2. Assess performance of Landsat satellite in mapping land cover change
3. Using InVEST Carbon Model to quantify the amount of carbon storage in the study area
4. To use Scenario-based model to model future projections of carbon sequestration and land cover change
5. To utilize the carbon sequestration and vegetation change data to inform planning for ecosystem services

This study successfully saw through the set objectives that it had set from the beginning. Land cover changed was mapped from 2007 to 2018 using the random forest classification that produced an overall accuracy of 76%. Landsat satellite performance was also assessed which gave a kappa coefficient of 0.65 for overall accuracy, 0.72 for classification and 0.76 for individual classification. This means that Landsat satellite can be used to perform land cover change with an accuracy that is high. The invest model was successfully utilise to quantify carbon and it is important to note that the study is the only one that has a contextualised carbon pool table (Table) for the specified land cover classes as described in table 1. The Scenario based model was usefully utilised to project future land cover, which in turn was used to quantify future land cover change. Finally, planning was informed using a framework that can be adopted by public and private entities.

6.4 LIMITATIONS

The images were available on different months and this influenced the spectral reflectance. Unfortunately, images could not be obtained for similar months for the chosen dates of the study. Inability to obtain all images in summer or high vigour time. To obtain the true vegetation vigour, summer seasons were considered. This study could not obtain images acquired during summer seasons for all dates however, this produced a relatively coarse spatial resolution that might have limited the accuracy level.
The 30m spatial resolution of the Landsat images poses challenges in correctly discriminating features especially in protected areas, which is comprised of features with varying reflectance properties.

6.5 SUGGESTIONS FOR FUTURE RESEARCH
More remote sensing data should be obtained on dates that are easily accessible. More scenarios must be created to improve the accuracy of the carbon model and the scenario-based model. To further validate the carbon results, a bigger study area might be needed and further research specifically on vegetation and carbon must be conducted in the study area. As the possibility of trade-offs was seen in the study, research based on ESs trade-offs with multiple scenarios specified to the study must be conducted to inform better and realistic land use planning and management practices in the Greater Limpopo Trans-frontier region. The methodologies of such studies both in land use mapping and carbon quantification provide useful knowledge to undertake similar studies in the future.

6.6 RECOMMENDATIONS
I highly recommend that further investigation be carried to see the correlation of population data and remote sensing images for the effective implementation of policy that will help maintain this dryland region. Furthermore, I highly recommend that further investigations be made through ecosystem services models using SOARES or Terrset to adequately see the quantifiable ESS prior and post land use and land cover change. I also recommend that further investigations be made on the relationship between ecosystems drivers and people’s perceptions.

6.7 FINAL CONCLUSIONS
Finally, this study provides useful information that can be generalised as follows; Remote sensing can be used effectively to determine the extent of generic vegetation types and urban growth over a given time period. In addition to mapping of land use and land cover change, it can be useful in assessing vegetation degradation since natural areas are being threatened by urban expansion and population growth. Landsat imagery is suitable enough in assessing land use and land cover dynamics particularly given the long-term and free availability of the images. In addition to the large spatial coverage it provides, it permits Landsat data to be used on studies that have wide spatial coverage. InVEST software can successfully calculate carbon storage and model future carbon storage using scenario-based models. Land Use planning is required to successfully manage and conserve ecosystems in semi-arid regions. This study also has a great potential in assisting informed decision-making. Although this study demonstrated the utility of Landsat
in monitoring land cover change, several drawbacks have been noted; the dissimilarity of image acquisition months.
7. REFERENCES


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