LAND USE /LAND COVER CHANGE AND ITS DRIVING FORCES IN MAGO NATIONAL PARK, SOUTHERN ETHIOPIA

MSc. THESIS

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LAND USE /LAND COVER CHANGE AND ITS DRIVING FORCES IN MAGO NATIONAL PARK, SOUTHERN ETHIOPIA

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A THESIS SUBMITTED TO THE DEPARTMENT OF GENERAL FORESTRY,
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IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE

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DECLARATION

I, Aklilu Wodebo Wola, hereby declare to the school of graduate studies, Hawassa University that this is my original work and all sources of materials used are duly acknowledged. This work had not been submitted to any other educational institutions for achieving any academic awards.

Aklilu Wodebo Wola	______________________	____________________
	Signature	Date

Approval sheet I

This is to certify that the thesis entitled **"Land Use /Land Cover Change and its Driving forces in Mago National Park, Southern Ethiopia"** submitted in partial fulfillment of the requirement for the degree of Masters of Science in Forest Resource Assessment and Monitoring, has been carried out by **Aklilu Wodebo**, **Id. No MSC/FrAm/R003/10** under my supervision. Therefore, I recommend that the student has fulfilled the requirements and hence hereby can submit the thesis to the department.

Aklilu Wodebo	______________________	______________________
	Signature	Date
Mersha Gebrehiwot (PhD)	______________________	______________________
Name of Advisor	Signature	Date

Approval sheet II

We the undersigned members of the Board of Examiners of the final open defense by Aklilu Wodebo have read and evaluated his thesis entitled **"Land Use /Land Cover Change and Its Driving forces in Mago National Park, Southern Ethiopia**" and examined the candidate. Accordingly, this is to certify that the thesis has been accepted in partial fulfillment of the requirement for the degree of Master of Science.

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Name of the Chairperson	Signature	Date
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Name of Internal Examiner	Signature	Date
______________________	____________________	__________________
Name of External Examiner	Signature	Date

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Contents

List of Acronyms

AOI	Area of Interest
CSA	Central Statistical Agency
FAO	Food and Agriculture Organization of the United Nations
FGDs	Focus Group Discussions
GIS	Geographic Information System
GPS	Global Positioning System
GTP	Ground Truthing Points
Ha	Hectare
HHS	Household Survey
Km	Kilometer
KIIs	key Informant Interviews
LULC	Land Use Land Cover
LUCC	Land Use Land Cover Change
M.A.S.L	Meters Above Sea Level
MNP	Mago National Park
MS	Micro Soft word
NASA	National Aeronautics Satellite Agency
NMAE	National Meteorological Agency of Ethiopia
NGOs	Non-Governmental Organizations
NIR	Near Infra-Red
OLI/TIRs	Operational Land Imager/Thermal Infrared sensor

QGIS	Quantum Geographic information Science
RGB	Red Green Blue
RS	Remote Sensing
SNNPR	Southern Nation Nationalities and peoples Region
SPSS	Statistical Package for the Social Sciences
TM	Thematic Mapper
USGS	United States Geological Survey
UTM	Universal Transvers Mercator
WGS84	World geodetic system 84

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Abstract

Land use land cover change analysis is one of the most particular techniques to understand how land was used in the past, what types of changes are to be expected in the future, as well as the forces and processes behind the changes. Thus, the objective of this study was to investigate the land use land cover changes and its driving forces in Mago National Park, southern Ethiopia. Satellite image of Landsat5 TM (1988, 1998 and 2008) and Landsat8 OLI/TIRS (2018) with a time span of 30 years were employed. In addition, field observation, and social survey were conducted to study the drivers of land use land cover changes. QGIS 3.2 and SPSS (for social data analysis) softwares' were used for satellite image processing, accuracy assessment, map preparation and descriptively analyze the driving forces of LULCC respectively. Supervised classification with maximum likelihood algorithm was conducted for satellite image analysis and generation of information using Quantum GIS 3.2 Post classification change detection method was applied to quantify the land use/land cover change. The result of the study indicated riverine forest, woodland, grassland, water body, degraded land and bare land as a major land use land cover class in the park. The result of land use land cover classification showed that in 1988 most of the study area was covered by woodland and grass land. In the first period (1988-1998), woodland, riverine forest, water body and bare land decreased by 6.76%, 37.98%, 22.37% and 70.14% respectively, while grass land, and degraded land increased by 16.11% and 85.67% respectively. In the second period, (1998 -2008), woodland, riverine forest and degraded land were decreased by 5.44%, 4.61%, and 80.74% respectively, while grass land, water body and bare land is increased by 14.74%, 3.76% and 52.58% respectively. From 2008-2018 riverine forest, grassland, water body and bare land decreased by 1.33%, 15.16% and 4.82% and 25.02% respectively, while woodland increased by 11.84%, and degraded land increased by 85.49% respectively. Riverine forest, water body, grass land and bare land showed decrement and that of woodland, degraded land indicated increment during study period. From 1988-2018, woodland, riverine forest, water body and bare land indicated decrement and the remaining grass land and bare land cover types indicated increment during study period. The result of social survey indicated that expansion of agriculture, human induced fire, overgrazing and hunting are proximate driving forces of the change in Mago National Park. Population pressure from a different area, poverty, decreased farmlands productivity; education, weak law enforcement and cultural factors are the major underlying causes of the observed changes. Therefore, proper land use planning, legal support, and strong law enforcement are the key recommendations to sustain natural resources of the study area.

Key words: *Social survey, Mago National Park, Landsat, GIS, Remote sensing, land use land cover*

1 INTRODUCTION

1.1 Background

Land is defined as a place on which all human activity is being conducted. It also used to produce wealth, grow economies and used as source of water, food and energy. These services will continue if only the land is not destroyed or degraded by human based actions (Molla, 2014) as cited by Adane, 2016. In reality, there remain only few landscapes and inaccessible location on the earth that are still in their natural state (Gomez et al., 2016).

Land cover refers to physical characteristics of earth's surface captured in the distribution of vegetation, crops, water, asphalt, desert etc. created by human activities (Burka, 2008). Land cover is observed directly in the field or by remote sensing. Whereas, land use-refers to man's activities on land which directly related to land (Ellis, 2007). Land cover change is highly relevant to understand the causes of changes in biodiversity and the rates and cause of LULCC (Pandey, 2002). LULC dynamics modify the availability of resources including vegetation, soil, water and others. Humans have been modifying land to obtain food and other essentials for thousands of years. LULC is important component to understand interactions of human activities with environment (Ellis, 2007).

To understand how LULCC affects earth systems, information is needed on what changes occur, where and when they occur, the rate at which they occur and the social and physical forces that drive those changes. LULC change occurs due to a natural or anthropogenic phenomenon (Pandian et al., 2014). The driving forces of LULCC are generally subdivided into two groups: proximate and underlying causes. Proximate causes are the activities and actions of local people that directly affect land use in order to fulfill their needs from the use of land. However, underlying causes are often external and beyond the control of local communities and are fundamental socio-economic and political processes that push proximate causes into immediate action on LULC including demographic, economic, technological, institutional and cultural factors (Haile, 2017). Economic factor is one of the major principal causes of LULCC. Economic variables such as low domestic costs, and increase in product price influence land use decision making by impacting land cover (Geist and Lambin, 2002). Cultural factors encompass motivations, attitudes, values and perceptions of individuals, communities and land managers. Proximate causes are immediate actions of local communities directly exerted on land resources due to underlying causes (Efrem et al., 2012). Recent changes in remote sensing and GIS have a new dimension and interactive approaches in mapping of land resources. During the last three decades, the availability of remotely sensed data with improved spatial and temporal resolutions have generated more energy to establish a proper relationship amongst various associated LULC (Wright et al., 2009).

In Ethiopia, fast population growth and spatial distribution have been affecting resource use (Tefera, 2011). Assessing the status of LULCC due to rapid growth of population, land degradation and poor resource management is essential. For better environmental analysis and sound decisions, reliable information about LULC is vital (Gebiaw et al., 2017; Tilahun and Teferi, 2015). Ethiopia is characterized by reduction of forest, woodlands, grasslands and shrub lands (Mideksa, 2010).
Change detection is a process of identifying changes in the state of an object by observing images at different times. The change detection studies try to find: pattern of LULCC, processes of LULCC and human response to LULCC. Change detection involves the ability to quantify temporal changes in LULC using multi-temporal data sets (Abd et al., 2016). There are four aspects of change detection which are important when monitoring natural resources. They include; detecting changes that have occurred; identifying nature of change; measuring area extent of change and lastly, assessing spatial pattern of change (Macleod and Congation, 1998). Monitoring

of land use/ land cover change is one of the main applications of remote sensing-based change detection (Franklin et al., 2000: Franklin, 2001) cited by Ratnayake, 2004.

The use of remote sensing data provides the most accurate means of measuring the extent and pattern of changes in cover conditions over a period of time (Miller et.al., 1998). Remote sensing has an important contribution for documenting the actual change in LULC in regional and global scales. Knowledge about LULC dynamics become important as the nation plans to overcome the problems of uncontrolled development and deteriorating of environmental quality as a whole (Alqurashi and Kumar, 2014). Satellite remote sensing data with their repetitive nature have proved to be quite useful in mapping LULC patterns and changes with time. GIS and RS techniques provide effective tools for analyzing land use dynamics (Sarma et al., 2001). Change detection analysis was performed to determine the nature; extent and rate of land cover change over time and space. This in return used as inputs to land management and policy decisions with regard to deforestation, land cover conversion and land degradation. Therefore, the aim of this research was, to assess, monitor, characterize and analyze spatio-temporal LULCC, rate and its cause by using GIS and RS technology in case of MNP, southern Ethiopia.

1.2 Statement of the Problem

LULCC modify availability of different important resources including vegetation, soil, water etc. Due to rising of population, lots of pressure has been imposed on the land resources in past years through worldwide (Bruijnzeel, 2004). The main problem in resource management is contained in how to take fast, consistent, accurate, cost-effective and up to date information. Reliable information on the status and trend of resources helps decision-makers for orienting policies and programs (Steven and Franklin, 2001). LULC has been intensely subjected to change globally in the form of conversion and their environmental functions and services have been weakened from time to time (Geist et al., 2006).

Ethiopia is a country well-endowed with diversified natural resources. Mago National Park is rich in different ecosystem and biodiversity. It is home for several fauna and different species (Wikipedia). Like many other developing countries, Ethiopia has been experiencing environmental degradation problems like LULC conversion, soil erosion, loss of forest and other vegetation covers and water resource degradation (MoA and WB 2007 cited by Berhan Gessesse and Woldeamlak Bewket, 2014). The rapid population growth and the low economic living standard have brought change in climate and hydrological status in the country (Haile, 2017). There are six ethnic groups which found around Mago National park, rely on natural resources for their fodder, firewood, and food. Most user settlements are located on the margins of the conservation area and have limited infrastructures and access to social services (Graham et al., 1996).

In Mago national park, however, the rate and areal extent of the LULC change is not well studied till date and also there is no full document which shows the clear trend, pattern and status of LULC change in the park. The natural resource management and LULCC status of Mago national park is not clearly stated and document for researchers and other audiences. Therefore, in view of the literature gaps indicated above this research was analyzed the LULCC and driving forces of change in the park from 1988 to 2018. Thus, for a sustainable LULC management in the Mago national Park, it is necessary to estimate and analyze land cover change on large spatial and temporal scales. LULCC detection based on remote sensing data has been established as essential tool for providing suitable and wide-ranging information to various decision support systems for natural resource management and sustainable development (Das, 2009). Remote sensing provides effective tool for monitoring different LULCC in big countries like Ethiopia. Analyzing land cover change is important for proper land use planning, management, decision making and implementation of different strategies in the park by looking back to the past, checking present and planning the future. Therefore, LULC change study is essential in describing the past and current situation and provides a starting point for present and future planning. This study, therefore, aimed to derive reliable information about LULC change, trends, magnitude and its causes for the selected study years from 1988 to 2018 using GIS and RS techniques in Mago National Park.

1.3 OBJECTIVES

1.3. 1 General Objective

- The general objective of the study was to investigate the trends and drivers of land use/land cover change in Mago National Park from 1988 to 2018.

1.3.2 Specific Objectives

The specific objectives of the study are;

i. To analyze land use/ land cover change in Mago National Park between 1988 and 2018

ii. To investigate the major driving forces behind the LULC changes in Mago National Park.

iii. To understand the perception and attitude of the local community towards land use/ land cover change in the Mago National Park.

1.4 Research Questions

The following research questions were designed to guide the study

i. What are the trends of LULCC in Mago National Park from 1988 to 2018?

ii. What are the major driving forces to land use/land cover change in the study area?

iii. To what extent is community aware on the factors that have driven the changes in LULC from the last three decades?

1.5 Significance of the Study

This research will help to get full information regarding LULCC that took place during the study periods; period 1 from 1988 to1998, period 2 from 1998 to 2008, period 3 from 2008 to 2018. Also, which land cover is dominant in the park, what are the driving forces of the change, the effects of change that happened in Mago National Park from 1988 to 2018. The satellite imageries help to show the real pattern of LULC in the study area for last 30 years. This finding mainly essential for Mago National Park managers, development planners, protected area managers and NGOs who have interested on land resource management programs as it evaluates the impact of their program on the well-being of land and base for further natural resource conservation. It also introduces the efficiency and accuracy of satellite images to indicate LULCC in combination with ground-based measurements. By analyzing LULCC trend and driving forces, it helps to understand how land has been used in the past, what type of changes are there currently. Moreover, it can provide data to policy and decision makers to design appropriate policies and strategies for monitoring resource degradation and promote sustainable management of resources.

1.6 Scope and Limitation of the Study

The research area is limited geographically to Mago National Park. The study investigated LULCC and associated driving forces in the park. Furthermore, the study includes the analysis and observation of the trend and magnitude of change by using both RS satellite images and ground-based measurements from the period 1988 to 2018 by using different analytical methods and software's. This study is having many limitations occurred during data collection like, unwillingness of some interviewees in providing correct data. The high-quality image resolution was not used for this study because of expensiveness of the images In fact, different data confirmation and validation methods were employed to reduce the limitations of this study to some extent. The study site has no well-arranged and written materials.

2 LITERATURE REVIEW

2.1 Land use and Land cover Change Concepts

Land use is the function of land to humans which usually emphasis the importance of land in an economic activity. The term land use relates to the human activity or economic function associated with a specific piece of land (Thomas et al., 2015). The term land cover relates to the type of feature present on the surface of the earth. Land use and land cover share a common source of change in the form of human activities that directly alter the physical environment (Campbell, 2002). Over the years, humans have attempted to extract higher value from land by converting/modifying natural cover types through diverse uses. Land use has been changing since people first began to manage their environment. The high spatial variability in LULC type, biophysical and socio-economic drivers of LULCC around the world result in variability in the causes and processes of LULCC (Serneels and Lambin, 2001).

2.1.1 Land Use Land Cover Change at Global and Ethiopia Perspective

LULCC occur at all scales, and changes at local scales can have cumulative impacts at broader scales. It has been stated that LULCC are driven by natural processes and direct effect of human activity. According to Lambin et al., (2003) land cover transformation did not stop, rather accelerated with the onset of industrial revolution, globalization of world economy, expansion of population and technological capacity.

Ethiopia had huge diversity in biological resources: forest, woody, and grass lands, shrubs and varied wildlife. Over the past decades, Ethiopia has seen a large increase in population and associated demand for agricultural products, which has caused increasing pressure on land resources (Messay, 2011; Molla, 2014). As a consequence, the country has experienced widespread conversion of natural vegetation into farmland, degradation of existing arable land, and reduced productivity. LULCC resulted in local climate change, noticeable as changes in rainfall patterns and increased frequency of droughts (Efrem et al., 2012; Kindu et al., 2013).

2.2 Driving Forces of Land use Land cover change

The main driving force of LULCC categorized in to technology capacity, socioeconomic organization, level of development and culture. In addition, extraordinary increase of population and the worldwide changes in lifestyles which are partly explained by rising per capita income and the growing influence of geopolitical, economic and military structure and strategies as important drivers (Heilig, 1994). The fundamental causes of LULCC includes deforestation, agricultural expansion, fuel wood consumption, demographic factors, institutional factors and their interaction with individual decision makers (Alan, 1999; Lambin and Geist, 2007). The efficacy of satellite image use can be improved by incorporating detailed field studies data. A narrative perspective of local resident perceptions can help to develop an understanding of land cover change and historic natural events (Bruzzone, 1997).

