Understanding Landscape Dynamics Using Spatial Metrics: A Case Study of Maseru City Council (MCC), Lesotho.

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This research is dedicated to my two daughters, Reatile and Boitumelo. You two are the main reason no matter how hard things are; I will always stand up for you.

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Abstract

Remote sensing provides accurate and timely data for earth's change detections for better decision making. Both land use and land covers (LULC) are important dynamics in understanding the dynamics interaction between human activities and the environment and the changes within the environment due to these interactions. Rapid population growth together with an irreversible process of urbanisation results in productive agricultural land which serves as the main source of livelihood under pressure for residential purposes. The reason being rapid urbanisation led to rapid increase of informal settlement in the developing countries and hence information about location and the extent of these informal settlements is needed to guide resources allocation distribution for upgrading and decision making processes. Thus a quantitative measure like the spatial metrics is used in this research to provide information on the rate and pattern of urban expansion for urban planners to device a mechanism for proper spatial planning and provide a management policy direction for solving complex problem of population growth and the encroachment of the informal settlements into fertile agricultural land along the urban peripheries emanating from internal and international migrations.

The study indicates that there has been an increase of 928 Ha in the built up land between 2005 and 2016, while at the same time the agricultural has decreased by 820 Ha at the expense of the built up land. This indicates that in 11 years, percentage decrease of 0.35% in agricultural land is lost for built up land annually. In the similar manner, around the urban peripheries there is a loss of 3.4% of agricultural land (60.36 Ha) annually for informal settlement between 2005 and 2016 The spatial metrics which provide the quantitative description of composition and configuration of landscape shows that the urban peripheries are gradually being transformed from being simple compact to being more fragmented and complex as indicated by Area Weighted Mean Patch Fractal Dimension (AWMPFD) greater than one. This study indicates a need for immediate intervention through planned settlement to cater for an ever increasing population growth from natural birth and different types of migrations.

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Acronyms

AVHRR	:	Advanced Very High Resolution Radiometer
CORINE	:	Coordination of Information on the Environment
FAO	:	Food and Agriculture Organization
GDP	:	Gross Domestic Product
GIS	:	Geographic Information Systems
LULC	:	Land Use Land Cover
LSPP	:	Lands, Survey and Physical Planning
MCC	:	Maseru City Council
MMC	:	Maseru Municipal Council
NDVI	:	Normalised Difference Vegetation Index
UN	:	United Nations
PHC	:	Population and Housing Census
SPLUMA	:	Spatial Planning and Land Use Management Act

CHAPTER 1: INTRODUCTION

1.1Background

Land is the most powerful source of food production in the ecosystem as it supports all kinds of life on the planet. Thus by improving the way we use and manage land, this will enhance business base effective use of land resource. This will at the same time contribute positively to the sustainable development (Misra et al, 2012). The failure to do so will see the land losing its richness through desertification and degradation due to human actives like over cultivation, overgrazing, deforestation, sporadic settlement, urbanisation and other human activities (Ramachandra et al, 2012)

Lesotho as argued by McCordic et al (2017) is under a serious threat of food insecurity both at local and national levels. With the increasing urban population growth there are some measures and mechanisms taken with the intention for bolstering food production within the country as argued by (McCordic et al, 2017). This then calls for immediate intervention of protection of agricultural land for food production as a measure of promoting food production.

"Urbanisation is the annual rate of change of the percentages of people living in urban area" Naab et al (2013). In the similar manner, Nsiah (2000) define urbanisation as "the shift from rural population to an urban population and include an increase in the number of people in the urban areas". The rapid urbanisation and fast growing population have caused a negative impact on the agricultural land and land management (Naab et al, 2013).

The rapid urbanisation, population pressure, shelter, industrial and commercial need of the fast growing city have stretched the land delivery system to the breaking point in most sub-Saharan countries (Naab et al, 2013). Lesotho is no exception to this urbanisation effect through its city centre Maseru. McCordic et al (2017) argued that like the rest of Africa: Lesotho is experiencing a process of rapid urbanisation with the urban proportion of the population grown from 2% in 1960 to 25% in 2008.

Agricultural land, being the main source of food in the ecosystem has been highly depleted as a result of the process of urbanisation where most of agricultural land has been illegally converted into residential land. Therefore, there is a need to assess the impact of the rapid urbanisation on the agricultural land in the developing city of Maseru. The rapid urbanisation of the city centre resulted in the major problem where the prime agricultural land has been transformed to other different types of land uses. These other different types of land use are believed to be for best use. The result of this transformation is agricultural land capacity is reduced due to urban sprawl on high quality agricultural land (Duran et al, 2012).

An irreversible process of urbanisation has resulted in changing land use patterns. Naab et al (2013) indicated that there are a number of competing demands for different land uses against the agricultural land use. The major competition as argued by Naab et al (2013) is competitions for residential, industry and commercial, civic and culture. The competition between these land uses tends to deprive agricultural lands in the bid for space in the urban place. Urbanisation usually takes place on some of the productive cropland. This urbanisation tends to add pressure to the already potentially strained future food systems and threatens livelihood in the vulnerable regions.

Singh and Kumar (2012) noted that the rapid growth of population demands effective and efficient land use measures. This is because Singh and Kumar (2012) argued that many land use practices are not sustainable. The unsustainable land use practices easily lead to considerable land degradation and loss of productivity. The results of unsustainable land use will see the land losing its fertility through desertification, dominance of built up land on what was once fertile land and the result will be a country dependent on foreign aid to support its population. There is a need for an immediate intervention action for proper land use practices. These actions should respond to social and economic needs of changing population and maximise sustainable land use. This will then ensure that long term availability of land resources is possible to continuously support increasing population demands. The reason being land is fixed in supply and does not increase with increasing population growth.

Naab et al, (2013) noted that "The key challenge of the urbanisation process is the rapid convention of large amount of prime agricultural land to urban land uses (mostly residential constructions), in the urban periphery". The key effect or consequences of this urbanisation is the lack of the prime agricultural lands for future generations. Naab et al (2013) argued that the result of uncontrolled urbanisation is the reduction in agricultural land productivity which ultimately reduces the standard of living and food insecurity within the country. "Agriculture which is the main source of livelihood of urban dwellers is seriously being threatened by rapid urbanisation" Naab et al (2013). Urbanisation results in the problem of where the agricultural land is limited and food production are reduced in the process and the overall result is national food insecurity.

1.2 Problem Statement

Naab et al (2013) "agriculture which is the main source of livelihood of peri-urban dwellers is seriously being threatened by rapid urbanisation because of the problem of scarcity of land for agricultural purposes that will arise". In a similar manner Misra et al (2012) argued that the world countries throughout are experiencing high rate of an unauthorised urban expansion at an alarming rate. Misra et al (2012) further indicated that "high rate of urban population growth has led to serious land use problems". The most dominant problems according to Misra et al (2012) are "loss of agricultural land, unauthorized urban sprawl, high land values, pollution, poverty and social unrest". All of these factors combined together results in difficult urban governance management and at the same time results in difficult task to manage and maintain healthy urban environment to avoid contagious diseases.

The major challenge in urban areas and around its peripheries is an illegal allocation of agricultural land for informal settlements / residential development. "This allocation of agricultural land for informal settlements purposes results in a reduction in the quantity (size) and quality of agricultural land" (Naab, 2013). The reduction of agricultural land leads to greater food insecurity. Misra et al (2012) indicates that this scenario of convention of agricultural land into informal settlements requires having up to date information on current existing land use information. Therefore, it is important to have timely information on land use land cover change together with the pattern of the informal urban growth expressed through the landscape metrics in order to direct the urban growth (see section 2.6.1). This timely data will inform the urban planners, decision makers and policy makers to act accordingly on issues of proper land use planning and physical planning for sustainable city development (Naab et al, 2013)

"Combination of remote sensing and spatial metrics can provide more spatially consistent and detailed information on urban structures and change" Herold et al (2003). Therefore, for efficient and effective spatial planning, remote sensing should be used to provide timely data about the current status of the earth's surface and at the same time spatial metric be used for monitoring and understanding spatial pattern of urban growth. In general, both remote sensing and spatial metrics should be used together than using either approach independently as argued by Herold et al (2003). This then calls a need for both remote sensing and GIS to provide timely data, specialised thematic maps and quantitative data about the status of the landscape. These data will then be used in ensuring proper spatial planning and ensuring the security of agricultural land for food production through law enforcement measures.

1.3 Research Aim

Misra et al (2012) argued that the "land use maps are important in providing up to date information on the type, location, spatial, distribution and extend of land use land cover". This is because according to Misra et al (2012) it is very important to be able to monitor urban land use land cover changes because information from land use land cover is very useful for policy makers, and particularly for town and regional planners.

This research is aimed at producing the land use land cover maps of the Maseru City Council (MCC) at different epochs in order to detect landscape changes particularly between built up land and agricultural land (none built up land). The quantitative information on land use changes will play a significant role in spatial planning decision making process and policy formulations. In a similar manner, the spatial metrics will be used for informal settlement configurations. The spatial metrics from the analysis will assists in developing spatial decision support to inform planning policy on impact of informal settlements on agricultural land.

1.4 Research Objectives

The main objectives of the study are to understand landscape dynamics which involves:

1) Temporal analysis of land use land cover patterns.

2) Assessment of the spatial patterns of urbanisation and expressing them through spatial metrics.

1.5 Research Questions

1) How will the complex decision making benefit from incorporation of remote sensing and GIS as the new decision analysis and support tool?

2) What spatial metrics will help support planning policy in Maseru City Council (MCC)?

1.6 Study area

Lesotho is the mountainous country about 30, 355 square kilometres enclosed within the Republic of South Africa (RSA). "The Country lies between 28° and 31° South latitude and between 27° and 30° East longitude" (National Environment Secretariat, 2000). The country is divided into 10 administrative districts. Lesotho's mountainous terrain influenced most of the land uses and their changes. The lowest attitude is 1400m above sea level in the lowlands, with the highest peak rising to 3482m above sea level in the highland (Chakela, 1999).

Lesotho is divided into four ecological zones, which are the Lowlands, Foothills, Mountain and Senqu River Valley according to Lesotho's Bureau of Statistics (2015). Figure 1 below is the map of Lesotho showing 10 districts and four ecological zones.

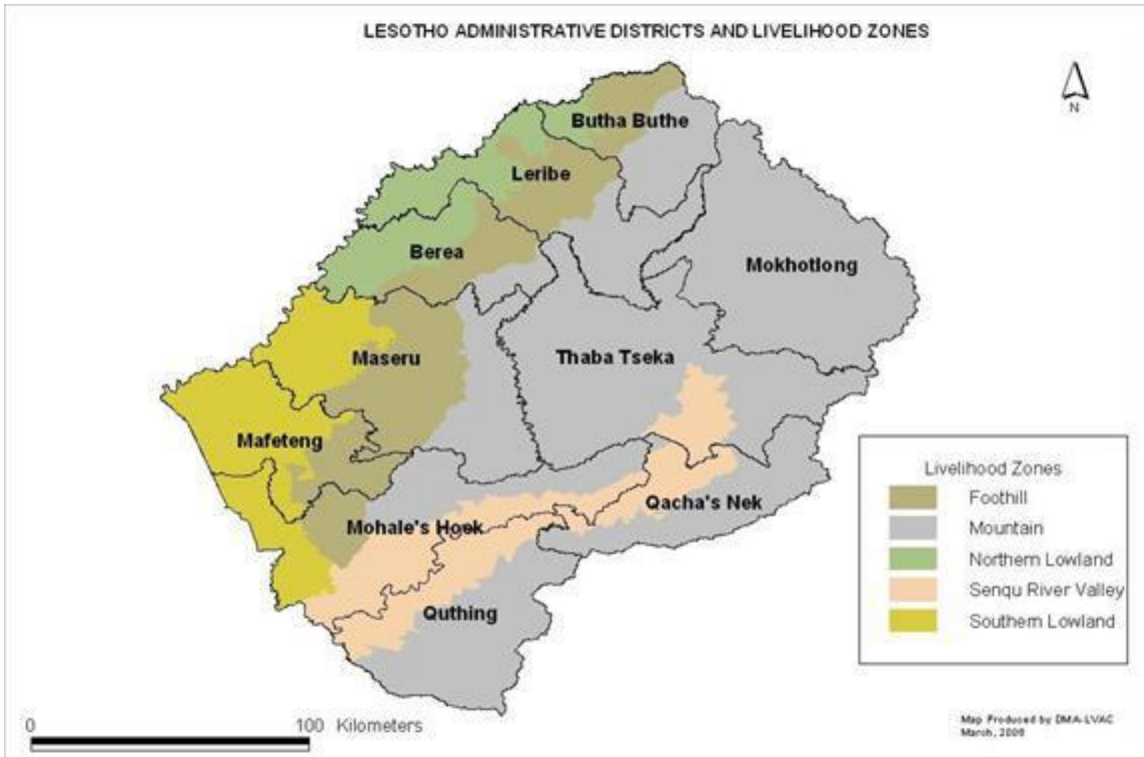


Figure 1: Lesotho administrative districts and livelihood zones, adapted from Majara (2005)

1.6.1 Maseru City Council (MCC)

Leduka (2012"The Maseru Municipal Council(MMC) was first established as Maseru City Council(MCC) in 1989, a corporative body created by the Urban Government Act (UGA) of 1983". Leduka (2012) further indicated that under the UGA the responsibilities of the MMC "included the delivery of municipal services, such as collection of waste, provision and maintenance of street and roads, as well as the management of the entire city". The MCC was not land allocating authority according to UGA of 1983; it only became land allocating authority in 1992 after the declaration by the Ministry of Interior, which was then ministry responsible for local government at the time according to (Leduka, 2012). Therefore, following the 1992 declaration, MCC responsibilities then encompasses land acquisition, servicing and disposal of land for sale (Leduka, 2012).

Lebentlele (2000) argued that MCC assumed its roles as land and planning authority in 1998 but the MCC has failed to perform the planning functions due to lack of finances and qualified staff within the planning department and as the results of this the development in Maseru continues to take place without any development permissions hence haphazard and unplanned developments. In the similar manner Leduka (2012) indicated that for the period between 1992 and 2003 the

MCC only formalised 23 plots annually into formal settlement in an attempt to provide urban land supply system. The major factor according to Leduka (2012) is that land is individually owned in Lesotho, and there is no vacant land for MCC within council boundaries for urban layouts and settlement planning. Therefore for MCC to acquire land for formal planning settlement layouts, it should negotiate with field owners and pay compensations. On the contrary to that Leduka (2012) argues that MCC lack of financial resources with which to pay compensation for acquiring masimo (fields) land results in the incapacity of city to provide or accommodate sites for planned urban developments. The result of financial constrains then deprived the MCC from any formal settlement layout and at the same time hampers MCC from delivering any significant amount of land into the market. The result of an inefficiency of MCC in supplying formal layout settlement is seen by people opting to informally acquire land from field owners through illegal subdivision of agricultural land for residential purposes.

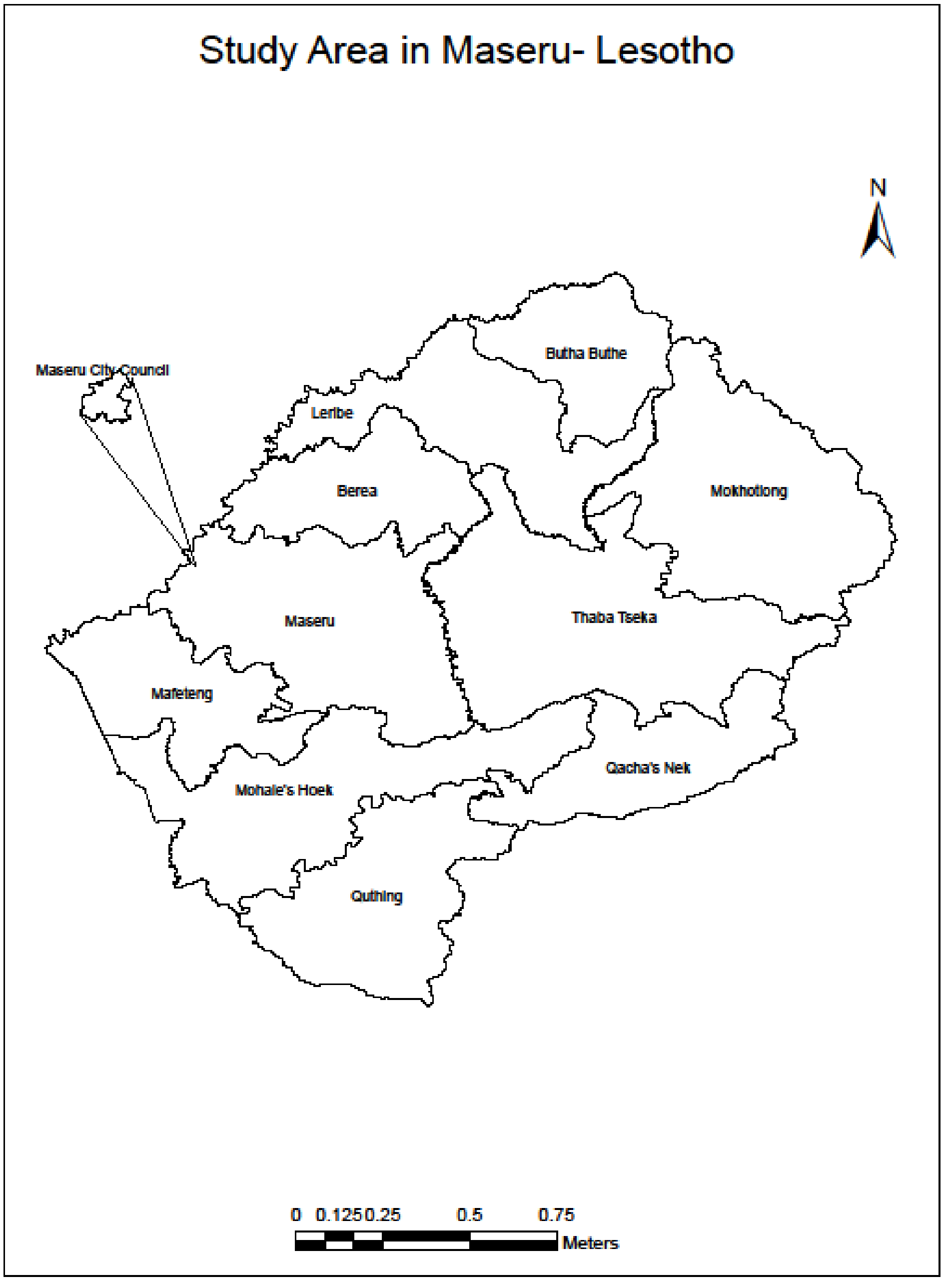


Figure 2: Location of the study area of Maseru City Council (MCC), adapted from Government of Lesotho (2010)

The figure 2 indicates the study area being Maseru City Council (MCC) in Maseru district, which is capital city of Lesotho. Maseru is at the border between Lesotho and Republic of South Africa (RSA) into province of the Free State. The Maseru City Council (MCC) urban boundary covers an area of 143.37 square kilometres. The major concern in this urban council and its urban peripheries is that most of what was agricultural land in 2005 is gradually changing into residential sites due to urbanisation. Figure 3 below indicates the Maseru City Council (MCC) zoning map of 2005.

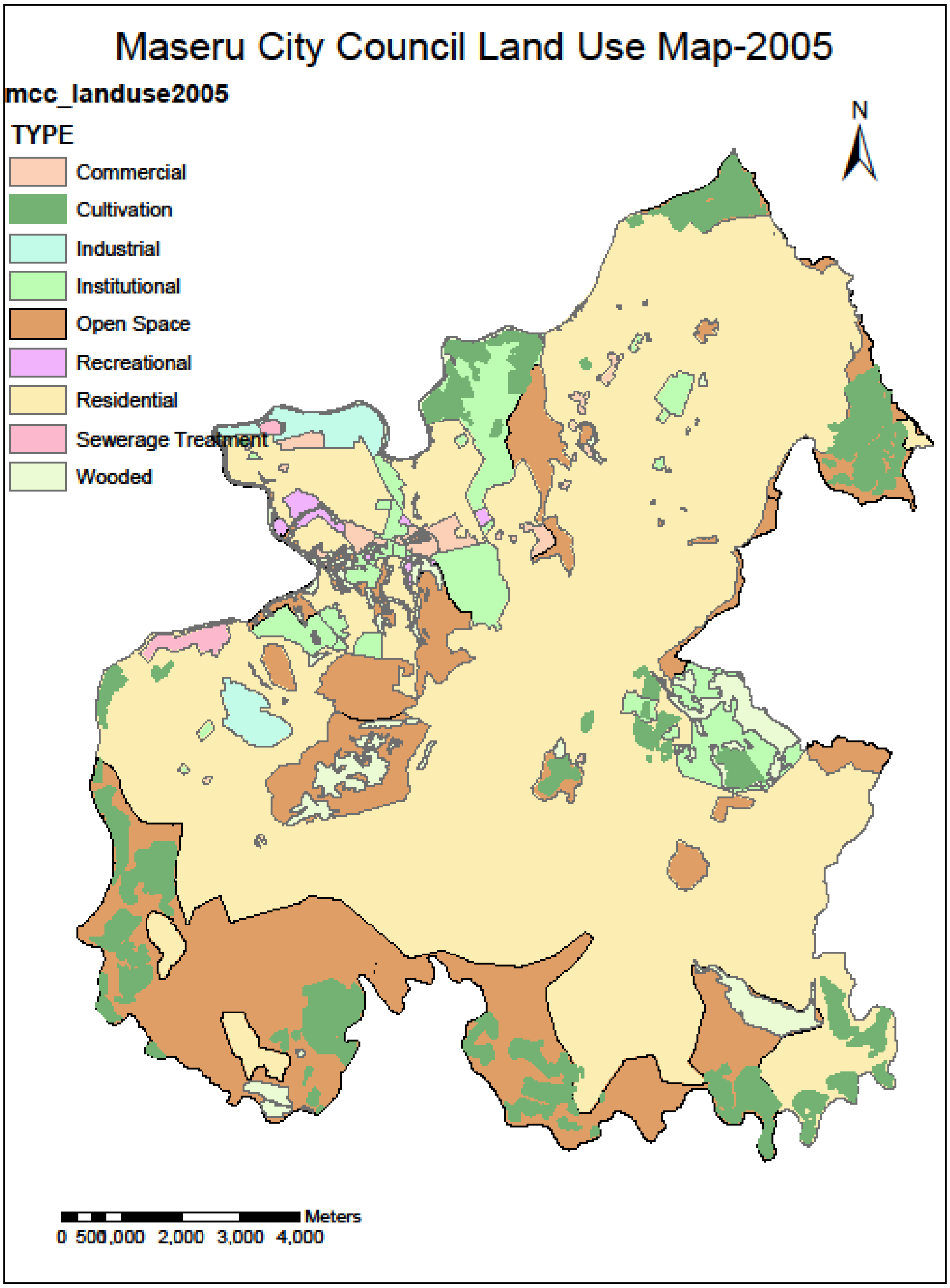


Figure 3: Maseru City Council (MCC) zoning map of 2005, adapted from Government of Lesotho (2010)

According to 2016 population and housing census (2016 PHC) the total population of the country were approximately 2,007,201 million people (Lesotho-Bureau of Statistics, 2018). Maseru being the capital town has a population of 519,186 people and has the largest concentration of population and highest growth rate and experiencing a rapid land used changes. The total area of Maseru is 4,279 square kilometres. The 2006 census indicates annual growth rate of 0.08%, which indicates a substantial decline from the annual growth of 1.5% during the period 1986 to 1996. Although the population growth has decreases between 1986 and 1996 compared to growth rate of 0.08% in 2006, there has been 0.68% increase from 2006 to 2016 according to 2016 PHC report (Bureau of Statistics, 2018). This population growth resulted in high movement of the people from rural to urban making land resource highly vulnerable and thus need a proper spatial planning due to an increasing demand for land.

Woodfine (2013) indicates that "livelihoods in Lesotho are characterised by a fundamental dependence on the natural resource". Most of the people in Lesotho live on subsistence agriculture, small-scale horticulture and livestock keeping. Woodfine (2013) further indicated that some people live on harvesting of wild resources (including food, medicinal plants and wood). Apart from these natural resources, Lesotho people are highly dependent on agricultural products for income generating activities like sheep and goats mohair harvesting/ shredding.

1.7 Organisation of dissertation

This research is conducted through five chapters where **Chapter 1**, briefly introduces the important of land within the ecosystem and how the changes on landscape affect life. The chapter highlights the problem stament, the research objectives, the research questions and the entire aim of the research.

Chapter 2, this chapter describes the theoretical and the related literature reviews on land user land cover changes and landscape dynamics using remote sensing and the statistical landscape metrics describing land use land cover changes with time. This chapter contains reviews on remote sensing, spatial metrics, image classification techniques, landscape structures and accuracy assessment procedures.

Chapter 3, the chapter clearly defined the methodologies used in the study to achieve an intended goal of producing land use land cover classification maps and its quantification through spatial metrics. It indicates the chronological activities from data acquisition, data preparation, processing and the analysis of the data.

Chapter 4, this chapter presents data analysis and the results where land use land cover maps are produced and the spatial metrics are used to quantitatively and qualitatively explains the informal urban patterns along the MCC peripheries. The results are presented as maps and are being interpreted to find the possible driving forces behind the informal urban expansion into agricultural land.

Chapters 5, the explanation emanating from previous chapters are conveyed in this chapter and moreover, assessment is made whether or not the research objectives have been met. This chapter also makes some recommendations based on this study and the possible other studies using this research as the baseline.

1.7 Conclusion

Remote sensing combined together with spatial metrics can be used simultaneously in analysis and modelling the urban growth and landscape changes (Herold et al, 2003). This is because the two approaches used together will help with better understanding and representation of urban dynamics, which involves urban structure and changes. Ramachandra et al (2012) also indicates that it is paramount to understand the patterns of changes within the landscape as a result of human process. This understanding will help town and regional land use planners to identify and understand all the requirements of change in land use land cover within the landscape. Thus, the quantitative information from remote sensing and spatial metric will help in rational planning processes and decision making.

