**Addis Ababa University**

**School of Civil and Environmental Engineering**

**Stream of Geodesy and Geomatics Engineering**

# Land Use Land Cover Prediction Using Cellular Automata-Markov Model in Kulfo River Watershed

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**Addis Ababa Addis**
**May 30, 2023**

**Approval page**

The thesis prepared by Seble Gezahegn,land use land cover prediction using cellular automata-markov model in kulfo river watershed and submitted in fulfillment of the requirements for the Degree of Master in Geodesy andGeomanticEngineering

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# Land Use Land Cover Prediction Using Cellular Automata Markov Model in Kulfo River Watershed.

**By**

**Seble Gezahegn**

A Thesis Submitted to School of Graduate Studies in Partial Fulfillment of the Requirement for Degree of Master in Geodesy and Geomatics Engineering.

**Declarations**

I,……………….. , Registration Number/I.D. Number…, do hereby declare that this Thesis is my original work and that it has not been submitted partially; or in full, by any other person for an award of a degree in any other university/institution.

____________________________ ____________ _________________

Authors name Signature Date

This Thesis has been submitted for examination with my approval as College supervisor.

Dr.____________________________ ____________ _________________

Advisor Signature Date

## Acknowledgments

First, and foremost, I thank God for giving me the opportunity to pursue my graduate study at school of Civil and Environmental Engineering, Addis Ababa University. I would like to acknowledge the efforts, support, guidance, cooperation and encouragement of numerous people who directly and indirectly participated in the process and finalization of this Thesis.

I owe many thanks to express my sincere gratitude to my advisor Dr. Degefie Tibebe for his excellent guidance, critical comments and corrections and encouragement throughout my research time.

Most especially, I thank my dearest parents for their inestimable support. Besides, my husband and my daughter Rakeb Dagim and to my son Bisrat Dagim who tolerated those years me stronger what I owe you for your continuous encouragement that enable me to complete my study Thank you all for being there for me all the time.

Finally, I want to extend my regards to all my friends and classmates whose names could not be mentioned, for their cooperation and healthy interaction.

## Abstract

Land use land cover change is created principally by human activities, activities manipulating the Earth's surface for some purpose such as agricultural, industrial and residential etc. Mapping and predicting of LULC is important to identify and evaluate the magnitude and the change within the watershed to ensure best future planning and management. This study was mainly focusing on predicting land use cover change in kulfo river watershed through remote sensing, geographic information system integrated with IDRISI selva software and CA-Markov chain model. Cellular automata coupling with Markova model was used to predicting and modeling land use cover change for the year 2036 and 2051. Land use map of 2000, 2011 and 2021 were generated from Landsat satellite images. Analyzing the pixel based image classification method. The land use cover maps were computed using Maximum Likelihood algorithm of supervised classification technique, in ENVI 5.3 and GIS 10.8. Predicted LULC is developed using IDRISI Selva Software, and calibrated and validated using classified 2021 LULC maps. Hence the quality and location coefficient were calculated based on compassion of the predicted LULC for 2021 with the actual 2021 for first scenarios. The outcome demonstrate that bare land that was 14.5 % in 2021 decrease to 13.3% and change to 12.5% in 2051, forest land will decline from 18.3 % in 2021 to 17.7% in 2036 and also 18.5 % in 2051, water body that was 0.9% in 2021 to 0.6% in 2031 and change to 0.4 % in 2051.In general, the forecast result shows that except for built up area and cultivated land all land use type decreased per year respectively. Hence the observed LULC changes were generated by the increase of population, this lead to the demand for cultivated land, rural settlement and the extraction of forest for fuel and other construction materials.

Keyword: Kulfo river watershed, land use/land cover change, CA-Markov Model

## Acronyms

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# CHAPTER ONE

# 1. INTRODUCTION

## 1.1 Background of the study

Land use is an important driver of global environment change, numerous studies in the last two decades have estimated the rates of tropical deforestation and other kinds of land-cover change around the world. For centuries, humans have been altering the earth's surface to produce food through agricultural activities (Assefa, 2012). In the past few decades, conversion of grassland, woodland, and forest into cropland and pasture has risen dramatically, especially in developing countries where a large proportion of human population depends on natural resources for their livelihoods (FAO, 2005).

The increasing demand for land and related resources often results in changes in land use/cover (Assefa, 2012) and it has local, national, regional and global causes (Olson et al., 2004). In developing countries, a high proportion of income, employment and export earnings stems from agricultural production. Access to land is the basis for economic and social life in both rural and urban areas.

Land through inappropriate agricultural practices, high Human and livestock population pressure have led to severe land cover change. In Ethiopia, also most Population lives in rural areas and depends directly on land for their livelihood (Tesfaye et al., 2014). This heavy dependence on peoples on land. Lead to soil erosion, land degradation and biodiversity loss. Soil erosion will again lead to loss of groundwater due to poor infiltration capacity and washed away of the soil nutrient and desertification will occur. This all will contribute to low productivity leading to poverty. Therefore, information on land use land cover, changing trends and optimal use of land resource have become predestined criteria for land use planning and effective natural resource management of an area.

LULC change models are usually applied to detect location of the changes occurred or will potentially occur (Halmy et al., 2015; Yagoub and Bizreh, 2014). By determining the factors of the changes, the models benefit through providing probabilistic prediction of possible changes may occur (Halmy et al., 2015). Technically, change analysis is carried out using historical land use data in which the past land transformations and transitions were assessed. The transition trend is incorporated with environmental variables to provide an estimate of future scenarios (Behera et al., 2012; Yagoub and Al Bizreh, 2014). Prediction of LULC changes is important to understand and highlight the potential modifications and alterations that might be happen to the landscape in the near future. Typically, changes occur due to increasing population, distance to roads or other facilities, type of the soil, environmental issues, and so on. LULC models are usually used to assess the cumulative impact of land use changes and develop the future scenarios (Behera et al., 2012; Halmy et al., 2015), which is important in providing support and help to land use planners, resource managers, and conservation practitioners in making decisions (Halmy et al., 2015; Memarian, et al., 2013; Parsa et al., 2016).

Due to these, modeling and predicting the dynamics of LU/LC is crucially important for managing the environment. Hence, identifying the rate and process of LU/LC changes is fundamental, which have national and international significance. However, the watershed LU/LC change is not well investigated. Thus, this study was aimed to assessing and predicting the LU/LC changes from 2000 to 2021 periods and predicts the situation to 2036 and 2051periods.

## 1.2 Statement of the problems

Kulfo watersheds in the south-western region of Ethiopia have been experiencing widespread land use cover changes over the past few years. In the past 20 years the watershed has been covered by dense forest trees and other wood biomass. Nowadays, there has been continuous expansion of various demands, soils erosion by flooding water especially on steep terrain, wildfire highly degraded the natural ecosystem and the watershed has experienced human-induced land degradation mainly due to agricultural expansion and unregulated LULC changes It seems obvious that large amount of soil has been lost to the Lake Chamo. This does not only degrade soil fertility over time by reducing the suitability of land for future agricultural use, but also supply high sediment load to streams and results in negative impact on the watershed. (Tilahun, 2015). In This research it is claimed that the increased of built up area and the declined of other land use type influence the pertinent features of watershed. Hence analysis and understanding the impact of Land use cover change in watershed are important for planning and management water resource and watershed area in general. This study designed the land use land cover change and predicts the future land use cover change in kulfo river watershed. The researcher also assessed the rate of land use cover change and transition probability matrix. There have been few studies conducted on LULC but no studies conduct on predicting the future land scape. Hence, this research was intended to fill this gap.

## 1.3 Objective of the study

### 1.3.1 General objective of the study

The general objective of the research is land use cover change prediction in kulfo river watershed through Cellular Automata with Markov chain model.

### 1.3.2 Specific objective

- To generate land use map of the study area during the period 2000, 2011, 2021.
- To assess the accuracy of the classified maps.
- To assess LULC- dynamics and change patterns in the past 22 year.
- To predict change in land use land cover CA- Markov chain model for the periods of 2036 and 2051.

## 1.4 Research questions

1. What are the spatiotemporal patterns of land use land cover change of the study area?
2. What are the major land use classes of the study area?
3. Dose Markov model can predict future land use land cover in good accuracy in the study area?

## 1.5 Scope and significance of the study

The study investigates land use land cover change in the study watershed and Predicting future land use land cover change by using CA- Markov chain modeling using IDRISI selva 17 geospatial software. To know the previous and present land use land cover change and predict the future land use cover change are a vital for local governments and policy makers to formulate and implement appropriate land management system in the watershed area.

## 1.6 Organization of the thesis

The thesis is organized in to five different chapters. In which the first chapter deals with, introduction to the research, statement of the problem, research objectives, questions, scope of the study and organization of the thesis. The second chapter contains literatures review. Chapter three provides details about data and methodology used in this study which, includes, methods of data collection and analysis, image classification, accuracy assessment methods and procedures of Cellular automata coupling with Markova chain models. Chapter four contains result and discussion. The last chapter contains conclusion and recommendations. Furthermore, it indicates limitations the study future research direct

# CHAPTER TWO

## 2. LITRATURE REVIEW

### 2.1 The concept of land use land covers change

Land cover has been defined by the attributes of the Earth's land surface and Immediate subsurface, including biota, soil, topography, surface and groundwater, And human (mainly built-up) structures. Land-cover conversions constitute the replacement of one cover type by another and are measured by a shift from one land-cover category to another, as is the case of agricultural expansion, deforestation, or change in urban extent. Contemporary land-cover change is generated principally by human activity, activity directed at manipulating the Earth's surface for some individual or societal need or want, such as agriculture (Turner et al., 1990; Ojima et al., 1994; Walker et al., 1999;Classman et al., 2005).

Land use has been defined as the purposes for which humans exploit the land cover. Regardless, land cover and land use are so intimately linked that understanding of either has required approaches for linking household and community surveys, demographic and agricultural censuses, and market data, among others, to remote sensing and geographical information systems (Fox et al., 2003)

Land use change is largely driven by the decision of the people and population growth, declining household farm size and income (Hamza and Iyela, 2012).In most developing countries like Ethiopia population growth has been a dominant cause of land use and land cover change than other forces (Sage, 1994).

Land use and land cover characteristics have many connections with hydrological cycle. The land use and land cover type can affect both the infiltration and runoff amount by following the falling of precipitation (Hougton, 1995).

Generally, knowing of the impacts of land use and land cover change on the natural resources like water resources depends on an understanding of the previous land use practices, current land use and land cover patterns, and projection of future land use and land cover, as affected by population size and distribution, economic development, technology, and other factors. The land use and land cover change assessment is an important step in planning sustainable land management that can help to minimize agro-biodiversity losses and land degradation, especially in developing countries like Ethiopia (Hadgu, 2008).

### 2.2 The Cause of Land Use land Cover change

There are various researches related with the causes of land use land cover change studies in Ethiopia. (Meyer and Turner, 1992; Houghton, 1994; Santa, 2011)

According to Meyer and Turner (1992) Land-cover changes refer to which conversion of the land-cover from one type of to another and modification of the conditions within a category and land-use change occurs initially at the level of land parcels when land managers decide that a change towards another land utilization type is desirable.

Houghton (1994) states that the change in land use land cover reflect the history and perhaps the future humankind. These changes are influenced by a variety of factors related to human population growth. Population growth is one of the major factors for land use land cover change. People are the most important natural resources, which is mutually inter-related and interdependent for their sustainable development (Santa, 2011).

According to United States Environmental Protection Agency (USEPA, 2004), identified the general causes of LU/LC are.

