



AFRICA CENTER OF EXCELLENCE FOR WATER MANAGEMENT

ADDIS ABABA UNIVERSITY



**Evaluating the Land Use and Land Cover Change Impact on
Streamflow, Kulfo Catchment**

M.Sc. THESIS

By

Assebe Anja

Advisor: - Dr. Ing Adane Abebe

September 2021

ACEWM/AAU, ETHIOPIA

**Evaluating the Land Use and Land Cover Change Impact on
Streamflow, Kulfo Catchment**

BY

ASSEBE ANJA ALEMU

A THESIS SUBMITTED TO THE DEPARTMENT OF HYDROLOGY AND WATER RESOURCES, SCHOOL OF POSTGRADUATE STUDIES, AFRICAN CENTER OF EXCELLENCE FOR WATER MANAGEMENT (ACEWM)/ Addis Ababa UNIVERSITY (AAU) IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER OF SCIENCE IN WATER MANAGEMENT SPECIALIZATION OF HYDROLOGY AND WATER RESOURCES.

September 2021

ACEWM/AAU, ETHIOPIA

ADVISOR THESIS SUBMISSION APPROVAL SHEET
SCHOOL OF GRADUATE STUDIES
AFRICA CENTER OF EXCELLENCE FOR WATER MANAGEMENT
ADDIS ABABA UNIVERSITY

This is to certify that the thesis entitled “**Evaluating the Land Use and Land Cover Change Impact On Streamflow, Kulfo Catchment** ” submitted in partial fulfillment of the requirements for the degree of Master’s with specialization in Hydrology and Water Resources, the Graduate Program of the Water management and has been carried out by Mr. ASSEBE ANJA under my supervision. Therefore, I confirm that the student has fulfilled the requirements and hence hereby can submit the thesis to the department for defense.



Dr.Ing Adane Abebe
(Advisor)

22/09/2021

Date

Approval Page

This thesis proposal entitled “**Evaluating the Land Use and Land Cover Change Impact On Streamflow, Kulfo Catchment** ” is approved by Advisor, Examiners, and Head of Africa Center of Excellence for Water Management for partial fulfillment of the requirement for Master of Science in Water Management Specialization of Hydrology and Water Resources.

Submitted by:

Assebe Anja Alemu
Name	Signature	Date

Thesis approval by:

Dr.Ing Adane Abebe	22/09/2021...
(Principal Advisor)	Signature	Date

Chairperson

.....
	Signature	Date

Examiner

.....
	Signature	Date

.....
	Signature	Date

Dr. Feleke Zewge
(Head of ACEWM)	Signature	Date

Netsanet Assefa (M.Sc)
(Coordinator)	Signature	Date

DECLARATION

I, Assebe Anja Alemu, declared this thesis as it's my original work. This has not been presented in any university before and will not be present to any other university by me or anyone to award similar or any other degree.

Signature

ACKNOWLEDGEMENT

First of all, I would like to thank God, the source of all knowledge, the owner of heaven and earth, for his priceless and miracle gifts to me because without him I would not do it.

I would also wish to express my sincere gratitude to my advisor, Dr. Ing Adane Abebe, for his willingness to work with me, for his kindness, and his patience, constructive ideas, and more.

I gratefully acknowledge all offices and personalities who have provided me the necessary data for my study: Ministry of Water, Irrigation and Energy, National Metrological Service Agency and Ethiopian Geospatial institute.

I would like to express my sincere gratitude to the African Center of Excellence for Water Management for providing a variety of learning materials, covering the research cost, and responding quickly to my questions as well as the staff members of the Center.

My heartfelt thanks go to Arba Minch University for permitting and sponsoring me to follow this Master of Science Program in Hydrology and Water Resources Management.

I would wish to thank my classmates, especially Mr. Tilaye Worku and Mr. Abdisa Sime for their invaluable support, advice, kindness, and sincerity. I appreciate their encouragements, comments, motivations and the inspirations of these two guys that makes me to conduct and finish this thesis work on time and in advance.

I wish to extend my gratitude to my family for their love, constant moral support, and ultimate support throughout my thesis work.

ABSTRACT

Stream flow is one of the major hydrological cycle components which can be altered and /or affected by different factors. From these, the Land Use Land Cover change is one of the main factors to alter and change the stream flow characteristics. Therefore, in this study, the LULC change impact on the stream flow was evaluated using the SWAT model for the case of Kulfo catchment which is situated in the Southern part of Ethiopia. Sensitivity, calibration, and validation were also conducted using sequential uncertainty fitting–version 2 (SUF2) in SWAT-CUP (Calibration and Uncertainty program) using historical streamflow data for each of the land use land cover years. Four different algorithms (SVM, CART, RF, and Navia's) which are existed in the Google Earth Engine were compared and the best performed was selected to generate the time-series LULC maps of, (1986, 2000, 2016, and 2020), the study area. The accuracy of these algorithms was evaluated corresponding to GCPs collected from the field. High resolution (30m) Landsat images which are thematic mapper (TM), Enhanced thematic mapper plus (ETM+), and Operational land imager (OLI) were used with the aid of historical trends and ground-based data used to train and validate the LULC maps generated from Google Earth Engine platform. As a result, the SVM algorithm was performed better in LULC classification than other algorithms which are compared in this study. In the analysis period of this study, the Vegetation land cover area has decreased from 18.81% to 3.1%, the agricultural land was increased from 19.44% to 57.12%, whereas the shrub land area has been decreased from 34.18% to 14.73%. Therefore, the effect of these LULC changes on stream flow was evaluated using Soil & water assessment tool (SWAT) model and high mean monthly and seasonal streamflow variability was observed in the analysis period of this study. These variabilities were increased from 6.72% to 7.85% monthly. In seasonal variability, the stream flow has decreased trend for all of the seasons (Kiremt, Belg, and Bega) from the year 2016 to 2020 whereas increased trend for the period of 2000 to 2016 (Kiremt, Belg and Bega). The Results from the calibration resulted in an acceptable range (0.6, 0.8, 0.75, and 0.75 for NSE and 0.75, 0.76, 0.79, and 0.81 for R2) between observed and simulated streamflow respectively. The results of validation were also fallen in the acceptable range (0.72, 0.6, 0.74, and 0.75 for NSE and 0.8, 0.75, 0.73, and 0.8 for R2) observed and simulated streamflow respectively.

Keywords: GEE, LULC, Streamflow, SWAT, SWAT-CUP, Machine Learning, Kulfo

TABLE OF CONTENTS

Approval Page	i
DECLARATION.....	ii
ACKNOWLEDGEMENT.....	iii
ABSTRACT	iv
ABBREVIATIONS AND ACRONYMS.....	viii
LIST OF FIGURES	ix
LIST OF TABLES	x
LIST OF APPENDIX.....	xi
1. INTRODUCTION	1
1.1 Background.....	1
1.2 Statement of the Problem.....	3
1.3 Objective of the Study	4
1.4 Research Questions.....	4
1.5 Scope of the Study	4
1.6 Significance of the Study	4
2. LITERATURE REVIEW	5
2.1. Overview of land use and land cover change	5
2.2. Causes of land-use and land-cover changes	5
2.3 Processing of land use and land cover map	6
2.4 Application of remote sensing	7
2.5 LULC Change detection	8
2.6 Land - cover and land-use change in Ethiopia.....	9
2.7 Google Earth Engine.....	10
2.7.1 Machine Learning Classifiers in GEE.....	11
2.7.1.1 Support Vector Machine (SVM)	12
2.7.1.2 Classification and Regression Trees (CART) Classifier	13

2.7.1.3 Random Forest (RF)	13
2.7.1.4 Naïve Bayes	14
2.8. Hydrological Models	15
2.8.1. Model selection criteria	15
2.8.2 Hydrological component of SWAT	17
2.9 Application of SWAT model in Ethiopia	18
3 MATERIALS AND METHODS	20
3.1. Description of Study Area	20
3.1.1 Topography	20
3.1.2 Climate of the study area.....	21
3.1.3 Soil	22
3.2 Data collection and methods.....	22
3.2.1 Field Data	23
3.2.3 Time series data.....	25
3.3 Data analysis and Quality checking.....	25
3.3.1 Filling of missed data	25
3.3.2 Consistency of Rainfall Data.....	26
3.3.3 Homogeneity and trend test	27
3.3.4 Test for outliers	28
3.4 Materials	29
3.5 Methods	29
3.5.1 Image pre-process in GEE.....	31
3.5.1.1 Acquiring Landsat Surface Reflectance image collection.....	31
3.5.1.2 Image mosaicking and cloud removing.....	31
3.5.1.3 Collection of Training Data.....	31
3.5.1.4 Image Classification	32
3.5.1.5 Land use land cover data Processing.....	32

3.6. SWAT Model.....	33
3.6.1 Model set up.....	33
3.7 Sensitivity Analysis	36
3.8 Model Calibration and Validation	37
3.9 Model Performance Evaluation	38
4. RESULTS AND DISCUSSION	41
4.1 Comparison of Classifications using Different GEE Classifiers	41
4.1.1 Accuracy Assessment.....	41
4.2 Historical LULC maps and Change detection	44
4.2.1 Accuracy assessment.....	44
4.2.2 Land use and land cover change	44
4.2.3 Land use and land cover change detection.....	48
4.3 Streamflow modeling.....	51
4.3.1 Flow Simulation and sensitivity analysis	51
4.3.2 Calibration and validation	52
4.4. Impact of land use and land cover change on streamflow	54
4.4.1 Change on Monthly streamflow	54
4.4.2 Change on Seasonal Stream flow	55
5. CONCLUSION AND RECOMMENDATIONS.....	57
5.1 Conclusion	57
5.2 Recommendations.....	58
REFERENCES	60
APPENDICES	74

ABBREVIATIONS AND ACRONYMS

API	Application Programming Interface
DEM	Digital elevation model
EMA	Ethiopian Meteorological Agency
GEE	Google earth engine
FAO	Food and agricultural organizations
GIS	Geographical information system
GPS	Geographical positioning system
HRU	Hydrological response units
LULU	Land use land cover
M ³ /s	Cubic meter per second
MOWIE	Ministry of Water Irrigation and Electricity
NMA	National Meteorological Agency
NSE	Nash Sutcliffe simulation efficiency
OLI	Operational Land Imager
R ²	Coefficient of determination
SWAT	Soil and water assessment tool
SWAT-CUP	Soil and water assessment tool calibration and uncertainty programs

LIST OF FIGURES

Figure 3.1 Location of the study area (Kulof Catchment).....	20
Figure 3.2 Study area descriptions: (A) Elevation map (B) Slope map of kulfo watershed	21
Figure 3.3 Mean monthly rainfall of stations in and around the Kulfo catchment.....	21
Figure 3. 4 Major Soil map of kulfo catchment	22
Figure 3.5 Digital Elevation model of Kulfo catchment	24
Figure 3.6 Test for consistency of rainfall station by DMC method.....	27
Figure 3.7 Homogeneity Test for rainfall stations.....	28
Figure 3.8 Training Data sets	32
Figure 3.9 Full Hydrological Response Unit (HRU) Map of kulfo Watershed	35
Figure 3.10 General workflow the study	40
Figure 4. 1 Classified land use/ cover map of Kulfo watershed for the year of A) 1986 B) 2000 C) 2016 D) 2020.....	46
Figure 4.2 The area coverage of land use/cover change in Kulfo catchment.....	48
Figure 4.3 Land use land cover change dynamics for the period A) 1986 to 2000 B) 1986 to 2016 C) 1986 to 2020 D) 2016 to 2020.....	49
Figure 4.4 Model Calibration and validation period for LULC 1986	53
Figure 4.5 Model Calibration and validation period for LULC 2016.	53
Figure 4.6 Model Calibration and validation period for LULC 2000.	54
Figure 4.7 Model Calibration and validation period for LULC 2020.	54
Figure 4.8 Monthly streamflow change over the study years.....	55

LIST OF TABLES

Table 3.1 dominant Soil types of kulfo catchment	25
Table 3.2 Summary of rainfall and stream gauging stations	25
Table 3.3 the materials and software tools used for this study were	29
Table 3.4 Original and the redefined land use/land cover types of kulfo catchment	33
Table 3.5 Some of the Parameters and their description including maximum and minimum values	37
Table 3.6 General performance ratings for recommended statistics for a monthly time step.	39
Table 4.1 Error matrix of the LULC map of the Kulfo catchment which was classified using the SVM algorithm for 2020.	42
Table 4.2 Summary of Overall classification accuracies and kappa statistics achieved by GEE machine learning classifiers	43
Table 4.3 Area coverage of each land use/cover type.	47
Table 4.4 Major changes in LULC classes from the period of 1986 to 2020 in the area and percentage coverage in the Kulfo watershed	50
Table 4.5 Sensitive parameters and its rank in Kulfo catchment using 1986 LULC map ..	52
Table 4.6 Model performance measures for calibration and validation	52
Table 4.7 Monthly streamflow change for the study period.....	54
Table 4.8 Seasonal mean monthly flow (m ³ /s)(4.8)	56
Table 4.9 Percentage of mean monthly flow change (m ³ /s)	56

LIST OF APPENDIX

Appendix A	Google Earth Engine land use land cover mapping codes.....	77
Appendix B1	Confusion Matrix using RF Classification.....	81
Appendix B2	Confusion Matrix using Naive Bayes Classification.....	82
Appendix B3	Confusion Matrix using CART Classification.....	82
Appendix C	LULC map of the Kulfo catchment that was classified using four different algorithms.....	83
Appendix D1	Error matrix for the 1986 LULC map.....	84
Appendix D2	Error matrix for the 2000 LULC map.....	85
Appendix D3	Error matrix for the 2016 LULC map.....	85
Appendix E1	Selected sensitive parameters of kulfo watershed using 2000 LULC.....	85
Appendix E2	Selected sensitive parameters of kulfo watershed for LULC map of 2016.....	86
Appendix E3	Selected sensitive parameters of kulfo watershed for the LULC map of 2020.....	86

1. INTRODUCTION

1.1 Background

Water resources are essential renewable resources that are the basis for existence and support the socio-economic development of a society (Destaa & Lemma, 2017). However, the degradation of these resources becomes a critical environmental problem (Ayana, Chemed, & Ekasit, 2012). Therefore, proper utilization of these resources requires assessment and management of the quantity and quality of the water resources both spatially and temporally.

The land is also the main type of natural resource on which a lot of human activities are undertaken such as agriculture, removal of forest for settlement, and building of infrastructure due to this activity the availability of different natural resources like vegetation, land fertility, or soil and water are affected. And also, it directly affects the amount of evapotranspiration, groundwater infiltration, and overland runoff (Fisseha et al., 2011; Tewabe and Fentahun, 2020).

Changes in land use and land cover have occurred at all times in the past, are presently ongoing, and are likely to continue in the future. Thus, human activities have modified the environment for thousands of years (Fisseha et al., 2011).

Roy, (2010) described that the changing of land use and land cover affects primarily vegetation, reducing its coverage which in turn leads to loss of biodiversity, erosion of natural soil, the availability of ground and surface water. It also negatively affects the potential use of an area and may ultimately lead to degradation and loss of soil productivity as well as pollution of water, soil, and air (Tegene, 2002; Alemu, 2015; Geetha, et al., 2019).

Hydrological processes involve several phenomena associated with the natural circulation of water. Among these phenomena, the separation of precipitated water into either infiltration into the soil or the generation of runoff is the one (Loewen and Pinheiro, 2017).

Among a lot of hydrological variables streamflow is an important one needed for water resource planning and management and ecosystem conservations (Khalid et al., 2017).

LUC is an important characteristic in the runoff process that affects infiltration, erosion, and evapotranspiration. Understanding the effects of historic LULC changes on river flow is required to understand the future effects of land use and land cover on streamflow of the watershed level. Along with these changes, considerable consequences are expected in the hydrological cycles and subsequent effects on water resources (Githu, 2009).

LULC change analysis provides the baseline data for a better understanding of how the land was used in the past and what types of change are expected in the future. Studies of land use and land cover changes also yield valuable information for analysis of the environmental impacts of human activities on climate change, streamflow, and others (Tegene, 2002).

In the world, the changing impacts of LULC on natural resources are extremely increasing (Berihun, et al., 2019). Particularly, very rapid changes are recognizable in Ethiopia due to the population pressure, resettlement programs, climate change, and other human and nature-induced driving forces (Marchant, et al., 2018).

Generally, LULC changes have a wide range of impacts on environmental and landscape attributes including the quality of water, land, and air resources, ecosystem processes, and functions (Rimal, 2011). Therefore, the detailed investigation of the change using remote sensing data and analysis techniques provides accurate, timely, and detailed information for monitoring changes in land use and land cover.

Satellite images cover a wide area and data from satellite images can be quickly extracted and processed using a computer. Only with the single image taken from the satellite sensor, many useful and valuable information that is related to various applications such as land cover, air quality, disaster management, urban planning, weather forecast, etc., can be interpreted. Thus, most researches for land resource management are focused on satellite image processing (Uddin et al., 2018).

Google earth engine (GEE) is currently used, an open-access cloud-based computing platform, for processing, utilizing, and executing complex calculations on historical global-scale satellite imagery. Additionally, it enables scientific analysis and visualization of geospatial datasets using advanced machine learning algorithms (Wagle et al., 2020; Google EarthEngine, 2012; Isabela Xavier Floreano, 2021).

Different kinds of models have been developed and applied to predict, assess, and monitor natural phenomena like streamflow and sediment yield from the catchment but the most widely applied and freely available one is the SWAT model which is a deterministic, continuous watershed model that can operate on daily and hourly time steps.

According to Jha (2011), the SWAT model is the best among the different hydrological models due to its capability for an application to large-scale watersheds (> 100 km²), interface with a Geographic Information System (GIS), continuous-time simulations

performance, and generation of the maximum number of sub-basins and ability to characterize the watershed in enough spatial detail.

1.2 Statement of the Problem

LULC dynamics is one of the foremost causes of land degradation, including deforestation and deterioration of soil and water quality and quantity, the decline in natural resources base, and ultimately the disruption of hydrology cycle such as infiltration, interception, erosion, and evapotranspiration (Rindfuss et al, 2004). High irrigation activity, land degradation, expansion of agriculture field and different activities were dominated in the caple of the decade for the case of Kulfo catchment. The catchment has been continuously used for agricultural purposes and different land features have been changed to cropland (Ashebir, 2018). These land use and land cover change have caused a lot of tension in the streamflow.

Kulfo River has crucial importance to the natural habitats of Abaya - Chamo basin as well as other land users in the catchment. Major environmental problems such as the changing of land use and land cover have been observed in recent years this in return alters the water availability, causes erosive landscapes, and low soil nutrients (Teshome, 2020).

Therefore, Understanding how these activities influence streamflow will enable planners to formulate policies towards minimizing the undesirable effects of future land-use and land cover changes on the hydrology of the river so that the hydrological cycle will not be significantly alerted. Besides planners local farmers will benefit more as well as researchers will gain fruitful knowledge. Therefore, the need for scientific research to minimize the impact of land use and land cover change on the streamflow of Kulfo catchment is essential.

Even if a lot of studies had been conducted on Kulfo catchment like model comparison on the performance of Rainfall-Runoff modeling (Abyot, 2008); the impact of climate change on kulfo river (Nega *et al.*, 2018; Tadelech, 2015) and land use and land cover changes and their effects on the landscape of Abaya-Chamo basin (Yohannes *et al.*, 2018).

Most researches have limitations on producing and quantifying dynamics of LULC map effects on stream flow. This limitation occurs in applying an appropriate classification algorithm for LULC classification. For instance (Neetu & Ray, 2019) classified land use land cover features and used RF classifier which is available on GEE with comparing it with other types of classifier just by assessing the accuracy depending on collected training data on the platform rather than using GCS.

1.3 Objective of the Study

Main Objective

The main objective of the study was to evaluate the land use land cover change impact on streamflow for the case of Kulfo catchment.

Specific Objectives

1. To evaluate the machine learning algorithms (classifier) for LULC classification.
2. To evaluate land use and land cover change observed from (1986 to 2020) over kulfo catchment.
3. To evaluate the impact of land use and land cover change on streamflow.

1.4 Research Questions

Based on the research objectives the following research questions were formulated.

- ❖ Which machine learning classifier is appropriate for the classification of land use and land cover for kulfo catchment?
- ❖ What are the main land use and land cover types and their areal coverage in kulfo catchment?
- ❖ How do land use and land cover affect (impacts) streamflow of Kulfo Catchment?

1.5 Scope of the Study

This study is limited to analyzing LULC change impacts on stream inflow in kulfo, catchment. And hydrologic modeling has been done using the SWAT model incorporated with GIS. The LULC change and map were identified using the google earth engine application for the periods of 1986, 2000 2016, and 2020. Furthermore, using these maps the streamflow has been modeled. This study only focuses on the impact of LULC change on streamflow.

1.6 Significance of the Study

The main significance of this study is understanding the impacts of LULC change on natural resources, streamflow so that its impact will be reduced and the findings of this study will give scientific clues for resource base analysis and development of effective and appropriate response strategies for sustainable management of natural resources. Currently, a lot of infrastructures are under building around the riparian of the river, kulfo, like recreational areas, water pumping wells to agricultural land, therefore, the result of this study will give better understanding to consider changing amount and types of land use and land cover on the watershed so that they can consider it.

2. LITERATURE REVIEW

2.1. Overview of land use and land cover change

Land is the ultimate resource of the biosphere and it has been changing for decades due to human and natural induced factors. Both terms, Land use, and land cover are different in their usage.

Land cover refers to the observed physical characteristics of the earth's surface such as water bodies, vegetation, and including those created by human activities for instance settlement area, agricultural lands, urbanized land features, exposed land surface due to removal of trees for plantation, and others, present on the Earth's surface (Gregorio, 2000). On the other hand, Land use describes the earth's physical future used by humans and their habitats (such as agriculture, settlements, industry, etc.) (Harshika et al., 2012; Sabzar et al., 2016).

Farda, (2017); Lunetta, (2006) briefly explained land use as a form of human effort to change land future to make a suitable environment for their life by doing different activities such as agricultural land, road, and settlement. According, to the author's environmental problems, are offend related to land-use change. Therefore the management of the environment through decision-making and future planning requires LULC change analysis.

The changing of land use and land cover may be either through conversion or modification of the land features (Lambin, 2003). Conversion refers to changes from one cover or use type to another (Sun, Liu, & Sha, 2016), while modification involves maintenance of the broad cover or use type in the face of changes in its attributes (Yoon, 2011).

Generally, land use and land cover change is the alteration of the terrestrial surface of the earth due to either natural or anthropogenic processes (Dinka and Chaka, 2019). Land use and land cover change is a major component of global environmental change and affects the functionality of the earth's system directly or indirectly (Ganasri, 2015).

2.2. Causes of land-use and land-cover changes

Looking at the driving forces of LULC change is very crucial in addressing the problems. The change is the result of different complex factors that control certain environmental, economic, and social conditions. The driving forces of LULC change may be formed by interactions of social, political, economic, demographic, technological, cultural, and biophysical variables (Msofe, Sheng, & Lyimo, 2019).

However, the factors that lead to changing of the LULC are broadly categorized as anthropogenic factors such as, increase in settlement associated with population growth, industrial development, irrigation, and urban growth (Ochuka et al., 2019) as well as developments, expansion of agricultural land and town (Rowcroft, 2005), deforestation, resettlements, shifting of cultivation and forest fire (Emiru et al., 2018).