The major challenge in Lesotho as indicated above is rapid expansion of built up land into agricultural land. Therefore, there is a need for proper spatial planning to ensure secured and sustainable food security with the prevailing environment of urbanisation. The challenge can be overcome through timely data provided through remote sensing and continuous analysis of such information through GIS. Therefore, from the foregoing discussion, it is apparent that the information on the current status of land use land cover is very important to be used as the baseline for other developmental activities and ensuring that one’s country is agriculturally sustainable.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

Land is one of the most important natural resource that supports life and developmental activities on the earth's surface according to Ezeomedo and Igbokwe (2013). "In order to use land optimally, it's not only necessary to have the information on existing land use land cover (LULC) but also the capacity to monitor dynamics of land use resulting out of both changing demands of increasing population and forces of nature acting to shape the landscape" (Opeyemi, 2006). "Remotely sensed satellite images provide an overview of the general terrain of the earth over a short time period and this information lead to a quick and truthful representation of the real world in the best possible way" Dubey and Singh (2012). There are a number of factors which contributes to Land use land cover pattern of a region and Opeyemi (2006) argued that these changes are an outcome of natural and socio-economic factors and their utilisation by man in space. Opeyemi (2006) indicates that it is important to have information on land use land cover because it will provide the optimal possibilities for proper land use for essential services selection. The three basic human needs of food, shelter and clothing requires proper spatial planning and proper equitable land use schemes for sustainable development. These land use schemes will ensure an equitable land use distribution to meet an increasingly demands for basic human needs and welfare as a result of an increasing population growth as indicated by Opeyemi (2006). This information on land use and land cover will also assists in monitoring the dynamics of land use changes resulting out of changing demand of increasing population changes due to natural causes and changes due to migrations as argued by Opeyemi (2006).

2.2 Land use and land cover

Land use and land cover, these two terms can bring a lot of confusion if not properly used. Sadoum and Al Rawashdeh (2009) "land cover as means all bodies that cover ground surface such as water bodies, forest, grazing land, rocks, and soil". On the contrary, "land use is concerned with change on the surface of the earth due to human activities such industrial, residential, and agricultural" (Sadoum and Al Rawashdeh, 2009).

Land use and land cover keep on changing and in most cases as the results of human activities to a larger extent compared to changes caused by natural phenomenon. The changes in land use and land cover according to Wang et al (2008) can have wide-ranging environmental consequences associated with them. Wang et al (2008) further indicated that these consequences include "loss of biodiversity, changes in emissions of trace gases affecting climate change, changes in hydrology and soil degradation". The dynamics of ever changing land use land covers influences or affect people differently under different environments. The results of these changes in the landscape according to Wang et al (2008) are "for example, influencing the spread of infectious diseases, interfering with the migration of species and affecting the risk of natural hazards".

Wang et al (2008) argued that understanding the magnitude and pattern of land cover is important. This is because the environment within and adjacent to our landscapes enables us to protect the areas. In the similar manner Wang et al (2008) indicated understanding the environment "helps establish a landscape context and offers a better understanding of how an ecosystem works". The knowledge of our ecosystem will help to protect our areas for future generation and also for population growth to fit into the broader landscape. This will again help spatial planner in making the informed decision of the entire landscape changes. In general, land cover changes are divided into conversions from one land cover type into another and transformations within a land cover type and most importantly factors leading to such land cover changes with time. Opeyemi (2006) indicated that "globally land cover today is altered principally by direct human use by agriculture and livestock raising, forest harvesting and management and urban and sub-urban construction and development". From the forgoing discussions, it is important to note that in order to use land optimally as argued by Opeyemi (2006), we need an information on the existing land use land cover coupled with capacity to monitor the dynamics of changes due to population changes and the forces of both man and nature acting on the landscape shaping the landscape.

From the foregoing discussing, it is evident that the understanding of land use land cover change is important as change detection is an important process in monitoring and managing natural resources and urban development. This is because land use land cove change provides quantitative analysis of the spatial distribution of the population of interest (e.g. land, hydrology and biodiversity in general). Tiwary et al (2008) used land use and land cover change detection technique in mapping of Delhi in India using Landsat TM and IRS LISSIII data from 1992 and 2004 respectively. In the same manner Opeyemi (2006) notes that ever since the launch of the first remote sensing satellite (Landsat-1) in 1972, land use and land cover studies were carried out on different scales for different users. The author further indicates that, waste land mapping of India was carried out on 1:1 million scales by NRSA using 1980 – 82 Landsat multi spectral scanner data and about 16.2% of waste lands were estimated based on the study.

2.3 Agricultural land

According to Economic Commission of Africa (2014) "In view of the pressure on an agricultural land from other uses including urban and peri-urban expansion, extractive industry and infrastructure development, there is an urgent need to promote inclusive land use planning at local and national level to address these multiple demand of the land resource both equitably and sustainably”.

The agricultural land is generally defined and further defined in the context of Lesotho with emphasis on the major or basic crops grown in Lesotho. The challenges faced by agricultural land will be discussed and similarly the contribution of agriculture towards the economy of Lesotho will be reviewed.

“Agriculture is the systematic raising of useful plants and livestock under the management of man” (Rimando, 2004). Thus, the agricultural land is specific piece of land within the landscape where the sole purpose of such land is for livestock and plants production only. In Lesotho, according to Lesotho’s Land Act of 2010, “agricultural land means land used exclusively or mainly for agriculture, whether as arable, pasture, grazing, orchard or seed growing, or for fish farming, forestry (including forestations), or for the breeding or keeping of livestock, including any creature kept for the production of food, wool, silk skins or fur” (Lesotho, Land Act 2010).

According to Gwimbi et al (2014) “the major crops grown in Lesotho in the order of importance are maize, sorghum, wheat, beans and peas”. There are other crops grown in Lesotho but to a lesser scale compared to the five mentioned above and those crops are potatoes and vegetables (Gwimbi et al, 2014). Gwimbi et al (2014) further indicated that among these five major crops grown in Lesotho, maize being the staple food is by far the most popular crop. “Maize, account for some 60% of the cropped area, sorghum between 10% and 20%, wheat about 10% and beans a further 6 %”(Gwimbi et al, 2014). As indicated above, in Lesotho there are five major crops: Maize, Wheat, Sorghum, Beans and Peas and the annual production based on 2013/2014 Crop Statistics Report is shown on the table 1 below.

According to Lesotho Water Partnership (2016), around 80% of the household in Lesotho live in the rural areas and 70% derive all, or part of their livelihood from agriculture or agricultural products. The Lesotho Water Partnership (2016) further indicated that although the contribution of agriculture to Gross Domestic Product (GDP) has decreased over time, from 20% thirty years ago to around 8%, agriculture is and still remains an important sector for increasing employment and rural income. By the same token, Lesotho Water Partnership (2016) argued that in the similar manner the crops and the livestock sector contributes 2.3% and 4.1% to GDP respectively in Lesotho

Table 1 : Area planted (Ha) to five major crops by district,2013/2014 agricultural year

District	Population	Total Area (Square Kilometres)	Maize	Wheat	Sorghum	Beans	Peas
Botha Bothe	118,242	1767	4000	400	1195	329	29

Leribe	337,521	2828	24,655	1373	3126	2864	75
Berea	262,616	2222	19,072	0	4230	3357	0
Maseru	519,186	4279	19,598	1025	2871	2089	72
Mafeteng	178,222	2119	22,326	0	3427	2234	0
Mohale's Hoek	165,590	3530	18,145	696	3938	2038	46
Quthing	115,469	2916	5535	721	2549	1818	77
Qacha's Nek	74,566	2349	2524	770	0	941	46
Mokhotlong	100,442	4075	17,189	5425	1087	1023	424
Thaba Tseka	135,347	4270	12,622	3308	1699	1775	217
Lesotho	**2,007,201**	**30,355**	**145,665**	**13,719**	**24,121**	**18,065**	**985**

Source: Modified from Lesotho Bureau of Statistics 2015

Agriculture in Lesotho as argued by Woodfine (2013) typically involves some low-yielding field crop production. As indicated earlier that in Lesotho agriculture is for subsistence and for that matter it is characterised by extremely limited vegetables production in homestead gardens and diminishing livestock production (Woodfine, 2013). The results of low crop yields are indicated by number of people experiencing food insecurity with only few households able to achieve food security. This generally means that "with the expansion of urban /peri urban areas, the amount of land available to grow crops per household has fallen steadily throughout the 20th century and continues in the 21st century" (Woodfine, 2013). Woodfine (2013) indicated that in terms of cereals production, Lesotho is currently not self –sufficient. This is because the country imports according to Woodfine (2013) more than 70% of its grain requirement come from the neighbouring Republic of South Africa.

It is worth noting that agricultural land should be closely monitored and be protected for sustainability. Fazal (2000) in a study of Saharanpur city noted that the city was not well planned and resulted in the urban expansion in different direction, the results of which was congested city covering the agricultural land on the urban fringe. This expansion resulted in northern part of Saharanpur city loss of the plantation due to industrial expansion. Therefore it is important to note that no matter the scale of food production, proper land use planning is needed to avoid continuous loss of agricultural land for residential purposes.

2.4 Urban sprawl

Chong (2017) “urban sprawl is a type of urban growth that describes the expansion of low density built-area”. There seems no consensus on official definition of urban sprawl, but a number of existing literatures indicates that generally, urban sprawl is characterised by changes in land uses with ultimate poorly planned or uneven urban growth patterns (Padmanaban et al, 2017 and Chong, 2017). This poorly planning leads into traffic congestion, increase water demand, increased energy demand and low density urban development (Chong, 2017). Though sprawl may not be seen difficult to identify with naked eyes as argued by Chong (2017) but there is a need to quantify urban sprawl to have information that will guide and influence policies and promote sustainable development resulting from population growth.

Urban sprawl according to Padmanaban et al (2017) is promoted by the by rapid population growth and this leads to the shrinkage or diminishing of the productive agricultural land. Apart from agricultural land diminishing, the changes in forest land in the sub urban areas in a similar manner alters ecosystem service according to Padmanaban et al (2017). This calls for a need to quantify urban sprawl to ensure effective urban planning, and environmental and ecosystem management. It is worth noting that the urban sprawl defined above should not be confused with informal settlement defined in section 2.5 below which is the main focus of this study.

2.5 Informal settlements

The major challenge in Lesotho is the emergence of the informal settlement along the urban fringe which affects agricultural land immensely. Informal settlement defined by UNSTAT (as cited in Muli, 2013) is “(1) areas where group of housing units have been constructed on land that, the occupants have no legal claim to, or occupy illegally: (2) unplanned settlement and area where housing is not in compliance with the current planning and building regulations (unauthorized housing)”. In Lesotho, informal settlement followed a second definition as characterised by dysfunctional settlement structures which include no planned structure or conventional planning principles. These informal settlements are characterised as argued by Leduka (2001) “by plot boundaries which are unknown or non-existent, and plot sizes varies greatly; this is because people change their agricultural land illegally to residential sites/plots and thereafter construct buildings without following planning standards as defined by Lesotho’s Town and Country Planning Act of 1980”. It is worth noting that the major challenge in Lesotho is the emergence of the informal settlement into agricultural land and therefore the informal settlement should not be used interchangeably with urban sprawl. The quantification of urban informal settlement is achieved through the use of the spatial metrics (2.6.1 below)

2.6 Landscape

Landscapes are not static. One of the factors affecting landscape changes immensely is human who continuously affects activities within the landscape in one way or the other. Gokyer (2013) argued that depending on intensive human effect, when pressure is increased on landscape, the consequences will be the alteration of the entire landscape over time due to human activities. There are a number of factor affecting changes in landscape and the common factors are climate changes, land use and human activities (Gokyer, 2013, Ramachandra et al, 2012 and Farina, 2000). It can be change mosaic structure, shape and size and frequencies (Farina 2000). Kavitha et al (2015) noted that the expansion of built-up land into other land uses has affected the food production in multiple ways. This is because as argued by Kavitha et al (2015) that an age-old farming land has been altered, the reason for the alteration is limited space for farming due to urban encroachment into agricultural land. This resulted in situation where traditional practice of farming from farmers and family farms have decreased due to migration to urban areas occupying large sums of land for built up according to Kavitha et al (2015)

"Landscape as heterogeneous land area, consisting of interaction sets between ecosystems" Farina (2000). The landscape is a spatial entity having the variable extent and scale and territorial extent. Farina (2000) "landscape ecology is a science branch of ecology to contribute related to the complexity studies (physical, biological and ecological) of ecology". Therefore, landscape ecology uses numbers, remote sensing, geographic information systems (GIS) and geo-statistical tool to understand the landscape changes.

Herold et al (2005) argued that an increase in the built up area because of urbanisation into agricultural land limit farmers of arable land to cultivate land and as a results reduce agricultural productivity. It is through the understanding of this landscape change, which will quantify effectively, extent of agricultural land degradations and factors leading to such changes (Herold et al, 2005: Farina, 2000 and Antrop, 2005) indicated five main competing powers affecting landscape changes as:

i. "Socio-economic forces: Urbanisation, industry, industrial activities
ii. Political forces: Incorrect application
iii. Technological forces: Car, roads, infrastructure facilities
iv. Natural forces: Avalanches, land slide, floods
v. Cultural Forces: Accessibility, human interventions, fire".

Antrop (2005) indicated that among the five powers indicated above, accessibility is the most important power within the forces. This is because whenever people arrive in the field they will find ways to enable easy access or movement from one point to another and in the process changes land uses for accessibility.

2.6.1 Landscape metrics/spatial metrics

In order to understand any change within the landscape, landscape metrics are used. Landscape metrics tools are used in landscape ecology (McGarigal et al, 2002). These tools are mostly used in spatial or landscape planning to support decision making and management decision on spatial planning according to McGarigal et al (2002). The understanding of the landscape structures and its complexity has been achieved successfully by the number of studies in literatures through the use of spatial metrics. The understanding of the complexity of the landscape structure helps to have the informed analysis on shape, pattern and size of the landscapes (Wu, 2004: Latiao and Ahern, 2002). McGarigal et al (2002) further indicates that landscape metrics help to calculate composition and configuration of the landscape as a whole. The two most important characteristics of the landscape composition and fragmentation help to easily monitor the increase and or the decrease of one type of the patch within the landscape and the reasons behind such changes. The information from these characteristics will then be used for rational decision making processes. Indeed, "landscape metrics help to understand changes in landscape from different perspectives that are visual ecological and cultural"(Gokyer, 2013).

Spatial metrics as defined by Herold et al (2003) are "measurements derived from the digital analysis of thematic-categorical maps exhibiting spatial heterogeneity at a specific scale and resolution". According to Herold et al (2003) "spatial metrics emphasizes the quantitative and aggregate nature of the metrics, since they provide global summary descriptors of individual measured or mapped features of the landscape (patches, patch classes, or the whole map/landscape)". This means it is important to know what the change in quantities within the landscape was previously, now and what to expect in future. Spatial metrics are sometimes used in landscape ecology, and they are known as landscape metrics (Herold et al, 2003). Bharath (2012) indicated that landscape metrics also known as spatial metrics are invaluable for understanding and characterising the urban processes and their consequences. Therefore, in this study the two terms, spatial metrics and landscape metrics will be used interchangeably to mean the same thing. Herold et al (2003) "when spatial metrics are applied to fields of research outside landscape ecology and across different kinds of environments (in particular, urban areas), the approaches and assumptions of landscape metrics may be more generally referred to as spatial metrics".

"Spatial metrics can be a useful tool for quantifying structure and pattern in categorical or thematic maps" Gokyer (2013). Ramachandra et al (2012) mentioned that the applications of landscape metrics include landscape ecology. It is important to note that land ecology is concerned with the quantity of species in the landscape, being number of patches, mean patch size, total edge and mean shape and spatial metrics provides those measures. There is a general understanding that landscape metrics are important tools which are used to understand landscape structure and landscape changes (Gokyer, 2013, and Ramachandra et al, 2012). In a similar manner, Ramachandra et al (2012) "spatial metrics have been widely used to study the structure, dynamic pattern with the underlying social, economic and political processes of urbanisation". Gokyer (2013) also emphases the fact that to use metrics, numeric data is obtained related to landscape structure. Therefore, the remote sensing is used to acquire this numeric data which is produced from both passive and active satellite images like Landsat, SPOT, orthophotos, Radar and air photos.

"Landscape metrics are used to quantify the spatial heterogeneity of individual patches, of all patches belonging to a common class, and of the landscape collection of patches" (Herold et al 2003). In a similar manner, Farina (2000) indicated that landscape metric can be calculated on three categories levels which are patch level, class level and landscape level. Herold et al (2003 patches are defined as homogenous regions within landscape which are characterised by one feature class or one type of species at the time or a specific landscape property. For example, there can be a class of a specific landscape property of interest, such as industrial land, parks, informal settlements, grassland, etc. Gokyer (2013) defines a patch as nonlinear area (polygon) which is less abundant.

Metrics are broadly classified into two types, firstly those that quantify the composition of map without any spatial attribute linked to it and the second type quantifies the spatial configuration of the map which has spatial information as base data for the calculation (Ramachandra et al 2012).It is worth noting that the spatial metric can be used to define the characteristic of any land land use changes, being either formal and or informal land uses.

There are a number of metrics to be used on the landscapes, and their merits differ depending on the objectives of the study. Herold et al (2003) , McGarigal et al, (2002) and Gokyer (2013)" the most commonly applied metrics are patch size, dominance, number of patches and density, edge length and density, nearest neighbour distance, fractal dimension, contagion, lacunarity, etc." according to The contagion index and fractal dimensions' metrics will be further explained as some of these spatial metric names carry the meanings themselves, for example, number of patches metrics simply indicates the number of different patches within the landscape.

"The contagion index measures the probability of neighbourhood pixels being of the same class" (Herold et al, 2003). This is based on the understanding that features close to one another show similar characteristics than feature that are further apart. In general term, this metric describes to what extent landscapes are aggregated or clumped (Herold et al, 2003). The interpretation of this metric is that landscapes consisting of large patches are relatively large, and therefore contagious landscape classes are indicated by high contagion index. If a landscape is dominated by a relatively greater number of small or highly fragmented patches, the contagion index is low.

Herold et al, (2003) “fractal dimension describes the complexity and fragmentation of a patch as a perimeter-to-area ration. Low values are derived when a patch has a compact rectangular form with a relatively small perimeter relative to the area. If the patches are more complex and fragmented, the perimeter increases and yields a higher fractal dimension”. There is no standard set of number of metrics which best describe the landscape or the urban environment according to Parker et al (2001). Parker et al (2001) “this is because specific set of metrics varies with the aim and objective of the study together with the characteristics of the urban landscape under investigation”.

Figure 4 below is a simple conceptual framework proposed by Herold et al (2005) to illustrate the three main components which are remote sensing, spatial metrics and urban modelling and their interaction in spatial planning usage. From the framework, there is a direct contribution of remote sensing to spatial data (relationship 1) and the combine use of remote sensing and spatial metrics always lead to the new understanding of how urban areas grow and change (relationship 2 and 3) through understanding the patter and the processes of urban growth.

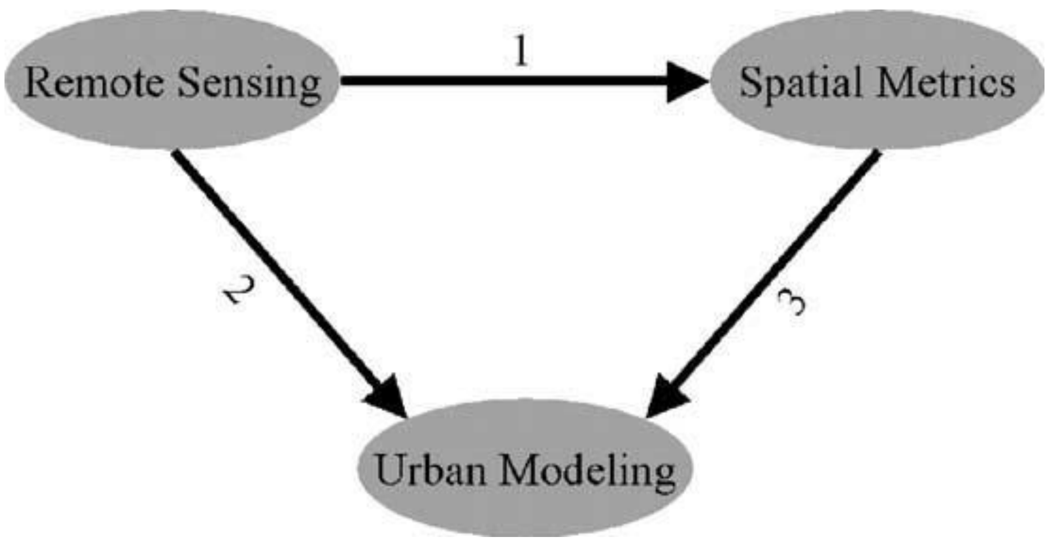


Figure 4: General framework for analysis and modelling of spatial urban dynamics (Herold et al, 2005)

Herold et al (2003) indicated that spatial metrics have been used to build variety of the urban models that indicates importance of spatial metrics towards their contribution in liking economic processes and the patterns of the land use.

2.7 Geospatial planning

Geo-information "concerns any kind of information, qualitative or metric, about the system earth-environment and furthermore the works of nature and man on it" (Lazaridou and Patmios, 2012). Lazaridous and Patmios (2012) further indicated that different scientific and technologic disciplines produce geo-information and their acquisition can be significantly supported by methods of photogrammetry and remote sensing. In generally, most of the human activities depend on geospatial information. This means there is a need to know where things are and how they relate and hence the spatial planning plays a significant role in understanding this interaction.

Spatial planning according to Miskell (2016) "is a 20-30year strategy that sets the strategic direction for a community to form the basis for the co-ordination of decision-making, infrastructure, service and investment". Miskell (2016) indicates that spatial planning "is a means of aligning other council plans, as well as providing a visual illustration of the intended future location, form and mix of residential, rural and business areas, along with the critical transport and infrastructure required to service those areas and any relevant environmental constraints (for example, natural hazards)".

In the similar manner, Collett (2013) indicate that planning has a major role to play in addressing threats to food security. In most cases during the spatial planning process, the issue of food security is not always considered according to Collett (2013). This then means for any country to be self-sustainable in terms of food production, the spatial planning should always be taken into consideration for any developmental activities within the landscape. Collett (2013) argued that coherent and multi-dimensional planning approach must be followed. This is because if all disciplines with stakes in land are brought together then sustainable agricultural development and food security needs will be met compared to situation where individuals are working in silos.

Taking a case of Lesotho for instance, there are number of ministries with interest on land. These are Ministry of local government, Forestry and Agriculture and if these ministries could be brought together for a 20-30-year spatial planning then a nationwide strategy could be devised on addressing issues of food security in the dispensation of urbanisation in the country compared to them working in silos.

"Urban planning plays a very important role in supplementing the capacity of cities to accommodate population growth" (Naab et al 2013). This is because good planning will make optimal use of available land effectively and efficiently while poor planning on the contrary will not. Nigan (2000) further argues that urban planning requires data on changing land use, urban sprawl and the environment.

The information on changing land use land cover changes provide knowledge on how the land has been changing over time. Therefore, an updated land use land cover maps are of great importance. The assembled knowledge on land use land cover through maps and otherwise will then be used as supporting tools for better decision making on how the he landscape has changed overtime. Nigan (2000) "monitoring of the land use land cover requires the support of two parameters-spatial resolution and temporal frequencies".

According to Collett (2013) "planners are trained to focus on communities, to conceptualize their environment and to collect, organize and disseminate information". Planners expertise allow them to understand the community spatial needs which include their concerns, the available resources within the landscape, and to play the advisory part on the possible equitable and reasonable resource distributions for proper spatial planning. Through the assembly of all information on the landscape, the planners as argued by Pothukuchi (2004) will further plays an important role of the linkage between decision makers, public, and private sectors on issues requiring recommendations on appropriate policies intended for preferred outcomes. This further boils down to the fact that, for planners to plan accordingly, they require up to date information on the current status of the earth's surface on timely basis. The failure to do so will be seen through the uncontrolled developmental activities, poor environment and ever expanding informal settlement and the results will be seen through food insecurity resulting from urbanisation.

In Lesotho, most of the people rely on agricultural land for livelihood and the Ministry of Local Government and chieftainship through the Land Use Planning Division in the Department of Lands, Survey and Physical Planning (LSPP). LSPP has the responsibility of drawing land use management plans and policies though it's Land Use Planning Division. Land Use Planning Division has powers to identify and protect land meant for agricultural production that will ensure sustainability in food security. This division upon completion of the soil suitability study/analysis, it can then recommend the appropriate use of the land based on the quality of the land. There are three legislations aimed at spatial planning and land tenure in Lesotho. These are Land Act of 2010, Town and Country Planning Act of 1980, Local Government Act of 1997 and Deeds Registry Act of 1968 accompanied by their respective regulations.

The above legislations sometimes cause confusion and the results of which makes planning difficult in Lesotho. Joscelyne (2015) indicated that in South Africa, "prior to Spatial Planning and Land Use Management Act (SPLUMA) a fragmented legal planning regime that is fraught with confusion and complexity existed". Gwimbi et al (2014) argued that the Lesotho Land Act of 2010 establishes the greater land tenure security for all land occupants against the arbitrary, land seizure and enhance greater gender equality in the land ownership and transactions and establishes a simplified framework for systematic land regularization. The author identified a gap in land policy that is in conflict with some status that deals with issues of land.

For instance, the Lesotho Land Act of 2010 does not discriminate and it provides equal title to land for both men and women. (Gwimbi, 2014) “However according to Deeds Registry Act of 1968, the act clearly stipulates that, no land can be registered in the name of married women in the community of property”. Therefore, these two Acts contradict each other and hence a need to harmonise them.

Lesotho’s Local Government Act of 1997 defines the powers of all local authorities in both schedule one and schedule two, which include, “inter alia: control of natural resources and environmental protection; public health (including waste collection and disposal); physical planning; land/site allocation; grazing control water resources; services for improvement of agriculture; and forestry”. In this study, Maseru City Council (MCC) as a local authority will be studies as a study area on issues of informal urban expansion and measures for improvement and protection of agricultural land.

The legal status of spatial planning can be regarded as an instrument which should be used to guide spatial planning, to inform the decision makers both at local and national levels (Joscelyne (2015).On the contrary to this, Joscelyne (2015) noted that confusion has arisen with regard to the structure plans, guidelines and Spatial Planning Developments (SDF) as the wording in certain acts alludes to be a more prescriptive status, this is perpetuated by different laws governing the instruments Joscelyne (2015).

