An assessment of land cover changes in Greater Giyani Municipality in South Africa

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DECLARATION

I, Matimba Mashele, declare that the dissertation, which I am submitting for the degree Masters of Science in Environmental Sciences at the University of North-West, is my own work and has not previously been submitted in its entirety or in part by me for a degree at this or any other tertiary institution for the purpose of obtaining any qualification.

Signed: ………Mashele M…………

Date: …………20-March-2022……

DEDICATION

I dedicate my research study to my wonderful mother, Ms. Gloria Nwamuzimba Mashele, and my lovely wife, Mrs. Nkhensani Mashele, who have helped me become the person I am today by supporting me emotionally, psychologically, and financially, to name a few. Finally, my three daughters Koutney Ntsakelo Mashele, Dzunisani Wandeme Mashele, and Dzunani Wanga Mashele, as well as my late sister Dzunisani Mashele.

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ABSTRACT

Detecting changes in land cover (LC) on the earth's surface is critical for obtaining continuous and exact information on any given area for any type of development planning. Anthropogenic-caused LC changes are one of the most important drivers of environmental change at any scale. Environmental changes continue to threaten the ecosystem's capacity to perform and offer environmental services that maintain communities' livelihoods. Population expansion, urbanization, high levels of migration, rising household numbers, and mounting development demands are all affecting the Greater Giyani Municipality in Limpopo province of South Africa. As a result of these variables, LC changes have occurred, as well as challenges such as urban sprawl, resource exploitation, and land degradation. However, little is known regarding LC alterations, such as where, when, and at what rate they occur. Understanding the drivers of LC change and how various factors influence LC changes in the research area is also critical.

Models that combine and evaluate a variety of LC change elements might help planners make better educated verdicts and achieve a stability between urban growth and environmental maintenance. In South Africa, however, the adoption of these models on a regional scale is quite limited. Models of LC change are useful if their structures are constructed on in-depth understanding of the system being studied and if the results are reliable. This study aimed to evaluate the state of land cover in Greater Giyani Municipality from 2000 to 2020 using remote sensing, as well as the factors that caused the changes, identify classes that were threatened within the municipality, and recommend possible strategies or procedures to address the change challenges.

An investigation of LC changes was conducted by integrating a quantitative and qualitative approach to better understand the changes, and their drivers. There was the use of satellite remotely sensed images (Landsat series) to measure which areas were covered by various land cover types, while document analysis, expert opinion in the form of semi-structured interviews with municipality town planners, and observation of the study area constituted qualitative data. Remote sensing and Geographical Information System were used for processing, analysing and presenting data through the ENVI 5.0 software. The Minimum Distance Classifier (MDC) through supervised classification was used to classify images into four land use land cover classes that included Bare Land, Vegetation, Waterbody and Built-up. To help analyse and present LC changes in the area, an adapted Driver-Pressure-State-Impact-Response (DPSIR) framework was used.

The results indicated that all maps attained an overall accuracy (AO) and Kappa coefficient (K) of >80% and 0.8 respectively. The vegetation cover indicated a decline of 5.97% between the years 2000-2007,22,59% between 2007-2014 increase of 3,82% between 2014-2020. The built-up indicated an increase of 0,42% between the years 2000-2007, 3.21% between 2007-2014 and 3,84% between 2014-2020. The bare land indicated an increase of 5,85% between the years 2000-2007, 19,0% between 2007-2014 and a decrease of 8,77% between 2014-2020. The waterbody indicated a decrease of 0,31% between the years 2000-2007, increase of 0,38% between 2007-2014 and 1.1% between 2014-2020. The LC changes in GGM are driven by demographic, technological, political, economic, cultural, and environmental factors. These factors must be considered in future planning policies and regulations to minimize negative environmental consequences while retaining socioeconomic benefits. This study, on the other hand, contributes to a better understanding of the elements that drive LC change and the adoption of the DPSIR framework as a model for LC change at a regional scale in the South African context. Policymakers can utilize the information as a reference to appropriately evaluate the influence that planning policies and other driving factors may partake in future LC trends in the Greater Giyani Municipality.

Key words: Remote sensing; Drivers; Models, DPSIR Framework

LIST OF ABBREVIATIONS AND ACRONYMS

AVHRR	Advanced Very High-Resolution Radiometer
CE	Commission Error
CVA	Change Vector Analysis
DAFF	Department of Agriculture, Forestry and Fishers
DN	Digital Number
DPSIR	Driver-Pressure-State-Impact-Response
EMT+	Enhanced Thematic Mapper plus
ENVI	Environmental for Visualizing Images
EPA	Environmental Protection Agency
FAO	Food and Agriculture Organization
GGM	Greater Giyani Municipality
GIS	Geological Information System
GSD	Ground Sample Distance
GVI	Greenness vegetation index
HRV	High Resolution Visible
HRVS	High Resolution Visible Spectral
IDP	Integrated Development plan
LC	Land Cover
LTDS	Long Term Development Strategy
LU	Land Use
LULC	Land Use Land Cover
LULCC	Land Use and Land Cover Change
LUMS	Land Use Management Scheme
MDC	Minimum Distance Classifier
MSI	Multi-Spectral Instrument
NDVI	Normalized Difference Vegetation Index
OA	Overall Accuracy
OLI	Operational Land Imager
PA	Producer`s Accuracy
PCA	Principal Component Analysis
RGB	Red, Green and Red

ROIs	Region of Interest
RPC	Rational Polynomial Coefficient
RS	Remote Sensing
SDF	Spatial Development Framework
SDP	Spatial Development Plan
SPLUMA	Spatial Planning and Land Use Management Act
SPOT	Satellite Pour I`Observation de la Terre (Satellite for observation of earth)
SWIR	Short Wave Infrared
TIRS	Thermal Infrared Sensor
TM	Thematic Mapper
UA	User`s Accuracy
USGS	United States Geological Survey
VNIR	Visible/Near Infrared

KEY DEFINITIONS

Land cover- can be defined as the physical or natural state of the Earth's surface.

Land use- can be defined as the manner in which human beings utilize the natural land and its resources.

Remote sensing (RS) - is the way toward examining the earth by satellite or high-flying aircrafts so as to acquire data about it without being in contact.

Geological information system (GIS) - is characterized as a computer-based system used for capturing, storing, recovering, controlling, analysing, and displaying topographically spatial data in order to promote development-oriented management and decision-making.

Electromagnetic spectrum is "the system that classifies, according to wavelength, all energy (from short cosmic to long radio) that moves, harmonically, at the constant velocity of light".

Change detection- observing changes in pixel value between pictures of a given area acquired at various times utilizing remote sensing.

Supervised classification-method based on the idea that a user can select sample pixels in an image that are characteristic of various classes, and then tell image processing software to utilize these training sites as references for classifying all pixels in the image.

Unsupervised classification- is when the software analyses an image and groups pixels with similar qualities without the user giving sample classes.

Training sites- also known as testing sets or input classes, these are groups of pixels that are determined based on the user's knowledge.

Natural resources- materials found in nature that can be utilized for monetary gain.

Monitoring environmental- the processes and actions that must take place in order to characterize and monitor environmental quality.

Spectral resolution- describes the ability of a sensor to discern distinct wavelength intervals in the electromagnetic spectrum.

Temporal resolution- refers to the frequency with which images of the same spot on the earth's surface are recorded.

Radiometric resolution- refers to a sensor's capacity to distinguish between objects that are viewable in the same portion of the electromagnetic spectrum.

Spatial resolution- refers to the dimension of the cell size that represents the amount of ground covered.

Post-classification change detection- the process of categorizing images from different time periods into a set of discrete categories using the same classification scheme.

Sensors- measures electromagnetic radiation in specified ranges (commonly referred to as bands) and can be found on board aircraft or satellites.

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CHAPTER 1: INTRODUCTION

1.1 Overview and Background

The world has been encountering quick urban population growth at phenomenal rates over the previous decades. As per the 2016 Revision of World Urbanization Prospects, 30% of the total population was urban in 1950 and it is assessed that in 2050, 68% of the total populace will be urban (United Nations, 2019). Further investigation demonstrates that by the year 2050, the world's urban population will grow by 2.5 billion people as a result of population growth and urbanization, with 90 % of this increase occurring in Africa and Asia (United Nations, 2019).

The prospect of living in urban regions is regularly related with better infrastructure, admittance to occupations, better wellbeing, training (education) and social administrations (Maree and Van Weele, 2018). Such insights lead to quick rural to urban relocation which adds to urban population growth and builds the interest on accommodation and other urban land uses (Willy, 2009). If not overseen and properly planned, urban growth can prompt significant issues like urban expansion, ecological degradation, deficient infrastructure, accommodation and transport shortages which all have an effect on the environment (United Nations, 2019).

In a South African setting, the Limpopo Province has been encountering quick and unseemly advancements in biodiversity territories, for the most part because of urban growth (Kirui et al. 2021). The Limpopo Province's State of the Environment Outlook Report reveals that the region is experiencing crucial population growth, growing family numbers, urbanization, infrastructural development, high levels of migration, agricultural expansion and escalation (Muavhi, 2020).

These trends have subsequently set off LC change and actuated issues like urban expansion, poor people marginalization, restricted community access to resources, land degradation and environmental change (Matlhodi et al. 2019). This poses a test to the national government authority which attempts progress toward a maintainable nation that shields the majority rule system by bringing essential basic access to services, overseeing inadequate resources and well-organized integrated planning while keeping up environment capacities (DEAT, 2020).

Understanding the drivers of LC change and analysing how different factors impact LC in meeting the challenge are therefore necessary (Costanza and Matthias, 2016). The tools that integrate and assess many factors of LC changes can be used to guide planners in making more informed decisions and, as a result, achieving a balance between urban development, growth, and environmental protection (Mohammed et al. 2022). A few countries have made adjustments to such tools as computer models which can help with investigating the outcomes of policies, human conduct and different drivers on LC patterns (Govindaraj et al. 2017).

These computer models are fundamental instruments which can help people in settling on more informed decisions through supplementation regarding existing mental modelling capacities (Costanza and Matthias, 2016). Verburg et al. (2004b: p313), depict LULC change models as "apparatuses to help the examination or analysis of the causes and outcomes of land use changes in order to understand the functioning land use framework and to support or help land use planning and policy." LULC change models are right now being carried out for the most part in developed nations and being utilized for planning decisions (Wilson, 2018).

1.2 Research problem

There are different patterns of LULC change models that have been created, executed worldwide and endorsed as significant in supporting LC decisions, thus far the execution of such models is inadequate in South Africa since there is narrow evidence of study and implementation. There is a need to evaluate and break down (analyse) LC change models' applicability and suitability in South Africa to think of appropriate models that better address a specific LC system. This poses a serious challenge to locales, for example, the Greater Giyani municipality situated within Limpopo Province. Central places or small towns in developing provinces, such as Limpopo, are areas undergoing rapid development, which has an influence on people's socio-economic lives while also endangering the environment.

The statistics for Greater Giyani Municipality (GGM) show that 33 738 (62, 4%) of individuals are jobless (Greater Giyani Municipality IDP, 2019 – 2020). This jobless population has occupied themselves with monetary exercises such as intensive crop farming at small, large scale, domestic live-stock farming, domestic fuel wood entrepreneurship and informal sector like street vendors. The municipality is concerned about the high unemployment rate and is taking steps to address it by implementing development plans based on socioeconomic factors and infrastructure, but they are still unable to properly address the problem, since the unemployment rate remains high (Greater Giyani Municipality IDP, 2019 – 2020).

The GGM Land Use Management Scheme (LUMS) and Spatial Development Framework (SDF) are the fundamental lower structures (framework) in charge of monitoring the municipality's development and infrastructural upgrades. It is a structure that ensures cost-effective and long-term development progress. Sustainable development investigates linking human settlements to economic activities while ensuring that progress does not compromise the environment. While the two structures above are putting efforts on sustaining land cover changes occurring within this municipality, the land cover state is still being threatened.

The reserved area of GGM is a significant wellspring of economic Aloe Vera species and wide scope of biodiversity that is being plunged into rapid land use patterns. This includes mixed crops of maize and vegetables for subsistence, commercial, settlement and development purposes (Greater Giyani Municipality IDP, 2019 – 2020). The LC changes have transformed the reserve areas sparse with bush fallow and marshy grasslands mixed with farmlands. However, little consideration is given to the extent of land changes that are taking place. There has been a significant expansion, growth of village settlements and infrastructure development in more areas proximal to GGM central town. The GGM protected permanent forest estate that acts as boundary to the reserve areas like Man`ombe wild lounge and golf course has also come under great pressure from fuel-wood forest product collectors. To date, no attempt of study has been made to record the GGM development growth together with the information on the LC changes. In the setting of GGM, understanding information about the nature of LC that took place, regions of occurrence, when it took place, rate at which it occurs and the drivers, processes that results in such changes is very much necessary.

1.3 Rationale for the study

Land resource utilization and demand have increased as a result of population growth and economic development. This has led to an increase of land cover change as well as categories of vegetation exploitation outcome. The LC is put under drastic challenge, due to mismanagement and failure to proper maintainable development. LC has been marked as the most important environmental issue every day and universally (Mas et al. 2017). The land change is the consequences of dwellers, and it is their responsibility to take actions against any land change which is not acceptable. Man, and biome rely on various land-use to perform various activities for survival. The changes brought to land cover may either be positive or negative. Somehow the changes have an impact on people's daily and ecosystem life. Since local municipalities continue to experience LC changes as an ongoing challenge, there is a knowledge vacuum in terms of the link between LULC changes, natural resource management, and integrated adaptation strategies on land cover changes. The GGM needs to understand the state of its land through assessments and modelling of LULC changes as well as their effects on natural resources. This research will provide information into present and future directions of changes in LC, as well as strategies for addressing the causes of these changes. The land cover changes need to be monitored, evaluated and assessed so that we can be able to manage the causative factors since the changes create imbalances to the ecosystem and environment as a whole. Furthermore, such information will be important when formulating recommendations on possible strategies and policies which may be implemented by the municipal authorities to improve land cover changes.

1.4 Research Aim and Objectives

Aim

The aim of this study was to evaluate the state of land cover in Greater Giyani Municipality from the year 2000-2020 through remote sensing and the causative factors of the changes.

Objectives

The following specific objectives will guide in achievement of the aim:

- To assess the land cover changes in Greater Giyani Municipality during the period of 2000-2020 through seven-year intervals.
- To identify factors responsible for the various changes observed and classes being threatened within the Municipality over this period.
- To recommend possible strategies or procedures that will improve the land cover change challenges associated with environmental imbalances within the Greater Giyani Municipality.

1.5 Dissertation structure

This dissertation is made up of six (6) chapters. These chapters are designed as follows:

Chapter one (1) includes the introduction of the study area, followed by research problems, motivation or rationale for the study, and concludes with the research aim and objectives.

Chapter two (2) forms the theory base of this research through a literature review on land use land cover change, drivers and modelling. This chapter covers the driving factors of land cover change, major concepts important in land use change modelling and classification or categorization of land use change models through remote sensing. The last part of this chapter will be the basis of land cover monitoring management in terms of policies and recommendations based on findings of other researchers.

Chapter three (3) describes the methods used in achieving research objectives through data gathering and analysis processes. The first focus is the study area description in terms of geographical location, population, climate and physical environment. The second part is data collection methods, method of processing, accuracy assessment techniques, LC changed analysis, the Driver-State-Pressure-Impact-Respond (DPSIR) framework. The third component is the data analysis describing the specific methods used to generate results.

Chapter four (4) will provide the results of the LC change analysis for the entire 20-year period sub-divided into 7-year intervals and reported into three sub-periods. The next section covers the driving factors identified from interviews, and DPSIR framework.

Chapter five (5) focuses on discussion of results provided in chapter four (4) and relating with existing literature to contribute to the knowledge gap of understanding the state of LC change in GGM. Chapter six (6) then provides the conclusions and recommendations towards strategies of managing the development process without compromising the state of the land.

CHAPTER 2: LITERATURE REVIEW

This chapter provides a summary of the literature on LULC changes as well as major concepts utilized in the study. The chapter presents major trends and conclusions from international and regional studies that used remote sensing (RS), Geographical Information System (GIS), Image classification, LC change detection approaches to monitor, assess, and simulate LC changes and patterns, as well as the implications of these changes.

2.1 Introduction

Respectable LUCC research has been accomplished throughout the last few decades. The approaches for monitoring and analysing LUCC have improved as a result of a better understanding of the causes and trends of LUCC (Lillesand et al. 2015). Increased understanding of the changes occurring in LULC will enable more valuable and dependable progress in detecting land resource changes on the earth's surface. Furthermore, a better understanding of LC change allows for a better knowledge of the impact of human activity. According to Matlhodi et al. (2019), LU refers to the social and economic characteristics of the land, such as the location of human activities on the land, whereas LC refers to the natural attribute and physical characteristic of the land. The geographic area of LC is gradually varied, and the change of time of LC has a distinct aspect change (Heistermann et al. 2006).

The use of GIS and RS in combination to investigate the issue of LC change is significant. Analyzing RS data with GIS tools is a practical technique to track changes in LC. To become more exact, RS is the science and art of gathering spatial, temporal, and spectral information about earth by satellite or high-flying aircrafts without being in contact. The remote sensing satellite image covers a large portion of the earth surface. As a result, remote sensing technology can give detailed and quantitative data on the land surface in a wide range of situations (Mauvhi, 2020).

2.1.1 Land

The United Nations Convention to Combat Desertification documentation defines land as, "the earthbound bio-beneficial system that contains soil, vegetation, other biota, and the environmental and hydrological processes that operate within the system" (United Nations, 2020: p2). A more comprehensive meaning of land is given in the Food and Agricultural organization (FAO) Land and Water Bulletin 2 (2015:p3), where land is portrayed as "a delineable space of the world's terrestrial surface, incorporating all attributes of the biosphere immediately above or below this surface, including those of the close surface environment, the soil and landscape frames, the surface hydrology (comprising shallow lakes, swamps, marshes, and rivers), the near-surface sedimentary layers and related groundwater hold, the plant and animal populations, the human settlement patterns and features by human activities (terracing, water stockpiling or waste constructions, streets, structures, and so forth)". Land as an asset is vital on the grounds that people live as well as play out all financial exercises ashore. In addition, land additionally upholds untamed life, characteristic vegetation, and transport and communication activities (DAFF, 2015).

2.1.2 Land Use

Land use (LU) can be characterized as the way in which individuals use the natural land and its resources. Land use portrays exercises, regularly connected with individuals that happen on the land, and represent the current utilization of land, for example residential areas, shopping centres, horticultural territories, industrial zones, and so forth (Prakasam, 2010). Worldwide land is turning into a limited resource because of monstrous change brought by individuals through agricultural and demographic pressures (Wulder et al. 2019).

2.1.3 Land Cover

Xiangping et al. (2021: p101) indicates that, "land cover is the biophysical condition of the world's surface and immediate subsurface." LC accordingly incorporates quality and types of all features over the earth like water, vegetation, soil, artificial surfaces, and so on. LC portrays the natural and anthropogenic features that can be seen on the world's surface, for example, grassland, waterbody, forest, bare-rocks and so on (Ibrahim-Bathis, 2015).