- Direct effect of human activity such as road and illegal house constructions and deforestations (Clearance of trees).
- Indirect effects of human activity is such as, water diversion leading to lowering of the water table.

### 2.3 LULC Changes and watersheds in Ethiopia

The researches that have been conducted in different parts of Ethiopia have shown that there were considerable land use and land cover changes in the country. Most of these studies indicated that, cultivated and agricultural land is expanded in expense of natural vegetation like forest, shrub and grass lands. For instance (EFAP, 1994; Gashaw, 2015; Abdi and Ekasit, 2012; Nyssen et al., 2004; Sewent, 2015)

According to EFAP (1994) in his study reporting that over 97% of the forest cover of the country had been lost. This is because of Conversion of forest and shrub and grass lands to agricultural land are prevalent in Ethiopia due to the lack of land use planning in the country. Abdi and Ekasit (2012) reported that the Fincha watershed is a typical example of watersheds in the country that had undergone land use changes. The watershed had gradually been encroached by agricultural and water bodies have increased in area by 60,606 (53.59%) in 1985 to 19,184 ha (93.10%), in 2005 respectively. During this period, tremendous losses in forest, grazing land, swamp area and shrub lands were observed. Glashaw (2018) showed that modeling the impact of land use land cover change on hydrology of upper Bule Nile river basin of Ethiopia. The hybrid land use classification technique for classifying time series Landsat images (1985, 2000 and 2015); the Cellular-Automata Markov (CA-Markov) model for prediction of the 2030 and 2045 LULC. The results showed that in the past three decades, cultivated land and built-up areas significantly increased while areas occupied by natural vegetation such as forest land, shrub lands and grasslands dwindled at a rapid rate. The predicted results suggest a continuation of the trend unless management interventions are made today. Sewnet (2015) reported that because of population increase and improper agricultural activity bush and wetlands have been declined whereas farm and settlement lands were expanded between the study years.

In Ethiopia some micro-level studies from aerial photo and satellite images have revealed agricultural land expansion at the expense of other land uses. These studies, confirmed the significant increase in cultivated and settlement lands at the expense of forestland, wetlands, riparian vegetation, grass lands and open access areas Nyssen et al., (2004). The catchment have shown continuous decline of forest, wetlands and expansion of farm and settlement area between 1973 and 2008 in Gilgel Abbay watershed Amare and Kameswara (2011, 2012).In kulfo watershed Land cover change analysis has shown an increment in the proportional of the Agricultural land from 11.9% to 14.39%, Bare land from 25.8% to 14.14%, Forest from 16% to 12.43%. Water body, remain stable, however, Shrub land increased from 29.28% to 36.82% in between 1985 to 2005 (Tilahune, 2015).

### 2.4 Land Modeling Tools

According to verburg et al., (2012), Land use modeling, at the present time, plays a pivotal role in many natural resources management and decision making processes. Land use models are effective tools to analyze the causes and consequences of land use-land cover change and create an enhanced understanding of the land use system in an area. The use of land change models is multi-dimensional. For example, they were used in biodiversity monitoring (Verburg et al., 2008), for estimating loss of vegetation cover (Echeverria, et al., 2008), for forest managements (Kamusoko et al., 2013), in urban expansion and planning (Sun, *et al.,* 2007).

Researchers around the globe have been devising and utilizing a wide variety of land use models, all of which are diverse in their formulations, objectives and capabilities. There are whole landscape models, distributional landscape models as well as spatial landscape models (Baker, 1989; Singh, 2003). Since the spatial details including natural and human processes have greater impacts on land use change system, spatial modeling has taken over other modeling methods in many studies. Progress in remote sensing and GIS research has made significant contributions in these spatial landscape modeling methods (Singh, 2003). The researcher used the following models listed here.

#### 2.4.1 Cellular Automata (CA)-Markov models

According to Regmi and Subedi, (2017), CA-Markov model is one of the commonly used models among many LULC modeling tools and techniques which model uses both spatial and temporal changes. CA-Markov model combines both cellular automata and Markov chain to predict land use land cover changes trends and characteristics over time. The integration of the CA-Markov model is considered to be valuable for modeling land-use changes and able to simulate and predict changes. In addition The CA-Markov model is the combination of Cellular Automata and transition probability matrix Generated by the cross-tabulation of two different images. This combination of the CA-Markov model provides a robust approach in Spatio-temporal dynamic modeling. Markov analysis is a powerful modeling and analysis technique with strong applications in time-based reliability and availability analysis. The reliability behavior of a system is represented using a state-transition diagram, which consists of a set of discrete states that the system can be in, and defines the speed at which transitions between those states take place. Markov models consist of comprehensive representations of possible chains of events, i.e. transitions within Systems which, in the case of reliability and availability analysis, correspond to sequences of failures and repair. Moreover, the CA-Markov is one of the planning support tools for the analysis of temporal changes and spatial distribution of LULC.

Generally the model uses the past land use cover map, transition probability matrix and the classified image of each land use type. Accordingly, the LULC for the year 2021 was predicted considering the LULC map of 2000 and 2011. Then the predicted LULC areas of 2021 will compared with the actual areas interpreted from 2021. After validating the Performance of the model, a real "prediction" for the year 2036 will carried out.

This model widely used to describe the dynamics of LULC changes, plant growth, urban sprawl, plant cover and modeling the watershed area. Hamad and Kolo, (2018) this enables for local government and policy makers sustainable land use management.

### 2.4.2 Application of CA- Markov Models

According to Walsh et al. (2008) a cellular Automat (CA) Model was applied for agricultural expansion and deforestation; a combination of various models has also been used in many studies as in Kamusoko et al., (2013) for modeling multiple land use processes. (Weng, 2002) Markov Chain as a simple land use model is a useful and popular tool in this context and covers large spatial extent. (Mubea et al., 2010). The Markov model calculates transition matrix for various land use features based on current driving factors and predicts the future land use change pattern if the driving forces continue in future Markov Chain has been successfully used in m any studies with few reported issues in varied settings; for example Weng (2002) employed Markov model along with remote sensing and GIS analysis to model land use dynamics in a coastal region of China; Islam & Ahmed (2011) modeled urban sprawl in Dhaka city using GIS aided Markova modeling, while Freier, et al. (2011) used Markov Chain for modeling rangelands under climate change scenarios in semi-arid environment of Morocco.

### 2.4.3 Equation of Markov Model

According to the USGS Global Visualization Viewer. (2018) we use the following equations to predicting of land use changes.

S (t, t + 1) = Pij × S (t)………………………………………………………… (1)

Where s (t) is the system status at the time of *t;* s (t+1) is the system status at the time of t + 1; *pig* is the transition probability matrix in a state which is calculated as follows.

$$p_{ij} = \begin{vmatrix} p_{11} & p_{1,2} & p_{1,n} \\ p_{2,1} & p_{2,2} & p_{2,n} \\ p_{n,1} & p_{n,2} & p_{n,n} \end{vmatrix} \quad 0 \leq p_{ij\leq 1})\text{………………} \; (2)$$

Where $P$ is the transition probability; $p_{ij}$stands for the probability of converting from current state $i$ to another state j in next time; $p_n$is the state probability of any time. The low transition will have a probability near (0) and the high transition

Has a probability near (1).

### 2.5 Remote sensing

According to Lillesan and Kiefer (2004), Remote Sensing is the science and art of acquiring information (spectral, spatial, and temporal) about material objects, area, or phenomenon, without coming in to physical contact with the objects, or area, phenomenon under investigation. Without direct contact, some means of transferring information through space must be utilized. In remote sensing, information transfer is accomplished by use of electromagnetic radiation.

Satellite images are one of the most important sources of raster data for GIS and image processing software. As the name implies, imagery can be obtained from many earth-orbiting satellites providing data gathered by a variety of sensors. Satellite data are referred to as imagery instead of photography, because the majority of satellite data are collected through Satellite images or data are available for land use classification, digital elevation model (DEM), updating highway network.

### 2.5.1 Image processing

Image processing is almost always the first step of any remote sensing application. Project but it is often given greater significance than it deserves. The image processing strategy proposed in this section is most relevant to these types of data, and its goal is the effective discrimination of different spectral and spatial targets.

In order to process remote sensing imagery digitally, the data must be recorded and available in a digital form suitable for storage on a computer tape or disk. Obviously, the other requirement for digital image processing is a computer system, sometimes referred to as an image analysis system, with the appropriate hardware and software to process the data.

The common image processing functions available in image analysis systems can be categorized into the following four categories:

- Preprocessing, image enhancement, image transformation and image classification and analysis. Preprocessing functions involve those operations that are normally required prior to the main data analysis and extraction of information, and are generally grouped as radiometric or Geometric corrections. Radiometric corrections include correcting the data for sensor irregularities and unwanted sensor or atmospheric noise, and converting the data so they accurately represent the reflected or emitted radiation measured by the sensor. Geometric corrections include correcting for geometric distortions due to sensor-Earth geometry variations, and conversion of the data to real world coordinates (e.g. latitude and longitude) on the Earth's surface.
- Image enhancement, is solely to improve the appearance of the imagery to assist in visual interpretation and analysis. Examples of enhancement functions include contrast stretching to increase the tonal distinction between various features in a scene, and spatial filtering to enhance (or suppress) specific spatial patterns in an image.
- Image transformations are operations similar in concept to those for image enhancement. However, unlike image enhancement operations which are normally applied only to a single channel of data at a time, image transformations usually involve combined processing of data from multiple spectral bands. Arithmetic operations (i.e. subtraction, addition, multiplication, division) are performed to combine and transform the original bands into "new" images which better display or highlight certain features in the scene.

- Image classification and analysis operations are used to digitally identify and classify pixels in the data. Classification is usually performed on multi-channel data sets (A) and this process assigns each pixel in an image to a particular class or theme (B) based on statistical characteristics of the pixel brightness values. There are a variety of approaches taken to perform digital classification. We will briefly describe the two generic approaches which are used most often, namely supervised and unsupervised classification.

### 2.5.2 Image classification

According to Weng (2012**)** Image classification refers to the extraction of differentiated classes or themes, usually land cover and land use categories, from raw remotely sensed digital satellite data. Image classification using remote sensing techniques has attracted the attention of research community as the results of classification are the backbone of environmental, social and economic applications (Lu and Weng, 2007). Because image classification is generated using a remotely sensed data, there are many factors that cause difficulty to achieve a more accurate result. Some of the factors are:

- The characteristics of a study area,
- Availability of high resolution remotely sensed data,
- Ancillary and ground reference data,
- Suitable classification algorithms and the analyst's experience, and
- Time constraint.

These factors highly determine the type of classification algorithm to be used for image classification (Sahalu, 2014). There are various image classification methods that can be applied to extract land cover information from remotely sensed images (Lu and Weng, 2007). The commonly used methods are discussed below.

#### 2.5.2.1 Object-Oriented Image Classification Methods

According to (Gao and Mas, 2008; Weng, 2012) the method of classification based on identifying image objects, or segments with similar texture, color and tone of spatially contiguous pixels. This approach allows for consideration of shape, size, and context as well as spectral content (MacLean and Congalton, 2012). The classification stage starts by grouping the neighboring pixels into meaningful areas. Qian et al., (2007) noted that in object oriented classification approach, single pixels cannot be classified rather homogenous image objects are extracted during segmentation step. Image analysis in object-oriented is based on contiguous, homogeneous image regions that are generated by initial image segmentation.