The author further indicates that importantly SPLUMA provides a uniform approach as home for spatial planning instrument, rectifying the problems of law as governing different instruments. Therefore, the legal status of spatial planning instruments under SPLUMA is persuasive and informative.

From the foregoing discussions, it is clear that the inconsistency in one’s country legislations could have a negative impact on the countries development and hence a need for harmonization of such legislatures. Lesotho should use a similar approach followed by South Africa in establishing SPLUMA to address challenges brought about by conflicting land laws governing spatial planning. In the meanwhile, GIS and remote sensing can be used to inform the policy and policy makers to realize the trends and pattern of urban growth through mapping and analysis of land cover land use. The results of this through mapping will trigger the land policies to be viewed holistically and not as silos for country development at large.

2.8 Remote sensing (RS) and Geographic Information Systems (GIS)

"Geographic Information Systems (GIS) is a technical tool widely used as part of effective urban planning approach" Naab et al (2013). This is because with GIS and remote sensing provide accurate information in land prices, supply of serviced land, present and the future land projects and housing can be accessed. Naab et al (2013) argues that information from remote sensing and GIS supports planning, decision making and trickles down to effective institutional capacity. There are a number of successful studies where both remote sensing and GIS have been used for monitoring land use and land cover changes (section 2.13 below.)

2.8.1 Geographic Information Systems (GIS)

Yarilgac (2012) "a geographic information system (GIS) or geographical Information System is a system that captures, stores, analyses, manages and presents data that are linked to location". In the simplest terms, GIS is the combination of cartography and database technology. "GIS are used in cartography, remote sensing, land surveying, photogrammetry, geography, urban planning, emergency management, navigation, and localized search engines" (Yarilgac, 2012).

Walz (2011) use of geographic information systems (GIS) is required to analyses landscape structure using landscape metrics. Walz (2011) " GIS is necessary due to the need to evaluate a large amount of spatial information such as land use information, habitat types, soil types) and in order to overlay and intersect this information with other information, enabling the parameters of landscape structure to be calculated". Walz (2011) further argued that, spatial reference units, e.g. natural or administrative units or regular fishnets) are required. Only by overlaying geo-referenced spatial data and computing partial complex mathematical formulas can ensure landscape structures in large areas are analysed (Walz, 2011). Vanier (2004) argued that GIS relates database records with their corresponding attributes data to the physical location and the result of this is the production of maps which are easy to interpret and analyses. In general GIS plays a significant role in visualising spatially referenced datasets on the map through data layering into different themes (i.e., roads, rivers, land uses, forests, buildings, etc.). This point is further emphasised by Peeters et.al (2012) that spatial analysis is the foundation of GIS and it also consists of techniques and methods used for data analysis and its spatial context. One technique predominately used in GIS is the spatial statistics, where location in addition to data attributes is very significant in the spatial statistical analysis. The statistical analysis helps to recognise, understand and quantify spatial patterns and their relationship in space.

2.8.2 Remote Sensing (RS)

Janssen and Huurneman et al (2001) "remote sensing in the broadest sense is, the measurement or acquisition of information of some property of an object or phenomenon, by recording device that is not in physical or intimate contact with the object or phenomenon under study, e.g. the utilization at a distance (as from aircraft, spacecraft or ship) of any device and its attendant display for gathering information pertinent to the environment, such as measurements of force fields, electromagnetic radiation or acoustic energy". In remote sensing there are number of techniques employed to acquire information without being in physical contact with an object of interest. These include use of the devices such as the camera, lasers and radio frequency receivers, radar systems, sonar seismographs, gravimeters, magnetometers and scintillation counters (Janssen and Huurneman et al, 2001).

Campbell (2002) understands that remote sensing is based on the fact that object on the earth surface reflects and emits electromagnetic radiation(EMR) and this radiation can be recorded by the remote sensor instruments which can be grouped into active and passive sensors as shown in figure 5 below. Campbell (2002)" passive remote sensing utilizes instrument designed to sense energy reflected or emitted by the earth, thus they depend totally on the external source of energy like the sun". On the contrary, active sensors (i.e. radar, Sonar and Laser) operate independently of solar terrestrial radiation and record reflection of their own transmitted energy, meaning energy is directly transmitted from the source to the surface object.

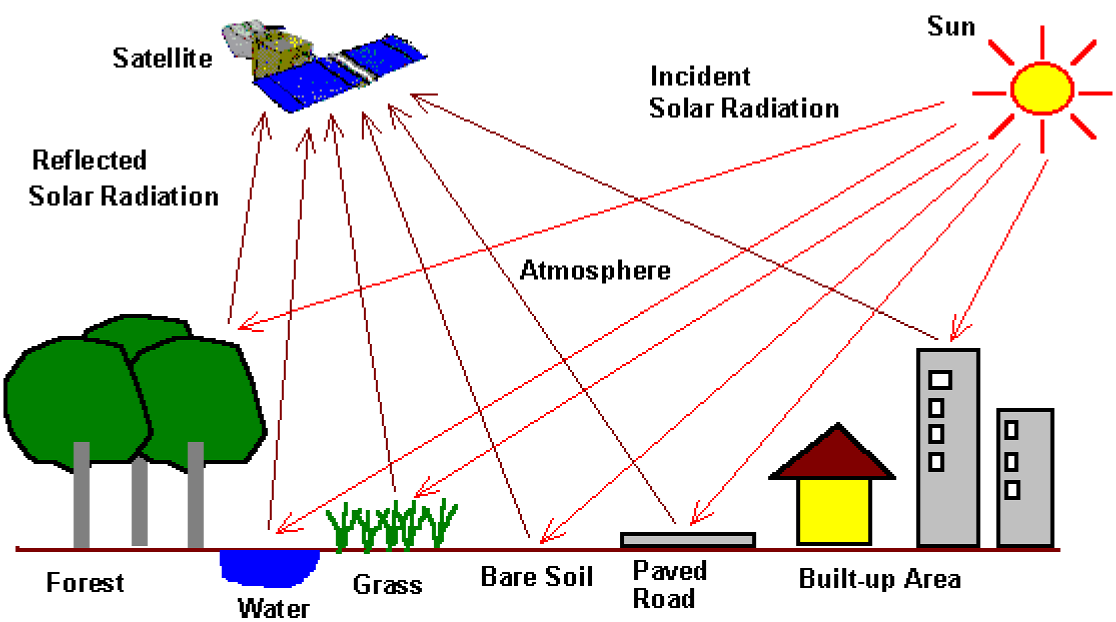


Figure 5: Remote sensing process, adapted from Bekalo (2009)

2.9 Image Classification

“Image classification is the systematic arrangement of various classes of land, based on certain similar characteristics, mainly used to identify and understand their fundamental utilities in order to satisfy the needs of human society in a given time and space” (Singh and Kumar ,2012). In the similar manner Lu and Weng (2007) indicated that there are several major steps of image classification to be followed in image classification. These steps according Lu and Weng (2007) may include but not limited to, “determination of a suitable classification system, selection of training samples, image pre-processing, and feature extraction, selection of suitable classification approaches, post-classification processing and accuracy assessment”. There are two major land use classifications systems which have been used efficiently with time for monitoring land use changes; these are supervised and unsupervised land use classification systems.

2.9.1 Supervised Image Classification

“Supervised image classification is a method in which the analyst first defines small areas called the training sites on the image to be used in supervising image classification”(Cerna and Chytry 2005). The training sites contains predictor variable in each sampling unit and assigns prior class to the sampling unit (Cerna and Chytry 2005). In supervised image classification, an analyst should know the area of study clearly. This is because the delineation of the training areas which is the representative of a land cover is most effective when an image analyst has knowledge of the geography of the study area as this will also help in identify the error due to difference in the spectral properties of the land cover classes (Aldosk et al, 2013).

2.9.2 Image Classification Algorithms

In supervised image classification, after the training samples sets have been defined, then the image classification is carried out based on the classification algorithms. There are a number of supervised classification algorithms and Janssen and Huurneman et al (2001) argued that the choice of the algorithm depends on the purpose of the classification and the characteristics of the image and the training data. The common classifiers are box classifier or parallelepiped, minimum distance to mean, maximum likelihood classifiers and sub-pixel based classifier.

2.9.2.1 Box Classifier or Parallelepiped Classifier

“The parallelepiped classifier uses a simple decision rule that is to find the upper and lower brightness values in each spectral dimension”(Walton, 2015). Janssen and Huurneman et al (2001) argued that the limit may be based on the minimum and maximum values or on the mean standard deviation per class. The author further indicates that when the lower and upper limits are used, they define the box-like area in the feature space, which is why it is called box classifier. The number of boxes depends on the number of classes. Thus during the classification, an unknown pixel will be checked to see if it falls in any of the boxes defined earlier. Hence any pixel that does not fall within any box will be classified as unknown class or reject class.

The major disadvantage of the box classifier according to Janssen and Huurneman et al (2001) is when the two or more classes overlap and in such cases, a pixel is arbitrarily or randomly assigned the level on the first box it encounters.

2.9.2.2 Maximum Likelihood Classifier

Irabo (2013) "maximum Likelihood is the most commonly used supervised classification and is based on the assumption that the training data statistics in each band are normally distributed". Janssen and Huurneman et al (2001) indicates that maximum likelihood classifier considers not only the cluster centre but also its shape, size and orientation. It considers the distances towards class means and calculates the variance-covariance matrix of each class. This means the statistical distance is a probability value: The probability that observation *x* belongs to specific cluster. The pixel is assigned to the class (Cluster) to which it has the highest probability (Janssen and Huurneman et al, 2001). "Maximum likelihood is widely used in remote sensing, in which the pixel with the maximum likelihood is classified into the corresponding class "(Kalra et al, 2013). Walton (2015) indicated that the accuracy of the Maximum Likelihood Classification method depends on the number of training pixels for each class. By the same token, if this number is not possible, inaccurate valuation of the covariance matrix will lead to poor classification.

2.9.2.3 Properties of the Images

Monitoring landscape changes based on remote sensing depends largely on image resolutions. There are basically four types of image resolutions, which are spatial, spectral, temporal and radiometric resolutions.

- **Spatial resolution**

"Spatial resolution refers to the smallest unit-area measured; it indicates the minimum size of object that can be detected" Janssen and Huurneman et al (2001). In a similar manner (Liang, Li and Wang et al 2012) "spatial resolution is the ground area image for the Instantaneous Field of View (IFOV) of the sensor or linear dimension of the ground represented by each pixel". For fast land use changes within a small area, a high spatial resolution image will mostly be suitable to monitor such rapid land use changes.

- **Spectral resolution**

According to Smit (2009), spectral resolution describes the ability of the sensor to define fine wave length. Generally, the finer the spectral resolution, the narrower the wavelength range for a particular channel or band. In a similar Bhatta (2010) "spectral resolution is the number and dimension of the specific wavelength interval in the electromagnetic spectrum in which remote sensing instrument is sensitive to".

- **Temporal resolution**

Janssen and Huurneman et al (2001) argued that temporal resolution is the time between two successive image acquisitions over the same location on earth. The frequency and the characteristics are determined by the design of satellite sensor and its orbital patterns (Liang, Li and Wang et al, 2012). Temporal resolution like the spatial resolution plays an important role in monitoring land use change, it is important that when comparing images of the same area, time of day, day of year and the season of the year are maintained. This helps to avoid change in temporal resolution as change in land use.

- **Radiometric resolution**

"Radiometric resolution is the dynamic range or the number of different output number in each band of data and it's determined by the number of bits into which the recorded radiation is divided "(Janssen and Huurneman et al, 2001. Bhatta (2010) argued that radiometric resolution has the ability to measure the properties of landscape objects. The radiometric characteristics describe the actual information content in an image.

2.9.2.4 Image Classification Nomenclature/classification schemas

The research objectives can only be realized through clearly defined land use classes for boundary delineations which will facilitate monitoring and cause of actions. Table 2 below indicates classification schema used in Lesotho.

Table 2: Reclassified South African land use land cover types for Lesotho (1995), adapted from Majara(2005)

CLASS	ORGINAL CATEGORY	NEW CLASS	NEW CATEGORY
11	Barren land and barren rock	1	Barren land

21 22 23	Cultivated: Temporary-commercial irrigated Cultivated: Temporary Commercial dry land Cultivated: temporary – semi-commercial/subsistence dry land	2	Cultivated : temporary
13 14 15	Degraded: forest and woodland Degraded: thickets and bush etc. Degraded: unimproved grassland	3	Degraded: thickets, bush land, unimproved grassland etc.
12	Donga and sheet erosion	4	Donga and gullies
2 8	Forest Forest plantation	5	Forest and forest plantation
5 7 4 3 6	Herb land Improved grassland Shrub land Thicket and bush land etc. Unimproved grassland	6	Grassland, shrub land and thickets
31	Mines and quarries	7	Mines and quarries
29 30 24	Urban/built-up land: commercial Urban/built-up land: industrial Urban/built-up land: residential	8	Urban/built-up land
9	Water bodies	9	Water bodies

10	wetland	10	Wetland

The similar land use classes above were used to produce the 2012 Lesotho National Land Use Map derived from Landsat 7 from the office of Chief Land Use Planner. The land use map was produced from the China Tech-Aid project in Lesotho for mapping different land uses in Lesotho.

2.10 Remote Sensing and Change Detention Analysis

Pathak (2014) "change detection is the processes of identifying differences in the state of an object or phenomenon by observing it at different times". Many techniques have been developed which can be organized into algebraic/statistical, change vector/transformation classification or combination of them (Pathak, 2014). There are a number of change detection algorithms that were documented in the literature according to Pathak (2014) which include the following: "Mono-temporal change delineation, Delta or post classification, Multi-dimensional temporal feature space analysis, Composite analysis, Image differencing, Multi temporal linear data transformation, Change vector analysis, Image regression, Multi-temporal biomass index, Background subtraction and Image rationing".

There is no universally optimal change detection technique, each technique has both its advantages and disadvantages but the choice of the techniques depends on the aim, objective and application. Abebe (2013) and Pathak (2014) indicate that the five most used change detection techniques in land use land cover changes are Post classification, Image rationing, Image differencing, Principal component analysis and Change vector analysis. Each of the five techniques is further discussed below.

- **Post Classification**

One of the mostly popularly used change detection method is post classification method because of its simplicity and its straight forward technique. In post classification comparison each date of rectified image is independently classified to fit a common land type schema. "The resulting land cover maps are then overlaid and compared on pixel by pixel basis "(Bhatta, 2010). This per pixel comparison can also be summarized in the from -to matrix. The from -to matrix shows every possible land cover changes under the original classification schema and the area of each changed class.

- **Image differencing**

Image differencing (also image subtraction) uses software algorithm to identify and quantify the changes between two temporal images. "Typically, two images which have been geometrically registered are used with the pixel values in one image being subtracted from the pixel value in another" (Bhatta, 2010). In such a change image (or difference image) areas whether there has been little or no change between the original images contains resultant brightness value around 0. While those areas where significant change has occurred contains higher values or lower than 0.

- **Image rationing**

Abebe (2013) "this is a method for change detection in which the two images from two dates are divided band by band and pixel by pixel". If the ratio of the two images is 1, then there is no change but if the ratio is greater than 1 or less than one, it then means there is a change between the images.

- **Principal component analysis (PCA)**

This is multivariate statistical method for data summarization and reduction. PCA is used to reduce the image dimensionality by defining new, uncorrelated bands composed of principal components of the input bands. The principal components are computed by examining the correlation between the input bands, grouping highly correlated band and then calculating the new bands that summaries the information contained in the original band set (Bhatta, 2010).

- **Change vector analysis**

This is an empirical method of detecting radiometric changes between multitudes of satellites images in a number of spectral bands. Balcik and Goksel (2012) "this method yields the information about the degree and type of spectral changes by calculating a vector magnitude and direction in multispectral change space for each pixel". The change vector analysis can be useful for evaluating continuous change such as a reduction in biomass, or an increase in soil moisture (Almutairi and Warner, 2010)

2.11 Accuracy Assessment

According to Santra and Christy (2012) an error matrix or confusion matrix or contingency matrix is a matrix aimed at assessing the reliability of the classified map and the confidence level of using such a map. Moreover, as a rule of thumb, all classified images should be accessed for their accuracy levels. "The confusion matrix contains information about the actual and predicted classifications done by the classification system" (Santra and Christy, 2012). The performance of such system is commonly evaluated by using classified image data and ground truth data in the matrix for assessment or comparisons. Santra and Christy (2012) further indicate that the number of correctly classified instances is based on the correctly classified data as the sum of data sets along the diagonal in the matrix: all other are incorrectly classified accurately.

The overall classification accuracy will then be calculated based on the correctly number of dataset or classes along the leading diagonal, this total number of correctly classes along the leading diagonal cells will be divided by the total number of cells as in shown in table 3 below and equation 1 below.

Apart from overall accuracy, there are other types of accuracies to be determined from the classified images. These are producer and user accuracies. The producer and user accuracies on the other hand are ways of measuring the class accuracy compared to overall accuracy which assess the accuracy of the whole classified image. Producer accuracy indicates the probability that a certain piece of land cover on the ground is really classified as such land cover. According to Adam et al (2013) "producer accuracy is based on the perspective of the maker of the classified map as to how accurate is the map". This generally means that for a given class as a reference plot, this accuracy define as to how many of the pixels on the map are labelled correctly. User' accuracy on the other hand refers to the probability that a certain land cover on the map is really classified as on the ground. Likewise, Adam et al (2013) "user's accuracy is based on the perspective of the use of the classified map as to how accurate is the map". Its aim is to determine from a given class, how many of the pixels on the map are actually what they say they are.

Table 3: Structure of confusion /error/contingency matrix

		Reference						
classification		**Class 1**	**Class 2**	**Class 3**	**Class n**	**Total**	**User's Accuracy**	**Commission Error**
	Class 1	X_{11}				X_{1+}	X_{11}/X_{1+}	$1-X_{11}/X_{1+}$
	Class 2		X_{22}			X_{2+}	X_{22}/X_{2+}	$1-X_{22}/X_{2+}$
	Class 3			X_{33}		X_{3+}	X_{33}/X_{3+}	$1-X_{33}/X_{3+}$
	Class n				X_{nn}	X_{n+}	X_{nn}/X_{n+}	$1-X_{nn}/X_{n+}$
	Total	X_{+1}	X_{+2}	X_{+3}	X_{+n}	ΣX_{ij}		
	Producer's Accuracy	X_{11}/X_{+1}	X_{22}/X_{+2}	X_{33}/X_{+3}	X_{nn}/X_{+n}			
	Omission Error	$1-X_{11}/X_{+1}$	$1-X_{22}/X_{+2}$	$1-X_{33}/X_{+3}$	$1-X_{nn}/X_{+n}$			

Confusion matrix adapted from Chuvieco and Huete (2009)

Global/Overall accuracy (A)

$$A = \frac{\Sigma_{i=1,n} x_{ii}}{\Sigma_{i=1,n} \Sigma_{j=1,n} x_{ij}}$$ ……………………………………………………...Equation 1

Congalton and Plourde (2003) Kappa analysis is a discrete multivariate technique for comparing error matrix. The author argue that the Kappa analysis assumes a multinomial distribution generating a Khat statistic that measure the difference between the actual and the chance (or random) between the map and the reference data. The value of Kappa is always less than or equal to 1 where the highest value of 1 indicates the perfect agreement while the value of 0 indicates lack of agreement. The table 4 below indicates the universal standard values of Kappa and their interpretations.

Kappa index/ coefficient (K)

$$\hat{\kappa} = \frac{n\Sigma_{i=1,n} X_{ii} - \Sigma_{i=i,n} X_{i+} X_{+i}}{n^2 - \Sigma_{i=i,n} X_{i+} X_{+i}}$$ ………………………………………………Equation 2

r =number of rows in the error matrix

X_{ii}= number of observations in row i column i (along the diagonal)

X_{i+}=the marginal total of row i (right of the matrix)

X_{+i}=the marginal total of column i (bottom of the matrix)

n= total number of observations included in the matrix

Table 4: Kappa coefficient interpretations

Kappa index/coefficient	**Interpretations**
< 0	No agreement
0.0-0.20	Slight agreement
0.21-0.40	Fair agreement

0.41-0.61	Moderate agreement
0.61-0.80	Substantial agreement
0.81-1.00	Almost perfect

2.12 Changes detections applications

Lu et al (2004) “good change detection research should provide the following information: (1) area change and change rate; (2) spatial distribution of changed types; (3) change trajectories of land cover types; and (4) accuracy assessment of change detection results”. Lu et al (2004) further argues that for projects on monitoring land use land cover changes with time, there are basically three major step to be followed for changed analysis to have been successfully carried out. These three major steps based on Lu et al (2004) are “: (1) image pre-processing including geometrical rectification and image registration, radiometric and atmospheric correction and topographic correction if the study area is in mountainous regions; (2) selection of suitable techniques to implement change direction analyses; and (3) accuracy assessment”.

Ten aspects of change detection application using remote sensing techniques according to Lu et al (2004) can be summarized as: (1) Land use land cover, (2) Forest and vegetation change, (3) Forest mortality, defoliation and damage assessment,(4) Deforestation, regeneration, and selective logging, (5) Wetlands change, (6) Landscape change, (7) Urban changes, (8) Environmental changes, (9) Forest fire and (10) Other applications such as crop monitoring shift, cultivation monitoring, roads segments change in glaciers mass balances.

Change detections can be performed at different landscape scale for number of reasons and a number of studies for different purposes have been conducted as indicated by the table 5 below:

Table 5: Change detection applications

Who are the authors, researchers and title?	**When was the research conducted?**	**Why did they conduct this research?** **Which concepts/theories were they exploring**	**How did they conduct this research?** **Which evidence did they use?**	**What were their findings?** **What did they argue?**	**My thoughts/ comments/ questions?** **What do I think of their study**	**Interesting references to other works-for later reading**
1. Yohannes, W.A, Cotter,M, Kelbono,G and Desslegn,W. Land Use and Land Cover Changes and Their Effects on Landscape of Abaya-Chamo Basin, Southern Ethiopia.	2017 Abaya-Chamo Basin(ABC), Southern Ethiopia	Examine Land use land cover changes, identify the driving forces behind them and analyse their effects on landscape of ABC between 1985, 1995 and 2010. Use Remote sensing, Field interviews, observations and landscape	Computed accuracy assessment, Interviews and group discussions used for accuracy assessment and to understand the driving forces -LULC fragmented due to anthropogenic and also small isolated patched as indicated by increase NP and decrease in MPS	LULC indicate significant reduction (shrub land, agricultural land and natural grassland decreased) -Built up area increased at a higher rate on agricultural land	Good study for monitoring factor leading to LULC and their patterns	Yohannes, W.A, Cotter,M, Kelbono,G and Desslegn,W (2018) Land Use and Land Cover Changes and Their Effects on Landscape of Abaya-Chamo Basin, Land 2018, 7, 2.

		matrices. -Use Landsat images (TM and ETM). -DEM -ERDAS IMAGINE, FRAGSTATS software- CORINE classification schema used	and CONTAG,GIS used for mapping			
2.Ramachandra, T.V,Aithal,B.H, and Sreekantha, S Spatial Metrics Based Landscape Structures and Dynamics Assessment for an Emerging Indian Metropolis	2012 Mysore City in Karnataka, India	Identify and understand trends of urban changes (from 1974 to 1994) -Integrate GIS, GRASS, Remote Sensing with gradient analysis, Quantify and monitor spatial	GPS for ground truth and collection of data, NDVI for vegetation cover, Post classification method used with Gaussian Maximum Likelihood Classifier for image classification, Accuracy	Unplanned development leads into urban sprawl, city is experiencing sprawl in all directions, highly fragmented urban classes, National classification system modified to address or	Spatial metrics would aid as decision support tool for unravelling the impact of classical urban sprawl	Ramachandra,T.V,Aithal B.H and Sreekantha,S(2012)Spatial Metrics Based Landscape Structures and Dynamics Assessment for an Emerging Indian Metropolis,IJARAI,Vol.1,No.1,2012

		configuration, Use Landsat mages, FRAGSTAS for spatial patterns	assessment and Kappa coefficient by ERDAS Imagine, GIS used for mapping	meet objectives of the study		
3.Murayama, Y and Zhao, Y Urban Dynamics Analysis Using Spatial Metrics; A Case of Yokohama	2006 Yokohama, Tokyo	Analysing urban dynamics at multi categories system using multiple spatial metrics -Use Remote sensing, Detailed Digital Information Metropolitan Area (DDIMA 10 m) -Use FRAGSTATS for spatial patterns -used nation classification	Transformation matrices used for spatial pattern Post classification technique used, GIS use for mapping,	Increase in built up area and built up area extending into water bodies. From spatial metrics, NP value for built up area decreased indicating urban growth in fringes of urban areas.	Remote sensing, GIS and spatial metrics can be used together to understand spatial patterns	Murayama and Zhao,Y (2006) Urban Dynamics Analysis Using Spatial Metrics; A Case of Yokohama, Tsukuba Geo-environment science,Vol.2,pp.9-18, Dec 26,2006

		scheme of Multi and binary category systems				
4.Mudau, N, Mhangara,P and Gebreslasie, M Monitoring urban growth around Rustenburg, South Africa using SPOT 5	2014 Rustenburg, South Africa	Understand urban growth for sustainable infrastructure development and service planning -Use remote sensing, SPOT 5 (2007,2009, 2012) to study urban growth -eCognition	Used multiple temporal SPOT 5 imagery to monitor land use changes, Used Post classification detection method, modified South African classification schema for land use classes(urban and non-urban classes)	Increase in urban areas, higher than Port Elizabeth due to natural population growth, post-apartheid urban development and increase in influx of people from neighbouring province and countries	Importance and accuracy of high spatial resolution imageries in mapping land use changes	Mudau,N, Mhangara,P and Gebreslasie, M (2014) Monitoring urban growth around Rustenburg, South Africa using SPOT 5,South African Journal of Geomatics, Vol.3, No.2, August 2014

		software used for classification -GIS(ArcGIS)used for mapping				

From the forgoing discussions, most of the researchers were monitoring land use land cover changes and the factors leading to such changes. Mudau et al (2014) indicated that an increase in urbanisation in Rustenburg was due to natural population growth, post-apartheid urban development, increase influx of people from neighbouring provinces and increase in mining activities. In a similar study, Yohannes et al (2018) found that the major driving force for land use land cover changes include, population growth which in most cases is a result of natural causes which includes birth and death rates, highland-lowland migration as a results of people moving away from rural lands in the highland for better standards of living in the lowland which promotes high rate of urbanisation, as well as regime change and subsequent policy shift of the current government. This is mainly because, as the results of political changes brought about by democracy, the raining government changes policies which might attract or disperse people and in the process results in the land use land cover changes.