2.1.4 Land Use and Land Cover

Land use and land cover are clearly connected; nonetheless, it ought to be noticed that a single LC can uphold various land uses and the other way around (Cabral and Costa, 2017). For instance, a land cover of grassland can uphold many land uses, such as grazing, recreation. Similarly, a single land use may happen on different land covers. The distinction between land use and land cover is illustrated below (Figure 1).

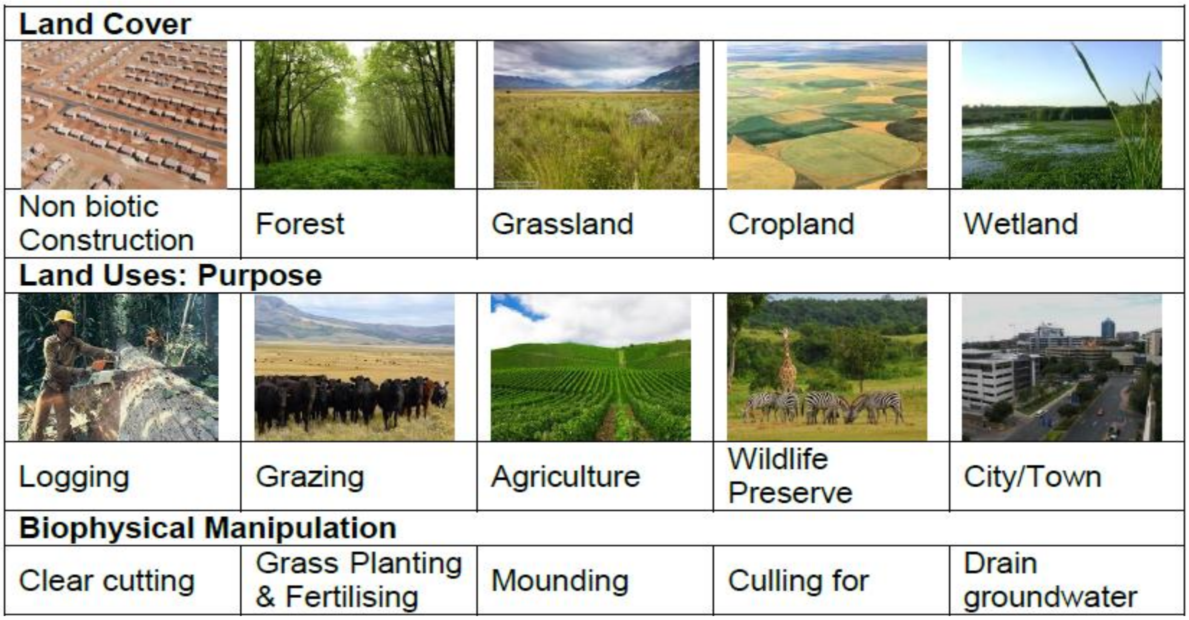

Figure 1: Distinguishing LULC [adapted form (Turner et al. 1994)]

2.2. Remote Sensing applications for Land Cover Change detection

Remote Sensing (RS) is a technique of getting-together data about the earth by using satellites or airplanes to observe it without being in contact or touch with it (Wulder et al. 2019). A Geographical Information System (GIS) is a computer-based tool for acquiring, storing, retrieving, manipulating, analysing, and visualizing topographically geographical data in order to improve development-oriented management and decision-making (Govindaraj et al. 2017). RS and GIS have become important tools for surveying changes in land usage and cover over the years (Peter et al. 2015 and Mehari et al. 2022). Satellite-based remote sensing has revolutionized the application of land changes since it can provide synoptic information of land at specific times (Govindaraj et al. 2017).

Kudakwashe and Mark (2010) outlines that, high temporal frequency, digital format suitable for computers, synoptic view, and wider range of geographic and spectral resolutions, RS data has become an essential source for change detection research. The capability and amount of information gathered by different sensing equipment varies significantly, and applicability is also dependent on the goals of each project. The spectral and spatial features of satellite images attained by several versions of a sensor device also change significantly (Cabral and Costa, 2017). Landsat instruments are an illustration of how image radiometric and spectral properties have improved over time, allowing for a better knowledge of land resources.

Landsat, Satellite Probatoire d'Obsersation de la Terre (SPOT), and Sentinel are the most common types of secondary data utilized in LC classification (Matlhodi et al. 2019). In the field of remote sensing, all of these secondary data have comparable and distinct characteristics, making them unique. The spatial and spectral resolution, which are important in the final products of computer processing, are distinguishing characteristics. The pixel detail of an image is referred to as spatial resolution (Kamwi et al. 2015). More detail and a smaller grid cell size are the benefits of high spatial resolution (Cabral and Costa, 2017). Lower spatial resolution, on the other hand, indicates less detail and larger pixel sizes. Spectral resolution, on the other hand, is defined as the amount of spectral detail in a band (Silva and Wu, 2015). Because it has a high spectral resolution, its bands are smaller. Broader bands with low spectral resolution cover a bigger percentage of the electromagnetic spectrum.

Landsat 9 was launched in 2021 and comprises of images from the Thermal Infrared Sensor (TIRS) and Operational Land Imager (OLI) with eleven (11) spectral bands and a spatial resolution of 30 meters for Bands 1 to 7 and 9 (Mehari et al. 2022). Thermal bands 10 and 11 are collected at 100 meters and are effective for delivering more precise surface temperatures. Band 8 (panchromatic) has a resolution of 15 meters, whereas bands 2-4 are for blue, green, and red, respectively. OLI collects data for nine spectral bands, all of which have a 30 m ground sample distance (GSD) except for the panchromatic band, which has a 15 m GSD. SPOT 7 was released in 2014 and provides 6-meter resolution multispectral (red, green, blue, and near-infrared) images, as well as 1.5-meter spatial resolution panchromatic images (Govindaraj et al. 2017). Sentinel-2 is the most recent satellite, carrying a multi-spectral instrument (MSI) with 13 spectral channels in the visible/near infrared (VNIR) and shortwave infrared (SWIR) spectrum ranges. The 10-meter spatial resolution within the 13 bands enables for continuous collaboration with the SPOT 7 and Landsat-8 missions, with a primary focus on land classification (Mehari et al. 2022). Landsat data is free to download on the USGS earth explorer, SPOT data is commercial, and Sentinel data is free to download on the Sentinel open access hub.

Over the last half-century, remote sensing imagery has been collected using a range of space-borne and airborne sensors, ranging from hyperspectral to multispectral sensors, with wavelengths ranging from observable to microwave and spatial resolutions ranging from sub-meter to kilometres (Matlhodi et al. 2019). Low or coarse resolutions, medium or moderate resolutions, fine or high resolutions, and very high resolutions are the four types of sensor spatial resolution (Wulder et al. 2019). These descriptors indicate the degree to which a satellite sensor can detect a surface feature or surface detail, because objects smaller than a sensor's spatial resolution cannot be distinguished, the smaller the resolution's dimensions, the more information one can detect in an image, and hence the 'higher' or 'finer' the resolution. Low or coarse spatial resolution indicates that a sensor's smallest area resolved is relatively big, meaning less detail (Muavhi, 2020). The spatial resolution of an image is often represented by the ground sampling distance (pixel size) after image re-sampling; however, this can differ from the spatial resolution of the sensor that captures the image (Mathanraj et al. 2021).

Chen (2017) defined low or coarse resolution as pixels with a ground sampling distance (GSD) of 30m or greater, medium resolution as pixels with a GSD of 2.0–30m, high resolution as pixels with a GSD of 0.5–2.0m, and very high resolution as pixels with a GSD of less than 0.5m. Images with low resolutions may be utilized in LULC classification only when a large number of classes needs to be identified, whereas images with relatively higher resolutions are used for fine-detailed LULC classifications (Cabral and Costa, 2017). When it comes to classification, LULC on a small scale usually requires high-resolution images, whereas large-scale classification requires low-resolution images. In general, for a classification at a local level, a fine-scale classification system is required, and high spatial resolution data such as SPOT data are appropriate. Medium spatial resolution data, like Landsat TM/ETM + and Sentinel, are the most commonly utilized data at a regional scale. On a continental or global scale, coarse spatial resolution data from satellites like AVHRR and MODIS image are desirable (Matlhodi et al. 2019).

The acquisition of remotely sensed data is routinely processed to account for any misrepresentation (distortion) caused by the characteristics of the imaging systems or conditions (Ibrahim-Bathis et al. 2015). The actions necessary to synchronize satellite observations from one period, to be compared and utilised to identify areas together with changes are known as pre-processing. Pre-processing comprises geometric and radiometric correction (Disperati and Virdis, 2015; Prakasam, 2010). The geometric calibration is known as ortho-rectification used to correct the angle of view of satellite sensors. It also corrects terrain relief and lens distortions, allowing images from various sensors from different times to be compared in the same way that maps with the same projections and scale (Cabral and Costa, 2017). When ortho-rectification is done wrongly, areas of land use change can be exaggerated causing inaccurate assignment of land use. Poorly co-registered data frequently results in overestimation of change since any apparent changes due to pixel mismatch (known to false change) are reported in addition to actual LC changes (Muavhi, 2020).

Change detection is described as the process of using remote sensing to determine or describe LC changes across time (Chen, 2017). LC change detection procedure identifies the distinctions in the state of an object or phenomenon by observing it at different times (Palmer et al. 2009). Change detection is a critical procedure in checking and managing natural resources or urban progression. Change detection therefore gives a quantitative investigation of the spatial appropriation of the territory of interest (Peter et al. 2015). It gives some premise to legitimate procedures on LC for viable land-use planning, management, and environmental recovery or socio-economic development in an area (Mas et al. 2017). Kudakwashe and Mark (2010) outlined four elements of change detection which are significant when observing natural resources namely:

- detecting the progressions that have happened,
- distinguishing the nature of the change,
- estimating the extent, degree of the change,
- surveying the spatial pattern of the change.

The ability to detect changes in the earth's surface features in actual time and with great accuracy lays the groundwork for a better understanding of the interactions and linkages between human and natural events, allowing for improved resource management and utilization (Kindu et al. 2015). Cabral and Costa (2017) claim that the LC change detection process has six essential phases. The nature of the change detection problem, the selection of appropriate remotely sensed data, image pre-processing, image processing or classification, change detection algorithm selection, and evaluation of change detection. The procedure of change detection can either be accomplished manually or automated with the guide of remote sensing. Silva and Wu (2015) explained that manual interpretation of change detection includes an observer or examiner characterizing areas of interest and looking at them between images of two different occasions. This works when assessing change between discrete classes. The automated method for change detection is in two forms: post-classification (PC) change detection and image differencing utilizing band ratios (Veldkamp and Lambin, 2001).

The PC change detection method is an exceptionally quantitative method and is generally utilized. In this method, two independently classified images and geometrically rectified images are compared on a pixel-by-pixel basis utilizing a developed change detection matrix (Wulder et al.

2019). Since the outputs from two individual maps are used in performing PC change detection, the general exactness of the change image relies upon the precision of the independently classified maps. In other words, the complete precision of the image is near the product of the accuracy yielded by the individual images. The benefit of this sort of technique is that most of the time, it does not need atmospheric correction. It gives information from and about change classes, and the correctly classified images can also be utilized as base maps for additional change detection analyses (Matlhodi et al. 2019). They used the PC change detection method and observed that this technique has limited difficulties that emerged due to the utilization of various sensors and the atmospheric conditions at the time of capture.

According to research that evaluated the effectiveness of various LC change detection techniques, no standard combination of data types and techniques can be applied to all ecosystems with similar success (Lu et al. 2017). Regardless, comparison analysis of separately produced classifications and simultaneous analysis of multi-temporal data are the two general techniques to change detection. Image differencing, rationing, principal component analysis, and change vector analysis are examples of simultaneous analysis techniques (EPA, 2015).

Image differencing change detection is defined as the technique of obtaining LC change results by deducting a digital number (DN) of a pixel on the first-date image from the second-date image (Peter et al. 2015). In this technique, areas that have not changed will have a pixel value of zero (0), whereas areas that have changed significantly will have positive or negative pixel values (Chen, 2017). Because it is simple, straightforward, and easy to interpret, image differencing is an extensively used change detection technique (Wulder et al. 2019). The most challenging part of this technique is selecting the threshold values for assessing whether a region has changed or not (Kindu et al. 2015). In addition, the technique provides sufficient information on the change itself. Atmospheric and non-surface radiance influences influence the outcomes of image differences (Govindaraj et al. 2017).

Image rationing change detection is done by calculating the ratio of the DN values of corresponding pixels on two images of the same bands obtained at different times (Cabral and Costa, 2017). In this technique, pixels with no change values are assigned the same value of one (1) for both dates, whereas pixels with values lower or higher than one (1) represent change (Kindu et al. 2015). The effects of radiance changes, shadows, image noise, and the angle of the sun are reduced when utilizing image rationing (Peter et al. 2015). Researchers, on the other hand, argue that this method makes it difficult to select threshold values and that the types of land cover change cannot be analysed.

Change vector analysis (CVA) is a multifunctional change detection technique that analyses the full spectral and temporal spectrum of image data, representing both the direction and amount of the change. The magnitude provides information on the level of change, whereas the direction provides information on the nature of change. CVA is a difficult technique to perform, but it has the ability to provide information on changes in overall data layers rather than just nominated bands (Kindu et al. 2015).

Principal component analysis (PCA) is a technique for transforming a correlated dataset into a smaller dataset for easier interpretation (Wulder et al. 2019). This technique allows the dataset to be made up of uncorrelated variables that represent the most important data from the original dataset (Govindaraj et al. 2017). The PCA can be done in two different ways. The first step is to combine both dates' data into a single file and analyse the component images. Second, after completing PCA, the second image data can be subtracted from a corresponding image of the first data, with the no-change areas being mapped in the first component and the changed areas being mapped in the last component (Kindu et al. 2015).

The most popular and widely utilized technique is PC comparison. This technique is a helpful and adaptable change detection technique for obtaining LC change information from images acquired by different sensors with varying spatial and spectral resolutions (Chen, 2017). The technique entails identifying changes in LC type and creating maps that depict the entire matrix of changes by coding the spectral classification findings for time one and time two either by pixel-by-pixel method (Matlhodi et al. 2019). The analyst is responsible for defining the various land cover classes. The two approaches of the post-classification comparison technique are supervised and unsupervised classification. The radiometric, geometric, atmospheric, and sensor variances between the two dates are minimized by the separated classification of pixels in the post-classification comparison (Wulder et al. 2019). This method takes time and expertise to develop high-quality classified images for each date, which has an impact on the ultimate accuracy.

2.2.1 Image classification approaches

The technique of classifying pixels in an image into a smaller number of individual LC classifications based on reflectance values is known as image classification (Disperati and Virdis, 2015). It involves generating distinctive LC classes from raw remotely sensed digital satellite data (Wilson, 2018). According to Muavhi (2020), the majority of image classification exercises are performed using raw digital number (DN) values, with little or no interest for actual spectrum radiances. Image classification occurs in two phases, according to Ibrahim-Bathis et al. (2015). To start, the user specifies the number and nature of the categories that will be used to characterize the land cover. Waterbody, built-up, bare terrain, and vegetation cover are examples of category classes. Second, using a decision-making method known as a classification rule, number labels are assigned to pixels based on their qualities. The images are classified using a sample set generated from training samples that represent the intended land cover and land use classes.

There are only roughly 157 different land cover classes, according to the Modified UNESCO Classifications scheme, and no study area will have all of them (GLOBE toolkit, 2018). However, this approach has limitations because the spectral signature of a habitat is not transferrable when measured in digital numbers (DN). These values are image-specific and are based on the viewing geometry of the satellite at the time the image was taken, such as the position of the sun, weather conditions, and so on (Disperati and Virdis, 2015). As a result, converting the DN values to a spectral signature with meaningful units is significantly more valuable because they can be compared from one image to the next. When the region of study is larger than a single scene or if scenes collected over a period of years are being compared, this procedure is known as image calibration (Ibrahim-Bathis et al. 2015; Cabral and Costa, 2017). Calibration is band-specific and is performed on every band of all images with reference to a similar radiometric reference, which entails converting DN to physical values of radiance or reflectance.

Classification schemes in change detection can either be unsupervised or supervised schemes. Unsupervised classification is where the results of pixel grouping depend on the software analysis of an image without the user giving sample classes (Matlhodi et al. 2019). Whereas supervised classification is the human-guided classification that utilizes the method of maximum likelihood calculation to classify the image based on the training sets (signatures) provided by the user field information (Kindu et al. 2015). The supervised direct multi-date classification decides the immediate transition of pixels starting with one class of pixels then onto the next by the utilization of a trained classifier (Kirui et al. 2021). The supervised methods include the utilization of ground truth data (training data) to play out a supervised classification on an image based on the training sets (signatures) provided by the user field information (Ibrahim-Bathis et al. 2015; Peter et al.

2015). Pons et al. (2015) states that this technique displays the time contrast relationship between the two images utilized in the analysis. The inconvenience of this strategy is that the training pixels utilized must be similar focusing on the ground in the two different dates.

Minimum distance to means, Maximum likelihood, and parallelepiped are some of the most often used supervised classification methods (Kirui et al. 2021). Parallelepiped classification is a method of classifying remotely sensed data in parallel using information from a group of signature files. The probability density function related to a specific training site signature is used to determine the maximum likelihood classification. Pixels are classified towards the most likely class based on a comparison of their probabilities of belonging to each of the signatures under consideration. It's also known as a Bayesian classifier because it will use Bayes Theorem to incorporate prior knowledge (Muavhi, 2020). Each class's prior knowledge is stated as a probability that it exists. It can be set to a single value that applies to all pixels. The Minimum Distance to Mean classifier sorts remotely sensed images into categories based on information in a set of signature files. The mean reflectance of each band for signature is used to determine the Minimum Distance to Means classification. Pixels are assigned to the class which has the mean that is closest to the pixel's value. The parallelepiped classification is based on a combination of lower and upper threshold reflectance values calculated for each band's signature. A pixel must have reflectance within this range for each band considered to be allocated to a specific class. The classification routines that are parallelepiped are the quickest. It's also the one that could be the least accurate (Disperati and Virdis, 2015).

2.2.2 Techniques of accuracy assessment of remote sensed images

Accuracy assessment is defined as the process of verifying whether a classified product or image meets the requirements of the desired application by evaluating the validity of land cover data in terms of thematic categories (Kamwi et al. 2015). In a nutshell, the degree to which image classification coincides with ground reference data is defined as accuracy assessment (Veldkamp and Lambin, 2001). Accuracy assessment can be used to offer an overall measure of the map's quality, which can then be used to compare alternative change detection systems (Kamwi et al. 2015). It also helps in gaining a better understanding of classification errors or classification results.

In accuracy assessment it is vital to remember that LC maps created from remote sensing data are never perfect (Disperati and Virdis, 2015; Govindaraj et al. 2017). The assessment of image classification accuracy uses ground reference data or other credible data sources to generate the assumed-true data. The accuracy assessment can give a comparison of categorization results versus known reference data on a category-by-category basis (Kudakwashe and Mark, 2010).