#### 2.5.2.2 Pixel-Based Image Classification Methods

According to (Qian et al, 2007; Weng, 2012). These types of classification automatically categorize all pixels in an image into land cover classes fundamentally based on spectral similarities. Pixel-based classification develops a signature by summing up all pixels. Thus, the developed signature contains the necessary things found in the training pixels but does not contain the influence of mixed pixels (Weng, 2012). According to Tadesse et al., (2003), there are two primary types of pixel-based classification algorithms applied to remotely sensed data: unsupervised and supervised.

In a supervised classification, the analyst identifies in the imagery homogeneous representative samples of the different surface cover types (information classes) of interest. These samples are referred to as training areas. The selection of appropriate training areas is based on the analyst's familiarity with the geographical area and their knowledge of the actual surface cover types present in the image. Thus, the analyst is "supervising" the categorization of a set of specific classes. The numerical information in all spectral bands for the pixels comprising these areas are used to "train" the computer to recognize spectrally similar areas for each class. Thus, in a supervised classification we are first identifying the information classes which are then used to determine the spectral classes which represent them.

Unsupervised classification in essence reverses the supervised classification process. Spectral classes are grouped first, based solely on the numerical information in the data, and are then matched by the analyst to information classes (if possible). Programs, called clustering algorithms, are used to determine the natural (statistical) groupings or structures in the data.

Usually, the analyst specifies how many groups or clusters are to be looked for in the data. In addition to specifying the desired number of classes, the analyst may also specify parameters related to the separation distance among the clusters and the variation within each cluster. The final result of this iterative clustering process may result in some clusters that the analyst will want to subsequently combine, or clusters that should be broken down further - each of these requiring a further application of the clustering algorithm. Thus, unsupervised classification is not completely without human intervention. However, it does not start with a pre-determined set of classes as in a supervised classification.

### 2.6 Geography information system (GIS)

According to Burrough and McDonnell (1998) Geographic information system referred to it as set of tools for collecting, storing, retrieving at will, transforming, and displaying spatial data from the real world for a particular set of purposes. Geographic Information System Is a computer based system that provides four sets of capabilities to geo-referenced data: data input, data management (storage and retrieval), manipulation and analysis, and finally data output (Arnoff, 1989).

Geographic Information Systems is a computer based system which is used to digitally reproduce and analyze the future at present on earth surface and the events that take place on it. Furthermore, a Geographic Information Systems integrates data, hardware, software and GPS to assist in the analysis and display of geographically referenced information. GIS is a general term that refers to any scientific effort integrates data to help researchers visualize, analyze, and explore geographically referenced information. A GIS provides facilities for data capture, data management, data manipulation and analysis, and the presentation of results in both graphic and report form, with a particular Emphasis upon preserving and utilizing inherent characteristics of spatial data. In addition to this utilize the land resources in sustainable way; a land use plan that incorporates the different land characteristics has a paramount importance. To incorporate the different land attributes that differ spatially and to identify the best suitable land use, GIS is a vital tool. Geographic Information Systems (GIS) incorporates database systems for spatial data. The ability to incorporate spatial data, manage it, analyze it, and answer spatial questions is the distinctive Characteristic of geographic information systems.

### 2.7 Application of remote sensing and geographic information for LULC

Remote sensing is science, art and technology of observing an object, scene or phenomenon by instrument-based techniques without physical contact. This is done by sensing and recording reflected or emitted energy and processing, analyzing, and applying that information. Remote sensing provides crucial data for Hydrological modeling like Digital Elevation Model and land cover data.

The importance of Remotely sensed imageries provide an efficient means of obtaining information on temporal trends and spatial distribution of urban areas needed for understanding, modeling and projecting land changes **(**Elvidge et al**.,** 2004). In case of inaccessible regions, this technique is perhaps the only method of obtaining the required data on a cost and time effective basis (Olorunfemi, 1983). Satellite imagery is able to provide more frequent data collection on a regular basis unlike aerial photographs. Although aerial photographs may provide more geometrically accurate maps but is limited in respect to its extent of coverage and expenses.

There are many problems related with land use land cover such as soil erosion, deterioration of environment, deforestation, population growth, drought conditions, shortage of drinking water etc. These are complex issues and require integrated responses. One difficulty in organizing such integration e.g. among soil, water, vegetation has been the lack of means to link the data in comparable and manageable sets. In order to overcome these difficulties GIS offers entry of many types of data in a single spatial framework and has capability of collection, compilation, storage, retrieval, analysis, manipulation, display and integration of environmental, economic and social data in a single system. With the invention of Remote Sensing and GIS techniques land use/cover mapping is a useful and detailed way to improve the selection of areas designed to agricultural, urban and/or industrial areas of a region (Selcuk *et al*., 2003). In addition to this GIS integrated with remote sensing with advance geo modeling, decision support system for planning and managing future watershed area.

### 2.8 Application in LULC mapping and prediction

There are different scholars used different model to represent and predict the change of land use cover changes.  According to Walsh et al. (2008) a cellular a automata mechanistic model was applied for modeling agricultural expansion and deforestation; However, Markov Chain as a simple land use model, is a useful and popular tool in this context and covers large spatial extent (Weng, 2002). The Markov model calculates transition matrix for various land use features based on current driving factors and predicts the future land use change pattern if the driving forces continue in future (Mubea et al., 2010). Markov Chain has been successfully used in  many studies with few reported issues in varied settings; for example  Marwa,(2015) employed Markov-CA model integrated with remote sensing and GIS analysis to model land use/land cover change detection and prediction in the north-western coastal desert of Egypt (Temesgen Gashaw et al., 2018) modeled the impact of land use cove change on hydrology, Ecosystem Functions and Services in the Upper Blue Nile Basin of Ethiopia, While Abdi and Ekasit, (2012)Analysis and Prediction  of land use f modeling using remote sensing and Markov in Fincha Watershed, Ethiopia.

**Conceptual Frame Work**

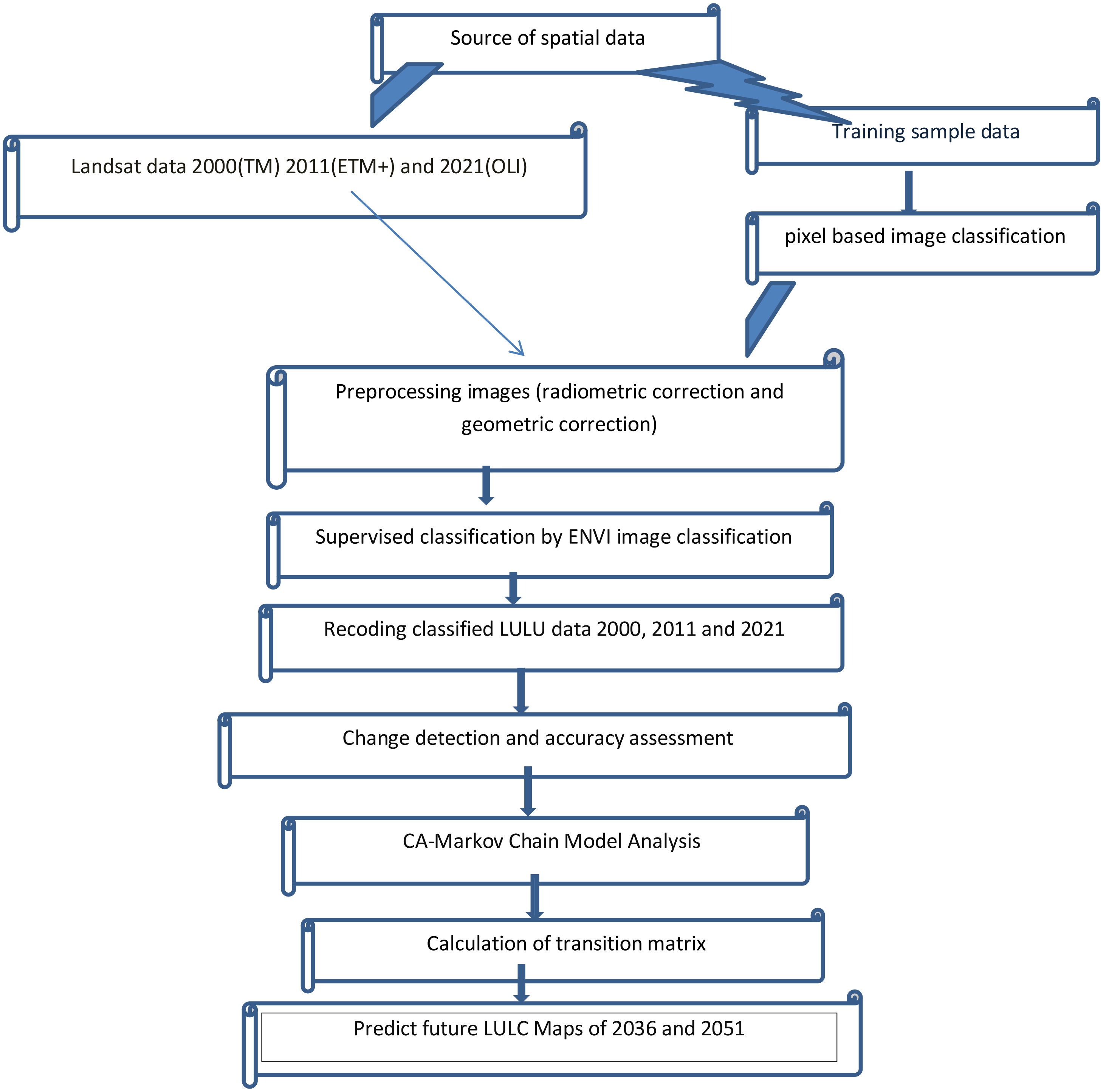


Figure 2.1 Flow chart Conceptual frame work

# CHAPTER THRE

## 3. MATERIALS AND METHODS

### 3.1 Location and extent of Kulfo river watershed

Kulfo river watershed is located in Gamo Zone, in southern Ethiopia, which is located one km away from the center of Arba Minch town and south west of Arba Minch Airport. Geographically it lies between 5º58'5’’N to 6º15’31’’N latitude and 37º18’12’’E to 37º36’19’’E, longitude. Kulfo River has a catchment area of approximately 410 km2 outlets at Lake Chamo, about 364 km2 at gauging site .the elevation range from 1180m to 3384m above sea level. The Kulfo River is a River in southern Ethiopia that rises in the western escapement of the Main Ethiopian Rift in the Guge Mountain. It flows through Areba Minch and then through the Nechisar National park on the isthmus between Lake Chamo and Lake Abaya. Kulfo river originates from the junction of Titika and Gulando River at 6o07’N latitude and 37o27’E longitude. At the upper part of the river the main tributaries drainage are baba, gulando and yereamo wear as the tributaries such as Wobale and Mojale drain to the middle part of the watershed and Korzha, Ambule and Titika to the lower part of the catchment area. The mean annual flow of Kulfo River at upper gauging station is 6.32 $m^3$ /s.

