ASSESSMENT OF LAND USE LAND COVER CHANGE IMPACT ON STREAM FLOW USING SWAT MODEL, THE CASE OF KULFO RIVER CATCHMENT, RIFT VALLEY BASIN, ETHIOPIA

MSc THESIS

OBSE FUFA ARFASA

HAWASSA UNIVERSITY, HAWASSA, ETHIOPIA

SEPTEMBER 2024

ASSESSMENT OF LAND USE / LAND COVER CHANGE IMPACT ON STREAM FLOW USING SWAT MODEL, THE CASE OF KULFO RIVER CATCHMENT, RIFT VALLEY BASIN, ETHIOPIA

A THESIS SUBMITTED TO

THE DEPARTMENT OF HYDRAULIC AND WATER RESOURCES ENGINEERING,

FACULTY OF BIOSYSTEMS AND WATER RESOURCES ENGINEERING,

INSTITUTE OF TECHNOLOGY, SCHOOL OF GRADUATE STUDIES

HAWASSA UNIVERSITY

HAWASSA, ETHIOPIA

OBSE FUFA ARFASA

IN PARTIAL FULFILLMENT OF THE

REQUIREMENTS FOR THE

DEGREE OF

MASTER OF SCIENCE IN HYDRAULIC ENGINEERING

(SPECIALIZATION: HYDRAULIC ENGINEERING)

SEPTEMBER 2024

SCHOOL OF GRADUATE STUDIES

HAWASSA UNIVERSITY ADVISORS' APPROVAL

This is to certify that the thesis entitled "*ASSESSMENT OF LAND USE / LAND COVER CHANGE IMPACT ON STREAM FLOW USING SWAT MODEL, THE CASE OF KULFO RIVER CATCHMENT, RIFT VALLEY BASIN*, ETHIOPIA" submitted in partial fulfillment of the requirements for the degree of Master's with specialization in Hydraulic Engineering, the Graduate Program of the Department of Hydraulics, and has been carried out by OBSE FUFA ARFASA (Id. No: 0015/14) under our supervision. Therefore, we recommend that the student has fulfilled the requirements and hence hereby can submit the thesis to the department.

Abebe Tadesse (PhD)	_____________	_______________
Name of the major advisor	signature	date
Girma Gadissa (Msc)	______________	_________________
Name of the co-advisor	signature	date

SCHOOL OF GRADUATE STUDIES

HAWASSA UNIVERSITY EXAMINERS' APPROVAL

We, the undersigned, members of the Board of Examiners of the final open defense by Obse Fufa have read and evaluated her thesis entitled "*ASSESSMENT OF LAND USE LAND COVER CHANGE IMPACT ON STREAM FLOW USING SWAT MODEL THE CASE OF KULFO RIVER CATCHMENT, RIFT VALLEY BASIN, ETHIOPIA"*, and examined the candidate. This is, therefore, to certify that the thesis has been accepted in partial fulfillment of the requirements for the degree

Name of Chairperson	Signature	Date
Name of Major Advisor	Signature	Date
Name of Internal Examiner	Signature	Date
Fikru Fentaw (PhD)		September 30, 2024
Name of External Examiner	Signature	Date
SGS Approval	Signature	Date

ACKNOWLEDGEMENT

I would like to take this opportunity to express my deepest gratitude to all those who have supported me throughout the process of writing my thesis.

First and foremost, I would like to thank almighty God. If he had been there to guide me, support me and be my strength I would not be here today. Also, I would like to thank my thesis advisor, Dr. Abebe Tadesse, and Co-advisor, Girma Gadissa, for their guidance and expertise. Their feedback and encouragement were invaluable in helping me navigate the challenges of research and writing.

I would also like to extend my appreciation to my family. Their belief in me gave me the strength to persevere through difficult times and stay focused on my goals. Also I would like to extend my gratitude to my dear friend, colleague and mentor Eng. Wondiye Haile, if it was not for his consistent mentorship, inspiration and support during the challenging time I have been through, I would not be here. I am grateful for all the things he has done for me during my journey of the whole MSc courses and research time.

My acknowledgment extends to all staff members of Ethiopian ministry of Water and Energy specially department of hydrology, National metrological agency, and Ethiopian geospatial information Agency for their polite full and committed cooperation during my data collection.

Finally, I would like to thank all the participants in my study for their willingness to share their experiences and insights, without which this research would not have been possible.