The reference data are the regions on the categorized image where the actual data categories are known. The reference points are normally chosen randomly across the image. The error matrix, also known as the confusion matrix, is used to report classification accuracy or error. When there is a disagreement between the classified data on the map and the real class on the validation data in the field or ground reference data, a classified error is calculated (Mauvhi, 2020). On a category-by-category basis, the error matrix compares the relationship between known reference data and classification results. Most metrics to estimate accuracy assessment are generated from error matrix or confusion error, depending on the user's goals. Overall accuracy (OA), User's Accuracy (UA), Producer's Accuracy (PA), and Kappa Coefficient (K) are the common accuracy assessment statistics produced from the error matrix of remote sensing image categorization or classification. By comparing how each pixel is classified to the actual land cover conditions produced from the ground truth data, the overall accuracy of the classified image is determined. The number of omission errors used to classify real-world LC types is a measure of how successfully they can be classified. The degree to which real-world land cover types can be classified is measured by producer accuracy. User accuracy is used to determine the chance of a categorized pixel matching the LC type of its associated real-world location. This is the probability that a categorized pixel matches the LC type of its real-world counterpart (Lillesand et al. 2015).

The difference between the actual and chance agreement between the map, the validation data on the ground is measured by the kappa coefficient. The more accurate the classification, the more useful it is to land managers and planners. The difference between real and chance agreement on both the map and validation data on the ground is measured by the kappa coefficient (Kudakwashe and Mark, 2010). The kappa coefficient values range from 0 to 1, and if the kappa coefficient equals 0, the categorized image and the reference image do not agree, and 1 kappa coefficient represents perfect agreement between the image and reference image (Matlhodi et al. 2019). In terms of percentage, strong agreement and good accuracy are indicated by a kappa coefficient of greater than 80 percent, a kappa coefficient of less than 40% indicates poor agreement, while a kappa value of 40-80 percent indicates moderate agreement (Govindaraj et al. 2017).

2.3 LULC change modelling

Hansen (2008) described LULC change models as tools to aid in the investigation of the causes and consequences of LU changes in order to fully understand how the LU framework functions and to help LU planning, legislative, and policy. Heistermann et al. (2006: p56) characterize a LULC model as "an instrument to compute the difference in area assigned to in any event once specific land use type." This depends on the way that LULC models can decide the measure of land utilized at a specific area, where LULC changes will happen and in investigation of LULC change drivers. The development of LULC change models has been impacted by three fundamental issues which are: the requirement for policy and planning, the accessibility of information and hypothetical developments from diverse fields with various approaches and points of view on what ought to be modelled (Wilson, 2018). However, the different LULC change models have been created and effectively applied in different regions of the world, to help with understanding land use dynamics and to simulate future LULC (Mathanraj et al. 2021).

Simulation of future LULC includes the combination of various disciplinary points of view, testing of assumptions, and improvement of structures for experimental information collection, creation of future framework situations and testing the impacts of policies on the land use framework (Robinson et al. 2007). Veldkamp and Lambin (2001) support this and highlight LULC change models' capacity to test future land use framework states through situation building based changes in chosen factors. Given that LULC has an impact on livelihoods, biodiversity, and global climate; Hansen (2008) report a surge in interest in LULC change modelling. As a result, many LULC change models have been developed to satisfy specific demands and to address when, where, and why LULC occur (Robinson et al., 2007; Veldkamp and Lambin, 2001; Wilson, 2018; Heistermann et al. 2006). Based on Bhattacharjee and Ghosh (2015) findings, LULC models can be used:

- to provide decision support for a variety of decisions, including the creation and implementation of appropriate policies and management strategies for the long-term management, use, and conservation of natural resources.

- to characterize the spatial and temporal relationships that exist between the drivers and the LULC changes that occur.
- to estimate or forecast future LULC pattern configurations under diverse biophysical situations such as socio-economic and climate change.
- as a tool for evaluating the environmental and socioeconomic impacts of past and future activities.

Wilson (2018) explained that there are various LULC model approaches designed to discover and simulate LULC changes. All models have been tested and proven to be effectively grounded on the nature and purpose of the various studies. Heistermann et al. (2006) in

Table 1 summarizes the model approaches and categorizes them into two groups, viz spatially explicit and non-economic LULC model.

Table 1. Categories of spatially explicit no-economic and economic models of LU changes

Model category	Main characteristics	Advantages	Disadvantages
Simulation (Cellular automata: CA)	– determine the discrete states of neighbouring cells – analyse the processes of urban growth	– Instructive and offer a practical approach	Simulation often yields complex and highly structured patterns
Estimation (Empirical models of LULC)	– They focus on some aspects of deforestation – Spatial biophysical – Socio-economic	– Well outcome Attempt to pinpoint the position of changes in terms of space.	Less successful to explain human behaviour
Hybrid	– Predict the land use/cover pattern in area.	Simple to understand.	Human behavior, on the other hand, is more difficult to describe.
Non-spatially explicit Models of microeconomics Models of regional economic development	Employ mostly economic theories.	Simple to understand.	Do not discuss the LULC spatial economic process at the parcel level.

Spatially explicit models	– basic deforestation model – Demonstrates how economic theory can be utilized to uncover potential endogeneity issues.	– Show the advantages of applying economic theory into the LULC models.	There is no direct connection between the observation unit and the decision maker.

2.4 Drivers of LC changes

LC drivers are factors or aspects that create changes in the phenomena of spatial features and have an impact on the evolution processes of land surfaces (Chen, 2017; Mauvhi, 2020). The LC change includes a conversion starting with one LC then onto the next or intensification of the present or current situation (Ellis, 2013). Individual landowners, communities, organizations, and governments control land use and make judgments on the best way to use land, which affects LULC changes. Collaborations between socio-economic factors like population and environmental factors (climate and topography) that change at different scales influence such decisions (Wubie et al. 2016). Therefore, environmental drivers will not affect LU change directly but do so for LC change, which effects land managers' decisions.

The LULC change can consequently be modelled as caused by the various socio-economic and environmental factors (Tizora et al. 2018). These factors are often alluded to as driving factors of LC change and classified as either proximate or underlying factors (Kamwi et al. 2015). The land is static, and how it is used shifts over time as a result of interactive relationships among underlying and proximate factors (Mathanraj et al. 2021). Understanding these elements is critical for determining the root reasons of LULC changes (Heistermann et al. 2006). It also assists in the development of realistic models for simulating future LC changes (Kindu et al. 2015). According to Mauvhi (2020), the drivers of LULC change throughout time, and their impacts change as the local environment changes.

The link between LC changes and the forces that drive them is complex and dynamic (Ellis, 2013). Proximate causes are local people's immediate actions in an attempt to reach their demands from the land, such as infrastructure and farming expansion (Matlhodi et al. 2019). Multiple factors, rather than just a single one, may explain LC change at the proximate level (Tizora et al. 2018). The proximate factors work at the local level like households, communities, or individual farms, whilst underlying causes are found at the regional and national levels such as municipality, district, province, or country (Leta et al. 2021). These proximate causes can be categorized into three: wood extension; farming development or expansion; and infrastructure extension (Figure 2). Figure 3 shows the underlying driving forces as socio-economic drivers which involve economic, cultural, demographic or socio-political, institutional factors, technological factors and they have a combined effect on LC rather than being single causes (Kamwi et al. 2015). Overall, underlying factors are commonly external and beyond local communities' control (Kindu et al. 2015).

Expansion of Agriculture	**Extraction of Wood**	**Infrastructure Improvements/Extension**
• Permanant/Ongoing Cultivation (Agriculture for Development Projects, Commercial farming, Subsitence farming.) • Shifting/Reposition Cultivation (Colonist and Traditional Reposition Cultivation) • Relocation • Cattle Farming	• Business purpose (private,state-run) • Domestic use fuel wood • Production of charcoal (industrial, domestic) • Pole wood (domestic)	• Transportation (roads and railway) • Infrastructure for the market (food market) • Expansion of settlements (rural, both urban/partly-urban)

Figure 2 : Proximate causes of LC change and their variables [adapted from (Lambin et al. 2000)].

POLICY AND INSTITUTIONAL FACTORS/ELEMENTS

- Formal/legal policy (on land,development, economic, taxation,economic, population movement)
- informal/illegal policy (mismanagement,corruption)

ECONOMIC FACTORS

Economic systems (unequality and associated factors such as unemployment, bad living conditions. foreign debts,economic crisis)

DEMOGRAPHIC FACTORS

- Population density, natural increase (fertility, mortality)
- Migration, population growth, and population distribution

TECHNOLOGICAL FACTOR

•Modern Agriculturlal development (LU intensification, LU extensification), Elements of agricultural production (factors relating to the land Food scarcity, for example, or labor-related factors)

CULTURAL FACTORS

- Values and beliefs of the public (Other public attitudes, such as modernism and lack of concern for the welfare of others, at dominance)
- behavior of individuals and households (unconcerned about environmental issues)

Figure 3: Underlying causes of LC change and their variables [adapted from (Lambin et al. 2000)].

The emphasis is usually on the underlying causes which comprise demographic, economic, political, environmental and cultural variables. This is on the grounds that unlike the proximate factors, underlying factors work at local levels (Tizora et al. 2018). Different laws and policies have a significant impact on LC transformation in South Africa. The Group Areas Act 41 of 1950 divided South Africans into distinct racial groups, with the white minority having a larger share of the territory and the black majority having smaller homelands. The utilization of land in past homelands altogether had an important impact on land cover, land use and livelihood options (Suma et al. 2021) and South Africa faces difficulties which stem from these inequalities. Apartheid not only isolated people based on their race, but it also resulted in inequity in housing, geographic region, environmental landscape, and facility distribution (Willy, 2009).

Apartheid spatial patterns were transformed into portions of "equity, integration, and sustainability" by post-apartheid policies and regulations (Rubin, 2018). However, government incentives such as the Reconstruction and Development Program (RDP) have replicated previous spatial patterns, resulting in human settlement on the periphery of cities with restricted access to resources and services. This is often due to a lack of reasonably priced, well-located land and the need to alleviate housing backlogs (Van Donk, 2013). This issue is additionally talked about under economic factors in this section.

The political and institutional factors can be structured as formal and casual or informal policies. The formal policies result in expected LC change while the informal policies are "misled policies" that result in unintended LC changes (Ashebir and Muluneh, 2018). Therefore, the legal framework that influences land use decisions in South Africa is looking according to the two structures: the formal policies in this section of the political factors which pay much attention to the spheres of government, policies and issues related with spacing and planning, that impact LC change. The 1996 South African Constitution sets out the rules for how government operates and establishes three levels of government: national, provincial, and local.

Sections 43, 44, 104, and 156 of the Constitution, as well as Section 40 of the Constitution, describe these three levels of legislative jurisdiction (1). According to the report, these levels are "distinctive, interdependent, and interrelated" (South Africa, 2017: p35) and are responsible for LU, spatial arranging, and planning in South Africa. Provincial planning, municipal planning, regional planning and development, as well as rural and urban development, are recognized in Schedules 4 and 5 of the South African Constitution as functional regions directly related to arranging and planning (Van Wyk, 2018). The Constitution does not accommodate the implications of these functional zones, leading or prompting unseemly turns of development and conflicts between the three spheres.

The South African SPLUMA No 16 of 2013 addresses some of these challenges by dividing spatial planning into three categories: national, provincial, and municipal. As a result, local municipal planning is the most extensive of them all, as it addresses both local and district issues. As indicated by SPLUMA 5(a0), "municipal planning includes the compilation, approval and review of integrated development plans and regulation of land use within municipal area where the nature, scale and intensity of the land use should not affect the provincial planning mandate of the provincial government or the national interest" (South Africa, 2017: p31). Municipalities are also mandatory to have a progressive system of plans (Figure 4) going from a broad strategic municipality plan where there is assigning of land use rights. These plans consist of the accompanying: "Long Term Development Strategy (LTDS); Integrated Development Plan (IDP); Spatial Development Framework (SDF); and Land Use Schemes (Forbes et al. 2017).

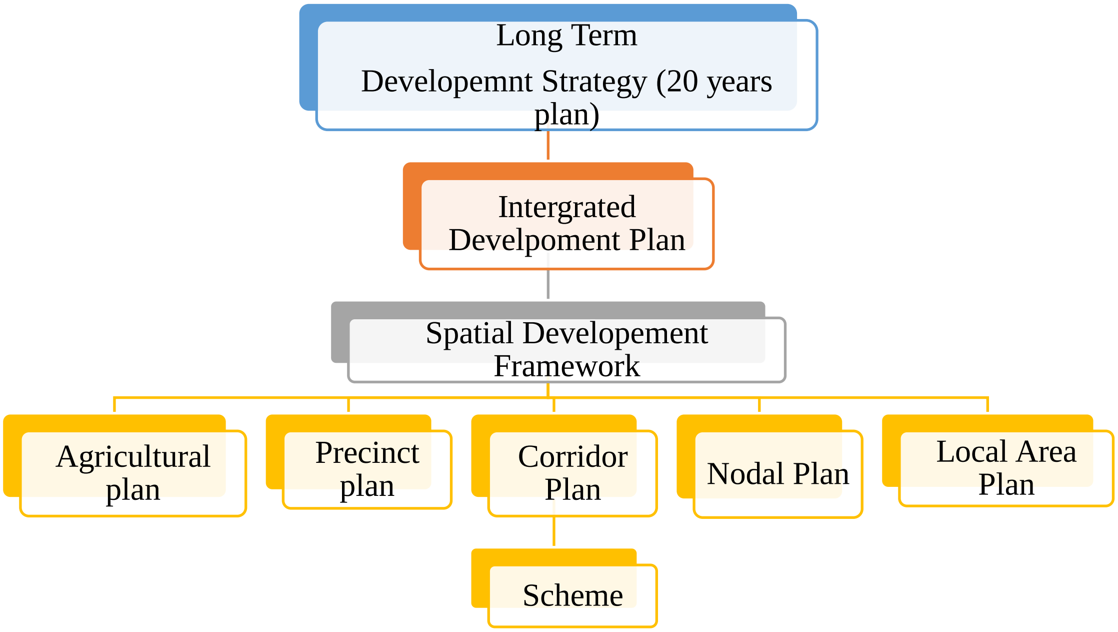

Figure 4: Conceptual Hierarchy of Plans [adapted from (Forbes at el. 2017)]

The Long-Term Development Strategy (LTDS) is the municipal schedule unfurling their strategy for achieving its development goals for a time of twenty years and beyond. It is straightforwardly related with the Integrated Development Plan (IDP), giving an extended strategy to completing the IDPs. It ought to be contained inside the framework of the IDP yet is generally as a self-contained plan.

Spatial Development Framework (SDF) is a legal prerequisite set out as the principal strategic planning instrument which should incorporate fundamental procedures for the LU managing system for each municipality. Schemes are planning or LU schemes organized in relations of the Provincial Ordinance Act which serve to maintain development administration inside a municipality. Other non-legal plans fall between SDF schemes and incorporate a Spatial Development Plan (SDP), Local Area Plan, Sector Plan, Corridor Plan, Nodal Plan, Precinct Plan, etc. They give an understanding of the SDF over a particular geographical area.

The informal policies can include corruption, mismanagement of land and unintended LC changes which affect misapplied policies (Ashebir and Muluneh, 2018). The present policies can become inappropriate if there are influential individuals or foreign powers that are unethical and interested in land expansions. Acts such as SPLUMA comprise of sectors which consent for exploitation of authority e.g., Section 55 gives the rightful portfolio responsible for spatial planning and land usage management a permission to release a portion of land from provisions of the Act.

A combination of social, political, demographic and economic factors drives internal and international migration in South Africa (Bakker et al. 2019). Migration or relocation is not a new phenomenon in Southern Africa, and it has a far longer history. The internal migration in South Africa is generally categorised by temporary circular immigration and long-lasting migration to inner-city areas (Fauvelle-Aymar, 2014). Improved job opportunities, education, access to improved health facilities, and other services and get-together with family members are some of the causes why people migrate within South Africa (South Africa, 2017).

Economic factors can include access to capital, investments, taxes, manufacturing, markets and transportation costs, subsidies, and technology (Barbier and Hochard, 2016). These economic factors inspire land administrators. Moreover, they are also inspired by the productivity and feasibility of a particular LU. Economic factors combined with technological and institutional factors play an important part in LU change. For example, giving agriculturalists admittance to funds, farming technology and markets can empower agribusiness growth and conversion of land (Gibson et al. 2015). According to the Department of Agriculture, Forestry, and Fisheries (DAFF), the number of profit-making farms in agribusiness has decreased from roughly 120 000 in 1950 to approximately 29 000 in 2015, with a corresponding increase in average farm size (DAFF, 2015). As a result, decreasing reliance on manual labour has resulted in employment losses and an increase in capital resources such as mechanisation.

Other than political, demographic, technological, environmental and economic factors, different cultural factors likewise play an important part in LC change (Gibson et al. 2015). Cultural factors comprise land administrators' beliefs, opinions, values, and perceptions, which influence LU choices (Wubie et al. 2016). The environmental factors are classified as the biophysical factors which "outline the natural ability or predisposing environmental conditions for land use change, with the set of abiotic and biotic factors – soils, climate, topography, lithology, relief, vegetation and hydrology" (Wubie et al. 2016: p42). According to studies, population growth, agricultural expansion, poverty, and the unsustainable use of biomass for all energy uses are some of the drivers that allow LULC changes in developing countries, particularly in rural communities surrounded by natural resources (Ibrahim-Bathis et al. 2015; Cabral and Costa, 2017). Chen (2017) revealed the most important drivers of LULC changes in developing nations include population growth, natural disasters such as drought, change in climate, globalization, and economic development. Overpopulation combined with poverty without alternative economic possibilities leads to increasing reliance and irresponsible extraction rates from the natural resource base, resulting in natural resource degradation, according to Ellis (2013). Between 1984 and 2010, population growth, illegal logging, and agricultural development were the most notable reasons of LULC changes in the Zambezi region of Northern Namibia, according to Kamwi et al. (2015). Kindu et al. (2015) investigated the drivers for LULC changes in the Munessa-Shashemene environment in Ethiopia's south-central highlands; they discovered that LULC changes were triggered by population increase, livestock farming, agriculture expansion, and the collection of fuel wood.

2.5 Summary

This chapter has presented a detailed account of studies, theories and methodology approaches used in the field of LULC changes analysis. The concept of land, LU, LC, LULC change have been discussed followed by how the continuing growing modern technology of RS is playing a vital role in helping researchers to identify the earth's natural state changes, patterns, with the aid of various techniques used for image classification and LC change detection processes. Various LC change models have been discussed, this included their application, characteristics, strength and limitation in different settings. LC change drivers, and the associated proximate, underlying causes, leading to such changes on the natural environment, resources have been explored. The results of various studies have demonstrated the need for a study focusing on location-specific changes to provide better and up-to-date information for land use planning and sustainable management of natural resources. Further findings suggest that determinants of LC changes of any landscape and impacts of such change are complex, diverse and vary from one area to another depending on the interaction of location-specific factors. These factors are interrelated at a local, national and global scale. The LC change classification, analysis, models, and drivers are important platforms to benefit with the development of policies and management strategies to monitor the LC changes.