2.3. Perception and attitude of the local community towards LCC

The analysis of community perceptions has gained popularity as a starting point in the context of resources management as local inhabitants possess far-reaching knowledge about their resource situations and problems. In other words, the use of geographic space is influenced by human perceptions and values (Creswell 2009). Lack of information about farmers understanding, preferences and priorities constrains planning of targeted land management strategies (Crossland et al.2018). Hence, for acceptable, effective and sustainable interventions such as for environmental management decisions, capacity building, awareness raising campaigns and public participation, exploring the local knowledge and perceptions is essential. decisions, capacity building, awareness raising campaigns and public participation, exploring the local knowledge and perceptions is indispensable. In general, perception is characterized by a number of factors, which are collected over the years. Human beings are in search of patterns and interrelations, in other words "readable and understandable spaces" (Esteves,2013).

Although physical conditions might be the same, the background of people's experience differs for each individual. This has implications for the sensual impressions that people develop and which determine their individual assessment of the world. In people's imagination, landscape consists mainly of natural elements and elements of a traditional cultural landscape. Two questions are important when considering the perception of landscape: (1) Which objects are recognized by a person? and (2) What value does the perceived object currently have? The views of the local people on the effects of land use/cover change can be analyzed through interviews and discussions. The local community perception towards land use/land cover change may be of highest of the good results like income and employment. The negative perception of local community regarding land use/land cover change includes no trees in the future since they are being cut down, loss of agricultural land etc. The anthropocentric concept that change will be detrimental to human existence and secondly that changes will be detrimental to life forms and environments on earth for which we steward.Contrary to government policy to alleviate poverty, the local people had a negative attitude (de Schutter 2011).

2.4 Digital Change Detection

Digital change detection is a technique used in remote sensing to determine the changes in a particular object of study between two or more time periods. It identifies differences in the state of an object by observing it at different times. Change detection analysis identifies and locates differences in the patterns of two temporal datasets at times t_0 and t_1 (Singh, 1989) (Thomas et al., 2015). It is useful in deforestation assessment, urban expansion and planning, damage assessment, crisis management and response, crop stress detection, etc. (Jensen, 1996).

2.5 Remote sensing and LULCC

2.5.1 Definition and History of Remote Sensing

Remote sensing is a science and art of obtaining information about an object or phenomenon through the analysis of data acquired by a device that is not in contact with the object, area or phenomenon under investigation (Thomas et al., 2015). The sensors that currently in use for recording information are divided in two groups: active and passive systems. The active sensors generate and transmit signals towards the object, then receive and record the returned signals after its interaction with the object. The passive sensors do not generate signals but detect and record the natural EME reflected and/or emitted from an object (Gibson and Power, 2000). The first Earth observation using a balloon in the 1860s is regarded as an important benchmark in the history of remote sensing (Lillesand et al., 2004). As technology advances, new methods are being developed all the time to cope with higher spatial resolutions, new data types and a combination of different data sources (Hoffman et al., 2001).

2.5.2 Remote Sensing for Land use Land cover Monitoring

Remote Sensing is a tool to make better resource management decisions. It can inform us in four areas: 1. Inventory –how much is there (hectares)? 2. Mapping –where is it (map)? 3. Classification –what is it (stratum)? 4. Monitoring –has it changed (gain or loss of forest)? The value of forests to the world's population is becoming increasingly evident and is clearly highlighted by the numerous multilateral environmental agreements (Defries and Achard, 2002). Remote sensing techniques provide a powerful tool for obtaining such information on vegetation. The reflectance characteristics of vegetation are dependent on the properties of the leaves including the orientation and the structure of the leaf canopy. In the visible portion of spectrum, reflection from blue and red light is comparatively low since these portions are absorbed by the plant for photosynthesis and vegetation reflects comparably more in the green light. The reflectance in the near infrared is highest but the amount is proportional to the leaf development or the cell structure of the leaves (Steven and Franklin, 2001).

2.5.3 Landsat Background in Remote Sensing

2.5.3.1 Thematic mapper (TM) and image

It was the launch of the first civilian RS satellite which is Landsat 1 in July 1972 that paved the way for the modern remote sensing applications in many fields including natural resources management. Approximate scene size is 170 km north-south by 183 km east-west. Landsat 5 Thematic Mapper (TM) was launched in 1984 and Landsat 5 images consist of seven spectral bands with a spatial resolution of 30 meters. Landsat5 TM operational imaging ended in November 2011 (Csaplovics 1992, Lillesand et al., 2004).

2.5.3.2 Operational Land Imager (OLI/TIRs)

Landsat8 is an American Earth observation satellite launched on February 11, 2013. It is the eighth satellite in the Landsat program; the seventh to reach orbit successfully. Originally called Landsat Data Continuity Mission (LDCM), it is collaboration between NASA and USGS. During the first 108 days in orbit, LDCM underwent checkout and verification by NASA and on 30 May 2013 operations were transferred from NASA to the USGS. (http://earthobservatory.nasa.gov/IOTD.)

2.5.4 Global Positioning System (GPS)

The development of satellite navigation systems was a major breakthrough in many fields. The navigation system with timing and ranging-GPS operated by the United States Ministry of Defense was the first system in place. It was developed in the late 1970s and 24 satellites were launched from 1989 to 1994. This technology may make it possible to navigate with higher accuracy, particularly in the open area like tropical dry region. There are many applications of GPS, some are navigation, positioning, time dissemination, georeferencing, site preparation, Insect and disease tracking, Forest fire monitoring and Research plots etc. (Kleinn, 2002).

2.5.5 Image Processing

Image processing is manipulating of remotely sensed digital data to create an end product, such as a change detection map. It includes four major components: preprocessing, classification, accuracy assessment, and change detection techniques. Furthermore, Landsat's spatial, spectral, temporal resolutions, its extensive and historical archive, and its accessibility have facilitated its use for monitoring LULC activities (Read and Lam 2002).

2.5.5.1 Pre-processing

Satellite imagery is affected by various factors, which decrease image quality. Moreover, image preprocessing is necessary before the information is extracted from the image because it ensures that the image is as close to the true radiant energy and spatial characteristics at the time of data collection. Therefore, preprocessing commonly comprises atmospheric correction, radiometric correction and geometric correction. Atmospheric errors are usually the result of haze, cloud or particles present in atmosphere. Geometric correction adjusts distortion effects due to Earth's rotation and curvature, sensor motion and adjusted by georeferencing (Lillesand et al., 2004).

2.5.5.2 Image enhancement

The image enhancement is employed to improve the visual interpretation of image, and the major purposes of it is to enhance the image contrast, and emphasize the necessary information in the image. Every pixel in an image has a range of brightness from 0 to 255. Moreover, the range of peak value is excessively steep and narrow which means brightness density of image is centralized (Ahlen, 2009).

2.6 Information Extraction and Classification

Classification is the process of sorting pixels into a finite number of individual classes based on their data file values. If a pixel satisfies certain set of criteria, it assigned to class that corresponds to those criteria (Jensen, 1996). The overall objective of classification is to automatically categorize all pixels in an image into land cover classes (Thomas et al., 2015). In order to improve the classification accuracy, the selection of appropriate classification method is required. This would also enable the analyst to detect changes successfully. Supervised classification is a type of the classification that is based on the prior knowledge of the researcher. In supervised training, the analyst relies on his own pattern recognition skills and a priori knowledge of the data to help the system to determine signatures for data classification. Since signatures need to accurately represent the classes to be identified, training samples might be selected repeatedly, evaluated and then new samples are taken or signatures are manipulated (merging, deleting) if necessary (Elnazir et al., 2004).

3 MATERIALS AND METHODS

3.1 Description of the Study Area

3.1.1 Location

Mago national park is one of the parks in Ethiopia located in SNNPR of Ethiopia. It is about 782 km south of Addis Ababa and north of a large 90° bend in the Omo River. The Mago national park was established in 1979. The Mago Park covers area about 1869.95 km^2. Geographically, the park lies between latitude 05°20'-05°50'N and longitude 36°00'-36°30'E. The elevation ranges from 400m.a.s.l on the plains in south, to 1,776 m on top of Mt Mago. The interior section of the park mainly consists of flat plains. However, periphery and boundaries, except to the south, are formed by the Mago and Mursi Mountains, associated ridges and chains of hills.

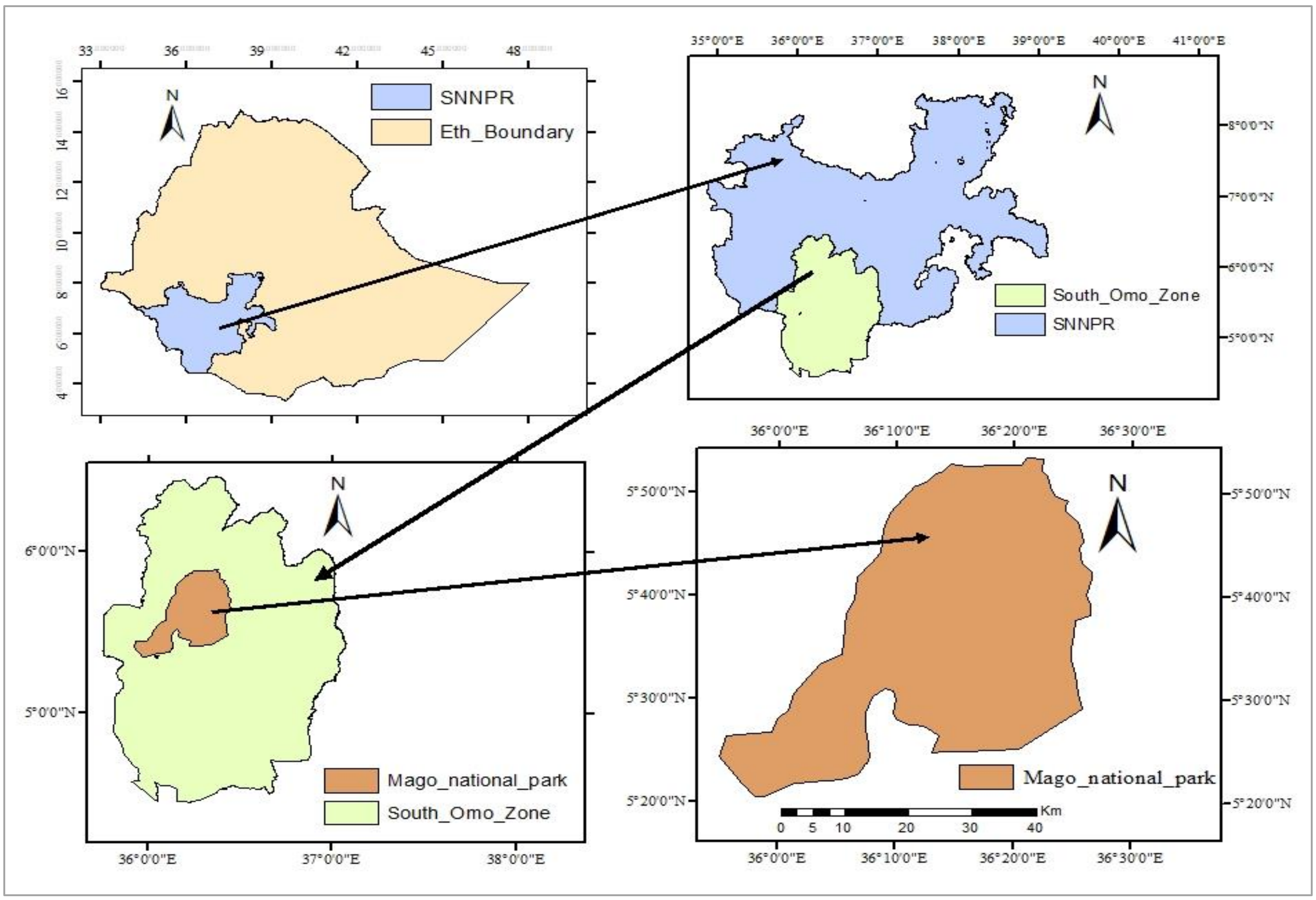


Figure 1: The Map of Study Site

The park is traversed by the permanently flowing Mago River and two of its tributaries, the Neri and Usno Rivers. The national park is bordered by three conservation areas: Tama Wildlife Reserve to the west, Omo National Park to the southwest and Murle Controlled Hunting Area to the south. MNP is surrounded by settled agriculturists and semi-pastoralists belonging to six tribal groups. The park office is 115 km north of Omorate and 26 km southwest of Jinka. Its highest point is Mount Mago 2528 meters. All roads to and from the park are unpaved. The Mago River traverses through the middle of the park and goes on to link with the Neri River at Mago Swamp. The river is about 750 kilometers long and comes from Gibe and finishes its journey at Lake Turkana. The park's headquarters is close to the Neri River and it is a dense forest area (Demeke and Bekele, 2000).

3.1.2 Climate of Mago National Park

The climate of Mago National Park is described as semi-arid with high mean annual temperature and solar radiation. The mean annual temperature varies from 24 to 38 °C. The annual rainfall recorded was 830 mm. The vegetation in the Mago Rift Valley is described as 50% of the area is bush and the rest is woodland, savanna bushland, savanna grassland and open grassland. The fauna of MNP is diverse. Some vertebrates are well documented by (Demeke and Bekele 2000).

3.1.2.1 Rain fall

According to the thirty-three years rainfall data of the study area from 1983-2016, the area has a bimodal rain fall distribution characterized by prolonged wet season from May to August (long rains) locally known as Kiremt and short wet season between September and November, locally known as Belg. The mean monthly rainfall of the area varies between 33.44 mm (February) and 168.95 mm (July). In January and February, the study area receive rainfall is less amount of rainfall.

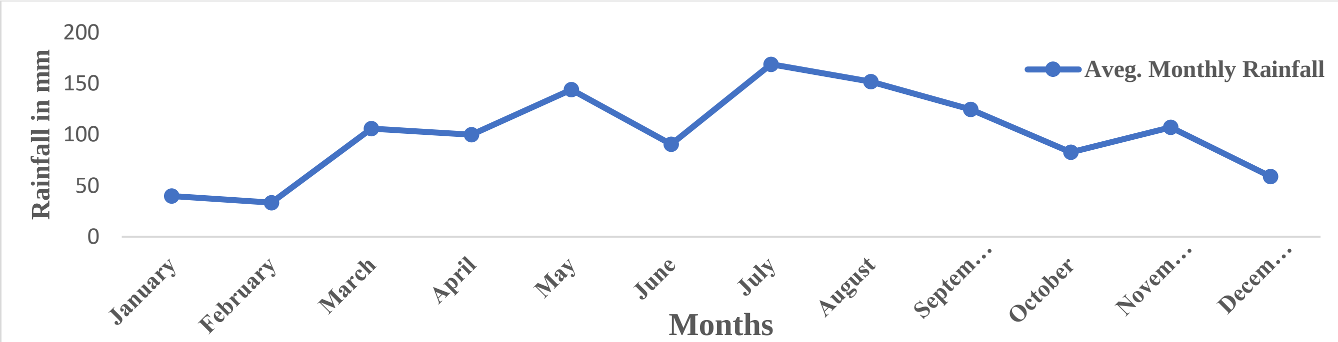


Figure 2: Average Monthly rainfall in MNP from 1983-2016 (Source: NMAE, 2019). Aveg.RF= Average rainfall

3.1.2.2 Temperature

According to the thirty-three years temperature data, average maximum monthly temperature is 34.79 °C and average minimum monthly temperature is 17.41°C

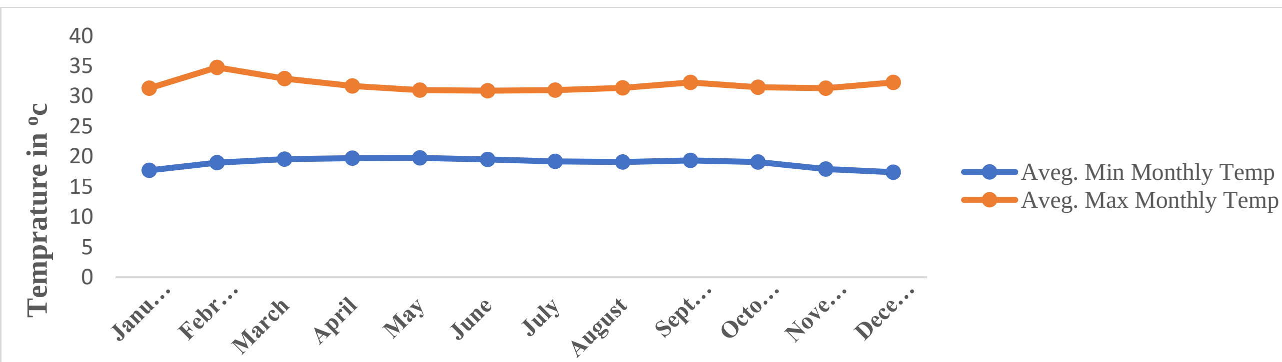


Figure 3: Average maximum and minimum monthly temperature of MNP from 1983-2016 (Source: - NMAE, 2019) Aveg.Min.Temp = Average minimum temperature, Aveg.Max.Temp = Average maximum temperature

3.1.3 Land features in the Mago National Park

In Mago National Park, fifty per cent of the area covers woodland (open and dense) and it consists savanna bushland, savanna grassland and open grassland. Currently, the park covers dense and open woodland, riverine forest grown around the river, rivers (Neri and mago) and ponds, grassland and degraded land. The extent of human disturbances is high in area of all the forest and other riverine vegetation (along the Omo, Mago and Neri Rivers) (Yirsaww and Afework, 2000).