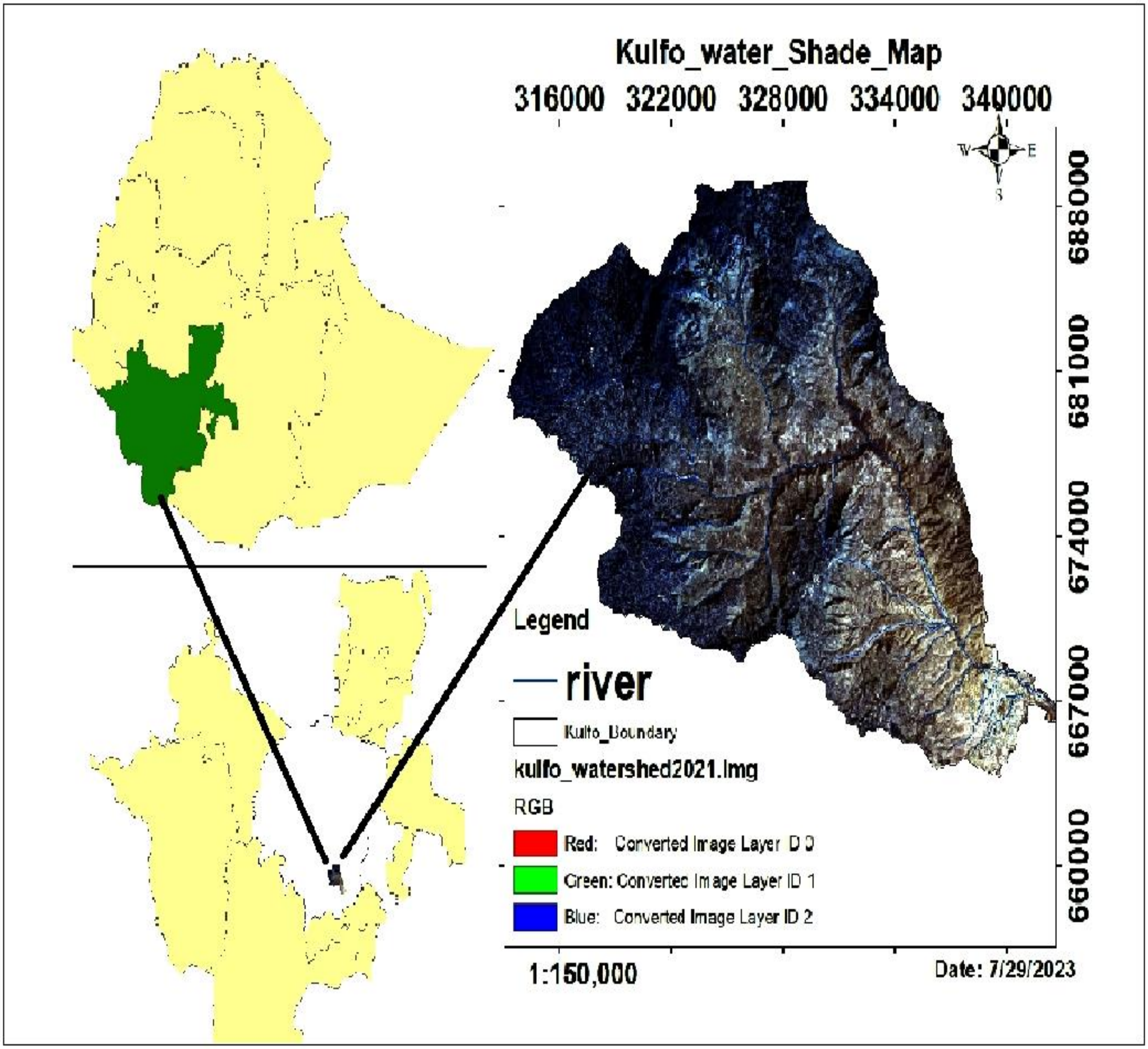


Figure 3.1 Location of Kulfo Watershed

### 3.2 Topography

Due to the nature of the position of catchment area of Kulfo River on the western side of the Ethiopian rift valley is characterized by steep topography in the upper part and almost flat at lower part and bounded by High Mountain. The elevation of the catchment lies between 3600 and 1108 meters above sea level

### 3.3 Climate

Kulfo watershed lies within the rift valley. Receiving an annual rain fall of 80% during March to October. The distribution varies between 35.5 mm in January and 195 mm in May. Raining season stretches from April to May and September to November while the dry season covers between Decembers to February. Monthly temperature ranges from 12.7 in November to 36.3 in March. The warmest season from January to March and the relative cloud season occur from October to December. Mean annual daily range of temperature is 12.6 while monthly value reaches as high as 17.6 in December.

### 3.4 Soil

The type of soil around Kulfo River is exogenous in its origin .i.e. mixture of soil formed from different parent's materials and hence difficult to give clear classification and description. However, reports indicate that the principal soil around the river is chromic Vertis oil, district nit soil and etheric nit soil. The dominant soil of the area is chromic Vertis oil is high and hence it is susceptible to erosion these soils are deep and have very good potential for agriculture. The nit soil of the area is intensely cultivated for annual crops (Kassa, 2007, Negash, 2013)

### 3.5 Socio economic condition

The socio economic condition of the population is mainly based on agriculture. The dowelling uses Kulfo River for their irrigation purpose. The man agricultural products in the upper part of the stream are barely, potato, bean, banana and Enset. Enset is the dominant food in the upper stream of the watershed. While livestock breading like sheep, goat and horse are practiced in the area.

### 3.6 Data source, materials and methods of the study

To generate land cover maps of the study area deferent time period remote sensing data used, Landsat imagery of the year 2000,2011 and 2021 data set will acquired  Landsat data will be downloaded free of charge from U.S Geological Survey (USGS) Center for Earth Resources Observation and science (EROS) And Global land covers facility website.

**Table 3.1 Landsat images used for land used cover change analysis**

| Landsat images | Sensor | Years of acquisition | Spatial resolution |
|---|---|---|---|
| Landsat | TM | 26 January 2000 | 30m |
| Landsat | ETM+ | 26 January 2011 | 30m |
| Landsat | OLI-TIRS | 28 January 2021 | 30m |

Source; http; USGS.geological survey

### 3.7 Image Acquisition materials

For his study, various Landsat data used such as, Thematic Mapper(TM) and Enhanced Thematic Mapper (ETM+) and OLI-TIRS (recent year image) data were obtained. The Landsat images used in this study collected from the archive of US Geological Survey and Global land cover facility. The acquired data set covered a period of 2000, 2011, and 2021.

ENVI 5.3, Arc Map 10.8 and CA-Markov model are used to carry out image preprocessing, map preparation and predicting. GIS software using for raster and vector data analysis and mapping in addition to this all the spatial metrics are calculated for each land use category using the software of IDRIS selva 17 which is geospatial software useful for predicting future land use type of 2036 and 2051.

### 3.7 Pre-Processing of image

Preprocessing of satellite images is essential and aims at the unique goal of establishing a more direct linkage between data and the biophysical phenomena it represents (Parsa et al., 2016). Therefore Atmospheric correction is aplied to all images using the Quick Atmospheric correction (QUAC) algorithm in the ENVI (Exiles Visual Information solution) image processing program version 4.8. Thus each image is Radiometric and geometrics corrections are performed using relative radiometric correction methods and Geometrics corrections methods.

### 3.8 Land Use Classification and Change Detection Analysis

#### 3.8.1Image classification and Accuracy assessment

A supervised classification with the maximum likelihood algorithm was used to classify the LUC change of the Images. Different supervised classification methods have been applied and tested extensively for land use planning and management in watershed. In this study a supervised classification using maximum likelihood (MLC) algorism, was applied based on the spectral differences between each class. These differences were used to subdivide the LULC of kulfo river watershed into separate classes. In order to execute a supervised classification, it is necessary to collect the 2000, 2011 and 2021 Landsat images and reference data from Google earth images from the corresponding time periods were collected. Spectral signatures from training areas, which are then used to train the classification algorithm (Chen and Stow 2002; Jusoff et al. 2009). Furthermore pixel based image classification is applied based on Prior knowledge of the study area to execute supervised classification, depending on previously collected training sites from certain areas of known lulc.In this study Google Earth images were used to check and classify the accuracy of classified images by using Arc GIS desktop software version 10.8. Fifty (250) controlling points collected randomly from the corresponding classified Google earth images of 2000, 2011 and 2021.Then the classified images compared with reference image by means of error matrix. Arc GIS 10.8 and ENVI 5.3Software were used for preprocessing, classifying the image and mapping and IDRSE selva 17.0 software's for prediction purpose respectively.

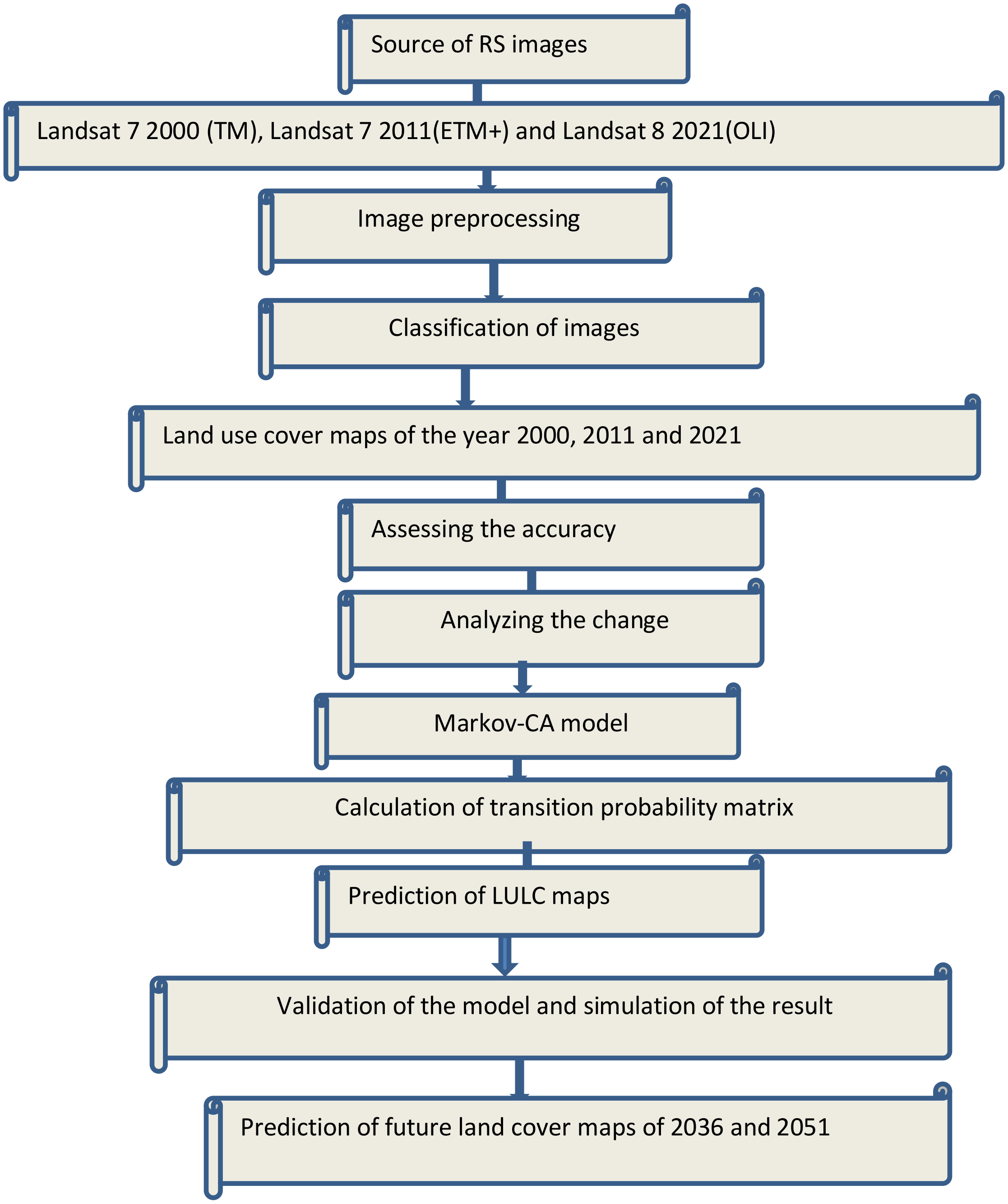


Figure 3.2 Flow chart shows methodology used in this study

**Accuracy Assessment** is a process used to estimate the accuracy of image classification by comparing the classified map with a reference map (Caetano *et al*, 2005).The accuracy of the classification is verified by taking sample points from Google earth images comparing with the classified map each year. And also the accuracy of the image classification assessed by computing using four general accuracy assessment measurements such as procedure accuracy, user accuracy, over all accuracy and kappa coefficient.