In a study conducted by Emiru et al., (2018) on bambasi wereda, Ethiopia, the land was continuously used and the area has been altered as well as modified due to anthropogenic and many other human activities. Hence, the land use and land cover, the climate has been potentially changed, and also the average temperature and rainfall increased and decreased respectively. These studies indicated the growth of population as the major factor for the disturbance of ecology.

In addition to the influence of anthropogenic activities on land use and land cover change, the variability in natural factors such as climate change and variability (Mendelsohn, 2011), soil conditions, and terrain characteristics have also accounted for land use and land cover changes.

2.3 Processing of land use and land cover map

In remote sensing, image classification is a method of deriving thematic information by grouping similar features by certain criteria or extracting information based on the reflectance of the object (Jensen, 2003). Digital image classification techniques assemble the reflectance statistics of individual pixels to represent LULC classes. These assembled pixels were grouped based on their reflectance properties of pixels called clusters. With this information, the users identify the number of clusters to get, which bands to use, and based on this the image classification software generates clusters. Nowadays, two kinds of image classification are widely used this are unsupervised and supervised classification.

In unsupervised classification remotely sensed images are classified based on their pixel spectral characteristics similarity. The software identifies and groups statistical pixels which have similar characteristics without using any ground truth data (Lillesand, 2004).

In the case of supervised classification, a representative sample of pixels from the picture will be selected by the users then the image processing software will use this pixel as a reference to classify all other pixels within the image. The main challenging of this approach is it needs prior knowledge about land cover types that are to be

classified and mapped. In this research supervised classification technique was used followed by unsupervised classification.

Unless the accuracy of the classified image is not checked the classification is not full. It is an important step in the image classification process because it is a measure of how many ground truth pixels were classified correctly.

Confusion matrix was widely used to determine the accuracy of classified LULC from different perspectives. These perspectives are User accuracy (from map users), Producer's accuracy (from map producer), and Overall accuracy (Moran, 2004). For this study, a careful analysis of the accuracy of the classified images has been conducted using an Error matrix.

2.4 Application of remote sensing

Remote Sensing (RS) is that the science and art of obtaining information about a physical object through the analysis of data acquired by a device that is not in contact with that physical object intended to be investigated (Lillesand, Kiefer, & Chipman, 2004). Remote sensing techniques have been widely used over the world for the study of historical changes in LULC.

The capability of remote sensing in facilitating the study of various features of the earth's surface and the spatial relationship between features, enabling to get information from areas that are not accessible for ground surveys like mountainous areas, saving time and effort when gathering information about a large area makes remote sensing method more advantageous from conventional ground-based methods (Ahmed, 2001).

The utility of different remote sensing data from different satellites has been demonstrated in many fields such as agriculture (Gebeyehu, 2019; Acharya, Pawar & Wable, 2018), cartography (Ferrari, 2019), civil engineering (JeganathanI, et al., 2017), environmental monitoring (Melesse et al ., 2007), forestry (Wubie, 2015), drought monitoring (Berhan, 2011), water resources management (Gebre, Tesfaye, & Taye, 2015); land resources analysis and land use planning (Somvanshi, PhoolKunwar, & Singh, 2018).

Some of the applications of remote sensing technology in mapping and studying the land use and land cover changes are; map and classify the land use and land cover (Assen, 2011), assess the spatial arrangement of land use and land cover (Mallupattu & Reddy, 2013), allow an analysis of time-series images used to analyze landscape history (Yang & Lo, 2001), analyze land use and land cover changes impact on Soil erosion (Lemilem et al., 2017), and report and analyze results of inventories including inputs to Geographic Information System

(GIS), provide a basis for model building (ALI, 2009). The open-source satellite imagery used in this study is derived from Landsat-5, Landsat-7, and Landsat 8 images that are offered on the GEE developer catalog (<https://developers.google.com/earthengine/datasets>).

The analysis of the LULC change in developing countries like Ethiopia becomes very easy due to the application and presence of remote sensing technology. Some of the important spatial data used in hydrological modeling which can be obtained from remote sensing are DEM and land cover maps.

2.5 LULC Change detection

Change detection is the identification of differences in two or more images of the same location captured at a different time (Singh, 1989). Many change detection methods were developed and used for various applications. However, the change detection techniques can be broadly divided into two approaches these approaches are Pre - Classification and Post-Classification.

In the pre-classification method, the image values are not classified for the analysis of the change. The most common and widely used pre-classification method is Vegetation Index Differencing (NDVI) (Zaitunah et al., 2018), normalized difference water index (NDWI) (Serrano, Shahidian, & Silva, 2019), Change Vector Analysis (CVA) (Xiaolu & Bo, 2011; Dewi, Bijker, & Stein, 2017), etc. They are straightforward, effective for identifying and locating change, and are easy to implement. However, three aspects are critical for pre-classification techniques: selecting suitable vegetation index to identify the changed areas and they cannot provide details of the nature of change or provide a matrix of change information.

The post-classification techniques classify images separately and compare the difference of images on a pixel by pixel basis and provide detailed 'from-to' change class information that is important for landscape monitoring (Ernani & Gabriels, 2006).

Generally speaking, selecting a suitable method of detecting change is very significant because there is no single method that can be efficiently applied to all study areas.

The result of change detection from imagery can be affected by several factors, such as; the quality of image registration between multi-temporal images (Tingting Dan, 2018; Luigi Barazzetti, 2014), change detection methods, and lack of knowledge about approaches as well as analyst's skill and experience (Shivangi Mishra, 2017), data sets availability and quality (Ayele, 2016), image pre-processing (Khorram et al ., 2013), the atmospheric

conditions and shadow present in the images (Gustav Tolt, 2011), acquisition times of the image (Khorram et al., 2013) and landscape and topography characteristics of the study areas.

2.6 Land - cover and land-use change in Ethiopia

There have been different studies conducted around different parts of Ethiopia following various approaches and methods for analyzing the land use and land cover changes. For instance, (Asitatie, 2019) studied how the hydrology of Rib catchment, Lake Tana sub-basin, is affected due to the impact of land use and land cover change. The study found an increase of cultivated land by 29.94% and an increment of the streamflow by 6.143m³/s.

Another study by Fentie et al., (2020) was conducted to determine LULC changes and their cumulative effects over 30 years (from 1989 to 2019) on the chemical and physical properties of soils within the Tejibara watershed. In this study the areal coverage of forest and grazing land has reduced causing the changing of the soil properties as result the land was degraded and in return, the productivity of the soil was reduced.

Similar studies have been conducted by Dinka & Chaka, (2019) on the Adi watershed, central highlands of Ethiopia. In this watershed, there was substantial LULC cover changes have occurred particularly the changing of the natural cover into managed agro systems. In addition to this, the study described that farmland has been rapidly expanded the consequence of this expansion caused a reduction of plants and the formation of deforestation.

Aneseyee et al., (2019) assessed the amount of erosion and sediment delivered from the Winike watershed, Omo Gibe Basin, because of the LULC cover change. The study found that high sediment loss and erosion from the cultivated land and in revers vegetation cover area experience reduction. The researcher statically measures the high correlation between soil loss and sediment delivery with the expansion of cultivated land.

Another study was conducted by Kinati et al., (2018 on the Didessa river basin, southwest Blue Nile, to analyze the effect of LULC change on river flow and soil erosion. The study has determined grassland, shrubland, and forest were the major LULC class that has been changed to cropland because of population increase.

Results of this study show that the LULC change that occurred during the study period resulted in an increment of average sediment yield by 20.9 t ha⁻¹ yr⁻¹.

Negese, (2021) performed a comprehensive review of different studies done so far in Ethiopia on the impacts of LULC change on soil erosion and hydrological responses. In his review, he found that due to the changing of LULC the rate of soil erosion and the hydrological imbalance increased and altered significantly in the country. He also noticed that among the available LULC types the features like forest land, shrubland, grassland, and cultivated (agricultural) land had been expanded more. Finally, the researcher concluded that the major cause of this change in Ethiopia is a human-induced problem for a different purpose, especially for agricultural needs.

All in all, LULC change is occurring rapidly in the world particularly in developing countries like Ethiopia. It has a variety of impacts ranging from climate change to loss of biodiversity. Therefore, it is important to analyze the changing trend and its impact in Ethiopia in general and in the kulfo catchment in particular.

2.7 Google Earth Engine

Google earth engine (GEE), powerful cloud-computing platform, which provides the entire Landsat collection and enables rapid scientific analysis, export (Navarro, 2017), and it makes simple for scientist, researchers, and developers to visualize a big geospatial dataset using advanced machine learning algorithms. In this platform, massive satellite images can be directly retrieved, image processing can be tested and performed using available machine learning algorithms (Tsai, 2018; Midekisa, 2017).

GEE is currently accessible to everyone who registered to use it through two web-based platforms: GEE Explorer and Code Editor (Gorelick et al., 2017). Since it is a new application different researches have been conducted using GEE. GEE contains a lot of data from satellites including the Landsat program up to several climate datasets.

GEE implemented for different applications. From these for the analysis of LULC change and provision of a good base for further analysis using a different platform (Wahap & Shafri, 2020). Its capability in detecting space-time land cover change

(Sidhu, Pebesma, & Câmara, 2018). GEE is very frequently used in investigating the Spatio-temporal distribution of drought conditions and identify drought severity.

The applications of GEE is very wide-ranging from drought assessment (Sazib & Bolten, 2018), mining, agriculture and ecosystem services (Goldblatt et al., 2017), drought monitoring, vegetation mapping, and monitoring (Poortinga, et al., 2018; Tsai, et al., 2018), mapping of cropland extent (Xiong et al., 2017; Prasad et al., 2017), historical land use land cover mapping (Geetha, Ashagowda, & Sudhira, 2019) up to disaster management and earth sciences (Sproles et al., 2018; Liu et al., 2018; Mateo et al, 2018; Lobo et al., 2018).

All in all, all studies agree on the capability of GEE in creating multi-temporal maps or conduct time series analysis by using the available satellite images in the platform, fast in terms of time and processing complexity of multiple datasets with minimal human interaction and intervention, analyzing a wide variety of data simultaneously in one consolidated system, GEE platform may be a very handy and rapid tool to succeed in satellite images and conduct remote sensing analysis of giant and long-term data efficiently.

Processing within the GEE has numerous advantages. The significant advantage of GEE is that the data are preprocessed to a ready-to-use and a huge amount of processed and unprocessed data can be easily managed (Gorelick, et al., 2017). To perform all the processing in the GEE users can add and create their data and collections using Google's cloud resources because the easily accessible and user-friendly properties of the GEE provide a convenient environment for interactive data and algorithm development (mutanga & kumar, 2019).

The main limitation of the GEE platform is its dependence on an internet connection and in filtering the cloud cover. In the wet season, it is very difficult to get an image that is free from cloud cover using the cloud cover masking function available on GEE. For instance, in this study for the year 2020, the cloud cover threshold has been selected as less than 1% but still, there was a cloud cover at the most upper part of the catchment.

2.7.1 Machine Learning Classifiers in GEE

Machine learning algorithms use inputs (imagery and training data) to group and classify pixels. The algorithm is a "black box", meaning the researcher can examine inputs and outputs. GEE offers several machine learning classifiers which can perform supervised and unsupervised classification. Popular types of supervised algorithms

The mapping has been successfully done with the best performance capability of the SVM classifier, and the overall accuracy was very high (Jamsran et al., 2019).

Shi & Yang, (2015), demonstrate the effectiveness of SVM for heterogeneous land cover mapping, the study found that SVM can significantly improve mapping accuracy, particularly for spectrally and spatially complex land cover categories. In addition to the mapping of land use and land cover, SVM has been used for various purposes for example in groundwater potential mapping (Naghbi, 2017), modeling low flow time series (Sahoo, 2019), and groundwater quality evaluation (Lin, JunMin, & XiaoXue, 2010).

All of the studies have found that SVM had strengths in terms of classification accuracy, training time as a limitation the studies suggested that the classification accuracy of SVM can be affected by the size and quality of the training sample.

2.7.1.2 Classification and Regression Trees (CART) Classifier

CART is an advanced technique and it's based on a decision tree (DT) classification algorithm which is built from a set of training data and the decision is selected from the attribute with the highest normalized information gain (Breiman et al., 1984).

The handling of both numerical and categorical data makes CART more advantageous in easy understanding, visualizing, and interpreting the classified images (Ray, 2019). Additionally, it differentiates the most significant variables from non-significant ones (Shelestov, 2017; Bittencourt & Clarke, 2003).

The CART classification algorithm repeatedly splits input data based on a statistical test to increase the similarity of the training data in the resulting node (Mondal et al., 2019).

The main limitation of the CART algorithm is the presence of high variance across samples this leads to occupancy of high variability in predicting classes and estimates (Hayes et al., 2015)

2.7.1.3 Random Forest (RF)

A random forest classifier uses training data and identifies statistical patterns in large datasets and uses a series of decision trees to select the best classification for all pixels within imagery (Figure 2.3) (Breiman, 2001). It is a nonparametric machine learning method that creates multiple decision trees which classify a random subset of the training data according to the covariate predictors. The final decisions of class and model construction are determined by the majority vote among all trees (Breiman,2001).

In a random forest, the user defines the number of trees and variables per split because the classifier performance is not sensitive to the number of variables per split (Breiman et al., 1984).

The Random forest method has several advantages such as more efficient results for large data (Herrera et al., 2019; Zakariah, 2014), can handle thousands of variables without reducing it (Rodriguez et al., 2012), gives an estimate of variables that are important in classification (Robin Genauer et al., 2010; Frauke Degenhardt et al., 2019), can produce unbiased estimates of generalization errors ((Siroky, 2009)) and computationally lighter than other tree ensemble methods.

There have been many studies showing the success of using the random forest, in land use and land cover mapping for example Nurfadila et al., (2019) used Sentinel 2 satellite data with 10 m spatial resolution for mapping of land use land cover change, as a result, more optimal land use and land cover maps have been produced with 95% overall accuracy.

Moreover, this classifier has been used widely to classify satellite data for wetland mapping (Masoud et al., 2017; Shaohong et al., 2016), cropland mapping (Oliphant, et al., 2019) , and natural hazard susceptibility area mapping (Taalab, Cheng, & Zhang, 2018; Sunmin et al., 2017).

2.7.1.4 Naïve Bayes

A naïve Bayes classifier uses or applies the Bayesian theory of probability and predictions of the unknown class assuming the features have strong (naïve) independence this makes the naïve Bayes classifier probabilistic model (Camargo et al., 2019).NB assumes that the feature class doesn't depend on the presence and absence of any other feature class instead it depends on the nature of the probability model this makes the datasets train quicker (Ratika Pradhan, 2010).

The ability to work with a few training data sets, easy to use and understand as well as quick training and classification make naïve Bayes algorithm classifier more advantageous from other types (Ho, 1998).

The NB classifier was effectively implemented for the assessment of gully erosion and landslide susceptibility (Chen et al., 2019), Spatial Prediction of Groundwater Potentiality, Assessing the spatial likelihood of flood hazard (Liu R. C., 2016),

2.8. Hydrological Models

Hydrological models are characterizations of the real-world system. The best model is the one that provides results that represents reality with the utilization of the smallest amount of parameter and less model complexity (Gayathri et al.,2015). A wide range of hydrological models was used by different researchers, however, the applications of those models are highly dependent on the purposes for which the modeling is made.

2.8.1. Model selection criteria

The selection of a particular model is a key issue to get a satisfactory result to a given problem and the selection is based on objectives formulated, data availability, the hydrological elements being modeled, and model simplicity (Vaze et al., 2011).

Dhami and Pandey, (2019) also stated that hydrological processes, governing equations, minimum data required, spatial and temporal scale of the model are the fundamental criteria that must be answered before selecting any hydrologic models.

There are many hydrological models developed to facilitate the simulation of water movement in watersheds until it forms stream flow this classification is generally based on the method of representation of the hydrological cycle or a component of the hydrologic cycle (Gayathri et al., 2015).

Hydrological models can be categorized into the following broad classes this is lumped or distributed, deterministic or stochastic, and conceptual and physically based models (Beven, 2000; Beven, 1985).

In lumped models, there is no spatial variability of the hydrologic parameters within the basin. Therefore, the response of the basin is evaluated only at the outlet without accounting for the detailed response of individual sub-basins (Cunderlik, 2003).

According to Cunderlik, (2003) distributed models require large amounts of data parameterization in each grid cell. He stated that distributed models can provide the highest degree of accuracy if input data are adequate and governing physical processes are modeled in detail and properly applied.

In distributed physically-based models streamflow simulation is based on complex mathematical equations. In semi-distributed models, the spatial variability of the model parameters is allowed by dividing the basin into several smaller sub-basins. The semi-

distributed models are more physical based when compared to lumped models, and that they require fewer input data than fully distributed models (Cunderlik, 2003).

Deterministic models permit only one outcome from a simulation with one set of inputs and parameter values while stochastic models allow for some randomness or uncertainty in the possible outcomes due to uncertainty in input variables, boundary conditions, or model parameters (Beven, 2000).

Conceptual models are based on a limited representation of the physical processes acting to produce the hydrological outputs, while physically based models are based more solidly on an understanding of the relevant physical processes.

Now a day there are so many comprehensive spatially distributed hydrologic models have been developed in the past decade due to advances in hydrologic sciences, Geographical Information systems (GIS), and remote sensing.

Every hydrologic model, because of its special structure and basic assumptions, is developed for a specific time and spatial scales. For example, The SHE (Systeme Hydrologique European) model is a fully distributed grid element based model The model can predict infiltration excess runoff, saturation excess runoff, groundwater flow, and subsurface contribution to the hydrograph but the application of the SHE model requires thousands of effective parameter values at the grid element scale (Abbot et al., (1986a, 1986)).

According to Nourani et al., (2011) HEC-HMS and unit hydrograph methods are not able to estimate exactly the amount of water content in the soil column, especially before and after long periods because these models are event-based and cannot be appropriately applied for long-term stream and sediment yield modeling.

The soil and water assessment tool (SWAT) is a public domain graphical user interface program and a deterministic, continuous watershed model that can operate on daily and hourly time steps (Addis, 2016).

Initially, the model was developed by the US Department of Agriculture – Agriculture Research Service (USDA-ARS) at the Grassland, Soil, and Water Research Laboratory in Temple, Texas (Arnold J. G., 1989). It simulates hydrological processes, sediment yield, nutrient loss, and pesticide losses into surface water and groundwater, and the effects of agricultural management practices on the water in large watersheds (Arnold J. G., 2012).

It has been used extensively by researchers worldwide because of its capability in simulating the characteristics of a catchment using different scenarios (Blainski et al., 2016), allows considerable spatial detail for basin-scale modeling (Heuvelmans, 2004), and users readily available inputs for weather, soil, land, and topography.

2.8.2 Hydrological component of SWAT

SWAT allows several different physical processes to be simulated in a watershed. Simulation of the hydrology of a watershed is done in two separate components. These are the land phase of the hydrologic cycle and the routing phase of the hydrological cycle (Neitsch et al, 2011). The land phase of the hydrologic cycle controls the water movement in the land and determines the water, sediment, nutrient, and pesticide amount that will be loaded into the mainstream. Hydrological components simulated in the land phase of the Hydrological cycle are canopy storage, infiltration, redistribution, and evapotranspiration, lateral subsurface flow, surface runoff, ponds, and tributary channels return flow for modeling purposes a watershed may be partitioned into several sub-watersheds or sub-basins.

In the land phase of the hydrologic cycle, SWAT simulates the hydrological cycle based on the water balance equation (Neitsch et al, 2011) and computed by:

$$S_{wt} = S_{wo} + \sum_{i=1}^t (R_{day} + Q_{surf} - E_a - W_{sep} - Q_{gw}) \dots \dots \dots Eq(2.2)$$

where: - S_{wt} is the final soil water content (mm), S_{wo} is the initial soil water content for day i (mm), t is the days (days), R_{day} is the day precipitation (mm), Q_{surf} is the surface runoff (mm), E_a is the evapotranspiration (mm), W_{sep} is the seepage from the bottom soil layer (mm) and Q_{gw} is the groundwater flow on the day i (mm).

The occurrence of surface runoff is caused whenever the rate of precipitation exceeds the rate of infiltration. In the SWAT model surface runoff is estimated either using the SCS curve number procedure (USDA-SCS, 1972), or the green and Ampt infiltration method (Green and Ampt, 1911). The SCS curve number method calculates runoff using the following Equation using daily or sub-daily rainfall for each HRUs.

$$Q_{surf} = \frac{(R_{day} - 0.2S)^2}{R_{day} + 0.8S} \dots \dots \dots eq(2.3)$$

Where: - Q_{surf} is the accumulated runoff or rainfall excess (mm), R_{day} is the rainfall depth for the day (mm), S is the retention parameter (mm).

The retention parameter is defined by equation 2.4

$$S = 25.4 * \frac{1000}{CN} - 10 \dots \dots \dots eq(2.4)$$

Where: - CN is the curve number for the day and it is a function of land use, soil permeability, and antecedent soil water condition.

SWAT calculates the peak runoff rate with a modified rational method. Many methods are developed to estimate potential evapotranspiration (PET). Three methods are incorporated into SWAT which are the penman-Monteith method (Monteith, 1965) , the Priestley-Taylor method (Priestley & Taylor, 1972), and the Hargreaves method (Hargreaves, 1985).

These methods have various data needs of climate variables. Penman-Monteith method requires solar radiation, air temperature, relative humidity, and wind speed, Priestley-Taylor method requires solar radiation, air temperature, and relative humidity and the Hargreaves method requires air temperature only. Based on the available data in the catchment, the Penman-Monteith method was selected.

The second hydrological component Simulation of the watershed is the flow routing phase, in which the water is routed in the channels network of the watershed, carrying the sediment, nutrients, and pesticides to the outlet. In the calculation of the water balance in the channel flow, the rate and velocity of flow are calculated by using manning’s equation, and the transmission and evaporation are also well considered by the model. The Storage routing is based on the continuity equation

$$\Delta V_{stored} = V_{in} - V_{out} \dots \dots \dots eq(2.5)$$

where:- ΔS_{stored} Is the change in volume of storage during the time step (m3), V_{in} Is the volume of inflow during the time step (m3), and V_{out} Is the volume of outflow during the time step (m³).

2.9 Application of SWAT model in Ethiopia

Bharti et al., (2020) in Rib watershed used SWAT model to analyzing sediment yield and it provides acceptable hydrological performance, and calibrated model provides information to apply the model in other ungauged watersheds of similar topography, land use, soil, and

climate for erosion assessment, and implementation of best management scenarios in Ethiopian.

The superiority of SWAT model performance was also assessed by Assfaw, (2019) in performing the trend of runoff and sediment yield in Megech Reservoir, Ethiopia. Additionally, Hailu Kendie Addis et al., (2016) modeled streamflow and sediment yield in Ethiopian highlands using the SWAT model, and the performance of the model was satisfactory.

The best performance capability of the SWAT model in simulating and predicting sediment yields from the Fincha watershed and hence can be used as a tool for water resources planning and management in the studying watershed has been done and suggested by (Ayana, Chemed, & Ekasit, 2012).

The ability of SWAT to adequately simulate stream flows was also assessed by Sime et al., (2020) in Toba sub-watershed, Ethiopia. The daily and monthly stream flows simulation, as well as modeling of the hydrological water balance in Lake Tana Basin, was successfully investigated by (Setegn et al., 2008). Betrie et al., (2011), applied the SWAT model to simulate daily sediment yield From the Upper Blue Nile basin under different Best Management Practice (BMP) scenarios on sediment reductions, as a result, good agreement between the observed and simulated daily sediment concentrations as the value of Nash-Sutcliffe efficiency was 0.83 obtained. Similarly, Temesgen Gashaw, (2021) evaluated Best Management Practices On Soil Erosion Reduction Using the SWAT Model for Gumara Watershed, Abbay (Upper Blue Nile), and the application of the combined Scenarios such as SSB & GW, and GW & RC reduces the high soil erosion in the Gumera watershed, and similar agro-ecological watersheds in Ethiopia and many other researchers in Ethiopia has been successfully calibrated and validated SWAT model.