The major surroundings in and around the Mago national park are the rivers and riverine forest, the various grasslands on the more level areas, and bush on the sides of the hills. There are mountainous areas with great views over the bush savanna. The largest trees found in the riverine forest beside Omo, Mago and Neri River. The riverine forest along the Omo River is important for several different bird groups, including herons and egrets, kingfishers, barbets, chats and thrushes, and flycatchers. One of the major attractions of the park is Hot Springs and areas along the lower Omo within the park are populated with a rich diversity of ethnic groups, including Aari, Male, Banna, Bongoso, Hamar, Kwegu, Karo and Mursi peoples. The park's best-known attraction is the Mursi, known for piercing their lips and inserting disks made of clay. (Demeke and Bekele 2000).

3.1.4 Wildlife inside Mago National Park

Mago National Park is on the route from Arba-Minch via Jinka to Lower Omo valley and it is a fascinating experience because of its isolated location and very few visitors and it gives a real feeling of how most of Africa was 50 years ago. The wildlife including most of the typical east African fauna and offers one of the wildest and most outstanding wildlife panoramas in Ethiopia. Mago National Park is considered an important habitat for animal populations particularly Buffalo, Giraffe, Elephant (approximately 150), warthog, tiang, lewel’s hartebeests, lesser-kudu. Greater-kudu, duiker, Burchell’s Zebra, Swayne’s Hartbeest, Oryx, Grant’s gazelle, gerenuk, giraffe. Cheetah, wild dog, lions, leopards, guereza, common baboon and vervet monkey are common and conspicuous. The Mago National Park is home to some 81 larger mammals and 300 species of bird (Demeke and Bekele, 2000). Hippos are widely distributed in Mago National Park. Leopards/Panthers can survive both hunting pressure and habitat change like in Mago National Park. Although rare, Lions, Elephants, and African Buffalos still roam the plains of MNP. Unfortunately, Giraffes have almost disappeared from the National Park. (Africa-Expert.com).

3.2. Materials Used

QGIS version 3.2 for image processing and SPSS IBP version 22 for the analysis of the driving forces of the change , MS Excel for statistical analysis , chart preparation,MS word for word - processing and GPS for field data collection were used.

3.3 Data Sources and Types

The primary data were collected by social survey (HHs, KIIs and FGDs) and GPS technology. Whereas, secondary data used include satellite image of selected years, Google earth, both published and unpublished materials, books, articles, reports and different materials from files of relevant institutions and internet websites about Mago National Park.

3.4 Data Collection Procedures

3.4.1 Spatial Data Collection

The required field data about the existing LULC types, historical trends in dominant LULCC and possible drivers of LULCC in the study area were collected using time series Landsat images downloaded for different Landsat groups. The selection of satellite images primarily considered: (i) the important events related to LULCC in the study area, and (ii) image quality to reduce the effect of fire and cloud cover. Based on this Landsat 5 TM (for the years 1988, 1998 and 2008) and Landsat 8 OLI/TIRs (for the year 2018) were used for the months with less cloud cover and fire effects. The satellite imageries from USGS earth explorer were downloaded for the chosen years (1988, 1998, 2008 and 2018). The satellites selected for this study are Landsat 5(TM) and 8 (OLI/TIRs). Landsat satellite images obtained from USGS for four periods; 1988, 1998, 2008 and 2018. The images were extracted to Tiff formats for processing and the detail of image properties are summarized in (table 1 in appendix I). The images were acquired from period

February month, as it is a clear sky season in the region, reducing atmospheric problems. To avoid the adverse effect of cloud cover on LULC classification, satellite image with less than 5% cloud cover images taken during the dry season depended on their availability. Images were collected in different ways in order to identify surface features in the study area.

Furthermore, during data collection in the field, household survey (HHS), focus group discussions (FGD) and key informant interview (KII) recognized human activities around MNP started increasingly in 1988 and population grows fast from 1998 forward. Therefore, 1988 was taken as a base year before population growth occurred at a higher rate and 1998, 2008 and 2018 being years of higher population growth around the Park. All of the images were downloaded in dry season which is February to have cloud free images. GPS for field surveying and social survey such as HHS, FGD and KII were also employed.

Field observation

Field observation is a complex method of data collection which in its nature involves the investigator to critically observe the phenomena under its primary state using the five sense organs (Gorman and Clayton, 2005). Before starting the fieldwork, a reconnaissance survey and informal interviews were conducted with different authorized bodies inside the park. Information such as current land use practices and its status, population and livelihood strategies in terms of their pressure on resources in the park were obtained during the reconnaissance survey. Field observation was carried out continuously throughout the data collection period in the field. During field observation photos of current LULC types were collected by using camera to support different steps of image processing.

The use of random sampling method for accuracy assessment is by means of error matrix based on stratified and randomly selected points across the classified image. Instead of purely random method, stratified random sampling is usually recommended, so that the sampling points are fairly distributed in each LULC change class (Das, 2009). This Stratified Sampling method works by separating the whole study area/population into groups based on a factor that may influence the variable being measured. With stratified sampling**,** it is possible to: partition the population into groups (strata), obtain a simple random sample from each stratum and collect data on each sampling unit that is randomly sampled from each stratum. Stratified sampling works best when a heterogeneous population is split into fairly homogeneous groups. Therefore, LULC classes in MNP were grouped based on homogeneous classes and from individual classes samples were taken randomly using GPS. GPS data includes X, Y coordinate and other attribute data. A stratified random sampling method was employed to collect total of 465 points for classification accuracy assessment.

Household Survey

Household survey was conducted to collect qualitative data which indicate the driving forces that lead to LULCC in MNP. Face-to-face interviews in the form of HHS, KIIs, and FGDs which guided by a checklist, and structured questionnaires were used in this study. Data concerning the driving force of LULCC collected via HHS, FGD and KII were analyzed qualitatively. Speech transcription and comprehension of speeches techniques were applied. The questionnaires were comprised open-ended questions to gather information about the perceptions of local communities on LULCC, and the drivers of these changes in MNP during the studied period (1988 to 2018). A questionnaire was preferred for this study as it provides insight into the drivers of LULC changes. The study employed a simple random sampling method to select respondents for the household interviews. The questionnaire had three sections covering the demographic and socioeconomic characteristics of the household, perceptions of local communities on LULCC, and causes of LULCC (Appendix II). HHS, FGDs and KIIs were carried out to obtain and gain detailed understanding of local people's perceptions on LULCC that had taken place in the MNP. FGD and KII were conducted to understand proximate and underlying driving forces of the change.

Totally, 153 sample households were selected by using simple random sampling techniques from the total household (1905) of the sampled kebeles based on the formula below. The sample size of the study area was determined by using Kothari formula shown in below (Kothari, 2004). Simple random probability sampling was used for determined sample size. Kothari sample size formula for determining sample size was become;

$$n = \frac{Z^2 * p * q * N}{e^2(N-1) + Z^2 * p * q} \text{ .... } \{1\}$$ Where;

n = sample size, Z = 95% confidence limit (interval) that is 1.96 given or constant,

P = 0.1 (population proportion to be included in the sample that is 10%) =it depends, q = None occurrence of event = 1-p = 1-0.1 that is (0.9), N = total number of (household) found in the study area, e= level of accuracy or sampling error (Where, $\alpha = 0.05$).

Following the formula, 153 household heads were used for data collection through a structured questionnaire. The sample size is proportional to total member of household size of each Kebele.

No.	Name of Sampled Kebeles	Total household	Sample	Sample in percent
1	Baytsemal	656	51	33.34
2	Goldiya	752	54	35.29
3	Kure	497	48	31.37
Total		1905	153	100.00

Table 1: Household Sample size (Source: Woreda Administration Office)

Focus Group Discussion (FGD)

FGD is an instrument of data collection which involves investigator in gathering group of participants together to discuss a certain issue. The role is to introduce the problem for discussion and facilitate the group to engage deeply in discussion in a good manner (Obang O. et al., 2017). The aim of FGD was to assess and analyze the extent and trend of LULCC that discussants perceived to have occurred in the park during last 30-year period between 1988 and 2018 and associated driving forces behind such change. This helps to compare discussants perception with the result of the RS and GIS analysis. As the park covers large area, only kebeles which are closest to the park were chosen. Based on the interest of researchers and theme of study, the number of participants in FGD can range from 4 to 10 (Jayasekara, 2012). For FGD and KII three kebeles (Goldiya, Kure and Baytsimal kebele) were selected purposely. Those kebeles were selected by considering agro-pastoral areas, their higher dependency on the park, security issues and accessibility for researchers. The groups were formed based on the size of total household from each Kebeles.

The participants of FGDs were selected purposively. Two purposive criteria were used to select participants in FGD. The first criteria are the age of participants i.e. elder peoples (household heads) who have lived long time in the study area and had detail information about the past and present situations of the study sites. A second criterion is capability to understand the topics, express their feelings and opinions. Only participants who have lived in the study area over 30 years and show willingness to be interviewed were involved in the FGD. The selected participants were assumed to have good knowledge and capacity to describe the historical LULCC in the study area. Accordingly, each focus groups contain 5-6 participants including elders, experts, park managers and others who have knowledge about the park. Totally, 12 groups and from this, 4 groups for Baytsemal, 5 groups for Kure and 3 groups for Goldiya formed from three Kebeles which are at the border and closest to the park were selected. It provides the way to get a random and representative sample.

No.	No. of FGD	Kebeles			Total
		Baytsemal	Goldiya	Kure	
1	Elders	41	39	43	123
2	Experts	1	1	2	4
3	Youths	7	8	11	26
Total		49	48	56	153

Table 2: Description of FGDs for Interview

Key Informant Interview (KII)

The main objective of KII is to collect detail information from specific group of people like community leaders, elderly group and professionals who have firsthand knowledge about the problems in the community (USAID, 1996). To gain detailed and additional information and cross-check the data collected from FGDs, few KIIs also conducted. In this, sample elder person from each sampled Kebeles, one Natural Resource Conservation and Management Expert from sampled districts, one Land Administration Office Coordinator and one Kebele administrator from each sample Kebeles, one expert from the park and one manager of the park were involved. Totally, 14 key informants were selected. The selection of elder key informants executed using snowball sampling method with the help of FGD participants. In Snowball sampling method, investigator selects a person who matches the criteria and it is also called as chain sampling (Alvi, 2016). In this sense, one elder person from each group were selected.

No.	No. of KIs	Kebeles			Total
		Baytsemal	Goldiya	Kure	
1	Elders	3	4	4	11
2	Experts	1			1
3	Land administration office coordinator	1			1
4	Park manager	1			1

Table 3: Description of KIIs

3.4.2 Secondary Data Collection

The secondary data collection starts from collecting and reviewing related books, researches, articles, papers and other related documents, from internet and libraries, etc.

3.5 Method of Data Analysis

3.5.1 Satellite Image processing and Analysis

The collected data was analyzed using quantitative and qualitative approaches. The LULCC detection was based on quantitative analysis and the driving forces of the change was analyzed by using qualitative method. There are three stages of image processing which are pre-processing, image rectification and image enhancement as clarified below.

3.5.1.1 Satellite Image preprocessing

Pre-processing refers to those operations preliminary to the main analysis. In the acquisition of data by remote sensing systems, instruments are used to record the intensity of electromagnetic energy reflected from the Earth's surface (Mather, 1999).

Satellite image preprocessing, analysis and post processing are the main procedures and steps in GIS to generate valuable information for discussion, planning, policy making and research. Satellite image pre-processing before change detection analysis is very important in order to establish more direct affiliation between the acquired data and biophysical phenomena. Before data processing, in geographic information system the required bands of the images were pre-processed. The boundary of MNP fall between two image scenes. Therefore, mosaicking process was done to have full image which cover the whole area of the park. Then Image stacking, defining specific study area, band setting, and image enhancement are the major image pre-processing techniques were employed. Multi pre-processing tasks were taken in QGIS 3.2. Remote sensing data in a raw format generally contains flaws such as noise, haze effect etc. Therefore, following correction operations were performed on the data during the pre-processing stage: atmospheric and radiometric correction.

3.5.1.2 Image enhancement

In order to aid visual interpretation, the visual appearance of the objects in the image can be improved by image enhancement techniques. Therefore, Image enhancement involved mathematical operations that are applied to remote sensing input data to improve the visual appearance of an image for better interpretation following digital image analysis (Lillesand et al., 2004). However, Band 4, 3 and 2 (False color composite) were used for classification of LULC. All images processing was carried out using QGIS 3.2 software.

3.5.1.3 Visual image Interpretation and classification

Image interpretation and classification is the analysis of different data sources for generating information. Visual interpretation and identification of digital imagery performed manually or visually with the help of both software and analyzer. Spatial data was examined and displayed as colored image by combining different channels or bands that represent different wavelengths. The band combinations for the image classification process considered as Landsat TM (1988, 1998 and 2008) were 432 and in Landsat OLI (2018) were 543 in false color combination which band 4 and

5 correspond to NIR, and bands 2 and 3 correspond to visible Green and Red band respectively. Extraction of land cover information from remotely sensed data be performed using supervised classification.

3.5.1.4 Supervised Classification Method

The objective of image classification is to classify all the pixels in an image into different categories by users (Lillesand et al., 2004). The aim of this procedure was to generate spatially explicit generalizations that show individual classes selected to represent different scales of land classes. Supervised classification is the process of using a known identity of specific sites in the remotely sensed data, which represent homogenous examples of land cover types to classify the remainder of the image. These areas are commonly referred to as training sites (Jensen, 1996). Thus, each pixel in this step in the image is classified into different class it most closely resembles. Supervised classification involved with the human cognition and experience (Lillesand et al., 2004). Supervised classification with Maximum likelihood classifier was utilized for image Classification and for the preparation of base maps for change detection. Maximum likelihood classifier is one of the most common parametric algorithms for image classification (Lillesand et al., 2004). Maximum likelihood classifier assumes normal distribution for each band and calculates the probability that individual pixel belongs to a given class. Pixel-based classification methods automatically categorize all pixels in an image into land cover classes fundamentally based on spectral similarities (Qianet et al., 2007; Weng, 2012). Supervised classification is chosen because, it classifies land uses based on training sites which are assigned by Classifier.

3.5.2 Accuracy Assessment

The accuracy is typically used to express the degree of “correctness” of a classification result. To verify to what extent the produced classification is compatible with what actually exists on the ground it is important to evaluate the accuracy of classification results (Owojori and Xie, 2005). Overall accuracy is the proportion of the total correctly classified pixels on the total number of pixels in the map. The best way for checking the result of classification is to check everything in each class which can be realized in QGIS 3.2 by the function of accuracy assessment (Bakr et al., 2010). Evaluation of accuracy of classified image can be done using error matrix. In the error matrices, procedure' accuracy refers to the ratio which is calculated by the number of correctly classified pixels in one class dividing the total number of classified pixels of this class; the user's accuracy refers to the ratio which is calculated by the number of correctly classified pixels in one class dividing the total number of reference pixels in this class; the overall classification accuracy is calculated by the number of correct referenced pixels dividing the total number of classified pixels (Bakr et al., 2010).

The Kappa coefficient result values are between 0 and 1, where the latter shows complete agreement, and is often multiplied by 100 to give a percentage measure of classification accuracy. Kappa values are grouped into three: value of kappa coefficient greater than 0.8 (80%) represent strong agreement, value of kappa coefficient between 0.4 and 0.8 (40-80%) represents moderate agreement, and value of kappa coefficient below 0.4 (40%) represents poor agreement (Rahman et al., 2006). The user's (correctly classified sample units divided by the sum of reference data sample points in the error matrix) and producer's accuracy(correctly classified sample units divided by the sum of classified data sample points in the error matrix) as well as elements of the error matrix was calculated to assess error patterns of the respective classification. The reference data used for accuracy assessment were obtained from GPS points during field work and google earth. GPS points used in accuracy assessment were independent of ground truths used in the classification. Confusion matrix was generated by crossing the two maps generated using the training sets and the independent data. The diagonal values of accuracy assessment table describe, correctly classified percent of each LULC classes and the other non-diagonal values are those which are incorrectly classified classes. The producer accuracy, user accuracy, overall accuracy, and Kappa coefficient were calculated for of 1988, 1998, 2008 and 2018 based on the formula given by Congalton and Green (2009).

