SPATIO-TEMPORAL RS. ANALYSIS AND PREDICTING LAND USE/LAND COVER CHANGE USING CA-MARKOV SIMULATION MODEL: A CASE STUDY OF GITEGA DISTRICT, BURUNDI

AUDACE NTAKIRUTIMANA

A Thesis Submitted to the Graduate School of Naresuan University
in Partial Fulfillment of the Requirements
for the Master of Science in (Geographic Information Science)
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has been approved by the Graduate School as partial fulfillment of the requirements for the Master of Science in Geographic Information Science of Naresuan University

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ABSTRACT

Spatial and temporal analysis of Land use and Land cover Change (LULC) is a widely used and effective method for monitoring environmental issues caused by humans at both local and global scales. Land use and land cover change play an important role in ensuring human well-being, particularly throughout regional socioeconomic development, and thus LULC is an important aspect of global environmental dynamics. The rapid increase in human population and associated livelihoods frequently causes problems for the biophysical environment and ecosystems, such as the loss of natural areas, particularly forests and natural vegetation due to urban development and agricultural expansion. The purpose of this study was to monitor land use and land cover change in the Gitega District, and also to simulate a future scenario in order to generate a long-term land use dataset using Geoinformatics. The first step was to use multi-temporal Landsat imagery from 1984, 2002, and 2019 to generate existing LULC maps using a combination of RS and GIS approaches. The supervised classification method was used to derive five major LULC classes, and the accuracy assessment resulted in an overall accuracy of more than 85

percent for all three years, with respective Kappa statistics of 83 percent and 91 percent. Net Change detection results showed that Agriculture had the greatest extension with an area of 94 km^2 and an annual rate of 2.9 km^2, a slight increase in Shrub Land by 5,5 km^2 and Built-up Area by 2 km^2, and a steep decline in Tree Cover of 62.5 km^2 with a rate of 1.79 km^2 per year, and Grass Land decreased 39 km^2 with a rate of 1.12 km^2 over the past 35 years. C-A Markov model was further calibrated to predict 2038 and 2057 LULC using the transition probability matrices between the existing and simulated LULC map of 2019. Evaluation and analysis of 2019, 2038 and 2057 simulation results showed an overall moderate agreement of 75 percent for Kappa statistics and the same trends of LULC change: Trees Cover, Grass Land, and Shrub Land are likely to decrease by 11.5 km^2, 13 km^2, 11.5 km^2 respectively, whereas Agriculture and Built-up Area will increase by 30 km^2 and 6 km^2 respectively in 2057. Overall, major LULC dynamics occurred by conversion large agriculture and possibly thereby, high degradation with soil erosion, loss and soil depletion are some Gitega District.

These research findings may assist decision-makers in gaining a thorough understanding of land use and land cover change patterns in order to devise the best strategies for land sustainable land use management, thereby avoiding future irreversible land degradation and environmental problems that may be difficult and costly to address over time.

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List of Abbreviations

Abbreviation	Terms
AC	Area Coverage
AOI	Area of Interest
ATCOR	Atmospheric Correction
AR	Annual Rate
C	Celsius
CA	Cellular Automata
DN	Digital Number
E	East
ERTS	Earth's resources Technology Satellite
ETM+	Enhanced Thematic Mapper Plus
EUROSTAT	European Union's Statistical Office
FAO	Food and Agriculture Organization
FRA	Forest Resource Assessment
GDP	Gross Domestic Product
IGEBU	Institut Géographique du Burundi
IPCC	Intergovernmental Panel on Climate Change
JICA	Japan International Cooperation Agency
KIA	Kappa index of Agreement
Km	Kilometers
LCM	Land Change Modeler
LULC	Land Use and Land Cover
m	meter
M	Magnitude
MC	Markov Chain
MIR	Middle Infrared
MLC	Maximum Likelihood Classification
MSS	Multi Spectral Scanner

N	North
NDVI	Normalized Difference Vegetation Index
NIR	Near-Infrared
Npr	Number of years period
OA	Overall Accuracy
OLI	Operational Land Imager
P	Percentage
P	Transition probability
PA	Producer’s Accuracy
PAN	Panchromatic image
PRASAB	Agriculture Rehabilitation and Support and Sustainable Land Management Project
RCMRD	Regional Centre for Mapping of Resources for Development
REDD	Reducing Emissions from Deforestation and Forest Degradation
RS	Remote Sensing
RBV	Return Bean Vidicon
S	South
SWIR	Short Wave Infrared
TICA	Thailand International Cooperation Agency
TM	Thematic Mapper
TIR	Thermal Infrared
TIRS	Thermal Infrared Sensor
UA	User’s Accuracy
UN	United Nations
UNCCD	United Nations Convention to Combat Desertification
UNOCHA	United Nations Office for the Coordination of Humanitarian Affairs
UTM	Universal Transverse Mercator
USGS	United States Geological Survey
W	West
WGS	World Geodetic System

CHAPTER I

INTRODUCTION

1.1 Background and significant of the study

Land use and land cover change (LULC) is widely recognized as an important component of global environmental change and plays an important role in ensuring regional socioeconomic development (Q. Liu & Shi, 2019). The land, as the core of the biophysical environment, serves a variety of functions such as agricultural resource, habitat, ecosystem, and wealth, among others (Bai, Dent, Olsson, & Schaepman, 2008). The LULC change alters the natural landscape, causing significant fragmentation or loss of habitats, which reduces human qualities (Boissière, Sheil, Basuki, Wan, & Le, 2009; E. F. R. Lambin, Mark Da & Geist, 2000). The rapid population with associated human livelihoods is prone to accelerate the rate of LULC change mostly in agricultural areas (Boissière et al., 2009; E. F. R. Lambin, Mark Da & Geist, 2000). These important issues of land use and land cover change have been reported in many parts of the globe (Meyer, Meyer, & BL Turner, 1994). According to global report (2000) by FAO, 24percent of the global land area was accounted for global degraded land due to deforestation for agricultural expansion in Africa south of the equator, South East Asia and South China, North Central Australia, Pampas and the Siberian and North American taiga regions (Bai et al., 2008). Land use and land cover changes often result in modifying physical dimension of spatial extent of LULC classes i.e. vegetated area, water etc., and consequently influence many mechanisms which lead to degradation of ecosystems and environment (Dregne & Chou, 1992).

As per Marathianou et al. (2000), LULC changes reduce normalized difference vegetation index (NDVI) of land, which in turn increase the occurrence of many other extreme impacts on the environment. List of such deleterious effects includes climate change, extreme radiative forcing, pollution and quality reduction of natural ecosystems, changes in hydrological regimes, runoff, soil loss and depletion of soil fertility (IPCC, 2019; Marathianou, Kosmas, Gerontidis, & Detsis, 2000; Niyogi, Mahmood, & Adegoke, 2009). Therefore, land use and land cover change information is worth needed in various fields of environment, especially in deforestation and disasters assessment, agriculture and land management, urban expansion planning (Ghosh et al., 2017; Turner, Lambin, & Reenberg, 2007). Inventory and monitoring of LULC changes are indispensable aspects for better understanding of change mechanism and modelling the impact of change on the environment and natural resources (Halmy, Gessler, Hicke, & Salem, 2015; Twisa & Buchroithner, 2019).

Remote Sensing and GIS have broadly proved to be very effective tools in assessing and analyzing land use and land cover changes (Dewan & Yamaguchi, 2009; Nijimbere, Lizana, & Riveros, 2019). These approaches enable to get multi-temporal datasets to qualitatively analyze spatial and temporal effects of phenomena and quantify the changes (Islam et al., 2018). Satellite data-based R.S has revolutionized the research of LULC change, throughout its virtual ability to provide synoptic information of land use and land cover at a particular time and location (Islam, Jashimuddin, Nath, & Nath, 2018), and multi-temporal information on LULC helps identify the features and areas of change in a region (James Richard Anderson, 1976; Patil, Desai, & Umrikar, 2012). GIS provides a database by integrating, visualizing, analyzing and producing maps (Mishra, Rai, & Mohan, 2014; Shen, 2019). It can also integrate past and current LULC maps for comparison and change detection over time (Surabuddin Mondal, Sharma, Kappas, & Garg, 2013). These compound approaches, namely Geoinformatics allow to assign spatial connotations to land use land cover changes as well as population pressure, climate, terrain, etc. as driving forces of these changes (Ghosh et al., 2017; E. F. R. Lambin, Mark Da & Geist, 2000; Pijanowski, Brown, Shellito, & Manik, 2002).

1.2 Problem statement

Burundi is a small landlocked country and the most densely populated country in Africa with 480 people/km^2 approximately and total area of 27,834 km^2 (UNdata, 2020). 92 percent of its 12 million people are framers depending directly on farming activity to ensure the livelihoods (Kamungi, Oketch, & Huggins, 2005; Nzabakenga, Feng, & Yaqin, 2013). Access to arable land had been a priority for any household and demand of agricultural land has been highly increased (Nzabakenga et al., 2013) and as result, the land has become a source of conflict and contestation. Between 2007and 2013, an average of 5451 per year conflicts was recorded (Bob, 2010). Thereby, the fast-high population growth has led to increasingly smaller plots of land per family and substantially intensified land scarcity (Kamungi et al., 2005; Nzabakenga et al., 2013). This has caused persistent environmental degradation due to agricultural expansion and intensification. Deforestation has substantially increased from 240 ha in 1996 to 30,000 ha in 2007, whereas forest areas decreased by 8.2 percent in 1990 to 6.3 percent in 2006. The latest researches show that there was cultivation expansion which covered approximately 1,351,000 ha between 2002 and 2010, and average of land use rate rose up to 72 percent in general (Nijimbere et al., 2019). Some regions of the countries are highly affected by the impact of LULC dynamics (Nzabakenga et al., 2013)

Gitega District, the National capital of Burundi and the seat of Gitega Province has witnessed the impact of Land use land cover change. Its topography and geographic position have been motivating the Governments since its inauguration in the 1680's. This second city has been always issued to be the administrative capital of the country and best place for serving the majority of the citizens (Lemarchand, 2017). Consequently, it is impressive for massive immigration with greater resulting to an increase in population density and thereby an increasing demand of agricultural land (Guichaoua, 1982). The recent return of its former capital status by Government of Burundi in 2019 was accompanied by the shifting of some important institutions, ministries, agencies, and organizations to Gitega, which was likely to override the issues of land use and land cover in the already congested area (Garg, 2020). The land degradation and environmental pressure arising from attractiveness of modernity and developmental infrastructures is no longer uncertain (Guichaoua, 1982) As of now, Gitega is classed as the third most affected area by land degradation in Burundi. The agricultural subsistence system on which most people live and the poor farming methods are major components of dramatic land use and land cover changes (Moore, 2007).

These problems stem from the country's small land area, high deforestation rates, and growing population. All of this has put undue strain on the land, forcing farmers to reduce or eliminate fallow periods in order to feed their families. (Leisz, 1996). Soil erosion, soil loss, and soil fertility depletion have increased as a result of forest clearing for agricultural purposes in Gitega district (Nijimbere et al., 2019; Niyuhire, 2018). Despite these alarming indicators of land degradation, Burundi lacks a multitemporal database on land use and land cover changes that could assist decision-makers in planning for sustainable land use (Islam et al., 2018; Ndzabandzaba, 2015).

1.3 Research questions

From the above problem statement, four research questions were raised:

1. What is the scheme of land use and land cover in Gitega District and which LULC type is mostly dominating?
2. What is the rate, trends and amount of LULC changes in Gitega?
3. What is going to happen in future if such LULC trends are likely to continue?
4. What is the benefit of using an integration of Cellular Automata and Markov Chain models in modelling LULC change?

1.4 Aim and objectives of the study

During the process of answering the above-mentioned questions, we will be generating a useful land use and land cover database. The following objectives were therefore framed:

1. To evaluate the trends, rate and amount of LULC changes over the past 35 years using multi-temporal Landsat data with R.S and GIS technology
2. To explore the past and current LULC changes and simulate two future scenarios using CA-Markov Simulation Model.

1.5 Significance and aims of the study

Although the land is currently faced with major issues in Burundi, we cannot entertain people to stop utilizing this natural reproductive resource. Through farming activities, the land is the most resource of income for about 95 percent of Burundians, thus the accessibility to land has been there a priority by any household. However due to the rapid increase in human population, the land has become insufficient and, in some households, it has reported as source of conflicts rather than a productive resource.

Despite these multiple issues observed in domain of land use, as of now Burundi doesn't have any specific dataset to explore the land use and land cover changes evolution and start managing the land and environment accordingly.

Eventually this because the creation of such land use dataset could be more expensive in the country with many challenges in human resources amplified by long and unrest civil war.

Geoinformatics and statistical models are proven to be effective methods for addressing address major components of Land and environmental problems. They have revolutionized land and environmental research by linking individual features or people to pixels, such as household survey data to land-cover data derived by remote sensing technology. These approaches help to monitor and analyze accurately the Land use and land cover change at real time and large scale and acquire and store data which could be very expensive or difficult to collect due to the time consuming and topographic extents

This study aims to evaluate LULC changes occurred by calculating statistical rates and magnitudes of change by land/land cover category over the past 35 years in Gitega District and also to simulate future scenarios with an assumption of continuation of current trends using the combination of RS, GIS and CA-Markov Chain modelling approaches.

Thus, this research will contribute to get the understanding of past and recent trends of LULC change at short and long-term basis and provide knowledge of future LULC change for eventually assist government policy and decision-makers in sustainable land use management and environmental conservation at Gitega regional scale and in the context of Burundi.

CHAPTER II

LITERATURE REVIEW

2.1 Land Use and Land Cover change around the world

2.1.1 Concept and function of land

According to historical a definition made by United Nations Convention to Combat Desertification documentation, the land is " the terrestrial bio-productive system that comprises soil, vegetation, other biota, and the ecological and hydrological processes that work within the system " (UNCCD, 1994)." For deep understanding, the definition of Land was completed by Food Agriculture Organization (FAO) stating that " land is a delineable area of the earth's terrestrial surface, encompassing all attributes of the biosphere immediately above or below this surface including those of the near-surface climate the soil and terrain forms, the surface hydrology (including shallow lakes, rivers, marshes, and swamps), the near-surface sedimentary layers and associated groundwater reserve, the plant and animal populations, the human settlement pattern and physical results of past and present human activity (terracing, water storage or drainage structures, roads, buildings, etc.) " (Sombroek & Sims, 1995).

2.1.2 Relationship between Land use and Land cover

Often confused and ambiguously replaced with each other, the concept of land use and land cover have different meaning. On the one hand, “land cover” is the observed biophysical cover of the earth’s surface which make reference to other elements in the landscape such as vegetation, water, soil, artificial surfaces, etc.,”(Eurostat, 2001). It corresponds to physical description of space which enables various landscape features to be distinguished as well as vegetation (forest, bushes, trees, fields), bare soil (sand, rugged area), water bodies etc. (Di Gregorio & Jansen, 1998). The land cover categories can be easily observed by human eyes at different distances between observation station and observed area, using aerial photographs or satellite images (Di Gregorio & Jansen, 1998; Eurostat, 2001).

On the other hand, the term “land use” is defined as all human activities, arrangements and inputs undertaken on a surface that induce land cover transformation (U. FAO, 1999; E. F. Lambin & Geist, 2008). The land use corresponds literally to functional description of a certain area in terms of its socioeconomic purposes (e.g. residential area, urban, industrial or commercial areas, Agricultural land, cropland, recreational parks or natural reserves, etc.) (Agarwal, 2002; Green, Kempka, & Lackey, 1994). Land use description is more complicated but still connected to the land cover even though the link is not evident, and contrary to the land cover, the land use can be difficult to observe. For instance, it is always difficult to decide whether the observed area is grassland, grazing land or vegetable garden. Decision upon coming information from source often requires additional knowledge of the area functions (Eurostat, 2001).

Although, there is a clear difference of meaning between these concepts, their relationship is still strong and very complex to understand as broadly recognized among scientists and global LULU studies (Fisher, Comber, & Wadsworth, 2005; Verburg, Van De Steeg, Veldkamp, & Willemen, 2009). In order to tackle this comprehension issue, the land use concept was linked to human activities and specifically, to the economic factors behind these actions, in order to get better understanding of land-use/land-cover relationships (Turner et al., 1995). For instance, the global Forest Resource Assessment (FRA 2000) of the FAO has been making different confusing definitions of forest. In the first definition of FRA 2000, the forest was described a land cover class "with a continuous vegetation cover in which tree crown cover exceeds 10 percent" (Matthews, 2001). After sometime, the official forest definition of FRA 2000 stated forest "land use class and the deforestation process as a land use change". Few years later, FRA 2005 performed forest definition by making more explicit that forest: "does not include land that is predominantly under agricultural or urban land use" and considers that "forest is land spanning more than 0.5 hectares with trees higher than 5 meters and a canopy cover of more than 10 percent, or trees able to reach these thresholds in situ"(FRA, 2020).

As aforementioned in the concepts and function of land, most of scientists and international organizations such as FAO (the United Nations' Food and Agriculture Agency) and EUROSTAT (the European Union's Statistical Office,) and global studies have been focusing on the establishment of relationship among land cover, land use dimensions and land functions with linkage to human activities (Eva & Lambin, 2000; Verburg et al., 2009).

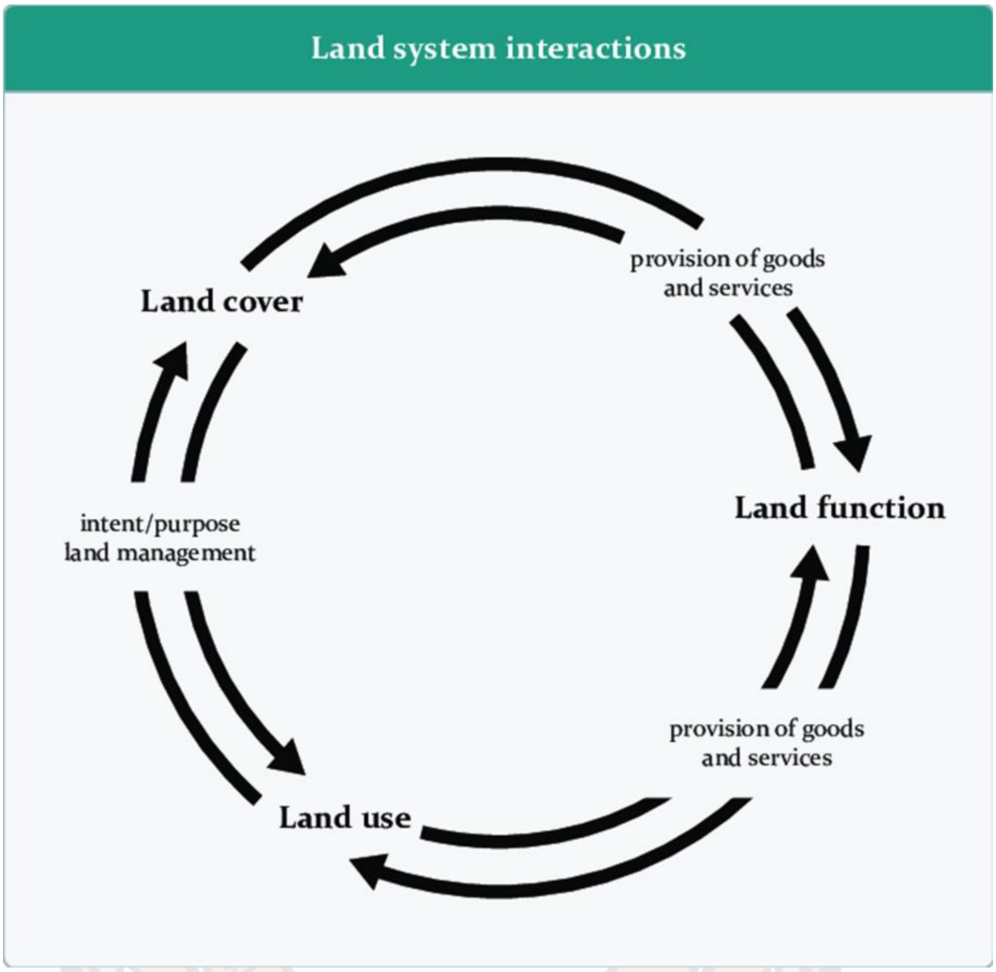

Figure 1 Land Use, Land Cover and Land function relationship

Source: Verburg et al., 2009

2.1.3 Driving factors of LULC change

Several driving factors determine land use and land cover change. From a distinctive analysis of relationship among land use, land cover and land function (**Figure 1**), it is clearly understood that most of the changes occurring in LULC patterns can be driven by human beings through provision of goods and services from land (Garg, 2020; Marchant et al., 2018). Furthermore, this analysis leads to understand how demographic and economic dynamics may influence demand for particular services and commodities which in turn drive LULC changes. Although, land use land cover change can also be influenced by other various natural processes such as, climate, topography, soil, water, human beings are still the main force activating these biophysical factors to occurrence of LULC Changes, this means physical and environmental drivers do not have a direct impact on land use and land cover changes (E. F. Lambin & Geist, 2008).

First of all, LULC change involves two general forms: conversion from one LULC to another i.e. from forest to agriculture, and modification within exiting LULC category i.e. intensification of cultivation in extensive agricultural area (Di Gregorio & Jansen, 1998; Turner et al., 1995). Consequently, the LULC changes induced by people at local scale can play a very important role on regional to global scales, with negative impacts on ecosystem functioning and services, biophysical variables such as climate change and ecological balance (Meyer et al., 1994). Marathianou et al. (2000) agreed that the LULC changes reduce normalized difference vegetation index (NDVI) of land, which in turn increase the occurrence of many other extreme impacts on the environment. List of such deleterious effects includes climate change, extreme radiative forcing, pollution and quality reduction of natural ecosystems, changes in hydrological regimes, runoff, soil loss and depletion of soil fertility (Marathianou et al., 2000; Niyogi et al., 2009).

Therefore, the driving factors of LULC change had been finally categorized into groups: proximate factors and underlying factors (E. F. Lambin et al., 2001; Zak, Cabido, Cáceres, & Díaz, 2008). Proximate driving factors are direct causes of modification of land cover type and are usually induced by anthropogenic activities such as built-up, agricultural extension, etc. However, underlying factors infer to a complexity of interactions among sociopolitical, demographic and environmental factors (E. F. Lambin et al., 2001; Miyamoto, Parid, Aini, & Michinaka, 2014). AS per explanatory classification of Lambin et al. (2001), proximate causes locally operate and they can be categorized into three subclasses namely agricultural expansion, wood extraction and infrastructures expansions and beneath them are several variables listed in **Figure 2**.

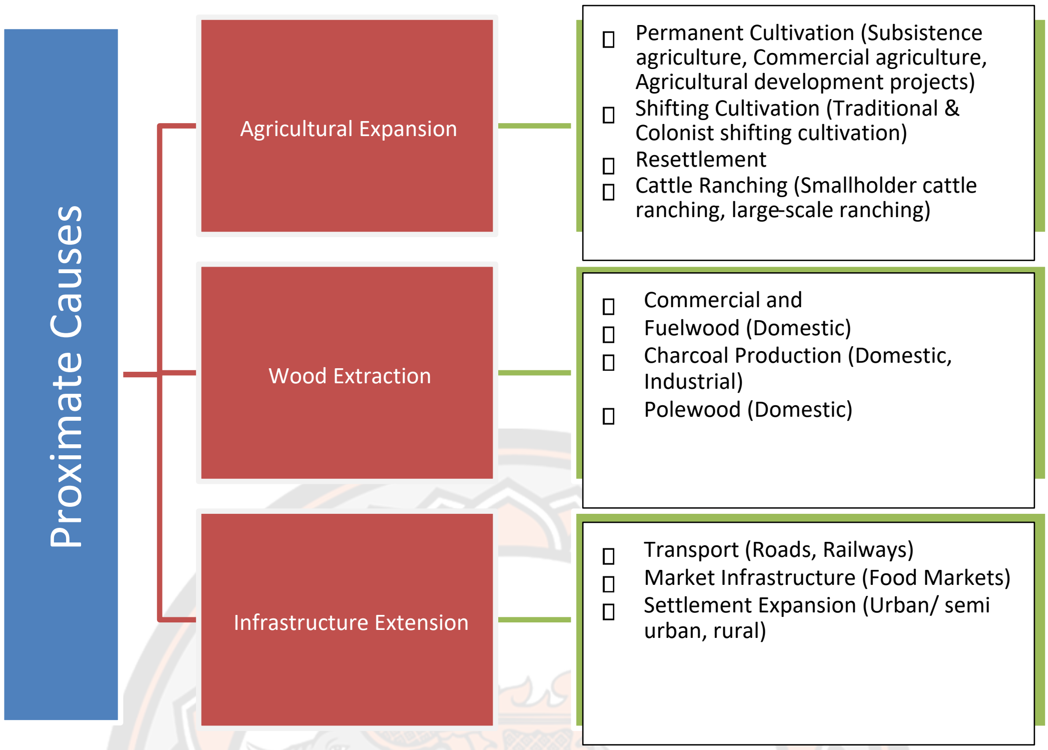

Figure 2 Proximate causes of LULC change and their variable

Source: Lambin et al., 2001

According to Reid et al. (2000) and Lambin et al. (2001), underlying factors of LULC change work at regional, national and global scales and they could also be categorized into government policy and institutional, demographic, economic, technological and cultural situations biophysical situations and linked diversifications as described in **Figure 3** (E. F. Lambin et al., 2001; Reid et al., 2000).