### 3.9 Land use cover change detection analysis

Performing land use changes in the years, post classification method is employed. By using conversion matrix analyses over all land use change as well as the gain and loss in each category between the year 2000 and 2021 will determine. In order to analyses the rate and percentage of land use cover change using the following formula. According (Motuma and Gizaw , 2018) percentage and rate calculating in the following equation**.**

$$percentage = \frac{(area\ of\ initial\ year - area\ of\ final\ year)}{area\ of\ initial\ year} * 100 \ldots\ldots\ldots\ldots\ldots\ldots\ldots 3$$

$$\boldsymbol{r} = \frac{\boldsymbol{Q_2 - Q1}}{\boldsymbol{t}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 4$$

Where: r, Q2, Q1, and t indicates the rate of change, recent year LULC in ha, initial year LULC in ha and interval year between initial and recent year respectively.

### 3.10 Prediction of land use land covers change

For this study, CA-Markov model. This model combines cellular automata and Markov chain to predict the LULC change trends and characteristics over time. Most LULC modeling tools uses CA-Markov model, which model both the spatial and temporal changes ( Regmi, R.R., S.K. Saha, 2017). CA-Markov models uses IDRIS selva version 17.0 for prediction of the year 2036 and 2051. Markov chain model uses transition probability matrix which enables to determine how land use cover change from the beginning date to the predicated date year. Furthermore the analysis of two different dates of the LULC images induces the transition matrices, a transition area matrix and a set of conditional probability image .Before predicting the future land use land cover of 2036 the model were first validate the land use cover change of 2021 using the kappa statistics' the system uses the same procedure the land use land cover the year 2021 will used. Then the predicted map of 2021 compared with the actual area interpreted with the actual interpreted map of 2021 .the result tasted with kappa statistics.

# CHAPTER FOUR

## 4. RESALTS AND DISCUSION

### 4.1 Land use land cover map of 2000

The classification result shows that LULC of maps significantly changes from one land use class to another class. Cultivated land accounted for the majority of the LULC in January 2000 with a total of 20945.6 Ha (54.0%) followed by forest land, barer land, built-up area, and water body accounting for 9538.7 Ha (24.6%), 4686.4 Ha (12.1%) and 2518.9 Ha (6.5%) and 1071.5 Ha (2.8%) respectively. the distribution of the land use class shown in the figure.

**Table 4.1 Description of land use type of 2000**

| LULC TYPE | 2000 | |
|---|---|---|
| | Area (ha) | Area (%) |
| Barer land | 4686.4 | 12.1 |
| Forest land | 9538.7 | 24.6 |
| Water body | 1071.5 | 2.8 |
| Built up area | 2518.9 | 6.5 |
| Cultivated land | 20945.6 | 54.0 |

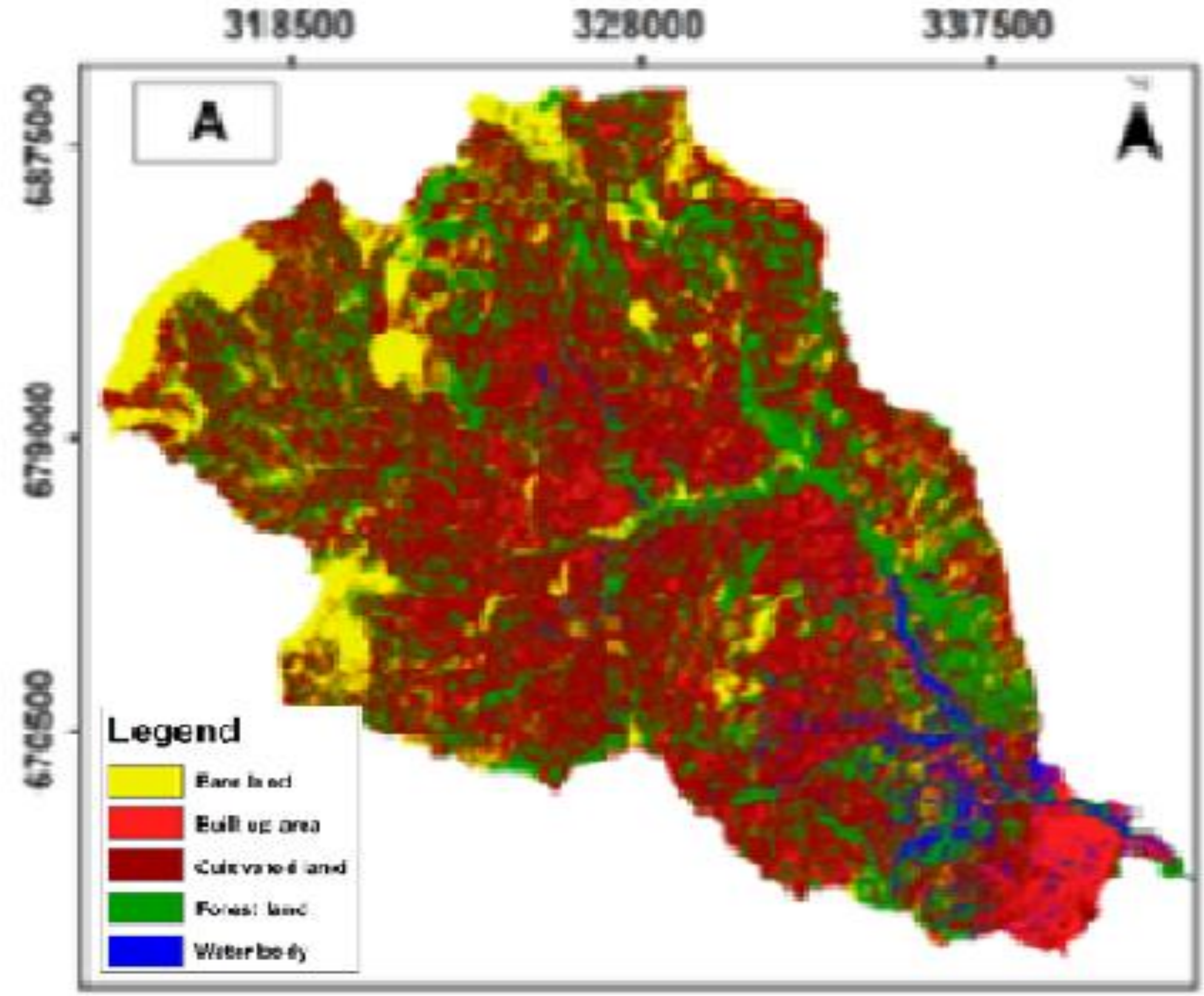


Figure 4.1 The year 2000 classified land use land cover map of kulfo watershed

### 4.2 Land Use Land Cover map of 2011

The land cover maps 2011 in figure indicated that cultivated land had the largest share with a total area of 18713.6 Ha, accounting for (48.3 %) of the total land covered in the study area. Compared to the previous 2000-year coverage, the extent of built-up area and bare land increased noticeably this year, with (5315.9 Ha (13.3 percent) and 6025.9 Ha (15.5 percent) respectively. In contrast, the coverage of forest land and water bodies decreases to 8005.1 Ha (20.7%) and 700.7 Ha (1.8%), respective

**Table 4.2 Description of land use type of 2011**

| LULC TYPE | 2011 | |
|---|---|---|
| | Area (ha) | Area (%) |
| Barer land | 6025.9 | 15.5 |
| Forest land | 8005.1 | 20.7 |
| Water body | 700.7 | 1.8 |
| Built up area | 5315.9 | 13.7 |
| Cultivated land | 18713.6 | 48.3 |

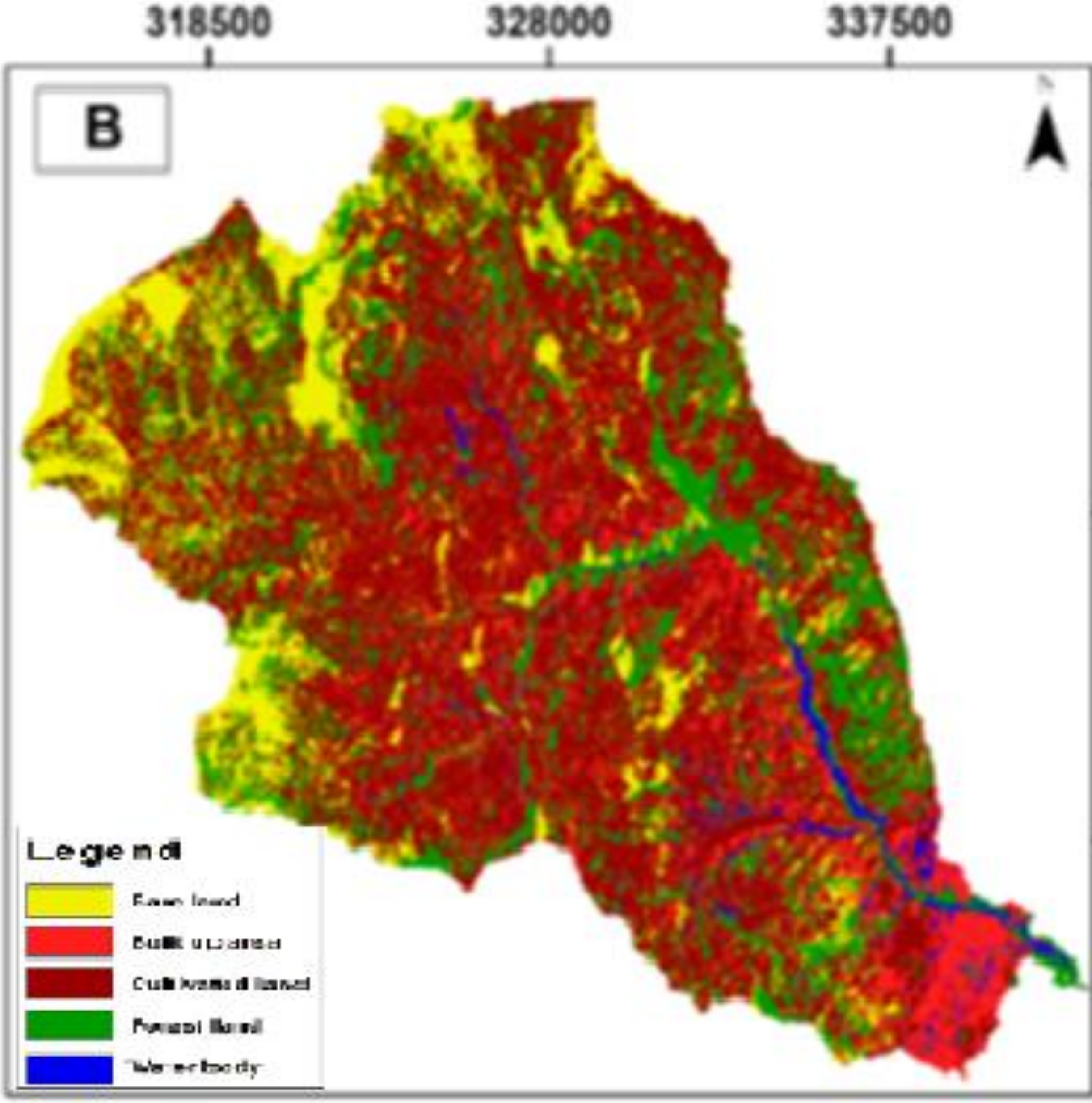


Figure 4.2 The year 2011 the classified land use land cover map of kulfo watershed

## 4.3 Land Use Land Cover map of 2021

For the year 2021the area coverage of cultivated land is declined but still makes up the majority of the study area's accounting for 18,479.3 Ha (47.7 %). In comparison to the preceding 22 years, the covered area of bare land and built-up area, which accounts for 613.9 Ha (14.5%) and 7247.2 (18.7%), respectively, demonstrates increasing tendencies in 2021. In contrast, the forest land and water body show a significantly declining trend, with corresponding values of 7076.5 Ha (18.3%) and 344.2 (0.9 percent) respectively.