Therefore, SWAT can be utilized very well for hydrological simulations and able to fairly explain the hydrological characteristics in the selected catchments and can be further extended to similar watersheds in the country, particularly in the kulfo watershed of Ethiopia.

3 MATERIALS AND METHODS

3.1. Description of Study Area

Kulfo catchment is located in the Abaya-Chamo sub-basin of the Southern Ethiopian Rift Valley and drains to Lake Chamo. The catchment area of Kulfo is about 362km² and lies at the middle to lower reach of Kulfo River, near the town of Arba Minch, extending between 5°55'N and 6°15'N latitude and 37°18'E and 37°36'E longitude and with a total length along the channel of 23km (Figure 3.1).

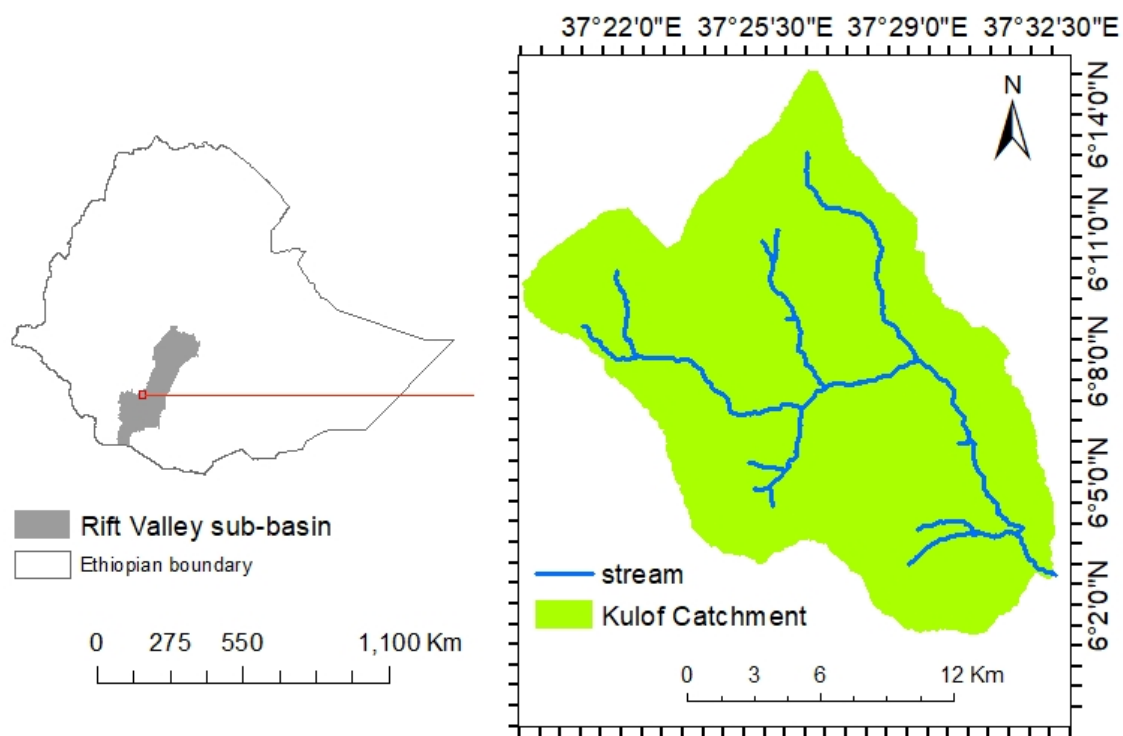


Figure 3.1 Location of the study area (Kulof Catchment)

3.1.1 Topography

The terrain characteristics of the study area were analyzed by using GIS as a result the study area was mountainous in the mid and upstream parts, and also the area is characterized by remarkable elevation difference that reaches from 3370 masl at the peak of the North-West to 1586 masl north-east and about 1227m above mean sea level at the termination to the lake Chamo (Figure 3.2 A).

The sloping terrain was classified based on the Food and agriculture organization (FAO, 1985) classification system (Figure 3.2B). About (45%) of the Kulfo catchment is classified as a steep slope and 23.5% of the terrain area is classified as very steep and 11.5% of the area is a moderately steep slope. Around 10.6% and 5.8% of the area are characterized under

sloping and gentle sloping. Only 1.5% of the area was an extremely steep slope and 2.33% of the lower catchment of the river is flat.

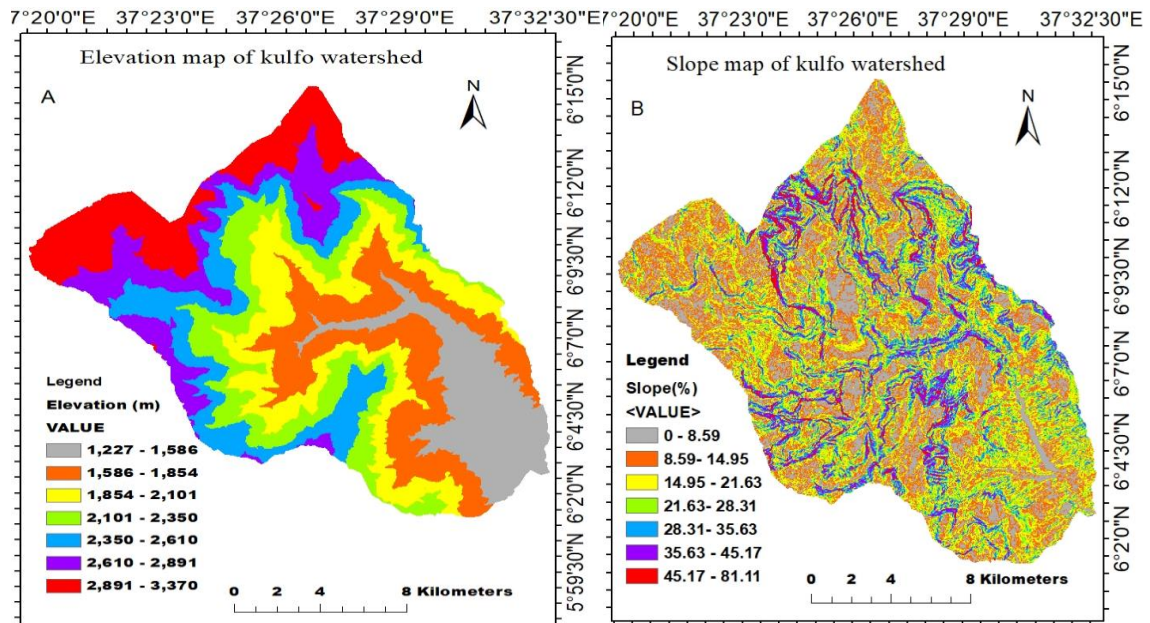


Figure 3.2 Study area descriptions: (A) Elevation map (B) Slope map of kulfo watershed

3.1.2 Climate of the study area

According to Ethiopian climate classification, the Kulfo catchment is characterized by hot semi-arid warm temperatures and a tropical climate. The average annual rainfall ranges from 665mm at Bilate to 1240mm at Chencha with an average maximum temperature of 31.2°C at Arbaminch and a minimum average temperature of 13.9°C at Chench (Abyot, 2008).

Figure 3.3 shows the average monthly rainfall of stations in and around the kulfo catchment. The average monthly rainfall is very high in April and May whereas it is very low from December to March.

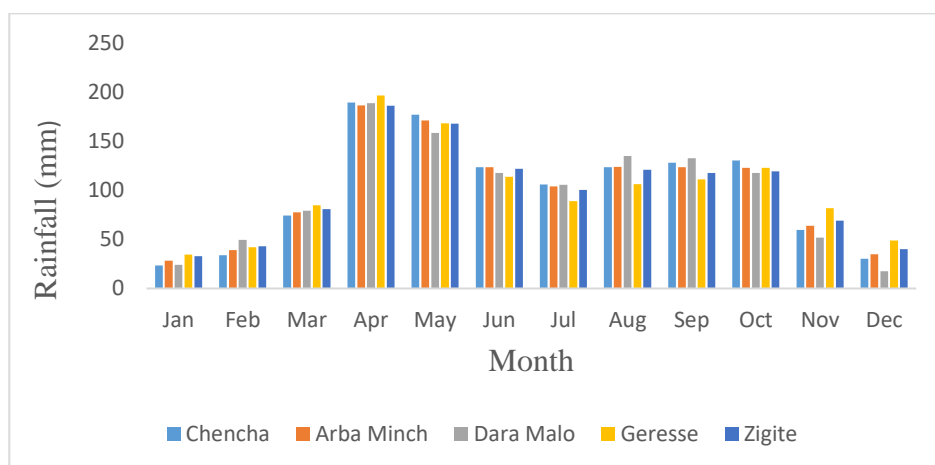


Figure 3.3 Mean monthly rainfall of stations in and around the Kulfo catchment.

3.1.3 Soil

The soil map produced in (Figure 3.4) shows that the catchment area is characterized by two major types of soil: Loam and Clay Loam. The most dominant soil texture is Clay loam, which covers about 65% of the catchment.

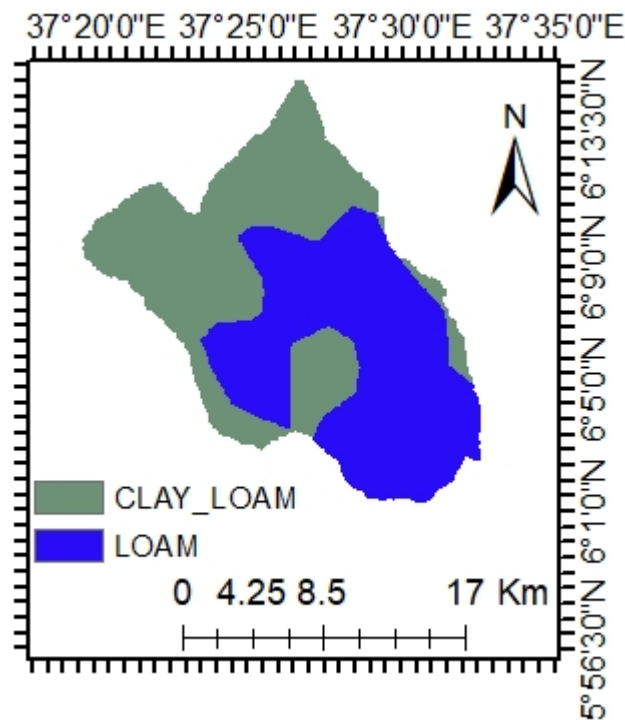


Figure 3. 4 Major Soil map of kulfo catchment

3.2 Data collection and methods

The impact of land use and land cover on streamflow on kulfo catchment has been evaluated using the SWAT model. For the completion of this study extensive fieldwork and secondary data were combined to prepare a historical LULC map.

In modeling a given watershed the quality and quantity of data, used, have a great influence on the performance of the model. Particularly, the SWAT (Soil and Water Assessment Tool) requires good quality of digital elevation model (DEM), Soil and land use and land cover data above all other necessary data. For this study, various necessary data were collected from different sources, primary and secondary data, and used. As primary data GCS collected from each of the pre-defined land use land cover types have been collected and to get full information about the past events, human intervention activities, and the previous land use land cover types, information's had been gathered from the local community. The secondary data used were DEM data, soil data, land use/land cover data, flow, and climatic data. Generally, the data are mainly classified into two main categories they are spatial and

time-series data. The types, quality, and quantity of data used in the development of the SWAT project in this study have been discussed in the next sections.

3.2.1 Field Data

Before visiting and going to the field the major land use land cover class were determined (identified) using an unsupervised classification method. Then several field visits, aided using GPS, were carried out to collect ground control points (GCPs). An informal interview was conducted to obtain additional information about the past LULC in the catchment. The main methods followed for the discussion and in-depth interview were interviewing selected peoples personally as well as preparing group discussion with the local communities for this systematic approaches were followed like a selection of elder peoples and landowners, making the number of interviewees more on the controversial area. About 50 selected elder and local communities were asked from different Kebele and areas of the catchment.

The major purpose of the field survey was to determine the major land use land cover class in the study area and for accuracy assessment.

A minimum of 40 and a maximum of 50 ground control points had been collected from the field from each of the classified land use and land cover classes. During the collection of GPS points, very high attention was given to the major key features that existed within the watershed since it helps more for georeferencing of classified images.

3.2.2. Spatial data

A digital elevation model (DEM) is an important spatial input for the automatic extraction of topographic parameters for the soil and water assessment tool (SWAT). Topography is defined by a DEM that describes the elevation of any point in a given area at a specific spatial resolution. The watershed characteristic like a length of the streamline, the main channel slope, the watershed area, the area slope varies for different types of DEM resolution (Waranyu, 2016).

So, DEM data has a significant effect on the hydrological modeling of a watershed. Therefore, in this study, the DEM (Digital Elevation Model) data with (30mx30m) resolution in raster format was used and projected to Transverse Mercator (UTM) on the spheroidal of WGS84 to correct the errors and fit into the model requirements. It was obtained from the ministry of water irrigation and electricity (MoWIE), GIS Department. Figure 3.5 shows the digital elevation model (DEM) of the kulfo watershed.

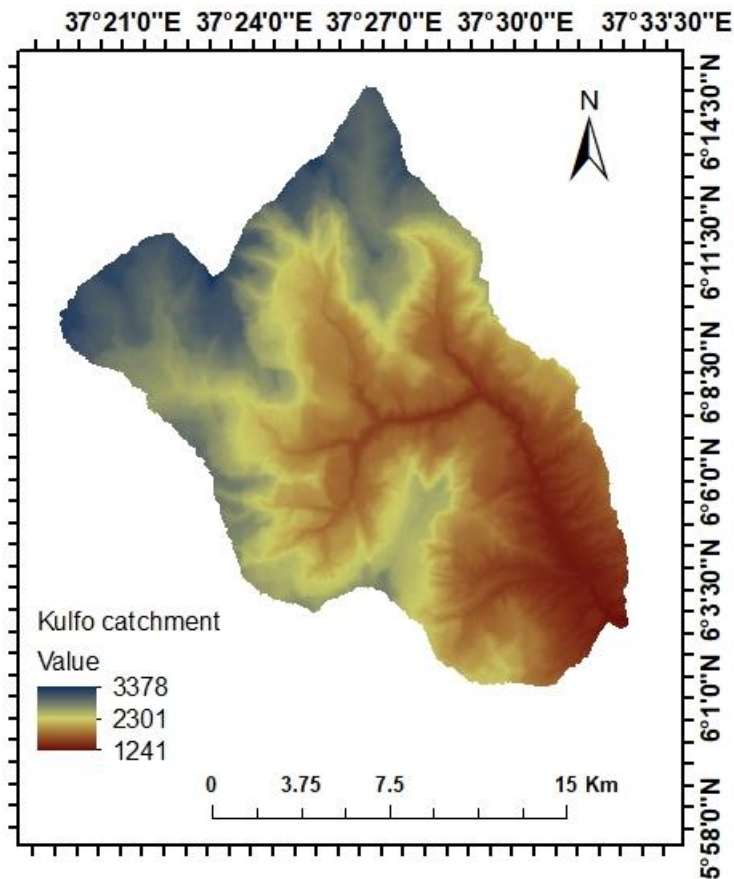


Figure 3.5 Digital Elevation model of Kulfo catchment

The second very important type of data used was land use and land cover which greatly affects the hydrological response of a watershed and defines the densities and types of land use found within a given area as well as determines the watershed characteristics. Therefore, detailed analysis and mapping of the land use/land cover is crucial for proper hydrological modeling

This study used the Google earth engine platform to analyze and map land use and land cover change from 1986-2020, as a result, the dominant land use type in 1986 was shrub land which covers 108.34 km² followed by agricultural land then after more than a decade in 2000 the catchment was dominated by agricultural land that occupies 34.49% of areal coverage whereas in 2016 the agricultural land increased and covers 47.95% of areal coverage and the recent year 2020, was dominated by agricultural land with areal coverage of 57.12% Table (4.3).

Soil data of the catchment was obtained from the ministry of water irrigation and electricity (MoWIE), GIS section. The determination of the available dominant soil types on the study

area was analyzed by using ArcGis 10.4 software as result the dominant soil types are Clay-Loam, and Loam.

Table 3.1 dominant Soil types of kulfo catchment

Soil Group Name	SNAME	Soil Group	Area (km2)
Clay Loam	CM	D	165.1
Loam	NT	C	157.704

3.2.3 Time series data

To simulate the hydrological condition of the catchment SWAT model needs hydrological and metrological data sets. The main metrological data sets used were daily data of precipitation, maximum and minimum temperature, relative humidity, wind speed, solar radiation, and sunshine hour which were obtained from the National Meteorological Services Agency (NMA) of Ethiopia with a different record length of the year.

Table 3.2 Summary of rainfall and stream gauging stations

S.NO	Station/Site	Latitude	Longitude	Elevation	Record length
1	Arba Minch	6.05	37.549	1652.59	1987-2004
2	Dara Malo	7.06	38.47	2005	1991-2003
3	Geresse	14.2	39.4	2506	1992-2002
4	Zigite	6.319	37.23	1914.25	1992-2005
5	Chencha	6.23	38.01	1813.36	1992-2004

For performing sensitivity analysis, calibration, and validation of the model, streamflow was required. Hydrological data like an observed daily flow which covers a period of 1991 to 2004 years was collected from the Ministry of Water, Irrigation and Electricity with some missed value for Arba Minch hydrological stations.

3.3 Data analysis and Quality checking

3.3.1 Filling of missed data

Some precipitation stations may have short breaks in the records because of the absence of the observer or because of instrumental failures thus filling in missed data is very vital to perform hydro-meteorology analysis and simulation using data of long time series.

There are methods to fill in missing data. These are: arithmetic mean method, normal ratio method, and inverse distance weighting method.

The arithmetic mean method can be used to fill in missed data when normal annual precipitation is within 10% of the gauge/station for which data are being reconstructed. The normal ratio method is used when the normal annual precipitation at any of the index stations differs from that of the precipitation station by more than 10%. In the absence of normal annual rainfall for the stations, the inverse distance weighting method can be used to fill the missed data.

In this research, the arithmetic mean of the entire period was used to fill the missed records for the stations with less than 10 percent missed records and by using Microsoft excel the regression formula is used to calculate the missing data of stations before the data is used by the model.

3.3.2 Consistency of Rainfall Data

Time-series data is consistent when the characteristics of the record have not changed concerning time. Some of the most common causes of the inconsistency of records are shifting of rain gauge station to a new location, the neighborhood of the station undergoing a marked change, change of ecosystem due to climates, and occurrence of observational error from a certain date.

Double mass curve analysis is the method used to check whether a recorded rainfall data in a given rain gage station is consistent or inconsistent. The method for checking the consistency of meteorological data using double mass curve analysis is determined by plotting the cumulative values of observed time series of station for which consistency need to be checked on one axis versus the cumulative value of observed time series of a group of a station on another axis and the station affected by the trend, a break in slope of the curve would indicate that conditions have changed that location.

The data series, which is inconsistent, adjusted to consistent values by proportionality.

$$S_i = \frac{\Delta Y}{\Delta X} \dots \dots \dots 3.1$$

where:- S_i – the slope of section I, ΔY – the change in the cumulative for gage Y between the end points of section I, ΔX – the change cumulative for the sum of the regional gage between the endpoints of section i.

$$P_{cx} = P_x * \frac{M_c}{M_a} \dots \dots \dots 3.2$$

$$KN = -3.62201 + 6.28446N^{\frac{1}{4}} - 2.49835N^{\frac{1}{2}} + 0.491436N^{\frac{3}{4}} - 0.037911 \dots \text{eq}(3.6)$$

Sample values greater than XH are considered to be high outliers, while those less than XL are considered lower outliers. Firstly, the time-series data have been arranged using the annual maximum model that takes only one representative value for each year in the study periods. Then using the formulas (equation 3.4 and equation 3.5) the outlier of the time series data have been checked and some values of outlier have been detected mostly in the maximum side for flow and rainfall.

3.3.5 Hydrological data analysis

For this study 13 years of flow, data was used from 1991-2004 was used for Arba Minch station only from this two-thirds for calibration (from 2003-2000) and one-third for validation (from 2001-2004) but two years for worm up period from 1991-1993 and the missing was completed by regression analysis.

3.4 Materials

Table 3.3 the materials and software tools used for this study were

No.	Materials	Version	Purpose of the material
1	ARC GIS	10.4	Preparation of and processing of data
2	Google earth engine		For land use land cover map processing and preparation
3	GPS	GARMIN	For the collection of ground truth points
4	SWAT	2012	Simulation
5	SWAT-CUP	5.1.6	Sensitivity analysis, calibration and validation
6	Weather database.	v01803	Preparation of weather generation
7	Google earth pro	7.2.3	For investigating historical images and Study area
8	MS EXCEL	2016	Statistical analysis, Chart, and graphs

3.5 Methods

The Google earth engine application, a JavaScript API, was used to analyze the spatial and temporal land use and land cover dynamics. The JavaScript API codes were taken from (<https://earthengine.google.org/>). However, the script was customized for the current usage (study area).

The Landsat series of satellites have provided continuous imagery for the past few decades. These images are contained in Google Earth Engine's public data archive and can be used to detect and estimate the long-term dynamic of land use land cover change.

Google Earth Engine greatly reduces the analysis time by utilizing Google's distributed computing infrastructure platform (<https://earthengine.google.org/>). It provides excellent performance in terms of enabling access to remote sensing products through the cloud platform and providing pre-processing to archived data from the US Geological Survey (USGS) collection (Zurqani, et al., 2020).

This paper uses annual composites Landsat Surface Reflectance images covering an area around 362km² of, kulfo, the catchment for classification and further analysis. Four annual composites images from four Landsat Series were used in this study.

When selecting the right type of data set several aspects have to be considered; the most important are availability, accessibility, and quality of the data (Aitkenhead and Aalders 2011).

The satellite imagery used in this study to classify LULC changes were the Landsat Thematic Mapper (TM) of 1986, the Landsat Enhanced Thematic Mapper Plus (ETM+) of 2000, the Landsat Enhanced Thematic Mapper Plus (ETM+) of 2016, and the Landsat Operational Land Imager (OLI) of 2020 each of them was analyzed individually and change detection analysis was done by performing pre-and post-change detection techniques.

A large number of high-quality samples were selected by visual interpretation and google earth images were used for selecting training samples to improve the classification accuracy. Four popular machine-learning algorithms of SVM, CART, RF, and Naive Bayes were employed to identify and map long-term LULC change.

The Landsat archived data from the US Geological Survey (USGS) collection was loaded as an Image Collection and the selected study area was injected into the GEE and displayed.

The LULC classification technique was applied and evaluated by developing code in the GEE platform using the supervised classification method and Landsat imagery for each chosen year.

In this study, four types of Machine learning classifier algorithms, available on GEE, were applied and the best performing one was selected. This Machine learning classifier algorithms were SVM, Random Forest, Naïve Bayes, and CART. After, processing the land

use and land cover map the result has been exported to google drive. All of the processing was conducted in GEE Code Editor (<https://code.earthengine.google.com/>).