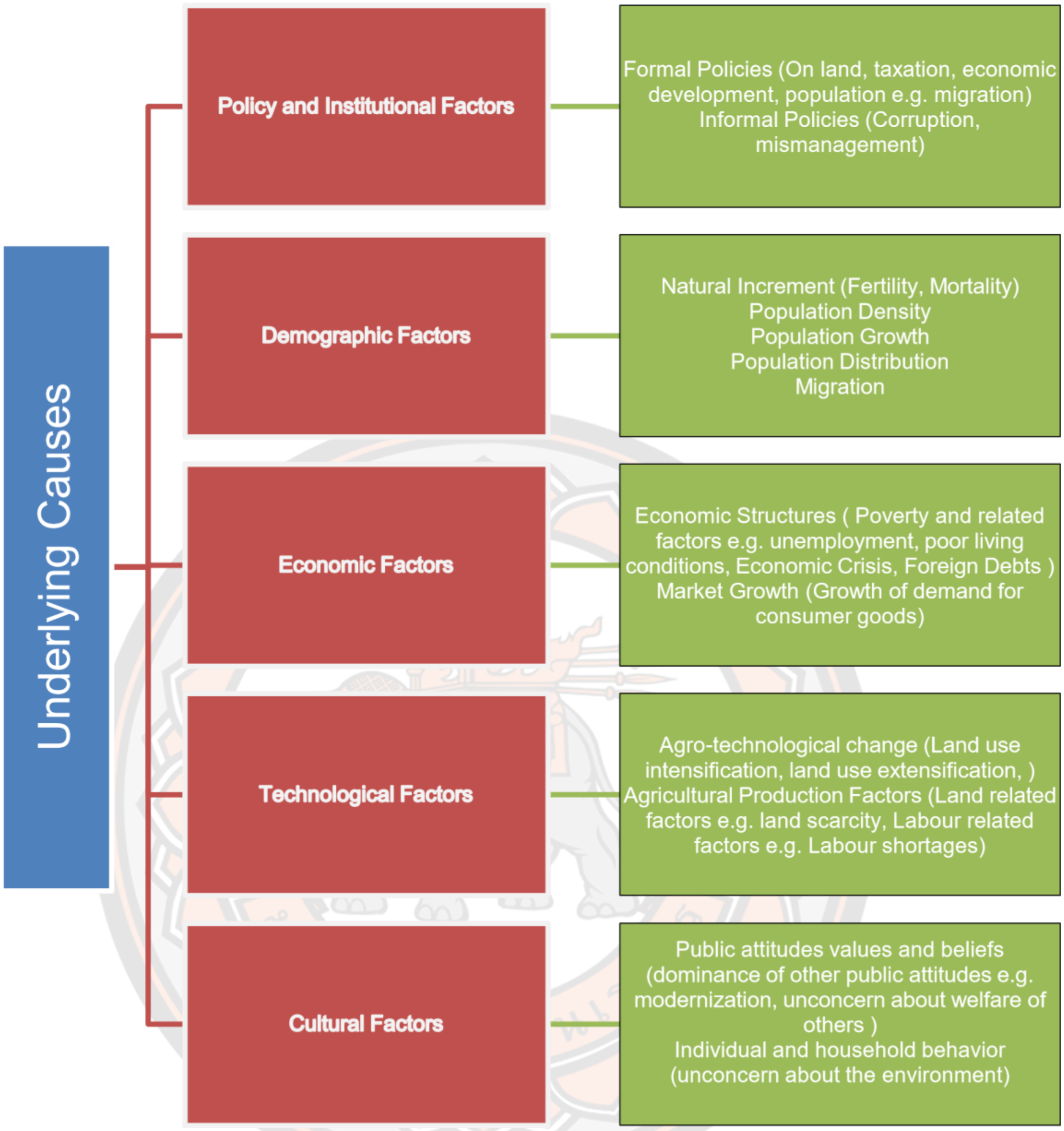

Figure 3 Underlying causes of LULC change and their variable

Source: Lambin et al., 2001

In sum, the land use and land cover change always leads to considerable loss of natural resources which in turn results in extreme climate changes and environmental vulnerabilities (Zak et al., 2008). Indeed, regional, national and global land conversion and consumption rates has rapidly increased, and undoubtedly will continue to increase as surely as human population grows up (Reid et al., 2000). Thus, population dynamics is quite important among driving factors since reallocation of land is required to accommodate the ever-increasing human beings. Obviously, demand for producing more from natural resources especially the land is so evident. Eventually, in order to meet such needs, the arable lands, built-up are bound to widely expand at the cost of the natural land cover such as forest and planted areas as exemplified in **Figure 4** (van Vliet, 2019).

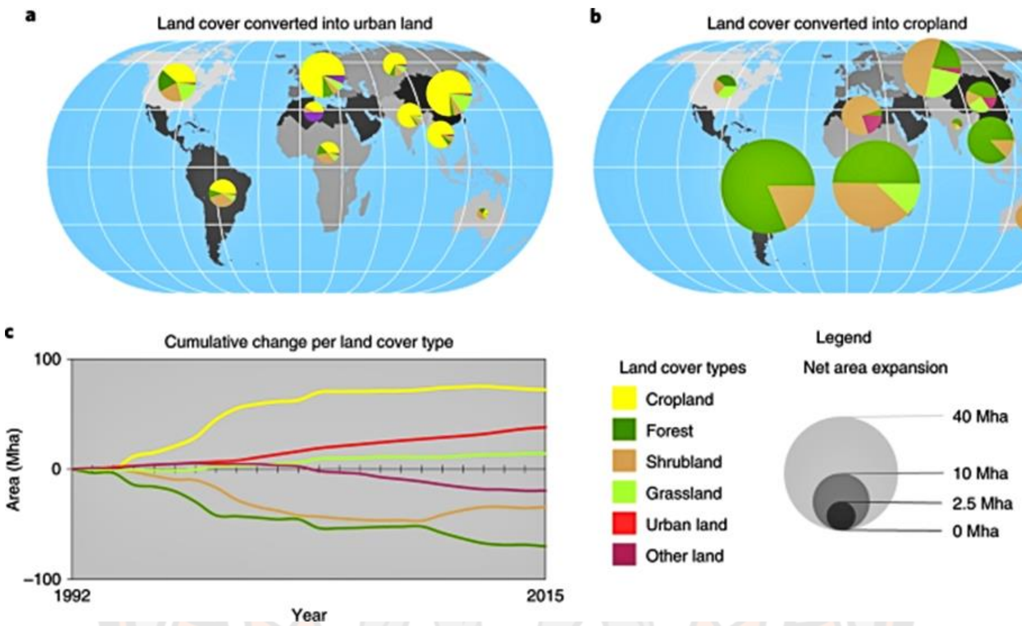

Figure 4: Observed global land cover changes between 1992 and 2015

Source: van Vliet, 2001

2.1.4 Burundi LULC context and driving forces of change

Burundi's total land area is approximately 25,700 km^2, 91 percent of which is classified as agricultural land. As of 2020, 92 percent of Burundi's 12 million people are traditional farmers living in rural areas (UNdata, 2020). Burundi's mild climate and plentiful rainfall make it suitable for intensive agriculture and livestock, where coffee, tea, cotton, tobacco, and sugarcane are all cash crops. Whereas bananas, corn, manioc, sweet potatoes, Irish potatoes, beans, peas, wheat, peanuts, vegetables, plantains, and fish are examples of subsistence crops. Ninety-four percent of Burundi's workforce is employed in agriculture. Concerning drivers of LULC change in Burundi and based on their explanatory operation scales given above, this section of study is focusing on driving forces in order to leave out the place for proximate causes of LUL Change in Gitega district.

2.1.4.1 Policy and instittutional factors

Burundi land access and tenure security have been all long on the country ‘s political agenda, and a land code has been under consideration for from time to time Burundi has a long history of using the law and public institutions to compel arbitrary land reallocations, which is almost structural in national legislation... The land law of 1961 stated that land held under customary tenure is part of the state's domain, with the state exercising reversionary rights if the land becomes unoccupied or otherwise abandoned. Individual farmers were only permitted to occupy and use the land. However, the land licensed and owned by European companies and church missions was not equally encumbered as freehold under the colonial system. Laws enacted in 1976 and 1977 expanded the state's control over land. The 1976 law reclaimed all land that had been illegally distributed by local administrative personnel (the bourgmestres) since independence. The institution of UBUGERERWA was therefore officially abolished by law in 1977. This was a system that allowed people to gain access to land by renting it out. To gain access to the land, the potential renter would approach someone who owned large portions of land. Traditionally, a potential renter would solicit access to the land with a gift of beer, and then negotiate the terms of use. The use rights were frequently insecure. The 1977 law also officially promoted the idea of villagization, or the relocation of families from their fields to villages, thus it is considered to contribute to the land use/land cover change in that period.

Clearly seen as driving factor of LULC change, 1986 Land Tenure Code was the first law devoted entirely to land tenure reform since independence. Due to its overall mission to promote the country's development and increase agricultural production, this law had recognized all previous granted titles and land registration as evidence that the land has been appropriated. It also recognized customary land rights. On the other hand, all unoccupied land officially belongs to the state, and all occupied land must be registered under the terms of the Land Tenure Code of 1986. However, the reality is that the 1986 land law is not fully understood by the entire population, and as a result, community-based tenure systems that locally regulate access to and use of land and the natural resource base continue to be used.

Concerning urbanization, the 1986 law reinforces this by stating that urban land must be registered and that the registration must be passed on when it is sold, inherited, or otherwise transferred from one owner to another. As Current scientist's policy makers discourse focuses on what are perceived to be the two major issues of agricultural land fragmentation and increasing degradation of the natural resource base, the government of Burundi is most concerned with these two areas, as well as how far the state land and forestry codes affect them. Despite the security provided by existing land occupancy systems and laws encouraging the fallowing of agricultural land in order to restore its fertility, there are still natural resource management and conservation issues in Burundi.

2.1.4.2 Demographic factors

Understanding a population's demographics can support to explain the causes and trends of LULC changes. various studies have shown that it is not only the number of people who matter the most the pressure on land, but also the aspects of population as well as its distribution such as household size, migration, and urbanization.

Burundi's land occupancy patterns have changed more as a result of demographic pressures than of government or market forces since independence. According to the United Nations report, in 1992, Burundi has 5.78 million people, and its demographic growth rate was 2.9 percent between 1980 and 1991. During the same time period, its urban population increased by 5.7 percent per year, but today only 6 percent of the population lives in cities (Leisz, 1996). Currently, it is the most densely populated country in Africa with 480 people/km^2 approximately and total area of 27,834 km^2 (UNdata, 2020). 92 percent of its 12 million people are framers depending directly on farming activity to ensure the livelihoods (Kamungi et al., 2005; Nzabakenga et al., 2013). **Figure 5** below shows the most densely populated country's provinces where the study occupies second topple position (UNOCHA, 2003).

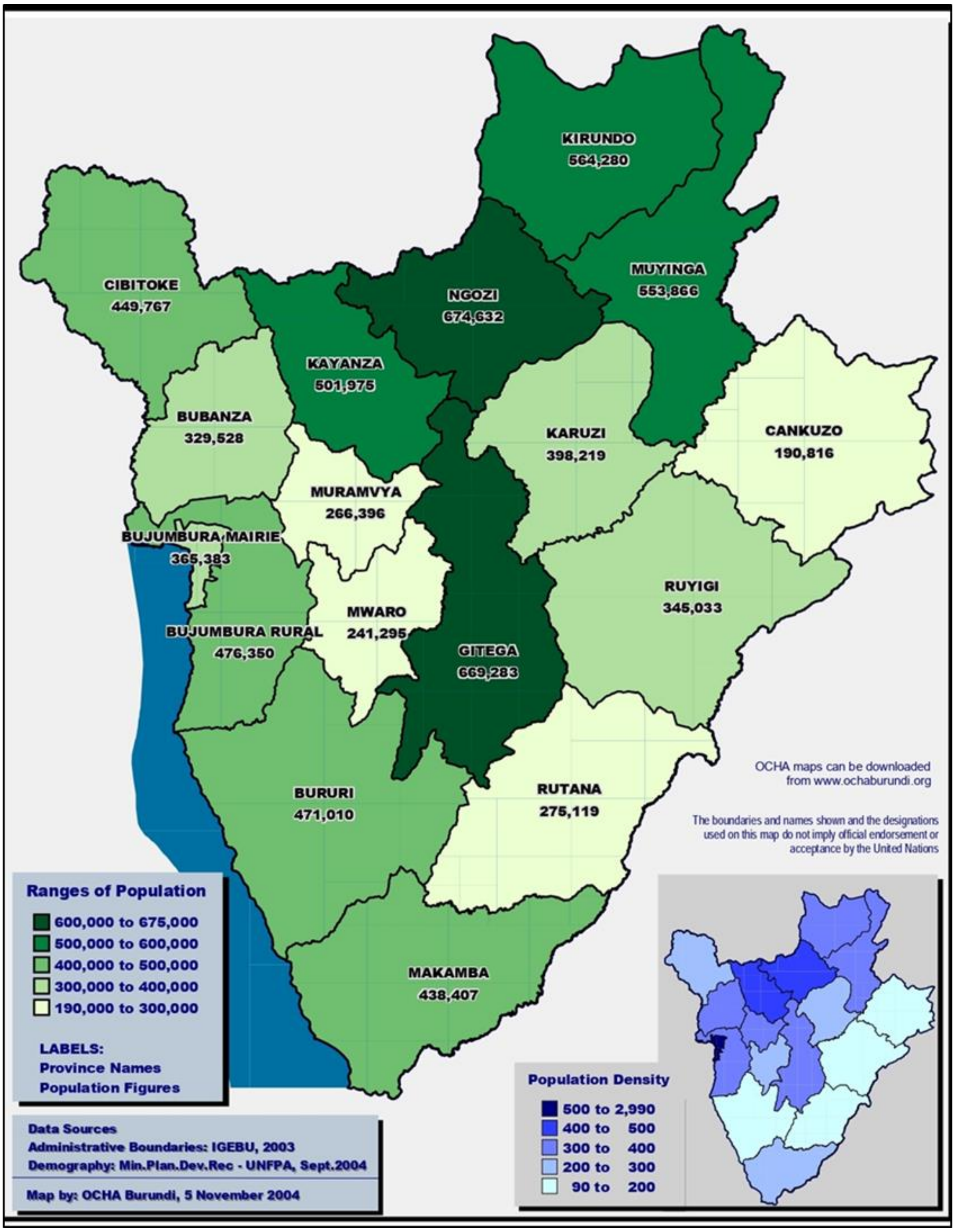

Figure 5 Map of population ranges and density per province in Burundi

Source: UNOCHA, 2003

- **Urbanization and migration**

Resulting from interaction of political, social, economic and demographic factors drives of LULC change in Burundi, the migration especially internal migration is longstanding phenomena. This migration type involves movements across provinces, or subdistrict within same country.

- **Internal migration**

Internal migration in Burundi has been mostly influenced by poverty, economic condition, political instability and civil war (State, Affairs, & Relations, 2000). Internal migration is characterized by temporary circular migration or permanent migration to the cities (Guichaoua, 1982). Circular migration entails moving to places of work or education whereas permanent residence remains in a rural or peri-urban setting (Kok & Collinson, 2006). The illustration in **Figure 6** shows the origin, direction, destination within internal migration system of top seven country regions

The following pillars make up the structure of urban areas or cities: economic development nodes, such as business and industrial sites; housing developments, such as residential and private developments; public transportation networks; infrastructure networks, such as water and sanitation. In case of the study area, the peace agreement issued in Arusha, 2002 between the parts in conflict brought back the peace and security to the country. In 2007, the democratic government of Burundi started the process to return Gitega its former status of the political capital city. Few months later, just after this official announcement, some changes in landscape of Gitega were observed, mostly the man-made features like cultivation, buildings, scattering roads and other infrastructures characterizing new construction appeared in Landscape.

In January 2019, some governmental institutions, ministries, agencies, and organizations were shifted into Gitega capital city. There is increasing demand of the land tenure in the already congested area. Citizens from across the country provinces hope to find the above-mentioned facilities have immigrated into Gitega District. This may have added land use and land cover changes.

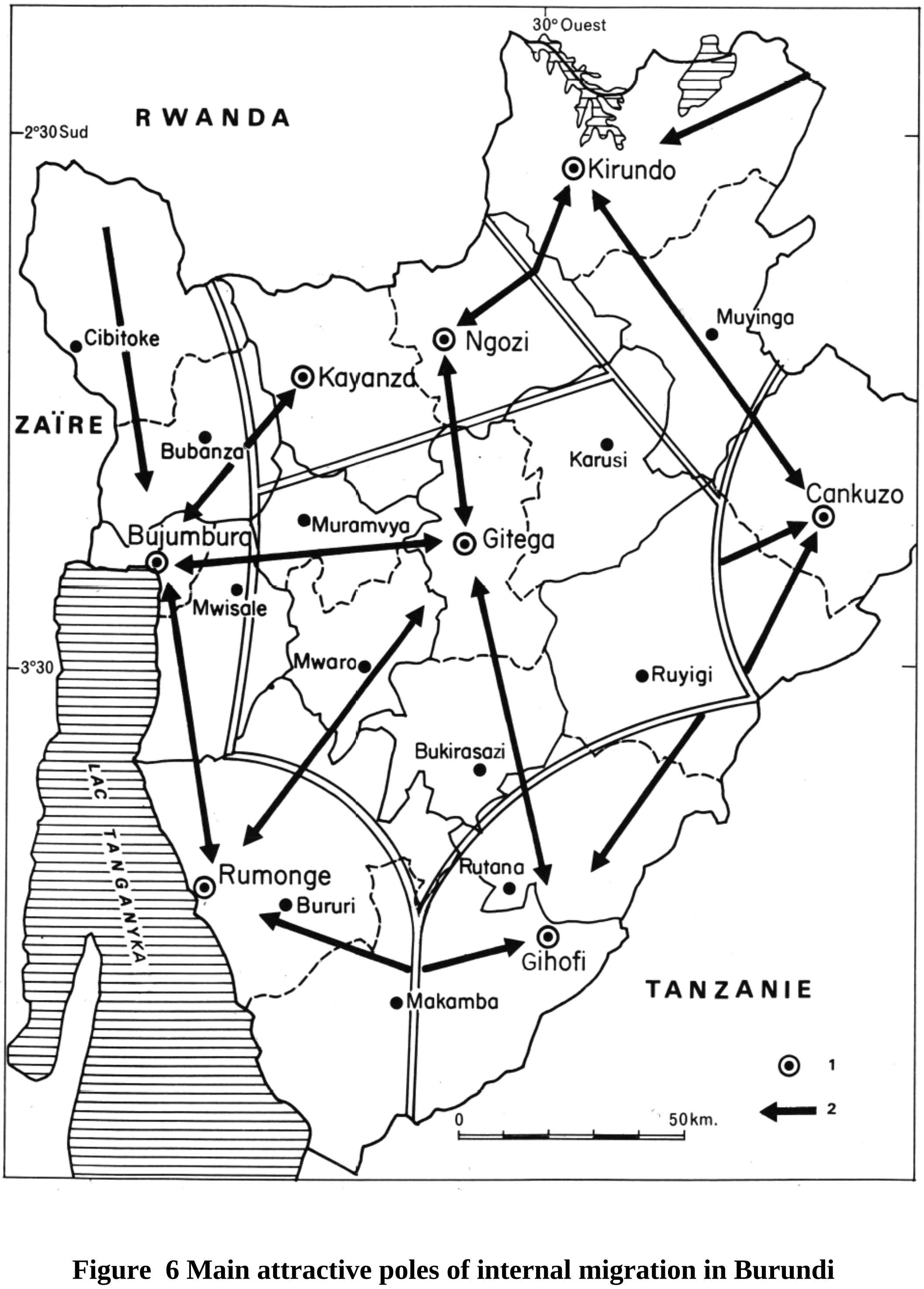

Figure 6 Main attractive poles of internal migration in Burundi

Source: Guichaoua, 1982

2.1.4.3 Economic and tecnhologic factors

According to land functional approach by Duhamel (1998), Land use refers to the description of land in terms of its socio-economic purposes(Duhamel, 1998). Thus, Taxes, investments, access to capital, markets, production and transportation costs, technology, and subsidies are all examples of economic factors (Barbier, 1997). These economic factors motivate land managers. Furthermore, they are motivated by the profitability and feasibility of a specific land use. Economic, institutional, and technological factors all play a significant role in land use change. Giving farmers access to capital, markets, and agricultural technology, for example, can encourage agricultural expansion and land conversion.

However, Burundi was a hierarchical society with a monarchy as its government prior to colonization, characterized by a description of the traditional system of government and land tenure in the twentieth century which introduced anachronisms that have now become enshrined as reality. This is among many other factors of complication system of the land and its mismanagement. First and foremost, under the customary land tenure system all land was considered to belong to the MWAMI (king) of Burundi. However, the MWAMI was not the all-powerful ruler that Germans and Belgians imagined him to be. Certain lands, those belonging to him personally, were available for the MWAMI to assign or lend as he pleased, but neither in practice nor in theory did he or his delegates have broad allocation authority over his subjects or their land.

Same as during the colonial era, Burundi remained a country of smallholder agricultural producers, with almost no land appropriated for European agriculture or industry. Aside from the changes made to the theoretical foundation of the land tenure system (as described above), there were few changes made to land tenure practices. The reason why the land use system in Burundi has been slightly influenced by technological development as well as industrial megalopolis expansions. With a few exceptions (such as urban areas, church mission lands, and minor agricultural and mining concessions), land holdings remained unregistered and held under the same tenure as previously.

However, the state lacks the resources to carry this out, and there has been no education of the population, including government officials, about official, national land use laws. Access to trees and tree products was also governed by rules in community-based tenure systems. These rules distinguished between those who had control and access rights to land and those who had the same types of rights to the trees on the land. For example, in the past, a person who planted the tree retained primary rights, determining who could harvest the tree's fruit and cut it down, even if he no longer owned the land on which the tree was planted. With the recent changes made in land tenure codes, there is some debate about whether the distinction between rights to trees and rights to land still holds. From this may be raised conflictual confrontations among individuals. However, the state may lack the resources to carry this out, and education of the population, and even of the government functionaries, regarding official, national, land tenure laws could not take place. In many places, administrators at the commune level look to community-based rules when regulating land tenure disputes rather than to the national law, and few in the rural population have registered their land with government officials.

From 1980s, new farming techniques (such as intercropping, relay cropping, and double cropping) and altered the crops grown in its fields) were introduced so as to increase agricultural production for feeding increasing population. As a result, there is increase reliance on manual labor (resulting in poor farming practices) and an increase in land degradation, soil losses and soil depletion and other impacts on natural resources.

- **Land market and demand**

Land markets are mechanisms through which land and housing rights, either separately or jointly, are voluntarily traded through transactions such as sales and leases. These transactions may occur on the formal land market or via informal channels such as informal land developers (Palmer, Fricska, Wehrmann, & Augustinus, 2009). There is fierce competition for land between the private and public sectors, with the private sector aiming to make as much profit from the land as possible while being unwilling to participate in the delivery of affordable housing projects. As a result, if the private sector gains access to land, it will mostly be used for office parks, shopping malls, and high-income families.

The rich and wealth influence generally the LULC changes: there is evidence that land is being bought and sold in Burundi, not just in titled areas but also in indigenous tenure systems. In some densely populated areas, purchasing land is one of the few ways for a new farmer to gain access to enough land to support himself and his family. However, it appears that less than 50 percent of rural farm land is obtained by purchasing it. It appears to be no difference whether the seller has registered the land or has control over it under community-based land tenure rules.

2.1.4.4 Cultural factors

In addition to demographic, technological, environmental, political and economic factors, land use change is influenced by a variety of cultural factors, Cultural factors include land managers' beliefs, attitudes, values, and perceptions, which influence land use decisions (E. F. Lambin & Geist, 2008).

Burundi since history, land is owned by an individual rather than a family linage. In past decades, a man obtained land rights by clearing, planting, and continuing to work the land, or by inheritance or purchase of land. Previously, by clearing and settling on land, an individual placed himself under the authority of the chief whose district the land was located (Leisz, 1996). In exchange for the chief's patronage and protection, as well as an acknowledgement of the chief's authority this man would be obligated to supply some of his produce and labor to the chief. As a result, the chief distributed unallocated land to individuals in need of land.

Under community-based land occupancy systems, land is held by individual heads of households and passed, for the most part, from father to son. From the past until today, land is inherited through the patrilineal line, from father to sons, either when the sons marry or when the father dies. However, women do not inherit land; instead, they have access to it through their husband, father, or another male relative. The nuclear family, rather than the extended family, is at the heart of land holding and inheritance rules, just as the nuclear family is the unit of production. In addition to fields, wealthy individual may also have rights to pasture and forest land, which are not under intensive cultivation. Despite being privately owned, access to such land has been usually shared with neighbors and relatives. In a certain way, neighbors' cattle may be allowed to graze on pasture (or fallow) land, and neighbors may be allowed to enter wooded areas to collect dead wood for firewood. Notice such permission does not include collecting fruit from or cutting live trees. Not everyone owns forest and pasture land, and granting others rights to one's land is both a way to alleviate the unequal distribution of land and an expression of the unequal wealth (and status) in Burundi.

These issues are related to the country's small land area, high deforestation rates, and growing population. All of this has put undue strain on the land, forcing farmers to reduce or eliminate fallow periods in order to produce enough food for their families. These same pressures are noted as the cause for a high deforestation, increasing land degradation, and destruction of rare flora and fauna found within the country. Thus, a complex relationship in which the cultural, legislative, and socioeconomic factors that contribute to land use change especially the deforestation need to be considered (Carr, Barbieri, Pan, & Iranavi, 2006). For instance, rural poor households, for example, lack the money and resources to invest in more productive farming methods and are unable to obtain land tenure and/or credit.

2.1.5 Proximate causes of LULC change in Gitega

Described from the perspective of the farmer, a community-based tenure appears to operate (and has operated) reasonably simply in Burundi. As also showed by FAO statistics, approximately 91 percent (25,700 km^2) of Burundi's total area (27,800 km^2) is used for agricultural production, including pasture land (JICA, 2014; Leisz, 1996). Land use land cover (LULC) in Gitega District is a complex pattern of Agricultural activities to meet the valuable needs of the populations. Besides this most important land function, the urban area characterized by open spaces, communication, and transportation features (roads and electrical lines) is also important.

Due to mild climate, two harvests a year comprise of maize, rice, wheat, potatoes soybeans etc, (which can be replanted after each harvest) and permanent crops which are not replanted after harvest like coffee, citrus and rubber. The latter may also include the flowering shrubs, fruit trees and vines as well. The Shrub or grazing lands are lands used for permanent pastures and meadows for at least 5 years to grow herbaceous forage, either cultivated or growing naturally. The Trees Covers also called

Woodland is area spanning with trees higher than five meters and a canopy cover of more than 10 percent that includes windbreaks, shelterbelts and corridors of trees greater than 0,5 ha and at least by 20 m wide.

In Gitega District, the above land use types are made available by the irrigation water or the rainfall. During the summer and spring season, the major portion of land is not cultivated due to the lack of rainfall and the vegetation cover declines on escarped hills except the vegetation covering the wetlands, the valleys near and around the rivers and streams. Besides, the land use and land cover include other categories of bare soil arisen by poor practices and improper techniques applied during farming activities and engineering construction system, some example of land cover and land use types are given in **Table 1**.

Table 1 Differentiation between Land use and Land cover type in Gitega

Land Cover				
				
Non-biotic construction	Forest/Trees	Grassland/ vegetation	Cultivated/Bare land/Agricultur e	Shrubs/ Deciduous/rock s
Land Use: Purposes				
				
Earthwork for construction	Construction system	croplands/ Agriculture	fragmented land / Scarcity	Town/City Buildings

2.2 GIS and Remote Sensing application for LULC change analysis

Geographic Information System (GIS) and Remote Sensing (RS) are generally methods used for capturing, saving, and analyzing the remotely sensed data and information. They are essential tools to create database and manipulate the considerable amount of data with complex geospatial operations that could be impossible to acquire due to price and time length requirements (Vanolya, Jelokhani-Niaraki, & Toomanian, 2019). GIS and RS are both foundation of Geospatial analysis for professionals to design and plan, analyze and execute a number of projects in various disciplines such as Engineering, Constructions, Architecture, Agriculture, Land Management, Urban Planning, Transport and many more. However, GIS and RS concepts are very different, though some ambiguities can remain in many users (Curran, 1987; Wilkinson, 1996).