The remotely sensed data was used to achieve the study objectives of the studies highlighted above. Yohannes et al (2018) and Ramachandra et al (2012) used Landsat data while Mudau et al (2014) used SPOT 5 for monitoring land cover changes. These researchers were monitoring changes ranging from a period of five years to 20 years' period.

From these studies, it's clear that any remotely sensed data with a reasonable temporal resolution can be used for monitoring land use changes based on the objectives of the study. This is because other researchers have used other remotely sensed data like Advanced Very High Resolution Radiometer (AVHRR), IKONOS, aerial images and othophotos, IRS, Detailed Digital Information Metropolitans Area (DDIMA 10m), Sentinel-2, etc. for monitoring land use changes and urban growth with time.

Once remotely sensed data is acquired for land use, the researchers then define the classification schemas to be used. Yohannes et al (2018) used Coordination of Information on the Environment (CORINE) land classification system or nomenclature. It is noted that different researchers used their national classification schemas for land used cover classification, or they modify their national classification schemas to address the objectives of their studies. Ramachandra et al (2012), Murayama and Zhao (2006) and Mudau et al (2014) modified their national classification schemas. The modification resulted either in between two to four land use classes in most cases, which were urban area/built up area, non-urban area, agricultural and water bodies.

Following the identification of the classification schema, Yohannes et al (2018), Ramachandra et al (2012), Murayama and Zhao (2006) and Mudau et al (2014) all used pixel based supervised image classification using the Maximum Likelihood algorithm. This was based on its advantages over other classification algorithms as indicated in section 2.7.3.3 above. In the similar manner the researchers performed post classification change detection by comparing land use land cover image maps based on pixel by pixel basis. Ramachandra et al (2012) went further computing Normalized Difference Vegetation Index (NDVI) for vegetation cover.

There are number of software's used in remote sensing for image classification, these includes ENVI, eCognition, ERDAS Imagine, etc. The Ramachandra et al (2012) and Yohannes et al (2018) used ERDAS imagine software for image classification while Mudau et al (2014) performed image analysis using eCognition. The results obtained from all the studies indicated the increase of expansion of the built up or urban area into other land uses. Every image classification performed was followed by computation of the accuracy assessment to give confidence level of the classified image. Based on the overall accuracy assessment performed on all the classified image and the Kappa index, all the studies obtain overall accuracy of more than 85% which indicates the success of the classification itself.

The other researchers further went on to use spatial metrics to understand the urban growth patterns. These metrics were used on the classified or categorical land use land cover map produced. The software used for spatial patterns was FRAGSTATS. Ramachandra et al (2012) Murayama and Zhao (2006) and Yohannes et al (2018) used the minimum of four spatial metrics among many spatial metrics to analyses urban patterns. The common metrics used includes, Class Area (CA), Number of Patches (NP), Largest Patch Index (LPI), Edge Density (ED), and Contagion (CONTAG). Some of these metrics are further defined in detail in section 2.14 below. The results from these metrics indicated the urban sprawl into the agricultural land and highly fragmented urban growth in all directions in most cases.

From the above discussions emanating from table 5, it is evident that there is no single remotely sensed data that is universally best considered for land use land cover change studies. This is because the choice of remotely sensed data is dependent on the research objectives, its merits and moreover the accessibility and availability of such data. Some of the researchers have used the Landsat because such data is easily available (free download) and its long history as its imagery availability dated way back in 1970's since its first launch in 1972. Moreover, landsat has an advantage of having a number of bands(more three natural RGB bands) which enable extensive data manipulation. There are other remotely sensed data which have a higher resolutions compared to landsat and hence the choice of the data sometimes depends on the finances. In a similar manner like Landsat, there are a number of image classification schemas, ranging from national to international schemas, and the choice of the image classification schema is dependent on the study objectives and sometimes both national and international schemas could be modified and merged to meet the research objectives.

The researchers above used different GIS and remote sensing software's for data analysis and for data presentation. The choice of software is again based on suitability and financial muscle. Thus, whether to use free or commercial software is user driven by his objectives. There are number of spatial metrics and all of them can be used to assess landscape pattern and hence no single universally accepted spatial metrics for monitoring landscape changes. Likewise the choice of the spatial metrics is user driven and its interpretation should always be given first priorities to avoid spatial metrics misinterpretations. In general, whether it is free or commercially used software, free or commercial acquired data, the yielding results shows that the expected results were obtained which are dependent of the analyst analysis and not necessarily on the software. In general, for studies similar to the above, it is important to clearly plan the study through defining the objectives, source of data, etc and the availability of resource to be used before beginning a study

Lastly, in general from the studies above, remote sensing has been used for data acquisition, GIS for mapping, FRAGSTATS software or it is plug-in ArcGIS for spatial patterns understanding and remote sensing software's for image classifications.

2.13 Remote Sensing in Land Use Land Cover Changes

Rimal (2011), "viewing the earth from space is now crucial to the understanding of the influence of man's activities on his natural resources base over time". This is mainly because the number of studies indicated that there are situations of rapid and often undocumented records on the land use land cover changes as the result of man's activities and hence remotely sensed data helps to monitor such changes due to man. Thus in order to overcome limitations brought about by the lack of data on land use land cover changes with time Rimal (2011) showed that observations of the earth from space will provide objective information of human activities and utilization of the landscape that have not been recorded in the past and for those areas that are inaccessible.

Nemeth et al (2013) determined land use and land cover changes in an urban area, in Tirupati from 1976 to 2003 by using Geographical Information Systems (GIS) and a remote sensing technology. The study showed significant expansion of built-up area and the decrease in agriculture area, water spread area and forest areas.

Misra et al (2012) shows the impact of urbanisation in Aurangabad city between 1989 and 2006. The study indicated significant decrease of agricultural area and an increase in settlement area from year 1989 to year 2006. In 1989, the agriculture area was 67. 048Sq.Km and in year 2006 it was 24. 449Sq.Km, the total decrease of agriculture area is 41.6 Sq.km i.e. 62.044% of total agriculture area in 1989 (Misra et al, 2012).

Rimal (2011) studied Kathmandu Metropolitan using remote sensing and GIS. The results showed a pattern where the urban or built-up areas in the Kathmandu had a noticeable increase and observed that the urban development change is very high in the city area, from 16.85% (10. 90sq.km) of the total land in 1976 to 66.61 (43. 10sq.km) in 2009. It showed 13.90% in 1976, 8.80% in 1989, 2.93% in 2001 and 2.32% in 2009. But the decrease of the forest seems constant in 2001 and 2009.

2.14 Urban Growth Pattern through Spatial Metrics

Landscape metrics are also known as spatial metrics. They provide important information about the underlying process that lead to changing land use land cover within the landscape. Moreover, the metrics provides the general characteristics and the consequences of dynamic changes within the landscapes. Bharath et al (2012) indicated that there are many landscape metrics that have been proposed to characterize the spatial configuration or composition for the individual landscape classes or the whole landscape. The choices of the metrics depend on the objective of the study under consideration. The most commonly used spatial metrics based on their successes in defining and characterising landscape configuration includes the following metrics: Number of patches (NP), Edge density (ED), Largest patch index (LPI), Area weighted mean patch fractal dimension (AWMPFD), and Euclidean nearest neighbour index (ENN).

Class Area (CA)/Total area (TA)

Class area is sometimes called total area (TA). It measures the absolute area of each land cover class and it is measured in hectors (division by 10.000 to covert to hectares). Class area is always greater than zero (CA>0).

$CA=\sum a_{ij} (1/10000)$ …………………………………………………………… Equation 3

(Class level metric)

a_{ij}= area in square meters of patch ij

Range: CA >0, without limit

McGarigal et al (2002) indicates that CA approaches zero as patch type becomes increasingly rare in the landscape. CA=TA when he total landscape consists of a single patch type (entire image consists of single patch). Thus the CA describes the growth in term of area or size (McGarigal et al, 2002).

Number of patches (NUMP)/NP

This metric is used to measure the number of patches in the landscape at class level. It measures the number of discontinuous urban area or individual urban units in the landscape (McGarigal et al, 2002). It is the indication of diversity or richness or diversity of the landscape.

NUMP=N……………………………………………………………………………. Equation 4

(Class level metric)

Range: $N \geq 1$, without limit and

NP is the number of patches in the landscape. This values ranges from 1 to infinity. For example, NUMP=1 when the landscape is dominated by a single patch. Thus the values indicates the spatial heterogeneity within the landscape based on the number of different types of land covers within the landscape under consideration. Therefore, the value measures the extent of subdivisions of urban areas. This is because when the NUMP gets higher then it indicates that the landscape is getting more diverse, heterogeneous and it's getting further fragmented according to (McGarigal et al, 2002).

Edge Density (ED)

ED equals the sum of the lengths of all edge segments in the landscape, divided by the total landscape area, multiplied by 10,000 (to convert hectares) based on (McGarigal et al, 2002 and Bekalo, 2009).

ED= (E/A) *10000……………………………………………………………Equation 5

(Class level metric)

E = Total length of edges in the landscape

A=total landscape area

Range: ED≥0

ED = 0, this value indicates that there is no edge in the landscape. This is because as argued by (McGarigal et al, 2002) that when the entire landscape consists of one single patch, then there is no landscape boundary or background because the landscape is homogeneous and hence no other patch form any other edge. In general, the ED value can only be zero only when the entire landscape is homogeneous with one class or species.

Largest Patch Index (LPI)

According to Herold et al (2003) largest patch index is the ratio of area by the largest patch of the landscape divided by the total area of the landscape. This measure is normally expressed as percentages. Abebe (2013) further indicated that the LPI is considered a measure of fragmentation of the urban landscape into smaller discrete patches versus the dominant core. The value of LPI increases when the urban areas become more aggregated and integrated with the urban cores.

$LPI = \left(\sum_{i=1}^{n} \frac{aij}{A}\right) 100$………………………………………………………….. Equation 6

(Class level metric)

a_{ij} = area in square meter (m^2) of patch ij

A= total area of landscape in square meters (m^2)

Range: 0<LPI≤100

LPI values become significantly small or approaches zero within the landscape when the land cover considered to be occupying the largest patch is very small. On the contrary LPI=100 when the entire landscape is dominated by a homogeneity of a single patch, this occurs in situations where the largest patch comprised of 100% of the entire landscape and hence there is no heterogeneity within the landscape (Abebe, 2013)

Area Weighted Mean Patch Fractal Dimension (AWMPFD)

"Fractal dimension is a measure of patch shape complexity which describes the convolution and fragmentation of patch as a perimeter –to-area ratio" (Abebe, 2013). This metrics weigh all fractal dimensions of all different classes within the landscape and then averages them to get general pattern of the entire landscape. Thus it's the average weighted fractal dimension values of all the same class. Herold et al (2005) indicates that AWMPFD gives improve measure of class fragmentation as it averages the fractal dimension of all patches by weightings larger land cover patches. McGarigal et al (2002) mentioned that when the patch has a compact regular form with relatively small perimeter relative area AWMFPD will be low and conversely if the patches are more irregular, complex and fragmented, the perimeter increases resulting in higher fractal dimension.

$AWMPFD= \sum^{m}_{i=1}\sum^{n}_{j=1}[(\frac{2\ln(0.25Pij)}{\ln aij})(\frac{aij}{A})]$…………………………………………..Equation 7

(Landscape level metric)

m=number of patches types

n=number of patches class

p_{ij} =perimeter of patches ij

a_{ij}=area of the patches ij

A=total area of the landscape

Range: $1 \leq AWMPFD \leq 2$

Euclidian Nearest Neighbor (ENN)

McGarigal et al (2002) ENN "equals the distance (m) to the nearest neighbouring patch of the same type, based on the shortest edge to edge distance (edge to edge distances are from the cell centre to cell centre)".

$ENN=h_{ij}$………………………………………………………………………Equation 8

(Landscape metric)

h_{ij} = distance (m) for patch ij to the nearest neighbouring patch of the same type (class) based on the edge to edge distance computed from the cell Centre to cell Centre

There are a number of successful studies where some of the above spatial metrics have been used to quantify categorical map patterns. Gokyer and Donmenz (2013) studied Amasre City which is a coastal settlement in Bartin. Landscape structure was quantified by using landscape matrices on land cover maps belonging to different years. Six metrics were used; Class area (CA), Total Landscape Area (TLA), Number of patches (NUMP), Mean Patch Size (MPS), Total Edge (TE) and Shannon's Diversity Index (SDI). From the study, fragmentation was evaluated with NUMP and MPS and shows the fragmentations decrease between year 2000 and 2011. Similarly, the TE decreases with time and SDI is not changed with time.

Ramachandra et al (2014) in a study of Chenmai or formerly Madraspattinam in India, to understand landscape pattern, three landscape metrics were employed, these are Number of Patches (NP), Normalized Land Shape Index (NLSI), and Clumpiness Index (CLUMPY). The study indicated increase in number of patches from 300 in 2000 to 1400 in 2012 which shows urban sprawl. Normalized Land Shape Index (NLSI) provide the measure of class aggregation and all four period indicated less values of 2013 compared to 1991, this means landscape consists of a single square patch or its maximally compact (almost square) and lastly, Clumpiness deal with aggregations and disaggregation for adjacent patches and the study indicated less compact growth or maximum disaggregation compared with the values of 2013.

Lastly, Bekalo (2009) monitored land use changes in Addis Ababa through spatial metrics using selected spatial metrics based on the study objectives. The results indicated that there is a significant urban sprawl and emergence of fragmented urban centre based on Edge Density (ED) and Patch Area (PA). Largest Patch Index (LPI) indicated that there are small and isolated fragmented urban sprawls connected with the core and main urban and lastly the AWMPD indicate the urban sprawl has radiated irregularly into different directions and this means the city expansion is not compact polygon.

2.15 Conclusion

Based on the number of successful studies where both remote sensing and GIS were used to monitor land use changes, this generally implies that, integrating remote sensing and GIS can produce an excellent technique for optimal land use planning and monitoring. From the number of studies conducted above, it's becoming obvious that the major driving force behind most the land use changes is due to human activities resulting from urbanisation. This then calls for immediate planning of land use for sustainable use through use of both GIS and remote sensing through providing timely data on spatial changes using remote sensing and performing analysis using GIS. In the similar manner, residential development or informal settlement occurring on the peri-urban areas and other changes can be quantified by using the spatial metrics in order to understand the dynamics of the urban development in the Maseru City Council (MCC).Moreover, it is evident that the choice of the both classification schema and the classification algorithm is very important in the production of the categorical maps to be used as baseline maps for other developmental activities.

CHAPTER 3: RESEARCH DATA AND METHODOLOGY

3.1 Introduction

This chapter defines the technique used to prepare datasets for the analysis of land use land cover changes, landscape patterns and the methodologies to achieve the objective of the study. They include explanation of data and data sources, methods of field data collections, image classification techniques applied based on merits from previous literatures, change detection method used, accuracy assessment, spatial metrics used and the software's used.

3.2 Research methodology

The major challenge in classifying remotely sensed data into thematic maps according to Lu and Weng (2007) is that many factors are taken into considerations. These factors include according to Lu and Weng (2007) the complexity of landscape in the study area. The landscape will be characterised by different features and their similarities in spectral reflectance might affect the thematic maps produced. The selected remotely sensed data, the type of remotely sensed data is very important in determining the accuracy of the classified image. Lastly, image pre-processing and classification approach may affect the success of the classification.

The overall method, technique, approach and material used to achieve the research objectives are summarized in the research methodology of flow diagram in figure 6 below. This research is conducted through three phases which are pre fieldwork, fieldwork and post fieldwork. In pre fieldwork, research proposal was developed which included research problem formulation, aim, objectives, research questions and defining the study area. In the second phase, information and data collection took place. These include both primary and secondary data collection. For example, this phase includes collection of ground truth observation/ points, visit to the number of places within the study area and secondary data from the literatures. For Example, the city centre was visited to view the new developments. In the last phase, post fieldwork, the data collected is processed and analysed and the results presented in order to meet the pre-defined objectives of the research. Finally, the conclusion was reached based on the data analysis and recommendations made from the study.

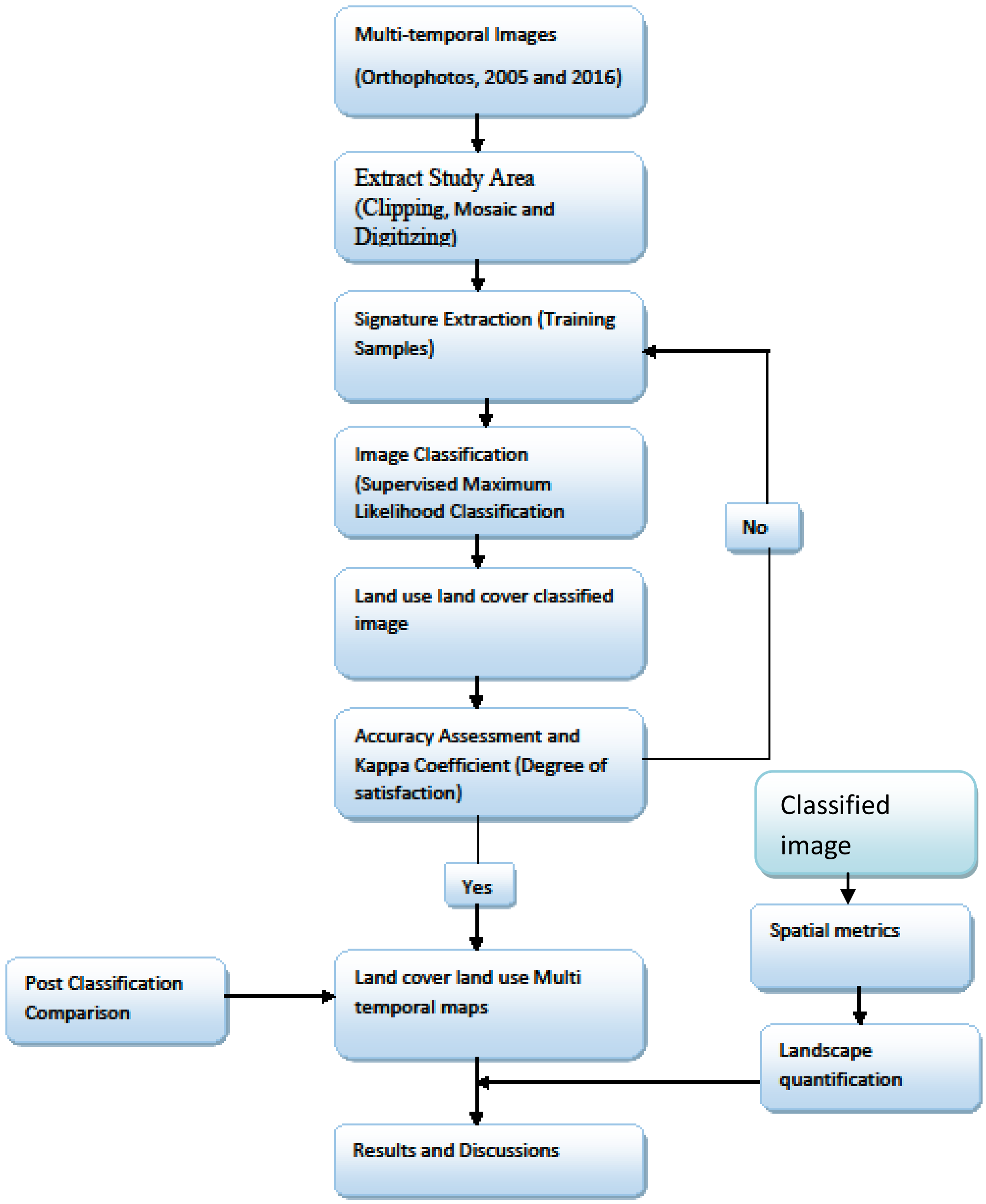


Figure 6: Research methodology/ flow diagram

3.3 Data Source and types

The data used in this study includes; administrative boundaries, topographic maps, and orthophotos. Both 2005 and 2016 orthophoto images of Maseru were also obtained from the office of the Chief Surveyor, Lesotho. The administrative boundary of Maseru City Council (MCC) was obtained from MCC GIS and Survey office. Orthophotos are "photographs that have been corrected for distortions due to tilting of the camera during the photographic survey, distortions from the camera lens, and relief distortions" (Ayhan et al, 2006). This means an orthophoto may then be used as a map. Thus, orthophotos are giving benefits, both for interpretation and for geometric and cartographic aspects. The high spatial resolution orthophotos are automatically classified compared to onscreen digitisation to avoid the subjectivity in image classification and moreover to speed up the image classification process. The table 6 below gives the summary of the data sets used in this study and the sources of such datasets

Table 6: Data types and sources

NUMBER	DATA TYPE	PRODUCTION	SPATIAL RESOLUTION	SOURCE
1	Orthophoto	2015	0.4 m	Office of Chief Surveyor
2	Orthophoto	2016	0.35 m	Office of Chief Surveyor
3	Maseru City Council (MCC) Boundary	2011	Softcopy shape file	Maseru City Council (MCC)

All data used in this study were projected to the Transverse Mercator projection system, South Africa Coordinate System (Lo 27), spheroid and datum was referenced to Cape

3.4 Software and other instruments used

ERDAS IMAGINE 2018, ArcGIS 10.5, Change Analyst ArcGIS Plug-in, Ashtech Pro-mark 2 GPS, XForm and FRASTATS tool 4.2.1

3.5 Classification Schemas

The classification nomenclature/schema was based on the objectives of the study coupled with the definition of agricultural land in section 2.3. The classification schema described in section 2.9.3.6 was modified and some of classes were merged and regrouped into two classes. These two classes were built-up land and non-built up land (agricultural land) as shown in table 7 below. The two land use classes will assist an analyst in the discussion and the analysis of an extent of the informal built up land into agricultural land within MCC and its peripheries.

In order to find the driving forces and the pattern of the informal settlement into the agricultural land along the MCC peripheries, the land use classes in table 7 were further redefined into agricultural land (non-built up land) and the roads (tarred and dirt / informal roads). The pattern of land use and land cover changes due to informal settlement were then analysed (section 4.4). This is because the major challenge in Lesotho is the emergence of the informal settlement along the urban fringe which affects agricultural land immensely.

Table 7: Regrouped land use classes

CLASS ID	CLASSES	DESCRIPTION
C1	Built-up land	Commercial, industrial, residential, roads, railway and other associated lands.
C2	Non built up land (Agricultural land)	Land used exclusively or mainly for agriculture, arable land, pasture, grazing, orchard or seed growing, or for fish farming, forestry (including forestations), or for the breeding or keeping or livestock, including any creature kept for the production of food, wool, silk, skins or fur(Land Act 2010), water bodies(wetlands, marshes, swaps, artificial lakes, dams and ponds)

3.6 Temporal image analysis

Monitoring landscape changes based on remote sensing depends largely on image resolutions (section 2.9.3.5 above). Nigan (2000) indicated that monitoring the land cover land use requires mostly two parameters which are spatial resolution and temporal frequencies. The combination of these resolutions, play an important role in detecting accurately land use changes with time. For instance, for fast growing urban area, high spatial, temporal and spectral resolutions will yield better result and help in better planning of such areas. On the contrary slow changes over large area do not necessarily requires high resolution imagery. Depending on the purpose of the study, combination of these resolutions should always be taken into considerations.

3.7 Image Classification process

"Image classification is a complex and time consuming process and in order to improve the classification accuracy, selection of appropriate classification method is required" (Bekalo, 2009). In this study, two multi temporal high spatial resolution (0.4 and 0.35m) orthophotos were used to analyse landscape dynamics and its pattern in Maseru City Council (MCC) and its peripheries for the past 11 years (2005 to 2016). Since orthophotos are already geometrically correct, there was no need for any image rectification. It is worth noting that the 2005 orthophoto has a little haze cover which might affect the image classification process.

Pixel based supervised maximum likelihood classification algorithm was used due to its popularity. This method of image classification is widely accepted in remote sensing as one of the best image classification technique based on the successful studies where it has been used and proven a success (see section 2.9.2.2). Supervised image classification requires the analyst to have prior knowledge of the study area in order to define training polygons correctly.

The Figure 7 below indicates the major steps in conducting a supervised image classification process (see section 2.9.2 for image algorithms and classifiers merits).

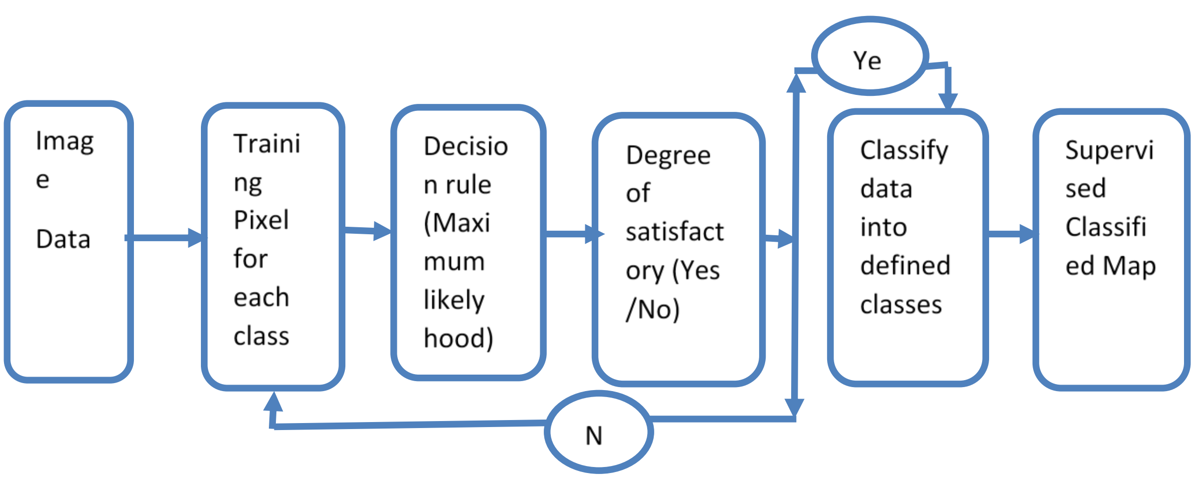


Figure 7: Supervised image classification process

The supervised image classification was performed using ERDAS IMAGINE 2018 software. The resulting land cover land use map was composed of two land classes which are built-up land and agricultural land (see section 3.5)

3.7.1 Image Mosaic and clipping

The study area is covered by 13 raster data sheets and hence a mosaic of these sheets was first done using ERDAS Imagine 2018. After image mosaic, the MCC administrative boundary was buffered by 2 km except along Mohokare (Caledon) river in the west which is boundary of Lesotho and the Republic of South Africa (RSA). Therefore, the study area and its 2 km buffer were used to clip the study area and its urban periphery.