3.5.1 Image pre-process in GEE

To avoid confusion and overcome timeout error four customized GEE Code Editor Scripts were used to the individual year separately (1986, 2000, 2016, and 2020). Each of the individual year images had passed the following main components of image preprocessing.

3.5.1.1 Acquiring Landsat Surface Reflectance image collection

The first step is accessing and acquiring data started by a function to call and make a composite image by calling a series of images from the Image Collections.

3.5.1.2 Image mosaicking and cloud removing

After acquiring the required image collections the next step was injecting the shapefile of the study area to google earth engine platform in the form of zipped file format and a selected year Landsat image collection is loaded by filtering the date of acquisition this is done to minimize the effect of the rainy season on the classification result. Then, a cloud-masking function was developed by assigning a cloud score to each pixel in the image collections for the removal of cloud covers, for this a cloud threshold of 1% and 5% was selected based on the visual interpretation of Landsat imagery. This cloud masking function computes a cloud-likelihood score to compare multiple views of the same point for a relative cloud likelihood, and pixels with a cloud-score higher than 1% and 5% were masked out. The filtered image collections were acquired after the cloud mask, and a limited date range was applied.

3.5.1.3 Collection of Training Data

For the collection of training data (samples) for land-cover types, the study area was clipped, and true color composite and false-color composite methods were used for the extraction of spectral and spatial features from Landsat images based on the pixel-based approach. This helps to select training points effectively for each of the land cover types.

In this study, six land use and land cover categories (Bare Land, Agricultural Land, vegetation, shrub land, and Grassland) have been detected and collected using the pixel-based approach.

To assess LULC change over time with GEE, a total of training samples ranging from 507 to 776 for the years 1986, 2000, 2016, and 2020, were selected and collected. Among these sample points, 70% were gathered as training samples during classification. The remaining points were used to verify the accuracy of the classification results.

In the distribution of training sample points moderately cultivated, croplands, farm Lands, and other types of plantation areas were classified under agricultural land cover class whereas plants like banana, avocado trees, and sugarcane which are planted around the river are grouped as a vegetable class and also areas which are moderately populated by trees and higher than shrub lands in height, as well as false banana, were reclassified under Mixed forest class.

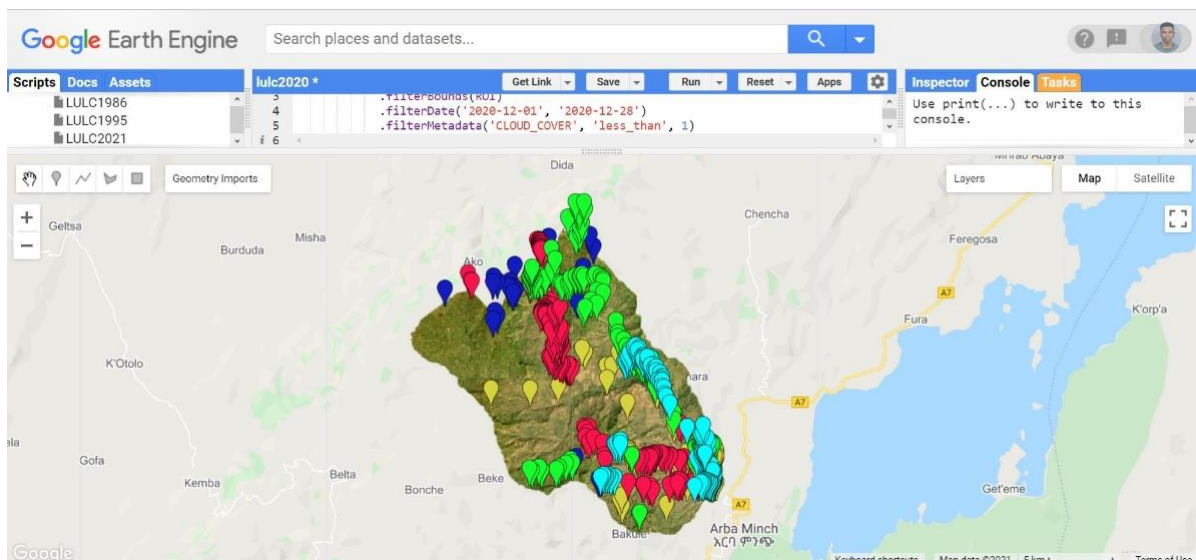


Figure 3.8 Training Data sets

3.5.1.4 Image Classification

The obtained image composites were then classified within the GEE using 4 different types of classifiers which were Support Vector Machines(SVM), Random Forest(RF), Naive Bayes, and CART algorithm with the following six land-cover categories bare land, agricultural land, vegetation, shrub land and Grassland and.

Finally, the relevant results from the analysis such as charts, images, maps, and tables from classified images were exported to google drive.

3.5.1.5 Land use land cover data Processing

The land use land cover is processed and generated by Google earth engine among the classified class of land use and land cover class the dominate one was agricultural land and the generated land use and land cover is converted to SWAT database code for running of SWAT model as shown in Table 3.4.

Table 3.4 Original and the redefined land use/land cover types of kulfo catchment

Original land use land cover	Redefined land use and land cover according to Swat database	SWAT code
Shrub land	Forest-Deciduous	FRSD
Agricultural land	Agricultural land closely grown	AGRC
Grassland	Range grasses	RNGE
Bare land	Barren	BARR
Mixed Forest	Forest mixed	FRST
Vegetation Cover	Forest-Evergreen	FRSE

3.6. SWAT Model

This study uses Arc swat 2012 to generate a hydrologic model of Streamflow from the study catchment, Kulfo, in a GIS used interface.

3.6.1 Model set up

SWAT allows a number of different physical processes to be simulated in a watershed. The simulated processes include surface runoff, infiltration, evapotranspiration (ET), lateral flow, percolation to shallow and deep aquifers, and channel routing (Neitsch, 2011; Arnold., 2012).

Arc SWAT pass three main preprocessing steps this are watershed delineation, hydrologic response unit (HRU) analysis, and weather data definition and SWAT model simulation part with that of sensitivity analysis, calibration, and validation. Therefore, the major steps of Arc SWAT preprocessing will be discussed in depth.

Watershed Delineation

The primary step in creating a new SWAT model project besides preparation of input data is watershed delineation from digital elevation model for this a new project set up and necessary folders as well as databases have to be created to store all the output data processed from the model.

The Watershed delineation process involves five major steps, DEM setup, stream definition, outlet definition, watershed outlets selection, and definition. After, a successful compilation of DEM setup and manual specification of the location of outlet on the DEM, the model automatically calculates the flow direction and flow accumulation as well as stream networks, sub-watersheds, and topographic parameters.

The size of the sub-basin in the watershed will affect the assumption of homogeneity. In this study, the delineation of the watershed has been done using 30m by 30m DEM resolution and the watershed outlet is manually added and selected for finalizing the watershed delineation. With this information, the model automatically delineates the watershed with 25 sub-watersheds for simulations.

Hydrological Response Unit Definition

After performing the automatic watershed delineation, the watershed was partitioned into hydrological response units (HRUs), lumped land areas within the sub-basin, which incorporates the same land use, soil, and management practice. Any parcels of lands within one sub-basin that share the same combination of these three features, land use, soil, and management practice, will be considered one HRU.

SWAT has predefined land use classes in its crop database. So it is necessary to prepare a look-up table, which refers to land use land cover classes found in hand with SWAT land use land cover. So, the Grid code of user soil and crop database was prepared and used as a bridge that connects the soil and land use map on one side and look-up table on the other side during land/soil/slope definition. After Land use, soil, and slope characterization were done each map of the watershed was overlaid to define a hydrologic response unit by setting a threshold for each map.

For this specific study a 5% threshold value for land use, 10% for soil, and 10% for slope were used. The HRU distribution in this study was determined by assigning multiple HRU to each sub-basin. For the recent year, 2020, 25 sub-basin and 75 HRUs were produced whereas for the year 2016 25-sub basin and 57 HRUs were created by integrating land use and land cover, soil, and slope maps. The full hydraulic response unit of the kulfo watershed for different year periods specified is shown in figure 3.9 below.

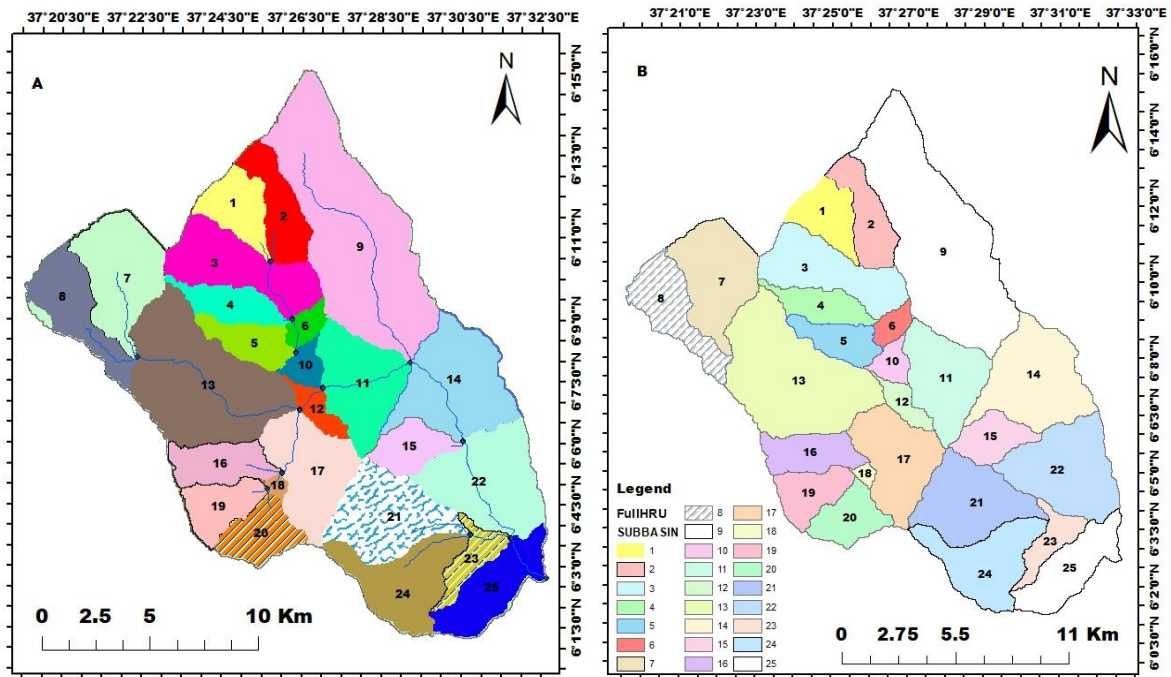


Figure 3.9 Full Hydrological Response Unit (HRU) Map of kulfo Watershed

Weather Data Definition

SWAT requires a long year's daily record of precipitation, maximum and minimum temperature, solar radiation, relative humidity, and wind speed.

The SWAT weather generator model (WXGEN) was used to fill missing values in weather data. Since most of the stations have no full weather data like that of relative humidity, solar radiation, and wind speed data by selecting one synoptic station which has full weather data SWAT generates the above data by using a weather generator. For this case, the Arba Minch station is a synoptic station that has full weather data and generates data for the other station. The Penman-Monteith method which utilizes the solar radiation, relative humidity, and wind speed data records were employed for the estimation of potential evapotranspiration (PET). Meteorological stations are also geo-referenced using latitude, longitude, and elevation data. The weather generator collects all information of climate data in one folder then from this the data has been imported to the SWAT 2012 model database.

The last step before a SWAT simulation is going to be run is to write all of the input files required by SWAT and produced from the preprocessed data from Arc SWAT. Once they are written, individual files can be edited through Arc SWAT, or externally.

Model simulation

After the model is set up the next step is running the model and the model runs daily from the year 1991 to 2004 by letting 1-year warm-up period. The output result cannot be used for further analysis without evaluating the ability of the model to predict stream flow through sensitivity analysis, model calibration, and model validation.

3.7 Sensitivity Analysis

The first step in the calibration and validation process in SWAT is the determination of the most sensitive parameters for a given watershed or sub-watershed. Sensitivity analysis was performed on the SWAT model to identify the influential parameters on the modeled streamflow. It is important to identify sensitive parameters for a model to avoid the problem of over-parameterization.

Lenhart et al., (2002) described the importance of sensitivity analysis as to allow the reduction of a number of parameters that must be estimated, thereby reducing the computational time required for model calibration. Once the sensitivity analysis is done calibration can be performed for a limited number of influential parameters.

To improve simulation results and thus understand the behavior of the hydrologic system in the Kulfo watershed, sensitivity analyses were conducted using the entire flow parameters for SWAT models. Therefore sensitivity analysis is used as an instrument for the assessment of the input parameters concerning their impact on model output (Lenhart et al. 2002).

The current version of the SWAT model, SWAT2012, provides algorithmic techniques for sensitivity analysis. Two types of sensitivity analysis are allowed when using SUFI2 (Sequential Uncertainty Fitting version 2). Global Sensitivity and One-at-a-time sensitivity analysis. The two aforementioned sensitivity analysis methods may yield different results since the sensitivity of one parameter depends on the value of other related parameters. In this study, global sensitivity analyses were performed and the ranking of the parameters was determined.

Table 3.5 Some of the Parameters and their description including maximum and minimum values

	Parameters	Description	Min	Max
1	SURLAG.bsn	Surface runoff lag time	0.05	24
2	SOL_ALB	Moist soil albedo	0	0.25
3	GW_DELAY	Ground water delay in days	0	500
4	REVAPMN	Threshold depth of water for revap to occur	0	500
5	SLSUBBSN	Average slope length	10	150
6	CH_N2	Average width of main channel	0	1000
7	RCHRG_DP	Deep aquifer percolation fraction	-1.35	0.18
8	CH_K2	Effective hydraulic conductivity in main channel alluvium	-0.01	500
9	SOL_AWC	Available water capacity of soil layer	0	1
10	EPCO	Plant uptake compensation factor	0	1
11	TLAPS	Temperature lapse rate	-10	10
12	CN_2	SCS runoff curve number	35	98
13	CH_ERODMO	Jan. channel erodibility factor	0	1
14	ALPHA_BF	Base flow alfa factor in days	0	1
15	GWQMN	Threshold depth of water for return flow to occur	0	5000

3.8 Model Calibration and Validation

Model calibration is an iterative exercise used to get the most suitable parameter in modeling. It involves the identification of the most important model parameters and changing the parameter set. The calibration was done on monthly time steps using the average measured streamflow of Kulfo catchment covering from January 1993 to December 2000. After the model was calibrated and got acceptable results the model was validated using measured data of average monthly streamflow of 4 years from January 2001 to December 2004.

Validation was done to compare the model outputs with an independent data set, that were set for the calibration process, without making further adjustments to the parameter values. The process continues till the simulation of the validation period of streamflow confirms best to the measured data of its correspondence so that the model performs satisfactorily. In the validation process, four-year flow data was used for all of the four land use land cover maps to evaluate the model accuracy.

Both model Calibration and validation were conducted by the SWAT Calibration and Uncertainty Program (SWAT-CUP) 2019, Version 5.2.1.1, which facilitates the calibration process (Arnold, et al., 2012). Among the available algorithm in the SWAT – the CUP SUFI-2 algorithm was used for model calibration, validation, and sensitivity analysis for this study. Among various evaluation coefficients allowed in SUFI-2, Nash Sutcliffe (NSE) was chosen for model optimization in SWAT-CUP.

3.9 Model Performance Evaluation

The performance of the model was evaluated by assessing the correlation between simulated and observed values using statistical measures. There are a lot of model statistical measures approaches available for instance Nash-Sutcliffe efficiency (NSE), Percent Bias (PBIAS), the ratio of the root mean square error to the standard deviation of measured data (RSR), and coefficient of determination (R^2).

The major statistical approaches for analyzing model performance used in this study were Nash-Sutcliffe efficiency (NSE) and coefficient of determination (R^2) because those approaches were widely used for model performance analysis.

The R^2 value is an indicator of the strength of the relationship between the observed and simulated values. R^2 ranges from 0.0 to 1.0 with higher values indicating better agreement (Legates and McCabe, 1999). And it is calculated using equation 3.1.

$$R^2 = \frac{\sum_{i=1}^n (Q_{obs} - \bar{Q}_{obs})(Q_{sim} - \bar{Q}_{sim})}{\sqrt{\sum_{i=1}^n (Q_{obs} - \bar{Q}_{obs})^2} \sqrt{\sum_{i=1}^n (Q_{sim} - \bar{Q}_{sim})^2}} \quad (3.1)$$

Where:- Q_{sim} and Q_{obs} are the simulated and observed values respectively, \bar{Q}_{obs} Is the mean of n observed values and \bar{Q}_{sim} is the mean of n simulated values

The other method was Nash-Sutcliffe efficiency (NSE) which is a normalized statistic that determines the relative magnitude of the residual variance compared to the measured data variance (Nash, 1970).

The overall flow and various approaches followed to achieve the research objectives are described as a flow chart in figure 3.10.

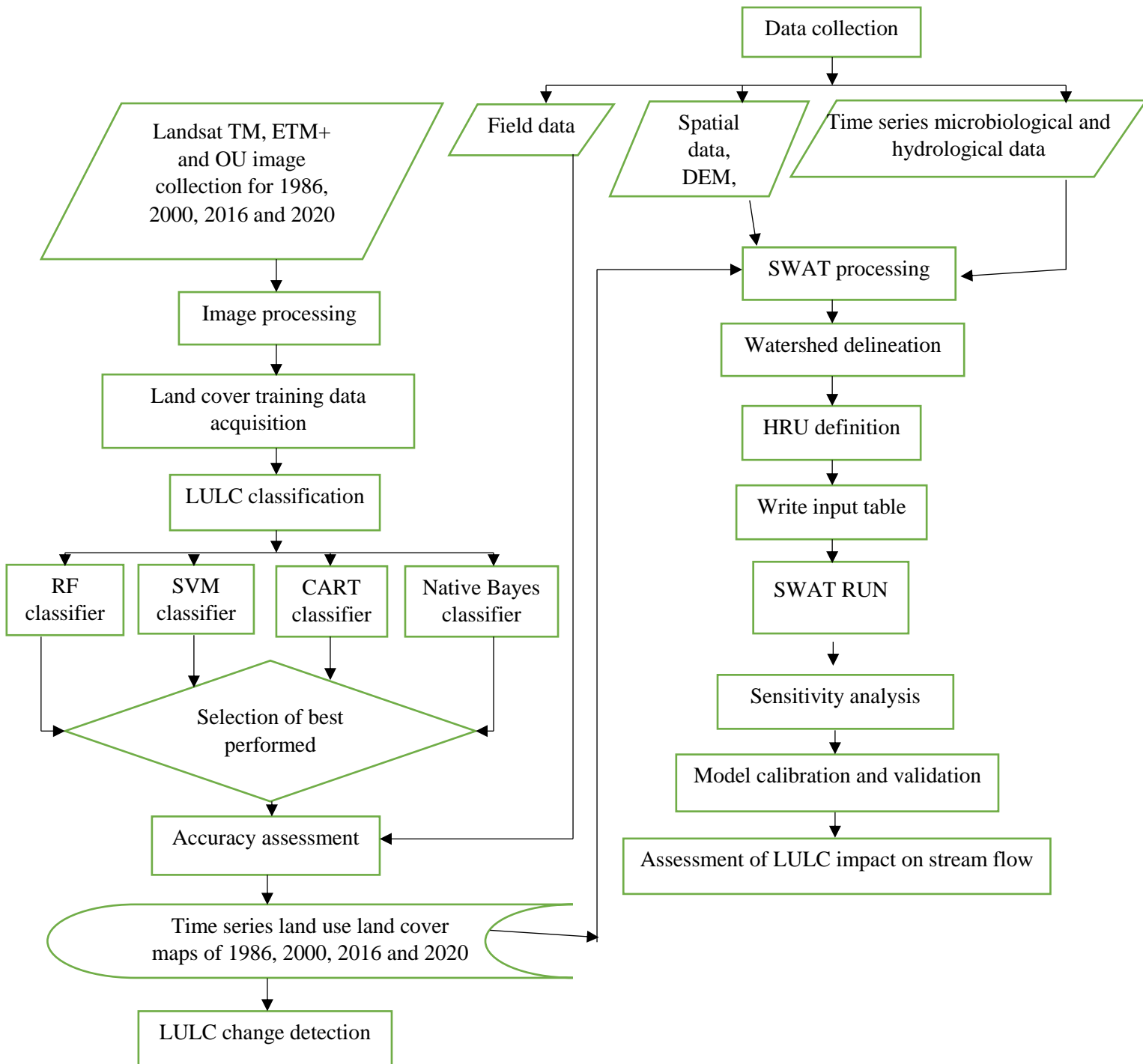


Figure 3.10 General workflow the study

4. RESULTS AND DISCUSSION

In this study, the google earth engine was used by implementing JavaScript for accessing, processing, performing the land use and land cover classification, and export the LULC maps which are detected from the Landsat Images. Accordingly, four machine learning classifiers (algorithms) that are widely used and available on GEE were applied and compared in LULC classification for the case of Kulfo catchment. However, based on their accuracies the best-outperformed algorithm was selected to generate time series LULC map of Kulfo catchment (1986, 2000, 2016, and 2020).

The accuracy of these maps was also evaluated corresponding to GCPs collected from the field (to compare the algorithms and for the time series LULC maps), Google Earth Image, and community information (for the time series LULC maps) using an error matrix and appropriate accuracy indices. The LULC change detection and the impact of the historical LULC change on streamflow were also presented in this section.

4.1 Comparison of Classifications using Different GEE Classifiers

In this study, four machine learning algorithms that were used for LULC classification were compared and evaluated. These classifiers, (RF, SVM, CART, and Naïve Bayes), are existed in the GEE. However, the accuracies and performance of these classifiers were evaluated corresponding to GCPs that were collected from the field using an error matrix.

The recent and free cloud cover Landsat image that was collected on the date of 2020-12-11 (<https://earthengine.google.com>) was used to classify and evaluate the algorithms in LULC classification for the case of Kulfo catchment.

4.1.1 Accuracy Assessment

The error matrix which is widely used to evaluate the accuracy of algorithms and methods used for LULC classification is applied in this study. However, the best-performed algorithm in the LULC classification was presented in Table 4.7. For the sake of clarity and reducing repetition, the error matrixes for the other Machin learning algorithms were described in the **appendices B**.

In the case of the SVM algorithm, the producer's accuracy was ranged from 53.33 % to 79.49 %. The algorithm was highly performed better in detecting the shrubland with 79.49% of accuracy, whereas the user's accuracy was ranged from 58.5% to 75% and it indicates the grassland detected as 75% off accuracy. High commission error was observed in the shrubland due to some of the shrubland pixels laid on the bare land features. The reason for

the occurrence of lower accuracy for these classes may be partly attributed to the horizontal spatial resolution (30m) of Landsat data (image) and generally smaller size of the feature areas as well as the sparse distribution of shrubland. This might confuse the algorithms in differentiating the shrubland and the bare lands. The overall accuracy of the algorithms was 86.71% and the statistical kappa coefficient was 0.861. This indicates that the algorithm ranged as very good (Taati et al., 2015).

Table 4.1 Error matrix of the LULC map of the Kulfo catchment which was classified using the SVM algorithm for 2020.