CHAPTER 3: METHODOLOGY

3.1 Introduction

This study integrated a quantitative and qualitative approach to better understand LULC changes, their drivers and classes which are more threatened. Recently, RS and GIS are very useful tools to understand the LULC changes and perform change detection. Satellite remotely sensed data is freely available, and it presents an up to date greater spatial and temporal coverage. The available remotely sensed data are easily obtained, analysed, interpreted, and stored using GIS (Ibrahim-Bathis et al. 2015).

This chapter discusses the steps followed to undertake the entire methodology in this study. The first section focuses on the study area, followed by data collection methods and lastly the data analysis. The detection and analysis of LC change drivers was carried out using Environmental for visualizing images (ENVI) software, RS imageries, interviews with municipal town planners, document analysis, and adaptation of the Driver-Pressure-State-Impact-Response framework (DPSIR). This framework establishes a methodology for providing the required indicators to decision makers in order to provide feedback on environmental quality and its impact on the future. The DPSIR framework assumes a series of underlying relationship chains, from "driving force" (human activities, economic sector) to "pressure" (waste, emissions) to "state" (chemical, physical, and biological) and the influence on ecosystems, human health and functions, ultimately leading to political "responses" (priority, goal setting, and indicators). The DPSIR framework is designed to support decision-making and will help provide possible strategies or procedures that can help improve LC changes in the study area. The analyses of maps on LC were utilized to show, evaluate changes on LC and this addressed the objective to identify the land classes being threatened and wrapped up with suggested recommendations to LC policies in the GGM. Interviews with municipal town planners (Appendix 2) as well as reviews of documents where the methods utilized to determine driving factors and their impacts on the LC changes. To report and organize the findings of the interviews into grouped themes presented as components of the framework, an adapted Driver-Pressure-State-Impact-Response (DPSIR) framework was utilized.

3.2 Study area

3.2.1 Overview and population

The Greater Giyani Municipality (Figure 5) is among five local municipalities in the Limpopo Province that fall within the Mopani District Municipality, with coordinates of -23°24'59.99" S and 30°44'59.99" E. Giyani is the municipality's only semi-urban region, covering an area of 4 172 km2. The municipality is divided into 31 wards, with 62 councillors. It contains ten traditional authority regions with a total of 93 villages. Giyani is the most populated town in terms of population density, employment prospects, retail, and recreational facilities (Greater Giyani Municipality IDP, 2019 - 2020).

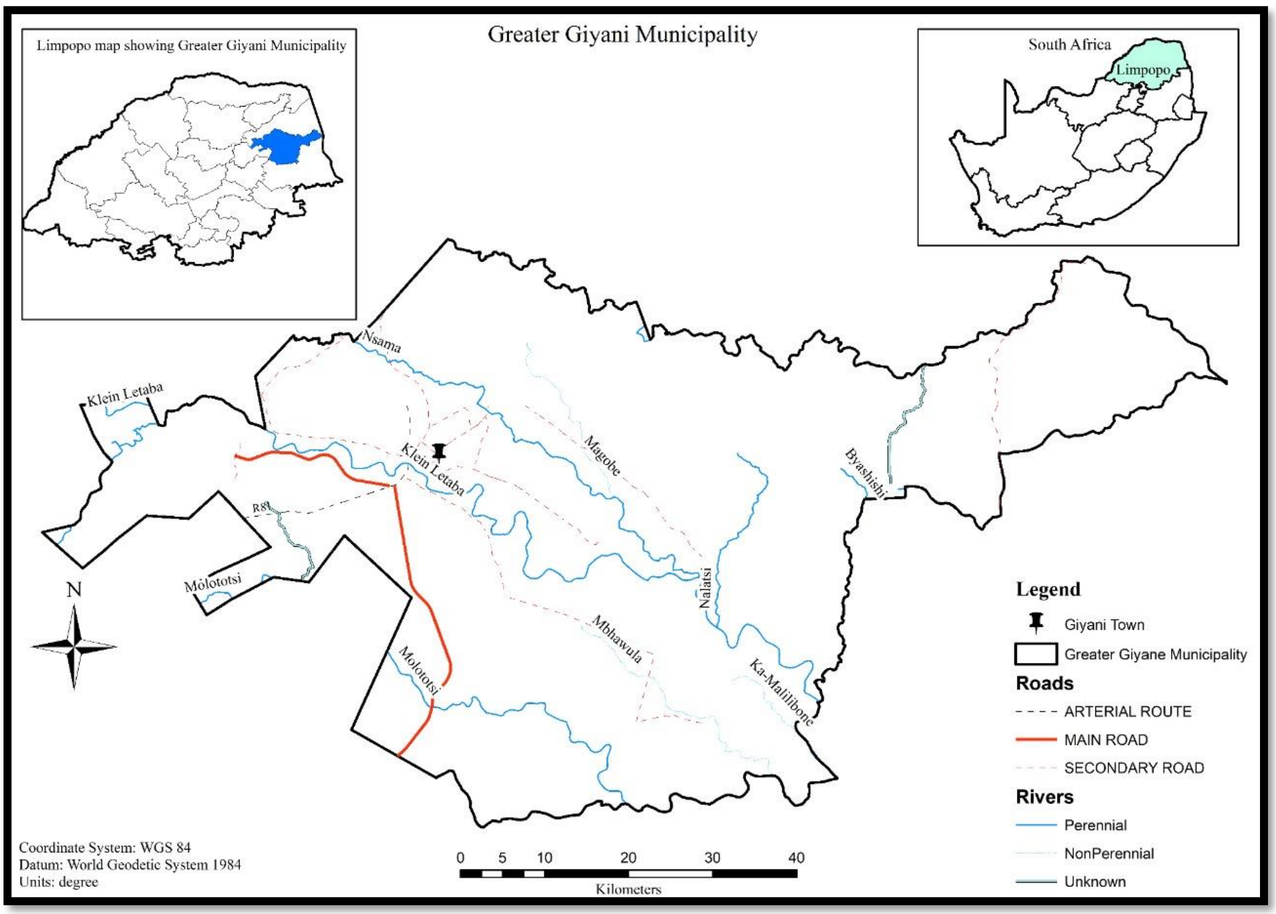

Figure 5: Greater Giyani Municipality map

The GGM population consists of 256 300 inhabitants with a total number of 70, 537 households, whereby more than quarter of these households reside proximal to the main single town, serving as a central place. The municipality has 31 wards grouped into 5 clusters. In most wards, the population exceeds 5000 people (Greater Giyani Municipality IDP, 2019 - 2020). The population of GGM comprises of blacks with the largest population of 92.1%, followed by Indians at 6.2% population. The other races like whites and coloured contribute 0.7% and 0.3% respectively. The other nationalities like Somalians, Pakistan contribute 0.7% of the total population (Greater Giyani Municipality IDP, 2019 - 2020).

3.3.2 Education and employment

The statistics indicate that a high number of people in the age groups 35 to 65+ years, did not have privilege to better education (51%), these may be the results of accessibility of schools, affordability of higher learning institutions and tribal laws whereby certain age groups were forced for animal herding or customary marriages. The current number of employed people at GGM is approximately 53%, with 47 % unemployment rate, leading to negative impact on environment and society as the people tend to depend on fuel-wood collection for sale, small-scale crops farming, live-stock growing as means of survival which eventually impacts on vegetation cover in different sites within GGM (Greater Giyani Municipality IDP, 2019 - 2020).

3.3.3 Climate

Giyani is located in a subtropical climate. It can get very hot in the summer, with maximum temperatures reaching 41 °C in the summer and 25 °C in the winter. Winters are pleasant during the day but freezing at night. The rainy season lasts from September to March, whereas the winter season lasts from April to August. The area receives between 100- 400mm of rain annually (Greater Giyani Municipality IDP, 2019 - 2020). GGM receives the Cyclonic or Frontal rain when warm and cold air meets each other particularly in summer, when the Kalahari High pressure cell migrates far north, allowing warm and moist air from South Indian Ocean to penetrate the interior via the coastal escarpment and meet with the cool dry air from South Atlantic Ocean (Mosase and Ahiablame, 2018). Such rainfall lasts for a few hours and has a direct influence on development, particularly agriculture, because it causes a shortage of surface water, causing the municipality to rely on groundwater via boreholes to irrigate the fields. GGM average rainfall amount (Figure 6) for the study period (2000-2020) indicates a fluctuating amount yearly. The highest rainfall amount for the study period is recorded in the first 7-year interval (200-2007) with the lowest recorded by the second interval (2007-2014).

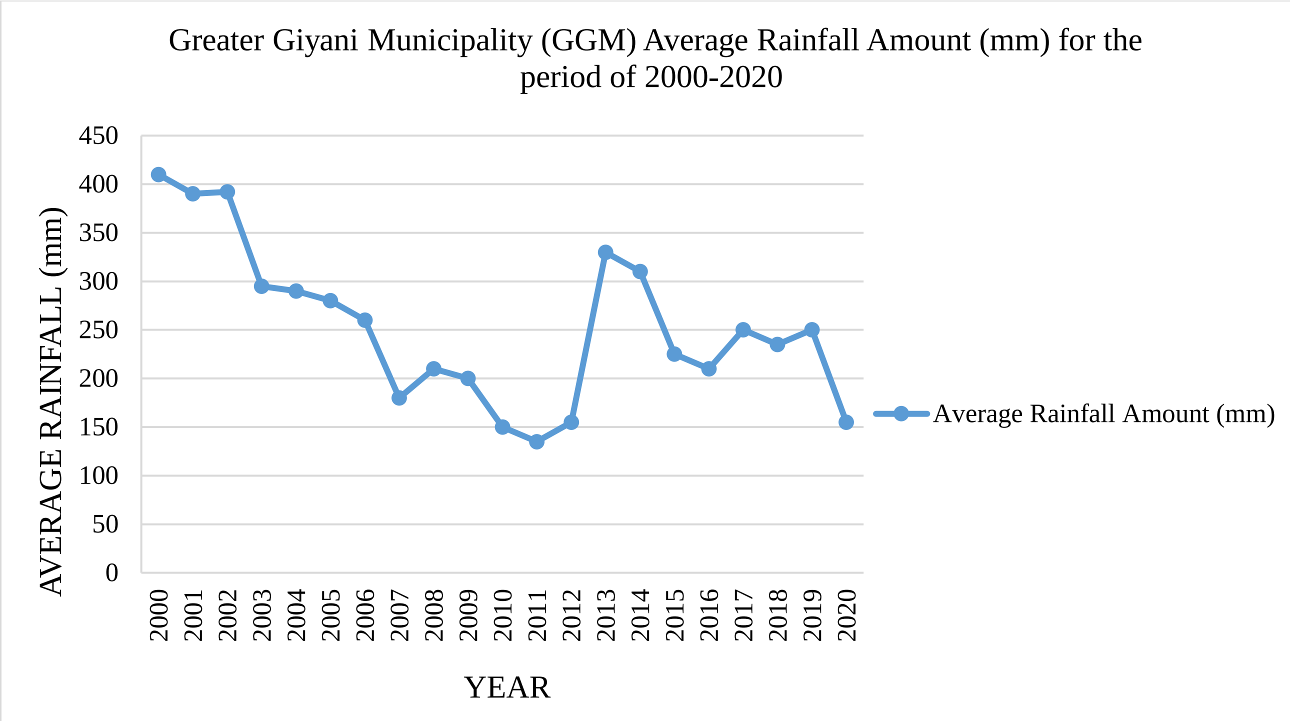

Figure 6: GGM average rainfall amount for the period of 2000-2020. (Source: South African Weather Services)

3.3.4 Physical environment of GGM

The Greater Giyani Municipality has a variety of soil types, and there is a mineral belt that runs from the west to the east of the municipality, towards the Kruger National Park. The area consists of 24 mines which are all currently at unused state, because of low production. Gold is found to be the dominant mineral within the entire area, with the little deposition of Silica in some areas (Greater Giyani Municipality IDP, 2019 - 2020).

Greater Giyani municipality is located in a low-lying area in north of Limpopo province (Figure 5) and characterized by abundance of flora species like Mopani and Marula trees and grassland. The main perennial drainage network or rivers include Groot Letaba, Middle Letaba, Klein Letaba, and Nsami, with Malatsi, Mbaula and Molototsi as the non-perennial rivers (Greater Giyani Municipality IDP, 2019 - 2020). The municipality has soil that is suitable for agriculture and arable land. The traditional authority controls the majority of the land in the municipality. Commercial farming is practiced on a smaller scale, and it is eventually superseded by subsistence farming. The rest of the land is grazed communally (Greater Giyani Municipality IDP, 2019 - 2020).

3.4 Data collection

3.4.1 Primary data

The first phase of primary data collection was through field visits to observe and gather ground truth data. The process of ground truthing is the way to collect information that is known to be real or true, provided by direct observations and measurements (Muavhi, 2020). The coordinates of the 'pixel' on a remotely sensed image were taken using tools like rational polynomial coefficient (RPC) Orthorectification and Image-to-Map registration in environment for visualizing images (ENVI) 5.0 software (Muavhi, 2020). The geographic coordinates were taken to site, with the aid of cell phone GPS to double check correlation of pixels in remotely sensed images and the real ground features. This data is considered to be crucial in the study, because it was useful during data analysis of supervised classification and validating the results through accuracy assessment.

The researcher collected the second phase of primary data through interviews or questionnaires with the GGM office responsible for planning, development and environmental management to find out about the challenges the municipality encounters on land cover management and personal or expected observations. The sample for interviews consisted of two (2) municipality town planners and one (1) Integrated Development Planning (IDP) managers within the municipality. Participants were chosen based on their portfolios, understanding of the GGM LC, and awareness of land use issues in the municipality.

Prior to the interviews, participants were told about the research and a consent form (Appendix 1) was emailed to them and explained to them. The researcher created an interview guide or questionnaire (Appendix 2) form as a tool used in collection of data via interviews and observations. The questionnaires consisted of 10 questions probing to understand the causes, results and solution to the LC changes within the municipality. This method was selected as it allowed exploration of issues relevant to the concerned municipality (Kudakwashe and Mark, 2010). The interviews were conducted telephonically due the COVID-19 pandemic meeting restrictions.

An interview guide consisting of key themes was constructed. However, there was no strict adherence to the interview guide and probing was used to explore new paths emanating from the respondent's answers and to obtain detailed information on a subject of discussion which the researcher had no prior knowledge. Relevant LC change documentation, such as the GGM Spatial

Development Framework (SDF), Growth Potential Study of Towns, State of the Environment Reports, various legislation, and the Spatial Planning and Land Use Management Act (SPLUMA), was used to validate, corroborate, and supplement data collected from interviews.

3.4.2 Secondary data collection

3.4.2.1 Satellite Datasets

Landsat 4-5 TM and Landsat 8 OLI/TIRS datasets (Table 2) were selected for this study to assist in showing the LC changes over time. Landsat satellites have the best ground resolution and spectral bands that are able to track land use and record land changes as a result of climate change, urbanization, forest fires, droughts, biomass changes (carbon assessment), and various other natural, man-made changes. These datasets were retrieved from the United States Geological Survey (USGS) site (https://earthexplorer.usgs.gov) maintained by the Earth Resources Observation and Science (EROS) Centre at Sioux Falls, South Dakota. The selected images were acquired during July which is the dry winter season commencing from May to September (Table 2). The winter season over this area rarely experiences cloud cover and makes it easier to access ground information necessary for LC mapping. The research considered the date and month in which the satellite imagery is captured for the spatiotemporal results interpretation and analysis.

Table 2: Downloaded Datasets/Satellite imagery with spatial resolution and wavelength range and bands.

Dataset Type	Scene ID	Band and wavelength range (µm)	Spatial resolution	Date of acquisition
Landsat 4-5 TM	LT05_L2SP_169076_20000729_20200907_02_T1	**Band 1(Blue)- 0.45-0.52** **Band 2 (Green)- 0.52-0.60** **Band 3 (Red)- 0.63-0.69**	**30 m**	2000/07/29
Landsat 4-5 TM	LT05_L2SP_169076_20070717_20200830_02_T1			2007/07/17
Landsat 8 OLI/TIRS	LC08_L2SP_169076_20140718_20200911_02_T1	**Band 2(Blue)- 0.45-0.52** **Band 3 (Green)- 0.53-0.59** **Band 4 (Red)- 0.64.0.67**	**30 m**	2014/07/18
Landsat 8 OLI/TIRS	LC08_L2SP_169076_20200702_20200825_02_T1			2020/07/02

3.4.2.2 Legislative framework

The study consulted the legislative arm of South Africa which guided governance of land issues which might influence some of the uses. The purpose was to investigate the legislation of South Africa from national to local levels that has interest on LC to enable identification of some drivers to the land use changes in GGM or that might pose challenges to the municipal authorities' proper management of the land. The Spatial Planning and Land Use Management Act (SPLUMA) 16 of 2013 in South Africa is responsible for LC changes, with the Land Use Management System (LUMS), Spatial Development Framework (SDF), and a Land Use Scheme (LUS) as important components of the LUMS and Spatial Development Planning (SDP). The legislative framework defines how various LC drivers cause change and how those changes might be mitigated (Kindu et al. 2015).

SPLUMA governs the establishment, functions, and operations of Municipal Planning Jurisdictions, as well as the facilitation and enforcement of land use and development measures, as well as issues pertaining to them. It has the potential to demonstrate the effects of social, economic, and technological issues as LC drivers (Ellis, 2013). The Land use Management System (LUMS) refers to all of the methods, procedures, and policies that a municipality needs to properly manage land and its use. LUMS therefore provide a legislative and policy framework that allows the government, particularly local government, to design land-use and land-development policies, plans, and strategies that address, confront, and resolve the country's spatial, economic, social, and environmental factors (Matlhodi et al. 2019). SDF facilitates functional and cohesive human settlements that are sustainable, improve resource efficiency, and enhance regional identity and character. Political, demographic, economic, and technological problems are all addressed and resolved through SDF (Mauvhi, 2020). SDP is crucial for delivering economic, social, and environmental advantages through improving investment and development circumstances, ensuring community benefits from development, and promoting sensible land and natural resource use for development (Kindu et al. 2015).

3.5 Data analysis

3.5.1 Processing and Classification of Landsat bands

Processing and classification of Landsat bands was carried out using ENVI 5.0 software. The three bands of each year were put together to create a new multiband image. To remove solar irradiance, atmospheric transmittance, instrument gain, topography impacts, and albedo effects from radiance data, the Log Residuals calibration was applied to the multiband image. This calibration tool turns radiance data into a pseudo-reflectance image that may be used to map different types of land cover (Ibrahim-Bathis et al. 2015). For each year of analysis, a true colour image was produced using a combination of band 3, 2, and 1 in red, green, and blue (RGB).