**Table 4.3Description of land use type of 2021**

| LULC TYPE | 2021 | |
|---|---|---|
| | Area(ha) | Area (%) |
| Bare Land | 5613 | 14.5 |
| Forest Land | 7076.5 | 18.3 |
| Water body | 344.2 | 0.9 |
| Built up area | 7244.2 | 18.7 |
| Cultivated land | 18479.3 | 47.7 |

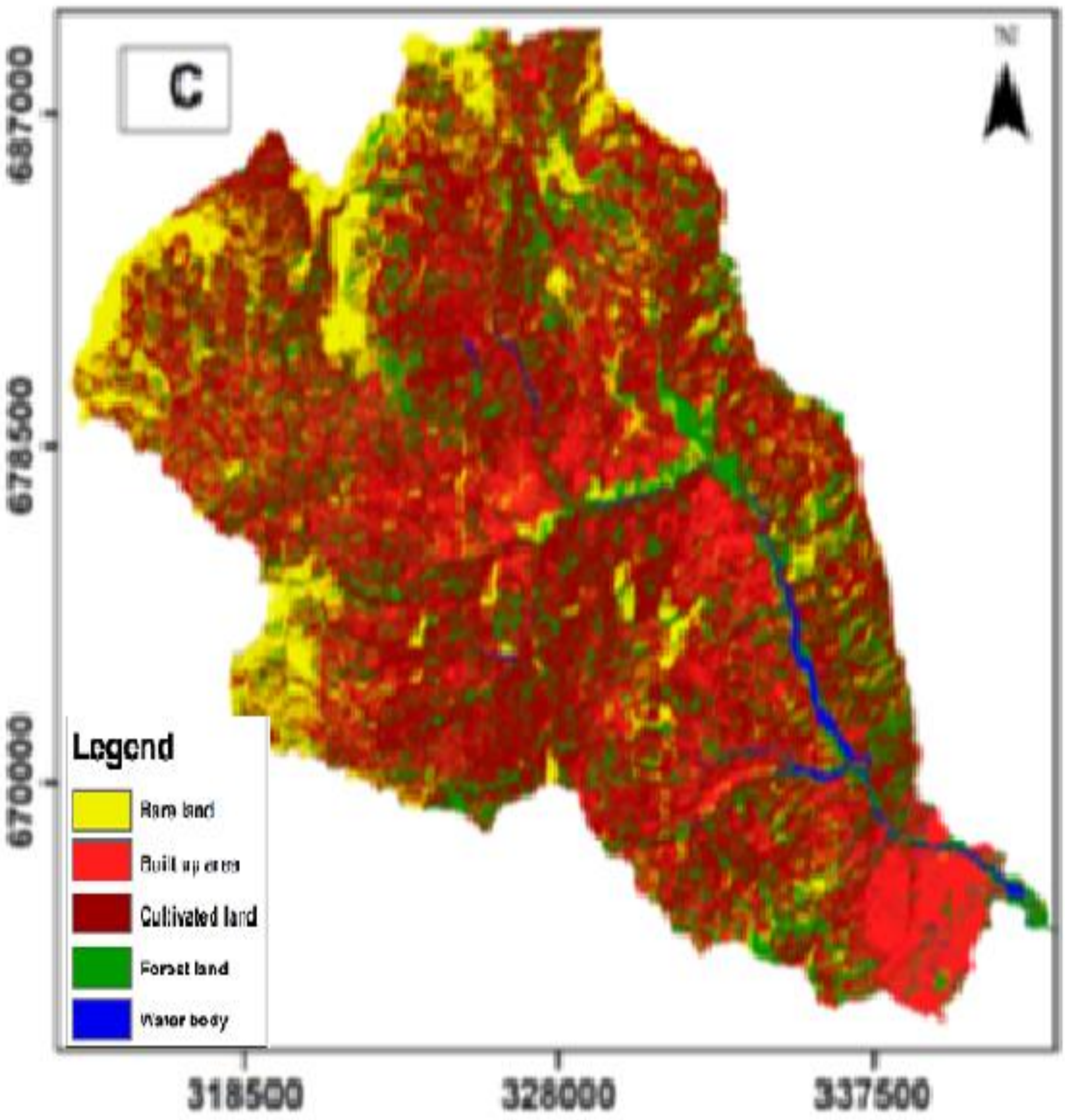


Figure 4.3 The year 2021 classified land use land cover map of kulfo watershed

### 4.4 Accuracy assessment of classified images.

Google Earth images were used to check the accuracy of classified images by using Arc GIS desktop software version 10.8. Fifty (50) controlling points were taken for each class randomly for all datasets of classified images. The projection and reference work was created by importing controlling points from Google Earth image in to the Arc GIS software. It was then cross-checked against the analyzed land use land cover (LULC) data to do an accuracy assessment.

The accuracy of LULC change analysis was evaluated by generating a confusion/error matrix in each LULC category of classified maps from 2000, 2011, and 2021. For evaluation purposes, the overall accuracy, kappa statistics, producer's and user's accuracy were used.

The overall accuracy and kappa statistics results of the three decades of classified images are presented in Table 4.4 the overall accuracy of 84.4%, 85.5%, and 87.6% was obtained for the classified images of 2000, 2011, and 2021 years, respectively (Table 4.4)

Producer’s accuracy (PA) of the individual types of the four classified maps varied from 76% (Built-up area) in 2000 to 94% (forest land and bare land) in 2000 and 2021 respectively. User’s accuracy (UA) was highest for the water body (97.9%) in 2000 and lowest for the forest land (72.4%) in 2011.

A kappa coefficient of 0.85, 0.81, and 0.84 resulted in 2000, 2011, and 2021 LULC maps, respectively. Hence, the results indicated a strong agreement between the classified images with ground truths.

**Table 4.4 Accuracy assessment of classified LULC maps for 2000, 2011, and 2021**

| LULC_Type | 2000 | | 2011 | | 2021 | |
|---|---|---|---|---|---|---|
| | Producer's accuracy (%) | User's accuracy (%) | Producer's accuracy (%) | User's accuracy (%) | Producer's accuracy (%) | User's accuracy (%) |
| Bare Land | 88 | 93.6 | 82 | 75.4 | 94 | 94 |
| Forest Land | 94.0 | 88.7 | 84 | 72.4 | 82 | 95.3 |
| Water Body | 92 | 97.9 | 90 | 95.7 | 98 | 92.5 |
| Built up area | 96.0 | 86.4 | 82 | 87.2 | 84 | 77.8 |
| Cultivated land | 92 | 78 | 88 | 99 | 80 | 80 |
| Overall accuracy (%) | 84.4 | | 85.5 | | 87.6 | |
| Kappa Coefficient | 0.85 | | 0.81 | | 0.84 | |

## 4.5 Land covers change analysis

Land use land cover change analysis was carried out over 2000, 2011, and 2021 years using Landsat images. Applying the pixel-based image classification method; the land use/cover map values were computed using the supervised classification technique and likelihood algorithm in ENVI 5.3 and ArcGIS10.8 software.

These land use land cover change values are divided into five parts because in this study area most of the previous studies have been divided into five parts. Thus, is divided into five sections, as shown in figure 4.4 bare land, cultivated land, forest land, built-up area, and water body.

The area of each class was calculated taking into account the pixel count and total area (study area). Thus, coverage of each classified area, (percentage) is tabulated, and the statistics of different types of land use areas and their proportions in different years are shown in table 4.5

According to Table 4.5 cultivated land accounted for the majority of the LULC in January 2000 with a total of 20945.6 Ha (54.0%) followed by forest land, bare land, built-up area, and water body accounting for 9538.7 ha (24.6%), 4686.4 ha (12.1%) and 2518.9 ha (6.5%) and 1071.5 ha (2.8%) respectively.

In January 2011, cultivated land had the largest share with a total area of 18713.6 Ha, accounting for 48.3 percent of the total land covered in the study area. Compared to the previous 2000-year coverage, the extent of built-up area and bare land increased noticeably this year, with (5315.9 ha (13.3 percent) and 6025.9 ha (15.5 percent) respectively. In contrast, the coverage of forest land and water bodies decreases to 8005.1 ha (20.7%) and 700.7 ha (1.8%), respective.

**Table 4.5 Area statistics for 2000, 2011, and 2021.**

| LULC-TYPE | 2000 | | 2011 | | 2021 | |
|---|---|---|---|---|---|---|
| | Area (ha) | Area (%) | Area (ha) | Area (%) | Area (ha) | Area (%) |
| Barer land | 4686.4 | 12.1 | 6025.9 | 15.5 | 5613.9 | 14.5 |
| Forest land | 9538.7 | 24.6 | 8005.1 | 20.7 | 7076.5 | 18.3 |
| Water body | 1071.5 | 2.8 | 700.7 | 1.8 | 344.2 | 0.9 |
| Built up area | 2518.9 | 6.5 | 5315.9 | 13.7 | 7244.2 | 18.7 |
| Cultivated land | 20945.6 | 54.0 | 18713.6 | 48.3 | 18479.3 | 47.7 |
| Total area | 38761.1 | | 38761.1 | | 38761.1 | |

Despite a tendency to decrease over time, as shown in Table 4.5 above, cultivated land still makes up the majority of the study area's covered extent in January 2021, accounting for 18,479.3 Ha (47.7 percent). In comparison to the preceding 22 years, the covered area of bare land and built-up area, which accounts for 5613.9 ha (14.5%) and 7247.2 (18.7%), respectively, demonstrates increasing tendencies in 2021. In contrast, the forest land and water body show demonstrates increasing tendencies in 2021. In contrast, the forest land and water body show a significantly declining trend, with corresponding values of 7076.5 Ha (18.3%) and 344.2 (0.9 percent) respectively.