Producer's accuracy $i = \frac{n_{ii}}{G_{ii}}$ …………………………………… {2}

User's accuracy $i = \frac{n_{ii}}{C_{ii}}$ ………………………………. {3}

Over all accuracy $= \frac{\Sigma_{i=1}^{k} n_{ii}}{n}$ …………………………..... {4}

Kappa coefficient (K) = $\frac{\Sigma_{i=1}^{k} n_{ii} - \Sigma_{i=1}^{k} (G_i C_i)}{n^2 - \Sigma_{i=1}^{k} (G_i C_i)}$ ………….. {5} where,

i =the class number, n = total number of classified pixels that are being compared to ground truth nii =the number of pixels belonging to the ground truth class i, that have also been classified with a class i, Ci =the total number of classified pixels belonging to class i and Gi = the total number of ground truth pixels belonging to class i.

3.5.3 Change Detection

Successful use of remote sensing for LULC change detection largely depends on an adequate understanding of the study area, the satellite imaging system and the various information extraction methods for change detection in order to achieve the aim of the present study (Yang and Lo, 2002). After the image classification, the post classification change detection was performed and evaluated with "from-to" change information (Macleod and Congalton, 1998). Essentially, digital nature of most satellite data makes it easily amenable for computer aided analysis, to automatically correlate and compare two sets of imagery taken of the same area at different time (Ratnayake, 2004). Based on images from different periods, the change detection function in QGIS 3.2 was used to detect the changed areas. Therefore, change detection was done to see which land use is changed to which one. Finally, the table generated with overall information about change matrix between study periods. According to Abate (2011), to compute the rate of LULCC; the following equation was performed for computing rate and percentage of LULC change.

$$R = \frac{Q_2 - Q_1}{T} \text{--} \{6\}$$

$$\%R = \left(\frac{Q_2 - Q_1}{Q_1}\right) \times 100 \text{--} \{7\}$$ Where,

R=rate of LULC change %R = Percentage of LULCC Q2=recent year of LULC in sq.km

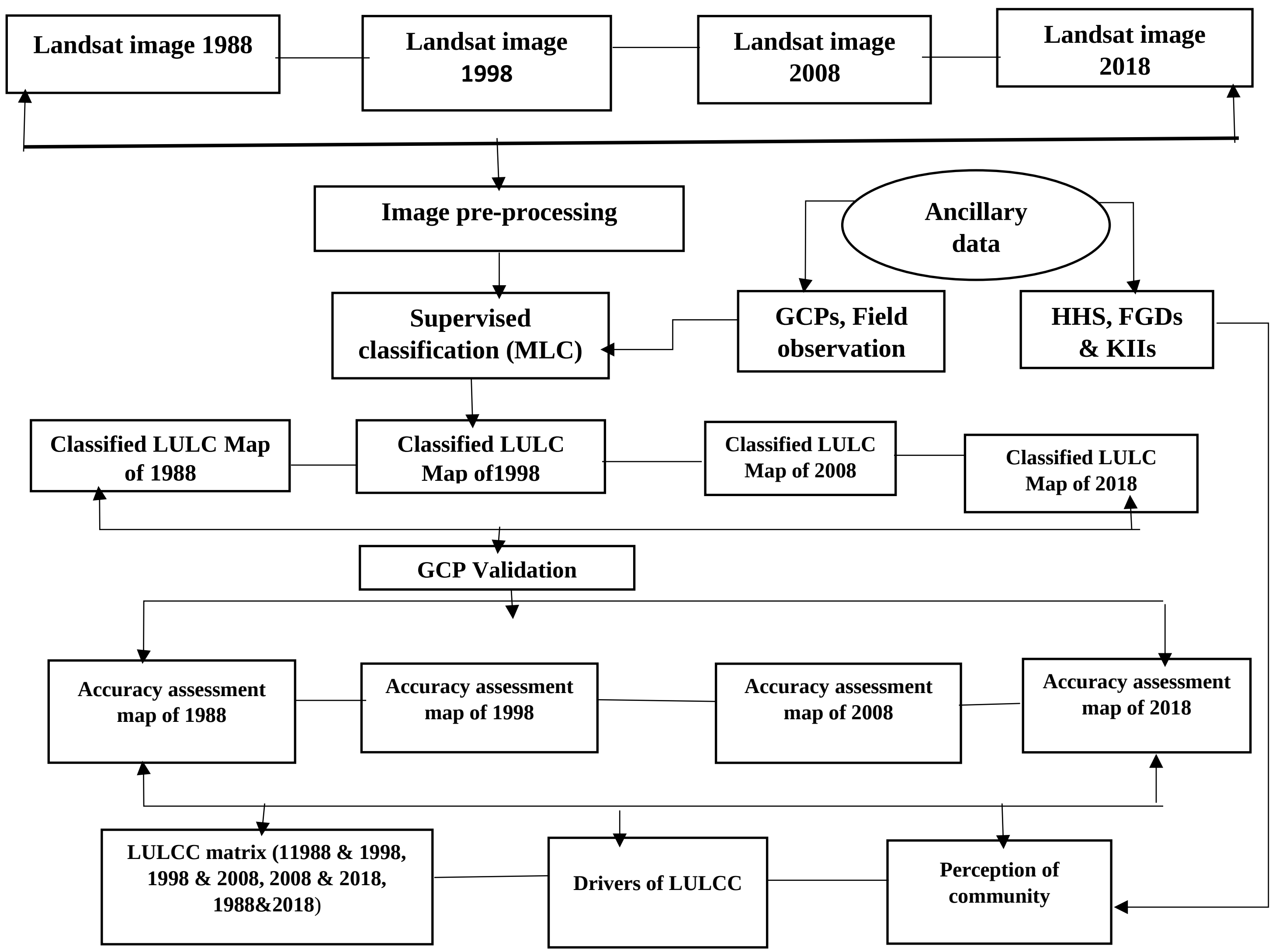
Q1= Initial year of LULC in sq.km, T = Interval year between initial and recent year

3.5.4 Identifying the driving forces of Land use/land cover Change in the Study Area

Assessing the driving forces behind LULCC is necessary if past patterns are to be explained and used in forecasting future patterns. Driving forces on LULCC can include almost any factor that influences human activity, including local culture, economics, environmental conditions, land policy and development programs and feedbacks between these factors, including past human activity on the land (DeFries et al., 2004).

Informal interviews with the local residents and stakeholders are crucial for understanding past land cover changes that might not be reflected in satellite images (Giri et al., 2003). All types of LULC including the services are highly affected by the rapidly changing world. Therefore, information from local inhabitants is an important aspect of land cover studies to better explain the local causal factors - in spite of the cost-intensive nature of collecting this data. Understanding factors that drives LULCC and its impacts in general is important for modeling, predicting environmental change and help respond to the change in most positive way to benefit the people (Tilahun and Teferi, 2015; Rawat and Kumar, 2015). Lastly, the causes of LULCC were identified based on interviewing park managers, workers, elders in nearby who have knowhow about the Park based on above discussed methods. This helps to identify the driving forces of LULCC on the Mago national park and to set different mitigation methods to minimize and control their impact on the park and to appreciate and continue if they have positive impact. The perception of community towards LULCC was also analyzed by using the result of feedback given by local community during field data collection.

Methodology Work Flow



4 RESULTS AND DISCUSSION

4.1 Land use/ land cover change trend and magnitude in Mago National Park

4.1.1 Characteristics of Land Use Land Cover Units

The result of classification based on supervised classification indicated six land cover classes: these were woodland, Grass land, riverine forest, water body, degraded land and bare land. The result of 1988 and 1998, 1998 and 2008, and 2008 and 2018 classification were used as inputs to produce change maps.

Table 4: Description of major LULC types identified in Mago National park

LULC types	Description
Water body	It refers to area naturally covered by water such as lakes, rivers snow or ice.
Woodland	Land that is mostly covered with dense growths of trees and shrubs that covers 0.2-20% of the area.
Grassland	Grasslands are areas where the vegetation is dominated by grasses
Riverine Forest	Expansion of forest on land until it was not defined as forest and which can be found mostly a long river or along valleys
Bare Land	Bare land is area that do not have an artificial cover as result of human activities. It includes bare rock areas, sands and deserts.
Degraded land	It is loss of production capacity of land and the reduction of the productive potential. It is the change in the provision of ecosystem goods and services.

Source: FAO,2013 Land Use Land Cover definition

4.1.2 Land Use Land Cover Mapping

Land Cover Types and its coverage in 1988

The classification result of year 1988 showed, six land cover classes with different percentage and area coverage in the park. In the classification forest was made to include natural forests around the river. In this classification, forests around river in Mago national park are grouped to have single class which is riverine forest for all of the classifications below this. According to Tesfaye et al., 2014 and Desalegn et.al., 2014, land cover types which cannot easily be identified grouped together to single class with highest reflectance. So, both researchers grouped both natural forest and plantation forests under forest category, rivers and forest around the river to riverine forest.

Table 5: Areas of LULC types in Mago National Park for the years from 1988 to 2018

LULC	**1988**		**1998**		**2008**		**2018**	
	Area (ha)	**%**	**Area (ha)**	**%**	**Area (ha)**	**%**	**Area (ha)**	**%**
Woodland	95109.99	50.85	88683.2	47.4	83860.28	45.38	93792.95	50.162
Riverine Forest	14106.59	7.59	8748.8	4.724	8345.24	4.998	8234.09	4.933
Grass land	66903.13	35.67	77679.64	41.42	89133.076	48.23	75616.79	39.843
Water body	278.81	0.14	216.43	0.222	224.57	0.157	213.74	0.168
Degraded land	2601.4	1.42	9276.34	4.96	1786.79	0.969	6403.14	3.435
Bare land	7990.454	4.33	2385.964	1.274	3640.418	0.266	2729.664	1.459
Total	**186990.374**	**100**	**186990.374**	**100**	**186990.374**	**100**	**186990.374**	**100**

From the classified image, the northern and southern mountainous area reflected in the same range as riverine forest and the percentage coverage of forest is higher. The LULC classification for 1988 from TM satellite image (Figure 4 below) showed that woodland (which include both dense and open) holds 50.85 %, riverine forest covers 7.59%, grass land holds 35.67%, water body (river and ponds) holds 0.14%, degraded land holds about 1.42% and that of bare land holds 4.33% of the park in 1988. The woodland and grass land are dominant cover types in the park, while water body holds very small percent in 1988 (Table 4 above).

The LULC classified maps were carried out successfully (see Figure.4-7 in below pages). The accuracy assessment indicated that the overall accuracies of classified LULC maps were higher than 85% (Tables 5- 8 below). The classified LULC map of 2018 was the highest with overall accuracy of 96.09% and kappa coefficient of 0.93, which the producer and user's accuracies of all land cover classes were indicated in (Table 5 appendix II). The classified LULC map of 2008 was gained overall accuracy with 94.25% and kappa coefficient with 0.90. In this classified map, the producer and user's accuracies of woodland, riverine forest, grassland, bare land and water body were indicated in (see Table 4 appendix). For other classified LULC maps of 1988 and 1998, the overall accuracies were 95.33%, 95.92% and the kappa coefficients were 0.90, and 0.912 respectively (Tables 2 and 3 appendix II).

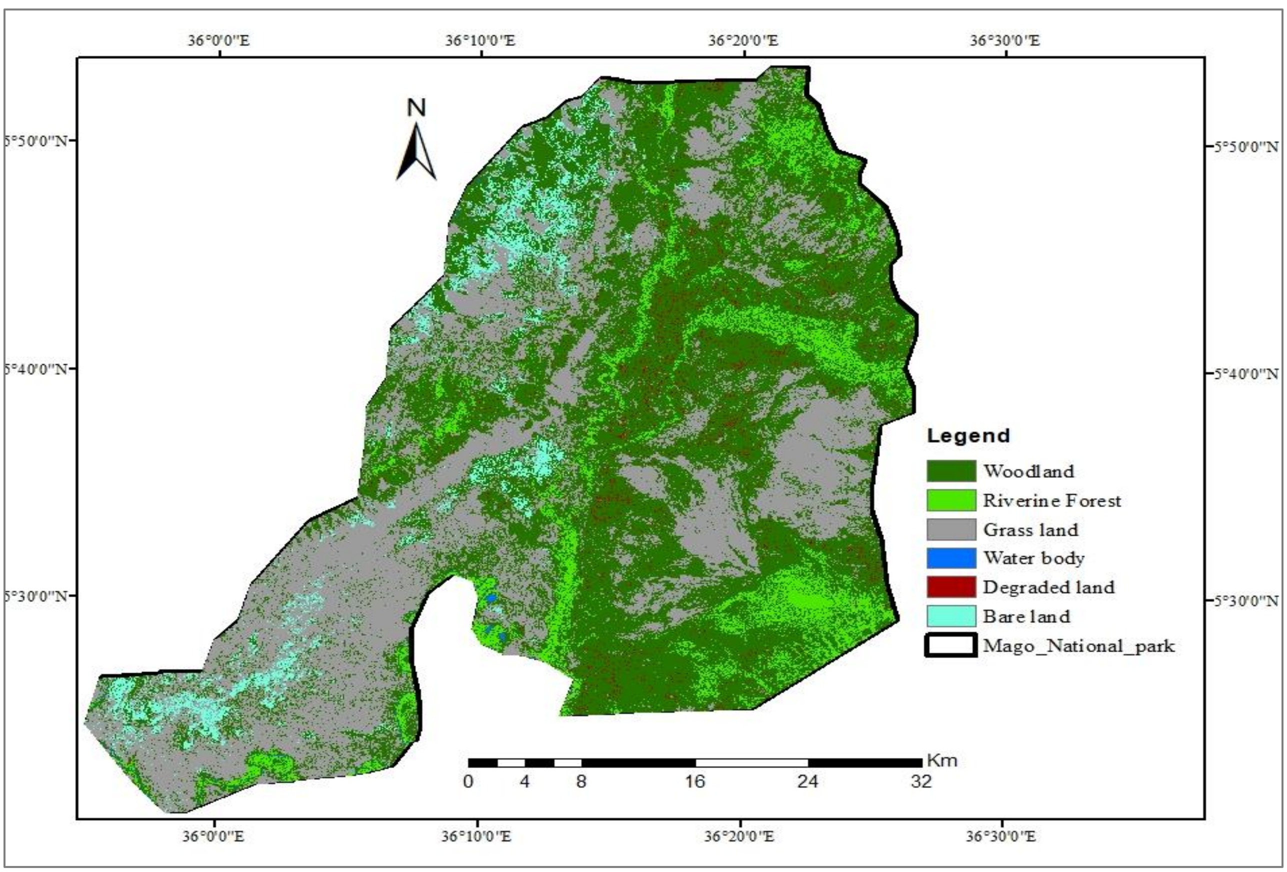


Figure 4a. LULC Map of MNP in 1988(source:Author)

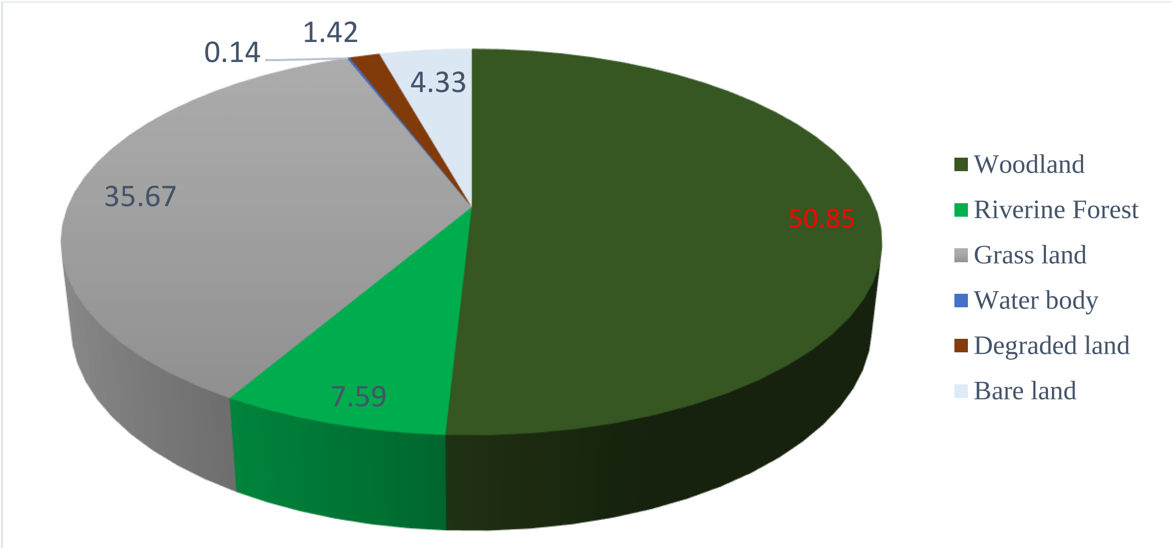


Figure 4b: area coverage in percentage of 1988(source:Author)

Land Cover Types and its coverage in 1998

The land cover classes were the same with that of 1988 but the percent of existence and area coverage is different. The shape of riverine forest is clearly differentiable and looks like shape of river from beginning to end. From the figure 5 below, woodland and grass land were dominant cover types also in this year (table 4 above) description. According to the (table 4 above), the amount of woodland covered about 47.4 %, riverine forest covers 4.724%, grass land holds 41.42%, water body holds 0.22%, degraded land holds about 4.96% and that of bare land holds 1.274% of the park in 1998. From the table and image, the amount of grassland, and degraded land increased in the year 1998 as compared to 1988. Riverine forest, woodland and water body indicated decrement between 1988 and 1998. From the (table 9 below), some of the land cover types showed increment and some of them indicated decrement within 10 years gaps.