The combination of band 3, 2 and 1 in Landsat 4-5 TM was chosen because the researcher focused on vegetation, built-up, bare land and waterbody land cover classes. The abovementioned band combination best suites and produces the best result (Muavhi, 2020). Vegetation can be detected by bands 1, 2 and 3, built-up area uses band 1, 2 and 3 or 1, 4, and 5. Waterbody uses band 1, 4 and 7 or 1, 2 and 3. Because the visible bands are used in this combination, the 3, 2 and 1 (RGB) band combination has the potential to produce the "natural colour" band combination, in which ground features appear in colours similar to their appearance to the human visual system, green for healthy vegetation, brown and yellow for unhealthy vegetation, very light colours for recently cleared fields, and grey for roads (Disperati and Virdis, 2015). According to Muavhi (2020), this band combination gives the best water penetration and sediment control. These band combinations are best used for urban studies or build up areas. Band 4, 3 and 2 (RGB) Landsat 8 OLI/TIRS all together are able to produce a true colour combination or normal RGB image of the visible light. The advantage of a true colour composite image (Figure 7) is that LULC types appear in their true forms which make it easier to identify them (Ibrahim-Bathis et al. 2015).

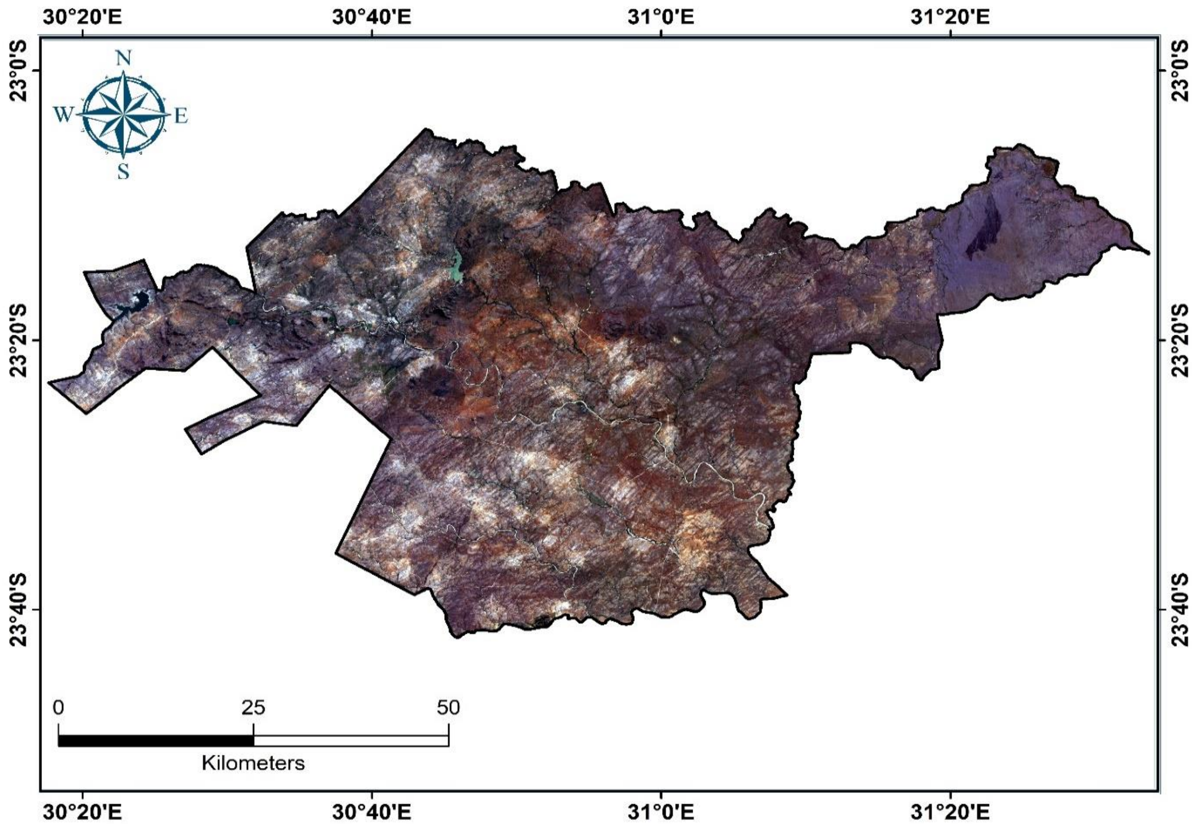

Figure 7: True Colour Composite image (TCC) of the study area. TCC for each year was created and used to gather training dataset of LULC

Regions of interest (ROIs) for GGM were constructed and retrieved from the true colour image for four LULC categories (Bare Land, Vegetation, Waterbody, and Built-up) to be utilized as training dataset for subsequent supervised classification using the Minimum Distance Classifier (MDC). The MDC takes the mean vectors of each training class and computes the Euclidean distance between each unknown pixel and the mean vector for that class (Disperati and Virdis, 2015). MDC is computationally simple and faster. It only requires the mean vectors for each band from the training data. Pixels in this method are assigned to the class that is spectrally closer to the sample mean. All pixels are classified to the nearest class; Table 4 shows the description of training classes used for supervised classification. However, before classification, the extracted ROIs were checked for homogeneity and separability with N-D Visualizer, which is required for proper LULC mapping (Cabral and Costa, 2017). N-D Visualizer investigates ROI separability by examining the distribution of points within each ROI and looks for overlap between land cover classes (Figure 8).

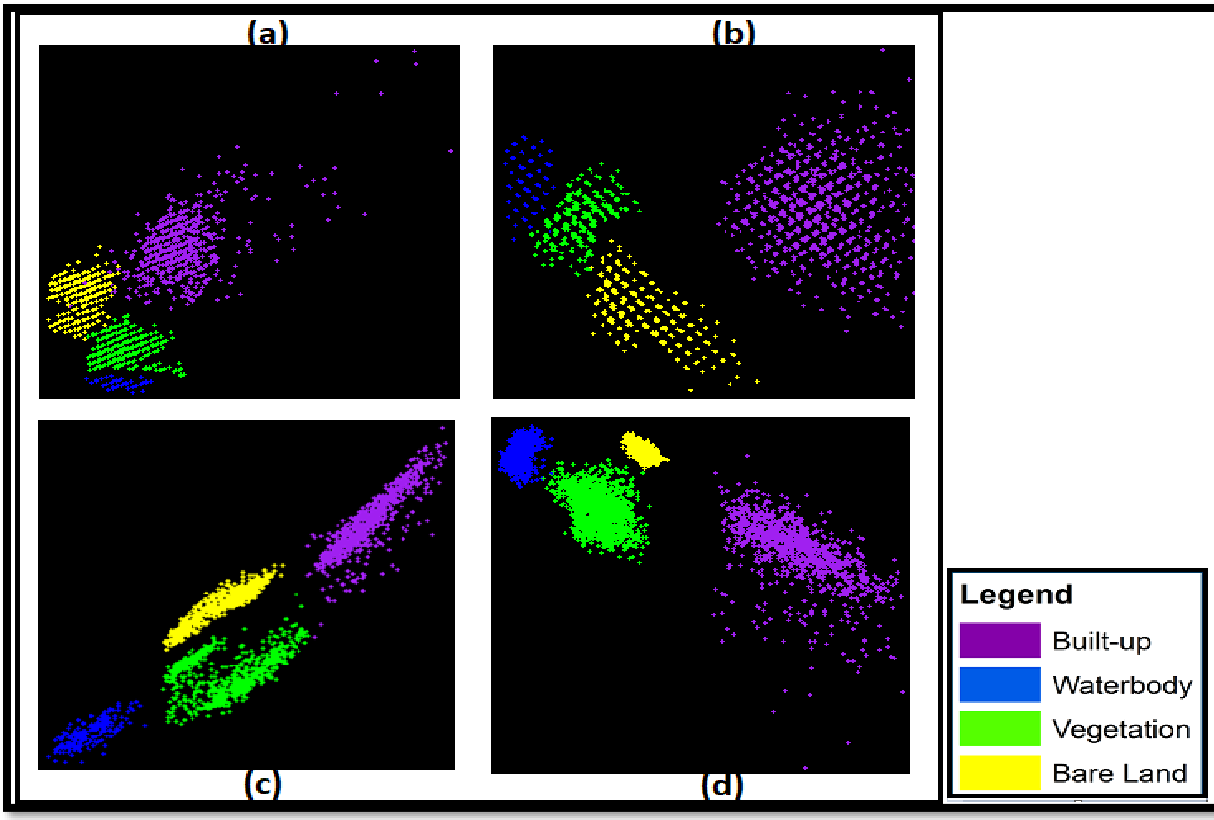

Figure 8: Training class separability images of (a) 2000, (b) 2007, (c) 2014 and (d) 2020.

The points within ROIs for every land cover type should cluster together and not extensively overlap to other land cover types. To report land cover separability, ENVI software uses Jeffries-Matusita and transform divergence separability measurements. The separability values, which range from 0 to 2, reflect how effectively the ROIs separate. Values greater than 1.8 imply that the ROI pairs are excellent separable (Cabral and Costa, 2017). All ROIs used as training datasets produced excellent separability of greater than 1.8 (Appendix 3).

3.5.2 Accuracy assessment technique

Any LC classification map created from remotely sensed images must include an accuracy assessment (Kamwi et al. 2015). To determine accuracy, the number of sample units assigned to each land cover class is compared to the validation data, also known as reference data or ground truth data. Field visits or the analysis of photos, images, or maps can be used to acquire validation data (Muavhi, 2020). This approach can be used to calculate the percentage of pixels from each class in the image that were successfully tagged by the classification algorithm, as well as the percentage of pixels from each class that were incorrectly labelled into each other (Ibrahim-Bathis et al. 2015). The data are tabulated to create a confusion matrix, which is subsequently subjected to various statistical analysis. The total number of pixels properly identified for all ground truth classes is divided by the total number of pixels in all ground truth classes to get the overall accuracy (OA). This can be computed as follows:

$$\mathrm{OA}\ (\%) = \mathrm{Nc}/\mathrm{Nt}$$

Where Nc is the number of correctly identified ground truth pixels, and Nt is the total number of ground truth pixels. The Kappa coefficient (K) is another accuracy metric that measures the difference between observed agreement between training, validation data and agreement that occurs by chance alone (Muavhi, 2020). Kappa coefficient can be mathematically expressed as follows:

$$\mathrm{K} = \frac{\mathrm{Po} - \mathrm{Pc}}{1 - \mathrm{Pc}}$$

Where Po is the proportion of pixels that agree, and Pc denotes the fraction of pixels that agree by chance. The Kappa coefficient may provide better classification accuracy than would be expected from random class assignment. The Kappa coefficient ranges from 0 to 1 (Ibrahim-Bathis et al. 2015). The K value exceeding 0.80 represents good classification (Muavhi, 2020). Individual class accuracy can also be estimated using producer's accuracy (PA), user's accuracy (UA), commission error (CE), and omission error (OE) in addition to the OA and K. The ratio of correctly classified ground truth pixels in a class to the total number of ground truth pixels in that class is known as PA (Kamwi et al. 2015). The accuracy of a producer's classification is a measure of how successfully a certain land cover has been classified. This can be mathematically expressed as:

$$\mathrm{PA}\ (\%) = \mathrm{Cc}/\mathrm{Ct}$$

Where Cc is the number of correctly classified ground truth pixels in a class, and Ct represents the total number of ground truth pixels in a class. UA is the ratio of correctly classified ground truth pixels for a class to the total number of pixels categorized as belonging to that class, and it is a measure of the map's precision and dependability (Disperati and Virdis, 2015). This measurement is critical because it tells the user how well the map resembles reality on the ground, and hence affects the level of confidence that can be placed in the map (Muavhi, 2020). The user's accuracy can be computed as follows:

$$\mathrm{UA}\ (\%) = \mathrm{Cc}/\mathrm{Tc}$$

Where Cc is the number of correctly classified ground truth pixels in a class, and Tc is the total number of ground truth pixels classified in that class. Calculating the misclassification errors is another approach of reporting the accuracies of individual classes (CE and OE). CE denotes ground truth pixels that belong to another class but have been labelled as belonging to the class of interest, whereas OE denotes ground truth pixels that belong to a certain class but have been misclassified by the method (Cabral and Costa, 2017). These two parameters can be computed as follows:

$$\mathrm{CE}\ (\%) = 1 - \mathrm{UA}$$

$$\mathrm{OE}\ (\%) = 1 - \mathrm{PA}$$

In this study, LC validation datasets (ground truth pixels) for multiple years (2000, 2007, 2014, and 2020) were acquired using Google Earth images corresponding to Landsat image acquisition dates. The Google Earth platform offers the advantage of allowing users to go back in time and zoom in on specific regions of interest at high spatial resolution, which is important for accurate mapping (Muavhi, 2020). ROIs of the four LULC classes were generated in Google Earth and transformed into vectors, which were then utilized as validation datasets in the ENVI software with the use of a confusion matrix. Validation classes were assessed for separability before the confusion matrix was implemented. Separability values of more than 1.8 were attained in all validation classes (Appendix 4), which represent good class separability in Figure 9 (Bindhu and Narasimhan, 2015).

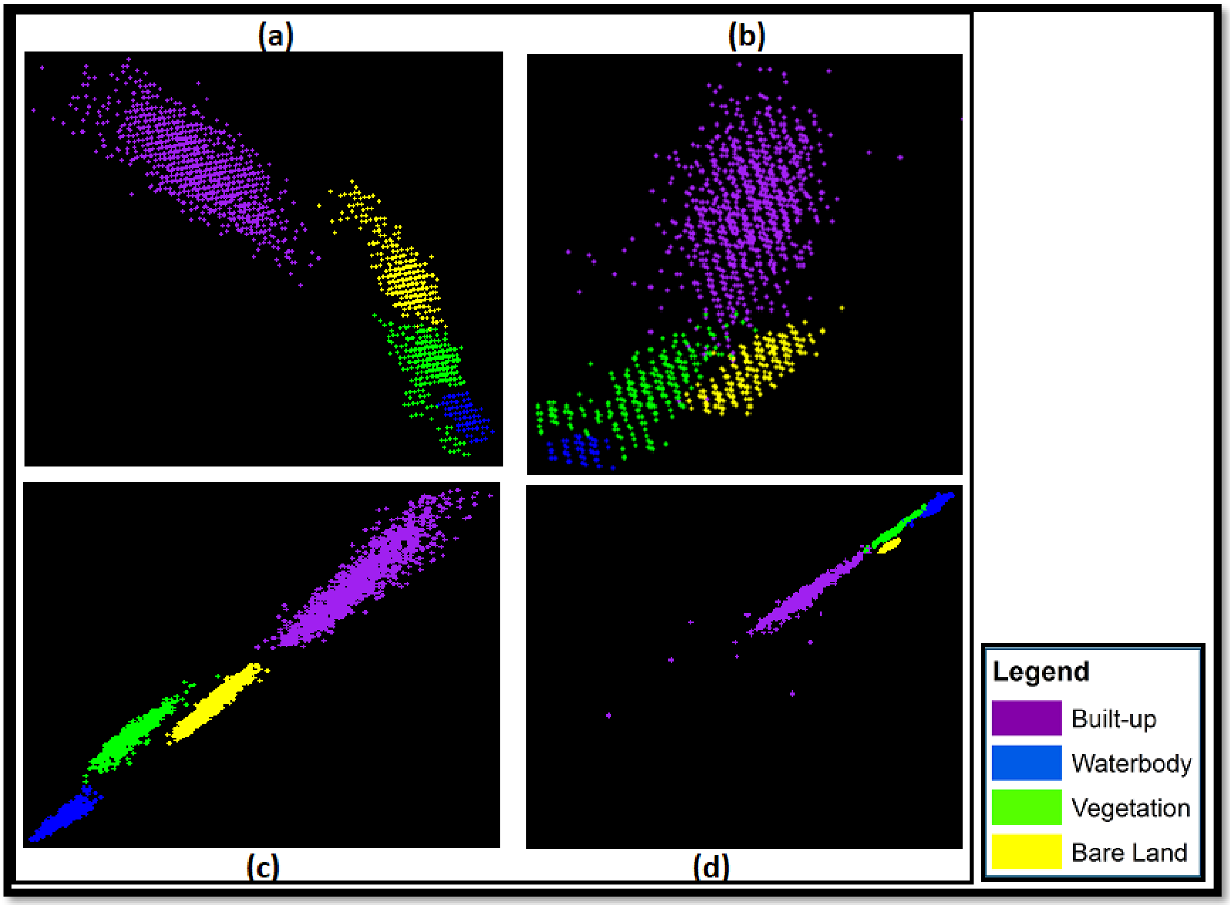

Figure 9: Validation class separability images of (a) 2000, (b) 2007, (c) 2014 and (d) 2020.

3.5.3 Driver-Pressure-State-Impact-Response (DPSIR) Framework

The DPSIR is an analytical framework for organizing reports and illustrating the environmental effects of human activities. The European Environmental Agency created this framework in the 1990s, and it has since been used in environmental research projects to aid planning decisions (Kristensen, 2016). In order to portray various aspects and challenges that developed from interviews and/or document readings, the DPSIR framework (Figure 10) was adopted in showing or assessing LULC changes in the study area.

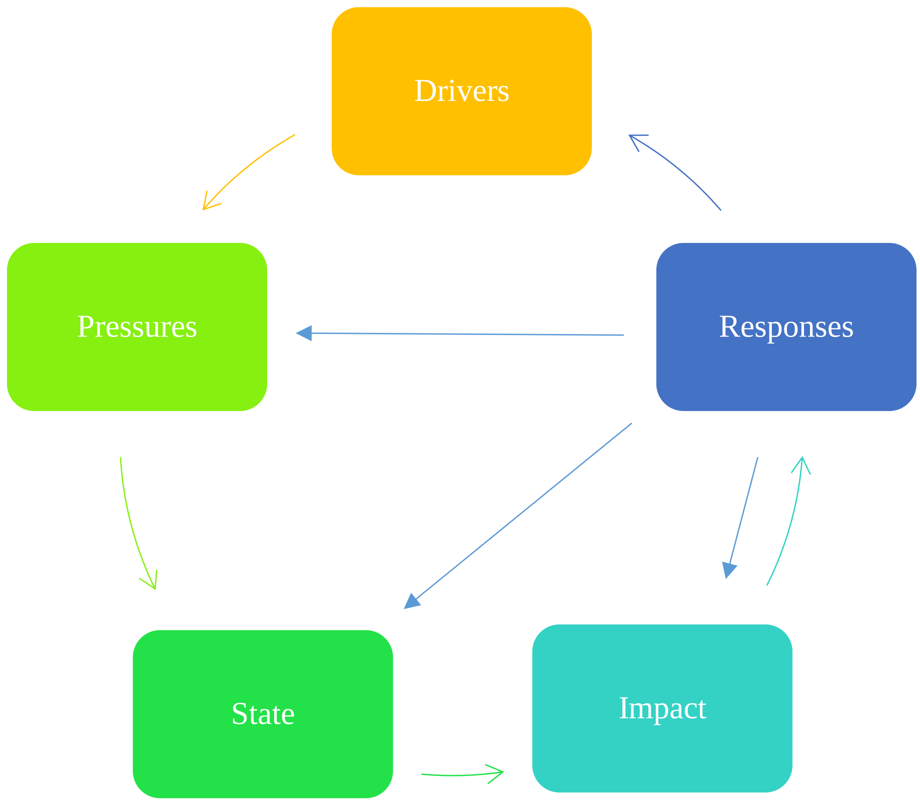

Figure 10: The DPSIR Framework adapted from Gabrielsen and Bosch, 2018.