	Bare Land	Grass Land	Shrub Land	Mixed forest	Agricultural land	Vegetation	Users Accuracy	Commission error
Bare Land	34	0	5	0	11	0	68.0%	32.0%
Grass Land	0	30	0	1	9	0	75%	25%
Shrub Land	10	1	31	3	4	4	58.5%	41.5%
Mixed forest	3	2	1	30	2	5	69.8%	30.2%
Agricultural land	5	13	0	2	40	5	65.0%	35.0%
Vegetation	1	1	2	2	9	35	70	30%
Sum	53	47	39	38	75	49	67.7	
Producers Accuracy %	64.15	63.83	79.49	78.95	53.33	71.43		
Omission Error%	35.85	36.17	20.51	21.05	46.67	28.57		

In the RF algorithm, the user's accuracy ranged from 69.2% to 97.7%. The mixed forest has about 97.7% user's accuracy with 2.3% of commission error. And also, the producer's accuracy is ranged between 66.67% and 93.62%. Among the land features, vegetation land cover obtained 93.62% of producer's accuracy with 6.38% of omission error. In this Machine learning algorithm, a high commission error of about 30.8% has been noticed at agricultural land because more of the agricultural land pixels are classified as mixed forest as well as some are laid on other land feature classes. Among the land feature class, the algorithm faced a challenge in differentiating agricultural land features from the mixed forest. However, The overall accuracy was 79.73% and the kappa coefficient was 0.79. Even if this classifier performed less when compared to the SVM classifier the algorithm was still good in

detecting LULC for the case of the Kulfo catchment. The complete error matrix of this classifier is found in **appendices C**.

In the case of the Naive Bayes algorithm, the percentage of user's accuracy was between 75 to 58.5 whereas producers' accuracy lays between 79.49% to 53.33%. Very high commission error occurs at shrubland around about 41.5%. This error occurs because some of the shrubland pixels were classified as bare land. This indicates that the Naive Bayes algorithm was not able to completely differentiate the shrubland and bare land feature class. In addition to this, some of the land feature classes share the pixel values of the shrubland. The overall and kappa coefficient of this algorithm were 66.4% and 0.64 respectively.

The final classifier was the CART algorithm this classifier got difficulty in classifying the shrubland and bare lands like that of the Naive Bayes algorithm. The producer's and user's accuracy range from 45.45% to 75.00% and from 56.6% to 70% respectively. The overall accuracy was 59.1% and the kappa coefficient was 0.58%. Based on the accuracy assessments CART algorithm was the least performed classifier out of the four machine learning classifiers.

In this study, the SVM machine learning algorithm was performed with better accuracy compared with other machine learning algorithms that were applied for LULC classification. Because kulfo catchment has a multi-feature and heterogenous LULC cover class for this type of catchment SVM is the best type of classification algorithm.

Finally, the overall accuracy and kappa statistics of all Machine learning algorithms have been stated in table 4.5 below. Based on the summary result of accuracy assessment the best-outperformed classifier was support Vector Machines (SVM) which has produced a much higher accuracy of 86.71% for overall accuracy and 0.861 for kappa coefficient.

Table 4.2 Summary of Overall classification accuracies and kappa statistics achieved by GEE machine learning classifiers

Classifier	Overall Accuracy (%)	Kappa Statistics
Support Vector Machines(SVM)	86.71	0.861
Random Forest(RF)	79.73	0.79
Fast Naive Bayes	66.4	0.64
CART	59.1	0.58

For more clarity, the classified LULC map of kulfo catchment using four different classifiers was shown in **Appendixes C**. In this study, the LULC map was classified into six different classes (Bare Land, Grass Land, Shrub Land, Mixed forest, agricultural land, and vegetation cover) using GEE.

4.2 Historical LULC maps and Change detection

The machine learning algorithm which was performed better in detecting the LULC map for the case of Kulfo catchment was selected to generate a historical LULC map for 1986, 2000, 2016, and 2020.

4.2.1 Accuracy assessment

The LULC maps are not very useful without quantitative statements about their accuracy. The accuracy of the maps for the year 2020 is presented as an error matrix above in Table 4.5 and for other periods it is described on **Appendices D**. The numbers along the diagonal of the matrix indicate the number of reference pixels that are accurately classified by the algorithm. The values outside the diagonal were shows misclassifications. As shown in Table 4.5, the algorithm got difficulties during the classification of some of the land cover/use features. For example, agricultural land pixels were classified as grass Land, Bare land as well as a mixed forest because of the reflectance similarity of agricultural land with the described land use land cover types. In Addition to this among other land use land cover class more of the vegetation cover class fall under agricultural land class. This indicates that the algorithm has been confused in detecting (classifying) the agricultural land class and vegetation covers. For the map of 2020, the overall accuracy was 86.71% & the kappa coefficient was 0.861. The classification accuracies are in acceptable ranges compared to the recommended overall accuracy of at least 85% and the Kappa coefficient of 75%.

4.2.2 Land use and land cover change

In this section, change detection of Kulfo catchment for 34 years is performed based on the previous classification results of time series data. As a result (Figure 4.2) shown below shows the land use and land cover maps of the Kulfo watershed during 1986, 2000 2016, and 2020 that have been generated from Image Collection LANDSAT/LT05/C01/T1_SR, LANDSAT/LE07/C01/T1_SR, and LANDSAT/LC08/C01/T1_SR respectively.

After the image processing and land cover detection six (agricultural land, grassland, shrubland, mixed forest cover, bare land, and vegetation cover) land use and land cover classes were determined for the years 1986, 2000, 2016, and 2020 respectively.

As shown in figure 4.2A the spatial distribution of land use land cover class throughout the catchment has a great difference in the 1986 land use and land cover map. For instance, the upper part of the watershed was highly covered with grassland and agricultural land were as the lower part was dominated by bare land and shrub land. Besides this, an increasing trend of agricultural land from the upper to the middle of the catchment was recognized (noticed).

During the period 2000, the upper part was covered with agricultural land, and vegetation cover was slightly increased when compared with the period of 1986 (Figure 4.2A and B). In the upper part of the watershed not only the agricultural land the bare land was also slightly expanded with the reduction of grassland and shrub land. At the most downstream part of the watershed, the bare land was slightly reduced at the expansion of agricultural land. Moreover, the agricultural land expanded along the riparian of the catchment.

All in all, among the land use and land cover class the increment of agricultural land was highly noticed.

By the year 2016, a considerable increment of bare land mixed with shrub land was observed at the middle and lower part of the watershed (Figure 4.2C). And also plantation of Banana and avocado vegetables were recognized at the downstream part and along the riparian of the catchment which was not available on the previous maps.

The final period 2020 shows dramatically expansion of agricultural land all over the catchment (Figure 4.2 D). In addition to this, the bare land and mixed shrub lands increased at the downstream right part of the catchment. The mixed forest above the middle part of the watershed increased this is because of the high plantation of false bananas.

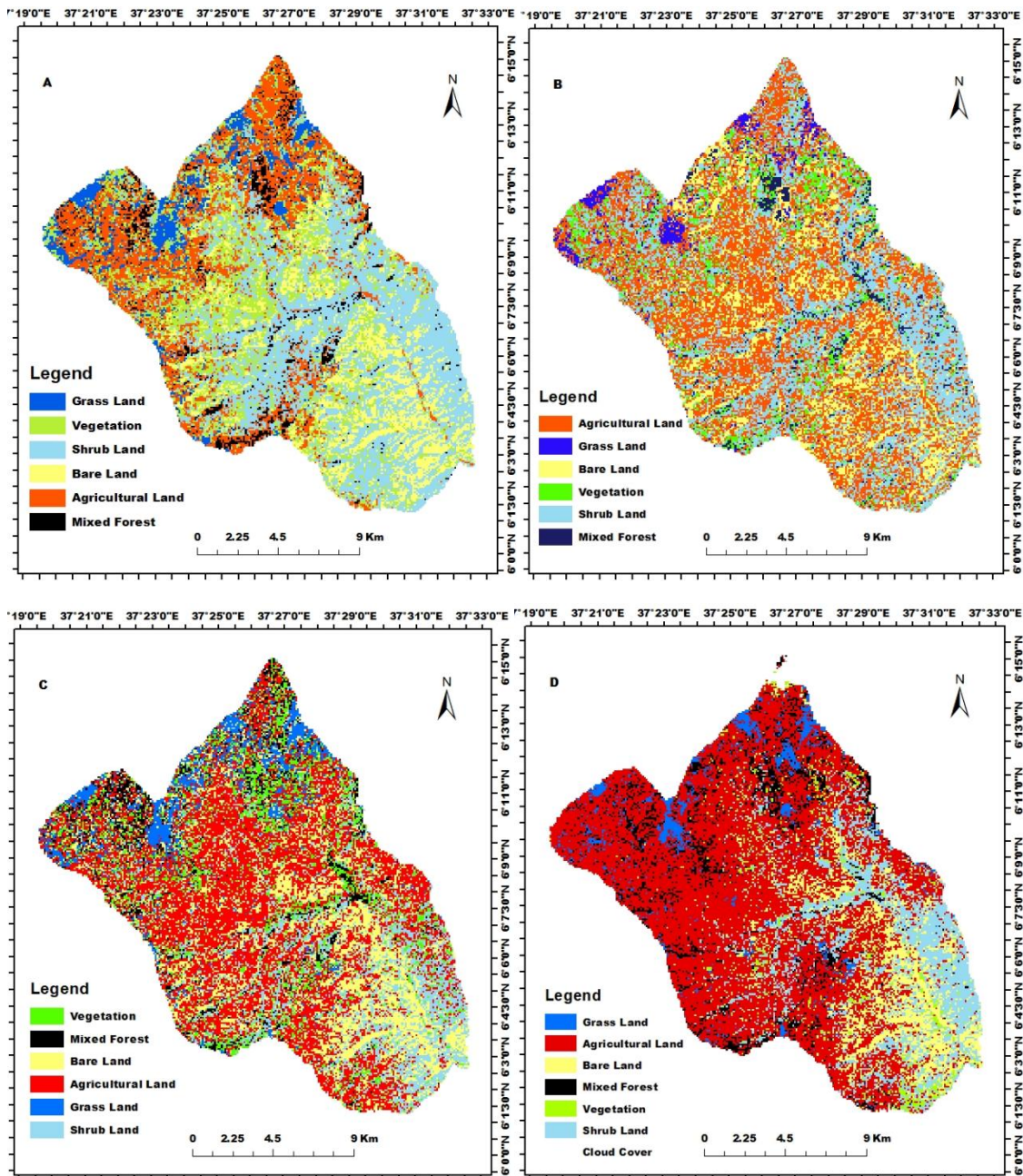


Figure 4.1 Classified land use/ cover map of Kulfo watershed for the year of A) 1986 B) 2000 C) 2016 D) 2020.

The land use and land cover map of 1986 (Figure 4.2A) and the percentage coverage of each land cover class (Table 4.6 and Figure 4.3) indicates that the Kulfo watershed is covered by 18.81% of vegetation land, 19.44% of agricultural land, 15.25% of bare land, 34.18% of shrub land, 0.434% of grassland and also 7.09% of mixed forest.

By the year 2000, the land cover map of 2000 (Figure 4.2B) and the percentage coverage of each land cover class (Table 4.6 and Figure 4.3) shows that the vegetation cover decreased to 7.26%, the agricultural land covers 39.48% of the watershed whereas 52.33% of the

watershed was occupied by other land use land cover types. During this period, vegetation, grassland, mixed forest, and shrub land in the catchment were mainly reduced. In contrast, the agricultural land was expanded in most parts of the catchment.

Similarly, about 47.95% of the watershed was dominantly coved by agricultural land, 20.55% by bare land, 15.92% by shrub land, and around 15.6% occupied by other types of land use land cover types during 2016 (Table 4.6 and Figure 4.3).

The recent year 2020 land use/ land cover map (Figure 4.2D) and the percentage coverage of each land cover class (Table 4.6 and Figure 4.3) shows that the catchment was covered by 57.12% of agricultural land, 11.68% of bare land, 14.73% of shrub land, 4.06% of grassland and 8.66% of mixed forest. In this recent land use map, some parts of vegetation, mixed forest, grassland, and shrub land were reduced and replaced mainly by agricultural land.

The spatial analysis result of the land-use dynamics was summarized as follows in Figure 4.3 and tabular form in Table 4.6. So, that it is simple to compare land use/land cover change patterns and the overall land-use dynamics with time.

Table 4.3 Area coverage of each land use/cover type.

LULC types	1986		2000		2016		2020	
	Km ²	%	Km ²	%	Km ²	%	Km ²	%
Vegetation	59.63	18.81	23.01	7.26	20.23	6.38	9.84	3.10
Agricultural land	61.614	19.44	125.14	39.48	151.978	47.95	181.025	57.12
Bare Land	48.433	15.28	50.83	16.04	65.123	20.55	37.006	11.68
Shrub Land	108.34	34.18	97.99	30.92	50.452	15.92	46.69	14.73
Grass Land	13.89	4.38	9.4508	2.98	15.26	4.81	12.88	4.06
Mixed Forest	25.025	7.90	10.503	3.31	13.97	4.41	27.45	8.66
Cloud Cover	0	0.00	0	0.00	0	0.00	2.03	0.64

Figure 4.2 shows the area coverage of each LULC in Kulfo watershed for different years' time periods including land use/cover of 1986, 2000, 2016, and 2020 year.

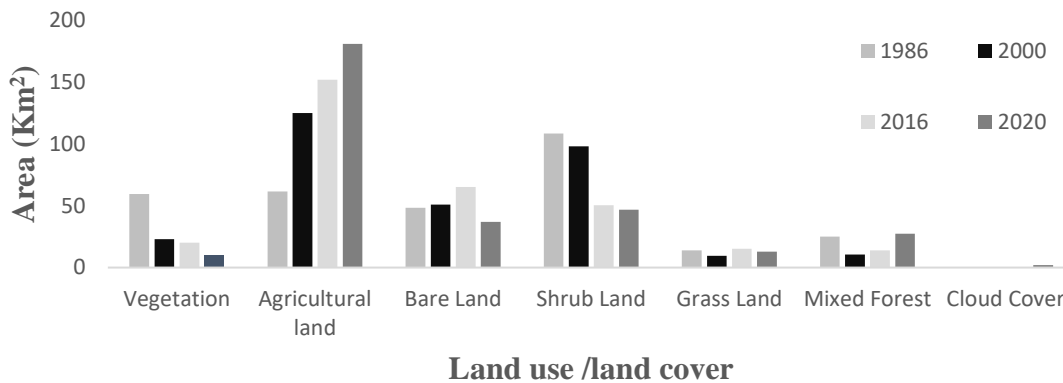


Figure 4.211 the area coverage of land use/cover change in Kulfo catchment.

4.2.3 Land use and land cover change detection

A change detection map that provides “from-to- class” change information was produced for each class of the study area. Figure 4.4 shows the changed land use and a land cover class of the study area indicated with a variety of different colors.

As shown in figure 4.4A during the year (1986 -2000) among the classified types of land use land cover class the bare land and vegetation covers have been more decreased and converted to agricultural land. Specifically, the upper part of vegetation and at the same time, bare land situated at the middle part of the watershed were changed to agricultural land.

Figure 4.4 B describes the land use and land cover class of the year 1986-2016, during this period the grassland and bare land converted almost to agricultural land. Moreover, the shrub land has been lost due to the changing of it to agricultural land. From this trend, one can conclude that agricultural activity was very high during this period.

At the same time figure, 4.3 C and D major losses were noticed in shrub land, vegetation cover and bare land whereas gain was observed in agricultural land.

All in all, the analysis of LULC for the study watershed revealed that agricultural land was predominant and showed slight continuous increment over the studied period (1986 -2020) in addition to figure 4.14 and table 4.10 shows clearly the areal coverage of each land use land cover class.

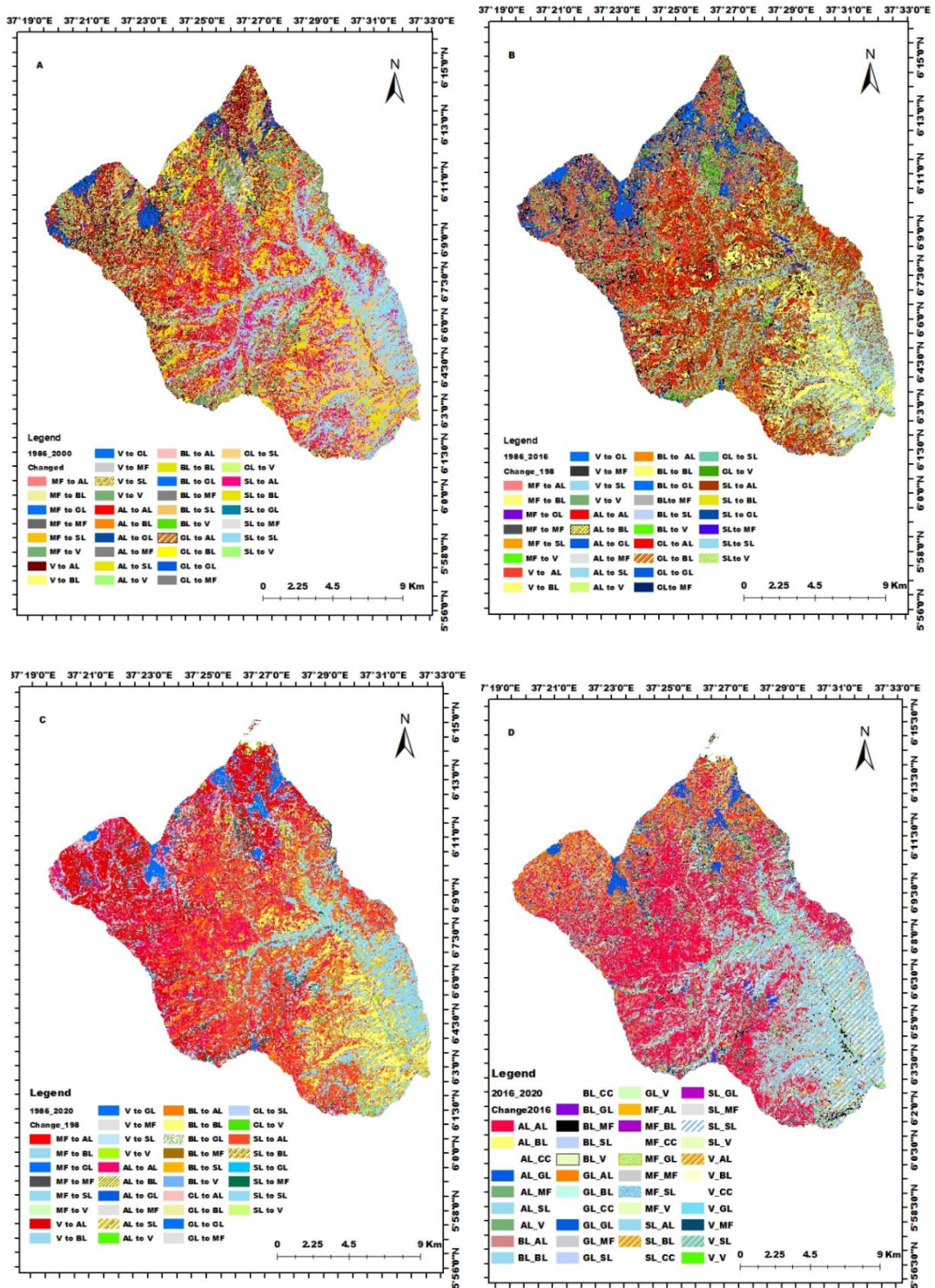


Figure 4.3 Land use land cover change dynamics for the period A) 1986 to 2000 B) 1986 to 2016 C) 1986 to 2020 D) 2016 to 2020.

Table 4.4 Major changes in LULC classes from the period of 1986 to 2020 in the area and percentage coverage in the Kulfo watershed.

LULC	Changed To	1986 - 2000		1986 - 2016		1986 - 2020		2016 - 2020	
		Area (km ²)	%	Area (km ²)	%	Area (km ²)	%	Area (km ²)	%
AL	AL	36.855	11.628	34.2405	10.803	45.264	14.373	97.218	30.870
	GL	1.7055	0.538	3.5271	1.113	2.4489	0.778	1.497	0.475
	BL	9.8334	3.103	11.6568	3.678	3.9042	1.239	4.555	1.446
	MF	0.1737	0.055	1.818	0.574	2.1132	0.671	3.174	1.008
	V	1.0251	0.323	2.5101	0.792	2.097	0.666	4.282	1.360
	SL	9.4788	2.991	5.319	1.678	2.97	0.943	13.031	4.138
GL	AL	6.7608	2.133	3.0744	0.970	11.634	3.695	11.660	3.702
	GL	5.8599	1.849	11.2806	3.559	6.511	2.067	7.340	2.331
	BL	5.4108	1.707	3.0753	0.970	0.161	0.051	0.347	0.110
	MF	0.1539	0.049	0.7146	0.225	0.847	0.269	0.227	0.072
	V	0.441	0.139	0.9216	0.291	0.197	0.063	0.362	0.115
	SL	0.8793	0.277	0.4392	0.139	0.089	0.028	0.151	0.048
BL	AL	17.9577	5.666	11.7864	3.719	21.02	6.674	32.699	10.383
	GL	0.0882	0.028	1.1178	0.353	1.007	0.319	2.618	0.831
	BL	25.137	7.931	26.9442	8.501	20.068	6.372	24.548	7.795
	MF	0.0225	0.007	0.0117	0.0036	0.055	0.017	0.614	0.195
	V	0.1107	0.034	0.3447	0.109	1.037	0.329	0.805	0.255
	SL	4.1445	1.308	7.2558	2.289	4.271	1.356	3.161	1.004
MF	AL	1.1079	0.350	1.6317	0.515	4.657	1.479	5.377	1.707
	GL	0.0108	0.003	0.0468	0.015	0.038	0.012	0.581	0.185
	BL	0.2691	0.085	0.2898	0.091	0.071	0.023	0.071	0.023
	MF	3.8034	1.200	5.2092	1.644	6.506	2.066	10.130	3.217
	V	5.166	1.630	4.7538	1.499	0.244	0.077	0.422	0.134
	SL	4.8132	1.519	3.2391	1.022	3.372	1.071	2.842	0.902
V	AL	23.9913	7.570	27.6111	8.712	44.466	14.119	14.539	4.616
	GL	1.3392	0.422	3.2211	1.016	1.301	0.413	0.423	0.134
	BL	2.1537	0.679	5.3136	1.676	0.947	0.301	0.345	0.109
	MF	2.4363	0.768	8.3727	2.642	14.567	4.625	9.797	3.111
	V	13.5702	4.282	16.8561	5.318	3.173	1.007	2.007	0.637
	SL	25.236	7.962	7.3521	2.320	2.980	0.946	8.627	2.739
SL	AL	38.4489	12.131	46.08	14.539	54.025	17.154	19.575	6.216
	GL	0.4878	0.154	0.9639	0.304	1.595	0.506	0.441	0.140
	BL	8.0739	2.547	17.3268	5.467	11.825	3.755	7.112	2.258
	MF	3.942	1.244	3.852	1.215	3.363	1.068	3.507	1.114
	V	2.637	0.832	10.7775	3.401	3.107	0.987	1.976	0.628
	SL	53.4132	16.853	28.0026	8.835	32.999	10.478	18.868	5.991

LULC=land use and land cover; AL=Agricultural Land; GL=grass land; MF= Mixed forest; BL=bare land; V = Vegetation; SL = Shrub Land; Km² = square kilometer (unit).

In the first period (1986-2000) about 2.133% grassland, 5.666% bare land, 0.349% mixed forest, and 12.13% Vegetation cover were converted to Agricultural land (Table 4.8). Conversely, about 7.01% (22.2165Km²) of agricultural land was converted to other LULC types in the same period (1986-2000).