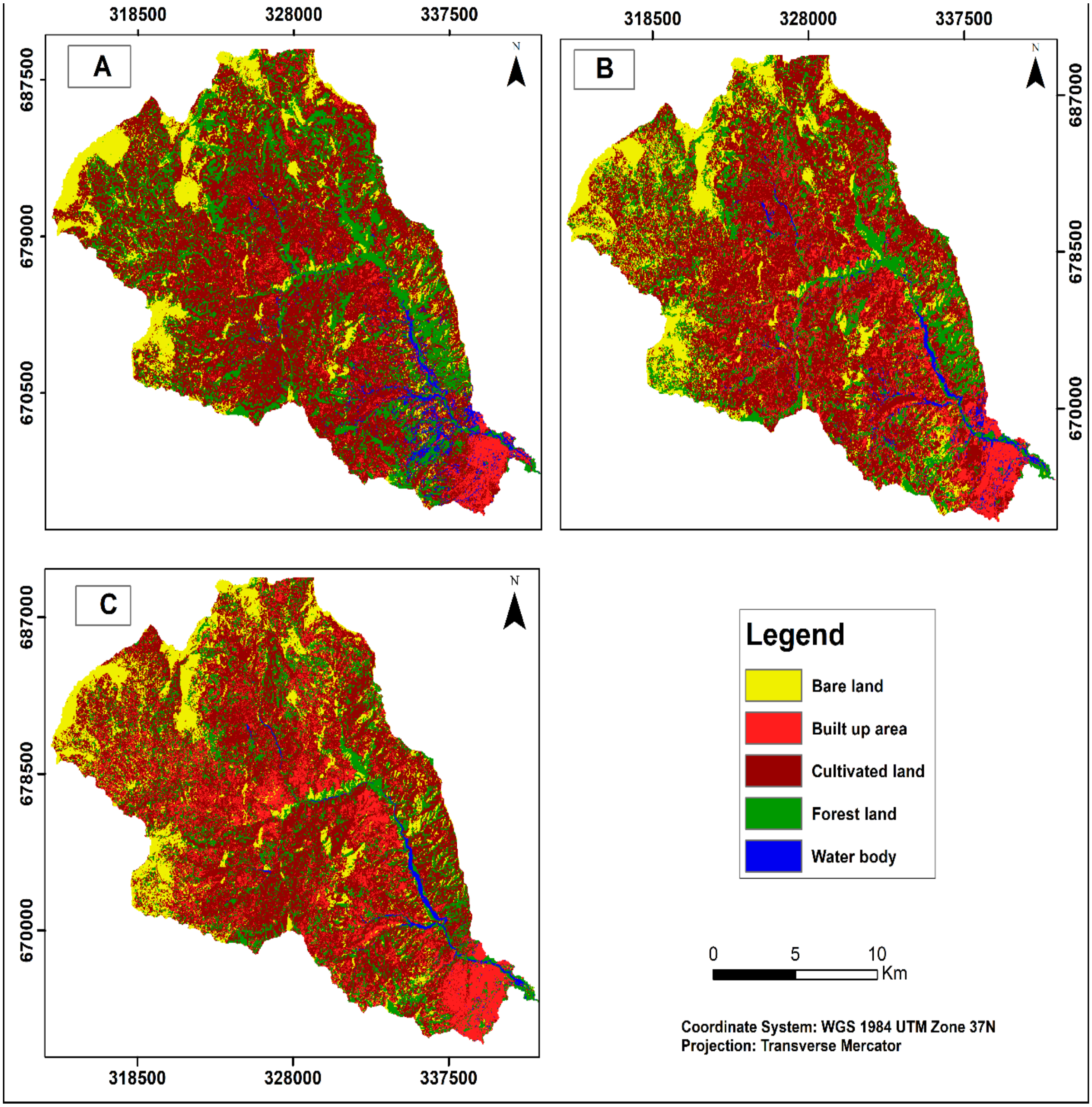


Figure 4.4 LULC map A) during 2000, B) during 2011 and C) during 2021

Overall, its area coverage, however, has been declining over the past 22 years cultivated land is the dominant LULC type in the study area from 2000 to 2021 years among classified LULC types. This indicates that it was influenced by other land use land cover types. Similarly, the forest land area, which is also the largest part of the land-use class, has significantly decreased. In addition to this water body area coverage shows a dramatic move down in all years. In another way, according to the least prevalent types of land use, the urban areas and bare land area extent increased from 2000 to 2021. The significant differences seen in the study area included a notable increase in built-up area, bare land, and a steep loss in forest land, water bodies, and cultivated land. Although the coverage of cultivated land, water bodies, and forests all decreased throughout the research periods, the rate of reduction in forest land and water bodies was the highest.

**Table 4.6 Changes in the area from 2000-2011, 2011-2021, 2000-2021**

| LULC-TYPE | 2000-2011 | | | 2011-2021 | | | 2000-2021 | | |
|---|---|---|---|---|---|---|---|---|---|
| | Area (ha) | Area (%) | **Rate of Change (ha/yr)** | Area (ha) | Area (%) | **Rate of Change (ha/yr)** | Area (ha) | Area (%) | **Rate of Change (ha/yr)** |
| Barer land | 1339.5 | 3.5 | 121.8 | -411.9 | -1.1 | -41.2 | 927.5 | 2.4 | 44.2 |
| Forest land | -1533.6 | -4.0 | -139.4 | -928.5 | -2.4 | -92.9 | 2462.1 | -6.4 | -117.2 |
| Water body | -370.9 | -1.0 | -33.7 | -356.5 | -0.9 | -35.6 | -727.4 | -1.9 | -34.6 |
| Built up area | 2797.0 | 7.2 | 254.3 | 1931.2 | 5.0 | 193.1 | 4728.2 | 12.2 | 225.2 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Cultivated land | -2232.0 | -5.8 | -202.9 | -234.3 | -0.6 | -23.4 | 2466.3 | -6.4 | -117.4 |

During the years 2000-2021, the largest change was observed in bere land and Built up area, which were 121.8 and 254.3 hectares respectively. Cultivated land and forest land showed a significant decrease in hectares per year, which is -202.9 and -139.4 respectively in the same years. On the other hand, the built-up area has significantly expanded between 2011 and 2021 and it is 193.1 hectares per year. The trend for forest land land area throughout the same years is decrease of -92.9 hectares per year.

In general the built-up area underwent the highest change between 2000 and 2021, at a rate of 225.2 hectares annually. The change in bare land was then 44.2 hectares per year. In contrast, cultivated land changed by -117.4 hectares per year, while forest land changed by -117.2 hectares annually and water changed by 34.6 hectares annually (Table 4.6)

**4.6 Land use land covers area change transition Probability Matrix**

As illustrated below in the (table4.7) cultivated land is the highest class with an unchanged area in the probability change matrix from 2000 to 2011, 2011 to 2021, and 2000 to 2021. The conversion of forest land, water bodies, and bare land was the major contributing land use for agricultural land. While forest land and bare land relatively have an unchanged area statistically than others (Built-up area and Water body).

**Table 4.7 Transition area matrix (Ha) of LULC between 2000-2011**

| | | 2011 | | | | | |
|---|---|---|---|---|---|---|---|
| | | Bare land | Built-up area | Cultivated land | Forest land | water body | Grand Total |
| 2000 | Bare land | 3210.9 | 100.5 | 944.3 | 339.1 | 1.5 | 4596.3 |
| | Built-up area | 26.6 | 971.7 | 1142.7 | 65.6 | 87.4 | 2293.9 |
| | Cultivated land | 1923.6 | 2713.6 | 14455.1 | 2135.3 | 218.8 | 21446.5 |
| | Forest land | 702.8 | 898.4 | 2357.1 | 5280.4 | 138.3 | 9377.0 |
| | water body | 57.1 | 303.4 | 268.0 | 165.7 | 226.3 | 1020.5 |
| | Grand Total | 5921.0 | 4987.6 | 19167.2 | 7986.2 | 672.2 | 38734.2 |

**Table 4.8 Land use change from 2000-2021**

| 2011 | | | | |
|---|---|---|---|---|
| | | Unchanged area ha | Transfer area ha | Gain area ha |
| 2000 | Bare land | 3210.9 | 1385.4 | 2710.1 |
| | Built-up area | 971.7 | 1322.2 | 4015.9 |
| | Cultivated land | 14455.1 | 6991.4 | 4712.1 |
| | Forest land | 5280.4 | 4096.7 | 2705.8 |
| | Water body | 226.3 | 794.2 | 445.9 |
| | Grand Total | 24144.4 | 14589.8 | 14589.8 |

According to the table 4.7 and 4.8 the highest proportions of the unchanged area are cultivated land (14455.1 ha), followed by forest land, bare land, built-up area, and water body (5280.4 Ha, 3210.9 ha, 971.7 and 226.3 ha, respectively). Cultivated land and forest land contributed the most between 2011 and 2021, with 6991.4 ha and 4096.7 ha of land, respectively. In contrast, cultivated and built-up areas gained the greatest share of land in the same years, with 4712.1 ha and 4015.9 ha, respectively.

**Table 4.9 Transition area matrix (ha) of LULC between 2011-2021**

| | 2021 | | | | | | |
|---|---|---|---|---|---|---|---|
| | | Bare land | Built-up area | Cultivated land | Forest land | Water body | Grand Total |
| | Bare land | 3623.7 | 451.2 | 1447.0 | 399.7 | 0.3 | 5921.8 |
| | Built-up area | 103.6 | 1753.3 | 2326.8 | 752.2 | 52.0 | 4987.8 |
| | Cultivated land | 1143.3 | 4187.3 | 11947.7 | 1861.8 | 27.0 | 19167.2 |
| 2011 | Forest land | 711.9 | 478.0 | 3041.2 | 3706.0 | 49.6 | 7986.8 |
| | Water body | 1.9 | 104.7 | 171.6 | 183.5 | 210.4 | 672.1 |
| | Grand Total | 5584.3 | 6974.5 | 18934.3 | 6903.2 | 339.3 | 17494.5 |

**Table 4.10 Land use change from 2011-2021**

| | 2021 | | | |
|---|---|---|---|---|
| 2011 | | Unchanged area Ha | Transfer area ha | Gain area ha |
| | Bare land | 3623.7 | 2298.1 | 1960.7 |
| | Built-up area | 1753.3 | 3234.5 | 5221.2 |
| | Cultivated land | 11947.7 | 7219.5 | 6986.6 |
| | Forest land | 3706.0 | 4280.7 | 3197.2 |
| | Water body | 210.4 | 461.7 | 128.9 |
| | Grand Total | 21241.1 | 17494.5 | 17494.5 |

As shown in the table 4.9and4.10 the cultivated land has the largest proportion of unchanged area at 11947.7 ha, followed by forest land, bare land, built-up area, and water body, which account for 3706 ha, 3626.7 ha, 1753.3 and 210 ha, respectively. Cultivated land and forest land contributed the most between 2011 and 2021, with 7219.5 and 4280.7 ha of land, respectively. In contrast, cultivated land and the built-up area gained the greatest share of land in the same years, with 6986.6 ha and 5221.2 ha, respectively. In comparison to other types of LULC, the water body has the lowest transfer and gain area.

**Table 4.11 Transition area matrix (ha) of LULC between 2000-2021**

| | | 2021 | | | | | |
|---|---|---|---|---|---|---|---|
| | | Bare land | Built-up area | Cultivated land | Forest land | Water body | Grand Total |
| 2000 | Bare land | 3528 | 2866 | 5776 | 2349 | 6 | 14525 |
| | Built-up area | 639 | 5603 | 7554 | 1917 | 358 | 16071 |
| | Cultivated land | 6786 | 17777 | 11979 | 12775 | 401 | 49718 |
| | Forest land | 4978 | 9129 | 11533 | 10143 | 266 | 36049 |
| | Water body | 541 | 2178 | 2943 | 1952 | 388 | 8002 |
| | Grand Total | 16472 | 37553 | 39785 | 29136 | 1419 | 124365 |

**Table 4.12 Land use change from 2000-2021**

| | 2021 | | | |
|---|---|---|---|---|
| 2000 | | Unchanged area Ha | Transfer area ha | Gain area ha |
| | Bare land | 3528 | 10997 | 12944 |
| | Built up area | 5603 | 10468 | 31950 |
| | Cultivated land | 11979 | 37739 | 27806 |
| | Forest land | 10143 | 25906 | 18993 |
| | Water body | 388 | 7614 | 1031 |
| | Grand Total | 31641 | 92724 | 92724 |

As shown in the tables 4.11 and 4.12 the highest proportions of the unchanged area are cultivated land which is 11979 ha following this forest land, built-up area, bare land, and water body accounting for 10143 ha, 5603 ha,3528 ha, and 388 ha respectively. Between 2000 and 2021 years, the largest contributors were cultivated land and forest land, with 37739 ha and 25906 ha of land respectively. On the other hand, Built-up area and cultivated land gained the largest share of land in 31950 Ha and 27806 ha respectively in the same years.