3.6 Summary

For the study to accomplish its objectives and eventually the main aim, a specific methodology had to be adopted and applied. Thus, primary data was acquired through interviews and secondary data acquired from the internet in the form of legislation, reports, research articles and satellite images from the USGS website. The ENVI 5.0 software was employed to process the satellite imagery, through the application of supervised image classification. The accuracy assessment technique was applied to compare LC classification results to ground referencing data. The DPSIR framework was also employed to describe the interaction between the society and the environment as well as existing legislation.

CHAPTER 4: RESULTS

4.1 Introduction

The results which were obtained from the use of remote sensing, GIS, LC changes and interviews with municipal IDP manger, town planners and document analysis are presented here. The results obtained from LC changes are presented in maps, tables and graphs. These results are presented in four periods indicating the year 2000, 2007, 2014 and 2020 map. The interview results are presented, whereby the main response facts noted are reported based on the interview guide used.

4.2 Description of land cover classes

The researcher utilized ground observation and general historical information gained from participants during the interview, to consider the following major LC classes within GGM (Table 3). Vegetation class includes forest, woodland, forest plantations and cultivated land. Commercially cultivated fields used for crop production. Waterbodies include any form of body that comprises water. This includes dams, canals, lakes, ponds, rivers and man-made water storage facilities. Bare land involves land soil or rock which is not covered by vegetation. This includes non-vegetated gully and donga characteristics that are often associated with considerable natural or man-made erosion along or near stream and flow lines. Built-up areas which are necessary for day-to-day human activities including social, personal and monetory purposes. This includes buildings serving the commercial, industrial, residential and service delivery.

Table 3: LC classes at GGM

LC CLASS	LC INCLUDED	DESCRIPTION
Vegetation	Forest, Woodland, Shrub-land, low fynbos, Grassland, Forest plantations Cultivated land	Natural / semi-natural indigenous forest dominated by tall trees/bush, grass, woodland areas, Planted forestry.
Waterbodies	Permanent water, Seasonal water, Wetlands and man-made waterbodies	Areas of open surface water which can either be natural and man-made.

Bare lands	Bare rock / soil, Degraded land	Non-vegetated donga and gully features
Built-up area	Commercial, Industrial, Residential, Informal, Schools etc.	Areas containing built-up structures, administrative, commercial, transport, health, schools, various residential and recreational fields

4.3 LC Changes of GGM during the period of 2000-2020

4.3.1 LC classification

The spatio-temporal analyses yielded LC maps of 2000, 2007, 2014 and 2020 using the MDC supervised classification algorithm. In the LC classification map of 2000 (Figure 11) vegetation dominated almost every part of the area, followed by bare-land cover. Built-up areas are scattered on the south and north-western part of GGM. Waterbody is the smallest land cover in this area with isolated patches around the central and north-western parts of GGM.

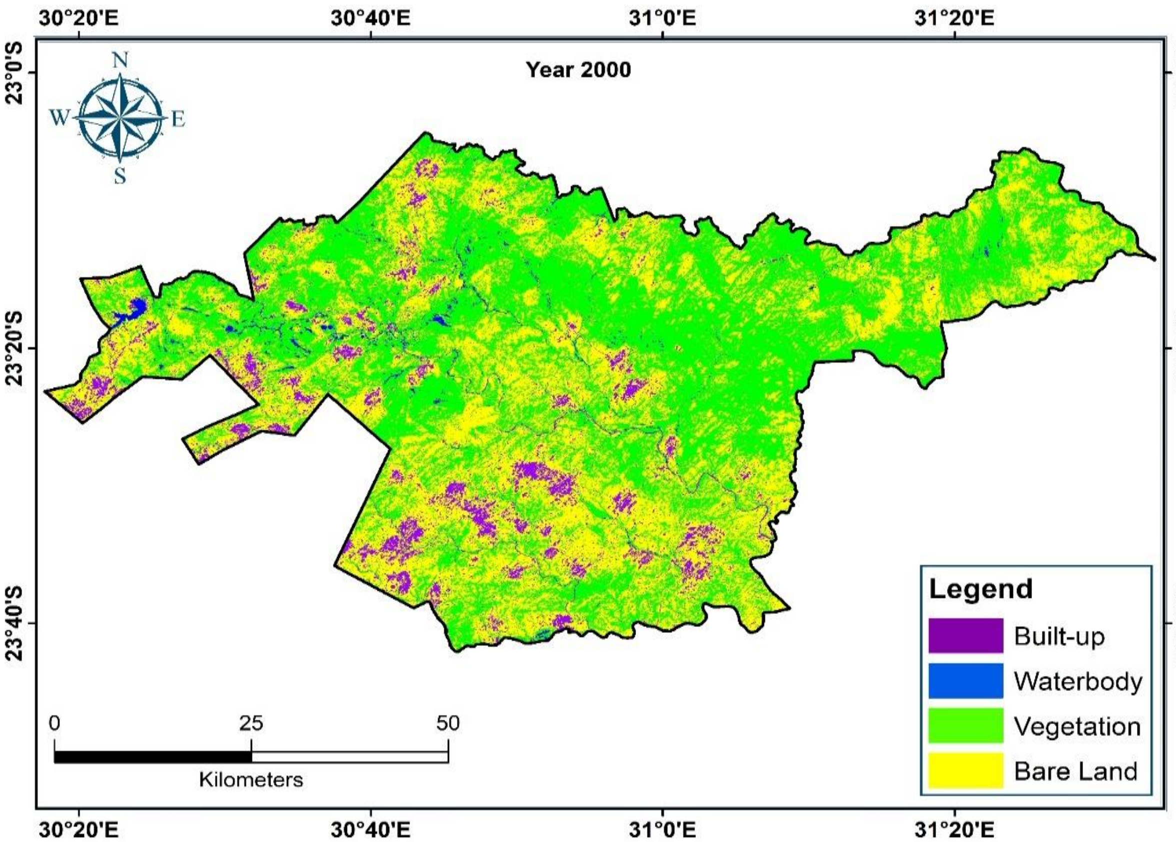

Figure 11: LC classification map of 2000.

In the LC classification map of 2007 (Figure 12), vegetation dominated the eastern area, followed by bare-land cover which covers more land in the southern portion and dominated patches all over the map. Built-up areas are scattered on the south, north-western and small patches over the northern margins of GGM. Waterbody is the smallest land cover on this area with isolated patches around the central, north-western and big portions over western marginal parts of GGM.

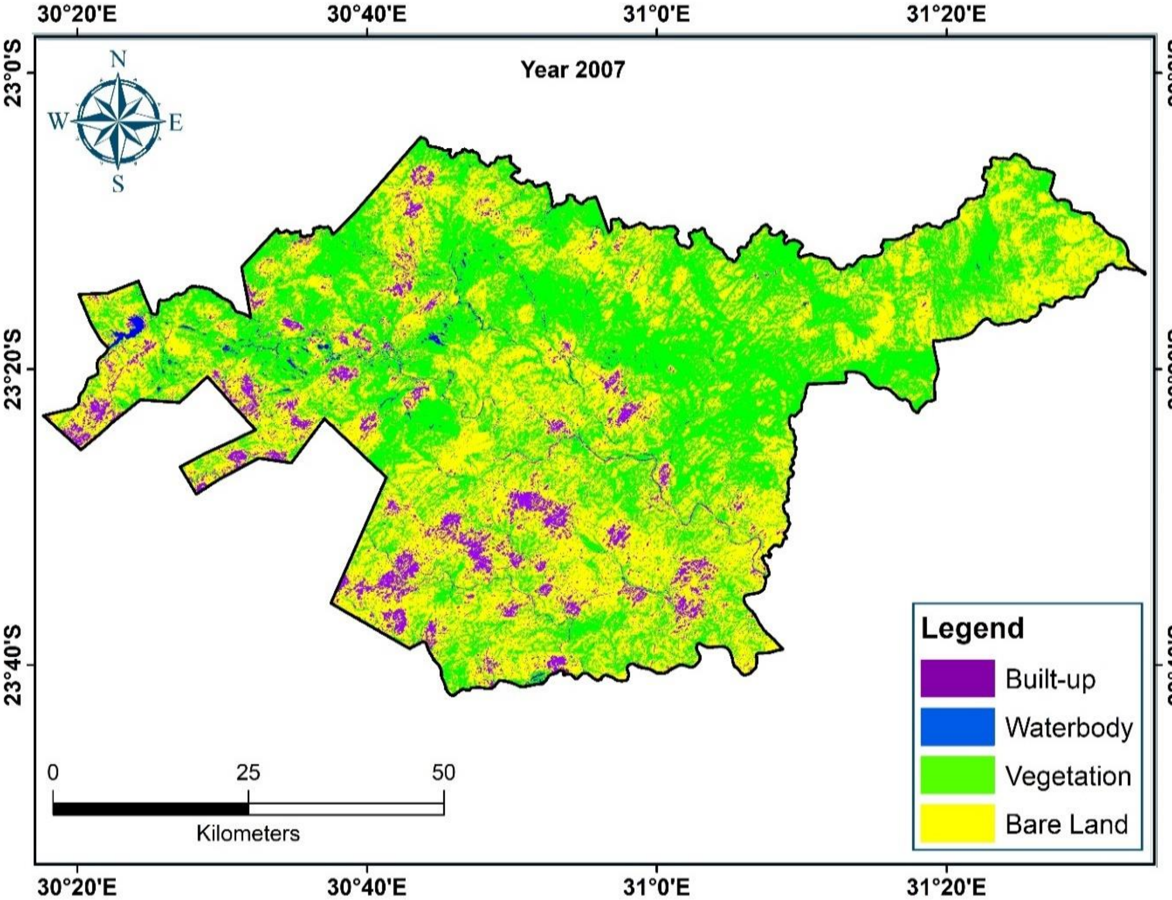

Figure 12: LC classification map of 2007.

In the LC classification map of 2014 (Figure 13), Bare land dominates almost part of the area with more domination on the eastern part of the area, followed by vegetation cover which is less dominating yet partially scattered on the central, north-margins and the western part. Built-up areas are scattered throughout the map. Waterbody is the smallest land cover on the area, with little isolated patches on the central and north-western part of the map.

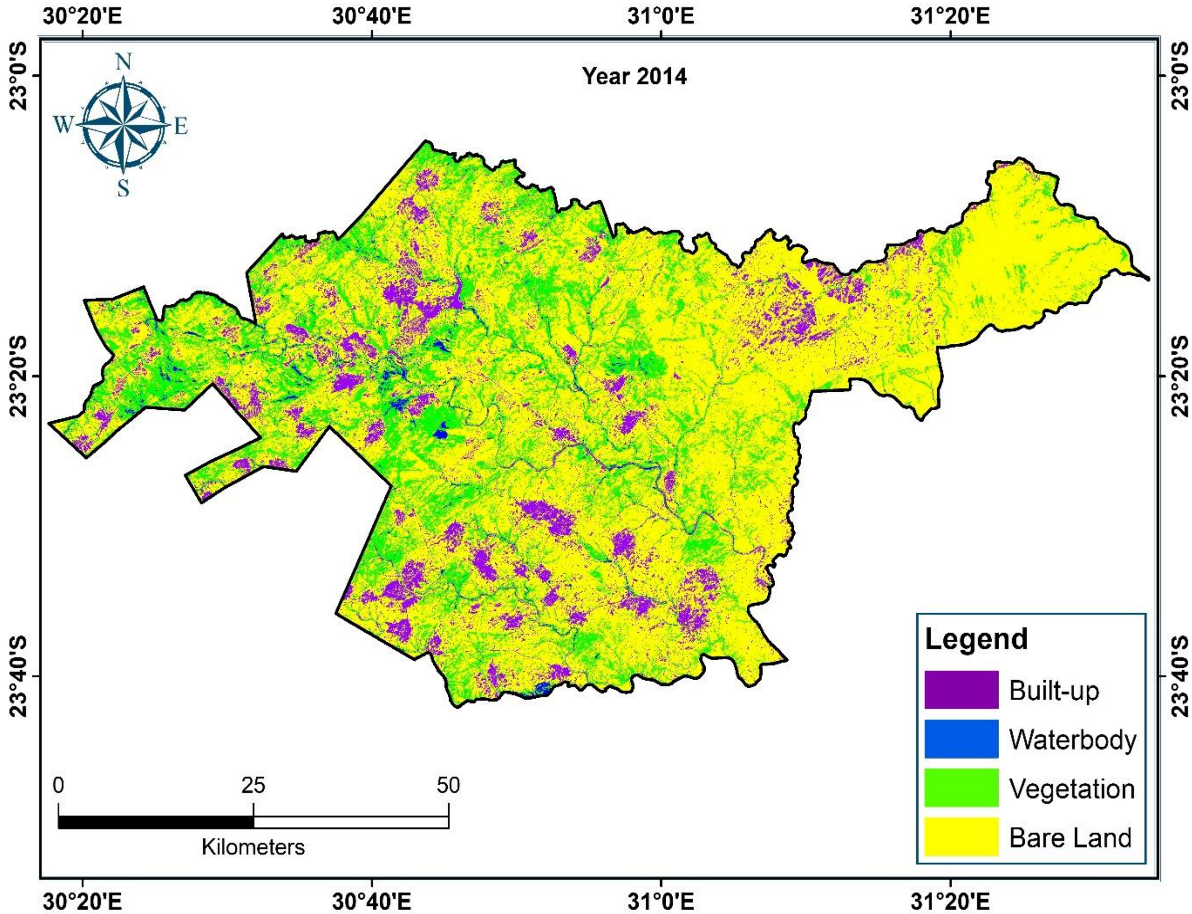

Figure 13: LC classification map of 2014

In the LC classification map of 2020 (Figure 14), Bare land dominates almost part of the area with more domination on the eastern part of the area, followed by vegetation cover which is less dominant on the central, north-margins, south and the western part with little display on the eastern part. Build up areas are scattered domination throughout the map. Waterbody is the smallest land cover on the area, with little isolated patches on the central and north-western part of the map.

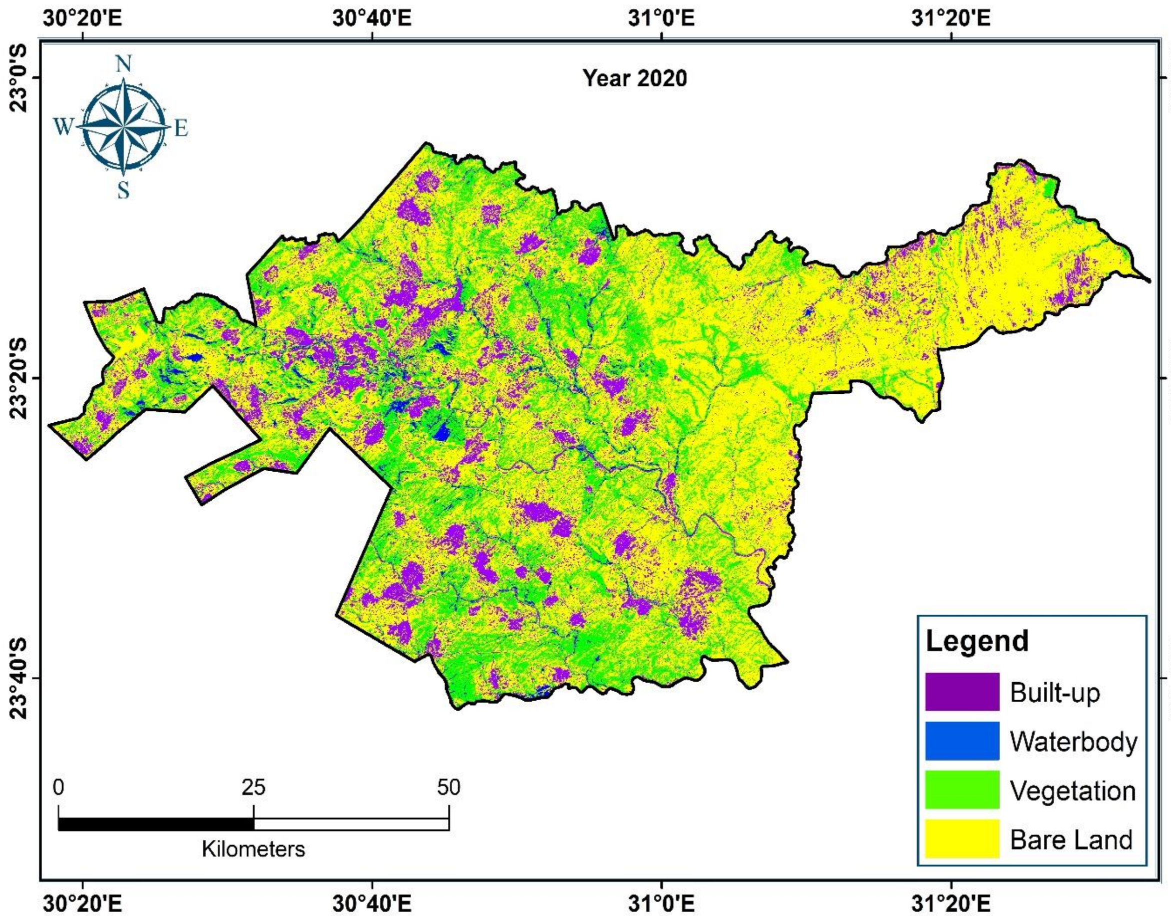

Figure 14: LC classification map of 2020.

The area coverage of LC types in each map was calculated (Table 4). The percentage of bare land area shows an increase throughout the study period, vegetation area decreasing between the years 2000-2014 with sharp decrease between the periods 2007-2014. The vegetation area slightly increases between the periods of 2014-2020. Built-up area is increasing throughout the study period. Waterbodies contribute a small percentage to the study area. These land covers fluctuate throughout the study period, with the lowest percentage in 2007 and highest in 2020.

Table 4: LC area coverage over the study period

LULC (Area)	Year 2000	Year 2007	Year 2014	Year 2020
Bare Land (%)	44.98	50.83	69.83	61.06
Vegetation (%)	48.10	42.13	19.54	23.36

Waterbody (%)	1.32	1.01	1.39	2.49
Built-up (%)	5.61	6.03	9.24	13.08

The spatiotemporal process was used to describe the integral change within GGM. This process shows the transition from one state to another in a change. Figure 15 comprises data from the four LC maps of GGM, and it was projected based on the results from Table 4 Which shows how the LC had changed in terms of percentage pertaining to the research study area years of interest.