GIS is Conventionally defined as a set of complex tools to acquire, store and retrieve, manipulate and analyze spatial data within a set procedure to support decision-making policies, thus GIS is a decision-support system involving an integration of spatially referenced data in solving various environmental problems (Malczewski, 1999). On the other hand, RS is defined as process of detecting and monitoring the physical characteristics of an area by measuring its reflected and emitted radiation at a certain distance from stational point. Because every data consists of measurement, Remote Sensing system helps to measure numerous objects and features making the earth's surface that reflect electromagnetic energy in unique base, and relevant formed data are namely "Satellite Images"(Campbell & Wynne, 2011). Remote sensed data acquired by the spacecraft are likely to be used in forecasting captured images of the land, seas, and ground etc, in order to make an overall assessment of the global weather, the oceans, atmosphere, hence RS methods are consistent with GIS (Green et al., 1994; Mennecke & West Jr, 2001). Remote sensing technology generates spatial data that can be converted with GIS software to extract the past and current information (Al-Bakri, Duqqah, & Brewer, 2013).

Since the 1970s (when the United States launched the first satellite for specific purpose of collecting data on the Earth's surface: Earth Resources Technology Satellite, ERTS-1), RS scientific community has attempted to improve techniques for detecting land use and land cover change (Humboldt, 2016; Pasquarella, Holden, Kaufman, & Woodcock, 2016).

Essential improvements were then achieved in technical capabilities of the sensors such as spatial, spectral and temporal resolutions, the characterization and calibration of different sensors. New potentialities of satellites and image processing algorithms were also performed to authentically represent the technological revolution for observing the Earth as shown in **Figure 7**.

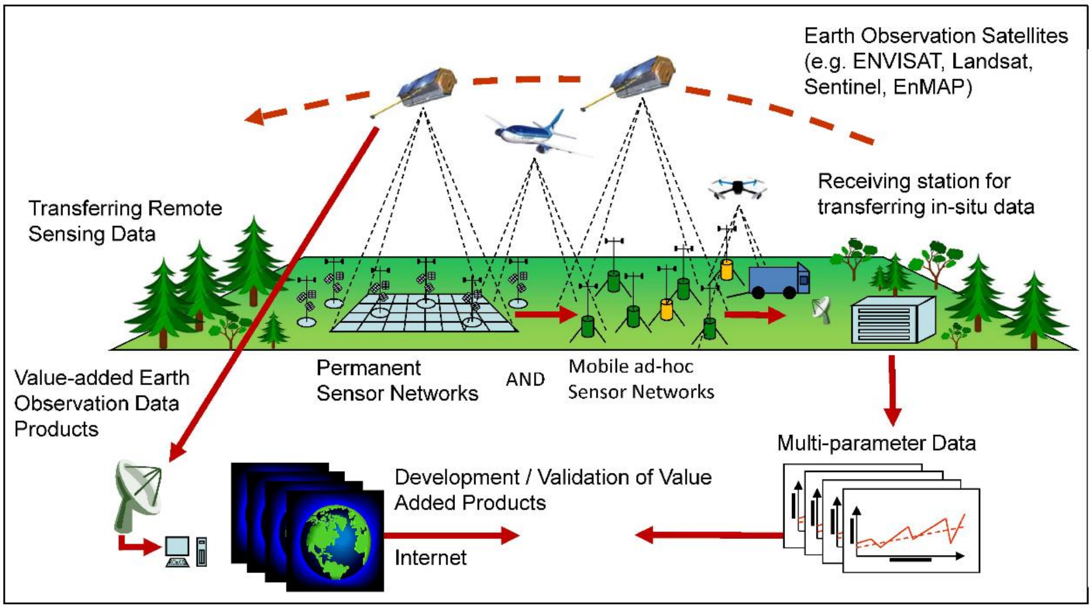

Figure 7 Linking different approaches with relative frequency monitoring, sensors, and different platforms of remote sensing acquisition and processing

Source: Lausch et al., 2018

The first and foremost aspect of remotely sensed data applications acquired from Earth-orbiting satellites is change detection due to repetitive coverage at short intervals and consistent image quality (James R Anderson, 1977; Ingram, Knapp, & Robinson, 1981; Nelson, 1983; Singh, 1986). Sequentially, Remote Sensing and GIS have broadly proved to be essential tools in assessing and analyzing land use and land cover changes (Dewan & Yamaguchi, 2009; Nijimbere et al., 2019). These approaches enable to generate a multi-temporal dataset through spatial and temporal analysis of events and phenomena and changes quantification (Islam et al., 2018).

Satellite data-based R.S has revolutionized the research of LULC change, throughout its virtual ability to provide synoptic information of land use and land cover at a particular time and location (James Richard Anderson, 1976; Patil et al., 2012), and multi-temporal information on LULC helps identify the features and areas of change in a region (Vila & Barbosa, 2010). Since the early 1980s, long-term multispectral satellite observations have been used to better understand the dynamics of terrestrial vegetation and appropriate ripostes to changes in climate and ecosystems (DeFries, 2008). RS process allows the detection of various land elements using satellite imagery, and thus now make possible to evaluate and identify land use components. For instance, very high spatial resolution images have a pixel resolution on the ground smaller than the size of a tree cover, they provide many pixels per object rather than many objects in a single pixel during Remote sensing-based classification process (Strahler, Woodcock, & Smith, 1986; Wulder, Hall, Coops, & Franklin, 2004). This property leads to easily identify almost all key land use elements as shown in (**Figure 8**).

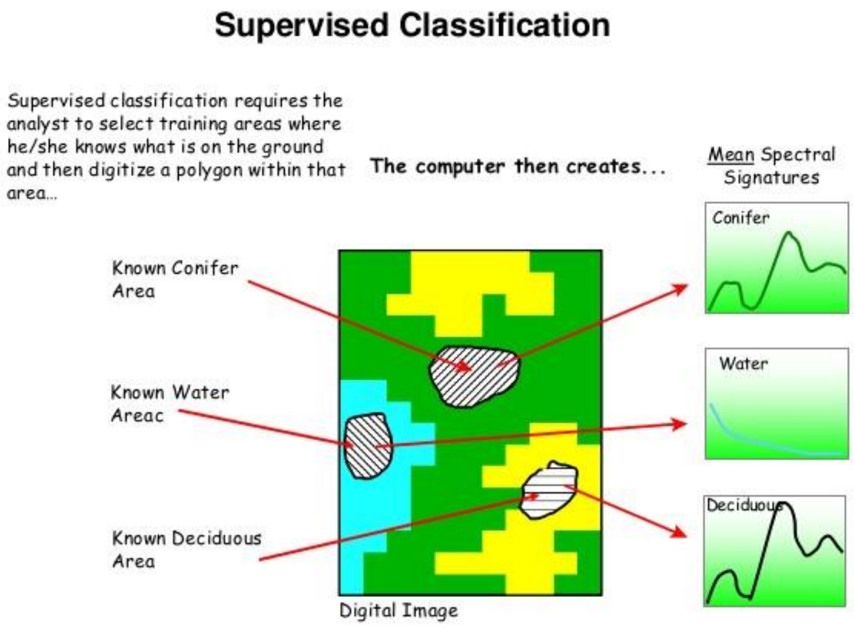

Figure 8 Key land elements mapping by using supervised

Source: Vandana, 2014

A careful analysis of pixel combinations allows the analysis of the spatial combination of key land features, which will be the first step towards the identification of land use/land cover classes by RS (**Figure 9**).

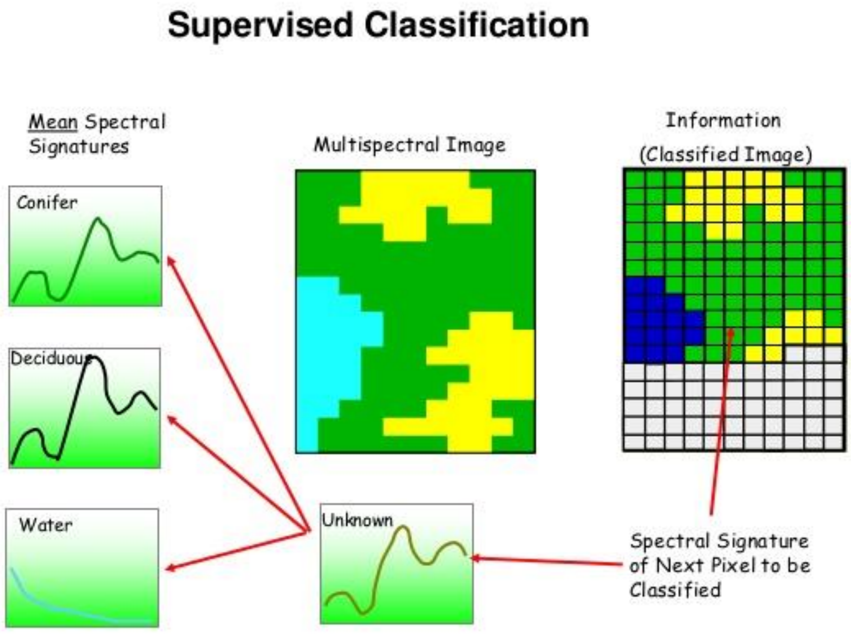

Figure 9 Influence of spatial resolution on the number and categories of land elements using maximum likelihood classification algorithm.

Source: Vandana, 2014

GIS provides a database by integrating and analyzing remote sensing data to produce maps (Mishra et al., 2014; Shen, 2019). It can also integrate past and current LULC maps for comparison and change detection over time (Surabuddin Mondal et al., 2013). These Compound approaches, namely Geoinformatics allow to assign spatial connotations to land use land cover changes as well as population pressure, climate, terrain, etc. as driving forces of these changes (Eva & Lambin, 2000; Ghosh et al., 2017; Pijanowski et al., 2002).

However, despite their ability and multiple advantages, the integration of RS and GIS technologies in research and studies as well as in LULC change monitoring is still very low in some countries (especially developing countries) and various reasons were provided (Lausch et al., 2018): (i) First of all, complex and large RS data often pose high technical and personal requirements for data management, storage, processing, analysis, and the derivation of different LULC categories. (ii) Secondly, the processing and analysis of RS data requires highly skilled RS training, extensive expertise, and the access to RS software and RS data with high spatial and spectral resolution: the land use recognition through RS can still be difficult to release since the land use is determined not only by the land cover elements, but also by the social and economic properties of the land. A group of trees, for example, may be categorized as woodland, cropland, or settlement depending on their human use (Lausch et al., 2018). (iii) Thirdly, the methodological approaches, variables, and recording parameters of LULC change inventory differ from those of close-range, air and spaceborne RS approaches.

In order to respond to some of these above-outlined scientific challenges, GIS and RS technology were therefore chosen to be applied in this study for exemplifying the essential need to use these tools in assessing and analyzing the LULC changes whether in presence of human resources challenges.

2.3 Models for LULC change simulation and prediction

Land is used for multiple purposes and therefore, the land use and cover change assessment starts from the land use identification (Lausch et al., 2018). Inventory and monitoring of land-use/land-cover changes are indispensable aspects for further understanding of change mechanism and modelling the impact of change on the land, environment and associated ecosystems at different scales (Turner et al., 1995). Dynamic land use and land cover change processes induced by anthropogenic activities are likely to influence global climate change occurrence, either directly or indirectly (Herold, Couclelis, & Clarke, 2005; E. F. Lambin et al., 2001). Land use change models are then proven tools for analyzing such causes and impacts of land use changes. They guide through a better understanding of the dynamics of the systems to develop the hypotheses that can be empirically tested.

As per explanation given in the section 2.1.3 of this study concerning drivers of LULC change, future LULC changes are always function of numerous driving variables (E. F. Lambin et al., 2001; Zak et al., 2008). Therefore, modelling of current and future LULC changes is a very essential aspect for further improvement of land use land use management and environmental conservation at short term and long terms basis. Over the past decades, a number of land use change models have been developed by the land use research community to meet the needs of the land use planning as well as to analyze and predict impacts for the future (Veldkamp & Lambin, 2001).

Literature described different sorts of models depending on different environmental disciplines such as: landscape ecology, disaster and deforestation assessment, urban planning, statistics and geographic information science emphasized on land use change studies (Goodchild, 2003; Veldkamp & Lambin, 2001). The diversity of models is due to differences in scientific disciplines, research goals, modelling approach, theoretical perspectives and scales of application. However, some scientists like Verburg et al. (2006) argue that despite this wide range of model’s availability, there is no single model that can be superior to model land use change (Verburg, 2006).

Eventually, the selection of a model is extremely function of the research objectives, problems and expected responses, the sort of data and its availability and the area of interest. Based on these above listed criteria, the selection of models to simulate and predict the LULC change for this research was importantly made by considering the research aspect and objectives, questions and expected results, data availability, and advantaged and flexible model for data processing to successfully achieve the objectives of this research.

The knowledge acquired from literature review of related studies has led us to find out that the majority of land use based-models are referred to cellular models which includes several spatial modelling techniques such as cellular automata and Markov models (Parker, Manson, Janssen, Hoffmann, & Deadman, 2003). Therefore, Cellular Automata (CA), Markov Chain (MC) and Land Change Modeler (LCM) were highly selected to be used in this study. The details and descriptions of these models are discussed in the sections below.

2.3.1 Cellular Automata model

In the 1940's, John Louis Von Neumann and Stanslaw Marcin Ulam pioneered the concept of "Cellular Automata" in the field of computer science. However, the purposes for which these concepts were applied were not the same. Von Neumann hoped to model biological self-production and theoretical machines (known as Kinematonns) that coexisted in his studies of livings (Kumar, 2003; Von Neumann, 1948), whereas Marcin Ulam devised the concept of "Cell Spaces" (a description of the physical structure of a Cellular Automaton, such as a grid of cells that can be either "on" or "off" (Maerivoet & De Moor, 2005).

For successful advancement, these two C-A pioneers began to collaborate and, as a result, overcame challenges in their careers. It is possible to say that "Cellular" is a Von Neumann term, and "Automaton" is a Marcin Ulam term (Torrens, 2000). Some years later, John Horton Conway followed them and attempted to apply the concept of Cellular Automata in the field of artificial life (Robot) called "Game of Life" in the 1970s. This type of "simulation Game" based on the cellular automata concept had become the most popular application of C-A models, which were discovered to be interesting and effective simulation tools (Gardner, 1970).

However, Stephen Wolfram's work in 1980 that related cellular Automata to all disciplines of science such as Biology, Sociology, Physics, Mathematics, and so on, resulted in the widespread popularization of C-A models. Based on empirical experiment, this scientist provided a comprehensive classification of C-A models as mathematical models for self-organizing statistical systems. (Gardner, 1970; Wolfram, 2002).

Aside from the disciplines listed above, the CA approach has been widely applied to a variety of other disciplines such as Natural Sciences, Geography (GIS), Environment, and Urban Planning. C-A and GIS models are combined to calibrate Cellular Automata in the real world for in-depth analysis and problem solving in social, economic, and environmental domains. As a result of its simplicity, flexibility, and suitability to incorporate both spatial and temporal dimensions of the process, this type of technology has been most preferred and used by numerous researchers in Land use change analysis and urban growth modelling (Kumar, 2003; Santé, García, Miranda, & Crecente, 2010; Torrens, 2000).

Based on the availability of social and economic data, decision-makers gain a better understanding of the reasons and influences of why and how land use and land cover type are changing, i.e. cities grasp their neighborhoods very quickly and manage accordingly, i.e. building an early warning system potentially resulting in land use and land cover changes (Weng, 2002).

2.3.1.1 Comprised elements of Cellular Automata

Torrens (2000) identified five elementary Cellular Automaton components, which are briefly described below:

a) The space represented by an array of cells, on which an automaton exists (lattice)

The cell space (lattice) is a discrete cell component. The lattice in an elementary C-A is one-dimensional (**Figure 10**). This is a linear spring made up of C-A elementary cells. The lattices, on the other hand, can be n-dimensional. C-A can have any dimensions and be of infinite proportions. (Torrens, 2000). In most cases, the lattices can be defined in any geometric shape, often as a regular grid: squares, rectangles, circular arrangements (hexagons), and torus (ring-shaped surface) for either one or two dimensional CA (**Figure 11**) (Andrews & Dobrin, 2005; Torrens, 2000).

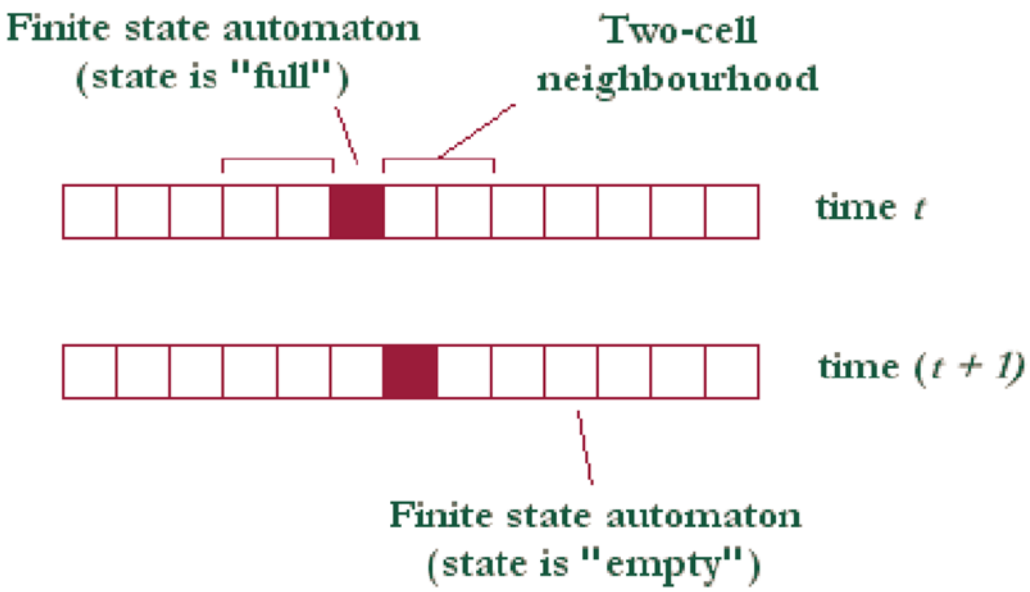

Figure 10 One-dimension Cellular Automata

Source : Andrews & Dobrin, 2005

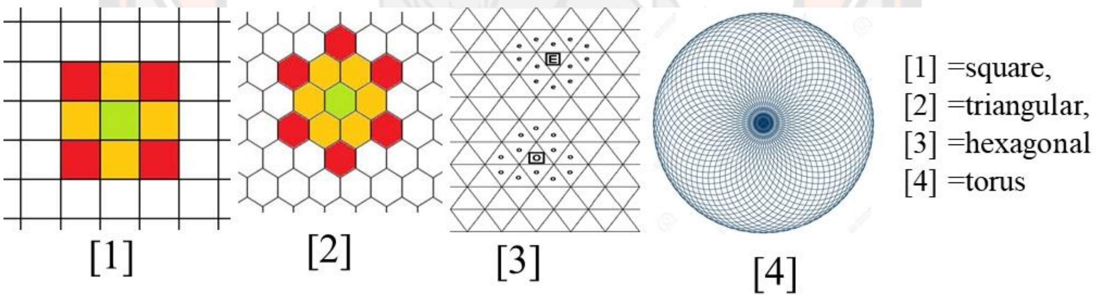

Figure 11 Two-dimensional Cellular Automata Grid

Source: Maerivoet & De Moor, 2005

CA is similar to raster GIS data because the CA uses regular grids to represent space cells (Kumar, 2003).

b) The cells in which the automaton exists than contains its state (s);

In this case, each cell in the C-A lattice can exist in a variety of states, which define the cell's occupancy. It is important to note that a cell is not limited to the integer domain; a cell can be empty or contain specific building blocks and attributes (i.e. molecule, particle, land use, organism, etc,).

A cell can be binary, with a constant of symbols representing zero, or it can have a continuous range of values (Von Neumann, 1948). Kumar (2003) recently introduced the concept of variegated cells, in which each edge can have its own independent rules for interacting with one another (Kumar, 2003) as exemplified in the below (**Figure 12**):

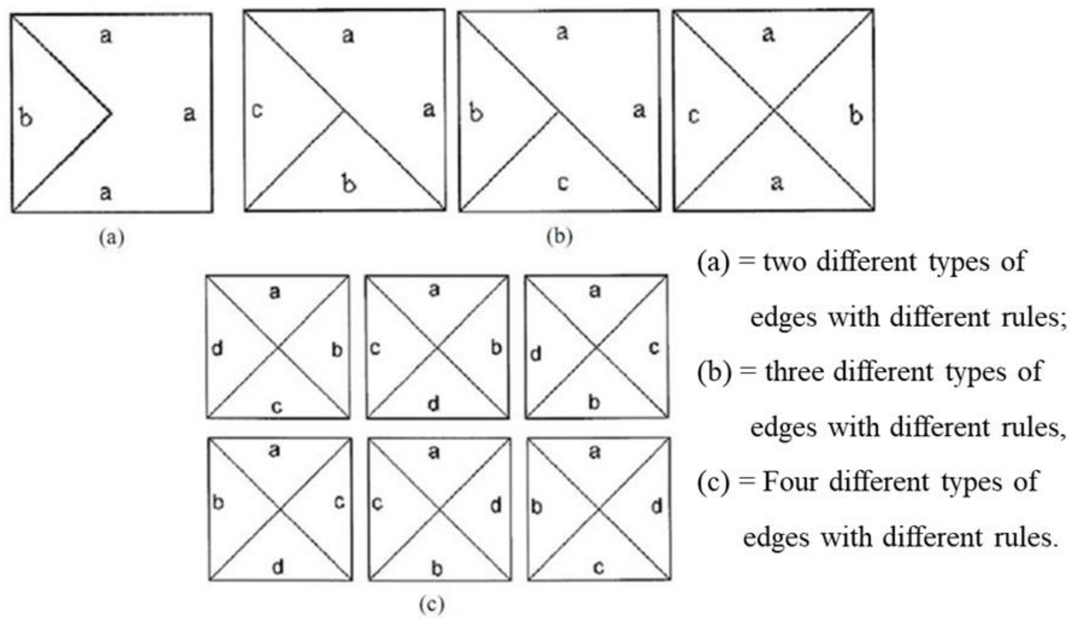

Figure 12 Example of variegated cells

Source: Kumar, 2003

c) The neighbourhood around the automaton;

Certain rules govern the movements and actions of cell ingredients on the lattice. Dynamic evolutions in a three-dimensional C-A lattice are determined by the nature of cells near the ingredient. This rule of cell proximity is referred to as the "neighbourhood condition."(Kumar, 2003). As shown in **Figures (10) and (11**), each cell in a one-dimensional C-A grid has neighbouring cells, whereas in a two-dimensional C-A grid, there are two ways to determine these neighbouring cells (Kier, Seybold, & Cheng, 2005; Kumar, 2003; Torrens, 2000): Von Neumann defined the first possibility of four neighbouring cells. This is the most common "Von Neumann neighbourhood" in the 2D C-A grid, and it includes four adjacent cells (W=west, E=east, N=north, and S=south), as well as the cell "C" itself. Moore introduced the second possibility of having eight neighbouring cells. This "Moore neighbourhood" is the most common example in the 2D C-A grid, and it adds four additional neighbouring cells to the five cells defined in Von Neumann's neighbourhood, as well as NE=north-east, NW=north-west, SE=south-east, and SW=south-west. Another useful neighbourhood is the extended Von Neumann neighbourhood, in which the four C cells are just beyond the four B cells" (Kier et al., 2005). All examples of these cell neighbourhoods are shown in (**Figure 13**)

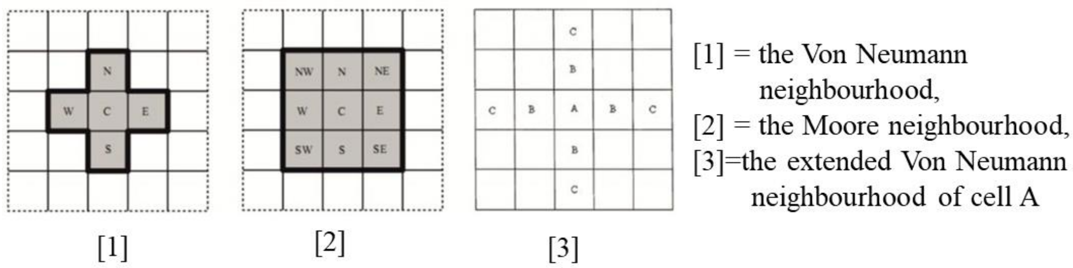

Figure 13 Two-dimensional CA neighborhoods

Source: Kier et al., 2005

d) Transition rules that describe the behavior of Cellular Automaton

The behaviors of ingredients on the grid are governed by a variety of rules. A transition rule affects a cell and its surroundings, causing the cell's stage to change from one discrete-time to another. As a result, the same rule is applied to all cell ingredients in parallel, resulting in subsequent dynamic evolutions of the CA system. The transition rules influence the likelihood that a cell ingredient, i.e. land cover type, will transform to another type of ingredient during each iteration of the simulation. These transition rules that govern the changes are summarized in three scenarios (Kier et al., 2005).

Case 1: If P_T(AB) = 1.0, then the transition A →B is certain to occur.

Case 2: If P_T(AB) = 0.0, then the transition A →B will never occur.

Case 3: If P_T(AB) = 0.5, then during each iteration, there will a 50 percent chance that the transition A →B will occur.

Because there are no probabilities for different outcomes, the first two cases (Case 1 and Case 2) are referred to as "Deterministic C-A Models." The third case is classified as a Stochastic (Probabilistic) C-A Model because it allows for different outcomes, such as the ingredient remaining unchanged or transforming to a different state, the temporal space in which the Automaton exists. Because time in CA is always discrete, time progresses in iterative steps of whatever length the model designer desires. The temporal evolution of cells destroys the independence of initial cell states, and the cells are updated simultaneously according to the transition rules in each step (Kier et al., 2005; Subedi, Subedi, & Thapa, 2013).

The strengths and weakness of CA in relation to the selection criteria in section for LULC change modelling are presented in **Table 2**.

Table 2 Cellular Automata strengths and weakness for LULC change modelling

Selection Criteria	**Advantages and Disadvantages**
Relevance	✓ CA adds spatial dimension to Markov by integrating neighborhood effects using a contiguity filter.
Linkage Potential	✓CA in IDRISI takes inputs of transition areas and suitability maps which can be created by other software. ✓The results of CA, in the form of a prediction maps can be easily understood and input in GIS software for visualization.
Transferability	✓ There are no modifications required when using the software.
User openness	✓ CA models are relatively easy to use and with knowledge of GIS analysis.
Data Requirements	✓ Markov models are generally not data hungry. The data inputs required are historical land use or land cover images for two time periods.
Model Cost	✓ CA is a module also available in Idrisi Selva. A student license was obtained for $39 for the purposes of this research. A one-month free trial is. Otherwise general license for Idrisi is $ 275.