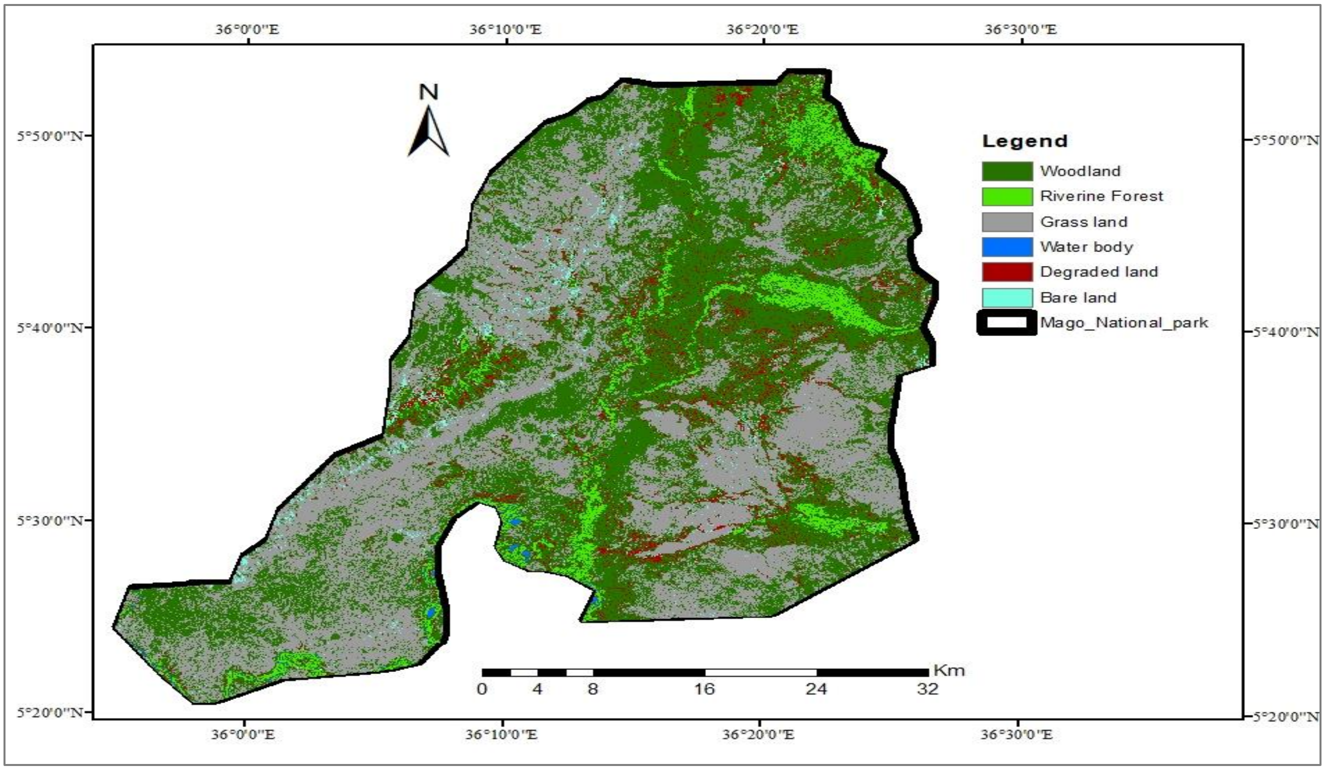


Figure 5a. LULC Map of MNP in 1998(source:Author)

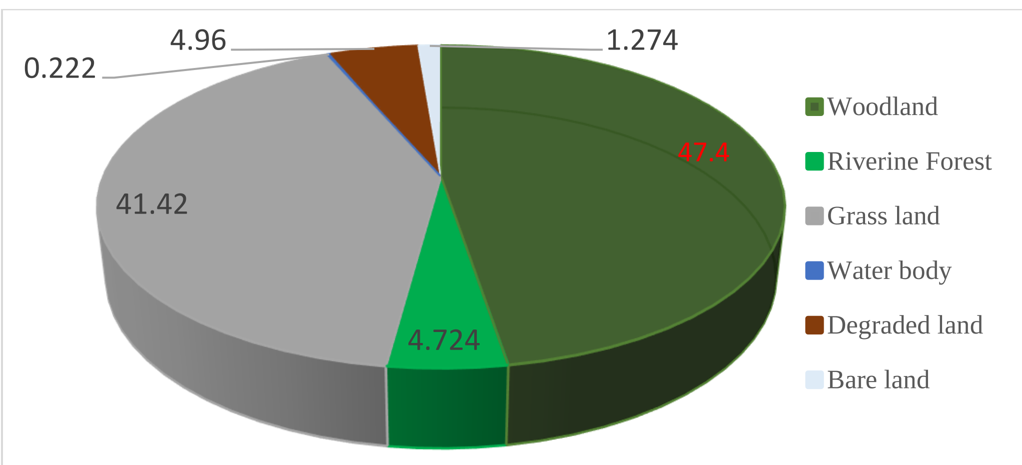


Figure 5b: area coverage in percentage of 1998(source:Author)

Land Cover Types and its coverage in 2008

The land cover classes were the same with that of 1988 and 1998 with different percent of presence and area coverage. The (table 4 above) clearly shows the description of area coverage and percent of occurrence of different land cover types. The Woodland which holds both open and dense woodland, riverine forest and that of degraded land indicated decrement in some amount.

On other hand water body which included river and ponds which found within the park, grass land and bare land indicated increment in large amount compared to last decade. From the figure 5a above, some of the northern mountainous area reflected in the same range as riverine forest due to high greenness of woodland. Even in the year 2008, the figure or table shows that, both woodland and grass land is dominant cover types in the park. Based on the result of (table 4 above), the woodland contains 45.38 %, riverine forest encompasses around 4.998%, and grass land holds 48.23%, water body 0.157%, degraded land 0.969% and that of bare land covers 0.266% of the park in 2008.

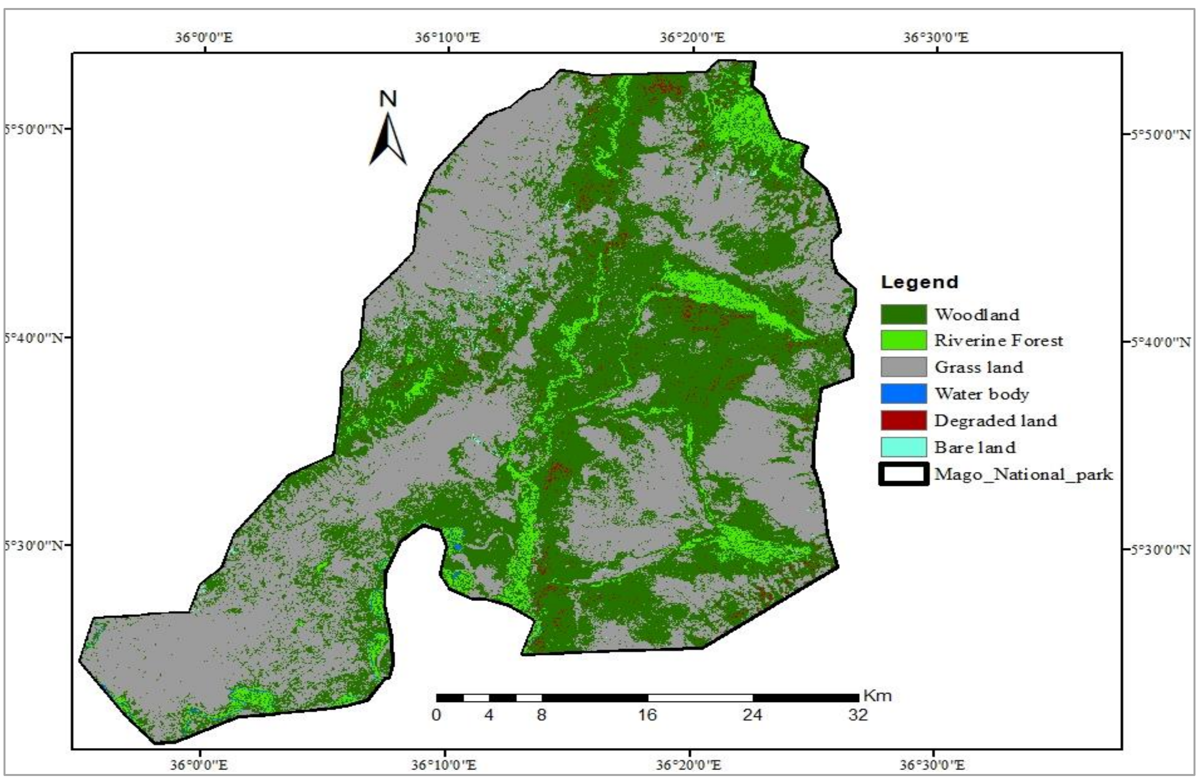


Figure 6a. LULC Map of MNP in 2008(source:Author)

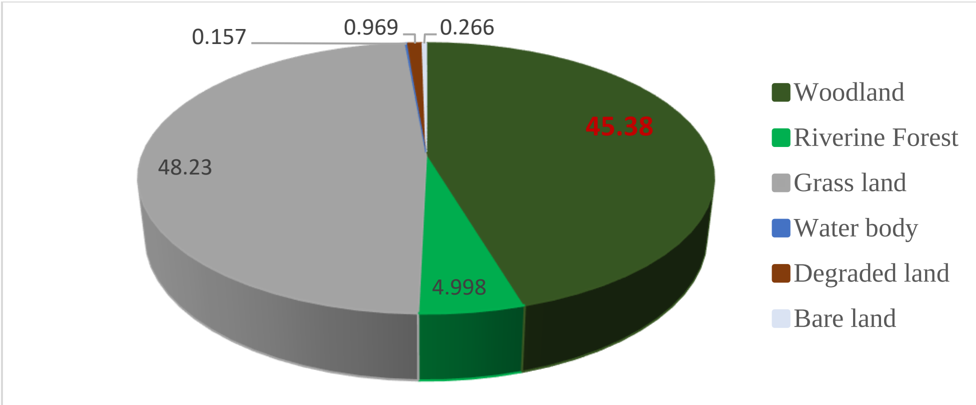


Figure 6b: area coverage in percentage of 2008(source:Author)

Land Cover Types and its coverage in 2018

As it is seen on the maps in 1988, 1998, 2008 and 2018; the greatest share of the land in MNP was covered by woodland and grass land and that of forest which follow the river next to them. The dense woodland occupied the norther and south western part of the study area, the all of middle part covered with grass and that of open woodland. The bare land and degraded land appeared around mountainous area of south and northern parts in the park.

From the result of supervised classification, even in the year of 2018; there are still six land use land cover classes in Mago Nation Park. The amount of woodland indicated increment in large amount during this year. Contrarily, bare land and degraded land also showed increment in this year than selected study periods. The classification report of Mago national park land use land cover in 2018 showed that there is change of both increment and decrement in area coverage. According to this, from (table 4 above), the woodland contains 50.162 %, riverine forest encompasses around 4.933%, grass land holds 39.843% which is decreased, water body 0.168%, degraded land 3.435% and that of bare land covers 1.459% which is increased when compared with the report in 2008.

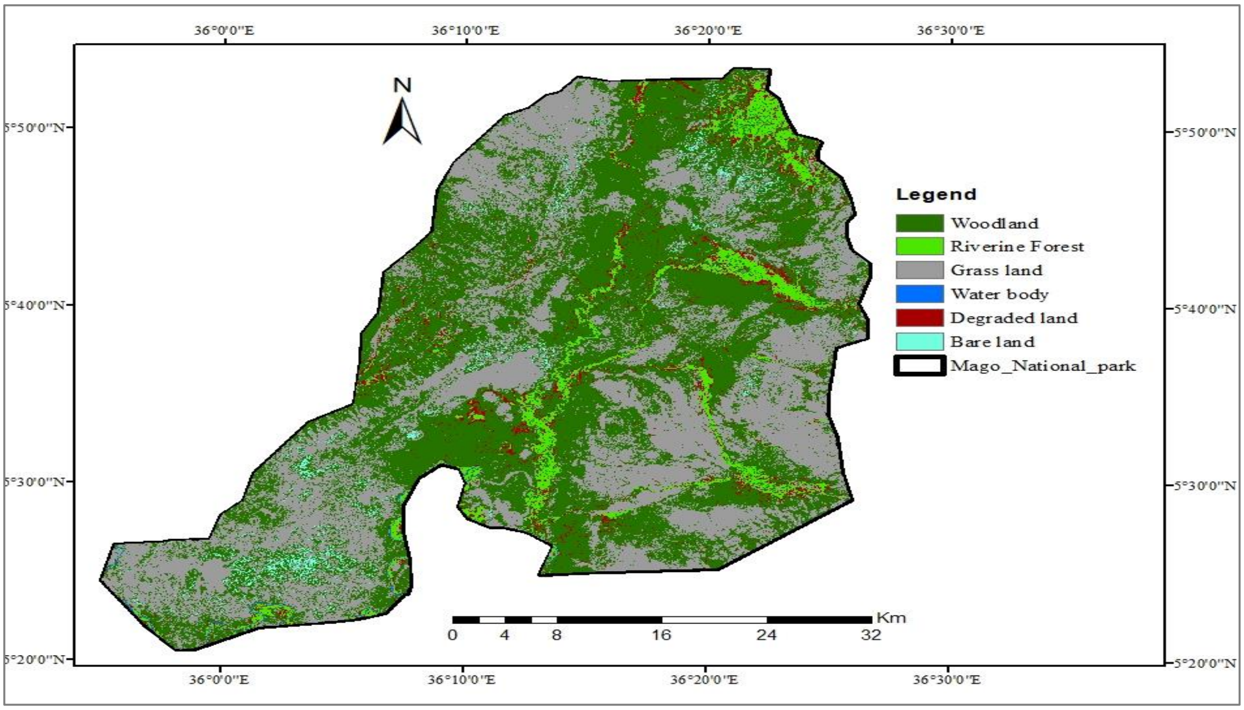


Figure 7a. LULC Map of MNP in 2018(source:Author)

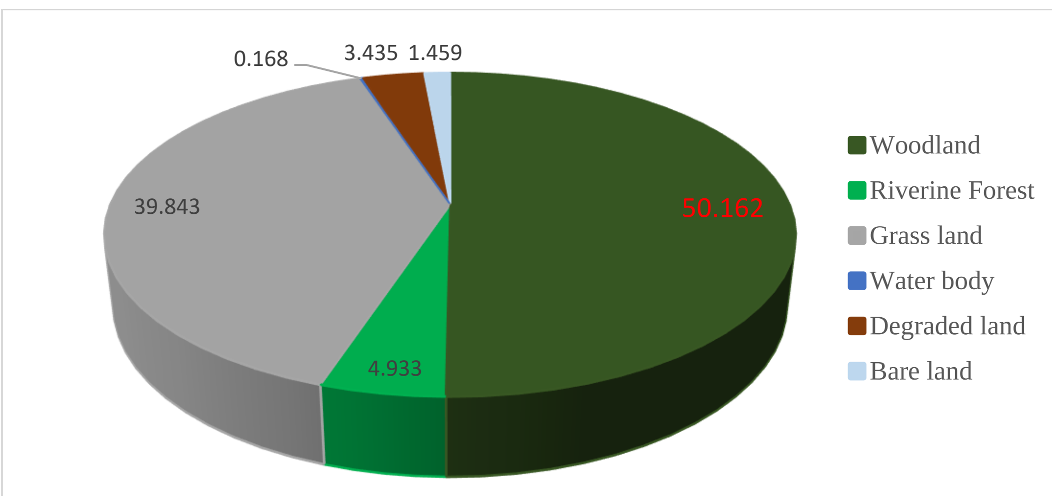


Figure 7b: area coverage in percentage of 2018(source:Author)

4.1.3. Accuracy assessment

Accuracy Assessment for LULC Mapping of 1988

The Confusion Matrix in Table 5 below showed that both commission and omission error and also the majority of the pixels were misclassified to one another and this is due to spectral similarities for the vegetation. Table 2 in appendix II also indicates user's accuracy, producer's accuracy, kappa coefficient and overall accuracy value for the classified image of 1988. The overall accuracy and kappa coefficient of this period of classification results 95.33% and 0.9 and accuracy of each LULC classes are presented in the table (Table 5 below).