3.7.2 Erdas Imagine 2018 image classification

The first step in image classification using Erdas Imagine starts by delineating training sites/polygons and generating signatures files. The analyst first selected and digitised polygons (training areas/polygons or area of interests) which are the representative of different land use classes. These training areas were then placed as Area of Interest (AOI) which will be used to generate the signature file. The second step involved merging the signatures, since one land use class was represented by a number of training areas (minimum of 30 training areas) to increase accuracy of the classification; their signatures were then merged together and renamed a defined land use class. The last step was the classification itself, the signature files created above were used as an input file with the selected classifier (maximum likelihood classifier) then runs a supervised image classification followed by accuracy assessment and the analysis of the classified image.

3.7.3 Training samples characteristics

In this study, the pixel based image classification approach was used. Firstly, the training samples which are typical representative of different land use classes were identified to represents different classes as defined by the classification schema based on the analyst knowledge of the study area. In the second stage, classification was performed using maximum likelihood algorithm or classifier. As indicated earlier that every classified image should be succeeded by accuracy assessment and as a results the final stage in image classification process was the assessment of the accuracy of the classified image. The stratified randomly generated ground truth points /observations were used and thereafter analysis of the confusion matrix performed. It is worth noting that feature used for training polygons have not been used as ground truth points for accuracy assessment. When selecting the training polygons, the following characteristics were born in mind that, (1) they should represent all classes defined by the classification schema, (2) relatively homogeneous and evenly distributed within the study area. (3) They should be numerous, minimum of 30 training polygons for each class based on analyst knowledge of the study area and (4) avoid mixed pixels at the edge of the objects.

3.7.3.1 Spectral reflectance curves

The orthophotos (both 2005 and 2016) used in this study uses true colour composites bands. These bands are visible red (band 3), visible green (band 2) and visible blue (banad1). These channels are important in that they create a true colour composite image which can be easily and visually interpreted because what a person would see is similar to a photograph of the same scene.

Energy from the sun, when reaching the earth's surface is absorbed, transmitted or reflected. The wavelength of the transmitted energy and the characteristics of the earth's surface (water bodies, bare soil, vegetation, etc.) are the determining factor whether the received energy from the source is being absorbed, transmitted or reflected back to space. The figure 8 below indicates spectral reflectance curve for some different objects and how they reflect energy.

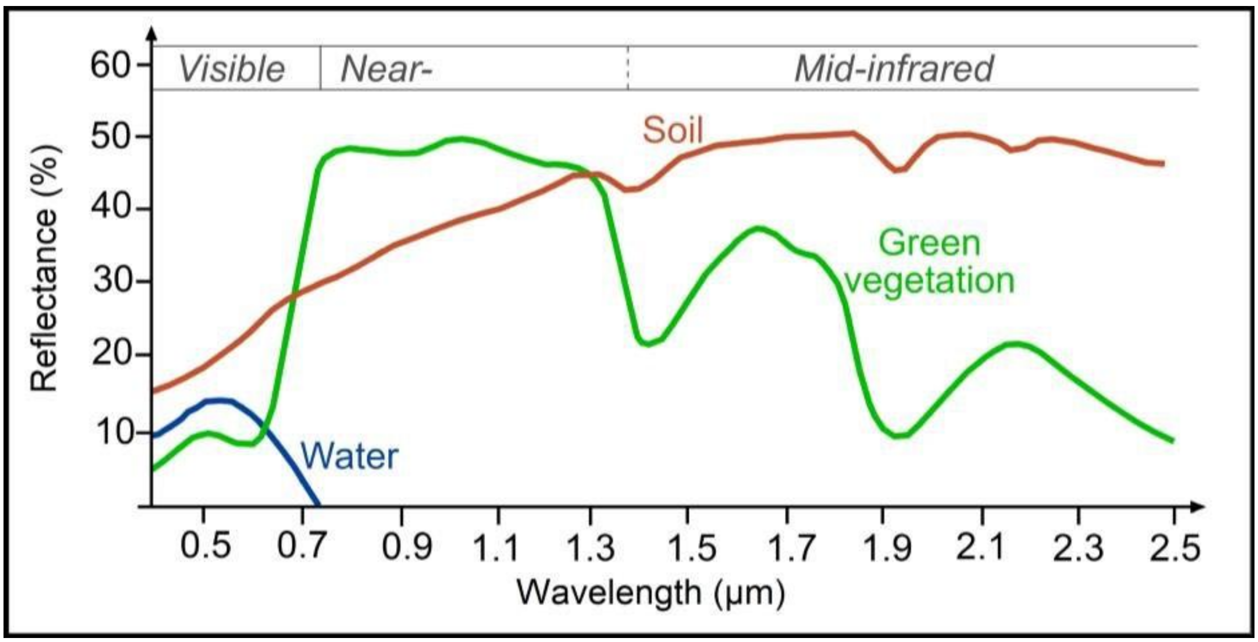


Figure 8: Spectral reflectance curve of three features

Figure 8 above indicates that different object reflects energy differently at different wavelengths. For example, in visible light range, soil reflects more than both water and green vegetation, but contrary to that, at near infra-red wavelength, green vegetation reflectance is higher than that of soil and water.

From the forgoing discussion, it's clear that there are times when the different objects reflect similarly both in visible and near infrared spectrum. This leads to spectral signatures overlap both in visible and near-infrared bands. These signature overlap are the causes of the image misclassification and the errors associated with image classification. These errors will be assessed through the error or confusion matrix. The image enhancement process before spectral signatures was applied in order to discriminate land cover classes and also to improve the image classification accuracies.

Maini and Aggarwal (2010) "Image enhancement is basically improving the interpretations or perception of information in image for human viewers and provide better input automated image processing". Image enhancement is a remote sensing technique used to modify the attributes of an image (Maini and Aggarwal, 2010. This reason being to improve the quality of image itself through adjustment of contrast of an image in order to make it more suitable for a given task and to a specific observer (Maini and Aggarwal, 2010). Image enhancement can be divided into two categories which are spatial domain method and frequency domain method. The spatial domain as indicated by Maini and Aggarwal (2010) deals directly with map pixels where pixels values are manipulated to achieve desired enhancements. There are number of different image enhancement techniques and all of them are aimed at improving image quality for better analysis. The most common techniques are contrast stretch, histogram equalisation, density slicing, histogram matching, edge enhancement and spatial filtering.

Janssen and Huurneman et al (2001) indicated that there are two important constraints to be taken into consideration when using the pixel based image classification. These constraints are that pixel based image classification results in (1) unique spectral classes and (2) each pixel is assigned to one class only and hence no pixel overlap. The spectral classes are classes that are directly linked to the spectral bands used in the classification according to Janssen and Huurneman et al (2001). Therefore, these spectral classes are directly linked to the surface characteristics. This generally implies that the spectral classes correspond uniquely to the land cover classes In image classification process it worth noting that, a spectral signature class can also be represented by several training classes/polygons especially in situation where feature spatial reflectance are not distinct. This is because of the variability within spectral class. For example, there are different types of sandy soil with different spectral characteristics as shown in spectral reflectance curve in figure 9 below. The spectral classes can then be merged together to give one land cover class of sandy soil.

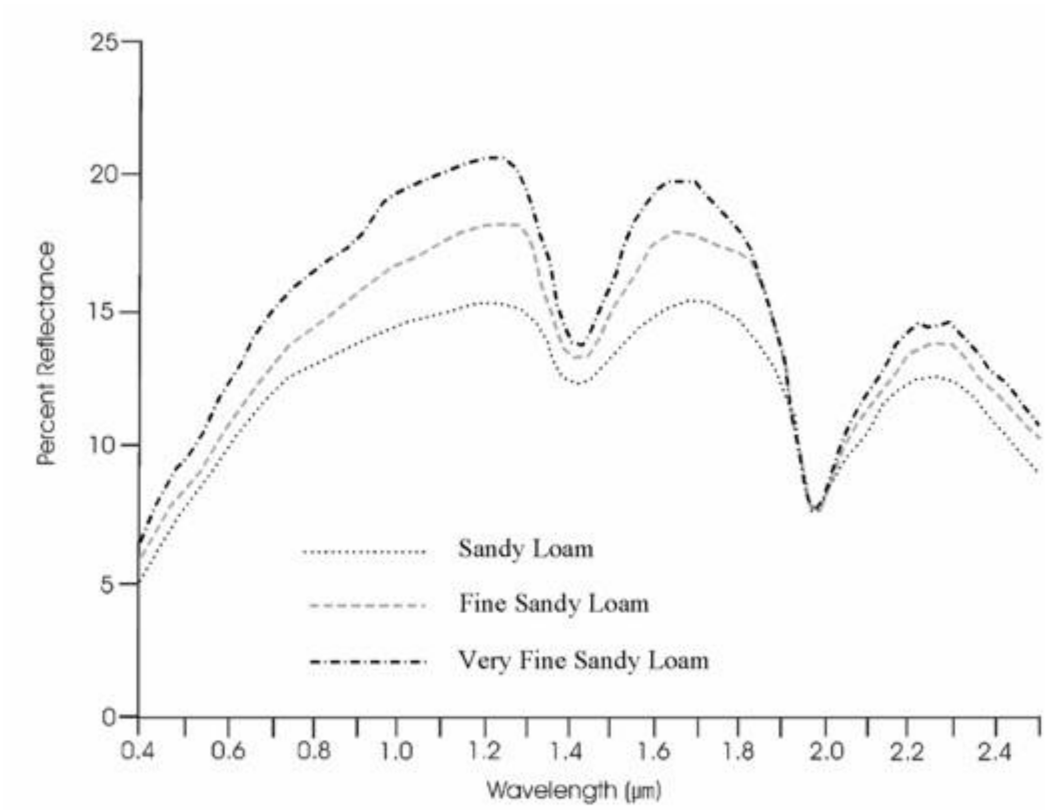


Figure 9: Spectral reflectance curves of sandy soils.

3.7.4 Field data collection

One of the most important primary data for image classification is the ground truth data as it indicates what is actually on the ground. The ground truth data represents what actually transpires on the ground. The ground truth data is used to access the accuracy of the map produced. The field work for ground truth was carried out during mid-year vacations, between 16 June and 22 July 2018 within Maseru City Council (MCC) boundaries and its buffered area. The simple stratified random sampling (quota) technique was used to determine the ground truth objects.

3.7.5 Reference Data

The reference data of more than 100 field survey objects or ground truth features was used. The minimum of 30 polygons were used for training polygons (minimum of 30 objects for each land use class) and a total of 165 objects (for both land built-up and non-built up land use classes) were used as the ground truth to assess the accuracy of the classified image. The number of sample features or ground truth points can be estimated based on binomial probability theory in equation 9 below though there is no general rule defining the actual number of ground truth for accuracy assessment.

$$N = \frac{Z^2\ (p)(q)}{E^2}$$ ……………………………………………………………………...Equation 9

N is the sample size

P is the expected accuracy of the entire map (overall accuracy)

q=100-p

Z=2

E is allowable error.

Example: Since the minimum overall accuracy of the classified image is 85%, and with 5% allowable error in image classification, then the sample size was calculated as:

$$N = \frac{2^2\ (85)(15)}{5^2}$$ = 204 sample objects

It is worth noting that features used for training areas have not been used for accuracy assessment to make sure that accuracy was unbiased. The simple stratified random sampling (quota) technique was used for the determination of the ground truth sample based on knowledge of the study area and its accessibility. The Ashtech Pro-mark 2 GPS was used for ground truth data collection. The Ashtech Pro-mark 2 GPS used have the following characteristics, desired horizontal accuracy of 0.020m+1ppm and desired vertical accuracy of 0.04m+2ppm. Appendix 1 indicates some of the ground truth observation/ features made with this GPS.

3.7.6 Accuracy Assessment

Abebe (2013) argued that in remote sensing land cover mapping studies, classification accuracy is the most important aspect to assess the reliability of the final product. Mandadhar et al (2009) similarly argued that the minimum levels of interpretation accuracy in the identification of land use and land cover categories from remote sensing data should be at least 85%. RCMRD-SERVIR Africa (2015) indicates that the acceptance threshold for overall accuracy according to USGS classification is 75%. On the contrary FAO (2016) indicated that there is no general rule as to which level of accuracy is good and which is not. The reason for no general rule according to FAO (2016) being the fact that the judgment on the validity depends on the purpose of the map and therefore each map should be dealt with independently as they are all unique cases. In this study the accuracy of image classification results was assessed using 165 ground truth features from simple stratified random sample points from the field work.

3.8 Spatial Metrics and definition of the spatial domain

Abebe (2013) indicated that in using the spatial metric, It's is important to first defined the spatial domain or extent within which the metrics will be applied on. This is because the spatial domain will influence the choice of the spatial metrics to be used, whether the spatial metrics will be used at class or landscape levels will be determined by the spatial domain. Abebe (2013) defined the spatial domain as the geographic extent under analysis and its sub-divisions. Depending on the study, an extent of the study area determines the spatial domain and in the similar manner, in this study the spatial domain is determined by the study area as defined by the administrative boundary of the Maseru City Council (MCC) and its 2 Km buffer.

Metrics are often used to quantify several aspects of spatial patterns argued McGarigal et al (2002). McGarigal et al (2002) further argued that it's seldom to find one-to-one connection between the spatial metric value and the pattern and hence most of the metrics describe the similar aspects of the landscape pattern and they are correlated among themselves. In the similar manner, Loveland (as cited in Bekalo, 2009)"indicates that a number of metrics have been developed to describe and quantify elements of patch shape complexity and spatial configuration relative to other patch types; however, it is not clear which will prove to be the informative and interpretable over large areas". The methodology used to derive spatial metrics is indicated in the flow diagram below, figure 10.

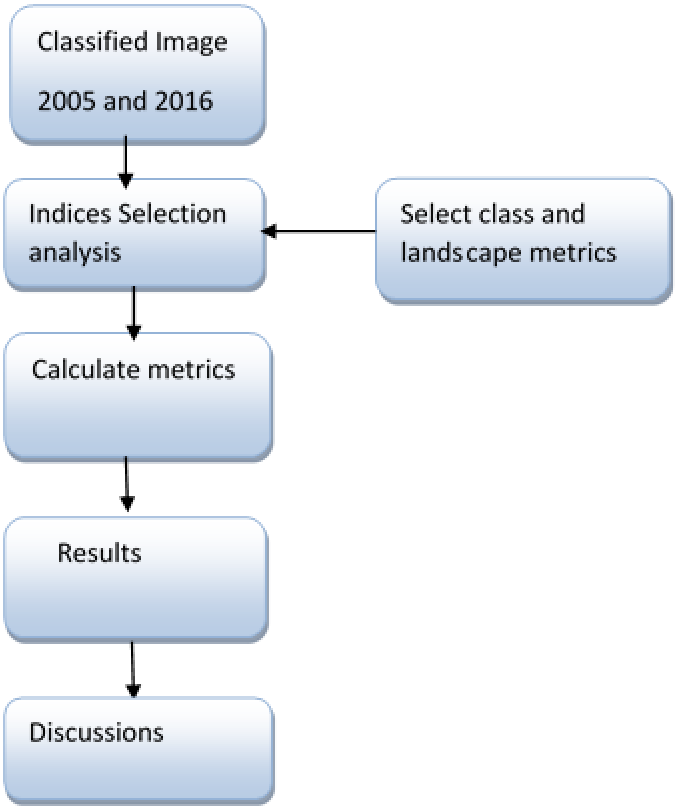


Figure 10: Methodology used for spatial metrics

In this study, five spatial metrics were used for understanding the growth patterns of the seven selected areas within the MCC peripheries which have an increasing number of informal settlements into agricultural land based on their ability to describe the composition and configuration of the landscape patterns both at class and landscape levels. These metrics are (1) Class Area (CA/TA), (2) Number of Patches (NP), (3) Edge Density (ED), (4) Largest Patch Index (LPI), (5) Area Weighed Mean Patch Fractal Dimension (AWMPFD).

Table 8: Spatial metrics used

Metrics	**Description**
Class Area (CA) or Total Area (TA)	This is a measure of an actual area of each land use land cover class
Number of Patches (NP)	This measure indicates the diversification of the landscape; thus it gives the actual number of different land use classes within the landscape.
Edge Density (ED)	It is the sum of the lengths of all edge segments

	in the landscape, divided by the total landscape area.
Largest Patch Index (LPI)	This is a ratio intended to find the relationship between the largest patch within the landscape to the landscape area itself
Area Weighted Mean Patch Fractal Dimension (AWMPFD)	This measure how complex, fragmented or diverse the shape of the landscape is. Its measure is based on the perimeter to area ratio.

3.9 CONCLUSION

The methods followed in image classification are of paramount in achieving the study objectives. In this chapter, the general methodology of the study was defined followed by how the image was classified in ERDAS IMAGINE 2018 using supervised maximum likelihood algorithm to obtain the required results with certain percentage of confidence defined by accuracy assessment. Moreover, the choice and the modification of the classification schemas to achieve study objective is defined. Finally, the steps followed in determining, the spatial metrics using FRAGSTAS software in preparation of data for analysis in an attempt to understand landscape dynamics have been elaborated and the metrics used defined.

CHAPTER 4: RESULTS AND DISCUSSIONS

4.1 Introduction

The objective of this study forms the basis of all the analysis carried out in this chapter. GIS and remote sensing are good tools to map different land cover land use changes in different spatio temporal scales. The analysis in this study is mostly performed through the ERDAS IMAGINE 18 and FRAGSTATS software's and presented in ArcGIS. The outcome of the research is presented and discussed sequentially. The results from the analysis are presented in the form of maps, charts and statistical tables. These results include quantitative value for current land use classes and the comparison of different land uses change. In order to determine the spatial pattern of land use change with time, the spatial metrics have been used and lastly the general accuracy assessment technique used to determine accuracy levels of the classified images and land use changes anticipated.

4.2 Land use maps

The basic requirement in determining the land use change is to first determine the static land use distribution. Therefore, static land use distribution for the years 2005 and 2016 was derived from the land use maps determined from the supervised image classification using maximum likelihood classification technique. The land use areas were calculated based on the number of pixel count per classified land use classes as presented in table 9 and table 10 below for respective years. The spatial resolution as indicated earlier plays a significant role in determining the areal extend of each land use class.

The land use land cover maps produced from the image classification of high spatial resolution orthophotos of 2005 and 2016 were validated using confusion matrix to determine the confidence level with which to use the classified maps. The classified images were validated independently by different sets of ground truth points/ reference data from those used for training the classifier (signature files). From the confusion matrix, the producer accuracy, user accuracy, overall accuracy and the Kappa coefficient were computed. The results from these accuracies show overall accuracy of more than 80% for classified images. Moreover, overall accuracy and the Kappa coefficient indicate the statistical acceptance of the classified image. The accuracies were computed in table 13 and table 14 for the years of study respectively.

The accuracy results indicated overall accuracy of 82.4% and 90.3% for years 2005 and 2016 respectively. This indicates an average accuracy of 86.4% for the classified maps. The kappa coefficient of 0.63 for 2005 and 0.80 for 2016 indicate the statistical substantial agreement with the classified images. It is worth noting that both low overall accuracy and low kappa coefficient in 2005 classified image is due to seasonality of the image acquisition which affected the spectral reflectance and hence image classification in general. Based on this accuracy, the produced land use map represents true land use land cover based on RCMRD-SERVIR Africa (2015) report that the minimum acceptance threshold for overall accuracy according to USGS classification is 75%.

A contributing factor to the lower classification accuracy and the reliability of the 2005 classified map is the misclassification due to similarities in reflectance of other features like dark loam soil which is similar to tarred road, time of the year the orthophoto was taken, differences in building roof tops, trees shades, and seasonality. The pixel area of 2005 orthophoto with spatial resolution of 0.4m is 0.16 square meters and for 2016 orthophoto with spatial resolution of 0.35 is 0.1225 square meters

Area (land use class) =number of count*pixel area (square meters)

Table 9: Land use distribution in 2005

Land use classes	Pixel count	Pixel area	Land use(m^2)	Land use(Ha)	Land use percentage
Built-up	463851876	0.16	74,216,300.16	7,421.63	31.3%
Non built-up (agricultural)	1018088803	0.16	162,894,208.48	16,289.42	68.7%
Total			237,110,508.64	23,711.05	100%

Table 10: Land use distribution in 2016

Land use classes	Pixel count	Pixel area	Land use(m^2)	Land use(Ha)	Land use percentage
Built-up	681602808	0.1225	83,496,343.98	8,349.63	35.1%
Non built-up (agricultural)	1262753791	0.1225	154,687,339.40	15,468.73	64.9%
Total			238,183,683.38	23,818.36	100%

Table 11: changes in land use between 2005 and 2016

Land use	Area(m^2)	Area(Ha)	Land use percentage change
Built-up	+9,280,042.84	+928.00	+3.8%
Non built-up (agricultural)	-8,206,869.08	-820.69	-3.8%

The important aspect of change detection is to determine which land use class changes to which other land use and to determine the driving forces behind such change in land uses. The post image classification technique was used to compare and monitor land use land cover changes and the results presented in table 9 and 10 above. The table 11 above is used to compare the changes in land use changes. From the table 11 above, there has been an increase of 928 Ha in the built-up land while there is at the same time the decrease of 820.69 Ha in non-built up land. This indicates that between 2005 and 2016 there has been a significant growth in the built up land. This increase is due to an increase in population growth and hence a need for new constructions. According to Lesotho's Bureau of Statistics (2018) Population and Housing Census (PHC) report of 2016, the population growth rate increased from 0.08% in 2006 to 0.68% in 2016.By the same token, the population residing in the Maseru area increased from 9.9% between 1996 and 2006, and again between 2006 and 2016 census the population increased by 20.2% indicating an increase of 10.3% (table below 12).

Table 12: Population and percentage distribution by place of birth and district, 1996, 2006, 2016 population and housing census

Urban/rural	Populations			Percentage changes	
	1996	**2006**	**2016**	**1996-2006**	**2006-2016**
Urban	293,323	421,655	685,938	43.8	62.7
Rural	1,414,239	1,444,816	1,321,263	2.2	-8.6
Botha-Bothe	109,905	110,320	118,242	0.4	7.2
Leribe	302,664	293,369	337,521	-3.1	15.0

Berea	241,946	250,006	262,616	3.3	5.0
Maseru	393,154	431,998	519,186	9.9	20.2
Mafeteng	213,455	192,621	178,222	-9.8	-7.5
Mohale's Hoek	185,459	176,928	165,590	-4.6	-6.4
Quthing	127,560	124,048	115,469	-2.8	-6.9
Qacha's Nek	72,886	69,749	74,566	-4.3	6.9
Mokhotlong	86,468	97,713	100,442	13	2.8
Thaba-Tseka	128,778	129,881	135,347	0.9	4.2
Total	**1,862,275**	**1,876,633**	**2,007,201**	**0.8**	**0.7**

Table adapted from Lesotho Bureau of Statistics (2018) 2016 Population and Housing Census (PHC)

The increase in percentage of people living in urban areas increased a pressure on agricultural land for residential purpose. From the table 12 above, it is evident that more people are moving away from the rural areas to urban area as indicated by 62.7% of people residing in urban areas between the years 2006 and 2016 compared to 43.8 of people in urban area between 1996 and 2006.This is due to the rate of migration seen in many developing African countries due to urbanisation.

When people arrive to the cities seeking better opportunities they often face a problem of insufficient affordable local houses. They then create informal housing structures which negatively affects the agricultural land as portrayed by a decrease in the non-built up land in 2016. Leduka (2001) indicated that in Lesotho, a significant in proportion of recent population increase is accommodated within the peri-urban settlements where the agricultural land is privately subdivided into plots for sale under the hand of the customary authorities. Leduka (2001) further argued that the chiefs are the ones responsible for the increase of the informal settlements as they are the ones issuing the illegal certification of allocation to plot buyers. "This resulted in the unattractive structures and forms of the build environments resulting from the sub-division sanctioned by the customary chief: un-serviced, inarticulate and low density urban sprawl due to allocation of large (more than 1000 square meters) irregular shaped plots" (Leduka,2001) and the this has been main characteristic of the informal settlements in Lesotho even today.

The results from the classified land use map indicates that the there is a 0.35% percentage decrease in agricultural land per year and at the same time the built up land percentage is increasing by 0.35% per year in 11 years (table 9 and table 10). The confusion matrix/error matrix had been used to assess the accuracy of the classified land use maps (figure 11 and 12 below).