Due to the rapid increase of agricultural activity in the area about 46.08km² (14.539%) shrubland, 27.611km² (8.722%) vegetation covers, and 11.7864Km² (3.719%) bare land was converted to agricultural land whereas 17.3268km² (5.467%) shrubland was converted to bare land during the year 1986 to 2016 (Table 4.8).

Similarly, the areas experienced the most severe loss of shrub and vegetation covers between the periods of 1986 – 2020. About 54.0252km² of shrubland, 44.4654km² vegetation, 21.0195km² of bare land, and 11.6361 km² of grassland were altered to Agricultural land conversely 13km² agricultural land converted to other types of land use land cover class (Table 4.8).

4.3 Streamflow modeling

SWAT CUP 2012 was used for sensitivity analysis and Sensitivity analysis was done by considering 30 flow-related parameters to identify which model parameter is top sensitive that has a significant influence on controlling streamflow in Kulfo watershed. Some of the parameters are CANMX, HRU_SLP, GW_REVAP, SURLAG, SOL_AWC, CN2, and more others.

4.3.1 Flow Simulation and sensitivity analysis

Sensitivity analysis of simulated streamflow for the watershed was performed using monthly observed streamflow using the SUFI2 program. Flow sensitivity analysis was carried out for a period of Thirteen years, which includes both two years of warm-up periods (from January 1, 1991, to December 31, 2004) and the calibration period (from January 1, 1993, to December 31, 2000). About 300, iteration has been done using SUFI2 program for flow calibration, and 27 parameters were reported as sensitive in different degree of sensitivity for streamflow. Out of 27 flow parameters, only selected top sensitive ones (Table 4.12 and **Appendices E**) were identified for the model to avoid model over parameterization. Table 4.12 shows the most sensitive parameters for the 1986 year of LULC map. For the map of 2000, 2016, and 2020 the most sensitive parameters are presented in **Appendices E**.

Table 4.5 Sensitive parameters and their rank in Kulfo catchment using 1986 LULC map.

No.	Parameter Name	t-Stat	P-Value	Rank
1	V__GWQMN.gw	-8.783	1.94 *10 ⁻¹⁶	1
2	V__GW_DELAY.gw	-3.94	0.000103	3
3	R__SOL_ALB (...).sol	-3.58	0.0004	4
4	R__HRU_SLP.hru	-2.4	0.02	5
5	A__SOL_AWC (...).sol	1.61	0.11	8
6	R__CN2.mgt	0.33	0.74	8
7	V__ALPHA_BF.gw	-0.13	0.90	10
8	R__GW_REVAP.gw	0.08	0.94	11

4.3.2 Calibration and validation

Based on the sensitive parameters calibration and validation of a flow was conducted for 1986, 2000, 2016, and 2020 land use land cover maps using observed streamflow by dividing the recorded streamflow data into two parts for calibration and validation.

Land use and land cover of 1986, 2000, 2016, and 2020 was calibrated for 7 years from January 1993 to December 2000 and Validated for an independent period of 4 years from January 2001 to December 2004.

The result of model performance during calibration and validation period of monthly streamflow demonstrated a good agreement between observed and simulated streamflow with the following coefficient of determination (R^2) and Nash-Sutcliffe efficiency (NSE) for land use and land cover map of 1986, 2000, 2016 and 2020 (Table 4.8).

Table 4.7 Model performance measures for calibration and validation.

Land use and land cover map	Calibration		Validation	
	R^2	NSE	R^2	NSE
1986	0.75	0.6	0.8	0.72
2000	0.76	0.8	0.75	0.6
2016	0.79	0.75	0.73	0.74
2020	0.81	0.75	0.8	0.75

Table 4.8 indicates the results of the simulation of the flow for the model performance that are adequately good during the calibration and validation periods. This indicates that the model performs well in simulating the generated streamflow from the catchment.

Therefore, the simulation results can be used in assessing the land use and cover impacts on stream flows.

In addition to the above statistical measures, the following line graph shows the relationship between observed and simulated streamflow during calibration and validation of land use land cover maps of the years 1986, 2000, 2016, and 2020. As we can see from the graph there was a great relation between stream flows observed and simulated.

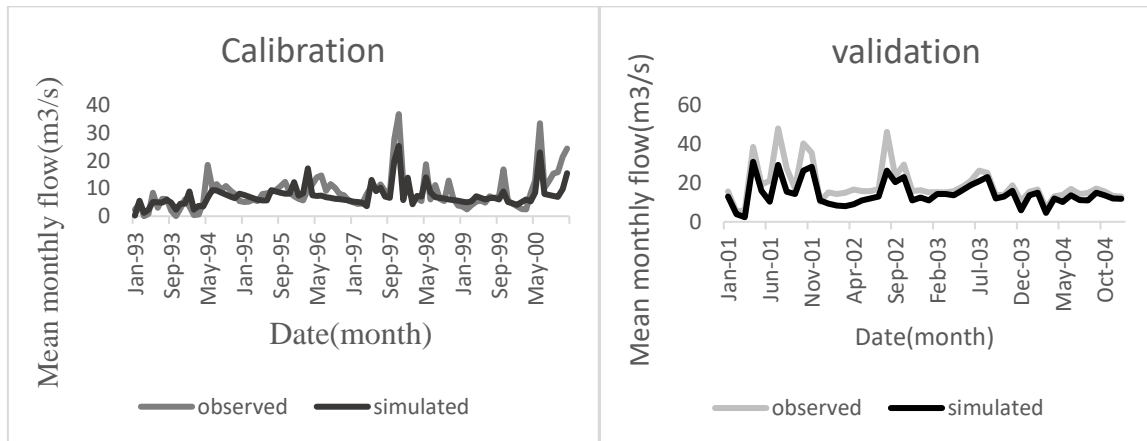


Figure 4.12 Model Calibration and validation period for LULC 1986

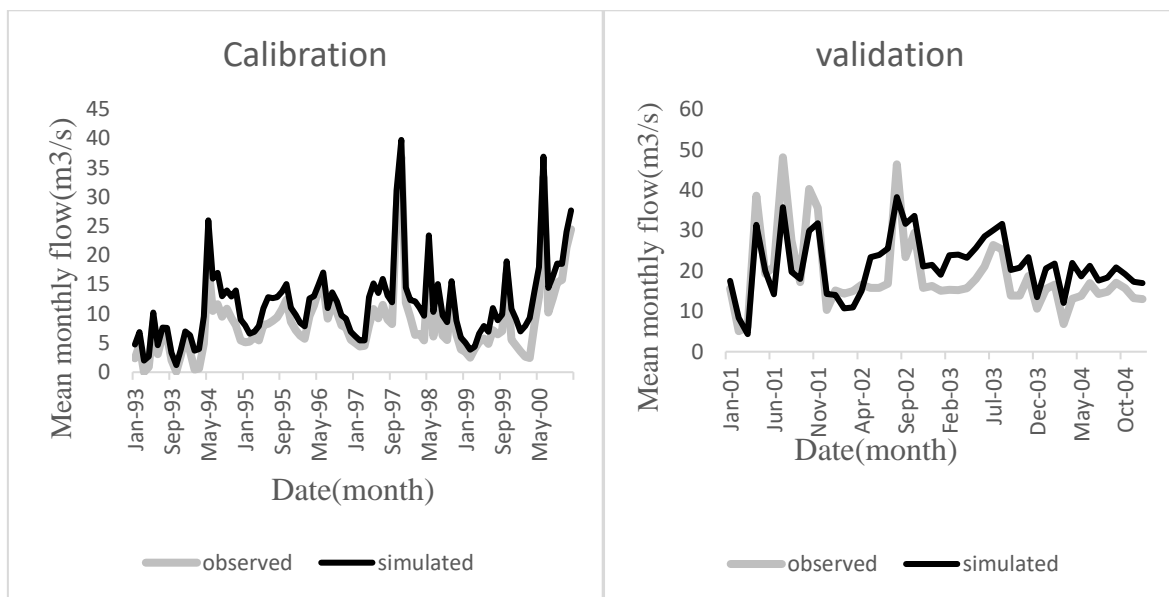


Figure 4.513 Model Calibration and validation period for LULC 2016.

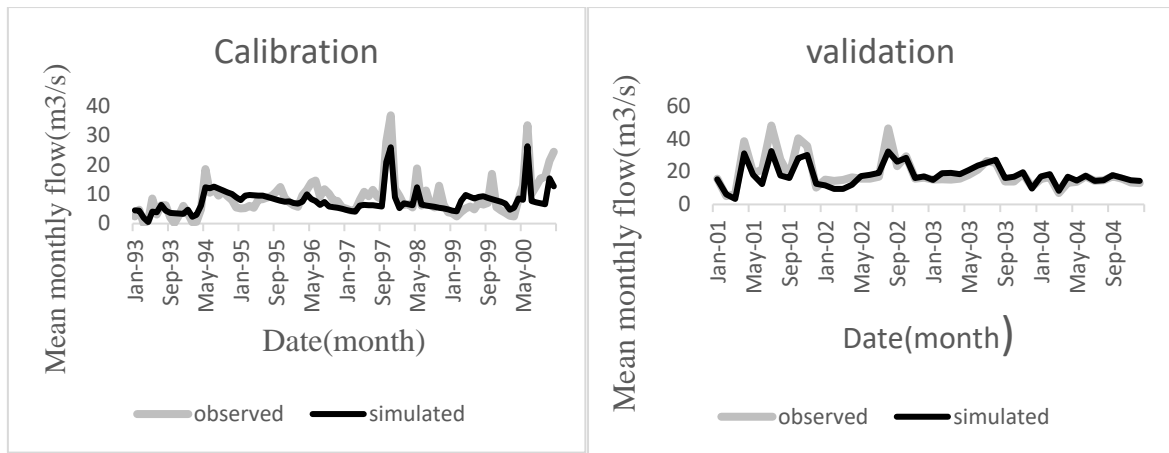


Figure 4.614 Model Calibration and validation period for LULC 2000.

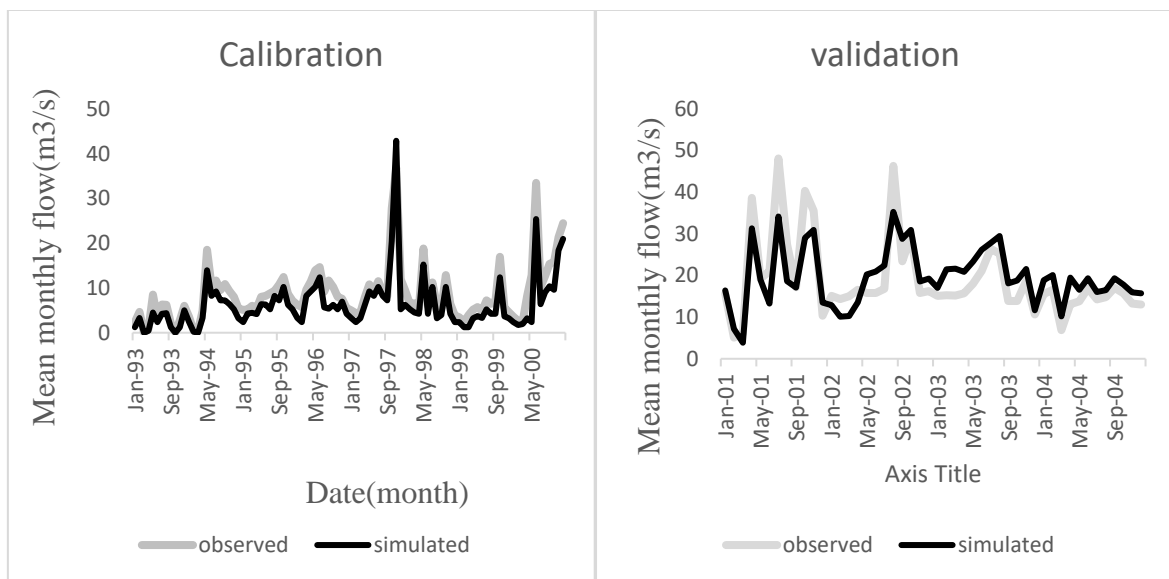


Figure 4.715 Model Calibration and validation period for LULC 2020.

4.4. Impact of land use and land cover change on streamflow

The main aim of this study was to assess the impact of land use and land cover changes on stream flows of Kulfo catchment. For this purpose, four different land use land cover maps were generated and used to produce four different SWAT model simulations.

4.4.1 Change on Monthly streamflow

Table 4.7 Monthly streamflow change for the study period

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Average
1986	3.60	2.72	3.36	5.06	8.37	11.49	8.85	7.90	7.17	8.2	8.89	5.05	6.72
2000	5.67	5.40	5.73	7.10	9.00	10.28	7.94	7.59	7.70	9.89	6.57	5.70	7.38
2016	7.01	5.84	5.88	9.09	9.66	11.99	12.66	11.64	10.55	7.98	8.96	9.92	9.265
2020	4.70	3.03	3.59	5.17	10.00	10.30	10.70	9.89	10.97	8.96	9.69	7.14	7.85

By the year 1986 the average monthly flow was low relative to other years this is due to the effect of shrub land which had very higher coverage on the catchment about 34.18% of the catchment (Table 4.6). The shrub land has high porosity and will delay the flow of water to the outlet of the catchment. However, the shrub land has been reduced by 30.92% at the year of 2000 with a complete increment of agricultural and bare land at the same time the streamflow increased from 6.72m³/s to 7.38m³/s (Table 4.14). This indicates that the increase of agricultural activity and conversion of land use and land cover class to bare land was responsible for the occurrence of this change on streamflow from the period of 1986 to 2000. Similarly, between the years 2000 to 2016, there was an increase of streamflow by 25.53%. During this period, both bare land and agricultural land have been increased (Table 4.14).

At the same time during the periods of 2016 to 2020 the reduction of streamflow was noticed from 9.265 to 7.85m³/s by 15.33%. At this period, the dominant land use land cover class was agricultural land. Agricultural land use more water and doesn't let the rainfall reach the outlet of the catchment because they have more porous media.

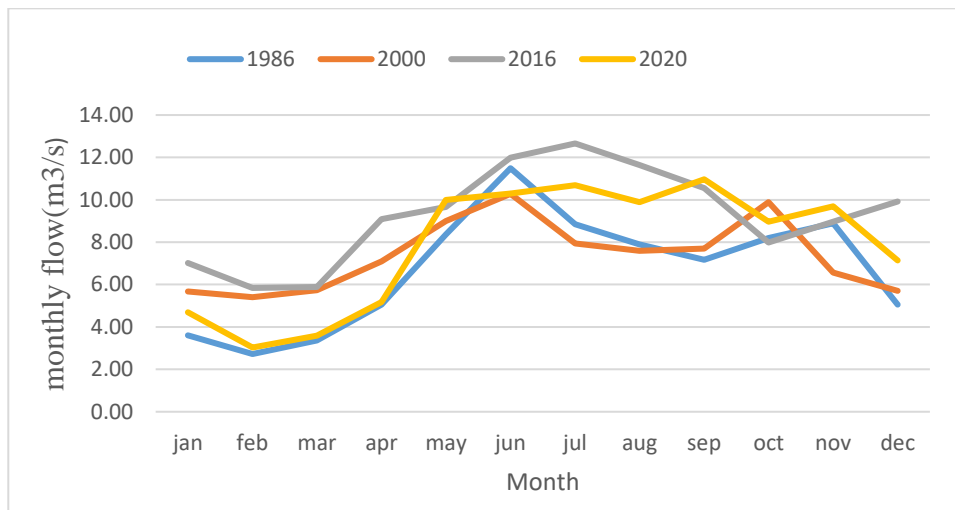


Figure 4.816 Monthly streamflow change over the study years.

4.4.2 Change on Seasonal Streamflow

For the analysis of seasonal streamflow the months of Feb, Mar, Apr, and May are considered as Belg season whereas Jun, Jul, Aug, and Sep are taken as Kiremt season additionally months Oct, Nov, Dec, and Jan are assigned for Bega season.

The seasonal streamflow showed in Tables 4.8 and 4.9 shows great variation throw-out three seasons because of LULC change. During Kiremt season, moderate decreases occurred

between the years 1986 to 2000 by 5.366%. During this year, except for agricultural land and bare land, all land features have been decreased. The increment of agricultural land was very high this, in turn, will consume more water leading to decreasing in streamflow in the catchment. The effect of LULC change was largest in Kiremit season from 2000 through 2016. During this period, two LULC features, vegetation, and bare land have been decreased and increased respectively. This change made stream flow increase by 39.78% in return. At the same time the smallest seasonal change was noticed in Bega season the stream flow increased from 1986 to 2000 by 8.12% and from 2000 to 2016 it increased by 7.62%. However, the streamflow has more reduced by 9.985 between the years 2016 to 2020 due to a considerable reduction in all land features except the agricultural land and mixed forest. However, for the year 1986-2000, the effect on streamflow varies in Belge season increased by 39.57% whereas decreased by 28.49%.

Generally, the streamflow has decreased trend from 2016 to 2020 for all of the seasons whereas there was an increasing trend for the period of 2000 to 2016.

Table 4.8 Seasonal mean monthly flow (m³ /s).

	Kiremt season	Belge season	Bega season
1986	8.8525	4.8775	6.435
2000	8.3775	6.8075	6.9575
2016	11.71	7.6175	8.4675
2020	10.465	5.4475	7.6225

Table 4.9 Percentage of mean monthly flow change (m³ /s).

	1986-2000 (%)	2000-2016 (%)	2016-2020 (%)
Kiremt season	-5.366	39.779	-10.6319
Belge season	39.569	11.898	-28.487
Bega season	8.12	21.7	-9.98

5. CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

In this study, the output of the google earth engine and hydrological model has been used to evaluate the impacts of land use land cover change on streamflow of the kulfo watershed.

Land use and land cover change were detected in the past 34 years from 1986 to 2020 in Kulfo catchment. Agricultural lands constitute the largest portion of the watersheds and increase from year to year because of increasing consumption of land use and cover due to population growth.

For the land use and land cover analysis, all data/images were acquired, processed, and analyzed in the GEE platform using a raw satellite image of Landsat 5 TM, Landsat 7 ETM+, and Landsat 8 OLI with 30m of spatial resolution for preparing land use land cover map of 1986, 2000, 2016 and 2020. Since, GEE does not provide post-classification and comparison the change detection was performed on separate software, ArcGIS.

Before classification of Landsat image pre-processing and processing was conducted for better classification and accuracy result. Among the applied machine learning classifier algorithms SVM performed better and it has the highest overall accuracy of 86.71% and kappa coefficient of 0.861.

The accuracy of the prepared land use and land cover was done using confusion matrixes which measure the degree of agreement correspondence to the reference data. The values of all the accuracy indicators were within the acceptable range of values. Therefore, the accuracy of the four maps was found adequate to use the maps for further analysis as per the objectives of this thesis.

The land use land cover analysis clearly shows that bare land, vegetation, and shrub land were accompanied by the increase of agricultural land. This shows that agricultural activity within the catchment is very high this, in turn, will affect the natural resources in particular the hydrological cycle in general.

The results in this study indicate that there is a noticeable change in the LULC of the Kulfo catchment over the past decades.

Streamflow from the catchment was determined from the SWAT model. The model simulated for different land use land cover maps each of the maps give a different result and the performance of the model has been perfectly measured using model evaluation statistics

for each of the simulated streamflow, as result for the land use land cover map of 1986 NSE and R^2 values for the calibration period was $NSE = 0.6$ and $R^2 = 0.75$ whereas for the validation period NSE was 0.72 and R^2 0.8. For the year of 2000 land use land cover map, it is completely different the NSE becomes 0.8 and R^2 was 0.76 for the calibration period but for the validation period NSE was 0.6 and R^2 was 0.75. The value of NSE was 0.75 and R^2 0.79 for the calibration and NSE was 0.74 and R^2 0.73 for validation for the year 2016.

For the recent year 2020, the NSE was 0.75 and R^2 0.81 and NSE was 0.75 and R^2 0.8 for calibration and validation periods respectively.

All of the model performance measures described above were in the acceptable range therefore SWAT model has perfectly simulated the streamflow in kulfo catchment.

The average monthly stream flows of the Kulfo catchment reduced from the year 1986 to 2000 by 30.92%. At the same time, the average streamflow increased by 25.53% during the year 2000 to 2016. During the recent period, the reduction of average streamflow was noticed by 15.33% from 9.265 to 7.85m³/s. The reduction of streamflow between the years 2016 and 2020 was may be due to a high percentage increase of bare land, a high percentage decrease of shrubs and grassland.

To analysis, the impact of LULC cover change on seasonal streamflow the months of the years have been divided into three seasons that are Kiremt, Belge, and Bega. There was a remarkable change in seasonal streamflow. The streamflow has decreased trend from 2016 to 2020 for all of the seasons whereas there was an increasing trend for the period of 2000 to 2016. Thus, the land use land cover change has affected the streamflow on kulfo catchment.

5.2 Recommendations

Based on the method and obtained results in this study some recommendations were stated as follow:-

1. The satellite data used has a spatial resolution of 30m with this resolution it is difficult to detect changes within the study area because the pixel values of each land use and land cover feature may be misclassified. These misclassified pixels are also caused by the limitation of a seasonal dataset of the area. However, for future studies, it is recommended to perform more accurate analysis at the micro-level with fine resolution data with ground truth details. An object-based classification and a fusion on spectral

indices need to be included and should also be considered to improve the accuracy of classification.

2. For validation of simulation result from the model one third of the historical stream data obtained from MOWIE has been used but it is better if measured stream flow data from the site is used for more representation and analysis of the changes.
3. The research was conducted by evaluating the effects of LULC changes on streamflow. However, the effects of LULC also have an impact on the component of streamflow of the catchment by changing the magnitude of surface runoff and groundwater flow. So, further research of this kind can be computed on the assessment of the impacts of LULC on streamflow components (water quality, surface run-off, base flow, and groundwater) analysis for the monthly and seasonal.
4. The soil data has been obtained from the Ministry of Water Irrigation and Electricity, Ethiopia, the spatial resolution of the soil map was very high this, in turn, leads to the reduction of the model performance in simulation. So, further research of this kind can get primary (field data) so that the accuracy and the performance of the model will increase.
5. In order to evaluate the effect of LULC change on seasonal streamflow, it is important to first consider and identify the rainfall pattern because a rainfall pattern varies from place to place, and from time to time, this type of situation has not been studied in this study. Instead, information about the seasonality of rainfall pattern on kulfo catchment has been taken from previous studies and articles, so if the rainfall conditions are carefully studied, the current output and many other things can be improved. The analysis of the rainfall pattern to get a better result on the variability of seasonal streamflow was strongly recommended.