Table 6: Confusion Matrix for the LULC Map of 1988

		Reference Data						
		1	**2**	**3**	**4**	**5**	**6**	**Total**
	1	**12700**	200	25	19	15	12	**12971**
	2	120	**2619**	0	0	6	0	**2745**
	3	63	67	**4685**	0	20	143	**4978**
Classified Data	**4**	0	0	2	**2500**	0	14	**2516**
	5	40	0	48	0	**1439**	0	**1527**
	6	35	0	133	0	32	**2202**	**2402**
	Total	**12958**	**2886**	**4893**	**2519**	**1512**	**2371**	**27139**

WL= Woodland RF= Riverine forest GL= Grassland WB= Water body DL= Degraded land BL=Bare land

Accuracy Assessment for LULC Mapping of 1998

LULC classification accuracy of year 1998 was approximately similar with the result of 1988. The overall accuracy and kappa coefficient of this period of classification results 95.92% and 0.912 respectively, and accuracy of each LULC classes is present in the table 3 in appendix II. For the classified image of 1998 error matrix are indicated in Table 6 and 29494 of the pixels were used as a sample unit during accuracy assessment. Overall classification accuracy of 95.92% and overall kappa statistics of 0.912 were gotten from this assessment (Table 3 appendix II) indicates**.**

Table 7: Confusion Matrix for the LULC Map of 1998

		Reference Data						
		1	**2**	**3**	**4**	**5**	**6**	**Total**
	1	**15270**	196	162	0	35	7	**15670**
	2	154	**1991**	5	0	5	0	**2155**
	3	79	96	**4391**	0	0	109	**4675**
Classified Data	**4**	31	0	0	**2552**	25	0	**2608**
	5	19	17	59	0	**1918**	43	**2056**
	6	65	10	125	19	0	**2111**	**2330**
	Total	**15618**	**2310**	**4742**	**2571**	**1983**	**2270**	**29494**

WL= Woodland RF= Riverine forest GL= Grassland WB= Water body DL= Degraded land BL=Bare land

Accuracy Assessment for LULC Mapping of 2008

The LULC classification accuracy of year 2008 was relatively not as good as 1988 image. The overall accuracy and kappa coefficient of this period classification results 94.25% and 0.90 and accuracy of each LULC classes is presented in table 4 appendix II. For the year 2008, error matrix of the classified image is described in Table 7 as the following.

Table 8: Confusion Matrix for the LULC Map of 2008

		Reference Data						
		1	**2**	**3**	**4**	**5**	**6**	**Total**
	1	**11049**	303	37	3	28	5	**11425**
	2	227	**3241**	0	0	0	0	**3468**
	3	116	46	**8471**	0	49	55	**8737**
Classified Data	**4**	15	0	0	**2438**	0	0	**2453**
	5	73	0	110	0	**3461**	29	**3673**
	6	125	3	151	0	53	**3232**	**3564**
	Total	**11605**	**3593**	**8769**	**2441**	**3591**	**3321**	**33320**

WL= Woodland RF= Riverine forest GL= Grassland WB= Water body DL= Degraded land BL=Bare land

Accuracy Assessment for LULC Mapping of 2018

The overall accuracy and kappa coefficient of this period results in 96.09% and 0.93and accuracy of each LULC classes is presented in the Table 5 in appendix II. For the year 2018, the error matrix of the classified image is described in Table 8 below whereby 29648 -pixel sample units were used for the accuracy assessment. But also, the classified image was having an overall classification accuracy of 96.09% and overall kappa statistics of 0.93 Table 5 appendix II.

Table 9: Confusion Matrix for the LULC Map of 2018

		Reference Data						
		1	**2**	**3**	**4**	**5**	**6**	**Total**
Classified Data	**1**	**15339**	196	92	1	27	1	**15656**
	2	150	**1994**	11	0	0	0	**2155**
	3	146	8	**4512**	0	0	9	**4675**
	4	5	0	0	**2613**	0	0	**2618**
	5	7	0	59	0	**1975**	15	**2056**
	6	2	3	121	0	7	**2355**	**2488**
	Total	**15649**	**2201**	**4795**	**2614**	**2009**	**2380**	**29648**

WL= Woodland RF= Riverine forest GL= Grassland WB= Water body DL= Degraded land BL=Bare land

Assessment of the rate of land cover change for three periods

The following table 9 below indicates the rate of change in different land cover types in Mago national park. The result shows increment and decrement of cover types between periods.

Table 10: Change in Land Use Land Cover between Periods

LULC	1988-1998 Rate (ha/yr.)	%	1998-2008 Rate (ha/yr.)	%	2008-2018 Rate (ha/yr.)	%	1988-2018 Rate (ha/yr.)	%
Woodland	-642.679	-6.76	-482.292	-5.44	993.27	11.84	-131.7	-1.385
Riverine forest	-535.779	-37.98	-40.36	-4.61	-11.115	-1.33	-587.25	-41.63
Grass land	1077.651	16.11	1145.34	14.74	-1351.63	-15.16	871.366	13.02
Water body	-62.38	-22.37	8.14	3.76	-10.83	-4.82	-65.07	-23.34
Degraded land	667.494	85.67	-748.955	-80.74	461.635	85.49	380.174	95.01
Bare land	-560.449	-70.14	125.45	52.58	-91.75	-25.02	-526.079	-65.838

+=Increase in the rate of land cover class **- =** Decrease in the rate of land cover class

Mago National Park practiced different LULC changes between 1988 and 2018. The area of woodland, riverine forest, grass land, water body, degraded land and bare land indicated a changing trend between the study periods from 1988 to 2018 (Figure 8 below).

In the period between 1988 and 1998, woodland decreased by 642.679 ha/yr. (-6.76%), riverine forest decreased by 535.779 ha/yr. (-37.98%) grassland increased by 1077.651 ha/yr. (16.11%), water body decreased by 62.38 ha/yr. (-22.37%), degraded land increased by 667.494ha/yr. (85.67%) and bare land decreased by 560.449 ha/yr. (-70.14%) respectively.

The result for the second period (1998-2008) showed that woodland, riverine forest and degraded land decreased by 482.292 ha/year (-5.44%), 40.36 ha/year (-4.61%), and 748.955 ha/year (-80.74%) respectively, whereas grass land, water body and bare land increased by 1145.34 ha/year (14.74%), 8.14 ha/year (3.76%) and 125.45 ha/year (52.58%) respectively.

Third period (2008-2018) showed that land under woodland, and degraded land indicated increment by 993.27 ha/year (11.84%) and 461.635ha/year (85.49%) respectively. Riverine forest, Grassland, water body and bare land were decreased by -11.115ha/year (-1.33%), -1351.63ha/year (-15.16%), -10.83 ha/year (-4.82%), and -91.75ha/year (-25.02%) respectively.

The rate of change between three decades which is between 1988 and 2018 indicated that woodland, riverine forest, water body and bare land decreased by -131.7 ha/yr. (-1.385%), -587.25 ha/yr. (-41.63%), -65.07 ha/yr. (-23.34%) and -526.079 ha/yr. (-65.838%) respectively. The remaining grassland and degraded land increased by 13.02% and 95.01% respectively (table 9 above).

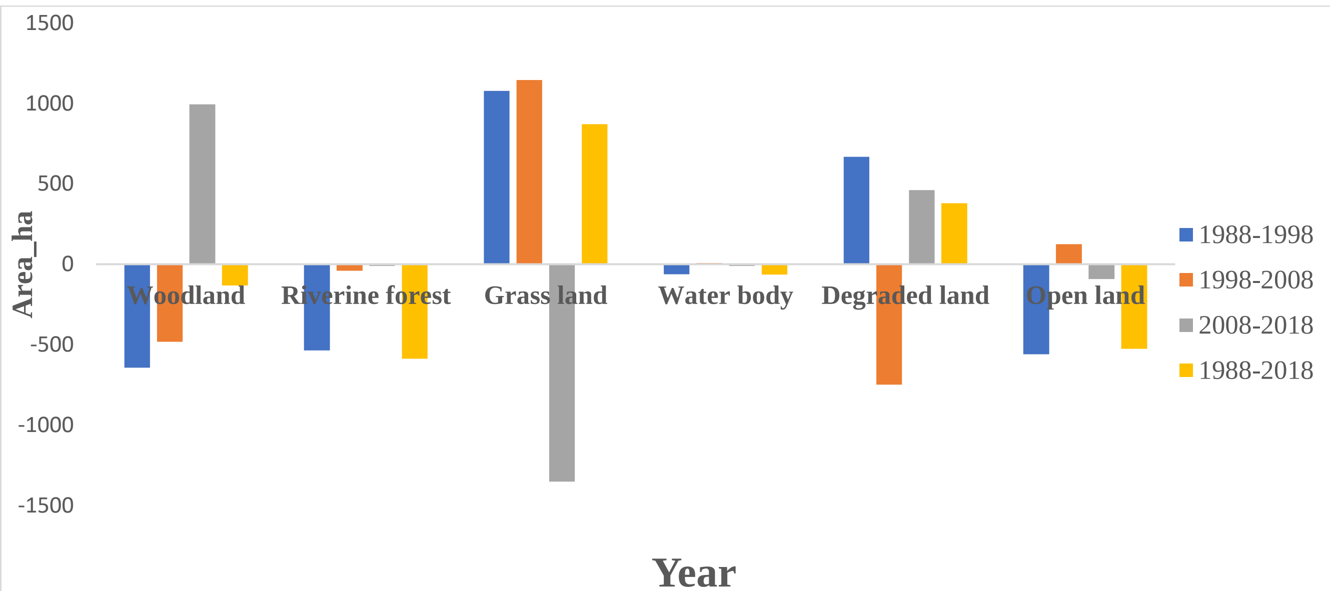


Figure 8: Annual rate of change (ha) of LULC classes in the study area from 1988 to 2018

4.1.4. Land Use Land Cover Change in Mago National park from 1988 to 2018

LULC class conversions in percent between 1988 and 1998

The change detection tables presented below are change matrices that show what are changed to what. The column of the table (1998, 2008, and 2018) represents the final stage and the row (1988, 1998, and 2008) represents the initial stage. The diagonal values of the table show the unchanged values, which are found in both times image. Unlike the diagonal values the class change tells the total changed image areas of each LULC of the initial stages. The row total represents the final stage area of LULC classes. In general, the LULCC in all land use types are not static; there is a significant LULCC observed in the area. LULCC between the time periods of 1988 and 1998, 1998 and 2008 and 2008 and 2018 is presented in the tables below respectively. Developing nations are experiencing rapid land cover change for a variety of reasons. Increasing population, poverty, and poor economic development are some of factors for these changes which eventually put pressure on natural resources (Kelarestaghi and Jeloudar, 2011).

There is some variation in the total areas covered by each of these below listed land cover types in the park. Major LULC change matrix from Table 10 below demonstrated that, the change analysis for a decade from 1988 to 1998. LULC change analysis from the Landsat imagery of TM indicated that starting from 1988 to 1998, the dominant woodland which is characterized by both dense and open woodland 59.02% was keep-on and large amount of it around 28.64% was changed to grass land and to other cover types in some amount as indicated by the table 10 below. On the other hand, riverine forest was converted to woodland in large amount around 35.84% by keeping 55.076% and the remaining amounts are converted to other type of cover types. The grass land keep-on around 68.41% of its coverage and the remaining converted to other cover types like 27.66%, and 2.17% of grass land converted to woodland and bare land respectively between 1988 and 1998. Degraded land also shown high percent of conversion around 74.504% of it changed to woodland and 13.02% of it converted to grass land and also the remaining percent converted to other land cover types only by keeping 11.3% of it from 1988 to 1998. Generally woodland and bare land was highly converted to grass land with great amount with in the decade.

Table 11: LULC Change detection matrix of 1988 and 1998

1988	1998												
	Woodland		**Riverine forest**		**Grass land**		**Water body**		**Degraded land**		**Bare land**		
	Area(ha)	**%**	**Area(ha)**	**%**	**Area(ha)**	**%**	**Area(ha)**	**%**	**Area (ha)**	**%**	**Area (ha)**	**%**	**Total**
Woodland	56131.9	**59.02**	3522.13	3.7	27240.06	28.64	184.59	0.19	7222.39	7.6	808.92	8.5	**95109.99**
Riverine forest	5055.91	35.84	7769.32	**55.076**	530.07	3.76	14.94	0.11	720.78	5.11	15.57	0.11	**14106.59**
Grass land	18502.87	27.66	184.86	0.28	45768.97	**68.41**	4.95	0.001	971.28	1.45	1470.2	2.17	**66903.13**
Water body	50.6	19.81	1.89	0.64	31.14	10.5	194.01	**68.66**	0.99	0.36	0.18	0.06	**278.81**
Degraded land	1938.16	74.504	24	0.00923	335.06	13.02	0.18	0.01	296.7	**11.3**	7.3	0.28	**2601.4**
Bare land	4207.664	53.19	1.8	0.92	3641.22	45.57	8.1	1.01	26.82	0.34	104.85	**1.31**	**7990.454**

LULC class conversions in percent between 1998 and 2008

The results of change between 1998 and 2008 also showed that there is conversion between land cover types. Compared with change between 1988 and 1998, the change among some cover types were less in percent by keeping their coverage in large extent. To put in number, woodland covers 60.87%, riverine forest covers 69.51%, and grass land continues 75.39% of their coverage in stated decade. But from woodland 32.87%, 4.43% and 1.64% converted to grass land, riverine forest, and to degraded land respectively. From riverine forest 25.5% and 3.25% were changed to woodland and grass land respectively and water body also indicated change with 6.00%, 7.6% and 1.03% to woodland and riverine forest and grass land respectively. Also, from grass land around 23.93% was converted to woodland in large. But degraded and bare land only continued 2.26% and 2.79% respectively and the remaining percent converted to woodland and grass land with large amount as indicated in table 11 below.

Table 12 LULC Change detection matrix of 1998 and 2008

1998	2008												
	Woodland		**Riverine forest**		**Grass land**		**Water body**		**Degraded land**		**Bare land**		
	Area (ha)	**%**	**Area (ha)**	**%**	**Area (ha)**	**%**	**Area (ha)**	**%**	**Area (ha)**	**%**	**Area (ha)**	**%**	**Total**
Woodland	53986.92	**60.87**	3929.65	4.43	29155.33	32.87	67.68	0.08	1456.22	1.64	**87.4**	0.1	**88683.2**
Riverine forest	3543.34	25.5	4899.69	**69.51**	197.05	3.25	3.06	0.53	104.13	1.19	1.53	0.02	**8748.8**
Grass land	18591.06	23.93	134.26	0.17	58560.66	**75.39**	10.53	0.013	42.21	0.05	340.92	0.44	**77679.64**
Water body	12.89	6.00	16.44	7.6	2.22	1.03	182.9	**84.51**	1.8	0.81	0.18	0.08	**216.43**
Degraded land	7616.5	82.11	364.32	3.92	1030.95	11.11	1.44	0.016	254.76	**2.26**	8.37	0.09	**9276.34**
Bare land	801.64	33.73	22.15	0.52	1486.9	62.92	0	0.016	8.72	0.37	66.554	**2.79**	**2385.964**

LULC class conversions in percent between 2008 and 2018

The land cover change analysis from Table 12 below verified that, for a decade from 2008 to 2018, all of the cover types indicated conversion to other cover types in different amount in this decade. Woodland, riverine forest, grass land and water body persevered only 67.68%, 93.28%, 78.25% and 66.82% respectively. But degraded and bare land conserved around 3.29% and 0.5% of its coverage and the remaining large part was converted to other cover types. Around 29.24%, 1.12% and 1.69% of woodland converted to grass land, riverine forest and degraded land respectively. 4.03%, 1.62% and 1.00% of riverine forest also changed to woodland, grass land and to degraded land respectively. Most of grass land changed to woodland in 20.82%. Water body largely converted to both woodland in 11.73% and to grass land in 16.8%. Bare land coverage indicated decrement in this year from above presented results. It only preserved about 0.5% and the remaining large part of 93.71% was converted to grass land, and 4.58% was converted to woodland. Generally, high rate of conversion between land cover types was take place in the study period.