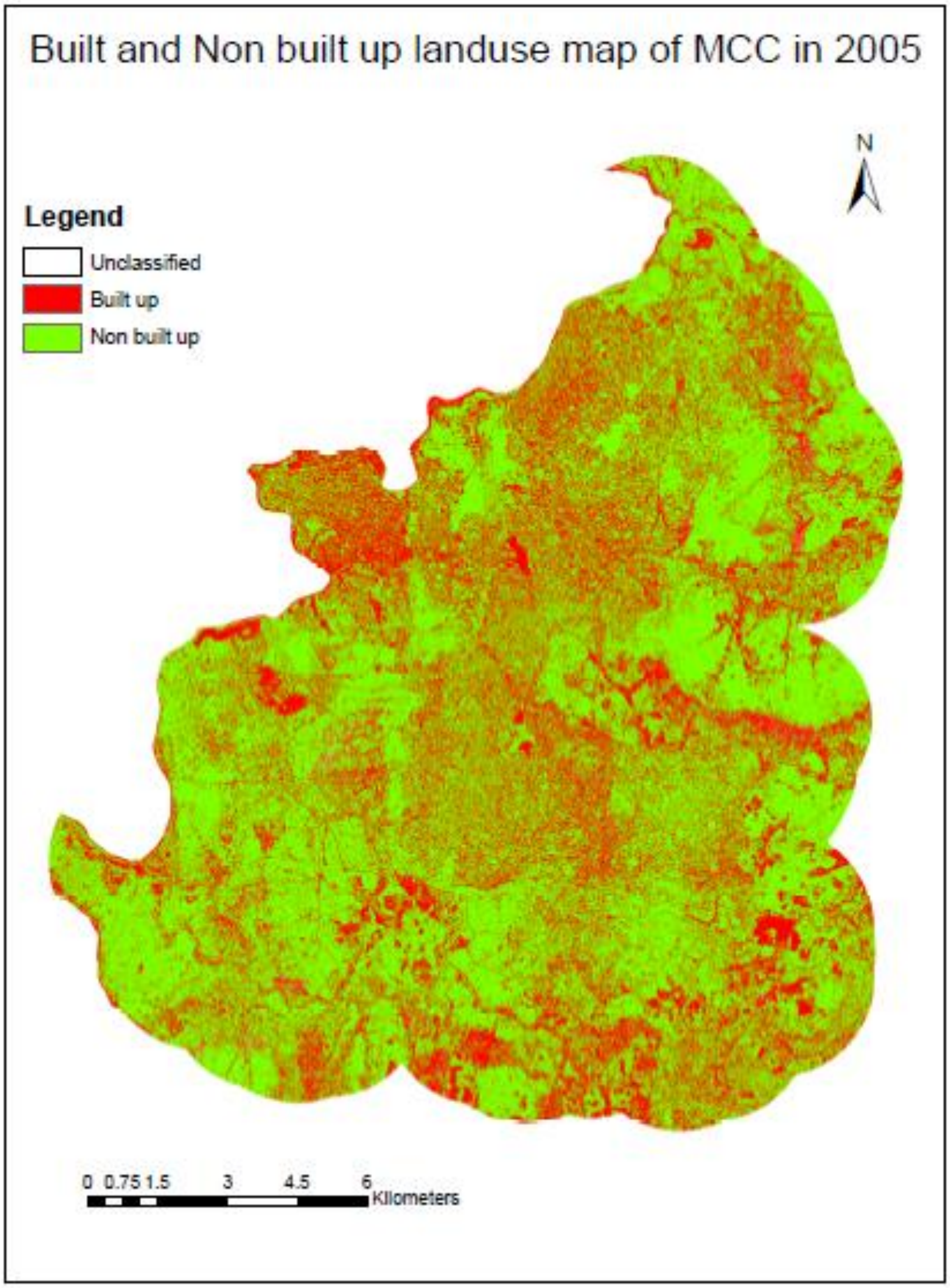


Figure 11:Built up and non-built up land use map of MCC and its urban peripheries in 2005

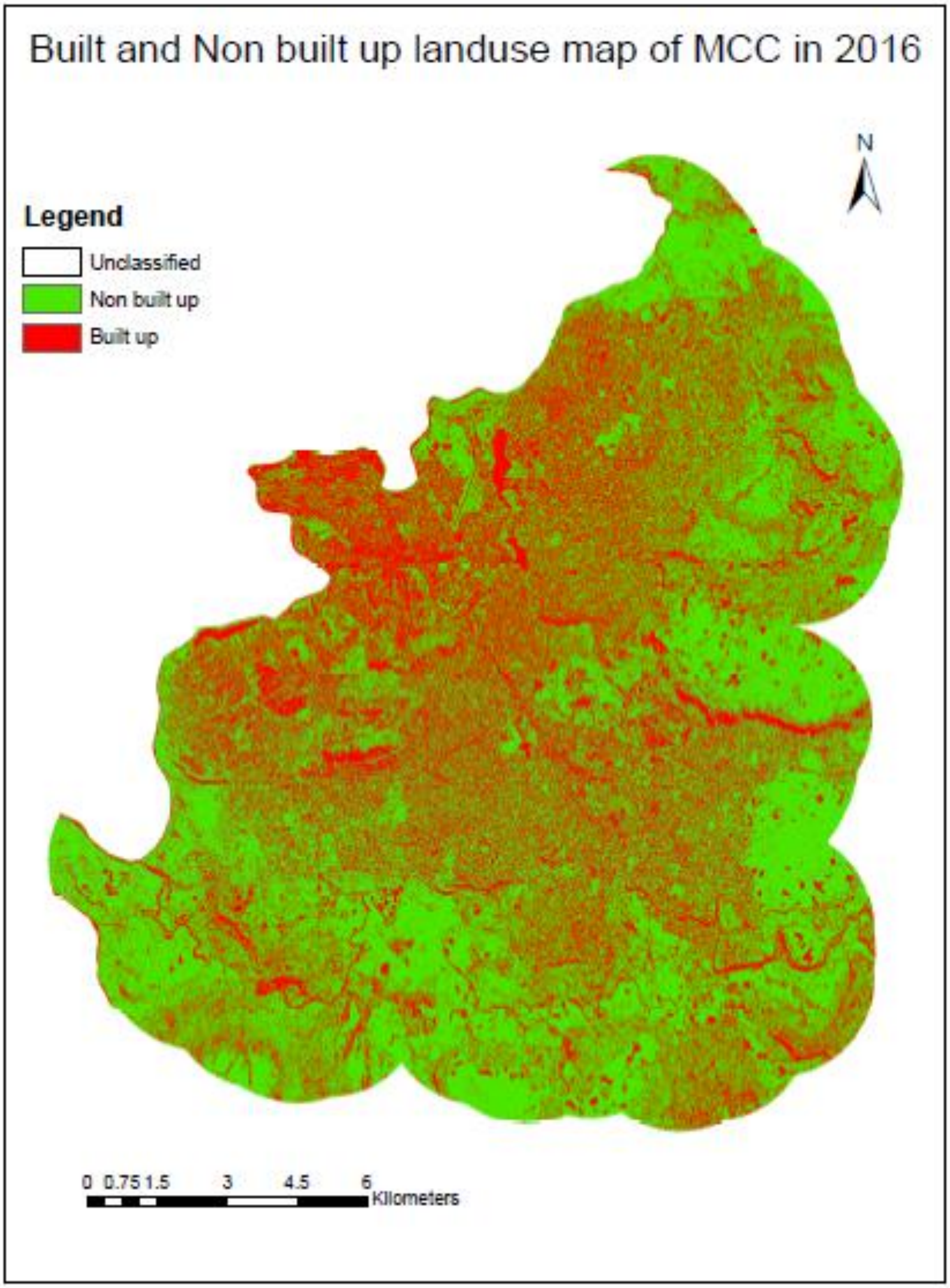


Figure 12: Built up and non-built up land use of MCC and its urban peripheries map in 2016

Table 13: Confusion matrix for land use map of 2005

	Reference map				
Classified map		Built-up	Non built-up	Grand total	User' accuracy
	Built-up	87	15	102	85.3%
	Non built-up	14	49	63	22.2%
	Grand total	101	64	165	**Overall Accuracy=82.4%**
	Producer's accuracy	86.1%	23.4%		**Kappa coefficient=0.63**

Overall accuracy (OA) = (87+49/165) *100=82.4%

Kappa coefficient=$\frac{165\,(87+49)-[(102*101)+(63*64)]}{165*162-[(102*101)+(63*64)]}$ =8106/12891=0.63

Table 14: Confusion matrix for land use map of 2016

	Reference map				
Classified map		Built-up	Non built-up	Grand total	User' accuracy
	Built-up	93	9	102	91.2%
	Non built-up	7	56	63	11.1%
	Grand total	100	65	165	**Overall Accuracy=90.3%** **Kappa coefficient=0.80**
	Producer's accuracy	93 %	13.8 %		

Overall accuracy (OA) = (93+56)/165) *100=90.3%

Kappa coefficient = $\frac{165\,(93+56)-[(102*100)+(63*65)]}{165*165-[(102*100)+(63*65)]}$=10290/12930=0.80

4.3 Land use maps by regions

As shown above that basic requirement in determining the land use change is to first determine the static land use distribution. In the first place, in Lesotho based on analyst knowledge of the study area, there are seven areas and or villages which are heavily affected by the urbanisation due to informal settlement resulting in heavy loss of agricultural land for informal settlements. These seven areas are Fooso, Makhoathi, Sekamaneng, Sehlabeng, Phuthalichaba, Temaneng (Mantsebo), and Abia. Following the classified images in figure 11 and figure 12 above, the seven mostly affected regions by informal settlements were visually compared and analysed. Before image reclassification within these seven villages, the informal buildings within these areas were first digitised and compared across different epochs (2005-2016) as shown in table 15 below and their spatial distribution shown from figure 13 to figure 19 below and thereafter these building were masked out in Erdas Imagine 2018 for supervised image classification.

Table 15:2005 and 2016 buildings comparisons

Area or Village name	2005 number of informal buildings	2016 number of informal buildings	Difference (Positive indicates increase in settlement size)	2005 buildings area occupied (m^2)	2016 buildings area occupied (m^2)	Differences in areas (m^2)
1.Fooso	177	379	+202	23,889.06	56,559.81	+32,670.75
2.Makhoathi	179	280	+101	17,062.72	28,099.73	+11,037.01
3.Sekamaneng	170	447	+277	10,665.55	41,601.39	+30,935.80
4.Sehlabeng	190	320	+130	14,215.59	41,014.66	+26,799.07
5.Phuthalichaba	149	258	+109	12,724.71	31,826.66	+19,101.95
6.Mantsebo	147	194	+47	10,414.16	16,130.18	+5,716.12
7.Abia	81	240	+159	5,673.68	27,857.71	+22,184.03
Total	1093	2118	+1025	94645.47	243090.14	+148,444.73

Figure 13: 2005 and 2016 Fooso area informal buildings / settlement distributions

The results from the data indicated the significant number of new construction (informal buildings) changes between 2005 and 2016. For example, in Fooso village, figure 13 above, total number of informal buildings increased from 1093 buildings in 2005 to 2118 in 2016. This indicates an increase in area of 3.27 Ha in the built up of the informal settlement. This indicates that at this rate of construction of informal settlement, in no time all the agricultural land will have been converted into residential or built up land.

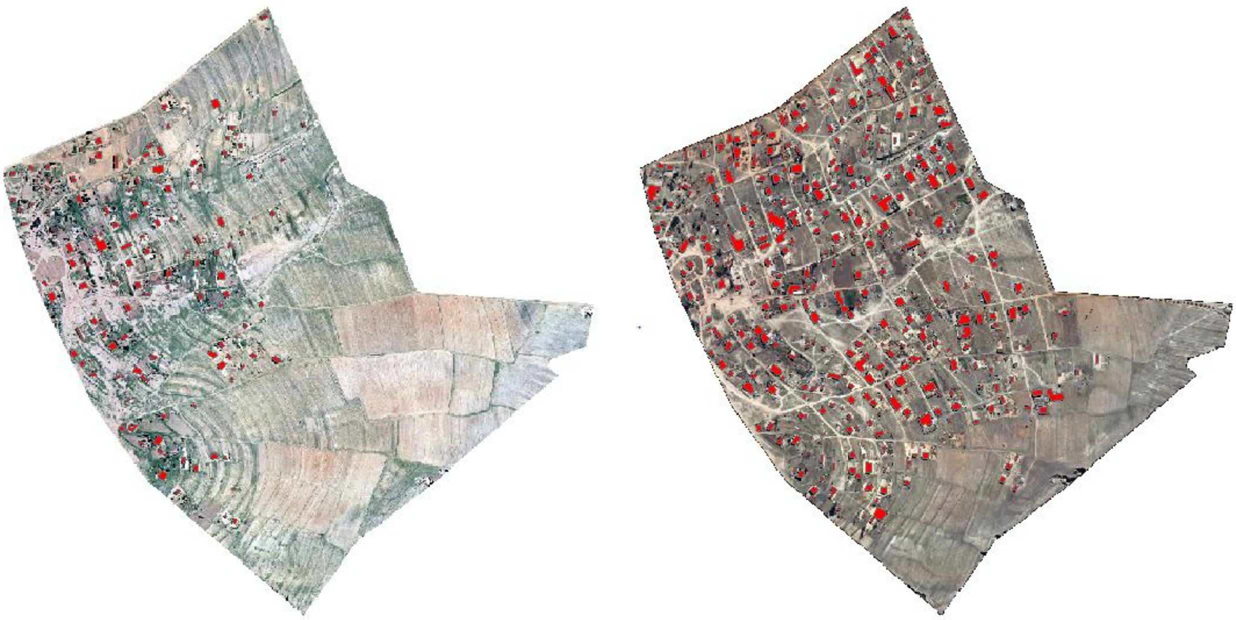


Figure 14:2005 and 2016 Sekamaneng area informal buildings/ settlements distributions

The Sekamaneng area (figure 14) shows a significant increase in the number of informal patches, the number of new informal settlements increased from170 to 477 units between 2005 and 2016 resulting in an increase of 30,935.80 m^2 or 3.09 Ha in area of the built up land in 2016.The current trend indicates an alarming rate at which the agricultural land is being converted into built-up land. The Sekamaneng area seems as one of the regions where it seems easy to acquire land for informal construction of homesteads; this is evident by the fact that the number of informal building in 2016 is more than twice those in 2005. This then calls for an immediate intervention through proper spatial planning and law enforcement to discourage people from continuing constructing informal settlement on the agricultural land which will results in the reduction of food supply resulting from insufficient land for agricultural plantations.

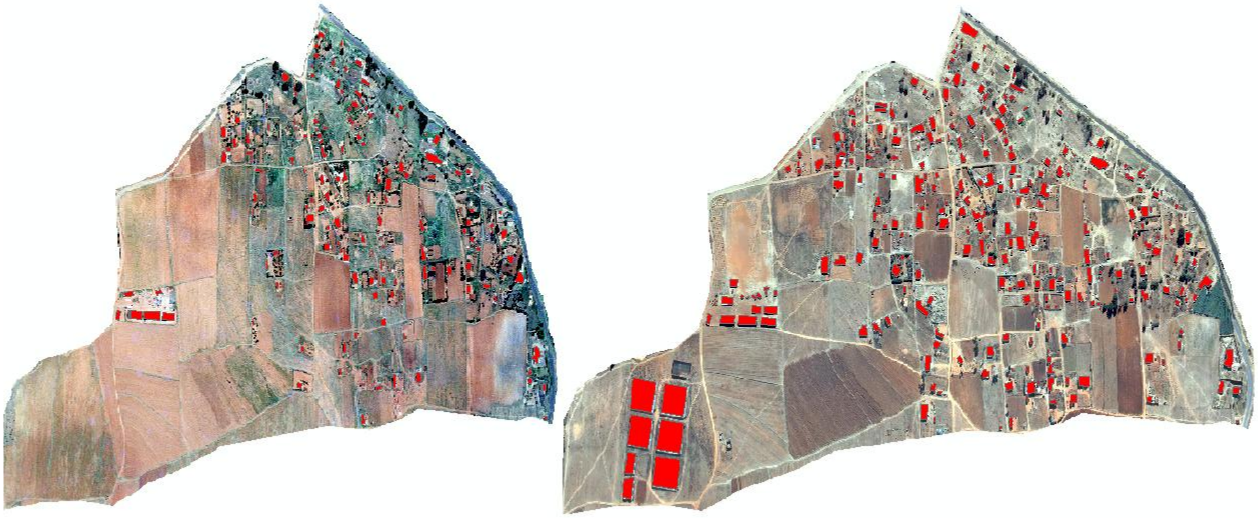


Figure 15: 2005 and 2016 Sehlabeng area informal buildings /settlements distributions

What has been a fertile soil in 2005 in Sehlabeng (figure 15) is gradually being converted into informal buildings; this is portrayed by an increase of number of informal buildings from 190 to 320 in 2016 occupying area of 26,799.07 m^2/ 2.68 Ha. The major driving force behind the increasing number of informal settlement in Sehlabeng area is the construction of school by the government in an attempt to increase the literacy level within the region. The school constructed tend to encourage people to continue building informal dwelling around the school area at the expense of the agricultural land and this will negatively affect food production for people around that area.

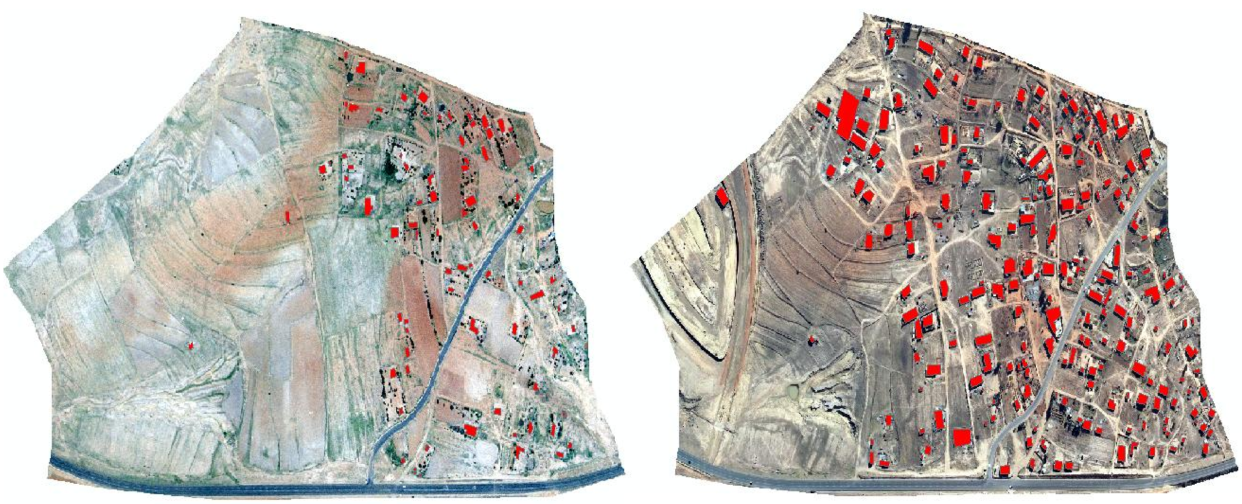


Figure 16: 2005 and 2016 Abia area informal buildings/ informal distributions

Abia region (figure 16) is one of the region heavily affected by informal settlement into the agricultural land, the number of newly constructed in 2016 is more than twice the number of informal building in 2005 and occupies an agricultural area of 2.22 Ha. The major driving force behind high rate of conversion of agricultural land into informal settlement around this area is their vicinity to Chine's clothes fabrics where most of the people from around the country come and seek employment for betterment of their lives. Once, employed people tend to look for cheap places to live which are close to their work station in an attempt to reduce travel expenses, the result of this is the illegal occupation of the agricultural and the construction of these number of informal settlements.

Figure 17:2005 and 2016 Phuthalichaba area informal buildings/ settlements distributions

The construction of the school on the agricultural land in this region is going to speed up the rate at which the agricultural is converted into informal settlement. This is already seen by an increase of number of informal building from 149 in 2005 to 258 units which occupy an area of 1.91 Ha. The similar trend is also observed in this region like in Sehlabeng area, where the immediate impact of the school construction is seen as the contributing factor towards the convention of the agricultural land into the informal settlements. The school is seen here as one way of trying to formalise the settlement around the area, but the correct procedures should be followed where spatial planning precedes any other developmental activities and not the other way round.

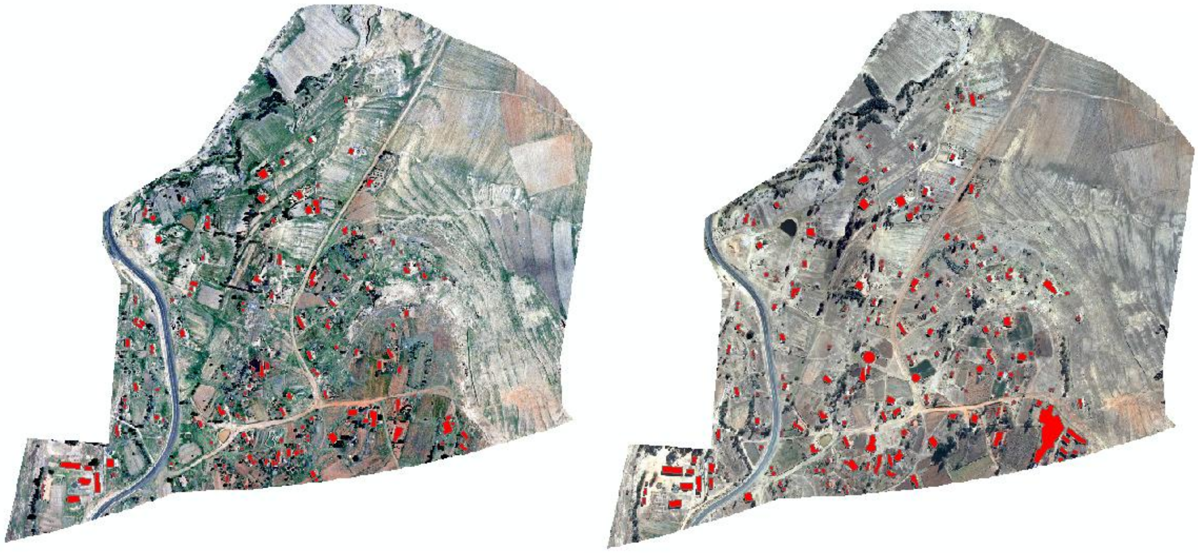


Figure 18: 2005 and 2016 Mantsebo area informal buildings/ settlements distributions

Mantsebo area (figure 18), in this region, informal settlement promotion is seen as the influence of the clothes fabrics not very far away from this region just like the Abia region in figure 16 above. These calls for immediate interventions as already the number of the informal settlement are being established in the agricultural. The number of built up units increased from 147 in 2005 to 194 in 2016 occupying and area of 5,716.12 square meters (0.57 Ha). This means when the number of the clothes fabrics increase around this area, then the number of this informal settlements will also increase in the similar manner.

Figure 19:2005 and 2016 Makhoathi area informal buildings /settlements distributions

Makhoathi (figure 19) like the rest of the seven regions within the urban fringe is experiencing a number of newly constructed buildings on an agricultural land. The number of informal building increased from 179 in 2005 to 280 in 2016 indicating an area of 11,037.01 square meters (1.10 Ha) of agricultural land being lost for the informal settlements.

In these seven selected regions, informal building areas for seven selected areas increased from 94,645.47 square meters (9.46 Ha) in 2005 to 243,090.14 square meters (24.3 Ha) in 2016.This indicated an increase of 148,444.73 square meters (14.8 Ha) at the expense of the agricultural land. Therefore, the average agricultural land lost for informal settlements is 1.35 Ha annually within the Maseru peri urban areas. The spatial distribution of these informal settlements in all seven regions clearly indicates the expansion of the built up land into the surrounding agricultural land and as such impacted on the decrement of agricultural land with informal buildings and these will result negatively on the food production.

It is worth noting that within the seven selected region, there are a similar factors promoting the increasing number of the informal settlements into agricultural land. One factor visible from the visual interpretations of the orthophoto maps is the construction of the schools, most of the schools have clearly been constructed on the agricultural land and hence people do not see anything wrong in constructing their informal settlement there if an institution like school could be constructed on an agricultural land. On the other hand, as shown above that most of the informal settlement is at the vicinity of the Chines clothes fabrics, and hence people opted to informally acquire land around such areas to reduce the travel expenses to and from their work places. This clearly indicated that there is a continued loss of the agricultural land for informal settlements. This requires remedial measures in the form of spatial planning in order to control and cater for the ever expanding population growth around the city centres. This will ensure that future generation is also not deprived from their basic needs of food from the agricultural land.

4.4 Spatio-temporal analysis of urban growth using spatial metrics

At the core of this study lies the understanding of the landscape dynamics which affects the agricultural land. The land use map is used to find the spatio-temporal dynamics of land use that has occurred over time. On the contrary, spatial metrics is a method that allows a user to devise a metrics based dynamic spatial patterns. These spatial pattern dynamics of land use were identified from seven selected regions mostly affected by informal urban settlements between the years 2005 and 2016 categorical maps.

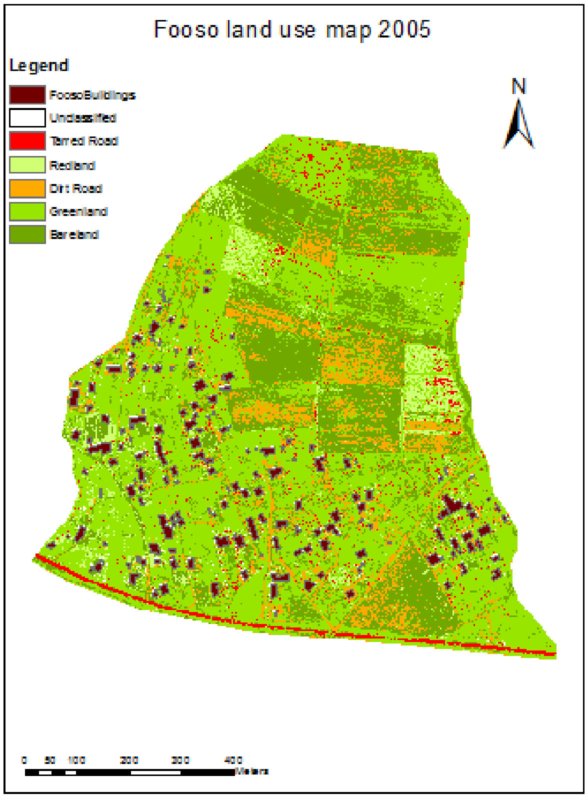
Bekalo (2009) indicated that in all geographical researches, the analysis of spatial phenomenon, spatial structures and spatial patterns are central themes which make the research geographical. This generally means that location, distance, direction, orientation and the patterns are of great importance in geography and hence in understanding landscape dynamics. FRAGSTATS software was used to compute the spatial metrics below, a constraining factor was that the FRAGSTATS software was intended to handle data less than 3GB at the time, therefore the classified/ categorical maps were clipped by regions (seven selected villages) in order to meet software's requirements.

The static land use distribution for the years 2005 and 2016 for the selected areas or villages was derived from the land use maps determined from the supervised maximum likelihood classification using pixel based approach. The seven selected regions were reclassified into roads (tarred and dirt) and agricultural land after masking/clipping out the informal buildings. From the table 15 above on the number of informal buildings, it became clear that the built up land is encroaching into the agricultural land. The seven selected regions were reclassified into roads (tar and dirt) and agricultural land with the aim of finding the driving forces behind the informal expansion into agricultural land. Therefore, a similar signature file for supervised image classification was used throughout the seven regions clipped from 2005 orthophoto. In a similar manner, for 2016 orthophoto, another signature file was used and the same signature file was used to reclassify the seven regions clipped from 2016 orthophoto. The main reason for using the same signature file to classify the selected regions was to be consistent with the image classification.