REFERENCES

- A. Midekisa, F. H. (2017, september 27). Mapping land cover change over continental Africa using Landsat and Google Earth Engine cloud computing. doi: <https://doi.org/10.1371/journal.pone.0184926>.
- A. Shelestov, M. L. (2017, Feb, 24,). Exploring Google Earth Engine Platform for Big Data Processing: Classification of Multi-Temporal Satellite Imagery for Crop Mapping,. *Front. Earth Sci.*,. doi: <https://doi.org/10.3389/feart.2017.00017>.
- Acharya, S., Pawar, S., & Wable, N. (2018, Apr). Application of Remote Sensing & GIS in Agriculture. *International Journal of Advanced Engineering Research and Science (IJAERS)*, Vol-5(Issue-4).
- Addis, H. K. (2016). Modeling streamflow and sediment using SWAT in the Ethiopian Highlands. . *I.nt J Agric & Biol Eng*, Vol.9, pp.51 – 66.
- Ahmed, G. (2001). *Mapping a Dry Shrub Forest for Biodiversity Conservation Planning. (A case study in the salt range of Pakistan, using remote sensing and GIS tools)*. Enschede, Netherlands: Forest Science Division, the International Institute for Geoinformation Science and Earth Observation (ITC).
- ALI, H. (2009). *Land use and land cover change, drivers and its impact: A comparative study from Kuhar Michael and Lenche Dima of Blue Nile and Awash Basins of Ethiopia*. CornellUniversity.
- Aneseyee, A. B., Elias, E., Soromessa, T., & Feyisa, G. L. (2019, December 9). Land use/land cover change effect on soil erosion and sediment delivery in the Winike watershed, Omo Gibe Basin, Ethiopia. (O. Wei, Ed.) *Science of the Total Environment*.
- Arnold J. G., S. R. (1989). Large area hydrologic modeling and assessment, Part I: model development. *Journal of American Water Resources Association*,, Vol. 34, pp. 73-89.
- Arnold, J. G. (2012). Soil and water assessment tool theoretical documentation version 2012. *Texas Water Resources Institute*. .

- Arnold, Moriasi, D. N., Gassman, P. W., Abbaspour, K. C., White, M. J., Srinivasan, R., & C. Santhi, R. D. (2012). SWAT: MODEL USE, CALIBRATION, AND VALIDATION. *American Society of Agricultural and Biological Engineers* ,, P.1493.
- Asitatie, A. N. (2019). Impact of Land Use/Land Cover Change on Hydrology of the Catchment: The Case of Upper Ribb Catchment, Lake Tana Sub Basin, Ethiopia. *Journal of Environment and Earth Science, Vol.9*.
- Assen, M. (2011). Land Use/ Cover Dynamics and Its Implications In The Dried Lake Alemaya Watershed, Astern Ethiopia. *Journal of Sustainable Development in Africa, V.13(No.4)*.
- Assessment of The Effects Of Climate Change On Land Use And Land Cover Using Remote Sensing: A Case Study From Kenya, DNC2015/03.
- Assfaw, A. T. (2019, November 18). Calibration, validation and performance evaluation of swat model for sediment yield modelling in megech reservoir catchment, ethiopia. *Journal of Environmental Geography*.
- Ayana, A. B., Chemed, E. D., & Ekasit, K. (2012). Simulation of Sediment Yield using SWAT Model in Fincha Watershed, Ethiopia. 283 - 297.
- Ayele, G. T. (2016). Multitemporal Land Use/Land Cover Change Detection for the Batena Watershed, Rift Valley Lakes Basin, Ethiopia.
- Ayodele, T. O. (2010). Types of Machine Learning Algorithms, *New Advances in Machine Learning*,. *Yagang Zhang (Ed.)*,.
- Bahari, N. I., Ahmad, A., & Aboobaid, B. M. (2014). Application of support vector machine for classification of multispectral data. *7th IGRSM International Remote Sensing & GIS Conference and Exhibition*. IOP Conf. Series: Earth and Environmental Science.
- Berhan, G. H. (2011). Using Satellite Images for Drought Monitoring: A Knowledge: A Knowledge Discovery Approach. *Journal of Strategic Innovation and Sustainability*, 7 (1), 135-153.
- Berihun, M., Tsunekawa, A., Haregeweyn, N., Meshesha, D., Adgo, E., Tsubo, M., . . . Sultan, D. (2019). Exploring land use/land cover changes, drivers and their

- implications in contrasting agro-ecological environments of Ethiopia. *Land Use Policy*, 87.
- Betrie, G. D. (2011). Sediment management modelling in the Blue Nile Basin using SWAT model. *Hydrology and Earth System Sciences*, 15(3), 807-818.
- Bharti, L. T. (2020). Modelling sediment yield of Rib watershed, Northwest Ethiopia. *ISH Journal of Hydraulic Engineering*.
- Bittencourt, H. R., & Clarke, R. T. (2003). Use of Classification and Regression Trees (CART) to Classify Remotely-Sensed Digital Images. *IEEE*.
- Blainski, É., Porras, E. A., Garbossa, L. H., & Pinheiro, A. (2016, November 27). Simulation of land use scenarios in the Camboriú River Basin using the SWAT model. *Brazilian Journal of Water Resources*.
- Breiman, L. (2001). Random Forests. *Mach. Learn*(45), PP. 5–32.
- Breiman, L. (pp. 5-32). Random Forests, *Mach. Learn.* (no. 1), vol. 45. doi:10.1023/A:1010933404324.
- Breiman, L., Friedman, J., Olshen, R., & Stone, C. (1984). *Classification and Regression Trees*. Monterey, CA, USA: Wadsworth & Brooks/Cole Advanced Books & Software.
- Breiman, L., Friedman, J., Stone, C., & Olshen, R. (1984). *Classification and Regression Trees*. Wadsworth & Brooks/Cole Advanced Books & Software.
- Camargo, F. F., Sano, E. E., Almeida, C. M., Mura, J. C., & Almeida, T. (2019, July 5). A Comparative Assessment of Machine-Learning Techniques for Land Use and Land Cover Classification of the Brazilian Tropical Savanna Using ALOS-2/PALSAR-2 Polarimetric Images. *remote sensing*.
- Destaa, H., & Lemma, B. (2017, September 01). SWAT based hydrological assessment and characterization of Lake Ziway sub-watersheds, Ethiopia. *Journal of Hydrology: Regional Studies*.
- Dewi, R., Bijker, W., & Stein, A. (2017). Change Vector Analysis to Monitor the Changes in Fuzzy Shorelines. *Remote Sensing*, Vol.9(no. 2). doi: <https://doi.org/10.3390/rs9020147>

- Di Gregorio, A. a. (2000). Land-cover classification: classification concepts and user manual,. *Food and Agriculture Organization (FAO) of the United Nations Rome*.
- Dinka M.O., Chaka D.D. (2019). Analysis of land use/land cover change in Adei watershed, Central Highlands of Ethiopia. *Journal of water and land development, No. 41 (IV–VI)*, p. 146–153. doi:DOI: 10.2478/jwld-2019-0038.
- DINKA, M. O., & Chaka, D. D. (2019). Analysis of land use/land cover change in Adei watershed, Central Highlands of Ethiopia. *Jornal of water and land development*(No. 41 (IV–VI)), p. 146–153. doi:DOI: 10.2478/jwld-2019-0038.
- Ernani, Z., & Gabriels, D. (2006). Detection of land cover changes using Landsat MSS, TM, ETM + Sensors in Yazd-Ardkan basin, Iran. *Proceedings of Agro Environ*, PP.513–519.
- FAO. (2012). *State of the World's Forest*. Rome, Italy.
- Farda, N. M. (2017). Multi-temporal Land Use Mapping of Coastal Wetlands Area using Machine Learning in Google Earth Engine. *IOP Conference Series: Earth and Environmental Science. The 5th Geoinformation Science Symposium*. IOP Publishing Ltd. doi:doi :10.1088/1755-1315/98/1/012042
- Fentie, S. F., Jembere, K., Fekadu, E., & Dessale, W. (2020, September 1). Land Use and Land Cover Dynamics and Properties of Soils under Different Land Uses in the Tejibara Watershed, Ethiopia. (P. C. McGuire, Ed.) *Hindawi the Scientific World Journal*.
- Ferrari, M. (2019, November 1). A Panoptic Cartography of Remote Sensing. P.132-142.
- Frauke Degenhardt, S. S. (2019, March). Evaluation of variable selection methods for random forests and omics data sets. *Briefings in Bioinformatics*,, *Volume 20*, (Issue 2,), Pp. 492–503,. doi: <https://doi.org/10.1093/bib/bbx124>
- Ganasri, B. a. (2015). Study of Land Use/Land Cover Dynamics through Classification Algorithms for Harangi Catchment Area, K. *Aquatic Procedia*,, P.1413-1420. doi: <https://doi.org/10.1016/j.aqpro.2015.02.183>
- Gebeyehu, M. N. (2019, May). Remote Sensing and GIS Application in Agriculture and Natural Resource Management. *International journal of Environmental and natural resources, V.19*(2).

- Gebre, T. K., Tesfaye, S., & Taye, G. (2015, April). Analysis of Watershed Attributes for Water Resources Management Using GIS: The Case of Chelekot Micro-Watershed, Tigray, Ethiopia. *Journal of Geographic Information System, Vol.7* (No.2).
- Geetha, M., Ashagowda, K., & Sudhira, S. (2019, September). Land Use and Land Cover Mapping of Davangere using Google Earth Engine. *International Journal of Recent Technology and Engineering (IJRTE), Volume-8*(Issue-3).
- Githu. (2009). Assessing the impacts of environmental change on the hydrology of the Nzoia catchment, in the Lake Victoria Basin. *Department of Hydrology and Hydraulic* .
- Goldblatt, R., Rivera Ballesteros, A., & Burney, J. (2017). High Spatial Resolution Visual Band Imagery Outperforms Medium Resolution Spectral Imagery for Ecosystem Assessment in the Semi-Arid Brazilian Sertão. *Remote Sens*.
- Gonfa. (1996). Climate classification of Ethiopia. Addis Ababa, Ethiopia. .
- Google EarthEngine. (2012). Retrieved February 5, 2014, from <https://earthengine.google.org/#intro>.
- Gorelick, N. H. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment*,, 18-27.
- Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment*, pp. 18-27. doi:DOI: 10.1016/j.rse.2017.06.031.
- Gustav Tolt, M. S. (2011, July). data, A shadow detection method for remote sensing images using VHR hyperspectral and LIDAR. *IEEE International Geoscience and Remote Sensing Symposium, IGARSS 2011*,, (pp. july 24-29, 2011). Vancouver, BC, Canada, J. doi:10.1109/IGARSS.2011.6050213
- Hargreaves, G. &. (1985). Reference crop evapotranspiration from Temperature. . *Applied Engineering in Agriculture* , pp.96-99.
- Hayes, T., Usami, S., Jacobucci, R., & McArdle, J. (2015). Using Classification and Regression Trees (CART) and random forests to analyze attrition: Results from two simulations. *Psychol. Aging*, P.911-929.

- Haykin, S. (2008). *Neural Networks and Learning Machines*. (3rd ed. ed.). United States of America,.
- Herrera, V. K. (2019, July 30). Random forest implementation and optimization for Big Data analytics on LexisNexis's high performance computing cluster platform. *Journal of Big Data*. doi:<https://doi.org/10.1186/s40537-019-0232-1>
- Heuvelmans, G. M. (2004). Analysis of the spatial variation in the parameters of the SWAT model with application in Flanders, Northern Belgium,. *Hydrol. Earth Syst. Sci.*, V.8, P.931–939.
- Ho, T. K. (1998). *The random subspace method for constructing decision forests*. (Vol. 20). IEEE Trans. Pattern Anal. Mach. Intell. doi: doi: 10.1109/34.709601
- Isabela Xavier Floreano, L. A. (2021, March 30). Land use/land cover (LULC) analysis (2009–2019) with Google Earth Engine and 2030 prediction using Markov-CA in the Rondônia State, Brazil. *Environ Monit Assess*.
- Jamsran, B.-E., Lin, C., Byambakhuu, I., Raash, J., & Akhmadi, K. (2019). Applying a support vector model to assess land cover changes in the Uvs Lake Basin ecoregion in Mongolia. *Information processing in agriculture* , pp.158–169.
- JeganathanI, C., P. K., K. G., Garg, R. D., Sinha, A. K., Avisek, K., & Hebbale, R. (2017). REMOTE SENSING AND GIS FOR CIVIL engineering applications and human development. *International Journal of Advancement in Remote Sensing, GIS and Geography, Vol.5, (No.1,)*, v. 1-18.
- Jensen, J. (2003). Introductory image processing: A remote sensing perspective. pp.467-494.
- Jha, M. (2011). Evaluating hydrologic response of an agricultural watershed for watershed analysis. *Water* 3, 604–617.
- Kabir Uddin , Mir Abdul Matin and Sajana Maharjan. (2018). Assessment of Land Cover Change and Its Impact on Changes in Soil Erosion Risk in Nepal. *Sustainability*, 1-20.
- Khorram, N. S. (2013). *Handbook of Satellite Applications*. (M. S.-L. Pelton J.N., Ed.) Springer, New York, NY.: Digital Image Acquisition: Preprocessing and Data Reduction. doi:https://doi.org/10.1007/978-1-4419-7671-0_46

- Kinati Chimdessa, S. Q. (2018, December 26). Effect of Land Use Land Cover and Climate Change on River Flow and Soil Loss in Didessa River Basin, South West Blue Nile, Ethiopia.
- Lambin, E. . (2003, July 16). Dynamics of land-use and land-cover change in tropical regions. *Annu. Rev. Environ. Resour.*
- Legates D.R and McCabe Jr., G. (1999). Evaluating the use of “goodness-of-fit” measures in hydrologic and hydroclimatic model validation. *Water Resour. Res.* 35 (1), 233–241.
- Lenhart et al. (2002). Modeling response of soil erosion and runoff to change in precipitation and cover. *Tucson, AZ 85719, USA: USDA-ARS Southwest Watershed Management Research Center.*
- Lillesand, T. M. (2004). *Remote sensing and Image interpretation* (5th ed.). New York: John and Sons, Inc.
- Lillesand, T., Kiefer, R., & Chipman, J. (2004). *Remote Sensing and Image Interpretation* (5th ed.). New York.: John Wiley & sons, Inc.
- Lin, C., JunMin, L., & XiaoXue, L. (2010). Application of Support Vector Machine in the groundwater quality evaluation. *Journal of Northwest A & F University - Natural Science, Vol.38* , pp.221-226 . Retrieved from <http://www.xnxbz.net/.../index.aspx>
- Lin, C., Wu, C.-C., Tsogt, K., Ouyang, Y.-C., & Chang, C.-I. (2015, February 9). Effects of atmospheric correction and pansharpening on LULC classification accuracy using WorldView-2 imagery. *Information processing in agriculture*, pp. 25-36.
- Liu, C.-C., Shieh, M.-C., Ke, M.-S., & Wang, K.-H. (2018). Flood Prevention and Emergency Response System Powered by Google Earth Engine. *Remote Sens.*(10, 1283.).
- Liu, R. C. (2016, August). Assessing spatial likelihood of flooding hazard using naïve Bayes and GIS: a case study in Bowen Basin, Australia. *Stoch Environ Res Risk Assess* 3, PP.1575–1590 . doi: <https://doi.org/10.1007/s00477-015-1198-y>
- Lobo, F., Souza-Filho, P., Novo, E., Carlos, F., & Barbosa, C. (2018). Mapping Mining Areas in the Brazilian Amazon Using MSI/Sentinel-2 Imagery (2017). *Remote Sens.*(10, 1178.).

- Luigi Barazzetti, M. S. (2014). Automatic Co-registration of Satellite Time Series via Least Squares Adjustment. *European Journal of Remote Sensing*, 47(1), 55-74,. doi: DOI: 10.5721/EuJRS20144705
- Mallupattu, P. K., & Reddy, J. R. (2013). Analysis of Land Use/Land Cover Changes Using Remote Sensing Data and GIS at an Urban Area, Tirupati, India. *The Scientific World Journal*. doi:http://dx.doi.org/10.1155/2013/268623
- Marchant, R., Richer, S., Boles, O., Capitani, C., Courtney-Mustaphi, C., Lane, P., . . . al, e. (2018). Drivers and trajectories of land cover change in East Africa: Human and environmental interactions from 6000 years ago to present. *Earth Sci. Rev.*(178), 322–378.
- Masoud, M., Bahram, S., Fariba, M., & Mahdi, M. (2017, May). Random forest wetland classification using ALOS-2 L-band, RADARSAT-2C-band, and TerraSAR-X imagery. *ISPRS Journal of Photogrammetry and Remote Sensing*, PP.13-31.
- Mateo-García, G., Gómez-Chova, L., Amorós-López, J., Muñoz-Marí, J., & Camps-Valls, G. (2018). Multitemporal Cloud Masking in the Google Earth Engine. *Remote Sens.*(10, 1079.).
- Melesse, A. M., Weng, Q., S.Thenkabail, P., & Senay, G. B. (2007, December 11). Remote Sensing Sensors and Applications in Environmental Resources Mapping and Modelling. *sensors* .
- Mendelsohn, R. (2011). Climate Change. In G. K. Ingram, & Y.-H. Hong (Ed.), *ISBN 978-1-55844-217-7*. the Lincoln Institute of Land Policy.
- Mondal, P., Liu, X., Fatoyinbo, T. E., & Lagomasino, D. (2019, December 6). Evaluating Combinations of Sentinel-2 Data and Machine-Learning Algorithms for Mangrove Mapping in West Africa. *remote sensing*.
- Monteith, L. (1965). Evaporation and the environment. In The state and Movement Of water in living organisms. *19th Symposia of the Society for Experimental Biology* (pp. pp. p. 205-234). London, U.K.: Cambridge University, Press.
- Msofe, N. K., Sheng, L., & Lyimo, J. (2019, January 18). Land Use Change Trends and Their Driving Forces in the Kilombero Valley Floodplain, Southeastern Tanzania. *sustainability* .

- Mutanga, O., & Kumar, L. (2019). Google Earth Engine Applications. *Remote Sensing*, 11(5). doi: DOI: 10.3390/rs11050591
- Naghibi, S. A. (2017, April 19). Application of Support Vector Machine, Random Forest, and Genetic Algorithm Optimized Random Forest Models in Groundwater Potential Mapping. *Water Resour Manage*, 31,, PP. 2761–2775. doi: <https://doi.org/10.1007/s11269-017-1660-3>
- Nash, J. a. (1970). River flow forecasting through conceptual models part I—a discussion of principles. *J. Hydrol.* 10 (3), 282–290.
- Navarro, J. A. (2017). First Experiences with Google Earth Engine. *Conference Paper* . doi:DOI: 10.5220/0006352702500255
- Neetu, & Ray, S. S. (2019). Exploring Machine Learning Classification Algorithms for Crop Classification Using Sentinel 2 Data. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, V. XLII-3/W6,
- Negese, A. (2021, February 16). Impacts of Land Use and Land Cover Change on Soil Erosion and Hydrological Responses in Ethiopia. (T. M. Miano, Ed.) *Applied and Environmental Soil Science*.
- Neitsch, S. L. (2011). Soil and water assessment ool theoretical documentation version 2009. *Texas Water Resources Institute* .
- Nurfadila, J. S., S. B., Neswati, R., Rukmana, D., & Zylshal, Z. (2019). Initial Results on Landuse/Landcover Classification Using Pixel-Based Random Forest Algorithm on Sentinel-2 Imagery over Enrekang Region. *IOP Conference Series: Earth and Environmental Science*.
- Oliphant, A. J., Thenkabail, P. S., Teluguntla, P., Xiong, J., Gumma, M. K., Congalton, R. G., & Yadav, K. (2019, May 22). Mapping cropland extent of Southeast and Northeast Asia using multi-year-time-series Landsat 30-m data using a random forest classifier on the GoogleEarth Engine Cloud. *Int J Appl Earth Obs Geoinformation*, pp.110-124.
- Poortinga, A., Clinton, N., Saah, D., Cutter, P., Chishtie, F., Markert, K., . . . Tran, L. (2018). An Operational Before-After-Control-Impact (BACI) Designed Platform for Vegetation Monitoring at Planetary Scale. *Remote Sens*.

- Priestley, C., & Taylor, R. (1972). The assessment of surface heat flux and Evaporation using large-scale parameters. *Mon. Weather Rev*, pp.81-92.
- Ratika Pradhan, M. K. (2010, October). Land Cover Classification of Remotely Sensed Satellite Data using Bayesian and Hybrid classifier. *International Journal of Computer Applications* , V. 7.
- Ray, S. S. (2019, July). EXPLORING MACHINE LEARNING CLASSIFICATION ALGORITHMS FOR CROP CLASSIFICATION USING SENTINEL 2 DATA. *Mahalanobis National Crop Forecast Centre, V. XLII-3*. doi:DOI: 10.5194/isprs-archives-XLII-3-W6-573-2019
- Robin Genuer, J.-M. P.-M. (2010). Variable selection using Random Forests. *Pattern Recognition Letters*,, pp.2225-2236.
- Rodriguez-Galiano, V. F., Ghimire, B., Rogan, J., & Rigol-Sanchez, J. P. (2012, January). An assessment of the effectiveness of a random forest classifier for land-cover classification. *Journal of Photogrammetry and Remote Sensing*, 93–104. doi:DOI: 10.1016/j.isprsjprs.2011.11.002
- Rowcroft, P. (2005). . Gaining Ground: The Socio-Economic Driving Forces Behind Decisions Regarding Land Use and Land change; An Overview, Working Paper 16: Vientiane, Laos,.
- Roy. P. S. and Roy.A. (2010). Land use and land cover change in India: A remote sensing & GIS perspective. *Journal of the Indian Institute of Science, VOL 90:4*.
- Rudrapal, D., & Subhedar, M. S. (2015, ,September). Land Cover Classification using Support Vector Machine. *International Journal of Engineering Research & Technology (IJERT), Vol. 4 (Issue 09)*.
- Sahoo, B. J. (2019). Application of Support Vector Regression for Modeling Low Flow Time Series. *KSCE J Civ Eng(23)*, pp.923–934. doi:https://doi.org/10.1007/s12205-018-0128-1
- Sazib, N., & Bolten, I. M. (2018). Leveraging Google Earth Engine for Drought Assessment using Global Soil Moisture Data . *Remote sensing* .

- Serrano, J., Shahidian, S., & Silva, J. M. (2019, January 1). Evaluation of Normalized Difference Water Index as a Tool for Monitoring Pasture Seasonal and Inter-Annual Variability in a Mediterranean Agro-Silvo-Pastoral System. *water*.
- Setegn, S. G. (2008). Hydrological modelling in the Lake Tana Basin, Ethiopia using SWAT model. *The Open Hydrology Journal*, , 49-62.
- Shaohong, T., Xianfeng, Z., Jie, T., & Quan, S. (2016, November 16). Random Forest Classification of Wetland Landcovers from Multi-Sensor Data in the Arid Region of Xinjiang, China. *remote sensing*.
- Shi, D., & Yang, X. (2015, January). Support Vector Machines for Land Cover. *A Geomatics Perspective, Springer Remote Sensing/Photogrammetry*,.
- Shivangi Mishra, P. S. (2017). Change Detection Techniques in Remote Sensing: A Review. *International Journal of Wireless and Mobile Communication for Industrial Systems, Vol. 4*, (No. 1), pp. 1-8.
- Sidhu, N., Pebesma, E., & Câmara, G. (2018). Using Google Earth Engine to detect land cover change: Singapore as a use case. *EUROPEAN JOURNAL OF REMOTE SENSING*,, VOL. 51, (NO. 1,), PP.486–500.
- Sime, F. G. (2020, November 3). Stream flow modeling using SWAT model and the model performance evaluation in Toba sub-watershed, Ethiopia. *Modeling Earth Systems and Environment*.
- Singh, A. (1989). Review article Digital change detection techniques using remotely sensed data. *International journal of remote sensing*, 989-1003.
- Siroky, D. S. (2009). Navigating Random Forests and related advances in algorithmic modeling. *Statistics Surveys, Vol. 3* , pp.147–163. doi:DOI: 10.1214/07-SS033
- Somvanshi, S., PhoolKunwar, & Singh, M. (2018, January). Remote Sensing And Gis Techniques for Sustainable Land Resource Management And Planning. *International Refereed Journal of Engineering and Science (IRJES), Volume 7*(Issue 1), PP. 11-24.
- Sproles, E., Crumley, R., Nolin, A., Mar, E., & Lopez Moreno, J. (2018). SnowCloudHydro—A New Framework for Forecasting Streamflow in Snowy, Data-Scarce Regions. *Remote Sens.*, 10 .