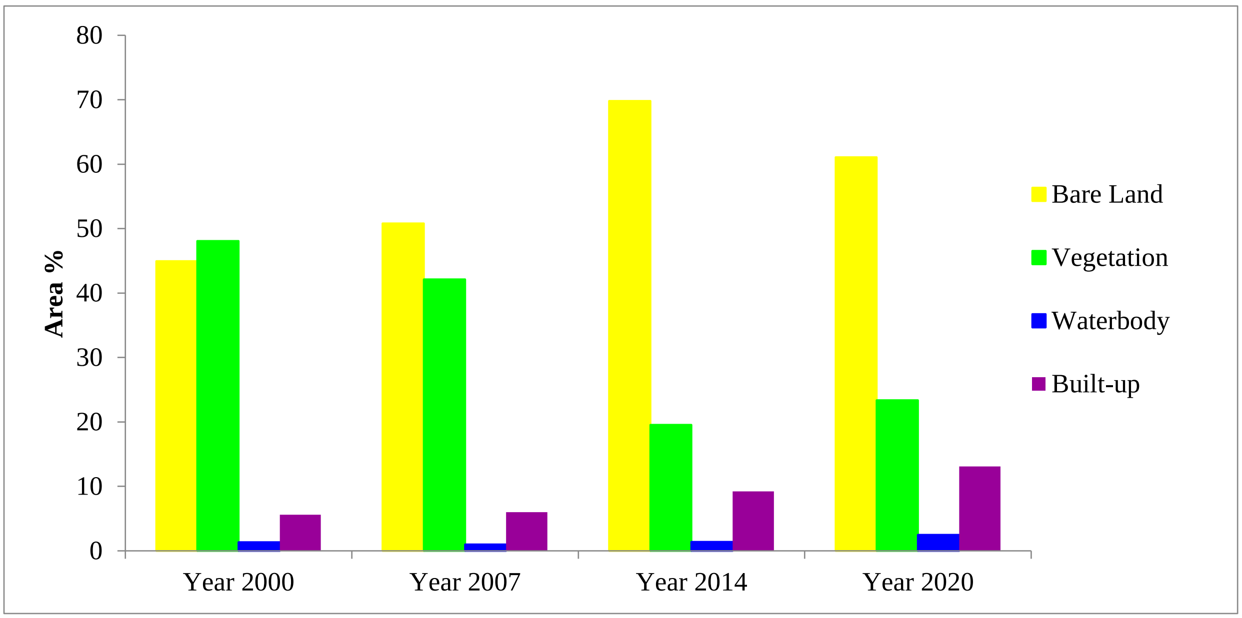

Figure 15: Area percentage of LC over the study period

In GGM, the vegetation as land cover under the investigated period covers different percentage, with 48.10%, for the year 2000, 42.13% for 2007, 19.54% for 2014 and 23.4% for 2020. The classification results indicate that there is a change in the vegetation cover with a decrease of 5.96% between 2000-2007, 22.58 % decrease between the period of 2007-2014, and slight increase of 3.82% between 2017 and 2020. Despite the periodic variations in change of vegetation, the overall rate of change during the whole period of analysis (2000-2020) is found to be 1.24% per annum, which resulted in a net decrease.

The built-up level in the GGM shows an increase, with slight increase from one period to another. In the 2000-2007 periods there was an increase of 0.42%. For the second period of the study which is 2007-2014, the level of built-up area continues to increase at 3.22% which is seven (7) times higher than the 2000-2007 period. The LC map for 2007 and 2014 shows a drastic increase of built-up areas in almost all spheres of the GGM. LC maps for the 2007-2014 periods indicate an alarming rate of built-up area on the north-western and south-western parts of GGM; this is the heartbeat or the central economic location of GGM. LC map for the 2014-2020 period shows steady increase of built-up by 3.84%, which is a similar trend compared to the 2007-2014 period. The bare land and vegetation proportion in the study period of 2000-2020 shows a significant relationship. During the period of 2000-2007 bare land increased by 5.85%, 2007-2014 period indicates a drastic increase of 18.99% and a decrease of 8.77% for 2014-2020 period. As discussed above on the vegetation trend, the bare land is inversely proportional to the vegetation cover within the GGM Waterbodies on LC map for 2000 covers 1.32%, 2007 covers 1.01%, 2014 covers 1.39% and great increase to 2.5% for 2020.

4.3.2 Accuracy assessment results

The accuracy assessment for the period of 2000, indicated that bare land and vegetation achieved lowest producer's accuracy (PA) and user's accuracy (UA), respectively, thus implying that some of the ground truth pixels belonging to either bare land or vegetation were misclassified as indicated by high commission error (CE) and omission error (OM). In 2007, it was vice versa. Vegetation produced lowest UA, while bare land attained lowest PA. The accuracy assessment for the period of 2014 and 2020 indicates that Vegetation produced lowest UA, while bare land attained lowest PA. In general, the pairs of these LC classes show relatively low, although acceptable, separability values compared to other pairs of LC types (Appendix 3 and Appendix 4). Most algorithms performed poorly when it came to classifying spatially overlapping land cover classes without any sharp boundaries. Nonetheless, all maps achieved an overall accuracy (AO) and a Kappa coefficient (K) of more than 80% and 0.8, respectively, indicating excellent classification. The LC validation data were obtained using the Google Earth platform and then utilized to assess the accuracies of the resulting maps using a confusion matrix. The calculated accuracies of the maps are shown in Figure 16.

Overall Accuracy = (3698/3847) 96.1269%
Kappa Coefficient = 0.9470

Ground Truth (Pixels)

Class	Vegetation	Bare land	Waterbody	Built-up	Total
Unclassified	0	0	0	0	0
Vegetation	947	0	0	13	960
Bare land	0	1101	0	89	1190
Waterbody	47	0	488	0	535
Built-up	0	0	0	1162	1162
Total	994	1101	488	1264	3847

Ground Truth (Percent)

Class	Vegetation	Bare land	Waterbody	Built-up	Total
Unclassified	0.00	0.00	0.00	0.00	0.00
Vegetation	95.27	0.00	0.00	1.03	24.95
Bare land	0.00	100.00	0.00	7.04	30.93
Waterbody	4.73	0.00	100.00	0.00	13.91
Built-up	0.00	0.00	0.00	91.93	30.21
Total	100.00	100.00	100.00	100.00	100.00

Class	Commission (Percent)	Omission (Percent)	Commission (Pixels)	Omission (Pixels)
Vegetation	1.35	4.73	13/960	47/994
Bare land	7.48	0.00	89/1190	0/1101
Waterbody	8.79	0.00	47/535	0/488
Built-up	0.00	8.07	0/1162	102/1264

Class	Prod. Acc. (Percent)	User Acc. (Percent)	Prod. Acc. (Pixels)	User Acc. (Pixels)
Vegetation	95.27	98.65	947/994	947/960
Bare land	100.00	92.52	1101/1101	1101/1190
Waterbody	100.00	91.21	488/488	488/535
Built-up	91.93	100.00	1162/1264	1162/1162

Figure 16: Accuracy assessment measurements of LC map of 2014

4.4 Land classes being threatened in GGM

The most threatened classes include vegetation and waterbodies. Woodland, shrubland and grassland are the most predominant vegetation classes within the study area. The proximate and underlying driving factors are responsible for threatening this class. The waterbodies include permanent, wetland and man-made waterbodies. Thus, the mentioned factors also threaten this class, though this class is found to be less threatened when compared to the harsh changes occurring at the vegetation class throughout the study period.

4.5 The DPSIR framework adaptation for LC change in GGM

The interviews with the GGM officials responsible for planning, development and environmental management were structured to bring out more information on the LC changes, factors responsible for changes, the role played by municipal policies and how the municipality is tackling the challenges that arise from LC changes. Below are the interview responses from one (1) IDP manager and two (2) municipality town planners within the municipality, which are organized into themes and incorporated with the DPSIR framework (Figure 10). The DPSIR framework is used to show how social activities affect LU change. Economic, demographic, and social changes in humanities, as well as lifestyle, consumption, and production patterns, are all drivers. Human activities and processes exert a strain on land resources as a result of these pressures, resulting in a variety of environmental conditions. Changes in the state of the environment have consequences, which are referred to as impacts in the framework.

4.5.1 Driving factors of LC change

The driving factors of LC change in GGM include the underlying and proximate factors (Figure 17). Underlying factors included economic, political, demographic, technological, cultural, and environmental variables, while the proximate factors included infrastructural and agricultural expansion.

Political factors

Legislation and policies for land use planning laws in the GGM is regulated by all three levels of government. National legislation relevant to planning, provincial and municipal policies must be aligned with national legislation and policies. Policies that stimulate or hamper growth have an impact on LU change (Saurab, 2018). The Urban Edge policy, for instance, demarcates the outer limits of urban development by defining the Urban Edge and tribal authority lines. The Urban Edge line is intended to prevent urban expansion or sprawl and protect natural resource boundaries, whereas the tribal authorities' lines are intended to safeguard tribal regions. Such legislation and policies seem not to be operating effectively due to the political powers, and GGM is expanding formlessly since policies are not adhered to by the people (Suma et al. 2021).

Economic factors

The economic development of the Limpopo, particularly GGM, has strong links with agriculture, livestock production, building materials production, e.g., tourism and shopping centres sectors, which the government intends to prioritize (Greater Giyani Municipality IDP, 2019 - 2020). The rationale behind this is that high potential sectors promote job creation and inclusive growth therefore resources can be channelled towards them instead of focusing on all sectors (Ashebir and Muluneh, 2018). This agrees with the Greater Giyani municipal Strategic goal of creating opportunities for growth and jobs leading to more establishments of projects for development and economic purposes like business (Greater Giyani Municipality IDP, 2019 - 2020).

Demographic factors

The GGM is one of South Africa's fastest-growing municipalities, with a rapidly growing population. Natural population growth is accompanied by influx of people from other regions via international, internal, and temporary circular migration. It is estimated the region experienced internal migration at over 10 000 people between 2000 and 2020 (Greater Giyani Municipality IDP, 2019 - 2020). Internal migration involves residents from neighbouring local municipalities such as Vhembe, Capricorn, Tzaneen, and Ba-Phalaborwa, and is motivated by perceptions of greater employment possibilities, better housing, education, and other amenities. The town of Giyani is home to more than half of the municipality's population and economic growth. External migration to GGM involves people from neighbouring countries such as Zimbabwe, Mozambique, Malawi, and Somalia, which leads to the growth of informal settlements with rampant crime, poverty, and a lack of basic amenities (Greater Giyani Municipality IDP, 2019 - 2020).

Environmental factors

Droughts, heat waves, and floods are common in the GGM, indicating the impact of climate change (Greater Giyani Municipality IDP, 2019 - 2020). The impact of climate change presents a challenge to the agricultural sector, both commercial and subsistence, which must raise food production to meet rising demand (Bakker et al. 2019). Water supply in the GGM is the most difficult element affecting agricultural productivity. Reduced crop yield, low earnings, and farm conversions to other land uses have all been attributed to the decrease in rainfall. Climate change has a negative influence on agriculture, as well as other industries that rely on agriculture for crucial inputs (Barbier and Hochard, 2016). Furthermore, the municipality's extremely hot and dry climate produces fires, which contribute to the destruction of vegetation.

Technological factors

Environmental factors discussed above have resulted in a drop in the number of farms producing crops and livestock, as well as farm unit consolidation to achieve economies of scale (Gibson et al. 2015). The consolidation of farms implies less reliance on labour and increased mechanization which results in job losses. Farm worker concerns have been noted in Limpopo's agricultural rural districts, particularly Tzaneen, Giyani, and Vhembe, as a result of employment losses caused by mechanization (Greater Giyani Municipality IDP, 2019 - 2020). These job losses gave rise to individual farm plots on subsistence basis since most inhabitants had acquired skills and knowledge in agricultural activities while still working on those farms prior to job losses.

Cultural factors

Cultural elements are concerned with people's views and attitudes toward land usage (Gibson et al. 2015). LU decisions in the GGM are made by the mayor's office, council, institutions, developers, and politicians, with little participation from the public. Most of the land is controlled by the tribal authorities and at their own will, without the municipal approval do whatever pleases them. The land is given to people for free and less cost with the believe that all people related to tribal authorities must have a piece of land as the sign of wealth, especially if this land is leading to proximity of Giyani town and the surrounding neighbourhoods or villages (Greater Giyani Municipality IDP, 2019 - 2020).

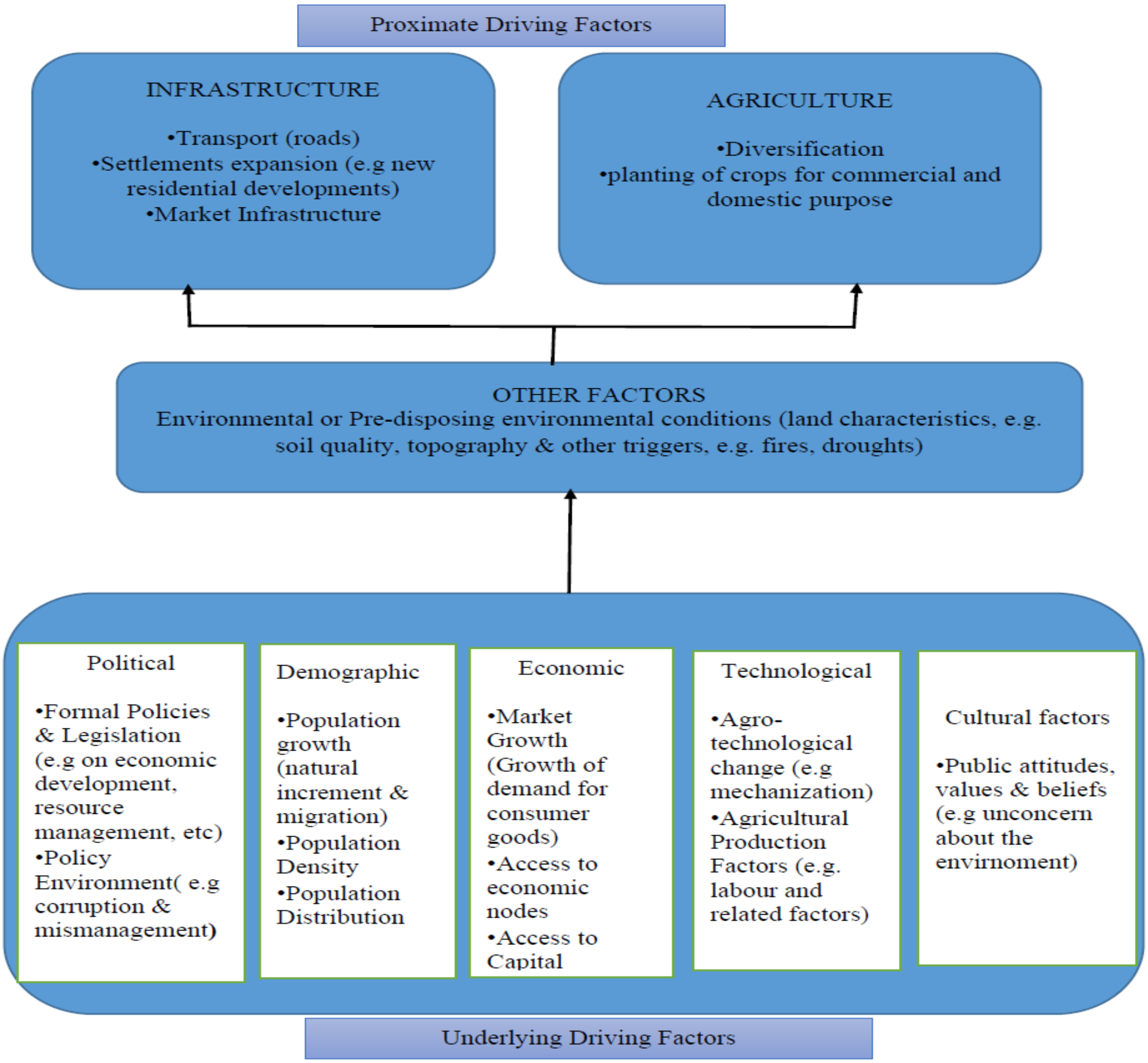

Figure 17: Driving factors of LC change in the Greater Giyani Municipality

4.5.2 Pressures

Human activities that put strain on land resources are influenced by economic, demographic, political, environmental, technological, and cultural factors. The most significant pressures arise from sectors with high economic development opportunities, such as Giyani town, which is the only town that serves the GGM population, Risinga view, which is located west of Giyani town, Xikukwani on the north margins and open land surrounding to GGM's main central place, and along the main permanent river, Klien Letaba, which is located in the south-western part of GGM.

Agriculture, residential areas, tourism, infrastructure, and the building industry have been recognized as sectors that interact with other connected sectors and promote LC change (Greater Giyani Municipality IDP, 2019 - 2020). Agriculture pressure is exerted in the form of land, water availability, and chemicals. All of the aforementioned sectors attract both inter-provincial and circular temporary migrants inside the province and neighbouring countries, putting pressure on transportation, housing, and services (Willy, 2009). Growth pressures in the municipality are also influenced by big investment on the building of shopping centres, taxi ranks, and building hardware's, rental and estate houses. Examples are Masingita group of company's malls, more than five building material hardware's which were built in a space of 3 years. Apart from the biggest mall built at GGM, there are more than three (3) shopping centres built around town found within one kilometre's radius (Greater Giyani Municipality IDP, 2019 - 2020).

4.5.3 State or Quality of land cover

The status of land in the GGM is affected by LC change factors along with resource pressure. The majority of LC changes and their consequences occur in the residential development, agricultural, and infrastructure sectors (Greater Giyani Municipality IDP, 2019 - 2020). The majority of land in the GGM is used for residential development. and past trends indicate an increase in new building plots in Giyani with a contrasting increase in residential areas in villages found on the periphery of Giyani town. The increase in agriculture is attributable to the availability of land and water along the main rivers, which flow all year. The increase in job and business opportunities has increased demand for residential, transportation, and other infrastructure, especially in areas near the town whereby developments such as shopping malls, guest houses, residential accommodation, and other land use play a role in the economy (Greater Giyani Municipality IDP, 2019 - 2020).

4.5.4 Impacts

The change in state of land usage within the municipality has both beneficial and bad implications. Agriculture as the dominating primary sector, among other things, supports food security, employment development, economic stability, and inputs to other businesses. On the other side poor farming techniques, overgrazing, and land clearing is causing a great erosion and soil degradation in most parts of the area leading to bare (Van Wyk, 2018). Water shortages and decreasing farming productivity have resulted in a drop in production as farmers turn to nonagricultural activities to sustain their needs. Job losses have resulted from the conversion of plantations to other land uses, and fires have been fueled by dry trees after clear-cutting, resulting in loss of biodiversity (Greater Giyani Municipality IDP, 2019 - 2020).

The view of the GGM as a better and improving municipality in relation to employment, development, and access to basic services has resulted in in-migration, putting a strain on transportation, accommodation, and other important infrastructure. As a result, there is more traffic, crime, unplanned settlements, yard housing, urban expansion, infrastructure development, and other environmental issues. Pressure from the infrastructure development business has led to numerous developments adjacent to the main roads like R81 within GGM and road improvements to improve connectivity between localities (Greater Giyani Municipality IDP, 2019 - 2020).

The construction of new commercial facilities, such as malls and hardware stores, as well as the continued supply of new building plots in areas close to the town, is projected to bring employment, diverse economic prospects, and development. However, quick changes to the ecosystem have put a pressure on the environment by means of economic service upgrade, expansion, and decentralization also result in land cover change. New roads, sewage works, power lines, and other infrastructure are among the various repercussions of infrastructural and residential growth.