The accuracies of the classified maps for seven regions were computed in table 17 below and the ground truth points for accuracies assessment were determined from the Google earth map and converted to Lo 27 coordinate system using Xform software. The ground truth references were chosen to be different from points features used for training signature files to avoid classification bias. The areas of classified images were calculated based on the number of pixel count per classified land use classes (section 4.2 above) and presented in table 16 for respective years below. In the similar manner the land use maps for selected areas are shown from figure 20 to figure 26 below.

Table 16: Different land use changes by villages/regions

Village /area name	2005 Land use areas(Ha)			2016 land use area(Ha)			Differences in land use area (2016-2005)		
	Tarred Road	Dirt Road	Agricultural land	Tarred Road	Dirt Road	Agricultural land	Tarred Road	Dirt Road	Agricultural land
1.Fooso	1.76	6.9	8.32	2.48	6.8	5.1	+0.72	-0.1	-3.22
2.Makhoathi	3.74	0.65	18.32	5.59	10.50	15.28	+1.85	+9.85	-3.04
3.Sekamaneng	0	8.15	27.65	2.75	7.56	12.06	-2.75	+1.63	-15.59
4.Sehlabeng	1.94	0.35	13.06	5.14	8.70	4.34	+3.2	+8.35	-8.72
5.Phuthalichaba	4.06	1.92	18.68	4.40	10.8	6.89	+0.34	+8.88	-11.82
6.Mantsebo	2.31	0.87	17.72	5.77	4.91	9.47	+3.46	+4.04	-8.25
7.Abia	1.70	4.65	20.52	5.54	6.20	10.77	+3.84	+1.55	-9.75
Totals	15.51	23.49	124.27	31.67	55.47	63.91	+16.16	+31.98	-60.36



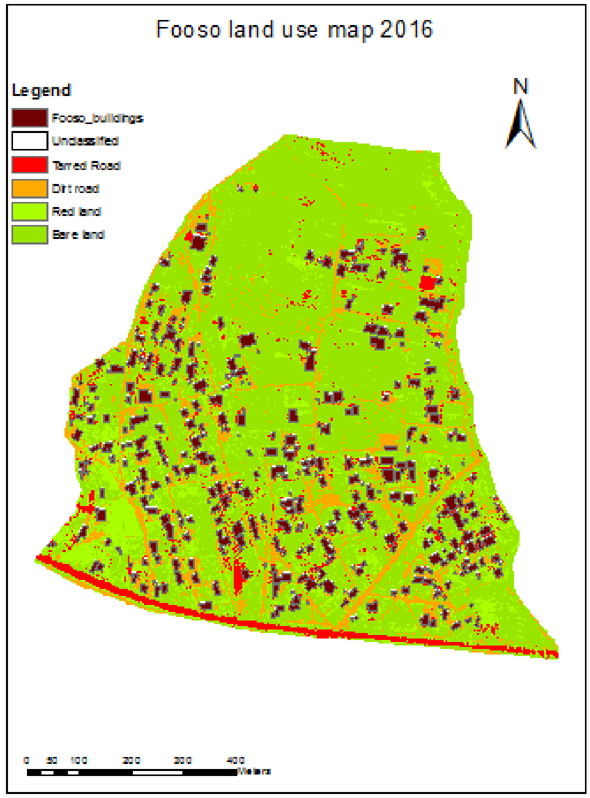


Figure 20: Comparison of land use map for fooso area between 2005 and 2016

The land use map for Fooso area (figure 20) above indicates a more pronounced dirt road in 2016 compared to in 2005 and pattern of informal settlement follows these dirt road network. It's is worth noting that these informal dirt roads are from soil or gravel roads, they are now more pronounced due to regular travel by the residents of these informal settlements. It is worth noting upon realising that there are no measures taken against them, then people continued with their expansion of the informal settlements into agricultural land. The results of this is the reduction of the large amount of agricultural land as a results of the informal dirt road network which ultimately promotes the transferability within the area and hence promotes construction of informal settlements. In Fooso region, the agricultural land has been reduced from 8.32 Ha in 2005 to 5.1 Ha. This indicates the reduction of 3.22 Ha in agricultural as a results of dirt road network.

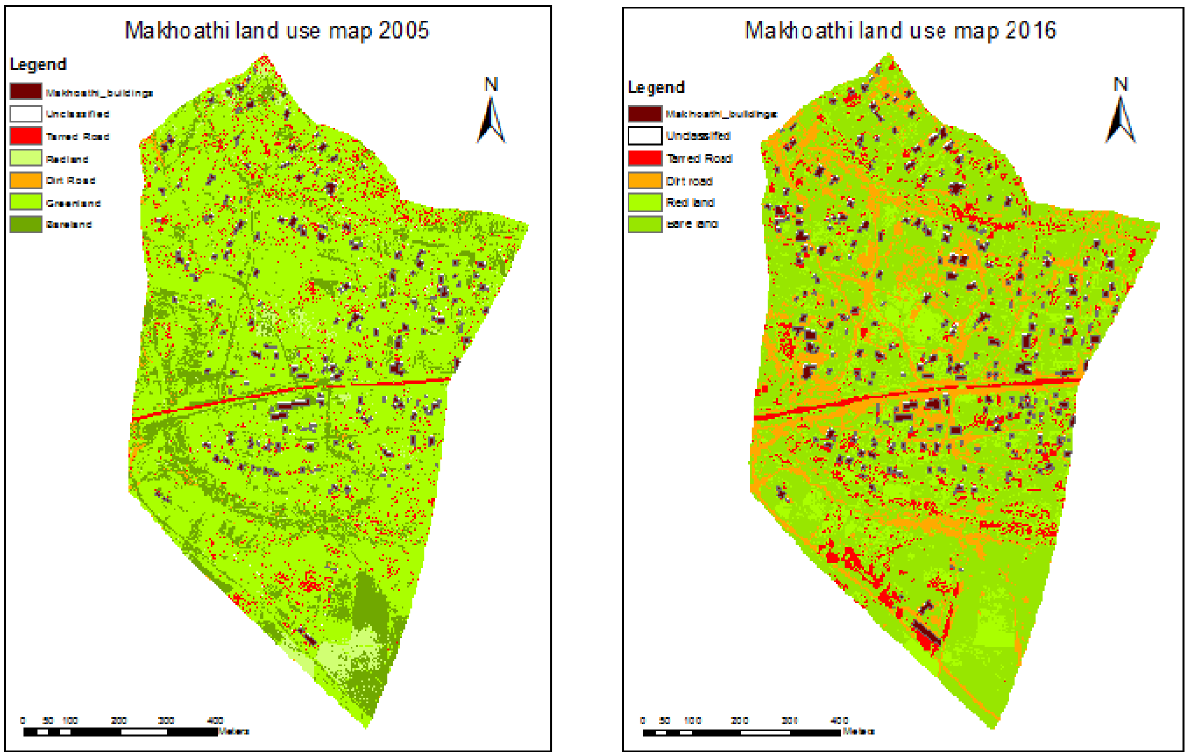


Figure 21: Comparisons of land use maps for Makhoathi area between 2005 and 2016

Makhoathi region (figure 21) is characterised by more pronounced dirt road network like in Fooso region. In addition to that, the area is characterised by number of regions seen as tarred road while in facts are the patches where an areas are being prepared for informal building as paving or the concrete block to be used for construction purposes. Within this region, area of informal dirt road increased from 0.65 Ha in 2005 to 10.50 Ha and at the same time the agricultural land decreased from 18.32 Ha in 2005 to 15.28 ha in 2016, this indicate the loss of 3.04 Ha of the agricultural where the major driving factor is seen as dirt roads expansions. This implies that the improvement in the dirt roads network will promote the expansion of the informal settlement within this area.

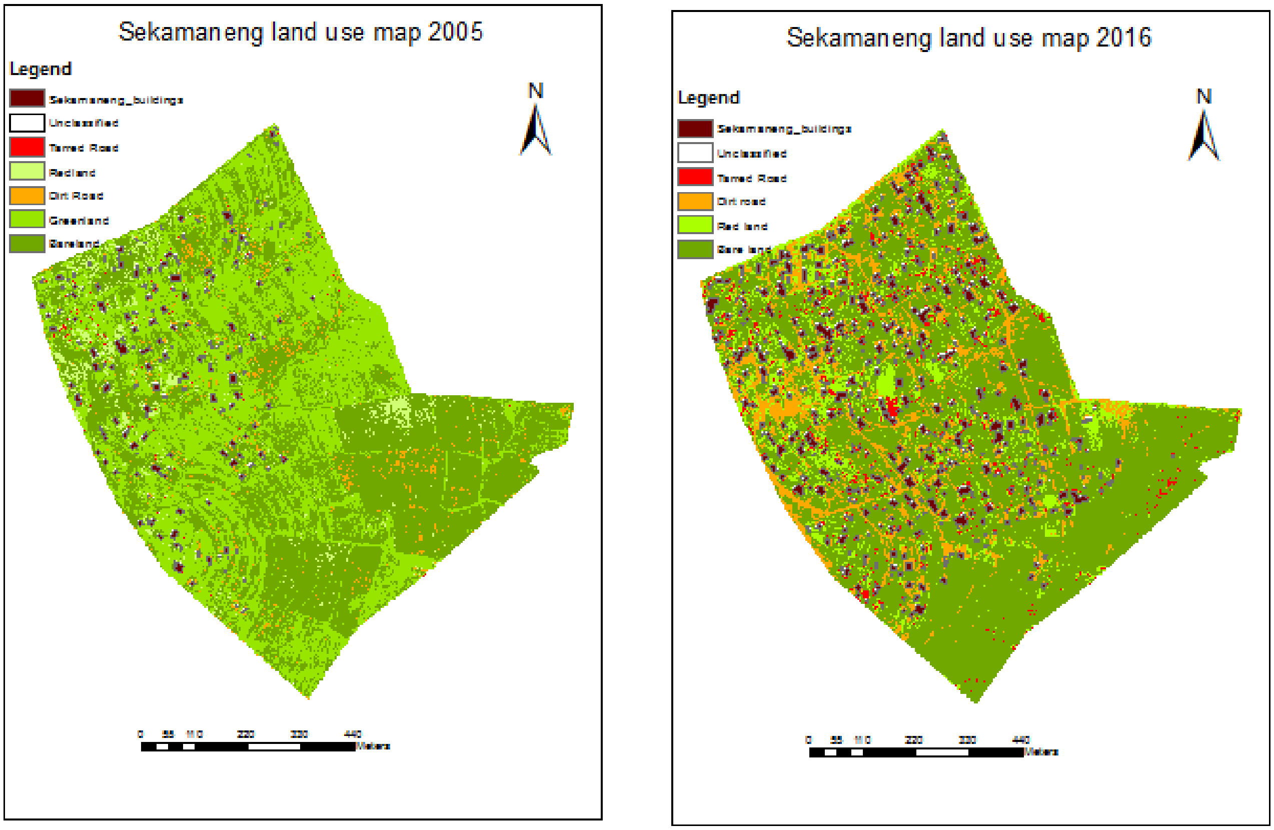


Figure 22: Comaparisions of land use maps for Sekamaneng area between 2005 and 2016

Sekamaneng (figure 22) is one region where a significant amount of agricultural land is being converted into informal settlement, there is no tarred road passing through this area but the tarred road is not very far from this area which could be the major cause of these more pronounced informal settlements into agricultural land. This region is characterised by significant decrease in the agricultural land, comparatively, the area occupied by agricultural land decreased from 27.65 Ha in 2005 to 12.06 ha in 2016 indicating the decrease of 15.59 Ha in agricultural land. This indicates that mostly of the agricultural land is either lost through the construction of informal settlement as shown earlier or through the informal road networks around the urban peripheries.

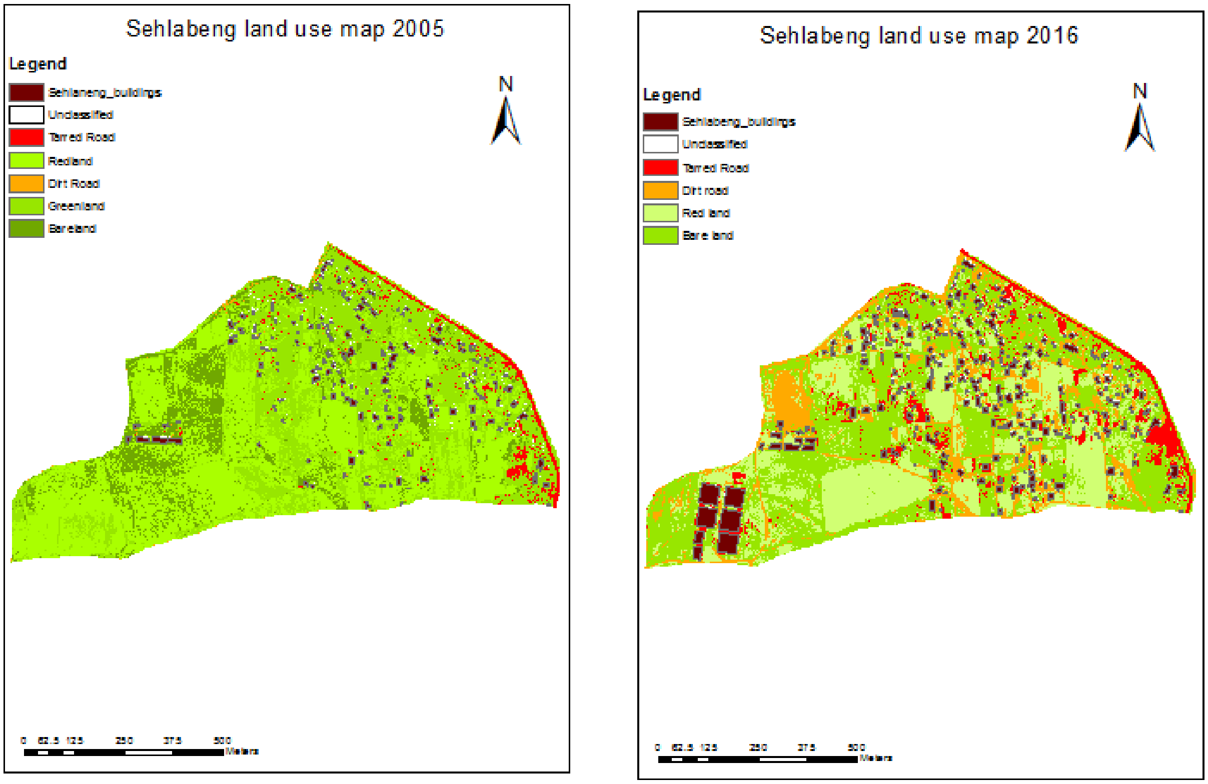


Figure 23: Comparisons of land use maps for Sehlabeng area between 2005 and 2016

The sehlabeng region (figure 23) informal settlements are mostly influence by construction of High School in the region. This school promotes the construction of informal duplex and single households for student's rental and all of these are at the expenses of the agricultural land. The categorical map above indicates that there has been a significant increase in the informal road network at shown by an increase in area from 0.35 Ha in 2005 to 8.70 Ha in 2016. This significant increase in informal road network is a result of school constructed around this area. This is because as a result of regular travels from and to school on daily basic, both people and the vehicle tend to create their own informal roads and in the process the agricultural is reduced. This is seen when comparing the agricultural area of 13.06 Ha in 2005 to that of 4.34 Ha. This indicates a decrease of 8.72 Ha in 11 years.

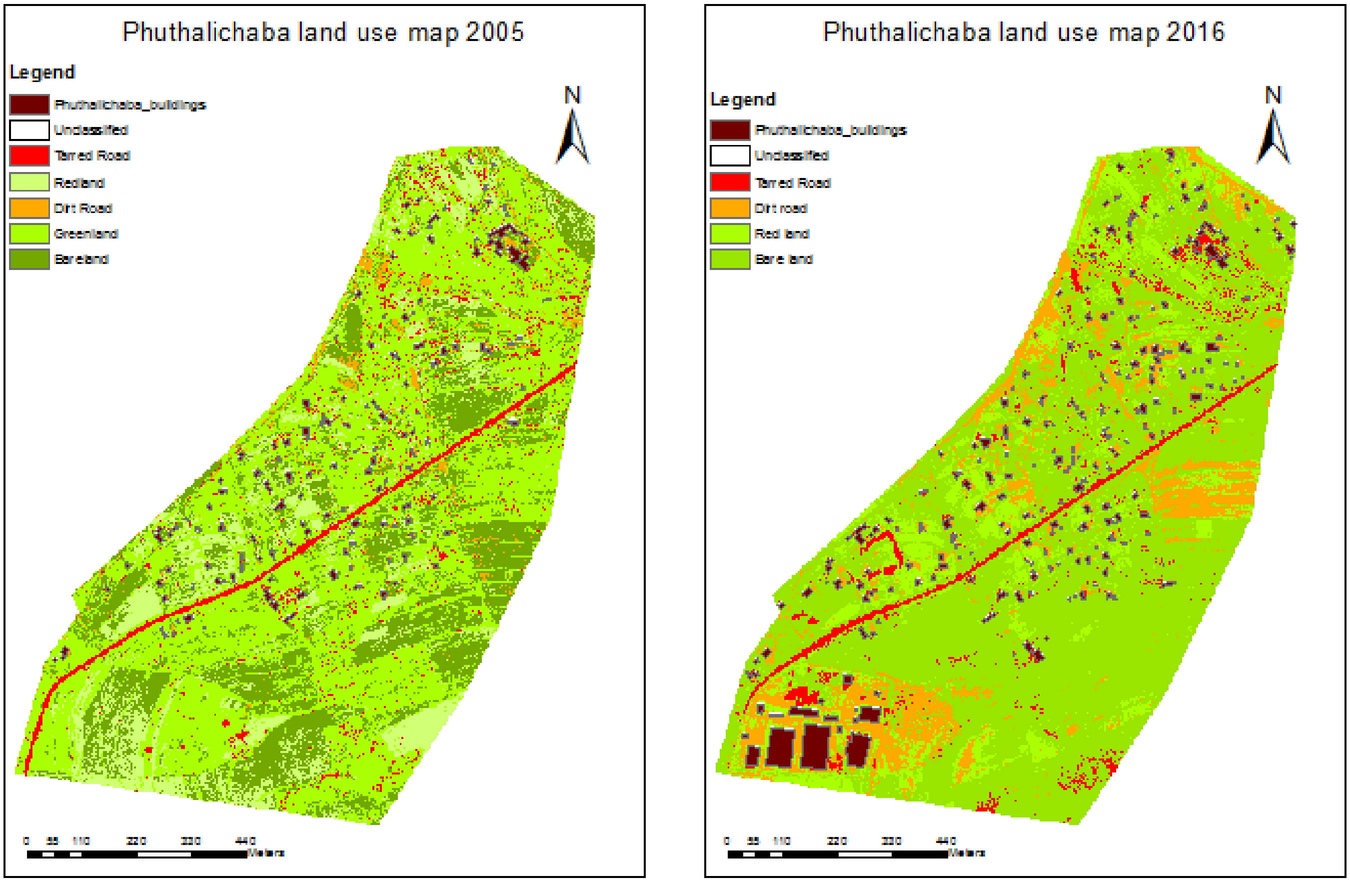


Figure 24: Comparisons of land use maps for Phuthalichaba area between 2005 and 2016

There is a great similarity between Sehlabeng (figure 23) and Phuthalichaba (figure 24) as the construction of High School is seen as the major driving force behind the construction of the informal settlement around these areas. Like the Sehlabeng area, the area of informal dirt road drastically increased from 1.92 Ha to 10.8 ha in 11 years between 2005 and 2016 indicating an increase of 8.35 Ha in informal roads and on the other hand agricultural land showed a decrease in area from 18.68 Ha to 6.89 Ha indicating a loss of 11.82 Ha of agricultural land. This agricultural land is lost to both informal settlements and the informal road network.

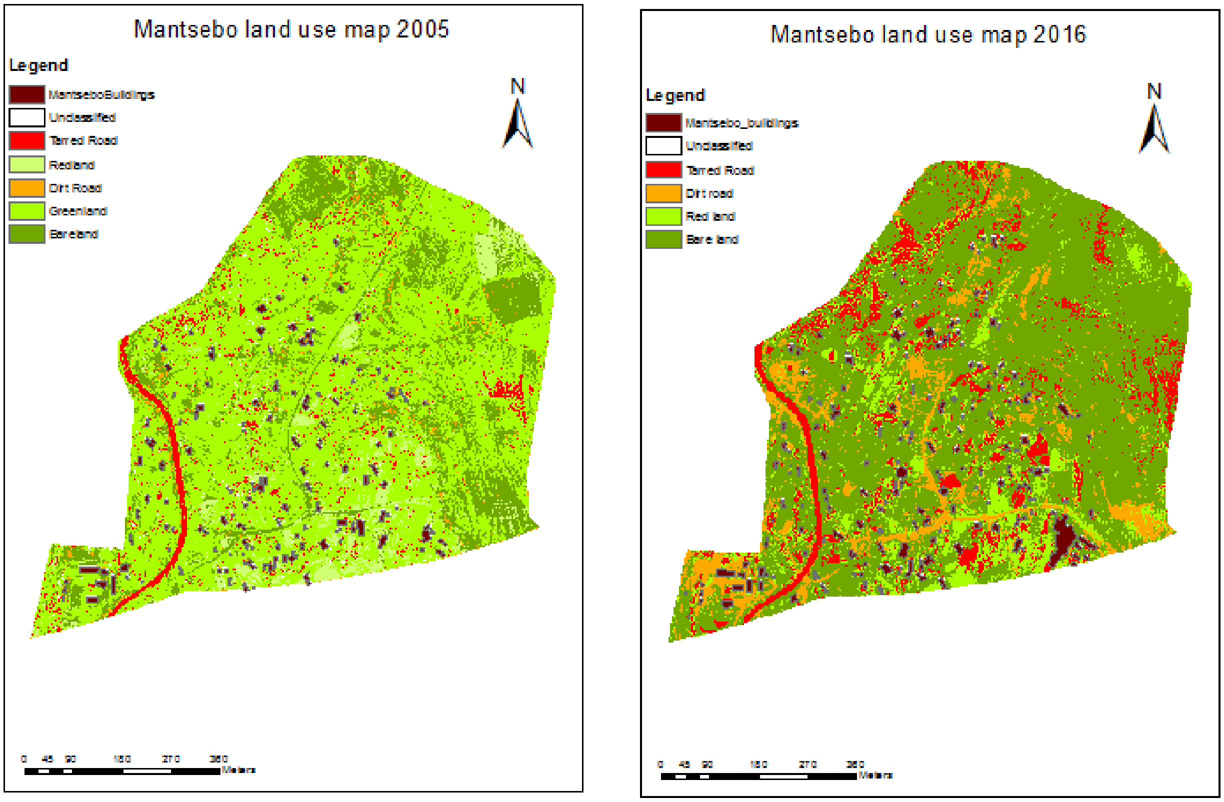
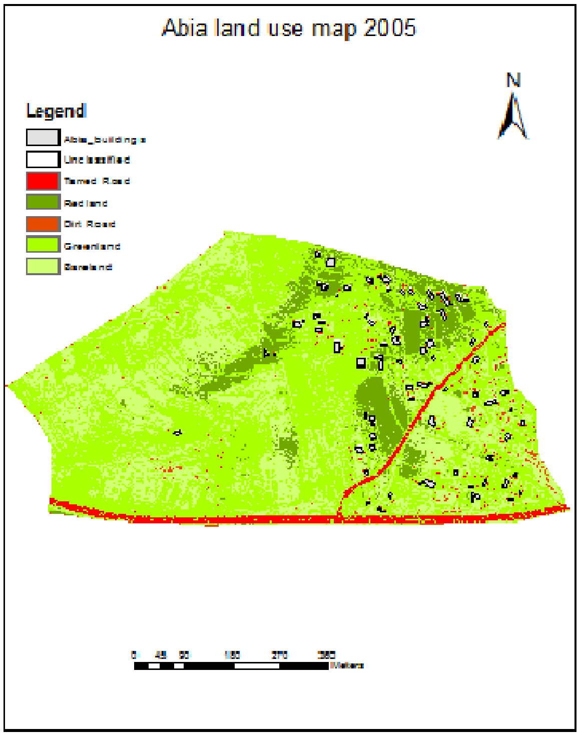


Figure 25: Comparsions of land use maps for Mantsebo area between 2005 and 2016

The Mantsebo region (figure 25) is one region where informal settlement is still at an early stage and need a proper planning. This is because there are a number of Chine's clothes fabrics under construction on the nearby region and this will affect the agricultural land with time for construction of small households for rental in future. This region is gradually changing its pattern as portrayed by an increase in informal dirt road from 0.87 Ha in 2005 to 4.91 ha in 2016 indicating an area increase of 4.04 Ha and in the similar manner, the area of the agricultural land is being reduced. In 2005 the agricultural land in the region was 17.72 Ha and in 2016 it has been reduced to 9.47 Ha, this indicates a reduction of 8.25 Ha in agricultural land as a result of both informal dirt road network and the informal settlements around the region.



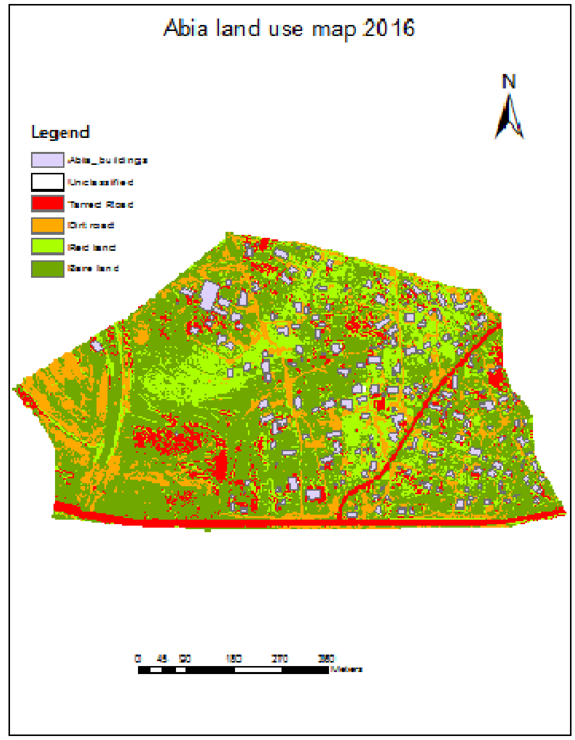


Figure 26: Comparisons of land use maps for Abia area between 2005 and 2016

The rate of the convention of agricultural land into informal settlement in Abia area is alarming, and it's clearly influenced by its vicinity to the tarred road couple with the proposed green environment estates called Green City intended for construction of low cost building using only green material within this area. This area is characterised by number of informal settlements. There has been an increase from 4.65 Ha in informal dirt road in 2005 to 6.20 Ha in 2016.The significant effect is seen on the reduction of agricultural land which have decreased from 20.52 Ha in 2005 to 10.77 Ha in 2016 indicating a reduction of 9.75 Ha as a results of both informal settlements and the informal dirt road.