- Sun, C., Liu, G., & Sha, X. (2016, August 5). Land-Use Conversion Changes the Multifractal Features of Particle-Size Distribution on the Loess Plateau of China. *International Journal of Environmental Research and Public Health*.
- Sunmin, L., Kim, J.-C., Jung, H.-S., Lee, M. J., & Lee, S. (2017, March 8). Spatial prediction of flood susceptibility using random-forest and boosted-tree models in Seoul metropolitan city, Korea. *Geomatics, Natural Hazards and Risk*. doi: <https://doi.org/10.1080/19475705.2017.1308971>
- Taalab, K., Cheng, T., & Zhang, Y. (2018). Mapping landslide susceptibility and types using Random Forest. *Journal of big earth data, Volume 2, (Issue 2)*.
- Taati, A., Sarmadian, F., Mousavi, A., Pour, C. T., & Shahir, A. H. (2015, March). Land Use Classification using Support Vector Machine and Maximum Likelihood Algorithms by Landsat 5 TM Images. *Engineering and Physical Sciences*.
- Tadesse, L., Suryabhagavan, K., Sridhar, G., & Legesse, G. (2017, May 11). Land use and land cover changes and Soil erosion in Yezat Watershed, North Western Ethiopia. *International Soil and Water Conservation Research*.
- Tegene, B. (2002). Land-Cover/Land-Use Changes in the Derekolli Catchment of. *Eastern Africa Social Science Research Review, V.18*.
- Temesgen Gashaw, Y. T. (2021). Evaluating the Effectiveness of Best Management Practices On Soil Erosion Reduction Using the SWAT Model: for the Case of Gumara Watershed, Abbay (Upper Blue Nile) Basin. *Environmental Management, 68*, 240–261.
- Tewabe.D and Fentahun.T. (2020). Assessing land use and land cover change detection using remote sensing in the Lake Tana Basin, Northwest Ethiopia. *Cogent Environmental Science, Vol.6:1*.
- Tingting Dan, Y. Y. (2018, July 5). Multi-Temporal Remote Sensing Image Registration Using Deep Convolutional Features. *IEEE*.
- Tsai, Y., Stow, D., Chen, H., Lewison, R., An, L., & Shi, L. (2018). Mapping Vegetation and Land Use Types in Fanjingshan National Nature Reserve Using Google Earth Engine. *Remote Sens*.

- Vapnik, V. (1999). An overview of statistical learning theory. *IEEE Trans. Neural Netw.*, V.10, 988–999.
- Wagle, N., Acharya, T., Kolluru, V., Huang, H., & Lee, D. (2020). Multi-Temporal Land Cover Change Mapping Using Google Earth Engine and Ensemble Learning Methods. *Applied Sciences*, 10(22):8083. doi: <https://doi.org/10.3390/app10228083>
- Wahap, N., & Shafri, H. Z. (2020). Utilization of Google Earth Engine (GEE) for land cover monitoring over Klang Valley, Malaysia. *IOP Conf. Series: Earth and Environmental Science*.
- Waranyu, B. a. (2016, January 19). DEM Resolution Impact on the Estimation of the Physical Characteristics of Watersheds by Using SWAT. *Advances in Civil Engineering*.
- Wubie. (2015, May). GIS and Remote Sensing Based Forest Change Detection For Sustainable Forest Management In Bench Maji Zone, Ethiopia. *International Journal of Remote Sensing & Geoscience (IJRSG)*.
- Wubie, M. A., & Melania, D. (2016). Patterns, causes and consequences of land use/cover dynamics in the Gumara watershed of Lake Tana basin, north western. *remoste sesing*.
- Xiaolu, S., & Bo, C. (2011). Change Detection Using Change Vector Analysis from . *Procedia Environmental Sciences* , pp.238 – 244.
- Xiong, J., Thenkabail, P. S., Gumma, M. K., Teluguntla, P., J. P., Congalton, R. G., . . . D. T. (2017, March 8). Automated cropland mapping of continental Africa using Google Earth Engine cloud computing. *Journal of Photogrammetry and Remote Sensing*, PP. 225 -244.
- Xiong, J., Thenkabail, P., Tilton, J., Gumma, M., Teluguntla, P., Oliphant, A., . . . Gorelick, N. (2017). Nominal 30-m Cropland Extent Map of Continental Africa by Integrating Pixel-Based and Object-Based Algorithms Using Sentinel-2 and Landsat-8 Data on Google Earth Engine. *Remote Sens.* .

- Y. H. Tsai, D. S. (2018, Jun 12). Mapping Vegetation and Land Use Types in Fanjingshan National Nature Reserve Using Google Earth Engine. *Remote Sens.* doi:doi:10.3390/rs10060927
- Yang, X., & Lo, C. P. (2001, Nov 25). Using a time series of satellite imagery to detect land use and land cover changes in the Atlanta,Georgia metropolitan area. *International Journal of Remote Sensing.*
- Yoon, H.-K. (2011, April). Human modification of korean landforms for geomantic purposes. *Geographical Review, Vol. 101*(No. 2), pp. 243-260.
- Zaitunah, A., Samsuri, S., Ahmad, A. G., & Safitri, R. A. (2018, March). Normalized difference vegetation index (ndvi) analysis for land cover types using landsat 8 oli in besitang watershed, Indonesia. *IOP Conference Series Earth and Environmental Science.* doi:: 10.1088/1755-1315/126/1/012112
- Zakariah, M. (2014, September). Classification of large datasets using Random Forest Algorithm in various applications: Survey. *International Journal of Engineering and Innovative Technology (IJEIT), Volume 4*(Issue 3).
- Zurqani, H., Post, C. J., Mikhailova, E., Cope, M. P., S.Allen, J., & Lytle, B. (2020). *Evaluating the integrity of forested riparian bufers over a large area using LiDAR data andGoogle Earth Engine.*

APPENDICES

APPENDIX A: Google Earth Engine land use land cover mapping codes

* Function to mask clouds based on the pixel_qa band of Landsat SR data.

* @param {ee.Image} image Input Landsat SR image

* @return {ee.Image} Cloudmasked Landsat image

*/

```
var cloudMaskL457 = function(image) {
```

```
  var qa = image.select('pixel_qa');
```

```
  // If the cloud bit (5) is set and the cloud confidence (7) is high
```

```
  // or the cloud shadow bit is set (3), then it's a bad pixel.
```

```
  var cloud = qa.bitwiseAnd(1 << 5)
```

```
    .and(qa.bitwiseAnd(1 << 7))
```

```
    .or(qa.bitwiseAnd(1 << 3));
```

```
  // Remove edge pixels that don't occur in all bands
```

```
  var mask2 = image.mask().reduce(ee.Reducer.min());
```

```
  return image.updateMask(cloud.not()).updateMask(mask2);
```

```
};
```

```
var image = ee.ImageCollection("LANDSAT/LT05/C01/T1_SR")
```

```
  .filterBounds(ROI)
```

```
  .filterDate('1986-11-01', '1986-12-28')
```

```
  .map(cloudMaskL457)
```

```
  .filterMetadata('CLOUD_COVER', 'less_than', 5)
```

```
  .first()
```

```
Map.centerObject(ROI,11);
```

```
var vizParams2 = {bands: ['B3', 'B2', 'B1'], min: 0, max: 3000, gamma: 1.4,};
```

```
Map.addLayer(image.clip(ROI), vizParams2, 'TRUE Landsat 1986');
```

```
var training_points=GrasLand.merge(Vegetation).merge(BareLand).merge(AGRICULTUR  
ALLand).merge(ShurebLand).merge(MixedLand);
```

```
var bands = ['B2', 'B3', 'B4', 'B5', 'B6', 'B7'];
```

```

var points = ee.FeatureCollection(training_points);
print(training_points);
var train_sam = image.select(bands).sampleRegions({
  collection: points,
  properties: ["LC"],
  scale: 30
});
// delet the nul
// Filter out the null property values and try again.
var trainingNoNulls = train_sam.filter(
  ee.Filter.notNull( train_sam.first().propertyNames()
);
var trained = ee.Classifier.smileRandomForest(10).train(trainingNoNulls , 'LC', bands);
var classified = image.select(bands).classify(trained);
Map.addLayer(classified.clip(ROI),
  {min: 0, max: 3, palette: ['#821dd6', '#12ff14', '#e5f727', '#ff3a14', '#00f5f5',
  '#16d620']},
  'classification 1986');
  print(trained.confusionMatrix().kappa(), 'kappa');
print(trained.confusionMatrix(), 'matrix');
// Convert lulc raster to polygons
var FLULC_vec = classified.reduceToVectors({
  scale: 30,
  geometryType:'polygon',
  geometry:ROI,
  maxPixels: 1e9,
  eightConnected: false,
  bestEffort:true,
  tileScale:4,

```

```

});
// Export LULC polygons as shape-file
Export.table.toDrive({
  collection:FLULC_vec,
  description:'FLULC_vec_shp',
  fileFormat:'SHP',
  fileNamePrefix:'FLULC_vec'
});
//Export the raster dataset
Export.image.toDrive({
  scale: 10,
  image: classified,
  description: 'LC_raster',
  fileNamePrefix: 'lulc',
  region:ROI,
  maxPixels: 1e8
});
//Areal coverage of land use land cover class (km2)
var area_1986 = ee.Image.pixelArea().divide(1000*1000).addBands(classified.clip(ROI))
  .reduceRegion({
    reducer: ee.Reducer.sum().group({
      groupField: 1,
      groupName: 'code',
    }),
    geometry: ROI,
    scale: 30,
    maxPixels:1e9
  }).get('groups');
print('Kulfo km2 (2016):', area_1986);
//SECTION 2 - Kulfo 2020

```

```

var image = ee.Image(ee.ImageCollection('LANDSAT/LC08/C01/T1_SR')
    .filterBounds(ROI)
    .filterDate('2020-12-01', '2020-12-28')
    .filterMetadata('CLOUD_COVER', 'less_than', 1)
    .first())
Map.centerObject(ROI,11);
var vizParams2 = {bands: ['B4', 'B3', 'B2'], min: 0, max: 3000, gamma: 1.4,};
Map.addLayer(image.clip(ROI), vizParams2, 'TRUE Landsat 2020');
var training_points =
BareLand.merge(AgriculturalLand).merge(vEGITATION).merge(shrubland).merge(Grass
land).merge(Cloude);
var bands = ['B2', 'B3', 'B4', 'B5', 'B6', 'B7'];
var points = ee.FeatureCollection(training_points);
print(training_points);
var train_sam = image.select(bands).sampleRegions({
    collection: points,
    properties: ["LC"],
    scale: 30
});
// delet the null
// Filter out the null property values and try again.
var trainingNoNulls = train_sam.filter(
    ee.Filter.notNull( train_sam.first().propertyNames())
);
var trained = ee.Classifier.smileRandomForest(10).train(trainingNoNulls , 'LC', bands);
var classified = image.select(bands).classify(trained);
Map.addLayer(classified.clip(ROI),
    {min: 0, max: 3, palette: ['#d6d53f', '#ff1450', '#18ff2f', '#00ffff', '#141dc2',
'#dcfaf5']},
    'classification 2016');
print(trained.confusionMatrix().kappa(), 'kappa');
print(trained.confusionMatrix(), 'matrix');

```

```
//Validation and training
// Splits data into training and validation groups. Set at 70% training/30% validation
var splitData = function(data){
  var dict = {};
  var randomTpixels = data.randomColumn();
  var trainingData = randomTpixels.filter(ee.Filter.lt('random', 0.7));
  var valiData = randomTpixels.filter(ee.Filter.gte('random', 0.3));
  dict.training = trainingData;
  dict.validation = valiData;
  return dict;
}
```

APPENDIX B Confusion Matrix using different classifier Algorithms from GEE

Appendix B1 Confusion Matrix using RF Classification

	Bare	Grass Land	Shrub Land	Mixed forest	Agricultural land	Vegetation	Users Accuracy%	Commission error %
Bare Land	36	0	6	0	6	2	72.0	28.0
Grass Land	5	32	0	1	2	0	80	20
Shrub Land	8	1	41	2	1	0	77.4	22.6
Mixed forest	0	0	0	42	1	0	97.7	2.3
Agricultural land	4	4	4	7	45	1	69.2	30.8
Vegetation	1	0	0	4	1	44	88	12
Sum	54	37	51	56	56	47	80.7	
Producers Accuracy%	66.6667	86.49	80.39	75.00	80.35	93.62		
Omission Error %	33.3333	13.51	19.61	25.00	19.64	6.38		

Appendix B2 Confusion Matrix using Fast Naive Bayes Classification

	Bare Land	Grass Land	Shrub Land	Mixed forest	Agricultural land	Vegetation	Users Accuracy%	Commission error %
Bare Land	34	0	5	0	11	0	68.0	32.0
Grass Land	0	30	0	1	9	0	75	25
Shrub Land	10	1	31	3	4	4	58.5	41.5

Mixed forest	3	2	1	30	2	5	69.8	30.2
Agricultural land	5	13	0	2	40	5	65.0	35.0
Vegetation	1	1	2	2	9	35	70	30
Sum	53	47	39	38	75	49	67.7	
Producers Accuracy %	64.15	63.83	79.49	78.95	53.33	71.43		
Omission Error %	35.85	36.17	20.51	21.05	46.67	28.57		

Appendix B3 Confusion Matrix using CART Classification

	Bare Land	Grass Land	Shrub Land	Mixed forest	Agricultural land	Vegetation	Users Accuracy%	Commission error %
Bare	30	0	4	0	14	2	60.0	40.0
Grass Land	2	23	6	0	6	3	57.5	42.5
Shrub Land	10	5	30	2	0	6	56.6	43.4
Mixed forest	4	1	0	30	6	2	69.8	30.2
Agricultural land	5	13	0	9	30	8	65.0	35.0
Vegetation	0	3	0	2	10	35	70	30
Sum	51	45	40	43	66	56	63.1	
Producers%	58.82	51.11	75.00	69.77	45.45	62.50		
Omission Error %	41.18	48.89	25.00	30.23	54.55	37.50		

APPENDIX C: LULC map of the Kulfo catchment that were classified using four different algorithms

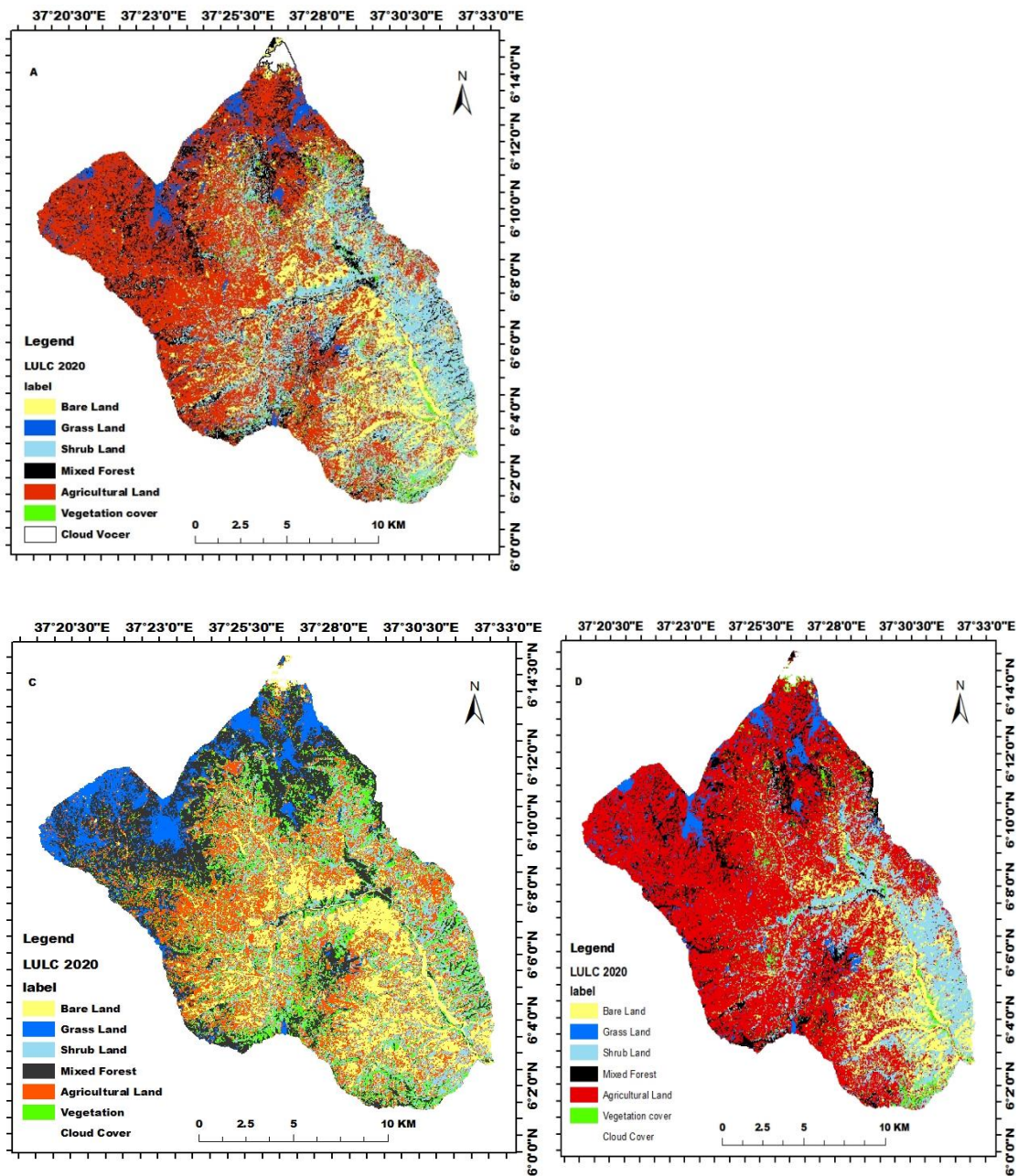


Figure XXX Land cover maps of Kulfo catchment that were generated using (A) SVM, (B) RF, (C) Fast Naive Bayes and (D) CART machine learning algorithms using Landsat OLI image collected at the date of 2020 – 12 -11 (<https://earthengine.google.com>).

APPENDIX D: - Error matrix for classified LULC maps of kulfo catchment A) 1986 B) 2000 and C) 2016

Appendix D1 Error matrix for the 1986 LULC map

	Bare Land	Grass Land	Shrub Land	Mixed Forest	Agricultural Land	Vegetation	Sum	Users Accuracy %	Commission error %
Bare	40	0	5	0	5	0	50	80.0	20.0
Grass Land	0	35	0	1	4	0	40	87.5	12.5
Shrub Land	4	1	45	3	3	3	59	76.3	23.7
Mixed forest	3	2	1	30	2	5	43	69.8	30.2
Agricultural land	3	7	0	2	50	3	65	65.0	35.0
Vegetation	1	1	2	2	4	40	50	80	20
Sum	51	46	53	38	68	51		76.4	
Producers %	78.43	76.09	84.91	78.95	73.53	78.43			240
Omission Error %	21.57	23.91	15.09	21.05	26.47	21.57			
		Over all accuracy = 78.2							
		Kappa coefficient = 0.76							

Appendix D2 Error matrix for the 2000 LULC map

	Bare	Grass Land	Shrub Land	Mixed forest	Agricultural land	Vegetation	Sum	Users Accuracy %	Commission error %
Bare	42	0	3	0	3	2	50	84.0	16.0
Grass Land	5	32	0	1	2	0	40	80	20
Shrub Land	8	1	41	2	1	0	53	77.4	22.6
Mixed forest	0	0	0	42	1	0	43	97.7	2.3
Agricultural land	4	4	4	7	45	1	65	69.2	30.8
Vegetation	1	0	0	4	1	44	50	88	12
Sum	60	37	48	56	53	47			
Producers%	70.00	86.49	85.42	75	84.91	93.62			
Omission Error %	30.00	13.51	14.58	25	15.09	6.38			
		Over all accuracy = 81.73							
		Kappa coefficient = 0.811							

Appendix D3 Error matrix for the 2016 LULC map

	Bare Land	Grass Land	Shrub Land	Mixed forest	Agricultural land	Vegetation	Sum	Users Accuracy %	Commission error %
Bare	45	0	3	0	2	0	50	90.0	10.0
Grass Land	1	37	0	0	2	0	40	92.5	7.5
Shrub Land	3	0	46	3	0	1	53	86.8	13.2
Mixed forest	0	1	3	37	2	0	43	86.0	14.0
Agricultural land	4	3	5	4	50	0	66	75.8	24.2
Vegetation	0	0	1	1	2	46	50	92	8
Sum	53	41	58	45	58	47			
Producers %	84.91	90.24	79.31	82.22	86.21	97.87			
Omission Error %	15.13	9.76	20.7	17.78	13.79	2.13			
		Over all accuracy = 86.71							
		Kappa coefficient = 0.862							

APPENDIX E: Selected sensitive parameters of kulfo watershed

A) Selected sensitive parameters of kulfo watershed using 2000 LULC

No.	Parameter Name	t-Stat	P-Value	Rank
1	V__SURLAG .bsn	-7.688	8.86×10^{-14}	1
2	V__GW_DELAY.gw	-6.19	1.35×10^{-09}	2
3	R__GW_REVAP.gw	2.73	0.01	3
4	V__REVAPMN.gw	1.83	0.07	6
5	R__SFTMP .bsn	1.63	0.10	7
6	R__RCHRG_DP.gw	-1.21	0.23	8
7	A__SOL_AWC(..).sol	-1.14	0.25	9
8	R__CN2.mgt	-1.12	0.26	10

B) Selected sensitive parameters of kulfo watershed for LULC map of 2016

No.	Parameter Name	t-Stat	P-Value	Rank
1	V__CH_K2.rte	17.05	0.00	1
2	V__ALPHA_BF.gw	-7.33	0.00	2
3	R__CH_ERODMO (...).rte	-1.80	0.07	3
4	V__GW_DELAY.gw	-1.63	0.11	4
6	V__GWQMN.gw	1.59	0.11	6

7	V__SURLAG.bsn	-1.59	0.11	7
8	V__REVAPMN.gw	-1.34	0.18	8
9	R__SOL_ALB (..).sol	-1.17	0.24	9
10	A__SOL_AWC(..).sol	-1.13	0.26	11
11	R__CN2.mgt	1.09	0.28	12
12	V__CH_N2.rte	1.02	0.31	13

C) Selected sensitive parameters of kulfo watershed for the LULC map of 2020

No.	Parameter Name	t-Stat	P-Value	Rank
1	V__GWQMN.gw	-8.50	0.00	1
2	V__SURLAG.bsn	-7.22	0.00	2
3	V__GW_DELAY.gw	-3.80	0.00	3
4	R__SOL_ALB (...).sol	-3.58	0.00	4
5	R__SLSUBBSN.hru	-2.42	0.02	5
6	R__CH_N2.rte	1.65	0.10	8
7	R__RCHRG_DP.gw	-1.35	0.18	10
8	R__CH_K2.rte	1.24	0.21	12
9	R__TLAPS.sub	1.13	0.26	14
10	A__SOL_AWC (..).sol	-0.06	0.95	15