2.3.2 Markov Chain Model

Invented by a Mathematician Russian, Andrei Andreevich Markov (1858-1922) in 1906, A Markov chain is a stochastic process describing a sequence of possible events in which the probability of each event depends only on the state attained in the former event. This type of statistical model employs an integer of random variables that are dependent on the valuable parameter (e.g. a time).

Markov chain property is a countably infinite sequence, in which the chain moves state at discrete time steps, gives a discrete-time Markov chain. A discrete-time stochastic process X_d = [X_n, n = 0, 1,2,3, is a countable collection of random variables indexed by non-negative integer. Continuous-time stochastic process X_C = [X_t, $0 \leq t \leq \infty$] is an uncountable collection of random variables indexed by non-negative real numbers. In general, Markov chain is defined as a random process that has a property characterized by memoryless-ness, i.e. the transition from one state to another on state space takes place depending on the current state only and not on the past state that the process went through. It is critical to note that a random process can only be classified as a Markov chain when, in a sequence (series), every event that is about to occur depends solely on the current state and eventually forms a kind of chain. Despite the fact that, in the formal operation of the Markov chain, a number of events occur independently one after the other, this fits appreciation when the next state is reached. Thus, Markov chain process involves a measure of uncertainties (Ghosh et al., 2017).

Burnham pioneered the use of the Markov Chain model for land use modelling in the field of LULC studies. The Markov chain model depicts and predicts changes in land use and land cover from one time to the next. The current state at a given time t is determined solely by the state at time t-1 before it, and the future state is determined solely by the current state in the Markovian process (Burnham, 1973; Ghosh et al., 2017). Equation [1] explains the calculation of the prediction of LULC changes (Behera, Borate, Panda, Behera, & Roy, 2012; Sathees, Nisha, & Mathew, 2014):

$$S\,(t, t+1) = P_{ij} \times S\,(t) \tag{1}$$

In general, the Markov Chain calculates how much land use is likely to change between the most recent date and the predicted date. The transition probabilities file called transition matrix contains the outputs of this Markovian process. This transition matrix records the likelihood that each LULUC class will change to every other class. The land-use changes analysis is achieved in Markov chain modelling for two different periods of the LULC images. The procedure is carried out in three steps: The use of transition matrices, a transition area matrix, and a conditional probability image, as well as the IDRISI software package developed by Clark Labs, makes the work simple (Eastman, 2009; Mishra et al., 2014)

2.3.2.1 Transition probabilities matrix

The transition matrix is defined as the result of cross-tabulating two images and adjusting for proportional error. This transition matrix, denoted as “transition probabilities.txt,” records the likelihood that each LULC category will change to every other category. This transition probability matrix is very useful in some situations where determining the factors causing the change in land use is difficult (Turner et al., 1995).

2.3.2.2 Transition area matrix

The transition area matrix records the number of pixels that are expected to change from one land use/land cover type to another over the next time period. This matrix is created by multiplying each column in the transition probability matrix by the number of cells in the later image that correspond to the corresponding land use. The rows represent the older land cover categories, and the columns represent the newer land cover categories, in this file saved with the name “transition area.txt” as a result of software operations outputs. This transition area matrix is also used to create the suitability map (Eastman, 2009; Mishra et al., 2014).

2.3.2.3 Conditional probability area image

The Markov chain always returns a set of conditional probability images based on the transition probability matrix. As a projection from the latter of the two LULC images, these images report the likelihood that each land cover type would be found at each location in the following phase. These files are the most important key finders in the Markov process, and they can be used during the classification of remote sensing imagery and the prediction of future land use for the specified period (Eastman, 2009; Ozturk, 2015).

The summary of advantage, disadvantage and ability of Markov chain for modelling of land use change and its specific properties are presented in **Table 3**

Table 3 Markov Chain strengths and weakness for LULC change modelling

Selection Criteria	Advantages and Disadvantages	
Relevance	✓	Markov can depict the direction of LULC change hence it is very useful in analyzing future land use demands. Future projections on LULC patterns can also be calculated by using drivers such as population growth, migration and economic growth patterns.
	χ	Markov assumes that the factors that produced changes will continue in future. This can be overcome by using Markov with Land Change Modeler (LCM) to manipulate transition probability matrix by considering or incorporating other driving factors.
	χ	In Markov, land use at a certain location is only influenced by the previous state of land use and not the surrounding land uses. However, spatial dimension can be added by incorporating cellular automata models.
Linkage Potential	✓	The results from Markov analysis are presented in the form of transition maps and can be statistically quantified and easily understood by decision-makers.
	✓	Markov transition matrices can be used in models such as CA and LCM to provide a framework for analysis of future land use demands.
Transferability	✓	There are no modifications required when using the software.
User Openness	✓	Markov models are relatively easy to use and with knowledge of GIS and statistics.
	✓	Markov can simplify complex processes of land use change in the form of transition probability matrices, making it an easy sketch planning tool.
Data Requirements	✓	Markov models don't generally need complicated data. The only data input required are just historical land use or land cover images for two time- periods.
Model Cost	✓	Markov is available as a module in Idrisi Selva. A student license can be purchased for $39 for the purposes of this research, or you can get a one-month free trial. Otherwise, the general license for Idrisi is $ 275.

2.3.3 Cellular Automata and Markov Chain integration

Lambin et al. (2001) has described integrated modelling as an effective technique for predicting future scenarios on a larger scale. In this regard, CA-Markov combines the concepts of Cellular Automata and Markov Chain which are modules available IDRISI Selva 17 with other GIS Analysis tools. The first phase in CA-Markov involves the comparison of two historic land use maps in order to calculate the quantity of change for each land use category. As described d in section 2.3.1, Markov generates a transition probability matrix and conditional probability images. The next step is to simulate the location of change based on the concepts of suitability maps and contiguity filter.

Suitability maps specify the suitability of each pixel for transitioning to any land use at a specific time. These suitability maps can be generated by including some variables such as socioeconomic and demographic parameters together with conditional probability images produced by Markov and the suitability maps are then further weighted using a CA contiguity filter. Cellular Automata model is used to convert Markov into a spatially explicit model as it implements the 1st law of Geography by using a contiguity rule: where a pixel that is close to a specific LULC type is most likely to change to that category as compared to a pixel that is further far away.

The concept of nearby is determined by a spatial filter that the user specifies. CA-Markov in IDRISI Selva requires a certain number of iterations to decide the number of time-steps that will be used for simulation. CA-Markov was therefore implemented in this study due to these attractive advantages. However, this future prediction was easily made due to data availability since CA-Markov would require at least two sets of LULC maps (e.g. input 1984 and 2002 maps and 2002 and 2019 LULC maps as a validation map) for this study. However, due to some data limitations, such as lack of demographic and socioeconomic data, this study did not include drivers in the LULC Change modelling.

2.3.4 Land Change Modeler

Land Change Modeler (LCM) is an innovative land planning for supporting decision makers through land management and environment preservation. It also is an integrated tool in IDRISI Selva 17.0 oriented to model causes and impacts of land use conversion and can leads to the specific analysis of biodiversity conservation (Eastman, 2009). This software was invented by Clark Labs for assessing different land and land cover change scenarios and linked environmental impacts. During prediction process, with an automated user-friendly workflow, the model adopts the Markov Chains analysis for a spatial allocation of simulated land cover scores (Gupta & Sharma, 2020).

As an essential tool for the assessment and prediction of LULC change and due to its organized implications around the major task areas, it has been widely applied in various topics around the world: change analysis, LULC change prediction, habitat and biodiversity impact assessment and planning interventions etc., Eastman (2009) stated that there is a facility in LCM to support projects towards Reducing Emissions from Deforestation and Forest Degradation (REDD). The REDD facility uses the land change scenarios generated by LCM to evaluate future emissions scenarios.

In addition to that efficiency in detecting, analyzing and quantifying the change of land use and land cover patterns, LCM data input requirement are land cover images for two time- periods, with matching classes, legend and characteristics and identical extent projections in rows and columns marked with X and Y. With these two LULC maps between different periods as input parameters, land use change assessment is performed and three types of outputs in form of graphs are generated. The first graph indicates the gains and losses for each LULC category, the second graph represents the net changes of LULC category, calculating by adding gains and subtracting losses from the earlier LULC map. The third graph evaluates the contributions to changes experienced by LULC class due to other different LULC classes contributing to net change. Thus, this model was selected and applied in this study.

CHAPTER III

RESEARCH METHODOLOGY

3.1 Study area description

3.1.1 Geolocation and population

Gitega is the second largest city and Political Capital of Burundi and the seat of the Gitega Province. It is located on the Central Burundian Plateau at an elevation of 1,705 m above sea level (asl), about 100 kilometers east of Bujumbura, the economic capital city. Geographically, Gitega District is located in the center of Burundi at a specific grid reference of "03° 25' 35" South Latitude and 29° 50' 37" East Longitude (**Figure 14**). It lies on the northwestern shoulder of the Birohe-Rugari-Songa Mountain range (1,700–2,000 m asl), which is separated from the Cene Mountains (2,000 m asl) by the Mutwenzi River. It covers a total area of 315 km^2, and according to the 2008 census, the District of Gitega has a population of 150,001 people with a density of 476 inhabitants/km^2 (Niyuhire, 2018). In Gitega region, agriculture is the main activity, with livestock breeding (goats and sheep), grazing, and small-scale agriculture producing banana, peanut, sweet potato, manioc, bean, corn, and coffee.

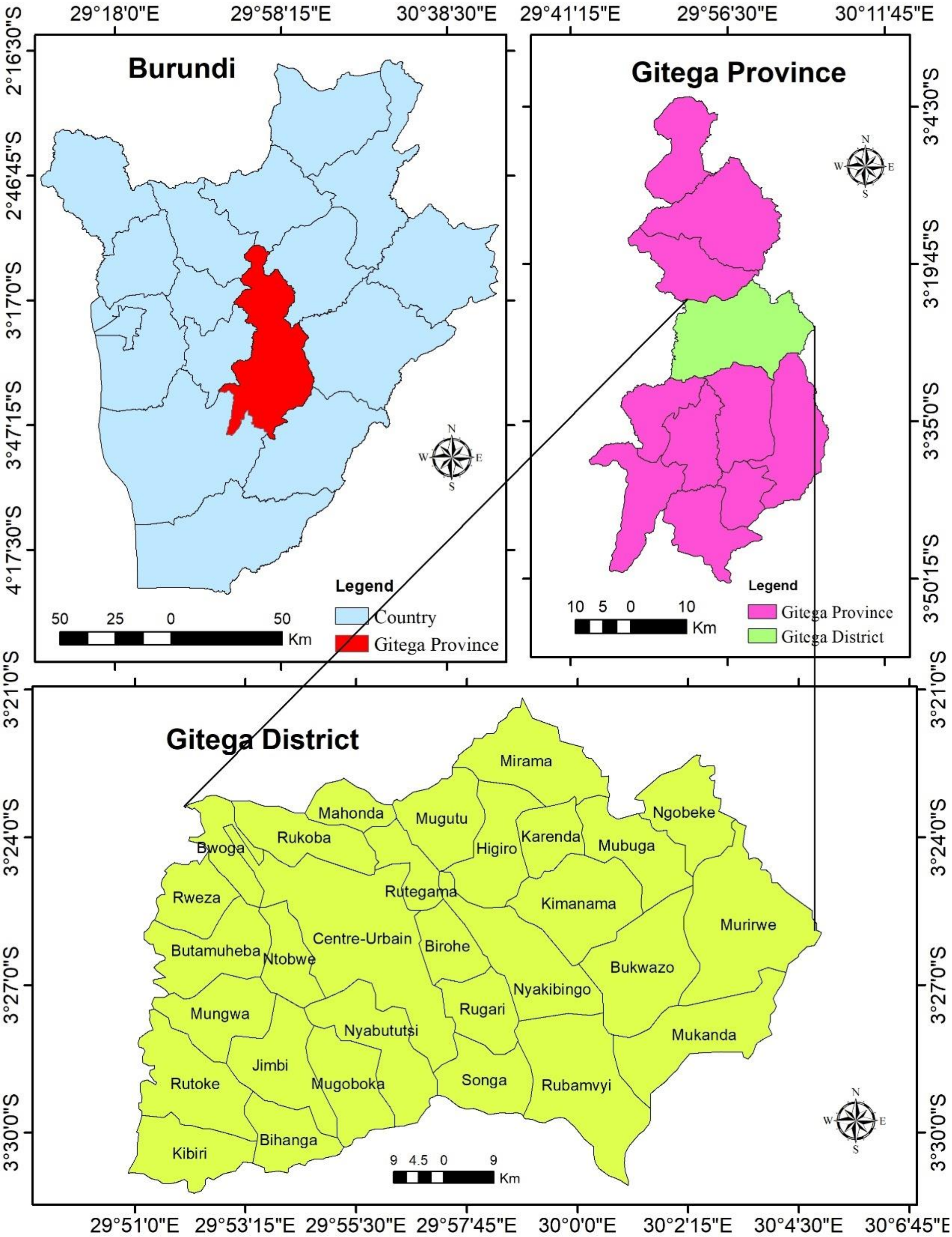

Figure 14 Location map of the study area

3.1.2 Physical and climatic condition

In Burundi, subsurface weathering and aquifer evolution are characterized by (1) faults associated with ancient (post-)Mesoproterozoic tectonics and ongoing rifting associated with the East African graben system, and (2) the development of horizontal fractures and fissures in the aftermath of initial weathering during exhumation (3) Mesozoic-Cenozoic denudation and planation surfaces, as well as the formation of respective deep weathering profiles, and (4) the shaping of Holocene topography, with a particular emphasis on linear erosion features and anthropogenic stripping of soil and saprolite.

Thus, Gitega has a landscape dominated by plateau dispersed by hills, valleys and moderate plains rising between 1,600 – 2,000 m. According to the Gitega sheet of the "Geological map of Burundi," the lithology of the Central Burundian Plateau, where Gitega is located, consists primarily of low to intermediate metamorphic pelitic to psammitic metasediments and extensive areas of intrusive rocks. Climate is subtropical highland and tropical savanna climate depicted by summer and winter (Vassolo et al., 2019). The data from the "Institut Géographique du Burundi," (IGEBU) recorded at Gitega airport station shows that the region has a moderate climate with maximum annual temperatures ranging from 24.1 to 27.7 °C and minimum values ranging from 11.9 to 14.8 °C (Vassolo et al., 2019). Whereas, the mean annual precipitation at the Gitega airport station is generally 1,178 mm, with a distinct dry period from May to October and minimum rainfalls in June and July. The springs used for Gitega's water supply emerge at points where the gently sloping hills meet the gentle slopes of the valleys. The tectono-metamorphic complexes Kiryama and Vyanda are the dominant lithostratigraphic units.

This Central Burundian Plateau is the relic of an ancient planation surface, most likely the late Tertiary Kagera surface (Rossi 1980), with distinctive demi-orange relief. Denudation and peneplanation cycles have resulted in staged surfaces and, locally, topographic inversion reinforced by lateritic ferricretes. These are common and can be seen as mesa-like hilltops or as distinct scarps on the steeper lower slopes, where they often formed within saprolitic schist. The ferricretes, which are frequently more than 6 m thick and occur as both pisolithic layers and continuous vermiform ironstones, have a high potential to influence the infiltration and runoff regime. Field observations indicate that ferricretes are rather absorptive (Vassolo et al., 2019).

3.2 Data source and collection

3.2.1 Landsat data overview

Landsat program had been evolving since 1970'S when was launched the first Landsat before known as "Earth's resources Technology Satellite (ERTS)" assigned to acquire data about Earth 'structures (Pasquarella et al., 2016). Over the past four decades, continuous Landsat evolution program has been launching various Landsat named chronologically until the most recent version (Landsat 8) launched in 2013 (Humboldt, 2016). As matter of fact, some generation failed their missions, thus the most of remote sensing-based studies have famously used online data amounted on Landsat 5 TM (Thematic Mapper), Landsat 7 ETM+ (Enhanced Thematic Mapper Plus) and Landsat 8 OLI (Operation Land Imager) (Woodcock et al., 2008).

Table 4 List of Landsat generations

Satellite	Launch	Decommissioned	Sensors
Landsat 1	July 23,1972	January 6,1978	MSS/RBV
Landsat 2	January 22,1975	July 27, 1983	MSS/RBV
Landsat 3	March 5, 1978	September 7, 1983	MSS/RBV
Landsat 4	July 16, 1982	June 15, 2001	MSS/TM
Landsat 5	March 1, 1984	2013	MSS/TM
Landsat 6	October 5, 1993	Did not achieve orbit	ETM
Landsat 7	April 15, 1999	Operational	ETM+
Landsat 8	February 11, 2013	Operational	OLI/TIRS

Source: Humboldt, 2016

Landsat imagery collected on Landsat 5 TM and Landsat 7 ETM+ comprises 7 bands identified based on their information coverage and resolution (3 visible bands, 2 Near-Infrared, bands, 1 Thermal band, and 1 Middle-Infrared band).

Table 5 Spectral bands detail on Landsat 5 TM and Landsat 7 ETM+

Band No.	Name	Wavelength (µm)	Spatial resolution (m)
Band 1	Blue	0.45 - 0.52	30
Band 2	Green	0.52 - 0.60	30
Band 3	Red	0.63 - 0.69	30
Band 4	NIR	0.76 - 0.90	30
Band 5	SWIR	1.55 - 1.75	30
Band 6	TIR	10.4 - 12.50	30
Band 7	MIR	2.08 - 2.34	30

Source: Humboldt, 2016

Whilst, Landsat 8 carries two sensors, the Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS). Landsat 8 has 16-bit radiometric resolution and also has more than 7 bands (greater spectral resolution) compared to earlier Landsat version (Humboldt, 2016)

Table 6 Spectral bands detail on Landsat 8 OLI/TIRS

Band No.	Name	Wavelength (µm)	Spatial resolution (m)
Band 1	Coastal	0.43 – 0.45	30
Band 2	Blue	0.45 – 0.51	30
Band 3	Green	0.53 – 0.59	30
Band 4	Red	0.64 – 0.67	30
Band 5	NIR	0.85 – 0.88	30
Band 6	SWIR 1	1.57 – 1.65	30
Band 7	SWIR 2	2.11 – 2.29	30
Band 8	PAN	0.50 – 0.68	15
Band 9	Cirrus	1.36 – 1.38	30
Band 10	TIRS 1	10.6 – 11.19	100
Band 11	TIRS 2	11.5 – 12.51	100

Source: Humboldt, 2016

3.2.3 Ancillary data

This section of the research elaborates ancillary data collecting from different institutions and organizations.

3.2.3.1 Previous land cover maps

The ancient land use and land cover data of Burundi are contained in the Atlas of Burundi prepared by Association pour l'Atlas du Burundi which had produced various sheets covering different regions for various fields such as physical environment, history of the country until 1962, Population and economic information: agriculture, livestock, fishing, industry, transport, energy, mining (Burundi., 1979). The toposheet 29 of Burundian Atlas covering Gitega shown in **Figure 15** is used as reference data for preliminarily identifying the possible LULC classes in this study.

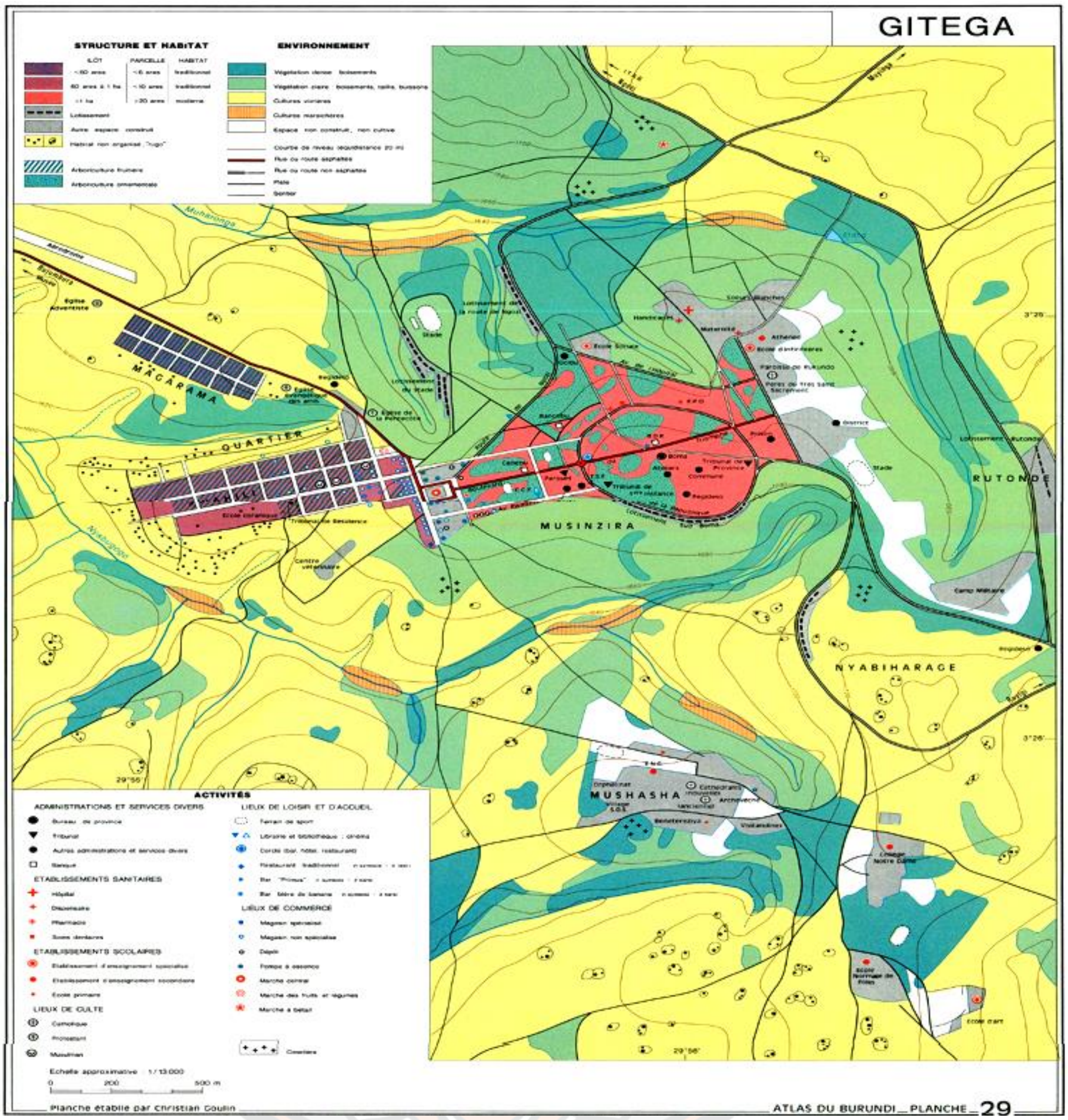

Figure 15 Ancient land use of Gitega

Source: Burundi., 1979

Furthermore, apart from that longstanding land use data containing specific information Gitega, it is also needed to look for the newest updated land use and land cover data in Burundi, Thus Land use and cover map of Burundi produced in the year 2016 and which is available online (RCMRD, 2016) and it was reclassified in order to be used as reference during image classification in this study (**Figure 16**). It was also used for easy analysis and classification accuracy assessment during.

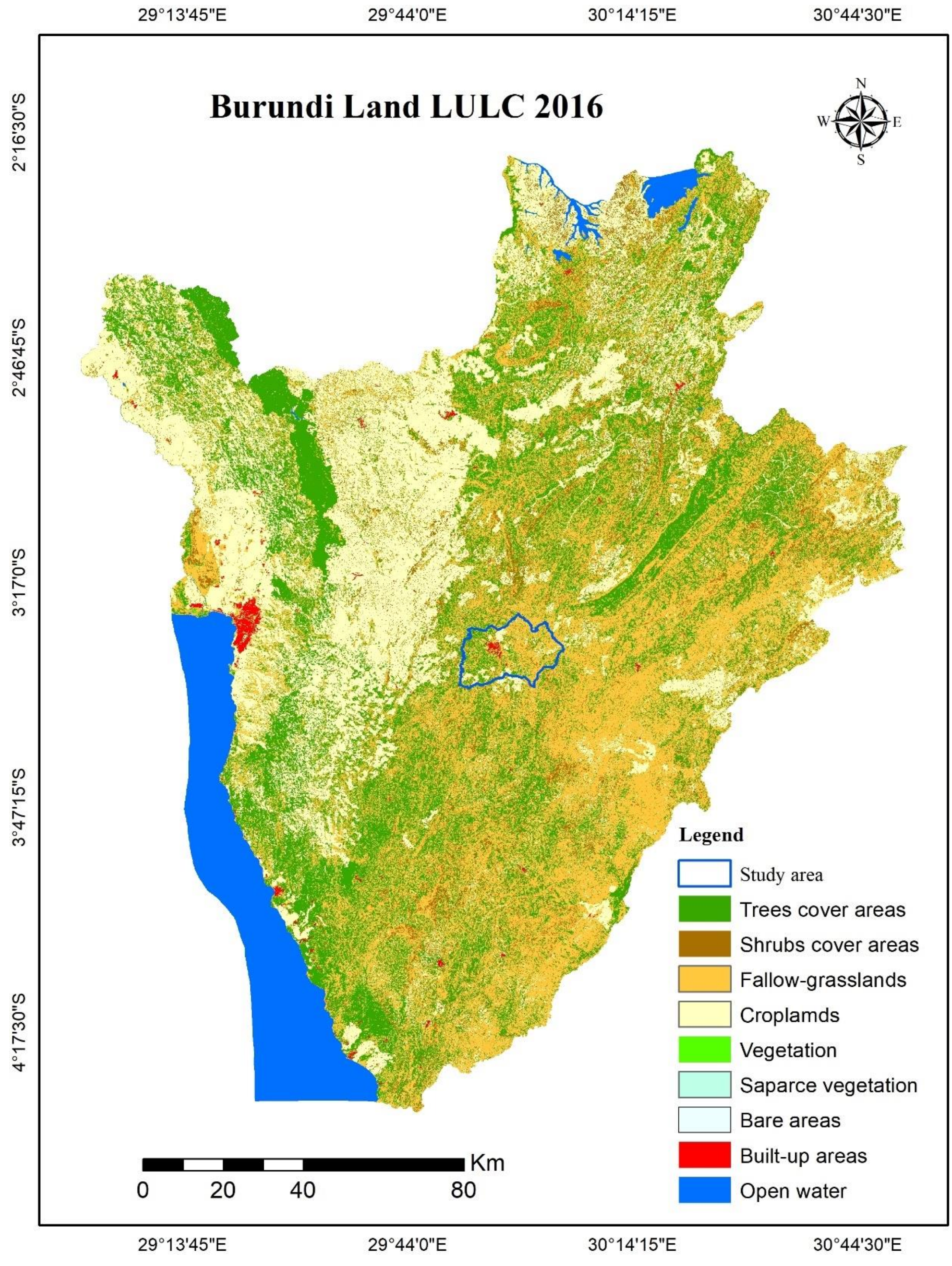

Figure 16 Burundi Land cover map for year 2016

Source: Updated from RCMRD, 2016

3.2.2 Satellite data

Landsat Images with 30 m resolution were downloaded from the United States Geological Survey (USGS) resource repository (http://earthexpolorer.usgs.gov/). These images with a little bit different anniversary date were selected for good quality (cloud cover less than 10percent), because some satellite data with same anniversary date were unfortunately covered with too much clouds. The first image was acquired on 20 June 1984 by Thematic Mapper (TM) sensor onboard on Landsat 5. The second image was taken by the Enhanced Thematic Mapper Plus (ETM+) mounted on Landsat 7 on 17 August 2002, and the third image was acquired using Operation Land Imager (OLI) onboard Landsat 8 on 23 July 2019.