**Table 4.13 Land use land cover area change matrix**

| LULC_Type | 2000-2011 | | | 2011-2021 | | | 2000-2021 | | |
|---|---|---|---|---|---|---|---|---|---|
| | Area (ha) | Area (%) | **Rate of Change (ha/yr )** | Area (ha) | Area (%) | **Rate of Change (ha/yr)** | Area (ha) | Area (%) | **Rate of Change (ha/yr )** |
| Bare land | 1339.5 | 3.5 | 121.8 | -411.9 | -1.1 | -41.2 | 927.5 | 2.4 | 44.2 |
| Forest land | -1533.6 | -4.0 | -139.4 | -928.5 | -2.4 | -92.9 | -2462.1 | -6.4 | -117.2 |
| Water body | -370.9 | -1.0 | -33.7 | -356.5 | -0.9 | -35.6 | -727.4 | -1.9 | -34.6 |
| Built-up area | 2797.0 | 7.2 | 254.3 | 1931.2 | 5.0 | 193.1 | 4728.2 | 12.2 | 225.2 |
| Cultivated land | -2232.0 | -5.8 | -202.9 | -234.3 | -0.6 | -23.4 | -2466.3 | -6.4 | -117.4 |

### 4.7 Validation of the model

Any prediction-based studies must include the models validation as a key component. In this study, model validation was done in IDRISI Selva software to compare the simulated 2021 LULC map with the actual 2021 LULC map to assess the accuracy of the result. Hence, the quality and location coefficient were calculated based on a comparison of the predicted LULC for 2021 with the actual LULC map for 2021 for the fires scenario. The validation results of the models summary between the simulated and actual LULC tests are shown below Table4.14

**Table 4.14 LULC change validation bases on simulated and actual 2021**

| LULC-Type | Simulated 2021 | | Actual 2021 | |
|---|---|---|---|---|
| | Area (ha) | Area (%) | Area (ha) | Area (%) |
| Bare land | 5165.7 | 13.3 | 5613.9 | 14.5 |
| Forest land | 6985.7 | 18.0 | 7076.5 | 18.3 |
| Water-body | 254.2 | 0.7 | 344.2 | 0.9 |
| Built-up area | 7696.8 | 19.9 | 7247.2 | 18.7 |
| Cultivated land | 18658.7 | 48.1 | 18479.3 | 47.7 |
| Total area | 38761.1 | 100.0 | 38761.1 | 100.0 |

To verify the effectiveness of this model, the first thing that was done to verify whether it was effective or not. Hence, the 2021 model using the set parameters and compared with the real one. Therefore, in table 4.14 the results show that the simulated and actual area coverage and percent ratio show statistically close results. Accordingly, it was confirmed that it was acceptable.

The other and most commonly used method is the kappa coefficient calculation between the predicted map and the actual land use map. Kappa-indices, kno (kappa for no information), klocation (kappa for location), kstandard (kappa for the standard), and klocationstrata (kappa for stratum-level location) wear used to evaluate the acceptances of the model prediction as shown in the table 4. 15

**Table 4.15 The k-index values of the simulated LULC map of 2021**

| | |
|---|---|
| Kno | 0.9229 |
| Klocation | 0.9169 |
| Klocationstrata | 0.9169 |
| Kstandard | 0.9049 |

Table 4.15 shows the statistics for kno, klocation, klocationstrata, and kstandard predicted LULC of 2021 were 0.9229, 0.9169, 0.9169, and 0.9049 respectively. All agreement indicator values showed very good agreement between the real and simulated LULC maps. Because all validation result values were greater than 80%, the Markov simulation model was model was well-designed and the accuracy evaluation was adequate, especially for the simulated map of 2021**.**

### 4.8 Land use land covers prediction

The future LULC changes are predicted in 2036 and 2051. For the periods 2021-2036 and 2036-2051, the transition probabilities matrix was used to examine the future probable percentages of changes in LULC.

**Table 4.16 Predicted land use land cover area statistics of 2036 and 2051 against actual 2021**

| | 2021 | | 2036 | | 2051 | |
|---|---|---|---|---|---|---|
| LULC-Type | Area (ha) | Area (%) | Area (ha) | Area (%) | Area (ha) | Area (%) |
| Bare land | 5613.9 | 14.5 | 5140.1 | 13.3 | 4829.6 | 12.5 |
| Forest land | 7076.5 | 18.3 | 6947.4 | 17.9 | 6918.6 | 17.8 |
| Water-body | 344.2 | 0.9 | 242.5 | 0.6 | 193.9 | 0.5 |
| Built up area | 7247.2 | 18.7 | 8485.1 | 21.9 | 9163.3 | 23.6 |
| Cultivated land | 18479.3 | 47.7 | 17946.1 | 46.3 | 17655.8 | 45.6 |
| Total | 3876.1 | 100.0 | 38761.1 | 100.0 | 38761.1 | 100.0 |

The outcome demonstrates that bare land was 5613.9 ha (14.5%) in 2021 and fell to 5140.1 ha (13.3%) in 2036. overall, there was a 473.8 Ha (-1.5%) change from 2021 to 2036. In 30 years, or 2051, it would have decreased even further by (-2.5%) or (784.3 ha).

The forest land declined from 7076.5 ha (18.3%) in 2021 to 6947.4 ha (17.9%) in 2036, a reduction of percent -0.4(129.1ha) over fifteen years. additionally, forest land in 2051 decreased by -0.5 %( 157.9ha), demonstrating a persistent decline in performance.

Water-body had 344.2 ha (0.9%) in 2021 and decreased to 242.5 ha (0.6%) in 2036. Also, over thirty years, the water body shows a decreasing trend of 150.3 ha (-0.4%)

The CA-Markov result demonstrates significant rise in a built-up area (1238.3 ha, 3.2%) between 2021 and 2036. The outcome also demonstrates rising trends in 2051, which account for 1916.1 ha (4.9%) over the ensuring 30 years.

Although cultivated land has better coverage than others, it has shown a declining trend in the future thirty years. The prediction results shows that this has decreased by 823.5 ha (-2.14%) (See table 4.16)

In general, the forcust results show that except for built-up land area, all of them show decreasing trends to the influence of each other

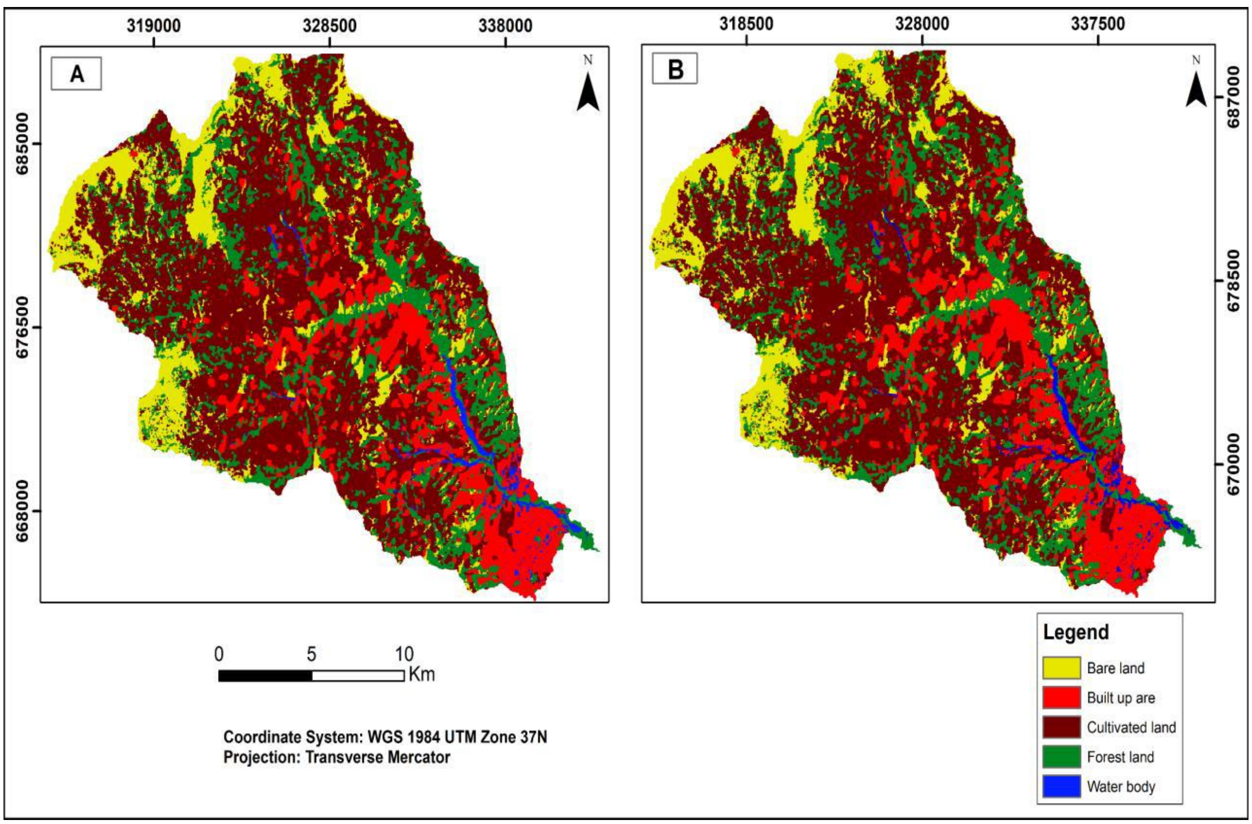


Figure 4.5 The predicted 2036(A) and 2015 (B) LULC in kulfo watershed

# CAPTER FIVE

# 5. CONCLUSIONS AND RECOMMENDATIONS

## 5.1 Conclusions

The main objective of this study was as to analyzing and predict land use land cover change over the past twenty two decades by considering Landsat imagery of 2000, 2011 and 2021 in kulfo watershed using remote sensing, GIS, and CA-Markov model. Land use land cover studies have to support different future planning management and resolve environmental issues. This research used Multi-temporal Landsat imagery of (2000 MT), Enhanced Thematic Mapper (2011ETM+) and operational land imagery (OLI) 2021  satellites were used to derive LULC maps. This land sat images integrated with CA-Markov model to process and predicts the future spatial and temporal changes of land use land cover maps. During 2000-2021a significant expansion built-up area and declined rate of other land use classes.

Expansion of built up area result to the increase of agriculture and influence to other land use types this influence the pertinent futures of watershed area. The increasing of cultivated and built up area at the expense of water body, forest and bare land are expected to continue in 2036 and 2051 periods unless land management policy and regulations are implemented in the watershed.

### 5.2 Recommendations

The experiences obtained from this study put forward some recommendations for future research.

- Cellular automata markov model Integrated with land use cover change could be applied to predict the future land scape of kulfo watershed. This enabls for stakeholders and decision maker's better choices for land and water resource planning and management in the study area.
- Land use land cover changes in the study area mainly caused by increasing of population, and built up area so this results to inbalance between the supply and demand in its annual crop production so successive effort is required by the ministry of agriculture and family planning should be given widely and continuously through formal and informal education given by health officers.
- Monitoring land use change and land scape process is important.

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