Table 17: Classified map accuracies by regions/areas

Region	2005 Classified map accuracies				2016 Classified map accuracies			
	OA	**PA**	**UA**	**K**	**OA**	**PA**	**UA**	**K**
1.Fooso	77.8	A=84.6 R=28.6	A=73.3 R=16.7	0.56	96.3	A=100 R=7.7	A=93.3 R=0	0.85
2.Makhoathi	70.4	A=76.9 R=35.7	A=66.7 R=25	0.41	85.2	A=92.3 R=21.4	A=100 R=16.7	0.70
3.Sekamaneng	85.2	A=78.9 R=0	A=100 R=33.3	0.69	92.6	A=88.2 R=0	A=100 R=16.7	0.85
4.Sehlabeng	77.8	A=73.7 R=12.5	A=93.3 R=41.7	0.53	81.5	A=81.3 R=18.2	A=86.7 R=25	0.62
5.Phuthalichaba	63.0	A=69.2 R=42.9	A=60 R=33.3	0.21	88.9	A=87.5 R=9.1	A=93.3 R=16.7	0.77
6.Mantsebo	96.3	A=93.8 R=0	A=100 R=8.3	0.92	63.0	A=60 R=50	A=60 R=33.3	0.25
7.Abia	88.8	A=83.3 R=0	A=100 R=25	0.77	70.4	A=81.8 R=37.5	A=60 R=16.7	0.42

OA= Overall accuracy, PA=Producer accuracy, UA= User accuracy, K= Kappa coefficient, A= Agricultural land use and R= Road network land use

In general, the data revealed that the classified maps clearly indicated the relationship between the number of buildings, informal road network (dirt soil roads and gravel road) and the agricultural land. This is because, there has been an increase in the area of 8.49 Ha of dirt road network which is proportional to the number of newly constructed informal buildings between 2005 and 2016.This means most of the informal buildings have been influenced by the construction of dirt road network. This is mainly seen throughout the seven regions, where on average there has been an increase in the area of informal dirt roads and this promotes accessibility within the areas and hence promotes emergence of new dwellings in the form of informal settlements.

On the contrary, agricultural land is inversely proportional to the number of new informal building constructions. This is because, new dirt roads construction is being constructed on the agricultural land, similarly to the construction of the new homes as indicated by the reduction of the agricultural land by 60.36 Ha between 2005 and 2016 (table 16 above). This clearly indicates that the agricultural land at the urban peripheries is under greater threat from both the informal housing and the informal dirt roads. Therefore, at this rate of convention of productive agricultural into informal settlements and informal roads network it is going to be hard for people meet their basic needs of food from agricultural land if proper land use planning is not encouraged.

The foregoing discussions indicated 37.1 % percentage decrease in the agricultural land for informal settlements and informal road networks between 2005 and 2016. This shows the 3.4 % annual decrease in agricultural land along the urban peripheries .Contrary to the decrease in the agricultural land, the informal road network has increased by 19.6 % in 11 years, indicating that the informal roads increased by 1.8 % per year in the urban peripheries. This will impact negatively on the food production on the country dependent on the agricultural production like Lesotho (Gwimbi et al, 2014). This then calls for an immediate intervention through law enforcements, especially on spatial planning in order to accommodate the population growth and ensuring that the requirements of the basic needs of life like shelter are met and are in line with the United Nations (UN) sustainable development goals (SDGs).

Lesotho's Bureau of Statistics (2018) through 2016 Population and Housing Census (PHC) report indicated that the increase in population growth results in high demand for land around the city or urban areas. The lack of legislation especially land use policy in Lesotho resulted in people occupying agricultural land illegally and resulting in the unplanned informal urban settlements along the urban periphery. According to Lesotho's Population and Housing Census (PHC) report, Maseru district has the highest districts migrants at 36.4% (50,658 people) peri-urban migrants and urban migrants at 43.4% (279,472 people) and then generally 39.7% of the in-migrants had migrated into Maseru as shown by table 18 below. This generally means an increase in population needs additional space for settlements and construction. This requires spatial data acquired from remote sensing for proper spatial planning to accommodate population growth and at the same time protecting the agricultural land.

Table 18: Lesotho citizen that were migrants by districts of enumeration, 2016 PHC

District of enumeration	Number of Urban migrants	Number Peri-urban migrants	In-Migration (%)
Botha Bothe	26,294	-	3.9
Leribe	102,908	17,572	15.4
Berea	83,383	23,774	17.8
Maseru	279,472	50,658	39.7
Mafeteng	39,750	18,579	6.6
Mohale's Hoek	40,037	3,552	5.3
Quthing	27,314	7,459	3.2
Qacha's Nek	15,913	3,616	2.7
Mokhotlong	12,938	3,579	2
Thaba Tseka	15,248	10,281	3.4
Total	643,257	139,070	100

Table modified from Bureau of Statistics (2018) PHC report of 2016

4.5 Area and or village based analysis of growth pattern using spatial metrics

The quantification of an urban growth at a larger spatial scale may not provide sufficient insight to relate the spatial patterns to the underlying process (Abebe, 2013). In the similar manner, Herold et al (2003) argued that it is difficult to relate changes observed in the metrics to a particular location in the landscape without visual interpretations. Thus spatial patterns analysis using spatial metrics was performed on the seven mostly affected regions by the informal settlements along the urban periphery (section 4.5.1 to 4.5.5 below). Based on the observed urban growth dynamics, it is important to investigate spatial development of the peri-urban area. In this context, peri-urban are all the areas located immediately outside the MCC boundary. Within the peri-urban areas, there are seven mostly affected regions where the analysis of the thematic maps will be based on and the two land use classes of agricultural land and roads (tarred and dirt) will be compared.

For the analysis purposes, spatial metrics constituting road network (both tarred and dirt roads) and those making up the agricultural land (green land, bare land and red land) from categorical land use maps above (figure 20 to figure 26) were merged together. The merged land use types with the corresponding spatial metrics were then reclassified as road network and the agricultural land as shown in table 19 below.

Table 19: Landscape metrics by regions for the study period 2005 and 2016

Spatial Metrics	**2005 Spatial metrics by regions/areas**		**2016 Spatial metrics by regions/areas**	
1	**Fooso area**		**Fooso area**	
	Roads	**Agriculture**	**Roads**	**Agriculture**
CA	8.66	55.4	11.42	49.25
NP	25133	40856	12899	18829
LPI	1.11	24.98	2.08	33.59
ED	2081.45	6478.87	1696	3899
AWMPFD	1.43		1.42	
2	**Makhoathi area**		**Makhoathi area**	
CA	4.4	62.9	16.09	50.21
NP	17,596	23,033	16,419	23,198
LPI	0.49	42.4	1.87	16.29
ED	1,109.37	4078.66	1,806.82	4216.55
AWMPFD	1.39		1.38	
3	**Sekamaneng area**		**Sekamaneng area**	
CA	1.72	61.16	10.31	49.74
NP	14810	28790	12868	19702
LPI	0.02	27.35	0.74	30.2
ED	561.83	4375.67	1212.31	2920.04
AWMPFD	1.32		1.30	
4	**Sehlabeng area**		**Sehlabeng area**	
CA	2.29	56.64	3.84	43.46

NP	8166	33776	10238	18780
LPI	0.52	32.29	4.5	10.25
ED	501.88	5444.25	1417	3413.70
AWMPFD	1.39		1.34	
5	**Phuthalichaba area**		**Phuthalichaba area**	
CA	5.99	80.01	15.24	68.92
NP	20669	52798	17388	24256
LPI	0.94	16.5	1.97	33.76
ED	942.18	5341.34	1272.54	2910.9
AWMPFD	1.37		1.36	
6	**Mantsebo area**		**Mantsebo area**	
CA	3.19	48.83	10.67	40.8
NP	14410	26644	13787	15701
LPI	0.76	36.39	1.66	35.69
ED	1054.03	5621.60	1828.70	3531.46
AWMPFD	1.42		1.42	
7	**Abia area**		**Abia area**	
CA	2.05	41.97	11.60	29.98
NP	5040	24867	10315	15557
LPI	1.83	35.36	3.83	20.08
ED	561.91	7560.16	2349.35	5246.95
AWMPFD	1.48		1.45	

CA=Class area/total area, NP=Number of patches, LPA=Largest patch index, ED= Edge density and AWMPFD= Area Weighted Mean Patch Fractal Dimension.

4.5.1 Class Area (CA)/Total Area (TA)

This is a good technique for analysing and comparing the spatial extent of the road network and the agricultural land. The calculated CA for seven regions indicated an increase in CA which means an increase in informal road network fragmentation. This increase in road network fragmentation promotes the new construction of informal settlements as portrayed in table 15 above. On the contrary, agricultural land CA indicates the continuous decrease in fragmentation due to road network and these results in decrease in the agricultural land.

In Fooso area, CA for agricultural land decreased from 55.4 to 49.25, In Makhoathi it decreased from 62.9 to 50.21, Sekamaneng reduced from 61.16 to 49.74, Sehlabeng from 56.64 to 43.46, Phuthalichaba from 80.01 to 68.92, Mantsebo from 48.83 to 40.8 and lastly, Abia from 41.97 to 29.98. The observed trend is the decrease in the area occupied by agricultural land within all seven selected areas. In general, CA indicates that when road network area increases, the agricultural land areas decrease and results negatively on food production in the urban peripheries of MCC.

4.5.2 Number of Patches (NUMP)

The number of patches metrics is aimed at quantifying the number of individual roads and agricultural land. This metric like CA above indicates consistent increase in the number of fragments making up the road network while on the contrary; the total number of fragments making up the agricultural is continuously decreasing. In Fooso region, NUMP for agricultural land decreased from 40,856 to 18,829,in Sekamaneng it decreased from 28,790 to 19,702, in Sehlabeng from 33,776 to 18,780, Makhoathi the value increased from 23,033 to 23,198, in Phuthalichaba decreased from 52,798 to 24,256, in Mantsebo decresed from 26,644 to 15,701 and in Abia it decreased from 24,867 to 15,557.The general trend observed is the reduction in the number of patches making up the agricultural land which is mostly lost to built up land as already indicated by CA above. there is also a significant increased in the NP for roads as shown that in Abia for instance, NUMP increased from 5,040 to 10,315 and Sehlabeng increased from 8,166 to 10,238. This is mainly because, new constructions of these road networks takes place on the agricultural land to a lesser extend compared to the informal settlement as indicated by the continuous decrease of agricultural land at the expense of the road network and informal settlements.

4.5.3 Edge Density(ED)

This indicator measures the total length of the edge of the urban patches. Bekalo (2009) indicated that when the total length of the edge of the land use patch increases with the increase in land use fragmentation, then the increment in the number of patches can lead to the increment of edge density. The comparison of ED indicates the increased values for roads in 2016 compared to in 2005 and on the other hand the values of ED for agricultural land continue to decrease for agricultural land between 2005 and 2016. In Makoathi region, the ED value for roads increased from 1,109.37 to 1,806.82, in Sekamaneng it increased from 561.83 to 1,212.31, Sehlabeng from 501.88 to 1,417, in Phuthalichaba from 942.18 to 1,272.54, Mantsebo from 1,054.03 to 1,828.70 and in Abia region ED for roads increased from 561.91 to 2,349.35.On the contrary the ED values from agricultural land continues to decreased throughout the regions. In Fooso area, ED for Agricultural land decreased from 6,478.87 to 3,899, in Sekamaneng from 4,375.67 to 2,920.04,in Sehlabeng from 5,444.25 to 3,413.70, in Phuthalichaba from 5,341.34 to 2,910.9, in Mantsebo from 5,621.60 to 3,531.40 and in Abia from 7,560.16 to 5,246.94. This indicates the greater development of informal urban expansion as the results of improved informal road network and this result into emergence of number of disconnected fragmented informal settlements at the expenses of agricultural land as seen by the continued decrease in the ED for agricultural land with time.

4.5.4 Largest Patch Index (LPI)

LPI metric indicates the contagion of the smaller isolated patches into one of the largest patch and at the same time indicates the development of some urban centres around the already existing largest patch. This metrics indicates that 2016 LPI values for road network, small as they are, are greater than those of 2005.In Fooso region, the LPI value for road network increased from 1.11 to 2.08, in Makhoathi from 0.49 to 1.87, in Sekamaneng from 0.02 to 0.74,in Sehlabeng from 0.52 to 4.5, in Phuthalichaba from 0.94 to 1.97, in Mantsebo from 0.76 to 1.66 and in Abia from 1.83 to 3.83.This indicates that areas constituting road network are gradually being aggregated and integrated into a larger road network area. In the similar manner, the LPI for agricultural land continues decreasing indicating that the largest area within an area which was agricultural land in 2005 was decreasing as portrayed by low LPI values in 2016. For instance in Makhoathi region, the value decreased from 42.4 to 16.29 and in Sehlabeng it decreased from 32.29 to 10.25 and a similar trend is observed throughout the seven regions except in Fooso region. On average the results indicates the depletion of the agricultural land for road network improvements.

4.5.5 Area Weighted Mean Patch Fractal Dimension (AWMPFD)

This spatial metrics is used to determine the level of crumbling or fragmentation and compilation of patched in an attempt to understand the how complex a landscape polygon is. These fragmentation and complexity is based on the perimeter-area proportion and this measure ranges between 1 and 2. A low value (close to 1) of AWMPFD indicates a compact rectangular form while high values denote more complex and fragmented landscape. In Fooso region AWMPFD changed from 1.43 to 1.42, in Makhoathi is from 1.39 to 1.38, in Sekamaneng is 1.32 to 1.30, in Sehlabeng is 1.37 to 1.36 ,in Mantsebo is 1.42 to 1.42 and lastly in Abia is 1.48 to 1.42. The average value of AWMPFD for the study period is 1.39. This value indicates that our peripheries are gradually and constantly being transformed from simple compact and regular forms into a more complex, irregular and fragmented patches due to informal urban settlement expansion.

4.6 Conclusion

From the foregoing discussions, the data reveals that there is a continued encroachment of the agricultural land by the informal settlement as indicated by the spatial metrics. The reason for the encroachment is the urbanisation and need for affordable housing near work opportunities. Observed is an improved informal road network (dirt roads) which promotes accessibility and transferability within the urban peripheries. The spatial metrics further indicates that our landscape is gradually being transformed from a simple rectangular form into a more complex landscape due to this uncontrolled development at the urban peripheries. The complexity of the landscape is through the Area Weighted Mean Patch Fractal Dimension (AWMPFD) value of more than one. The AWMPFD is a good measure of general trend of landscape pattern compared to other metrics which analyses landscape pattern at only class levels. This generally means that the produced land use maps both at MCC and regional levels provide an important baseline data. This data should be used for planning purposes to cater for ever growing population growth which needs space for new constructions.

CHAPTER 5: CONCLUSION AND RECOMMENDATIONS

5.1 Introduction

Conclusion will be based on the research aim and objectives defined earlier in chapter one. The specific conclusions will be based on the research aim, objectives and questions as to how the research answered the questions. Finally, the recommendations will be made based on results of the study.

5.2 Specific conclusions and findings

5.2.1 Research aim: To produce land use land cover maps of MCC at different epochs to detect the land use changes between built up land and the agricultural land (non-built up land)

The main aim of the research of producing land use map have been achieved and the changes between built up and the agricultural land determined and further explained in section 5.2.2 below. Apart from that the land use map for the MCC, seven regional land use maps at the urban peripheries (within 2 Km MCC buffer) were also determined in order to determine the driving force behind the expansion of the informal settlements into the agricultural land.

5.2.2 Objective 1: Temporal analysis of land use land cover patterns

In the last 11 years, between the years 2005 and 2016, the land in Maseru City Council (MCC) and its peri-urban (within 2 km) areas have experienced an extensive illegal land use changes in the form of informal settlements. Based on the multi-temporal image classification of two epochs, 2005 and 2016 on the built-up and non-built up land uses, the classified maps indicate an increase in the built-up land and the densification of the urban centres and the adjoining MCC urban peripheries in all directions except the western region where it is the boundary between Lesotho and Republic of South Africa (RSA). Based on the study, the synoptic analysis indicates that the built-up land has increased by 928 Ha between 2005 and 2016 and at the same time the non-built-up land or agricultural land has decreased by 820.69 Ha. This indicates an annual average growth rate of 0.35 % in built-up land at the expense of agricultural land.

5.2.3 Objective 2: Assessment of spatial patterns of urbanisation and expressing them through spatial metrics

The understanding of an extent and rate of urban growth is not enough in the analysis of landscape changes. Therefore, in order to fill this gap, five spatial metrics were used in the study to understand the urban growth patterns. The selected five spatial metrics were based on the literatures according to their capacity to measure the different aspects of the landscape patterns like configuration, area, shape, etc. The selected spatial metrics are Class Area (CA), Number of Patches (NP), Edge Density(ED), Largest Patch Index (LPI), and Area Weighted Mean Patch Fractal Dimension (AWMPFD). These spatial metrics helped to understand the dynamics of the landscapes changes at more specific locations at city peripheries (see 5.2.4 below).

5.2.4 Research question 1, how will the complex decision making benefit from incorporation of remote sensing and geographic information system as the new decision analysis and support tool?

Both GIS and remote sensing have been used to clip, classify, and analyses the urban growth and factors leading into the agricultural land encroachment. The better understanding of the changing patterns and the urban dynamics requires the more specific locations within the study areas. Therefore, seven explicit regions namely, Fooso, Makhoathi, Sekamaneng, Sehlabeng, Phuthalichaba, Mantsebo and Abia regions were identified and further analysed individually based on the impact of the informal settlement within these areas/regions. All the five spatial metrics were applied on these regions at both class and landscape levels in order to understand the growth patterns and the reason behind such growth.

Based on these spatial metrics, they indicated general increase in CA, NP, ED, LPI and AWMPFD on dirt road network land use (soil roads and gravel roads), while the same metrics applied on non-built up land (agricultural land), they indicated an average continuous decreasing spatial metrics values. These spatial metrics therefore indicates that an improve road network takes place on the agricultural land, and hence promotes the construction of the new informal settlement due to improved road network (both dirt and gravel). The improved road network on the contrary affected agricultural and food production negatively. This is portrayed by increased average value of AWMPFD being greater than one, which indicates that the landscape is gradually being transformed from a simple compact or rectangular form to a more complex and fragmented landscape.

Therefore the above research question has been adequately addressed because as the results of the outcome of GIS and remote sensing through the spatial metrics, then the policy direction could be drawn based on this technology to support decision proposed for future developmental activities directions.

5.2.5 Research question 2, what spatial metrics will help support planning policy in Maseru City Council (MCC)?

This study revealed that no single spatial metrics is good enough to define or guide national, regional or local decision making process, but the combination of the number of spatial metrics used together. In general, the AWMPFD is a good spatial metric to be used in combination with other spatial metric because it gives the general pattern of the entire landscape compared to other spatial metrics which characterizes the landscape only at class levels.

5.3 Conclusion

The land use land cover change over time is seen as the results of combined effects of social, economic, demographic and environmental variables. This means for the planning purposes, the extent, patterns, and characteristics of the changes in the landscape is very important in planning and managing decisions based on spatial characteristics overtime. This generally implies that an updated spatial data in the form of land use land cover is important for planners about land related resources and the future development and the decision makers and spatial planner's plays significant roles in advising decision makers on land related issues. The research revealed that the combination of GIS, remote sensing and the spatial metrics provide an excellent tool for mapping, quantifying and analysis of temporal land use land cover patterns at different scales within the landscape.

5.4 Recommendations

The study indicated the important of the land use relative to ever growing population resulting in uncontrolled urbanisation and to an increase in informal settlements. Therefore, it is recommended that the similar studies be carried out within the urban boundaries and their peripheries throughout country in order to have a quantified data on the status informal settlements around the urban centres. This will help spatial planners planned accordingly based on the quantified data for an ever growing urbanisation process around the city centres due to migrations and natural causes. The results of such studies will lead into a better national land use policy formulation which will result in good spatial planning and equitable land distribution and ensure that food production as one basic need of life is met.

5.5 Future researches

This study has explored the use of remote sensing and the spatial metrics successfully in understanding growth patterns and quantifying the urban growth and factors leading to such growth in the urban periphery of the MCC. The quality of the information obtained from the spatial metric is dependent of the quality of the classification itself and hence for future studies, the accuracy of the image classification could be improved through the use of the medium spatial resolution imagery which is mostly appropriate for the ERDAS software's used in this study. This will help solving problem of salt and pepper effect and hence improves the classification accuracy.

This research can be the start of monitoring informal growth in the peri-urban areas. However, for further understanding of how the expansion of informal settlement will impact MCC there needs continued research in the form of modelling the growth. The model results will help the planners and most importantly the policy makers to devise urban growth policies based on the current scenarios of an ever population growth and completion between different land uses.

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Appendix 1: Some ground truth observation made with GPS

Site Positions

Maseru

Horizontal Coordinate System: S.Africa Plane Co-ordinate System **Date:** 11/07/18

Height System: Ellips. Ht. **Project File:** GroundTr.spr

Desired Horizontal Accuracy: 0.020m + 1ppm

Desired Vertical Accuracy: 0.04m + 2ppm

Confidence Level: 95% Err.

Linear Units of Measure: Meters

Site ID	Site Descriptor	Position		95% Error	Fix Status	Position Status
1. BASE	**1010148**	East.	-46129.743	0.000	Fixed	**Processed**
		Nrth.	3246147.808	0.000	Fixed	
		Elev.	1557.8	0.000	Fixed	
2. 1001	**1000**	East.	-52504.555	0.006		**Processed**
		Nrth.	3238542.884	0.006		
3. 1002	**1000**	East.	-52757.671	0.006		**Processed**
		Nrth	3238322.810	0.006		
3. 1003	**1000**	East.	-52863.136	0.006		**Processed**
		Nrth	3238494.191	0.008		
4. 1004	**1000**	East	-52660.234	0.004		**Processed**
		Nrth	3238599.656	0.008		
5. 1005	**1000**	East.	-52971.363	0.004		**Processed**

		Nrth.	3237863.234	0.006	
6. 1006	**1000**	East.	-53217.961	0.008	**Processed**
		Nrth	3238166.976	0.002	
7. 1007	**1000**	East.	-53225.369	0.004	**Processed**
		Nrth	3238307.735	0.003	
8. 1008	**1000**	East	-52898.343	0.006	**Processed**
		Nrth	3238316.201	0.010	
9. 1009	**1000**	East.	-52763.35	0.008	**Processed**
		Nrth.	3238121.468	0.004	
10. 1010	**1000**	East.	-54930.612	0.020	**Processed**
		Nrth	3236808.867	0.006	
11. 1011	**1000**	East.	-54602.528	0.006	**Processed**
		Nrth	3236904.117	0.008	
12. 1012	**1000**	East	-54727.411	0.004	**Processed**
		Nrth	3237113.668	0.002	
13. 1013	**1000**	East.	-55089.362	0.008	**Processed**
		Nrth.	3237124.251	0.006	

14. 1014	**1000**	East.	-56135.262	0.004	**Processed**
		Nrth	3238271.487	0.002	
15. 1015	**1000**	East.	-56481.867	0.006	**Processed**
		Nrth	3238721.279	0.010	
16. 1016	**1000**	East	-56370.742	0.004	**Processed**
		Nrth	3238210.632	0.004	
17. 1017	**1000**	East.	-56092.929	0.008	**Processed**
		Nrth.	3237988.382	0.006	
18. 1018	**1000**	East.	-55225.094	0.004	**Processed**
		Nrth	3242372.537	0.002	
19. 1019	**1000**	East.	-54944.635	0.006	**Processed**
		Nrth	3242798.517	0.008	
20. 1020	**1000**	East	-55166.885	0.004	**Processed**
		Nrth	3243055.163	0.010	
21. 1021	**1000**	East.	-51532.495	0.006	**Processed**
		Nrth.	3243316.483	0.002	
22. 1022	**1000**	East.	-51483.441	0.008	**Processed**
		Nrth	3243317.753	0.006	
23. 1023	**1000**	East.	-51409.622	0.002	**Processed**

		Nrth	3243339.660	0.004	
24. 1024	**1000**	East	-48094.548	0.004	**Processed**
		Nrth	3245527.930	0.008	
25. 1025	**1000**	East.	-47908.323	0.008	**Processed**
		Nrth.	3245642.530	0.008	
26. 1026	**1000**	East.	-44974.957	0.010	**Processed**
		Nrth	3246719.826	0.006	
27. 1027	**1000**	East.	-44343.900	0.006	**Processed**
		Nrth	3247547.884	0.008	
28. 1028	**1000**	East	-47591.514	0.002	**Processed**
		Nrth	3250793.395	0.008	
29. 1029	**1000**	East.	-50300.229	0.006	**Processed**
		Nrth.	3253031.159	0.006	
30. 1030	**1000**	East.	-53614.264	0.008	**Processed**
		Nrth	3252457.246	0.002	
31. 1031	**1000**	East.	-54530.465	0.004	**Processed**
		Nrth	3253951.792	0.006	
32. 1032	**1000**	East	-56567.136	0.004	**Processed**

		Nrth	3254443.604	0.008	
33. 1033	**1000**	East.	-54568.850	0.006	**Processed**
		Nrth.	3255961.535	0.006	
34. 1034	**1000**	East.	-45873.664	0.002	**Processed**
		Nrth	3255133.099	0.004	
35. 1035	**1000**	East.	-42776.964	0.006	**Processed**
		Nrth	3247054.817	0.008	
36. 1036	**1000**	East	-45707.718	0.002	**Processed**
		Nrth	3251913.811	0.008	
37. 1037	**1000**	East.	-46104.951	0.006	**Processed**
		Nrth.	3244354.025	0.006	
38. 1038	**1000**	East.	-45376.732	0.008	**Processed**
		Nrth	3242796.294	0.006	
39. 1039	**1000**	East.	46000.821	0.004	**Processed**
		Nrth	3241916.589	0.002	