These three dates: 1984, 2002 and 2019 were chosen according to our research purpose of displaying a longstanding LULC change analysis over time. The meaningful use of such three dates was to have at least two periods during which we can detect the change of LULC and also to proceed on the comparison of the state of each LULC class in the first and second period. Hence, the first period ranges from 1984 to 2022: 18 years period. The second period ranges from 2002 to 2019: 17 years. This difference of 1 year in terms of interval between the first and second dates was made by an ambition of having an image of good quality, suitable for visual analysis to extract all necessary information. Again, two images acquired on two different date are also mandatory for running CA-Markov model in order to simulate and predict the future scenario.

Furthermore, the selected bands for LULC classification included visible (Red, Green and Blue) and infrared (one near Infrared band) for Landsat 8. All these images were taken on satellite track path/row:173/062 and projected in Universal Transverse Mercator (UTM) with WGS-84 datum 36 N. The **Table 7** shows the paths and rows and different acquisition dates of the Landsat imagery used for this research study.

Table 7 Description of Landsat data collected during summer

Satellite Sensor	Path/Row	Acquisition Date	Bands	Resolution
Landsat 5 TM	172/062	20 June 1984	2, 3, 4	30 m
Landsat 7 ETM	172/062	17 August 2002	2, 3, 4	30 m
Landsat 8 OLI	172/062	23 July 2019	3, 4, 5	30 m

3.3 Research methodology framework

In order to successfully achieve the overall objectives and results assigned to this study, the aforementioned data are processed, analyzed and examined through the following main phases:

i) Data Processing

ii) Data and Result Analysis

iii) Simulation Result and Model Validation

The general conceptual research framework is outlined in **Figure 17**. The first phase involves Landsat image preparation by correcting eventual errors occurred during image capture, and classification of satellite data using appropriate tools available in GIS and IDRISI Software. The second phase comprises the data and results analysis where the classification results are examined to find out how accurate are the obtained LULC maps using the most common method of confusion matrix which generates User's, Producer's and Overall accuracies along with calculation of Kappa Statistics, and after what, the change analysis is made. In the final phase, one the validation of classification results is done, the simulation of these results is done using Markov Chain (MC) and Cellular Automata (CA)- Markov Chain Models.

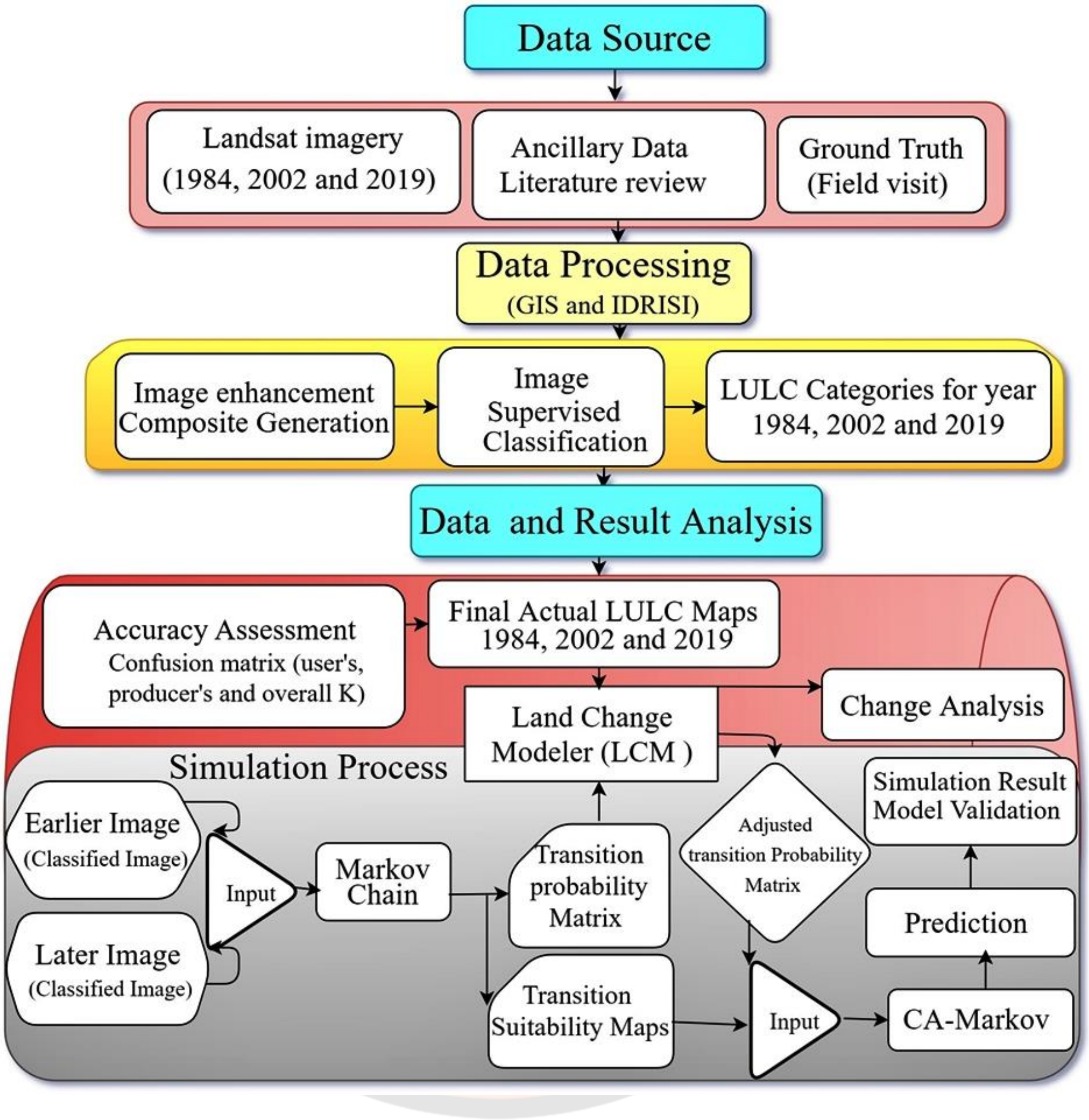

Figure 17 General methodological chart

3.3.1 Data processing

According to Jensen (2005), digital change detection can be affected by a number of influencing variables such as spatial, spectral, radiometric resolution, temporal constraints, atmospheric conditions, and soil moisture conditions (Im & Jensen, 2005). It was therefore needed to proceed first with image corrections such radiometric and atmospheric calibration in order to get precise image visible and readable for conducting a good change detection.

3.3.1.1 Image enhancement

Landsat data were selected because they are almost of good quality for image classification and land use change detection. As all these satellite data were acquired with less than 10 percent of cloud cover, and image pre-processing was going on with creating a multispectral image through combining three useful bands for LULC image classification (Lillesand, Kiefer, & Chipman, 2015). Firstly, each useful band of satellite data in this study was calibrated for noise removal using appropriate module available in Idrisi selva software. In this step, basic information about image acquisition was needed such, sun elevation angle, spectral radiant (LMin) scaled to the minimum quantized calibrated pixel value (QCalMin) in watt m-2sr-1µm-1 and the spectral radiance (LMax) scaled to the maximum quantized calibrated pixel value (QCalMax) in wattm-2sr-1µm-1 (acquired directly from image metadata file). This important technique for image transformation provided details about data at different time frames. We finally use ATCOR 2 module in Idrisi software which converts the digital numbers (DNs) of each pixel of each scene to a sensor spectral radiance (L) in mWcm-2sr-1µm-1 using the following equation (1) and after module operation, obtained reflectance value of scene's pixel ranges from 0 to 1(Eastman, 2009; Richter & Schläpfer, 2013):

$$L = C0 + C1 \times DN \qquad (1)$$

Where, L is the at sensor spectral radiance, C0 and C1 are radiometric calibration coefficients calculated from LMax and LMin for each spectral band and DN stands for the digital number of each pixel.

Afterward, we used the technique of Window Composite Band using again the module embedded in Idrisi Selva.17 software to enhance images quality through increasing the brightness using basically three bands (red, green and blue) as presented in **Figure 18, 19 and 20**. This purpose of this method was to improve the appearance of images and to assist in subsequent visual and analysis. More importantly, image enhancement involves the technique for increasing the distinction interpretation between features by improving tonal differentiation between various features in a scene using contrast stretching techniques.

Figure 18 Corrected satellite image acquired on Landsat 5 TM (1984-06-20)

Figure 19 Corrected satellite image acquired on Landsat 7 ETM (2002-08-17)

Figure 20 Corrected satellite image acquired on Landsat 8 OLI (2019-07-23)

3.3.1.2 Image classification

Image classification designs the process of assigning pixels to informational classes of interest. A good classification method must involve spectral or pattern recognition in order to generate a cluster of classes from multispectral images covering the Area of Interest (AOI). The aim of image classification in this research is to extract the spectral information contained in multispectral images and generate cluster classes that match well the informational classes of interest. The area coverage of the various classes of multispectral images will be compared to further determine changes that have taken place between the study dates.

Therefore, based on the worldwide and common classification scheme in Land use/land cover system (James Richard Anderson, 1976), existing land cover data and field visit done in the area of interest (AOI), we have preliminarily grouped all characteristics of LULC classes that could not be easy to determine and this was done according to our classification purpose. Five major Land use/land cover categories were listed to be considered during digital image classification (**Table 8**).

Table 8 LULC classes description based on Anderson classification scheme 1976

LULC Class	Subcategories	Description
Agriculture	Cultivated land, croplands, Vegetable gardens,	Cultivated fields used for crop production, Non-or poor vegetated areas, and gully features, typically associated with significant natural or man-induced erosion activities along or in association with stream and flow lines
Built-up Area	Urban, Commercial, Industrial, Residential, Informal, Schools, etc.,	Areas containing built-up structures, commercial, administrative, health, transport, various residential, schools and sports playgrounds,
Grass Land	Grassland, Fallow lands	Natural / semi natural grass dominated areas. Includes sparse bushland and woodland areas, areas that are primarily vegetated on a seasonal or permanent or daily basis (e.g. in valley alongside the streams of water)
Shrub Land	Shrubland, Bare rock / soil, deciduous, degraded land	Natural / semi-natural grass dominated areas tree with clear canopy, deciduous and arid land, meadows and pastures
Trees Cover	Forest, Woodland, Plantations mature trees, young trees, temporary clear-felled stand	Natural vegetation / forest dominated by tall trees and where canopy heights are > 5m, Planted forest used for growing commercial timber tree species

Land use and land cover classes can be well achieved by classifying satellite images based on the reflected signals from the earth surface materials. LULC classification refers also to the socio-economic activities which are interpreted from the land cover in the context of surrounding features in the area of interest. In this study, image classification was done using a very common and widely method of Supervised classification in Idrisi selva.17 software in order to finally get the land use and land cover classes. After the determination of the LULC classes, a menu of these classes was developed in accordance with the colors observed on the enhanced Landsat images for each land use and land cover classification and for mapping process. Using a widely color scheme for satellite imagery interpretation displayed in **Figure 21,**

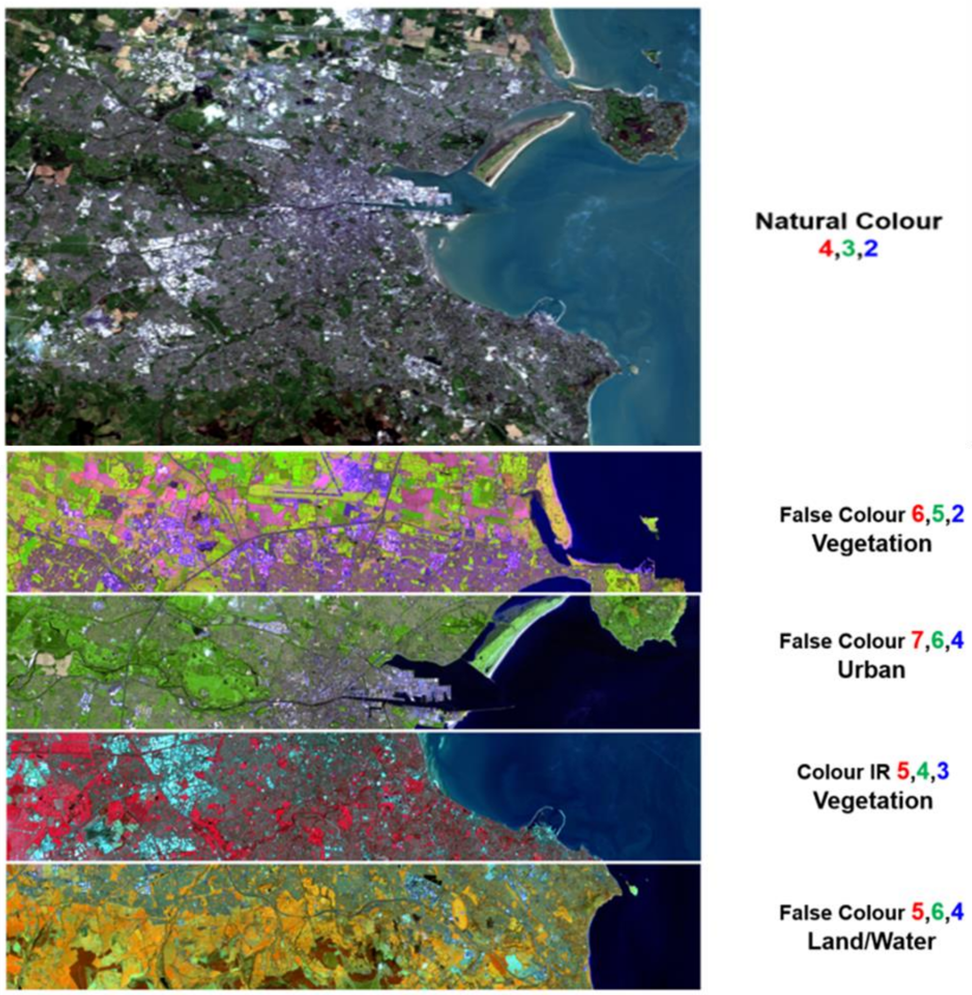

Figure 21 standard interpretation of LULC classes based on colors scheme

"Training sits "was therefore made by selecting a number of representative samples for each LULC class. This was finally achieved using Idrisi software which applied training samples on the entire image and a signature file which stored selected samples with reliable spectral information was generated (**Figure 22**). These Sample objects are selected based on x and y coordinates of the imported training site.

The last step was to run a classification using Maxim likelihood algorithm (Patil et al., 2012), and we finally got the LULC images with five LULC classes previously noted as Agriculture, Built Area, Grass Land, Shrub Land and Trees Cover as shown in given example for 2019 Landsat image classification result in **Figure 23**.

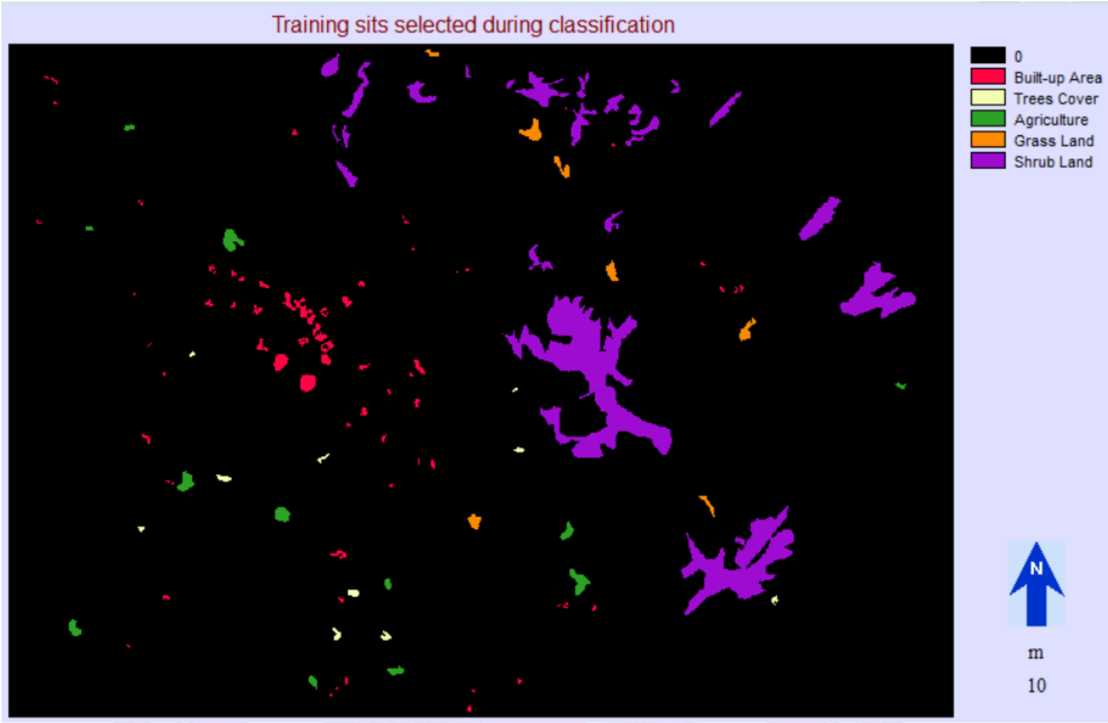

Figure 22 Sample training area mask used to classify the images of 2019

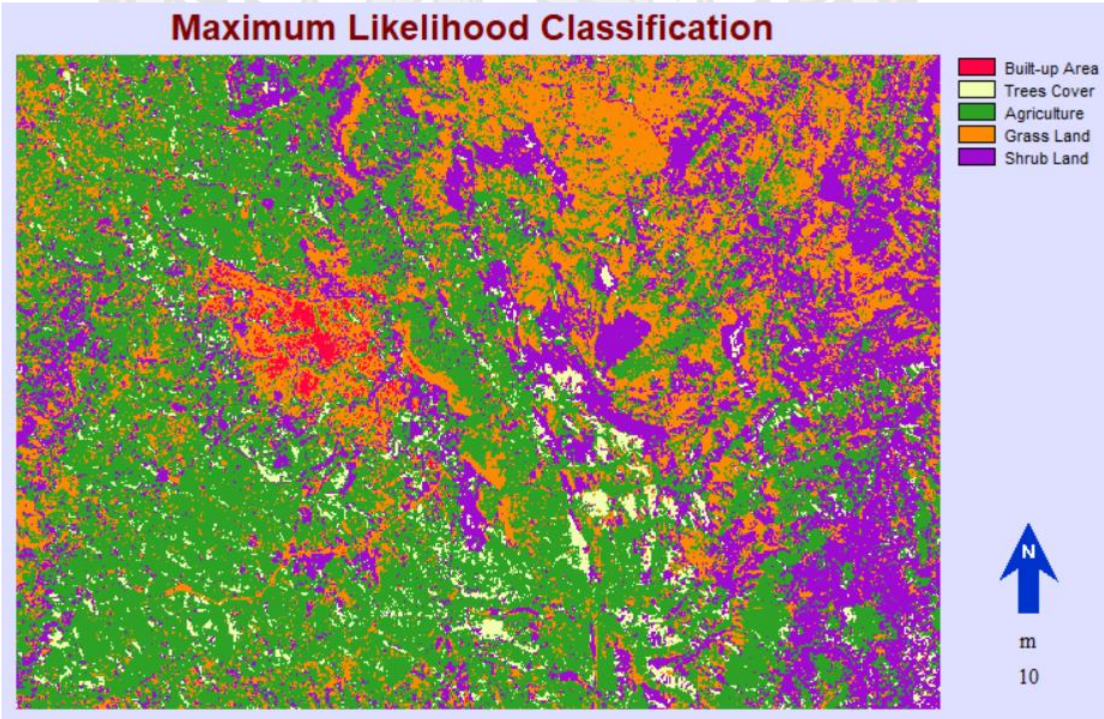

Figure 23 Image classification output for Landsat 8 OLI acquired on 2019-07-23

CHAPTER IV

RESULTS AND DISCUSSION

4.1 Classification results evaluation and mapping.

Quantitative method was applied in this study to establish the correspondence between the classification results and the reference image. The sampling sites for the accuracy assessment were selected from random sampling using different sets of coordinates from the training sample locations. Stratified random sampling similar, but slightly different, from the procedure used earlier for the selection of training parcels was used. The high-resolution contemporary satellite imagery available on Google Earth pro has been used to collect the ground truth data for 1984, 2002 and 2019 maps. a total number of 30 sample pixels (6 pixels for each of the land cover classifications) were produced using stratified sample random method with ArcGIS software to characterize image classification accuracy (Pulighe, Baiocchi, & Lupia, 2016; Tilahun & Islam, 2015). The sampling sites had spread across entire classified area for each image to ensure that all land use and cover classes were considered in the accuracy assessment. **Figure 24** shows accuracy assessment location over the Landsat 5 TM classification, **Figure 25** shows the accuracy assessment locations generated over the Landsat 7 ETM classification and **Figure 26** shows the accuracy assessment locations generated over the Landsat 8 OLI classification. Using same X and Y coordinates extent, these selected randomly points were connected to correspondingly Google Earth features (**Figure 27**) in order to match accuracy between classifier and the ground truth data as exemplified in **Figure 28** for Landsat 8 OLI image. Details on randomly points for ground truth control and relevant evidence of the good classification in this study are given in the section of appendix.

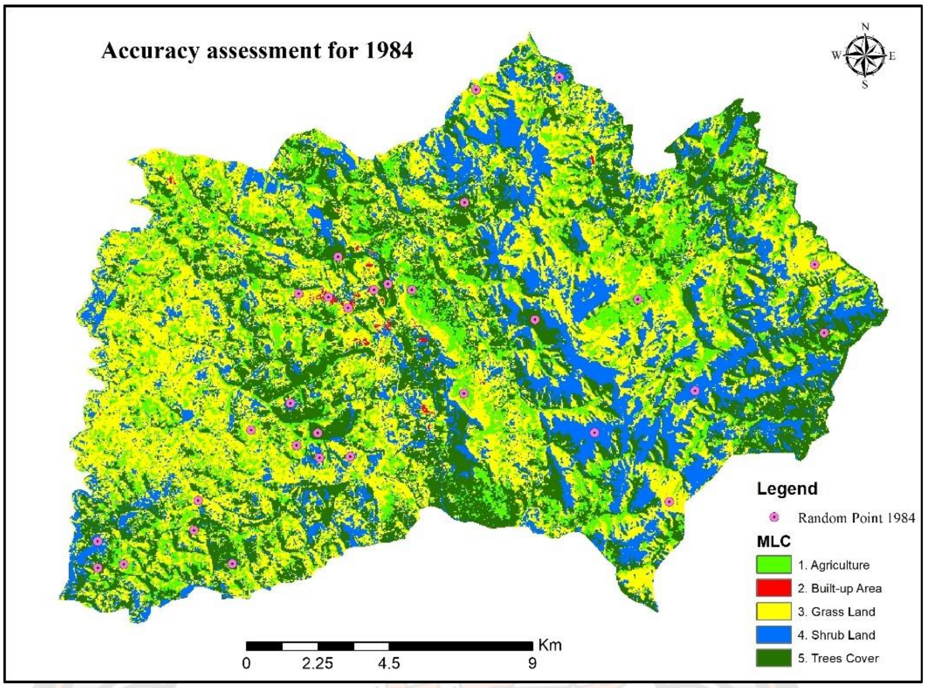

Figure 24 Accuracy assessment generated over the MLC for Landsat 5 TM 1984

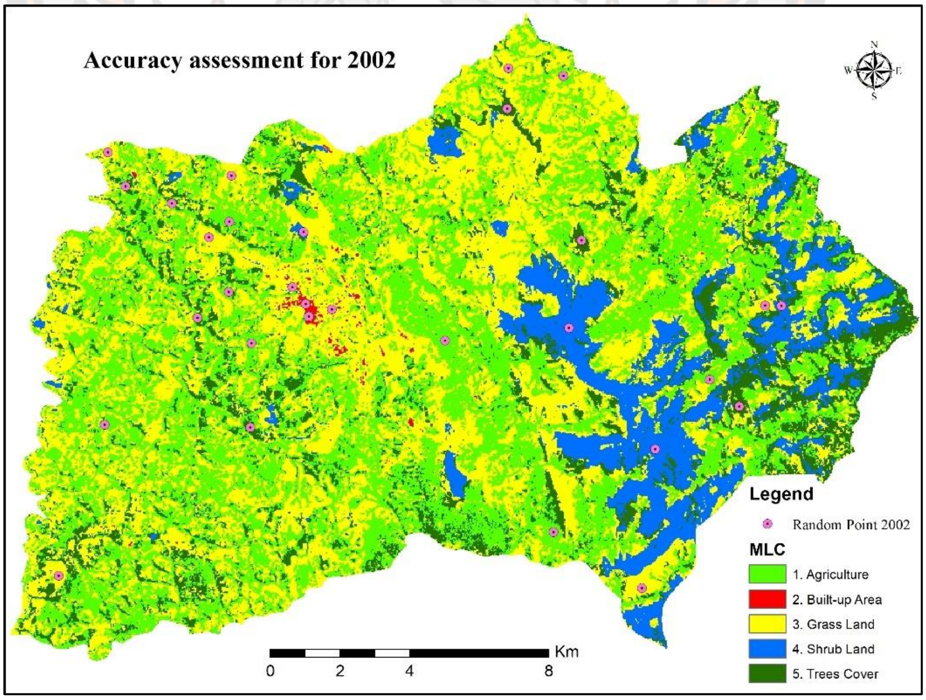

Figure 25 Accuracy assessment generated over the MLC for Landsat 7 ETM 2002

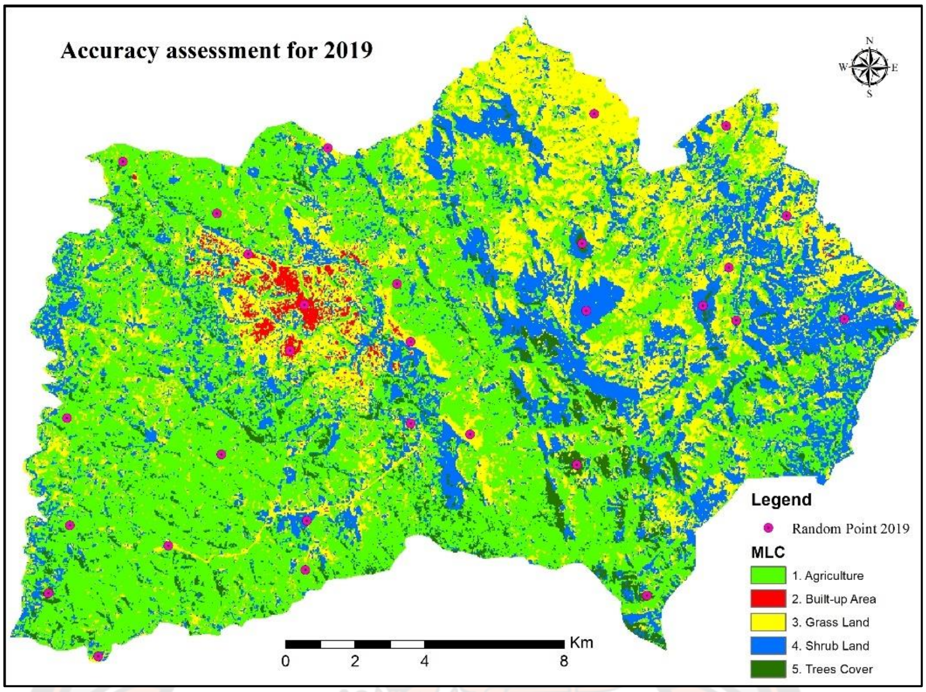

Figure 26 Accuracy assessment generated over the MLC for Landsat 8 OLI 2002

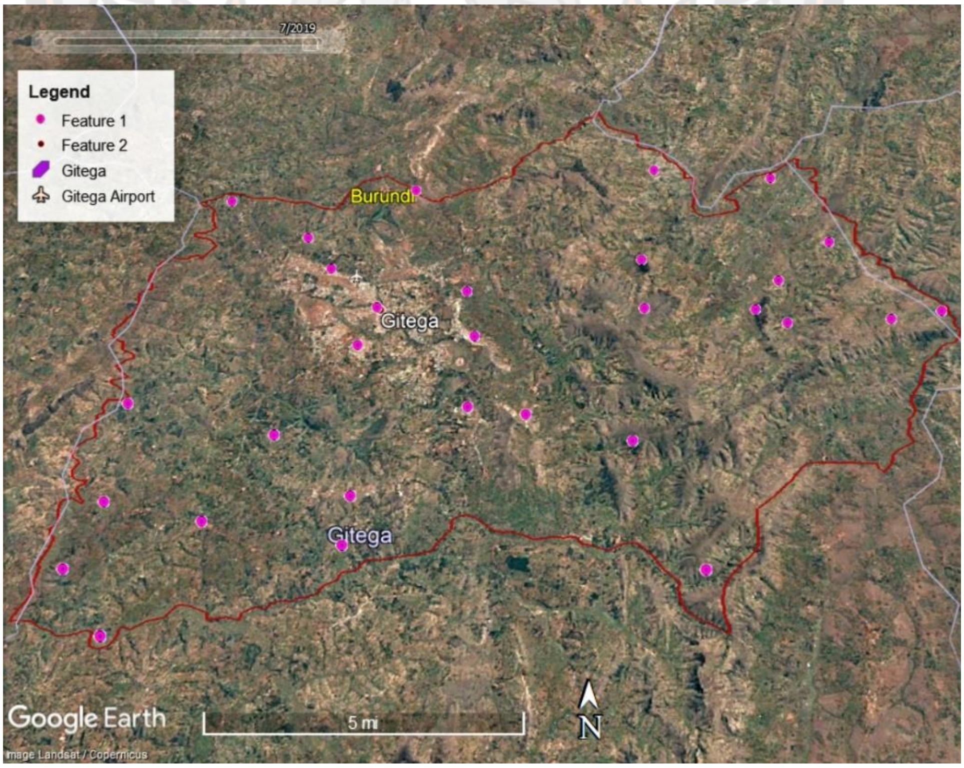

Figure 27 Ground point control with Google Earth for 2019classification accuracy assessment