To everyone who has played a part in this journey, I am truly grateful for your support and encouragement. Thank you for believing in me and helping me reach this milestone.

LIST OF ABBREVIATIONS

AAT	All At Time
AOI	Area of Interest
CRV	Central Rift Valley
DEM	Digital Elevation Model
ERDAS	Earth Resources Data Analysis System
ET	Evapotranspiration
FAO	Food and Agricultural Organization
GCP	Ground Control Points
GIS	Geographic Information System
GIZ	*Deutsche Gesellschaft für Internationale Zusammenarbeit*
GPS	Geographic Positioning System
GUI	Graphical User Interface
GW_Q	Ground Water Flow
HEC-HMS	Hydraulic Engineering Centre-Hydrologic Modeling System
HRU	Hydrologic Response Unit
HSPF	Hydrological simulation program Fortran
LULC	Land Use Land Cover
LULCC	Land Use Land Cover Change
MERET	Managing Environmental Resources to Enable Transitions
MoA	Ministry of Agriculture
MoWE	Ministry of Water and Energy
NDVI	Normalized Difference Vegetation Index
NMA	National metrology agency
NSE	Nash and Sutcliffe simulation efficiency
OLI	Operational Land Imager
PBIS	Percent bias
R^2	Coefficient of Determination
SCS	Soil Conservation Service
SUFI	Sequential Uncertainty Fitting
SURQ	Surface Runoff
SWAT	Soil and Water Assessment Tool
TIS	Thermal Infrared Sensor

TM	Thematic Mapper
UNESCO	United Nations Educational, Scientific and Cultural Organization
USGS	United States Geological Survey
WFP	World Food Program
WGEN	Weather Generator
WWF	Worldwide Fund for Nature

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ABSTRACT

In order to conserve land and water resources and ensure its long-term sustainability, land use land cover change dynamics and its impact on the water resources of watersheds have emerged as key issues in hydrology. The main objective of this study was to investigate impact of land use land cover change on stream flow of Kulfo River. ERDAS IMAGINE-2015 using the maximum likelihood algorithm of supervised classification was used to evaluate changes in land use and land cover of study area. Land sat-5 images of year 2000 and 2010 as well as land sat-8 images of year 2022 obtained from USGS with spatial resolution of 30m were used for land use land cover classification. Accuracy of model to classify land features accurately and precisely was evaluated by making comparison matrix between classified classes with those collected by GPS and from Google earth. Kappa coefficient from comparison matrix has been used to evaluate performance of model and it has been determined over 80% for all classification periods verifying the accuracy of classification. From comparison observed from each periods of land use land cover maps, there are some significant changes on land use and land cover features of study area. Over the past study years, the watershed has undergone significant changes, including the expansion of agricultural land and towns at the expense of the reduction of grassland, forest, and shrub area. Those LULC maps of different periods were varied as SWAT inputs while maintaining the remaining inputs the same in order to evaluate its impact on stream flow using SWAT model. The sensitivity analysis, calibration and validation was conducted using Sequential Uncertainty Fitting (SUFI-2) within SWAT-CUP. The calibration results showed very good match of simulation with observation with Nash-Sutcliff efficiency (NSE) of 0.81, coefficient of determination (R^2) of 0.83, root mean square error (RMSE) of 0.12 and percent of bias (PBIAS) of -0.1.Perspective objective functions during validation have been determined as 0.84,0.86,0.01 and 0.03 respectively. Well calibrated stream flow for different periods has been compared to evaluate impact of LULC changes on stream flow. It has been pointed out that some increases in agricultural land and urbanization promoted runoff formation by reducing water infiltration into deep soil, result in an increase in surface runoff and a decrease in ground water flow. It is also revealed by the study that increased surface due to land use land cover change is more significant during wet seasons than that of dry seasons. The study's methodology and findings will be pertinent to environmental policy makers and other relevant bodies which will involve in the development, occupancy, and management of resources related to water and land.