Table 13: LULC Change detection matrix of 2008 and 2018

2008	2018												
	Woodland		**Riverine forest**		**Grass land**		**Water body**		**Degraded land**		**Bare land**		
	Area (ha)	**%**	**Area (ha)**	**%**	**Area (ha)**	**%**	**Area (ha)**	**%**	**Area (ha)**	**%**	**Area (ha)**	**%**	**Total**
Woodland	56758.94	**67.68**	939.75	1.12	24518.55	29.24	114.03	0.14	1416.06	1.69	112.95	0.13	**83860.28**
Riverine forest	336.37	4.03	7784.55	**93.28**	135.6	1.62	2.97	0.03	83.86	1.00	1.89	0.02	**8345.24**
Grass land	18560.63	20.82	98.64	0.11	69748.67	**78.25**	10.54	0.01	35.506	0.03	689.09	0.54	**89143.08**
Water body	14.92	11.73	3.68	4.59	25.04	16.8	180.55	**66.82**	0.38	0.04	0	0	**224.57**
Degraded land	1336.43	74.79	28.41	1.59	362.49	20.29	0	0	58.83	**3.29**	0.63	0.03	**1786.79**
Bare land	166.56	4.58	4.05	0.11	3411.6	93.71	0.99	0.03	39.038	1.07	18.18	**0.5**	**3640.418**

LULC class conversions in percent between 1988 and 2018

The results of change between 1988 and 2018 also indicated that there is conversion between land cover types. As shown by table 13 below, all of the LULC types indicated conversion from one type to another. According to this, woodland keep 69.22%, riverine forest covers 53.35%, grass land continues 63.85%, water body keeps 68.85%, degraded land continues 11.7% and that of bare land keeps 23.14% of their coverage in stated decade. But from woodland 20.23% was converted to grass land, from riverine forest 41.65% converted to woodland, 33.04% of grass land converted to woodland, from water body 25.68% converted to woodland, from degraded land 79.54% was converted to woodland and that of 70.93% of bare land converted to grass land between 1988 and 2018. The conversion amount is indicated in table 13 below as follows.

Table 14: LULC Change detection matrix of 1988 and 2018

1988	2018												
	Woodland		**Riverine forest**		**Grass land**		**Water body**		**Degraded land**		**Bare land**		
	Area(ha)	**%**	**Area(ha)**	**%**	**Area(ha)**	**%**	**Area(ha)**	**%**	**Area (ha)**	**%**	**Area (ha)**	**%**	**Total**
Woodland	58387.99	**69.22**	3034.34	3.6	17061.06	20.23	12.89	0.02	5036.5	5.97	811.22	0.96	**84344**
Riverine forest	3829.41	41.65	4905.33	**53.35**	127.26	1.38	6.44	0.07	313.32	3.41	12.15	0.13	**9193.91**
Grass land	30055.33	33.04	186.2	0.2	58073.37	**63.85**	12.22	0.01	831.95	0.91	1796.9	1.98	**90955.97**
Water body	67.68	25.68	3.06	1.16	10.47	3.97	180.86	**68.63**	1.44	0.55	0	0	**263.51**
Degraded land	1436.97	79.54	104.13	5.76	42.21	2.34	1.15	0.06	211.45	**11.7**	10.72	0.59	**1806.63**
Bare land	15.57	3.65	1.03	0.24	302.42	70.93	0.18	0.04	8.48	1.99	98.67	**23.14**	**426.35**

4.1.5 Trend of LULCC in Mago national park (1988-2018)

MNP have experienced different LULCC between 1988 and 2018. The land under riverine forest and bare land decreased continuously between the indicated years. In contrast, the area of woodland, degraded land and grass land indicated a fluctuating trend between the study periods. These cover types show increment and decrement with in years rather than showing continues relation.

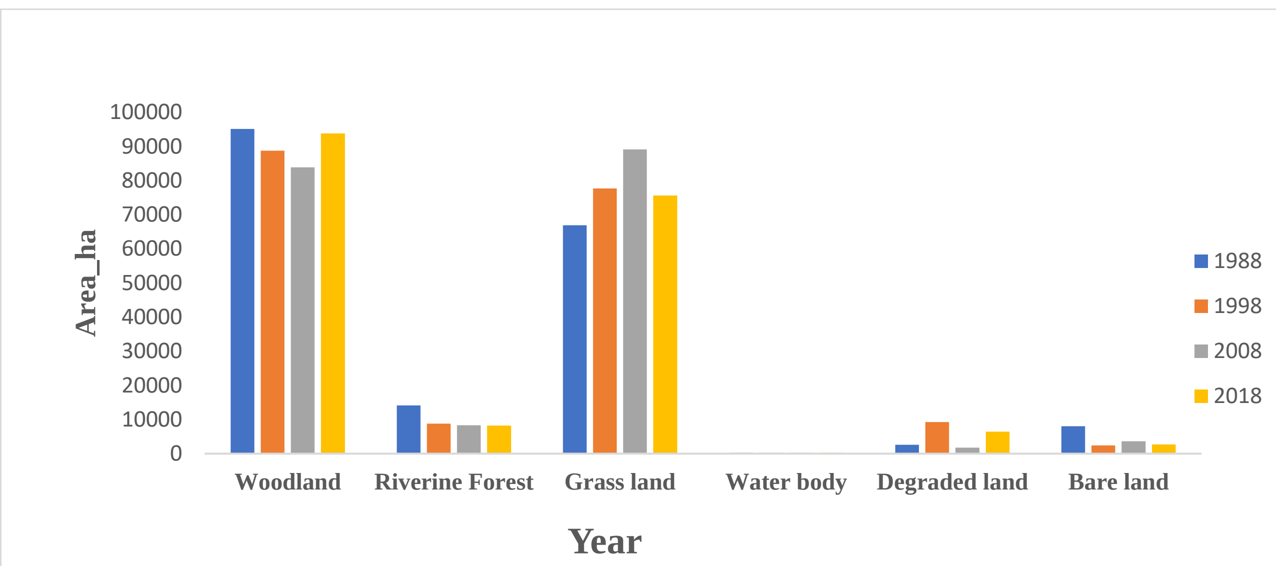


Figure 9: Trend of Land use/ land cover change from 1988 to 2018.

4.2 Drivers of Land Use Land Cover Changes in Mago National Park

According to the survey result a multiple driver contributed to LULC change in the study area. Similar to the remote sensing data analysis result, survey results were also indicated that woodland, grass land, and riverine forest and other cover types found in the MNP were changed to other cover types in different amount and percentage. Although LULCC are the result of human influences and natural processes (Geist et al., 2006). Obviously, there is LULCC with multidimensional driving factors and associated adverse impacts out there in different parts of Ethiopia. Number of factors such as socio-economic, demographic and government infrastructure development and investment policies stimulated massive scale of land cover conversions in the study area (Kiros and Desalegn, 2019).

The main drivers of LULCC in Ethiopia were growing demand for house hold energy, expansion of agricultural farmland and overgrazing. Massive loss of forest cover at the expense of cultivated land, pasture land and settlements, the rate at which farmland increase over time had declined mainly due to shortage of available suitable land for cultivation (Bewket and Abebe 2013).

LULCC in the Mago national park is a result of several proximate/direct and underlying/indirect causes. The result of discussions and interviews conducted with HH heads, FGD participants and KII in the study area indicated that there are a number of driving forces which lead to LULCC in the Mago national park. Based on the results of the FGDs and other secondary data sources, agricultural and grazing land expansion, forest fire and wood extractions were among major proximate factors that have caused LULC change in the study area. Livestock and population increase, climate variability and decrease in farmland productivity were among the major underlying factors driving proximate causes of the LULC changes in MNP. The findings of this research based on the household surveys, FGDs, and KIIs pointed-out to local communities perceiving firewood collection, agricultural expansion, over-grazing, and fire raised by community, cutting tree for house construction, farm implementing material collection and hunting as the important proximate drivers of LULCC in MNP. These proximate drivers were caused by high poverty levels, population growth, rainfall and temperature variability, lack of law enforcement, poor access to an alternative-energy supply, and high cost of agricultural input.

In Baytsemal kebele around 65% are hunters, 20% pastoralist and 15% farmers and in case of Goldiya kebele 60% hunting, 30% pastoralist and 10% farmers. But in Kure kebele most of the community are farmers and in percentage around 75% are farmers, 20% pastoralists and 5% hunters. From the survey, most of the peoples are hunters and pastoralists, directly or indirectly the communities put pressure on the park. The residents deforest or clear trees for fuel wood/energy, hunting, for building houses, to have farm land and for grazing. In addition to the above-mentioned direct reasons of change, there are also different underlying causes of LULC changes. Livestock rearing is an essential player of the livelihood of the communities in the study area. They were sources of cash income, milk and meat. As indicated by respondents, the park is not respected by large proportion of the community. This is because of the involvement of government management and restriction to use the resources freely. Due to this sometimes there is war between scouts (park rangers) and residents who close the park for hunting, grazing, cutting trees for fire wood and etc. another basic cause is that of lack knowledge. The community lacks knowledge about the use of resources in the park without damaging its existence.

From the analysis, from selected kebeles approximately around 20% have positive attitude towards park meaning they know how the existence of resources helps them and the environment but the remaining 80% have negative attitude and they also oppose involvement of government and they want to freely access by hunting, grazing, cutting firewood and other access. To stop and reduce change of cover types, it is better to teach and work with the local community by creating awareness. Unless creating awareness, it is impossible to stop the conversion between land cover types as local community thought that, they have right to use and access every resource in the park as the park is located on their land. The interviewers also presented that, the local community is suffering from problems due to change in the park including variability in amount of rainfall and temperature, low product, drought, soil fertility loss, loss of animal and plant life, etc. Finally, they recommended government to involve and work with local community by being close and participating them.

4.2.1 Proximate (Direct) Causes of Land Use/Land Cover Change in MNP

The causes or driving forces of land use/land cover change in Mago national park were identified and presented based on the result of social survey as indicated below. Causes for LULCC are broadly grouped in to two namely; Natural and human with diverse driving forces. However, we sense natural effects like climate effect in the long run but impacts due to human intervention is most of immediate when compared with natural effects (Woldeamlak, 2002).

Agriculture expansion: Factors like farmland expansion, population pressure, deforestation and collection of woods for construction and charcoal production for fuel consumption, poor land tenure policy and land fragmentations have been significant driving factors in SNNPR state, (Mathewos, 2019). The expansion of diversified agricultural activities, wood extraction and infrastructure extension are clusters of proximate causes of LULC changes (Geist et al., 2006).

The aggregate results of respondents put agricultural expansion as a major driver of LULCC in the study area. In MNP, agriculture is growing gradually under weak technological support and determined environmental challenges. The trend of crop production, as supposed by respondents was declined. The rain-fed farming activity and livestock husbandry are the major livelihoods of the community in the Mago national park. The agricultural land expansion of small land holder is the most widespread proximate driver of LULC dynamics and ecosystem changes. They were practicing oxen driven ploughing for producing annual crops due to they are dependent on crop production for their household food consumption and for survival. As a result, the livelihood activity had its own impact on LULC of the park. Respondents also indicated that there is lack of farming technologies. There is no adaptation to produce high yield in small agricultural land or there is no practice of using agricultural inputs such as inorganic fertilizers, improved seed and herbicides to get better yield. This is also revealed as cause for LULC change in the MNP. To satisfy their food consumption requirement, those crop dependent communities' clear vegetation in the park and plough land due to Crop produced by their own land is not enough. As described by discussion and interview with focus groups and key informants' expansion of agriculture which includes subsistence crop farming is the major driver of LULCC in MNP. Agriculture is increasing from different parts of the park. Rural communities in Mago national park depend by hunting as a common survival strategy in the case of land degradation, failure of crop production, soil infertility, frequent and prolonged droughts, and unreliable rainfall and temperature.

Local communities living around MNP are also forced to clear woodlands for additional agricultural land or to sustain their livelihoods. As supposed by key informants and through focus-group discussions, rainfall and temperature has been very variable in the park. As a result, those communities push towards other land uses like grass land, shrub/bush land, and woodlands to have additional land for agriculture.

Overgrazing: In areas where there is overgrazing, the density of wood land cover largely decreased and often resulted in shifting to other places. There is significant woody land cover reduction in pastoral areas due to large livestock population (Mathewos,2019). The result of respondents reported that increasing livestock in population and density along with prevalence of free grazing system are major causes of LULCC and land degradation in the park. According to Badege 2001, dominant mixed farming practices of Ethiopian highlands without appropriate and integrated land management practices were major driving forces of vegetation loss and land degradation. In other hand, free grazing is also one of the major drivers of LULCC in the park.

Firewood collection: As any other developing countries, farming communities around Mago national park have used firewood as sources of energy. Firewood collection is the top important proximate drivers of LULC changes in Mago national park specially starting from 2000. This is directly associated with the use of three-stone open-fire stoves by the community. This kind of domestic cooking stove enable households to use more firewood, thereby aggravating deforestation and forest degradation. The use of three-stone open-fire stoves results in indoor-air pollution, which severely impacts human health. This explains the vegetation-cover loss in the study area between during study period. The community usually burn the grass and woodlands land to make a pass way for going to grazing land for their cattle's. According to the answer of respondents, to reach to grazing place, they opened the way by using fire. This is the main reason for wildfire incidences. According to key informants and groups discussions, the other thing causing wildfire is that people living around the park clear trees land for cultivation by using fire. The discussants also indicated that, fire is used as a tool for cleaning woodland for expansion of grassland and agricultural land. This is supported by LULCC analysis which showed loss of vegetation and degradation which showed LULCC in the park. Although majority of communities use different types of trees in MNP as sources of energy presently, people around the park have used woodlands for household energy consumption. Survey results of study also shown that, local community uses riverine forest and woodland as energy sources.

Wood for house and farm implementing material construction: Wood extraction to fulfill the demand of fuel and house construction is one of the major drivers for clearing wide area of vegetation cover and trees in the park. Demand for construction of house and farm implementing materials from forest and woodlands have been causing land cover change in the study area. According to local communities' response, major disturbance was started mainly during clearing of trees for house construction. They also cut trees for construction of farm implementing materials, and also to renew their house by cutting trees. Clear-cutting of trees for firewood, charcoal and constructional materials without replacement is a critical problem contributing to the loss of various forms of vegetation in general and native tree species in particular and this indicates that harvesting of fuel and pole woods for commercial purposes and domestic uses were the leading causes of deforestation in Africa. The result of respondents of both focus group discussion and key informants also revealed that, the increasing demand of tree products such as firewood, construction materials and other domestic uses around the park was one of the major driving forces of land cover change (Geist and Lambin 2001).

4.2.2 Underlying (indirect) causes of LULC Change in MNP

The complexes of technological, economic, demographic, political, institutional and socio-cultural factors are grouped under underlying causes of LULC changes. Thirdly, biophysical triggers such as topography, landslides, droughts, and natural fires are referred to as biophysical factors that underpin LULCC (Geist et al., 2006). The underlying drivers of LULCC from a range of demographic, economic, and technological factors were identified by FGDs and KII in the study area. The population growth, poverty, food insecurity, agricultural inputs and farming technologies change, less educated power and drought caused in gradual change in the economic activities of communities surrounding the study area and widely drought showed a large part of underlying causes according to the survey analysis.

Demographic Factors*:* The high population growth and densities have resulted in increased demand for food and subsequently resulted in rapid transformations of land cover, particularly forests (Getahun et al., 2017). The demographic characteristics mainly population growth and population density are indirect factors for LULCC through the increasing needs for additional lands for farming and grazing as well as demands for tree products for firewood and construction materials. According to Geist et al., (2006), land cover types conversion due to demographic pressure are more serious largely in tropical regions such as Latin America, Africa and Southeast Asia. The land cover conditions of the Ethiopian highlands have been modified or significantly transformed by the rapidly increasing population pressure and growing livestock population. Human population in the highlands has grown fast on the limited land area and almost every piece of land is converted into cultivated land to produce food (Muluneh, 2003). As other parts of the country Ethiopia, the number of populations around the park was also indicated fast population growth through time according to the report of CSA. The population size is increasing from time to time. As confirmed by interviewers and discussants, low level of education and polygamous marriages could be some good reasons for rapid human population growth in the MNP. The population growth on the other hand increased the demand for agricultural land, fuel wood and construction materials. This in return put pressure on the park by removal and extraction of resources. The majority of the local communities felt that population growth increased during the study period. Due to these, there is increase in demand for food, construction material and fuel wood resulting from population pressure, local farmers are forced to expand farm lands at the expense of different vegetation covers. The high population growth and densities have resulted in increased demand for food and subsequently resulted in rapid transformations of land cover (Rahmato 2009; Getahun et al., 2017).

Weak law enforcement: The other problem raised by community related to land cover changes in MNP was associated with the officials. Political/institutional factors were found to be underlying drivers of LULCC in the park. Weak institutional involvement to implement rules designed by higher government organs to keep and protect park from natural and man-made factors is one of the underlying causes for LULC change in the area. It was understood from KIIs and FGDs that most of policies and strategies were not successful due to lack of proper implementation and incorporation among the concerned stakeholders; agriculture, investment, forestry sectors and legal system. These caused huge destruction of natural resources in the country in general and the study area in particular. According to key informants, the regulation is not strong and can't stop the surrounding community from entering and using resources in the park.