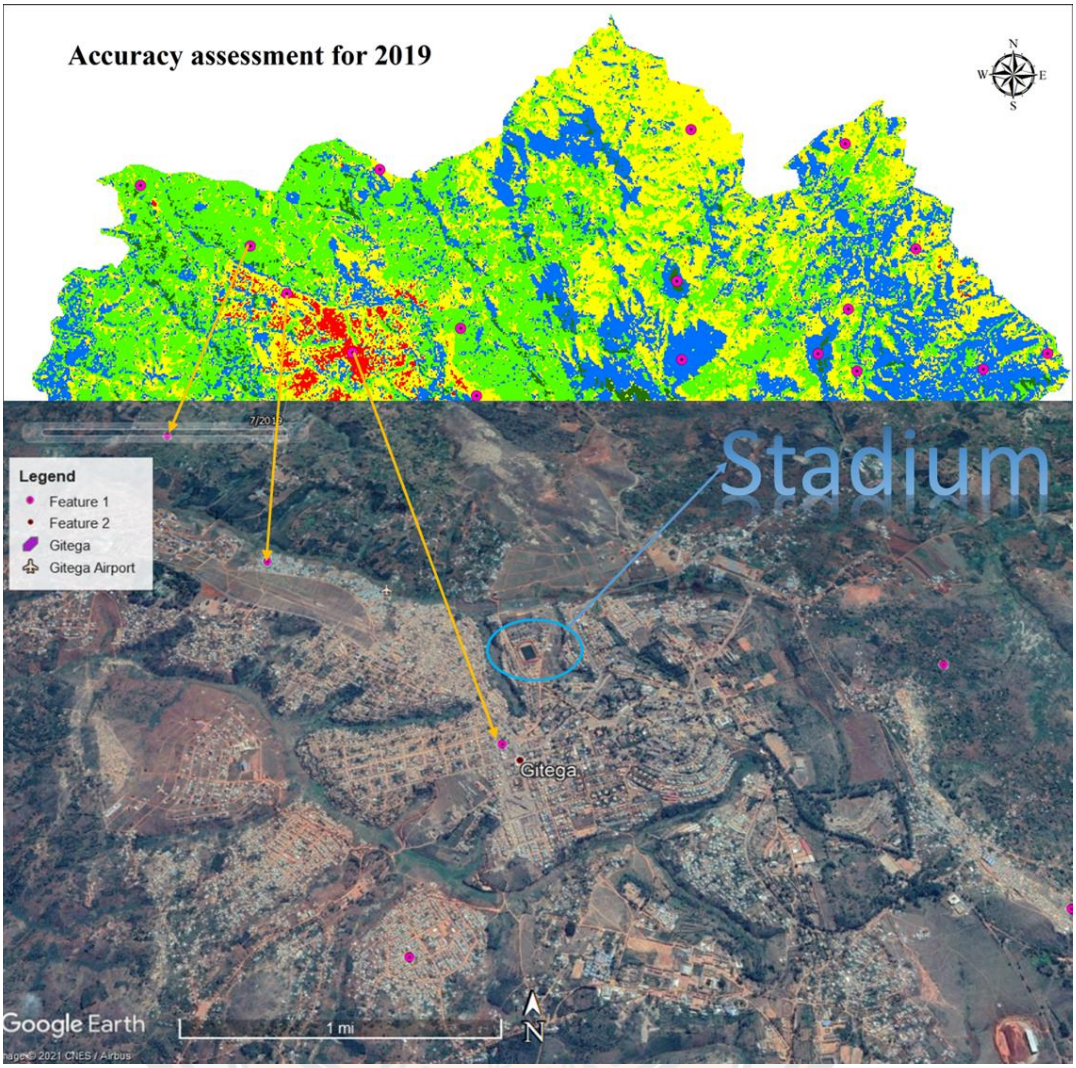

Figure 28. Synchronization of 2019 classified LULC map and aerial Google Earth image for performing classification accuracy assessment.

Figure 29 Field photo 2019 corresponding to the selected stadium in figure 30 showing classification accuracy for 2019 image.

Figure 30 Field photo showing built-up area as appearing in both classified and aerial Google image given in the figure 29

The performance of image classification accuracy was made using the class values and ground truth values, and ultimately the confusion matrices were generated to report the accuracy of each LULC classification in terms of overall accuracy (OA) user's accuracy (UA), producer's accuracy (PA) and kappa statistics (K) coefficient (Dewan & Yamaguchi, 2009; Rwanga & Ndambuki, 2017).

Users accuracy (UA)

In General, Users accuracy (**UA**) refers to the number of correctly classified pixels in each class (category) divided by the total number of pixels that were classified in that category of the classified image (row). It reflects the probability that a pixel classified into a given category (Classified Map) actually represents that category on the ground (Reference Data). In this present study, results from User's accuracy in the year 1984 range from 62.5 percent to 100percent, same as in the year 2002. In 1984, the maximum class accuracy was 100 percent which was systematically found in Agriculture, Built-up Area and Trees Cover (correctly classified), while the lowest value was Grass Land with an accuracy of 62.5 percent as presented in **Table 9.** However, in 2002, the high-class accuracy of 100 percent was systematically obtained in Built-up Area, Shrub Land and in Trees Cover, whereas minimum accuracy of 62.5 percent was Grass Land as shown in **Table 10.** Unlike the above results accuracy, 2019 image was correctly classified with results accuracy ranging from 80 percent to 100 percent as indicated in **Table 11**. This was due to the utilization of a good image from Landsat 8 OLI offering higher spatial resolution more than Landsat 7 and backwards. According to Woodcock et al., 2008, very high spatial resolution images provide many pixels per object rather than many objects in a single pixel during classification process (Woodcock et al., 2008; Wulder et al., 2004).

Producer's accuracy (PA)

Producer's accuracy denotes the number of correctly classified pixels in each category divided by the total number of pixels in the reference data to be of that category (column total). This quantitative procedure shows how well reference pixels of the ground cover category are classified). Results from Producer's accuracy in this study showed that in 1984, the maximum accuracy of 100 percent were Built-up Area, Grass Land and Trees cover, and equal lower value classes were both Agriculture and Shrub

Land as displayed in **Table 9.** In 2002, Built-up and Trees Cover where are maximum producer's accuracy (100percent) than other LULC classes (**Table 10**). In the year of 2019, all classes were maximum accuracy with 100percent, except Shrub Land which was low value class with 66.6 percent as represented in **Table 11**

Overall accuracy (OA)

OA calculates the percentage of total classified pixels that truly labelled into the specific land cover and is computed by dividing the total correctly classified pixels (TCS or the sum of the diagonals) by the number of reference pixels (TS) in the error matrix shown in equations 2, 3 and 4

$$\boldsymbol{OA} = \frac{\Sigma TCS_{ij}}{TS} \quad (2)$$

$$\boldsymbol{PA} = \frac{\Sigma TCS_{ij}}{TSc_i} \quad (3)$$

$$\boldsymbol{UA} = \frac{\Sigma TCS_{ij}}{TSr_i} \quad (4)$$

Where TCS_{ij} is the total number of the correctly classified pixels in row i and column j, TS is the total reference sample, TSc_j is the total number of pixels in column j and TSr_i is the total number of pixels in the row i.

The quantitative measure of the level of agreement was done with utilization of kappa statistic (K) assumed that a K of 1 indicates ideal agreement, whereas a kappa of 0 indicates agreement equivalent to chance to truly classify the pixels. Then k statistic was computed in the equation 5:

$$\boldsymbol{k} = \frac{(\mathrm{TS} \times \mathrm{TCS}) - \Sigma\, TSc_j\, TSr_i}{TS^2 - \Sigma(TSc_j\ - TSr_i\ )} \quad (5)$$

Where TCS_{ij} is the total number of the correctly classified pixels in row i and column j,

TS is the total reference sample, TSc_j is the total number of pixels in column j and TSr_i is the total number of pixels in the row i.

Table 9 Confusion matrix for land cover map of 1984

	LULC Map (Maximum Likelihood Classification)							
	LULC Classes	Agriculture	Built-Up Area	Grass Land	Shrub Land	Trees Cover	Total	User's (%)
Aerial image (Google Earth)	Agriculture	5	0	0	0	0	5	100
	Built-up Area	0	3	0	0	0	3	100
	Grass Land	1	0	5	2	0	8	62.5
	Shrub Land	1	0	0	5	0	6	83.3
	Trees Cove	0	0	0	0	8	8	100
	Total	7	3	5	7	8	30	
	Producer's (%)	71.4	100	100	71.4	100		
	Overall Accuracy							**86.6**
	Kappa Statistics							**83**

Table 10 Confusion matrix for land cover map of 2002

	LULC Map (Maximum Likelihood Classification)							
	LULC Classes	Agriculture	Built-Up Area	Grass Land	Shrub Land	Trees Cover	Total	User's (%)
Aerial image (Google Earth)	Agriculture	7	0	1	0	0	8	87.5
	Built-up Area	0	3	0	0	0	3	100
	Grass Land	1	0	5	2	0	8	62.5
	Shrub Land	0	0	0	4	0	4	100
	Trees Cove	0	0	0	0	7	7	100
	Total	8	3	6	6	7	30	
	Producer's (%)	87.5	100	83.3	66.6	100		
	Overall Accuracy							**86.6**
	Kappa Statistics							**83**

Table 11 Confusion matrix for land cover map of 2019

	LULC Map (Maximum Likelihood Classification)							
	LULC Classes	Agriculture	Built-Up Area	Grass Land	Shrub Land	Trees Cover	Total	User's (%)
Aerial image (Google Earth)	Agriculture	7	0	0	0	0	7	100
	Built-up Area	0	4	0	1	0	4	80
	Grass Land	0	0	8	1	0	9	88.5
	Shrub Land	0	0	0	4	0	4	100
	Trees Cove	0	0	0	0	5	5	100
	Total	7	4	8	6	5	30	
	Producer's (%)	100	100	100	66.6	100		
	Overall Accuracy							**93.3**
	Kappa Statistics							**91.5**

Furthermore, diversity of information and reporting documents on the land use and environmental sate like Agriculture Rehabilitation and Support and Sustainable Land Management (PRASAB), and other various legislation and policy documents from different governmental agencies e.g. Ministry of Environment, Agriculture and Livestock, were acquired from the internet and examined to retrieve relevant LULC information for research results validation

Table 12 Summary of accuracy assessment for 1984, 2002 and 2019 image classification

year	**1984**		**2002**		**2019**	
Land use/Land Cover	Producer	User	Producer	User	Producer	User
Agriculture	71	100	87	87	100	100
Built-up Area	100	100	100	100	100	80
Grass Land	100	62	82	62	100	88
Shrub Land	71	83	66	100	66	100
Trees Cover	100	100	100	100	100	100
Overall Accuracy	86		86		93	
Overall Kappa Statistic	0.83		0.83		0.91	

The evaluation metric results presented in the (**Table 12**) revealed an equal overall accuracy of 86 percent for 1984 and 2002 maps, while for 2019 map the overall accuracy was higher as 93percent, and Kappa coefficient was 0.83 and 0.91 respectively. These evaluation results justified a very good accuracy of the classified images with minimal error in the classification method (Lillesand et al., 2015; Rwanga & Ndambuki, 2017). After this validation of image classification, the results were further exported from Idrisi to ArcGIS software for further necessary mapping. The **Figure 31, 32 and 33** represent the LULC maps resulting from image classification for year 1984, 2002 and 2019 respectively, whereas (**Table 13**) records the rea of each LULC class at different time frames.

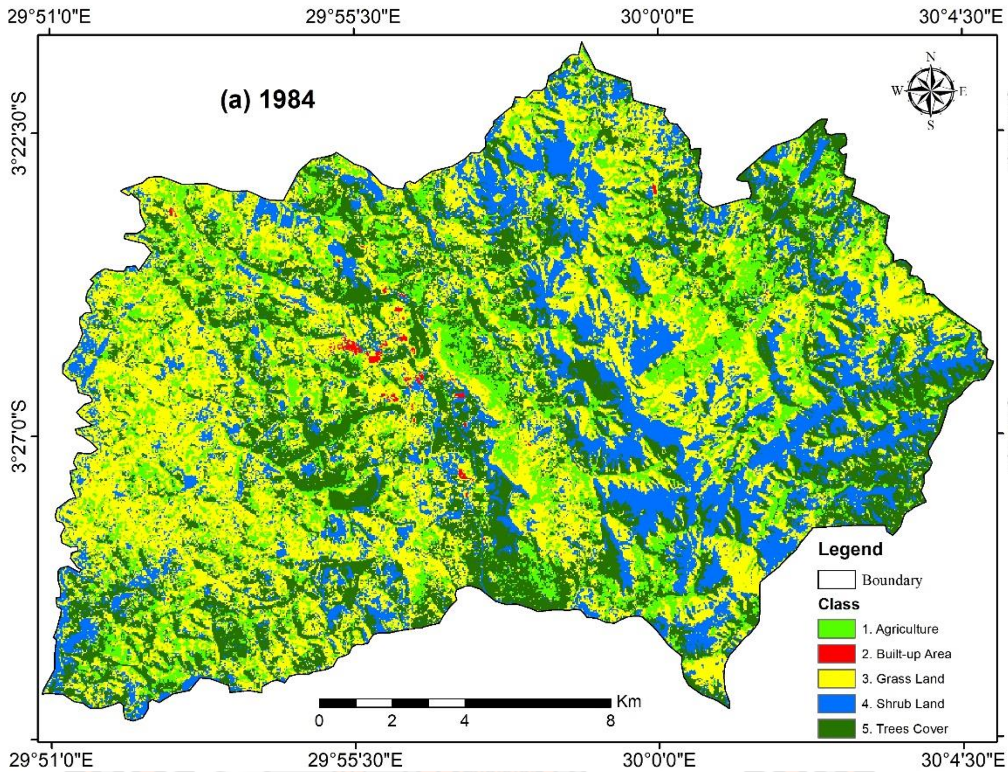

Figure 31. LULC map of year 1984

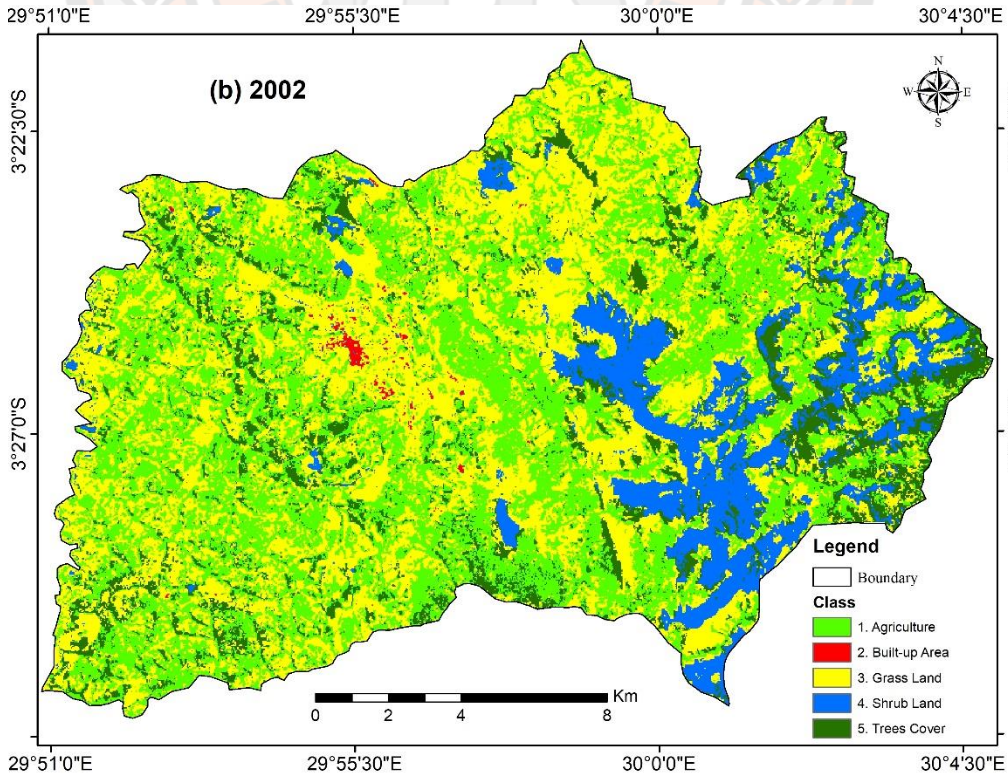

Figure 32 LULC map of year 2002.

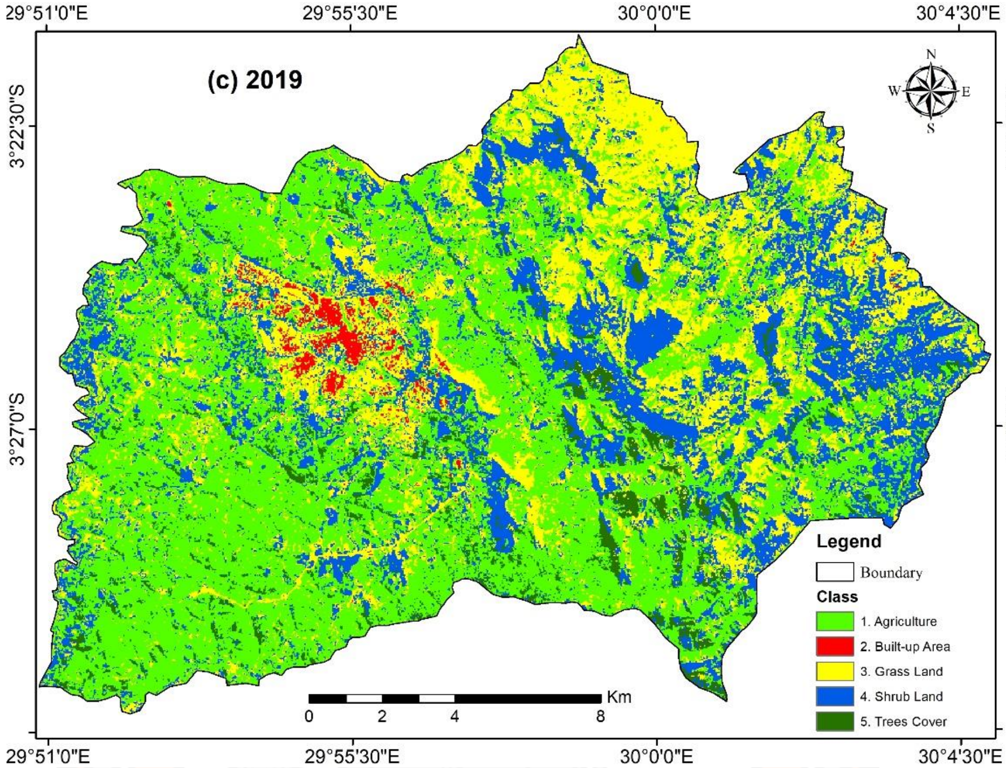

Figure 33 LULC map of year 2019

Table 13 Temporal area distribution of LULC in km^2 by year

LULC	1984	2002	2019
Agriculture	48	111.5	142
Built-up Area	1	1.5	3
Grass Land	112	121	73
Shrub Land	61	31	66.5
Trees Cover	81	38	18.5

4.2 Change detection

As defined by Singh et al. (1989), Change detection is the process of identifying differences in the state of an object or phenomenon by observing it at different time (Singh, 1989). Thus, the aim of LULC change detection is to discern those areas on digital images that represent change features of interest (e.g., forest clearing or land covert land-use change) between two or more time periods.

In this study, Land use and land cover change detection was done through quantifying the decreasing and increasing amount of area in each LULC class at different time periods. Therefore, the magnitude of change (M) for each LULC category has been calculated by subtracting the area coverage (AC) from former and later time periods specifically denoted as AC_2 and AC_1 for the 2nd and 1st years respectively in the Equation (6) follows (Islam et al., 2018):

$$M = MAC_2 - MAC_1 \qquad (6)$$

Where M is the magnitude of change?

AC_1 is the area coverage of LULC class at the first year,

AC_2 is the area coverage of LULC class at the second year.

The percentage of change (P) was calculated by dividing the magnitude of change (M) by area coverage of LULC class at the first year (MAC_1) multiplied by 100 as expressed in the following Equation (7):

$$P = \frac{M \times 100}{MAC_1} \qquad (7)$$

The annual rate of change (AR) for each land use type was then obtained by dividing the magnitude of change (M) by the number of years period (N_{pr}) which corresponds to the difference between the last and first year periods i.e. a number of 35 years (2019-1984) was used to calculate the annual rate of change in this research bay using Equation (8):

$$AR = \frac{M}{N_{pr}} \qquad (8)$$

4.3 LULC change analysis results

The LULC changes analysis enables to understand physical modification or loss of features in the natural landscape such as, vegetation and forests clearing, agricultural land, waterbody as worth useful information for planning land use and environmental conservation (Wang, Munkhnasan, & Lee, 2021). We applied comparative method to analyze 5 LULC classes from classified image-based remote sensing of years 1984, 2002 and 2019 presented in the **Figure 31, 32 and 33**.