4.5.5 Response by human

The municipality and its stakeholders are doing the most out of the worrying situation of LC changes by adopting and implementing policies and procedures that are proved to be effective in another municipality. The municipal policies are reviewed more often with the report on how the LC changes are taking place. Policy laws and legislations are playing their role in keeping the LC in a better state for the benefit of sustainable ways. The municipality has enforced the effectiveness of the policy laws by introducing a task team which deals with the ongoing monitoring of the LC changes (Greater Giyani Municipality IDP, 2019 - 2020). The adoption and implementation policies like LU legislation, environmental policies, ongoing monitoring projects and making public awareness programs on the importance of sustaining LC.

CHAPTER 5: DISCUSSION

5.1 Spatiotemporal analysis of LULC classification changes

Many researchers across the world are increasingly recognizing changes in LULC of any environment at the spatiotemporal scale as a major cause of environmental change. As a result, this has become a serious concern for natural resource management and monitoring (Maree and Van Weele, 2018; Matlhodi et al. 2019; Muavhi, 2020). The LC classification results from this study indicated that there were LC changes within the period of investigation (2000-2020). The major changes were characterized by decline in vegetation cover throughout the first 14 years (2000-2014), and a small increase in the last six-year (2014-2020). In contrast, built up area and bare land classes displayed an increase throughout the study area. On the other hand, waterbodies displayed a decrease between the first 7-year interval (2000-2007) and increase in the last two 7-year intervals (2007-2014 -2020).

The overall rate of change in vegetation cover level during the whole period of analysis (2000-2020) is found to be 1.24% per annum. There are many motives that led to the decline in the level of vegetation cover. Vegetation decline was the result of increase in cultivation or farming practice since more vegetation cover is cleared for crops plantation, leading to sparse vegetation cover after harvesting and winter seasons, residential expansion, urban development projects and vegetation clearance for domestic use or profit purposes like fuel wood. Vegetation decrease level between the period of 2000-2007 was experienced in the south and south-west of the GGM. These changes were more practiced along the major transport route connecting GGM and Ba-Phalaborwa municipalities (mining specialized municipality) because inhabitants believed that practicing business along major routes gives economic advantages since such main routes have a high volume of users. More crop farming, fuel wood production and new residential plots were the common practice that led to more vegetation removal or clearance. These findings are comparable to those found elsewhere, where rural populations' activities such as commercial and subsistence agricultural practices resulted in a decline in vegetation cover and wetlands (Peter et al. 2015; Govindaraj et al. 2017; Matlhodi et al. 2019; Muavhi, 2020).

Furthermore, soil fertility and water availability along the main GGM Rivers named Klein Letaba and Nsama which are located in the southern and northern parts of Giyani respectively also made a great contribution to the decrease in the vegetation level since more farming has been practiced along these main water sources, more vegetation cover is deforested. More than 60% of the fruits and vegetables sold within the municipality (Giyani town), are locally grown here (GGM, IDP 2020). Another source leading to the decrease in the level of vegetation is the increase in livestock population as a result of overgrazing the fields. GGM is classified as a municipality serving 90% of the rural living population, where people living in these villages still believe in their traditional customs that having more livestock symbolizes power and wealth (GGM, IDP 2020). During pasture shortage, livestock (cows, donkeys, sheep and goats) contribute to the loss of vegetation as they consume almost every available vegetation to maintain their daily diets, hence leading to permanent vegetation loss and bare soil or land exposure. Overgrazing has a negative influence on the vegetation cover, which allows erosion and compaction of the soil due to wind and erosion, according to DEAT (2020). This lowers the ability of plants to develop and water to penetrate the soil, harming soil microorganisms and causing major land erosion.

Natural factors are also playing a role in the loss of vegetation cover which include unreliable rainfall, land degradation and soil moisture stress that puts much strain on the vegetation. The period of year 2007-2014 is marked as one of the prolonged periods of rainfall shortage across Limpopo province. As a result, more vegetation was lost, together with the crops in the farming plots leading to low production and low income (GGM, IDP 2020). Vegetation level increased at a lower rate between the years 2014-2020, this was because of the sufficient rainfall experienced between the year 2018- early 2020 (GGM, IDP 2020). Furthermore, a recent study by Matlhodi et al. (2019) discovered that local communities believed the LC changes occurred in the Gaborone dam catchment, which had impacts for their livelihoods and food production due to a prolonged dry spell. Some of the consequences included decreased nutrient absorption by vegetation, increasing soil temperatures, disturbed microbial activity, and changes in organic matter breakdown.

The level of built-up area displayed an increase throughout the study periods of the year 2000-2020. The LC classification maps show that the whole municipality experienced the building development or expansion, from all directions. As for the other land cover classes like vegetation and bare land, they displayed an inverse proportional trend, since the vegetation decrease translated to bare land increasing.

The classified LC maps for the year 2000-2007 indicated that this increase is more based along the main major transport route converging from south and west of Giyani. The northern and eastern part of Giyani town does not show much of the changes because the building density remained the same; with more building-up expansion introduced to the areas like Ngove and Dzumeri tribal authorities in the western part of Giyani. The built-up area indicated an increase near main routes to Giyani town along the R81 route from Polokwane city, R529 from Tzaneen town and R578 from Luis-Trichadt all converging to GGM town. For the second period of the study which is 2007-2014, the level of built-up area continues to increase at 3.22% which is seven times higher than the 2000-2007 periods.

The LC map for 2007 and 2014 shows a drastic increase of built-up areas in almost all spheres of the GGM. These trends were lifted by the big investments made by Masingita Group of companies, Vahlavi Group, and unknown individuals who invested heavily on the property and infrastructure at GGM due to the development programs like allocation of more land for residential purposes around the villages proximal to the Giyani town. Another cause of increase in built up area is the global well known soccer tournament organised by Federation Internationale de Football association (FIFA), that was hosted by South Africa in 2010. These hosting rights motivated more people to engage themselves in development with the hope of higher returns or profit since Limpopo province was chosen to host some of the games and pre-match training at Peter Mokaba stadium and Giyani stadium respectively. LC classification map for the 2007-2014 period indicates an increase of built-up area on the north-western and south-western parts of GGM, this is the heartbeat or the central economic location of GGM. Masingita Group of companies invested in building the biggest shopping centre (mall) in GGM, which had put a lot of strain and stress on the environment since more vegetation and waterbodies were cleared (GGM, IDP 2020).

The infrastructure development for tourism hospitality especially towards this global soccer event resulted in more houses and entertainment places being introduced to GGM. Rental houses, guest houses, picnic sites and more land plots near main routes or accessible sites were built with a perception of monetary returns and investment after the major soccer tournament. Data from the municipal officials indicate that, for the 2007-2014 periods, the municipality registered 32 guest houses, 21 picnic sites, and seven new shopping plazas near deep rural areas. Allocation of new residential building plots around GGM main shopping centre resulted in an increase of residential neighbourhoods. The biggest new residential plots include the Risinga, Xikukwane eco-park, Siyandani new lines located in the south, Bode-Dzingi-Dzingi stands, Ndhengeza located in the north, Dzumeri and Ngove Tribal residential area in the western part of Giyani town. Risinga residential area was introduced in the year 2009 located approximately nine kilometres from the Giyani town. This residential area is growing very fast and attracting more working-class people. More municipal reserved areas like Man`ombe game reserve and golf club field are enclosed by this residential area now considered threatened by expansion of residential development. These findings are in accordance with those of Govindaraj et al. (2017) and Mas et al. (2017) who discovered that development projects in the Gomukhi River Basin have resulted in an increase in built-up area (residential). Their studies found that as the amount of bare land increased, the rate of vegetation clearance decreased. Bitelli and Mandanici (2015) and Matlhodi et al. (2019) found similar results in their investigations of the Gaborone dam basin and the Fayyum Oasis, respectively. Their research revealed that vegetation cover declined as a result of increased urbanization and industrialization, which is classed in this study as built-up. LULC classification maps demonstrated that the waterbodies in GGM cover a small portion; this is because the area receives limited rainfall seasonally between September and March (GGM, IDP 2020). Dams and rivers are active only for those rainy periods and become dry a few months after rainfall. Klein Letaba river in the south, Nsama River in the north, middle Letaba dam in the west, Makosha dam in the east and few dams located in commercial farming plots like ZZ2 northern part, Constantia citrus in the west are the only waterbodies which contains water throughout the year (GGM, IDP 2020). Waterbody levels by volumes display fluctuations year after year depending on the amount of rainfall received. The main reason for this low proportion of waterbodies is that Limpopo province receives no or less rainfall during winter (April to August) and the LULC maps were created from imagery taken during winter season (July). Continued changes in the LC, according to Kudakwashe and Mark (2010), Mas et al. (2017), and Willy (2009), have a negative effect on water resources such as wetlands and waterbodies. The findings agree with those of Peter et al. (2015), who found that rivers and dams in Mubi Metropolis dropped by 3% and 11%, respectively, from 2007 to 2013 of rain shortage.

5.2 Driving factors of LC change

To identify the factors that drive LC changes and classes that are under threat in the Greater Giyani municipality, the following procedures were undertaken. The interviews with the municipality officials responsible for planning and adapting of the DPSIR framework. The two steps yielded positive feedback by revealing that GGM LC changes are caused by a diverse interconnected factor. Some changes are brought about by political factors such as legislation and policies aiming at alleviating poverty, increasing access to essential services, eliminating disparities, and supporting economic growth.

The patterns of LC changes in Greater Giyani municipality are dependable on transport routes and water resource nodes for economic growth. The agriculture, tourism and economic development and residential sectors in this municipality attract more individuals in terms of investment and residing, resulting in in-migration from other neighbouring municipalities. As a result of migration and natural population growth, the extent and intensity of pressure placed on resources rises, changing the state of the land.

As proposed by Ashebir and Muluneh (2018) the driving factors of LC change were classified into proximate and underlying causes. Agriculture and Infrastructure expansion were identified as proximal causes based on interviews and document analysis, while economic, political, technological, demographic, and cultural variables were recognized as underlying causes. To better understand these drivers, the DPSIR framework was revised to explain how driving factors result in human actions that exert pressure on the resources, resulting in a variety of environmental states that have major consequences and require responses. To avoid undesirable impacts of changes in LC, strategies and policies based on responses to major drivers of LC and their impacts are recommended. The LC classification analysis, the insights gathered during interviews and the DPSIR framework had played a vital role in identifying the classes which are being threatened. The classes indicate both negative and positive gains, with the trend of inversely proportional relationship. Vegetation is observed as the main negatively threatened class throughout the study, followed by fluctuating positive and negative effects of waterbody. The built-up and bare land class indicate the positive gain while vegetation indicates the reverse trend. The proximate and underlying driving factors are responsible for threatening these classes.

5.3 Proposed possible strategies for LC change challenges in GGM

The study has evaluated the state of LC in GGM, by showing the LC changes and identifying the factors responsible for changes. The results reveal that changes had taken place in the study area, and such LC changes are the result of underlying and proximate factors. Based on the findings of this study, the following recommendations are made:

1. In the state of the ongoing growing farming activities, it will be important to build and strengthen non-farm/off-farm income-generating businesses due to agriculture's inadequate capacity to protect the land and ecosystem.
2. To counteract the degrading vegetation level and avoid further negative effects of plant species leading to their loss or extinction, vegetation resource development, conservation, and usage measures must be developed and implemented.
3. GGM in conjunction with other responsible stakeholders must implement and adopt the formulated plans, guidelines, policies, strategies and solutions that promote land use planning, natural resource management in the study area.
4. Land allocated for some investors in GGM is accomplished even without approval of some stakeholders responsible for land management, as shown by socio-economic factors, resulting in land mismanagement. As a result, prior to providing land to investors or making comparable decisions, complete participation and consent from all stakeholders responsible for land allocation is essential for proper land management.
5. Crop production is reduced due to soil infertility because of scarce rainfall episodes, and there is a need to provide alternative and viable sources of water within the municipality. This will ensure that both commercial and subsistence farmers can improve crop production through irrigation schemes.
6. GGM must apply and use the adapted DPSIR Framework to help and guide on how the driving factors and human activities exert pressure on LULC change, and how to respond.
7. In order to adapt and implement LULC legislations and achieve their goals, land cover conservation is essential. This will assure that the value of land cover as a finite and irreplaceable resource is not exceeded by shorter-term, especially economic, rewards associated with development. In order to uphold this, changes or developments to land cover with potential harm, such as vegetation cover removal and waterbodies area depletion must be minimized. Adopting development approaches or technologies that allow the land to be returned to its pre-development state must be prioritized.

CHAPTER 6: CONCLUSIONS

The study has examined the spatial-temporal patterns and rate of LC changes in the GGM from 2000 to 2020 through remotely sensed images of Landsat using the minimum distance image classification algorithm. Among the four land classes used in this study, bare land was found to be the most dominant LC category with the waterbody being the least dominant category. For the changes, significant gains were observed under three categories: bare land (16.08% to the total area), built-up (7.48% to the total area) and waterbody (1.17% to the total area). On the other hand, significant losses were observed for vegetation between the years 2007-2014 (with 24.73% to the total area). Drought and expansion in built-up areas were identified as major driving factors that affect natural vegetation by decreasing and increasing the bare land. In addition, the increase in built-up areas was arising from population growth, internal migration, socio-economic development and infrastructural improvement in GGM.

The effective use of the DPSIR framework model helped to better understand the results from the LULC classification maps and the responses from expert interviews of municipal officials. This presented information that can help to ensure the long-term management of LULC classes. The study also highlighted that GGM had all the necessary LULC legislations and policies, but the implementation and adoption seem to be challenging. In order for GGM to maintain its land use plans, holistic sustainable development, there must be effective use of LULC policies and guidelines, with the adapted DPSIR framework. Overall, the results of this research could be incorporated into land planning and management to aid better decision-making, the development of evidence-based and environmentally friendly policies for the Greater Giyani Municipality, which is growing and improving.

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APPENDICES

Appendix 1: Consent for participation in a research interview

CONSENT FOR PARTICIPATION IN A RESEARCH INTERVIEW

Research title:

[An assessment of land cover changes in Greater Giyani Municipality in South Africa]

[RESEARCHER: MASHELE MATIMBA]

I agree to participate in an academic research project led by **Mr. MASHELE MATIMBA**. The purpose of the document is to specify the terms of my participation in the project through being interviewed.

1. I have been given sufficient information about this academic research project. The purpose of my participation as an interviewee in this project has been explained to me and is clear.
2. My participation as an interviewee in this project is voluntary. There is no explicit or implicit coercion whatsoever to participate.
3. My participation involves being interviewed by a researcher for his academic purposes. The interview will be hosted telephonically as per COVID 19 direct meeting regulations and laws. I also allow any recording or notes taking during the interview.
4. I have the right not to answer any questions, if I feel uncomfortable in any way during the interview session, I have the right to withdraw from the interview.
5. I have been given the explicit guarantees that, if I wish so, the researcher will not identify me by name or function in any reports using information obtained from this interview, and that my confidentiality as a participant in this study will remain secure.

PARTICIPANTS SIGNATURE	DATE
RESEARCHERS SIGNATURE	DATE

Appendix 2: Interview guide

LULC change interview guide questions

1. What are the most significant LULC changes that have occurred in this municipality in the past years?
2. Where did these changes takes place and why in those particular locations?
3. When did the changes occur and why?
4. Which factors are responsible for these changes?
5. What are the main reasons for these changes in LULC?
6. Have government policies played a role in LULC change?
7. What are the potential economic, social and environmental impacts of LULC changes?
8. What measures are implemented or considered by your municipality to address those potential impacts?
9. If the measures implemented by municipal doesn't work effectively, what do you think the state or condition of LULC change will be like in the coming years? And which measures or strategies you think will work effectively on combating land LULC changes?
10. What are the major factors affecting future state of LULC?

Appendix 3: Training class separability of 2014

```
Input File: LANDSAT_2014
    ROI Name: (Jeffries-Matusita, Transformed Divergence)

Bare land [Yellow] 1136 points:
    Waterbody [Blue] 218 points: (1.99999984 1.99999998)
    Vegetation [Green] 671 points: (1.99985092 2.00000000)
    Built-up [Purple] 744 points: (1.98089068 1.99263142)

Waterbody [Blue] 218 points:
    Bare land [Yellow] 1136 points: (1.99999984 1.99999998)
    Vegetation [Green] 671 points: (1.95930258 1.98049320)
    Built-up [Purple] 744 points: (1.99999984 2.00000000)

Vegetation [Green] 671 points:
    Bare land [Yellow] 1136 points: (1.99985092 2.00000000)
    Waterbody [Blue] 218 points: (1.95930258 1.98049320)
    Built-up [Purple] 744 points: (1.99590025 1.99872599)

Built-up [Purple] 744 points:
    Bare land [Yellow] 1136 points: (1.98089068 1.99263142)
    Waterbody [Blue] 218 points: (1.99999984 2.00000000)
    Vegetation [Green] 671 points: (1.99590025 1.99872599)

Pair Separation (least to most);

Waterbody [Blue] 218 points and Vegetation [Green] 671 points - 1.95930258
Bare land [Yellow] 1136 points and Built-up [Purple] 744 points - 1.98089068
Vegetation [Green] 671 points and Built-up [Purple] 744 points - 1.99590025
Bare land [Yellow] 1136 points and Vegetation [Green] 671 points - 1.99985092
Bare land [Yellow] 1136 points and Waterbody [Blue] 218 points - 1.99999984
Waterbody [Blue] 218 points and Built-up [Purple] 744 points - 1.99999984
```

Appendix 4: Validation class separability of 2014

```
Input File: LANDSAT_2014
    ROI Name: (Jeffries-Matusita, Transformed Divergence)

Vegetation [Green] 994 points:
    Bare land [Yellow] 1101 points: (1.99999966 1.99999998)
    Waterbody [Blue] 488 points: (1.99946618 1.99979046)
    Built-up [Purple] 1264 points: (1.99981806 1.99999979)

Bare land [Yellow] 1101 points:
    Vegetation [Green] 994 points: (1.99999966 1.99999998)
    Waterbody [Blue] 488 points: (2.00000000 2.00000000)
    Built-up [Purple] 1264 points: (1.96745350 1.99713154)

Waterbody [Blue] 488 points:
    Vegetation [Green] 994 points: (1.99946618 1.99979046)
    Bare land [Yellow] 1101 points: (2.00000000 2.00000000)
    Built-up [Purple] 1264 points: (1.99999668 2.00000000)

Built-up [Purple] 1264 points:
    Vegetation [Green] 994 points: (1.99981806 1.99999979)
    Bare land [Yellow] 1101 points: (1.96745350 1.99713154)
    Waterbody [Blue] 488 points: (1.99999668 2.00000000)

Pair Separation (least to most);

Bare land [Yellow] 1101 points and Built-up [Purple] 1264 points - 1.96745350
Vegetation [Green] 994 points and Waterbody [Blue] 488 points - 1.99946618
Vegetation [Green] 994 points and Built-up [Purple] 1264 points - 1.99981806
Waterbody [Blue] 488 points and Built-up [Purple] 1264 points - 1.99999668
Vegetation [Green] 994 points and Bare land [Yellow] 1101 points - 1.99999966
Bare land [Yellow] 1101 points and Waterbody [Blue] 488 points - 2.00000000
```