Education: This study has further revealed that, among main socioeconomic determinants, the education level of rural communities significantly affected their perceptions toward LULC drivers in study area. According to results of respondents, most of the community surrounding MNP are uneducated.

Socio-cultural factors: these factors were also shown as an important indirect driving forces of LULCC in the park. Among the specific factors, change in public attitude is the most frequently occurred underlying driving forces of land cover change as confirmed during discussion with the community. Also practice bee-keeping and killing different wild animals to get acceptance in the community (like elephant, lion, tiger, etc.). Generally, the limited exposure of the local community to protection of environment and weak institutional performance, deforestation and ignorance of their activities on the environment have forced LULC change in the study area.

Poverty: Among the fundamental drivers indirectly contributing to LULCC in MNP is poverty. This factor also leads to transformation of land cover types as Local communities are unable to buy agricultural inputs due to high poverty levels, high cost of agricultural inputs and lack of enough financial resources. The majority of local communities are characterized by high levels of poverty and lack of alternative livelihood sources to lead sustainable life. Poverty put pressure on environmental because people who are poor, under food insecurity and hungry always destroy their immediate environment for searching food, fire wood, and grazing land in order to survive (Adane, 2016). Therefore, local community dependence on the resources from MNP increase to sustain livestock and their life.

4.3 Local Community Perception on the drivers of LULCC

Table 15 shows that there is a general understanding that population pressure is leading to changes in land use and land cover in the study area.From the social survey (HHS,KIIs and FGDs) done to identify the drivers of land use land cover changes in Mago National Park the results were as follows; majority quantified 28.5 % population pressure, 22 % livestock and overgrazing, 17.5 % agricultural expansion,16.5% wood for fire and house construction,6.5% poverty,6% weak law enforcement,3% education and socio-cultural factors (Table 14). Interaction of human activities on the natural resources has caused great modification of land use land cover in Mago National Park. Respondents perceived that bare land and riverine forest significantly declined in the MNP.

In contrast, woodland, degraded land and grass land indicated a increment between the study periods. Key informants and FGDs also correctly perceived that bare land and riverine forest cover declined from 1988 to 2018.

The Effects of land use/cover change can be either positive or negative according the understanding level of local community. Most of the people have livestock and lead their life by animal raring. Grazing is an important activity in which the animals are left on their own to feed the grasses inside the park. Though such kind of open grazing/over grazing leads to land cover change. The local community have both positive and negative attitude towards the resources found in the park. Those who have negative attitude totally needs to access the resources without any restriction and those who have positive attitude wants to use the resource wisely by keeping the resources sustainability for the future. The attitude of some of local community is negative as the resources are restricted to use the resources freely, involvement of government to manage the resources in the park, and some of the community have positive attitude as they gain services like firewood, grass, food etc. from the park. They thought the park is important for balancing the environment. Therefore, limited amount of local community around the park respect and take care of resources in the park and also from the answer it is known that most of the community lack awareness about the importance of existence of the park for climate or environmental protection.

Table 15: Local communities perception on the drivers of LULCC (source: Author)

Drivers of LULCC	Response (%) in selected kebeles
Agricultural expansion	17.5
wood for fire and house construction	16.5
Livestock growth and overgrazing	22
Population pressure	28.5
Poverty	6.5
Weak policy enforcement	6
Education and socio-cultural factors	3

5. SUMMARY AND CONCLUSION

5.1. Summary and Conclusion

Mago national park has been experiencing different Land use land cover changes through time. Over the last three decades, the study area has shown amazing level of land use land cover change. The fundamental drivers of change in the study area were the combination of agricultural expansion, overgrazing, demographic dynamics (population growth and density), weak law enforcement, socio-cultural factors and poverty. There is massive conversion in riverine forest, woodland and that of water body with decrement from 1988 to 2018 which in return may have far reaching impact on environment and ecosystem services. This study was assessed the LULC change and tried to explore the major driving forces of the change in the Mago national park. Long term LULCC detection analysis was done by using remotely sensed images. The result also verified that social survey data is important source of information and additional details can be extracted regarding extent, driving forces, environmental and socioeconomic impacts of LULCC. This study identified LULCC and the driving forces in Mago national Park, Southern Ethiopia. The study used four consecutive multispectral images, Landsat TM images of 1988, 1998 and 2008 and OLI/TIRs image of 2018 for LULC change detection from 1988 to 2018. To achieve the objective of the study remote sensing and GIS techniques were basic tools used in this study. In order to know the possible drivers of land use/land cover changes of the area, Household survey, FGD and KII were carried out during field data collection.

Supervised classification with Maximum-likelihood algorithm was employed to monitor LULCC. Land cover post-classification change detection techniques were applied to determine the LULCC. From 1988 to 1998, 1998-2008, from 2008 to 2018 and 1988 to 2018 comparison had been made to understand LULCC. Generally, the land use/ land covers of the study area were classified into six classes, namely woodland, riverine forest, grassland, water body, degraded land and bare land. The results indicated that the decrement in woodland, riverine forest, water body and bare land, in contrast grass land and degraded land indicated increment between the year 1988 and 2018. This is also evident in most East African countries where areas under forest cover were converted to grazing land, farmland or used for charcoal production (Olson et al., 2004; Yonas et al., 2016). Similar trends have been observed in rangelands of southeast Ethiopia, and we are losing the most important woody species from time to time (Abate et al., 2010). The proximate driving forces of LULCC in Mago National Park are expansion of agricultural land, human made fire, overgrazing and hunting, whereas population and livestock pressure from a different area, unsustainable exploitation of forest, decreased farmlands productivity, lack of law enforcement and cultural factors are the major underlying causes of the observed changes.

The results of this study quantify dynamics of land cover change and point towards appropriate action to implement sustainable use of the ecosystem. Rather than keeping the park, it is better to work with community, create awareness as indicated by social survey analysis. From this research, most of the communities have negative attitude and want to access the park as they want, and also, they think that for all the changes happening on the park government should take the responsibility. Therefore, proper and integrated approach in implementing policies and strategies related to land resources management should be considered. Enhancing productivity using proper technologies needs to be induced to minimize expansion of agriculture into forest lands and it is better to teach, work with and create awareness of the communities rather than working alone.

5.2 Recommendation

Based on the findings of this study, the following recommendations are forwarded for policy implications and future research directions.

- As the park is one of national park, there should have well documented information about status, trend, and change of the park. There is no document about LULC and its change nowadays
- It is also important to characterize or analyze the relation between LULCC and climate variability (e.g. Temperature and rainfall, etc.)
- This study addressed only the change in LULC and its driving forces behind the change. Therefore, further study is required to assess impacts of LULCC.
- It is better to work research which integrate LULC and that of Wild-life existence or their migration to know if there is any relation between them.
- Improving productivity using alternative technologies desires to be encouraged to diminish expansion of agriculture into woodlands. Controlling the expansion of agriculture at the expense of woodlands requires the right policy packages by national and regional governments such as livelihood diversification and improving the productivity of existing farm lands through the provision of improved production inputs.
- Population increase has played a major role on LULCC and there should be strong family planning awareness creation campaigns with adequate health services from the zonal and woreda health extension services (offices).
- It is better to teach, create awareness and work with the communities.

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Appendix I: Table 1. Time series satellite images of the study area to analyze LULCC

Data type	Path/Row	Date of acquisition	Sensor	Resolution	Source	Spectral bands
Landsat5	P169R056 and P170R56	15/02/1988	TM	30-meter	USGS	1-5&7
Landsat5	P169/R056 and P170R56	25/02/1998	TM	30-meter	USGS	1-5&7
Landsat5	P169R056 and P170R56	15/02/2008	TM	30-meter	USGS	1-5&7
Landsat8	P169R056 and P170R56	15/02/2018	OLI	30-meter	USGS	1-5 &7

Appendix II: Accuracy totals and Kappa Coefficient

Table 2: Accuracy totals and Kappa coefficient for the LULC Map of 1988

Class name	Producer accuracy	User accuracy
Woodland	97.91	98
Riverine forest	95.4	90.07
Grass land	94.41	95.74
Water body	97.99	96.57
Degraded land	92.79	95.51
Bare land	91.67	92.87

Overall classification accuracy = 95.33 Overall kappa statistics = 0.9

Table 3: Accuracy totals and Kappa coefficient for the LULC Map of 1998

Class name	producer accuracy	user accuracy
Woodland	97.44	97.77
Riverine forest	92.38	86.19
Grass land	93.92	92.25
Water body	97.85	99.26
Degraded land	92.8	96.72
Bare land	90.6	92.99

Overall classification accuracy (%) = 95.92 Overall kappa statistics =0.912

Table 4: Accuracy totals and Kappa coefficient for the LULC Map of 2008

Class name	Producer accuracy (%)	User accuracy (%)
Woodland	96.7	95.2
Riverine forest	93.45	90.2
Grass land	96.9	96.6
Water body	99.21	99.87
Degraded land	94.22	96.37
Bare land	90.68	97.32

Overall classification accuracy (%) = 94.25 Overall kappa statistics =0.90

Table 5: Accuracy totals and Kappa coefficient for the LULC Map of 2018

Class name	Producer accuracy (%)	User accuracy (%)
Woodland	97.8	97
Riverine forest	92.52	90.05
Grass land	96.65	94.09
Water body	99.8	99.99
Degraded land	96.05	98.3
Bare land	94.65	98.9

Overall classification accuracy = 96.09 Overall kappa statistics = 0.93

Appendix III: Sample of Ground Truth Points of Land cover Types

Waypoint	X_COORD	Y_COORD	Description
WL01	206409.36	647445.13	Woodland
WL02	207080.08	647498.81	Woodland
WL03	206418.06	646794.12	Woodland
GL01	201776.21	645267.89	Grass Land
GL02	201686.98	644788.72	Grass Land
GL03	203294.69	643527.16	Grass Land
RF01	212976.08	608282.87	Riverian Forest
RF02	211754.81	608653.64	Riverian Forest
RF03	211247.47	608644.7	Riverian Forest
WB01	167769.20	593627.73	Water body
WB02	169326.75	593648.31	Water body
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.			
.			

Appendix IV: Checklist for Household Survey, Focus Group Discussion and Key Informant Interview

1. Name of respondent--- Mobile number------------------
2. Gender Male------------------- Female---------------------------
3. Level of education of respondent--

   Years of formal schooling completed----------------------------------- (0, illitrate)
4. Marital status of household head

   1. Single 2. Married 3. Divorced 4. Widowed 5 Widower
5. Age of household head -----------------years
6. Years of residence in this village------------------------
7. How many family members do you have in your household? ---------------------------------
8. Farming experience------------years, Farming system: Zero tillage ------, Modern-------, Animal rearing system extensive----------, semi intensive-------------, intensive----------, other----------
9. Please indicate the number, age and gender of your household members

No.	Age categories (years)	M	F	No. of family members working on the farm full time		No. of family members working on off/nonfarm activities		total
				M	F	M	F	
1	Children <7							
2	Between 7& 14							
3	Between 15&64							
4	Elder > 65							

B. Overview on MNP

10. Is the park respected by local people? (yes, no), if yes why---

11. What is the local name of the park? --

12. What is the traditional attitude of the local people on the park? ------------------------------------

13. What kind of benefits do you obtain from the park?

    -food, animal feed, energy, financial income, cultural benefit, health, climate

    What is the impact of the degradation of the park on your livelihood? Are there any changes in the park? Yes-----------------, No--------------------------------

- If yes, how can you evaluate the changes?

In terms of forest coverage---

In terms of plant and animal species extinction--

In terms of climate variability, rainfall, temperature ---

In terms of household food supply ---

In terms of animal feed: ---

In terms of household income: --

In terms of human and animal health: ---

When this change was started (onseted) what are the main reasons of the change in the park, (expansion of grazing land, the increasing number of humans and animals, expansion of farming land, migration, change in culture, climate change, others, Is there any relation between park land cover change and local climate change? Yes-------------------------, No---------------------------

If Yes, how can you explain---------------------------, what is its consequences? ---------------------

Who is responsible to these changes---?

What measure should be taken to minimize the extenuated plant and animal species? -------------

14. Is it acceptable trend in the local people to interfere in the park area to cultivate crops, to settled and rearing animals? Yes------------------, No------------------------
15. If Yes, how can you evaluate the trends of peoples to encroach the park area? ----------------------

Are there pastoralists who got legal agricultural land in the park area?

Yes---------------------, No------------------------If Yes, the number of households live in the park area----------------, the number of years they settled------, impacts they caused on the park health-----------------------------

16. What effect the temperature and rainfall trends have brought on agricultural production? ------

1. Decrease in crop yield production   4. Drought   5. Increased incident of pest
2. Decreased animal productivity   6. Change in sowing period
3. Decreased forage availability   7. Other (specify)

17. What are the main causes for those hazards? --

18. How do you traditionally/ locally estimate those climatic extremes? -----------------------------

19. Which social groups are more vulnerable to those hazards? Why? -------------------------------

20. Do the crops you cultivate and animals you raring now are the same with the crops or animals your father was growing/ rearing? If no, why you change it? -------------------------------------

21. What adjustments the community made to those long term and short-term change in rainfall and temperature? List them--

22. Do you have access to credit, food aid, extension, agricultural inputs, technologies and water for irrigation ---

23. Finally, what must be done in order to minimize the effect and increase the adaptive capacity of the community? By GO’s, NGO’s, and by local communities --------------------------------

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Checklist for key informants to understand the causes of land use/land cover changes in Mago National Park.

1. How many villages surround Mago National Park?

2. Are there boundaries between the villages and the Park?

4. Is the population in your village increased from 1988 to 2018?

5. What is the status of the Mago National Park from 1988 to 1998 to, 1998 to 2008 and 2008 to 2018?

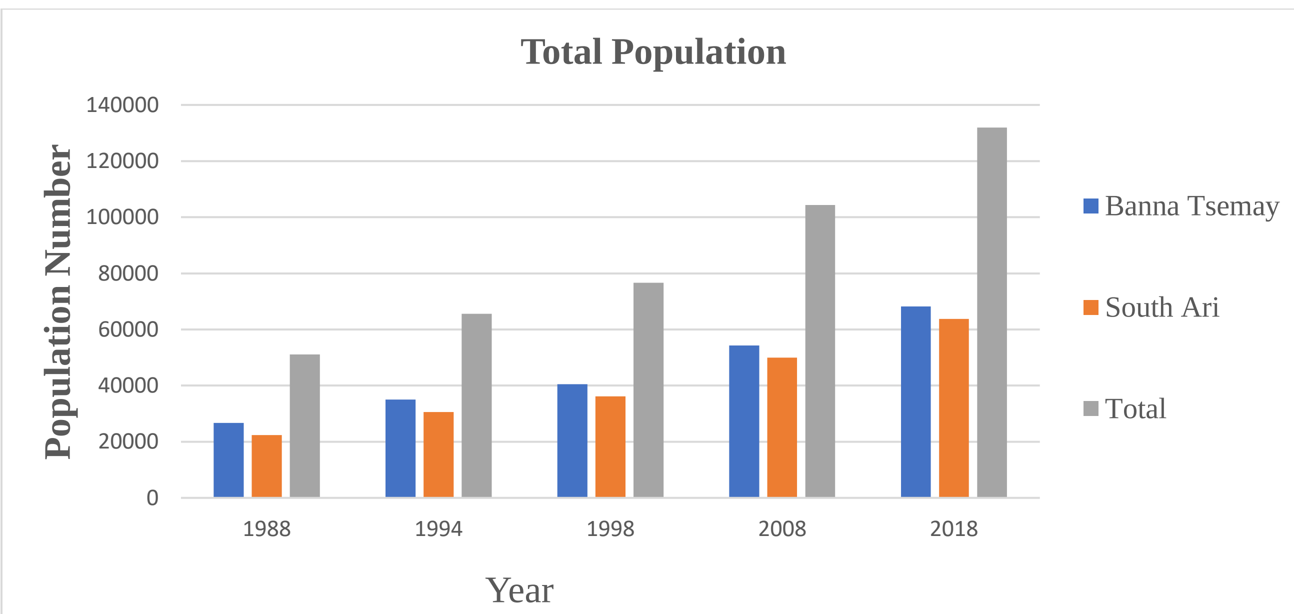
6. What are the land uses and land cover changes have been noticed from 1988 to 2018?

7. What are the effects that are faced by the communities around MNP due to changes in LULC?

8. What are the community involvements towards the changes in land use/land cover in MNP?

9. What do you think could be an appropriate way to avoid land use/land cover changes in MNP?

Appendix V: Estimated Total Population growth in Two Districts (1988-2018) derived from CSA.



Appendix VI: Sample Photos from field during data collection