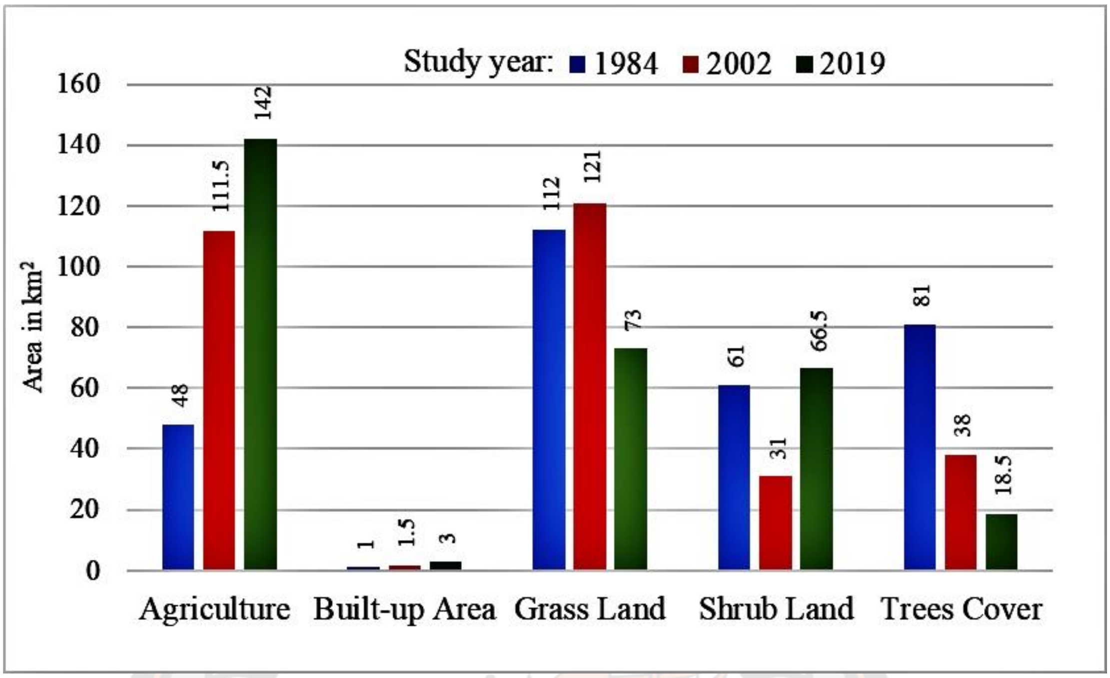

Figure 34 Comparison of existing LULC category by statistical area in km²

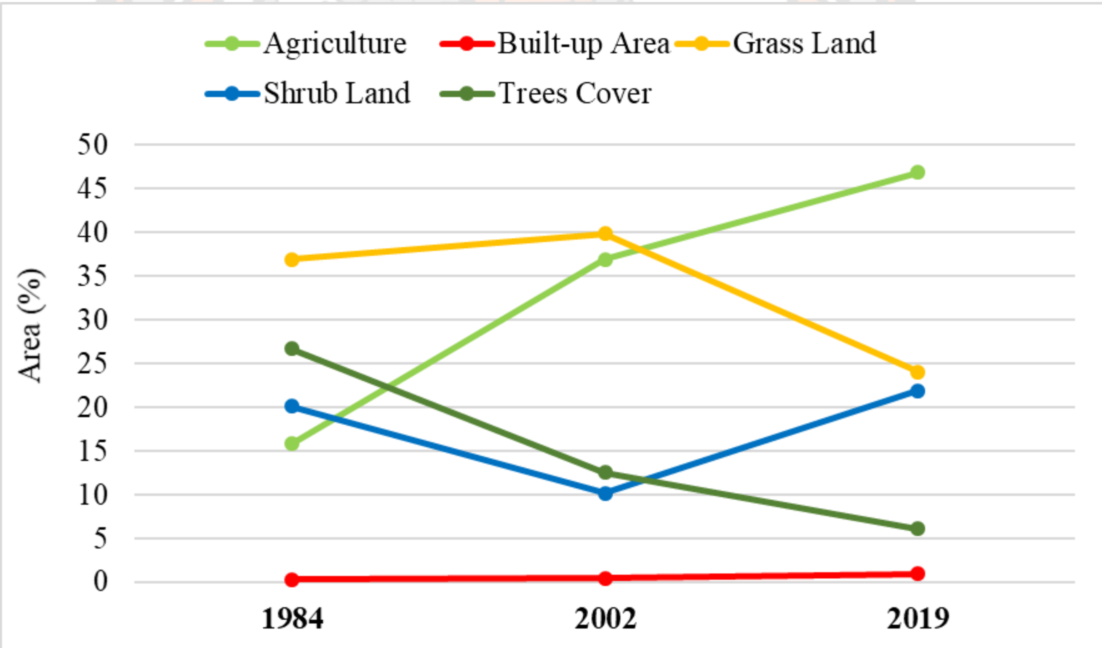

Figure 35 LULC change patterns by statistical area in percent over 35 years

The results from comparative analysis given in **Figure 34, 35** reveal a huge conversion of one LULC to others taking place across years. In 1984, Gitega landscape was extensively covered by Grassland and Trees Cover: 112 km^2 (36.97percent) and 81 km^2 (26.73percent) respectively. Shrub land is the 3rd dominant class covering 61 km^2 (20.13percent), while Agriculture and Built-up Area cover occupy 48 km^2 (15.84percent) and 1 km^2 (0.33percent) respectively. In the second year 2002, the study area was largely covered with Grass Land and Agriculture:121 km^2 (39.84percent) and 111.5 km^2 (36.92percent) respectively. However, Trees Cover and Shrub Land decreased to 38 km2 (12.24percent) and 31 km^2 (10.21percent) respectively, and Built-up Area has slightly increased. In 2019, the largest land cover is Agriculture with 142 km^2, an increase of 10 percent from 2002 to 2019. Grass Land took second areal position with 73 km^2 due to a decrease of 5 percent nearly. Shrub Land rose up to the 3rd position due to an increase by 11.74 percent with an area of 66,5 km^2, while Trees Cover steeply decreased by 6.44 percent and occupies 18.5 km^2. Built-up Area has a steady increase by 1.5 km2 from 2002-2019.

In order to get deep understanding, LULC changes detection was analyzed with Land Change Modeler (LCM) and the outcomes framed the above trends of LULC change patterns (**Figure 36**).

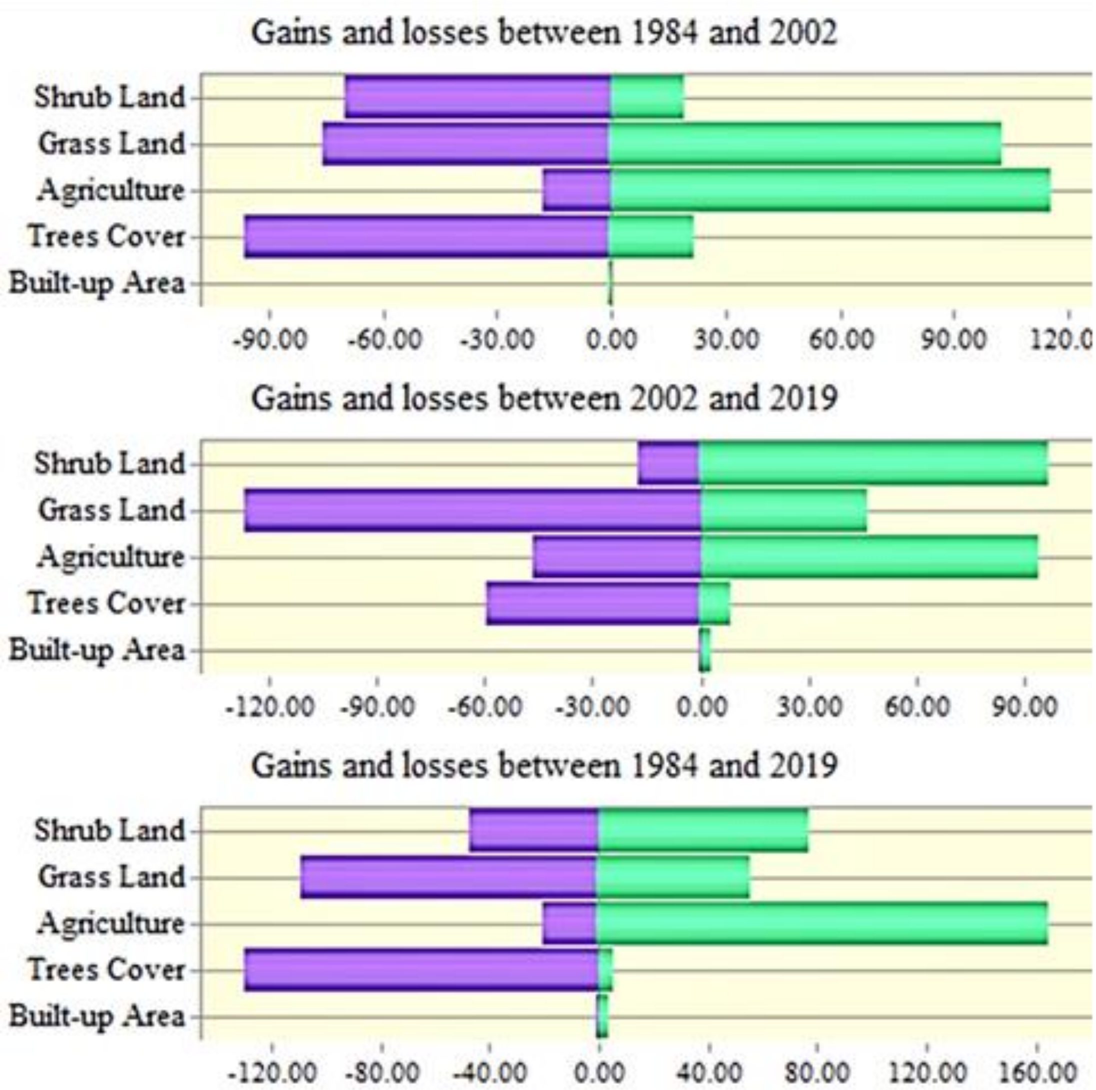

Figure 36 Gains (Green) and losses (Purple) by category of LULC in km^2

Using LCM model, Gupta and Sharma (2020) highlighted the outcomes of LULC dynamics studies over 50 years periods which are consistent with our results. These decreasing area in Trees Cover and Grass Land (by about 101,5 km^2 in total with annual rate of 2.9 km^2) has been converted mostly into Agriculture (94 km^2), and little to Shrub Land and Built-up Area (7,5 km^2 together) from 1984 to 2019.

4.4 CA-Markov for simulating the future LULC change

CA-Markov Chain Model (CA-MCM) is the most popular model among various tools and techniques used for modelling spatial and temporal changes (Sang, Zhang, Yang, Zhu, & Yun, 2011; Torrens, 2000). In the LULC changes modelling, the integration of the two models, Cellular Automata and Markov Chain models has been widely used for optimizing the simulation of LULC change (Borana & Yadav).

On the one hand, Markov Chain Model is a dynamic process based on Markovian random process that calculates the probability of changes from particular object (for example: Vegetation) into another objects (for example: Agriculture). Markov chain describes as transitional probability matrix in which the probability of each event depends only on the state attained in the previous event (Ghosh et al., 2017). Because of its immense ability to quantify the rates and states of conversion among and between categories respectively, it has been equally used in the LULC change modelling.

On the other hand, Cellular Automata (CA) is a discrete dynamic system consists of a regular network of finite state automata (cells) that can change in neighboring cells and simulate the evolution of two-dimensional objects in many different directions such as West, East, North, South and other adjacent directions (Kumar, 2003; Torrens, 2000). Obviously, GIS raster data is known to fairly have resemblance with cellular automata concept and eventually, this property has enabled CA to be as famous as model used in LULC changes simulation (Pijanowski et al., 2002; Surabuddin Mondal et al., 2013). Therefore, combination technique of the two above models was also applied in this research to simulate the LULC for 2019, 2038 and 2058 using Idrisi Selva 17.0 software (Nadoushan, Soffianian, & Alebrahim, 2015) . With two LULC maps of different time periods (defined as earlier and later images), transition probabilities between periods were then obtained using Markov Chain model using the following formulae (9) (Mondal, Sharma, Garg, & Kappas, 2016) :

$$S(t, t+1) = P_{ij} \times S(t) \qquad (9)$$

Where S (t) is the system status at time t;

S (t+1) is the system status at a time of t+1

P_{ij} is the transition probability obtained in equation (10) below:

$$P = |P_{ij}| = \begin{vmatrix} P_{1,1} P_{1,2} \ \dots P_{1,N} \\ P_{2,1} P_{2,2} \dots P_{2,N} \\ \dots\dots\dots \\ P_{N,1} P_{N,2} \dots P_{N,N} \end{vmatrix} \qquad 0 \leq P_{ij} \leq 1 \qquad (10)$$

Where P = the transition probability;

P_{ij} = stands for probability of changing from particular state i (for example a current land cover = class) to another state j (for example a projected land cover =class in next time)

P_N = The state probability of any time

N= Land cover type in Gitega District.

In the simulation process, Markov Chain produces a transitional probability matrix, a transitional area matrix and a set of conditional probability images (suitability images). The transition matrix records the probability of changing of each LULC category to every other category, while transitional area matrix contains the number of pixels that are expected to be converted from one LULC category to other categories over a specific period of time. On the other hand, the output conditional probability images represent the probability of each LULC class to be found in each pixel over the time (Eastman, 2009; Mishra et al., 2014).

In the present research, we used the 1984, 2002, 2019 LULC maps obtained from image classification to run Markov Chain. Firstly, the two land cover maps (1984 and 2002) representing the earlier image (time 1) and later image (time 2) were used to primely project the LULC map for 2019 (**Figure 38** and Markov Chain model provided a related crosstabulation of transition probability matrix shown in the (**Table 14 (a)**. This operation aimed to set and produce a suitability map matching the current rate and quantity of LULC change of Gitega district in 2019 which will be further used in simulating the future LULC changes.

As Markov Chain model is just calculating the probability of changes in landscape and doesn't have an ability to provide the spatial location of the future projected LULC change, a hybrid CA-Markov module in Idrisi Selva-17 was then used to solve this problem. it is an integrated Cellular automaton, Markov chain, multi-criteria and multi-objective model for spatial-explicit term and location of changes in prediction process (Sang et al., 2011). In this first step of LULC prediction process (1984 and 2002), we used 1984 LULC data as base map and Cellular automata iterations was set to 35 (as the time interval between 1984 and 2019 is 35 years) for predicting 2019 LUC map so that the simulation result could be compared with the existing LULC in order to evaluate the model performance (**Figure 37**) (Gupta & Sharma, 2020). To estimate 2019 LULC, we used the transition probability area matrix of 1984-2002, transition suitability map and a set window technique 5*5 kernel called standard contiguous filter and this to ensure that the neighboring pixels were used to create spatially explicit contiguous weights with an influence of each cell enclosed by the following matrix space (11):

$$\text{Contiguity filter } 5*5 = \begin{bmatrix} 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 1 & 1 & 0 \\ 1 & 1 & 1 & 1 & 1 \\ 0 & 1 & 1 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 \end{bmatrix} \qquad (11)$$

In general, contiguity filter 5*5 causes the gain of a land use category to occur near another existing category and rules out randomly the major change in land use/land cover patterns i.e. a pixel near a bare surface area is likely to change into barren land.

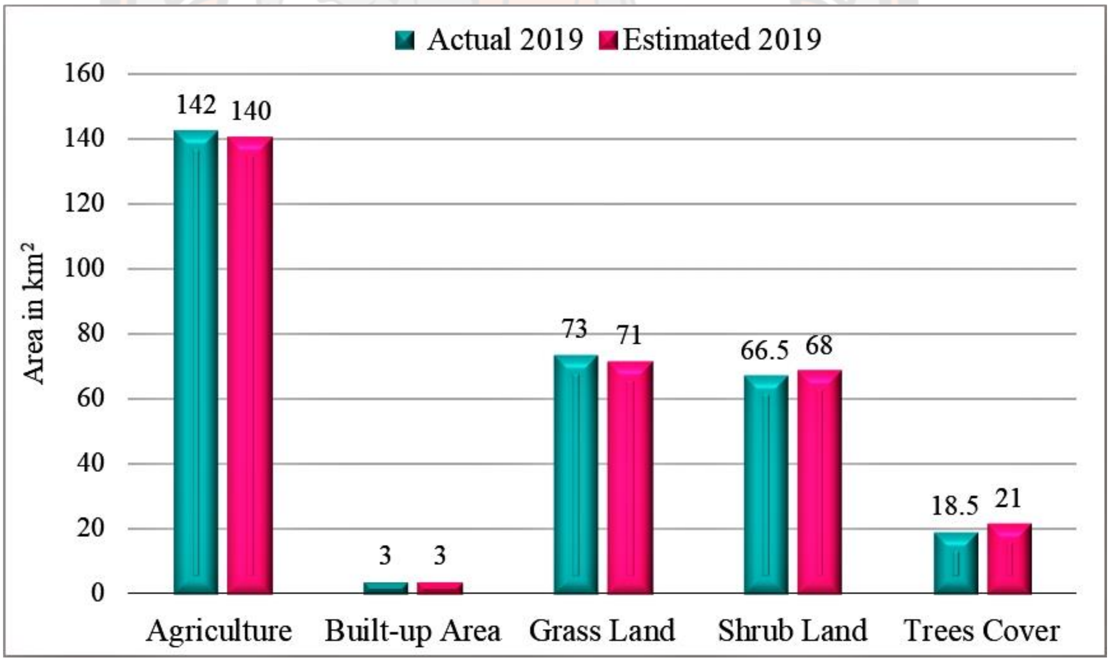

Figure 37 Area (in Km^2) of LULC category in actual and simulated maps (2019)

Upon successfully validation the simulated land cover data for year 2019, we moved on prediction for 2038 and 2057 LULC maps. In this process, we used actual land use map of 2019 as base data, transitional probability area matrices and transitional suitability maps were provided, and a 5*5 kernel size contiguity filter was set in simulating both 2038 and 2057 LULC map.

Table 14 Transition probability matrices used during simulation process

a. Probability of changing from ………… by 2019 to:

1984	**Agriculture**	**Built-up Area**	**Grass Land**	**Shrub Land**	**Trees Cover**	**Total**	**Omission**
Agriculture	0.629	0.0072	0.1051	0.2336	0.0251	1	0.371
Built-up Area	0.1401	0.4638	0.198	0.1903	0.0078	1	0.802
Grass Land	0.3922	0.0186	0.4532	0.1131	0.0229	1	0.9814
Shrub Land	0.2925	0.0166	0.3138	0.3534	0.0237	1	0.6466
Trees Cover	0.4634	0.0071	0.1968	0.294	0.0387	1	0.9613
Total	1.9172	0.5133	1.2669	1.1844	0.1182	5	
Commission	1.2882	0.0495	0.8137	0.831	0.0795		

b. Probability of changing from ……... by 2038 to:

2019	**Agriculture**	**Built-up Area**	**Grass Land**	**Shrub Land**	**Trees Cover**	**Total**	**Omission**
Agriculture	0.6824	0.0045	0.2076	0.0839	0.0216	1	0.3176
Built-up Area	0.1681	0.4321	0.1959	0.1987	0.0052	1	0.8041
Grass Land	0.5423	0.0021	0.3811	0.0601	0.0144	1	0.9979
Shrub Land	0.368	0.0175	0.3905	0.2139	0.0101	1	0.7861
Trees Cover	0.3706	0.0039	0.2147	0.3518	0.059	1	0.941
Total	2.1314	0.4601	1.3898	0.9084	0.1103	5	
Commission	1.449	0.028	1.0087	0.6945	0.0513		

c. Probability of changing from…………by 2057 to:

2019	**Agriculture**	**Built-up Area**	**Grass Land**	**Shrub Land**	**Trees Cover**	**Total**	**Omission**
Agriculture	0.7109	0.0027	0.1733	0.0901	0.023	1	0.2891
Built-up Area	0.1248	0.4901	0.2536	0.1256	0.0059	1	0.7464
Grass Land	0.4026	0.0034	0.3084	0.2591	0.0265	1	0.9966
Shrub Land	0.4801	0.0083	0.2102	0.2648	0.0366	1	0.7352
Trees Cover	0.6446	0.004	0.1124	0.2032	0.0358	1	0.9642
Total	2.363	0.5085	1.0579	0.9428	0.1278	5	
Commission	1.6521	0.0184	0.7495	0.678	0.092		

Table 14 (a), (b) and (c) records results from Markov Chain Analysis for exploring the probability of LULC conversions for all classes which could take place from1984 to 2019, 2019 to 2038 and 2019 to 2057 (Ghosh et al., 2017; Wang et al., 2021). For example, from 2019 to 2038, the probability of change for Agriculture to Agriculture is 68.24percent, while the probability of future change of Agriculture to Grass Land is 20.76percent. Trees Cover has a probability as low as 5.9 percent to remain as they are, but has a probability of 37.06 percent to change Agriculture and same process for other LULC classes. In the second prediction scenario, from 2019 to 2057, Agriculture has the highest probability of 71.09 percent to remain as Agriculture in 2057, whereas Trees Cover indicates the most declining probability of 3 percent to remain same in 2057. Built-up Area, Grass Land, and Shrub Land have probability of 49.01 percent, 30.84 percent, and 26.24 percent respectively, to remain as they are in 2019.

4.5 Accuracy assessment of simulated result and model validation.

The accuracy of the simulation results and the model validation were once done based on the comparison of the predicted LULC maps for 2019, 2038 and 2057 with the real LULC maps of 2019 (actual land use data). The Kappa statistics is the most widely method agreed to quantify the power and suitability of simulation model (Maingi, Kepner, & Edmonds, 2002), thus, this study utilized the submodule in Idrisi namely, GIS Analysis, to generate Kappa index of Agreement shown in **Table 15**. Basically, the module requires two land cover data denoted “comparison image and reference image” to provide Kappa index of Agreement (KIA) that breaks into several components of agreements or disagreement. So, the existing LULC map of 2019 has been frequently used as reference image to examine the simulated 2019,2038 and 2057 map (comparison image). The validation was done based on the assumption that the higher are the kappa values, the better are the used models (Borana & Yadav). The **Table 15** displays the values for kappa statistics noted as K_{no}, $K_{location}$, $K_{location\ strata}$ and $K_{standard}$ (overall k) of year 2019, which also ensure the reasonable accuracy of predicted LULC maps for 2038 (83, 87, 87 and 79 respectively) and for 2057 (78, 83, 83 and 75 respectively). All kappa index values surpass the minimum acceptable standard and they range from 65 percent to 89percent, indicating a high degree of agreement between projected and actual LULC map (Kundel & Polansky, 2003; van Vliet, Bregt, & Hagen-Zanker, 2011). Furthermore, these evaluation results prove that Markov Chain simulation model was successfully designed and had a good ability to specify accurately the location and quantity for all simulated LULC maps in this study.

Table 15 Accuracy assessment results by kappa statistics values for predicted maps

k Indicator	2019
K_{no}	0.7205
$K_{location}$	0.7569
$K_{location\ Strata}$	0.7569
$KS_{tandard}$	0.6565

4.6 Prediction results and change analysis for future scenario

CA-Markov Chain simulation model requires earlier and later LULC maps to predict the future scenario (Sang et al., 2011). The future LULC maps given in **Figure 39 and 40** for year 2038 and 2057 were predicted using 2019 real LULC map (**Figure 33**) and projected LULC maps of 2019 **(Figure 38)**. The future area distribution per LULC class is shown in **Table 16**.

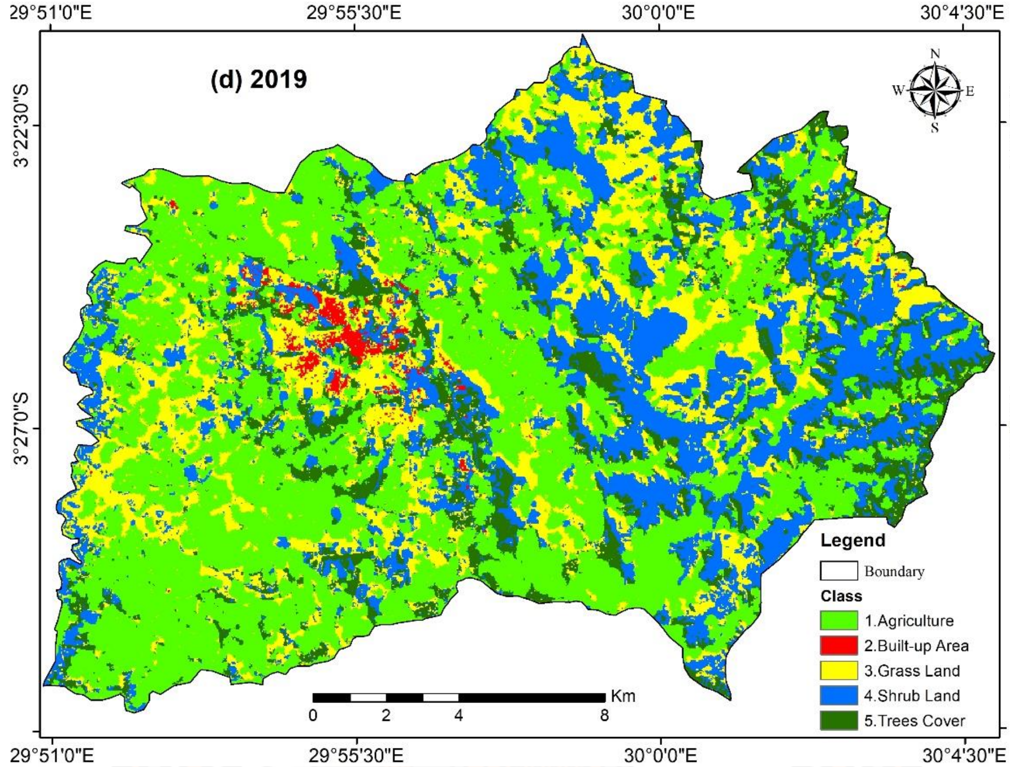

Figure 38 Predicted LULC map for 2019

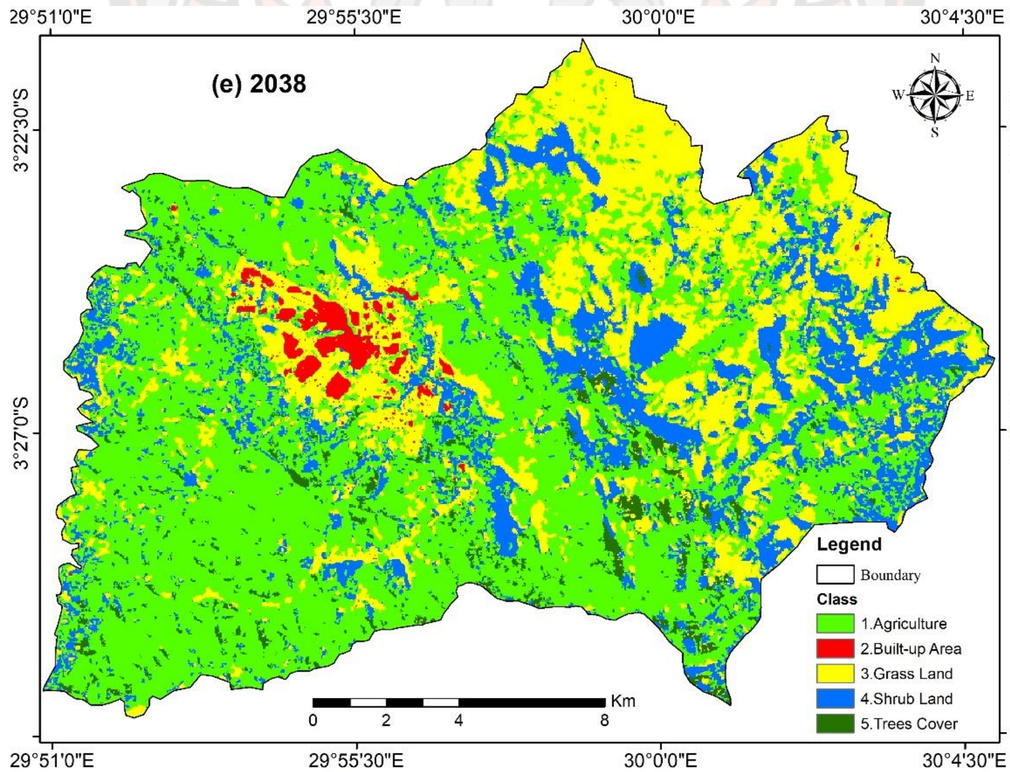

Figure 39 Predicted LULC map for 2038

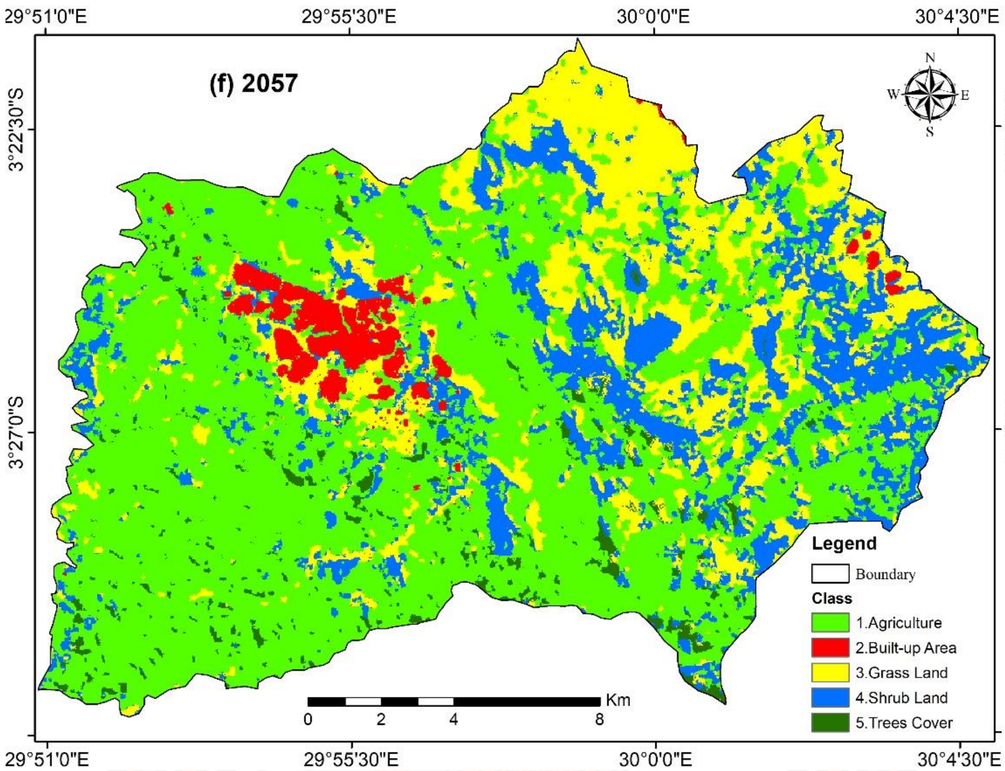

Figure 40 Predicted LULC maps for 2057

Table 16 Predicted area in km^2 by LULC category in different periods

Land cover type	2019	2038	2057
Agriculture	140	156	172
Built-up Area	3	5	9
Grass Land	71	78	60
Shrub Land	68	54	55
Trees Cover	21	10	7

Based on a quick analysis and observation of the future area distribution in LULC patterns as displayed in above **Table 16**, in the next 19 and 38 years, the landscape of Gitega District will be extensively dominated by Agriculture. According to this future areal distribution by LULC category, Agriculture will probably occupy more than 50 percent of the total area (156 km^2 in 2038 and 172 km^2 in 2057), while all other LULC classes (Built-up Area, Grass Land, Shrub Land) shall occupy less than

50 percent of the total area (total of 147 km^2 and 131 km^2 in 2038 and 2057 respectively).

Table 17 Change analysis of future projected LULC

	Simulated area (in km^2)		Change detection (in km^2)	
LULC category	**2038**	**2057**	**2038-2019**	**2057-2019**
Agriculture	156	172	14	30
Built-up Area	5	9	2	6
Grass Land	78	60	5	-13
Shrub Land	54	55	-12.5	-11.5
Trees Cover	10	7	-8.5	-11.5

From change analysis results of the future predicted LULC in **Table 17** and previous result from comparative analysis of existing LULC classes (**Figure 33**), Agriculture will continuously expand with by 14 km^2 and 30 km^2 in 2038 and 2057 respectively. Built-up Area will increase by 6 km^2 in 2057. However, Trees Cover, Grass Land and Shrub Land will be decreasing by 11.5 km^2, 13 km^2 and 11.5 km^2 respectively in 2057.

4.7 LULC change, socioeconomic and environmental linkage analysis.

An overview of LULC change analysis results over the time period of the current study (past 35 years and future 38 years) reveals a continuous trend and significant variability in land use and land cover patterns in Gitega District. In general, from the past to the present (1984-2019), Tree cover and grassland were continuously reduced by 62.5 km^2 at a rate of 1.79 km^2 per year and 39 km^2 at a rate of 1.12 km^2 per year, respectively. A net change, on the other hand, indicates a large extension in Agriculture of 94 km^2 at a rate of 2.68 km^2 per year. Similarly, the predicted LULC change trends, which show such continuous agricultural expansion at the expense of forest and vegetation, are similar to those reported by other LULC modelling studies.

(Henry, Maniatis, Gitz, Huberman, & Valentini, 2011; Mondal et al., 2016; Nadoushan et al., 2015; Wang et al., 2021).

In terms of environmental aspect, this kind of trends of LULC change, especially deforestation and agricultural expansion is also observed globally (FAO, 2016), and in many other developing countries (Alawamy, Balasundram, Hanif, & Sung, 2020; Berakhi, 2013; Islam et al., 2018). It is widely proved that the loss of forest and natural vegetation precedes the dramatic degradation of productive ecosystems and the loss of biodiversity. (Wang et al., 2021), the land degradation often spreads throughout the global environment (IPCC, 2019; Marathianou et al., 2000; Niyogi et al., 2009). Deforestation alters the hydrological process and has an impact on water conductivity, such as surface runoff, (El-Hassanin, Labib, & Gaber, 1993), and thus the occurrence of soil erosions and soil losses as observed in the study area (Henry et al., 2011; Nijimbere et al., 2019; Niyuhire, 2018; Nzabakenga et al., 2013).

In terms of social and economic implications, large agricultural expansion and outward expansion of built-up area indicate human encroachment on natural land resources and ecosystems (Y. Liu, Song, & Arp, 2012). Because the study area is a mix of urban and rural development, such land-use change can often result in short-term social and economic restructuring. Underprivileged people will inevitably lose their properties as a result of urbanization, whether through the land market or expropriation. As a result, the owners can flee and seek new residency in a distant city, where they can begin earning a new living (Wei & Ye, 2009). These types of LULC changes observed in Gitega District are more likely to be the result of rapid population growth, as evidenced by the highest density of 476 people per km^2, which increases demand for land use and, as a result, reduces ecosystem service functions. (Garrod & Willis, 1999). In any case, the heavy pressure on natural land resources and ecosystems severely hampers sustainable development, which requires proper use of natural resources while preserving capacity for future generations (Vihervaara, Kumpula, Tanskanen, & Burkhard, 2010). In this regard, it is critical to assess the environmental and socioeconomic impacts of agricultural expansion, steep declines in forest and natural vegetation, and urbanization.

CHAPTER V

CONCLUSION

5.1 Conclusion

This study has analyzed the rate and trends of change in LULC patterns quantified and predicted using Geoinformatics in Gitega District. The Change analysis was performed using 5 LULC classes obtained from images classification of years 1984, 2002, and 2019 and was highlighted with Land Change Modeler. The Markov Chain and CA-Markov models were used to forecast LULC changes in 2038 and 2057. Satisfactory accuracy was achieved, with good agreement of more than 85 percent and 82 percent for overall accuracy and Kappa statistics, respectively. As a result, RS, GIS, Cellular Automata, and Markov Chain models are effective tools for assessing and monitoring LULC changes in order to generate a multitemporal land use database that guides decision-makers toward land use planning and environmental protection.

Overall findings show a dramatic decrease in Tree Cover and Grass Land of 101,5 km^2, which was likely converted mostly to Agriculture (which increased by 94 km^2 at a rate of 2.68 km^2 per year) and little to Shrub Land and Built-up Area (7,5 km^2 combined) over the past 35 years. These findings reflect the current rate, trends, and magnitude of LULC changes as well as local policies in the study area. If Gitega is to avoid further irreversible land degradation and associated environmental problems, the government and policymakers must implement agroecological approaches and reforestation as soon as possible. Another aspect of addressing land use and land cover change issues should be the encouragement of village development (to decrease the instances of farmers living in their fields). Regarding the demographic drivers of LULC change and the land fragmentation issue, significant effort will be made to control population growth rates.

Similar trends in LULC change patterns are revealed by predictive result analysis. Agriculture has a 71.09 percent chance of remaining as Agriculture in 2057, with an expected area of 172 km^2 (56.76 percent). Tree coverage, on the other hand, has a 3 percent chance of remaining as Trees with an area of 7 km^2 in 2057.

Overall, the analysis of the results revealed that the Gitega District has consistently experienced high dynamics in land use land cover patterns, which are primarily dominated by conversion of the area into agricultural land. Prior to dramatic land degradation, the observed trends of LULC change, particularly agricultural expansion, were widely reported as the most significant drivers of deforestation and vegetation clearing. Deforestation changes hydrological processes and has an impact on water conductivity, such as surface runoff. In the study area, the Gitega region, where topographic inversion is likely to influence runoff regime, the multitemporal and spatial dataset produced in this study should be valuable information to consider in the future when performing land use management. Otherwise, the observed spectacular changes in LULC, exacerbated by poor agricultural practices, will continue to release biodiversity losses and general environmental issues.

The study results are potential to support decision-making to undertake restoration measures of land degradation and future sustainable land use management and environmental preservation. However, future study should consider the correlation of Gross Domestic Products (GDP) and Population Growth with these LULC changes analysis results.

5.2 Research limitations and suggestions

Due to the persistent pandemic Covid-19 outbreak which has forced most of Governments around the world to implement restrictions and precautionary measures, as well as lockdown and confinement throughout our study period, it was not possible to collect ground data properly in the study area. As consequence, some important parameters such as socioeconomic and biophysical factors were excluded in the Markov Chain and CA-Markov simulation process, due to the lack of data.

Another limitation of the study was the use of Landsat imagery from a different anniversary day due to the need for high-quality images.

Therefore, the future research should consider the correlation of Gross Domestic Products (GDP) and Population Growth with these LULC changes analysis results.

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APPENDIX

APPENDIX

Appendix. Classification Accuracy Assessment Details

Appendix A1. Detail of random points used for 1984 accuracy assessment

Class Name	Class Id	Shape *	Point Id	MLC/User	GEE/Producer
Agriculture	1	Point	3	1	1
Built-up Area	2	Point	8	1	1
Grass Land	3	Point	11	1	1
Shrub Land	4	Point	18	1	1
Trees Cover	5	Point	23	1	1
		Point	1	2	2
		Point	5	2	2
		Point	22	2	2
		Point	4	3	3
		Point	9	3	4
		Point	13	3	3
		Point	15	3	3
		Point	17	3	3
		Point	21	3	1
		Point	28	3	3
		Point	29	3	4
		Point	7	4	4
		Point	12	4	4
		Point	19	4	4
		Point	20	4	4
		Point	24	4	4
		Point	26	4	1
		Point	2	5	5
		Point	6	5	5
		Point	10	5	5
		Point	14	5	5
		Point	16	5	5
		Point	25	5	5
		Point	27	5	5
		Point	30	5	5

Appendix A2. Detail of random points used for 2002 accuracy assessment

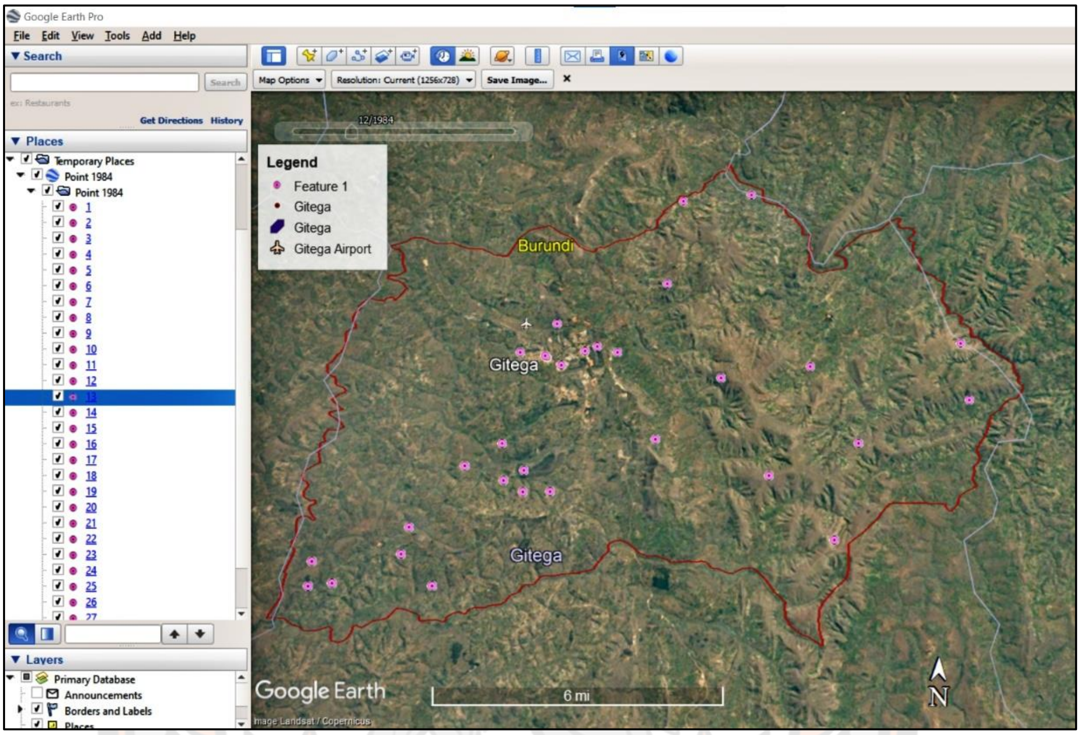
Class Name	**Class Id**	**Shape ***	**Point Id**	**MLC/User**	**GEE/Producer**
Agriculture	1	Point	15	1	1
Built-up Area	2	Point	8	1	1
Grass Land	3	Point	30	1	1
Shrub Land	4	Point	18	1	3
Trees Cover	5	Point	23	1	1
		Point	25	1	1
		Point	5	1	1
		Point	22	1	1
		Point	1	2	2
		Point	9	2	2
		Point	13	2	2
		Point	3	3	3
		Point	17	3	3
		Point	11	3	3
		Point	20	3	1
		Point	12	3	3
		Point	7	3	4
		Point	10	3	3
		Point	19	3	4
		Point	28	4	4
		Point	15	4	4
		Point	26	4	4
		Point	2	4	4
		Point	6	5	5
		Point	4	5	5
		Point	14	5	5
		Point	16	5	5
		Point	24	5	5
		Point	27	5	5
		Point	21	5	5

Appendix A3. Detail of random points used for 2019accuracy assessment

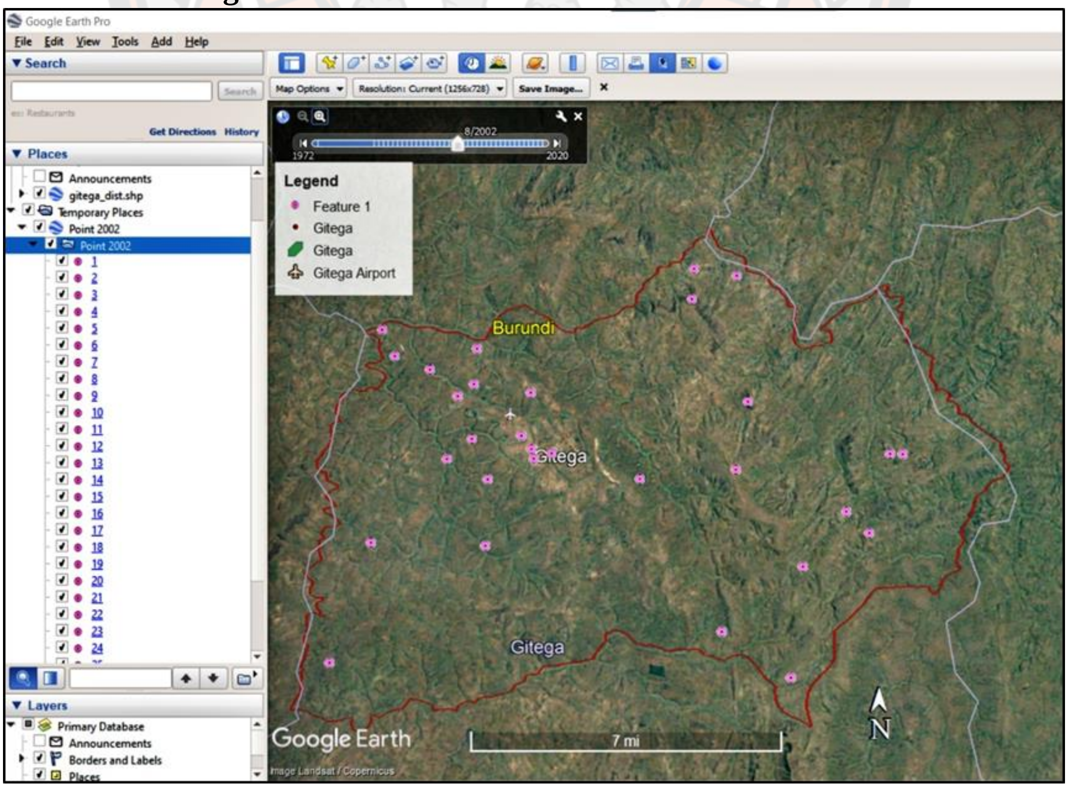
LClass Name	Class Id	Shape *	Point Id	MLC/User	GEE/Producer
Agriculture	1	Point	2	1	1
Built-up Area	2	Point	9	1	1
Grass Land	3	Point	11	1	1
Shrub Land	4	Point	15	1	1
Trees Cover	5	Point	17	1	1
		Point	18	1	1
		Point	28	1	1
		Point	1	2	2
		Point	8	2	2
		Point	20	2	2
		Point	23	2	4
		Point	29	2	2
		Point	3	3	3
		Point	6	3	3
		Point	10	3	3
		Point	13	3	3
		Point	16	3	3
		Point	19	3	3
		Point	21	3	3
		Point	22	3	3
		Point	25	3	4
		Point	4	4	4
		Point	12	4	4
		Point	24	4	4
		Point	26	4	4
		Point	5	5	5
		Point	7	5	5
		Point	14	5	5
		Point	27	5	5

Appendix B1. Aerial Google Earth image synchronized with random points for accuracy assessment

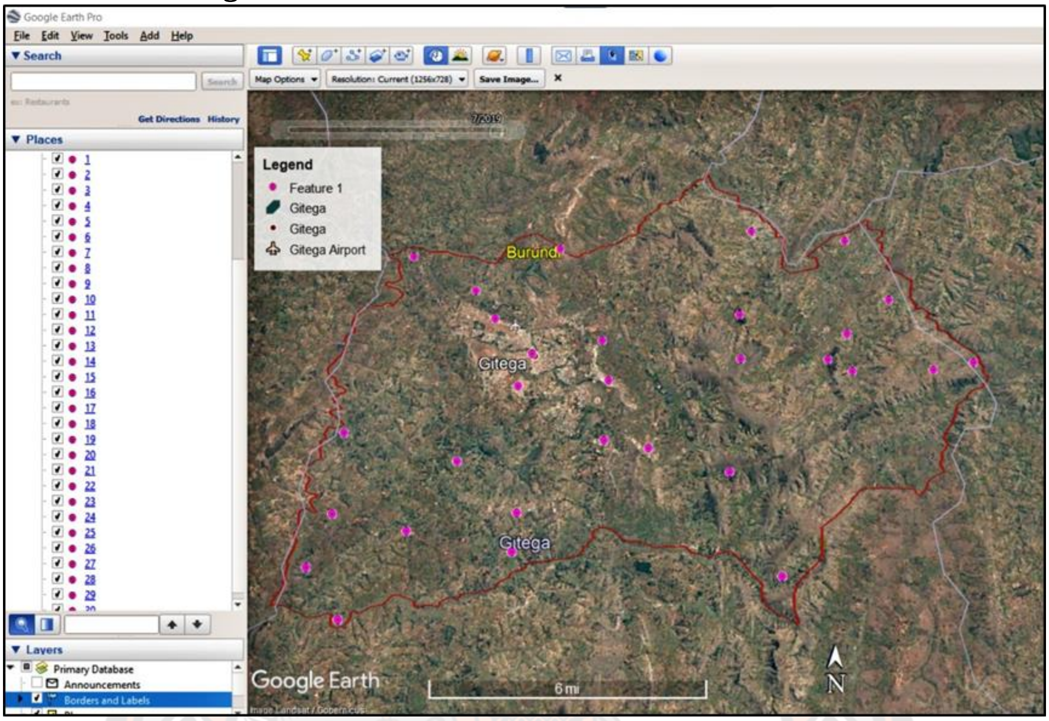
a. **1984 image classification**



b. **2002 image classification**

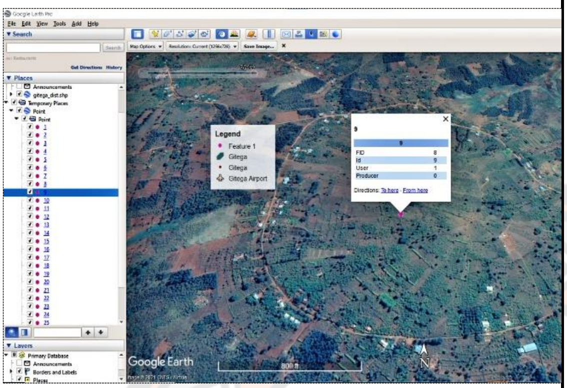


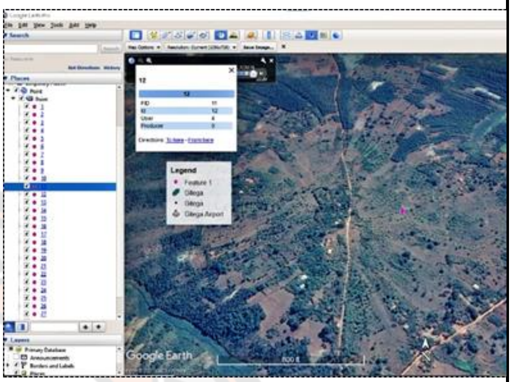
c. 2019 image classification



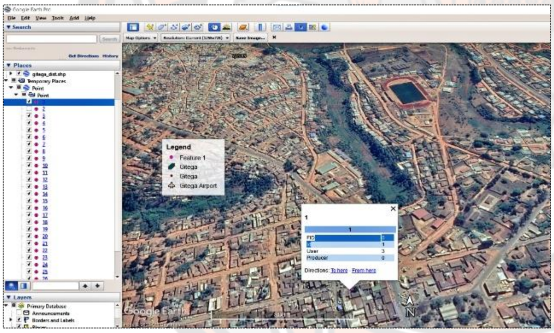
Appendix B2. Examples of Land use and land cover classes corresponding to the Raster classification for 2019 LULC map

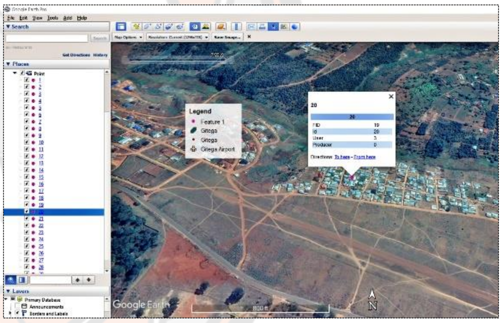
Agriculture



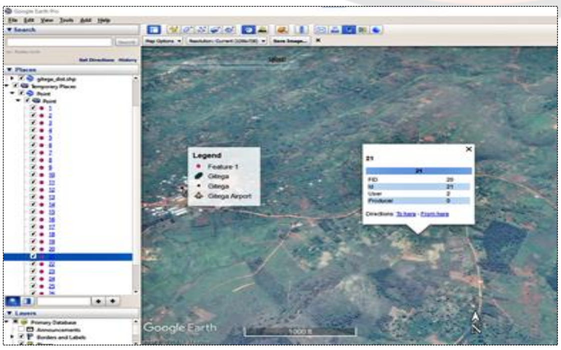


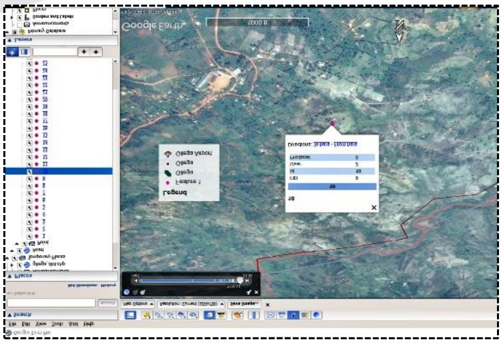
Built-up Area

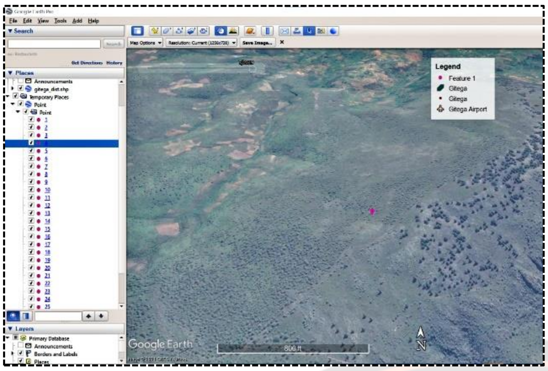
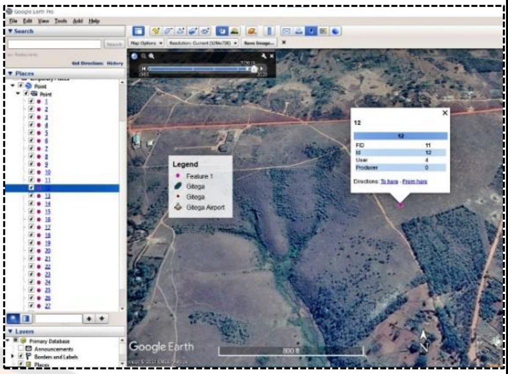
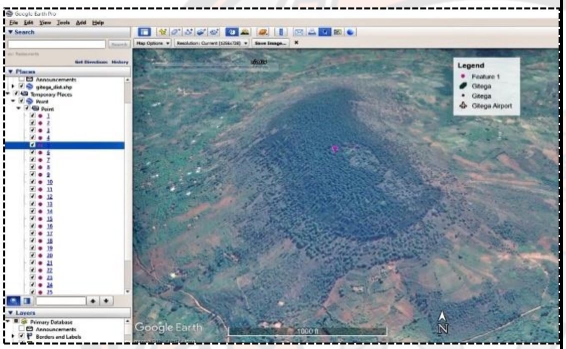
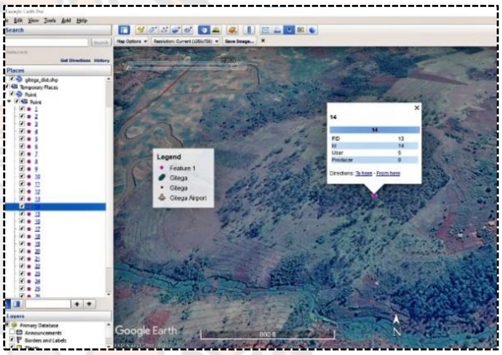




Grass Land





Shrub Land	
	
Trees Cover	
	

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