Key words: SWAT model, Kulfo watershed, Hydrological modeling, Rift valley basin

1. INTRODUCTION

1.1 Background of the study

Land use and land cover (LULC) are crucial elements in understanding the dynamics of our planet's surface. These studies provide valuable insights into how human activities, natural processes, and climate change affect the Earth's resources like soil and water resources. Land use and land cover change (LULCC) refers to the process of alteration or modification of the natural features of the land, like vegetation cover, soil properties, and topography, due to human activities caused by increase in population, increase in urbanization and depletion of natural resources(Hamza et al., 2012; Patel et al., 2019). Global and local environmental changes are primarily driven by changes in land use and land cover (LULC), which are brought about by the interplay of biophysical circumstances, demographic, and socioeconomic trends. At the local, regional, and global levels, it has multifaceted effects on vital Earth ecosystem services and functions(Näschen et al., 2019). Land cover and use change in general, and the conversion of natural land cover into agricultural land in particular, are significant ongoing occurrences in sub-Saharan African nations that are mostly brought about by human activity. Similar to other sub-Saharan African nations, the primary issue in many regions of Ethiopia where agriculture is the main driver of the national economy is the human-induced conversion of the natural land cover into cultivated land(Berihun et al., 2019; Gebresamuel et al., 2010).

In Ethiopia, a country known for its diverse landscapes, LULC has become a major concern as it the country experiences agricultural based economic policy and the population of country is increasing rapidly making second biggest African country undergoing rapid population change in Africa (Bekele & Hailemariam, 2010; Hailemariam, 2017; Meyer et al., 1992).

The Rift Valley is a highly prominent geographical feature in Ethiopia, distinguished by its unique topography and a series of lakes and rivers. This area, which is home to a sizable population, has seen considerable LULC over time, leading to notable changes in patterns of land use and land cover (Garedew et al., 2012; Meshesha et al., 2012; Mikias, 2015). This, in turn, has had a profound effect on stream flow dynamics. One of the primary consequences of LULC in this region is the alteration of vegetation cover. Deforestation, for instance, has accompanied the expansion of agricultural activities and the booming population(Garedew et al., 2009). The removal of forests and the conversion of land for agricultural purposes disrupt the natural hydrological cycle, leading to reduced infiltration rates and increased surface runoff (Van Dijk et al., 2007). Consequently, the stream flow within the Rift Valley has been affected, with increased instances of flash floods during the rainy season and decreased flow during the dry months(Meaza et al., 2019).

Moreover, the conversion of land to agriculture has often been coupled with poor agricultural practices, such as the excessive use of fertilizers and pesticides. These practices not only contaminate the water bodies but also disrupt the nutrient balance, affecting the overall water quality in the region. As a result, the stream flow and aquatic life have been adversely impacted, leading to the loss of biodiversity and further exacerbating the water scarcity challenges faced by the local communities(Chala, 2022). In the case of the Kulfo River catchment, LULCC has also played a significant role in altering the stream flow dynamics. The conversion of land for agricultural activities, overgrazing, and deforestation have resulted in erosion and soil degradation, consequently affecting the water retention capacity of the catchment. The reduced infiltration rates and increased runoff have caused an imbalance in the water cycle, leading to fluctuating stream flows and seasonal variations in water availability(Wankie, 2015).

To address the adverse effects of LULCC on stream flow in Ethiopia's Rift Valley and Kulfo River catchment, it is crucial to implement sustainable land use practices and promote conservation initiatives. Reforestation programs should be encouraged to restore vegetation cover, improve infiltration rates, and mitigate erosion. Sustainable agricultural practices, such as terracing and agroforestry, should be promoted to minimize soil degradation and retain water within the catchment. Furthermore, integrated water resources management strategies should be adopted to ensure the equitable distribution of water resources and mitigate the effects of LULCC on stream flow. This includes implementing efficient irrigation systems, encouraging water-saving techniques, and establishing protective measures for sensitive ecosystems(Nikolaou et al., 2020). In order to implement natural resources conservation practices of water, soil and land, effective evaluation of land use and land cover changes of specific watershed and assessment of its significant impact on ground and surface flow of water is crucial activity. This study has been aimed to assess significant impacts of land use and land cover changes on stream flow of Kulfo River.

1.2 Problem statement

The Kulfo watershed is a crucial area in relation to its water resources and a significant source of runoff for Chamo Lake. The Kulfo River contributes high amount overland flow from the unmeasured basin to Chamo Lake(Timotewos et al., 2020). Over the past few decades, the basin has seen changes in land use and land cover(Woldeyohannes et al., 2018). The basin is heavily farmed, and there has been significant population growth there and increases in urbanization. Land use and land cover change are closely tied to the hydrological processes. Since the hydrological processes are vulnerable to changes in land use and land cover, the Kulfo River displayed flow volatility. Deforestation, agricultural expansion, urbanization, and rapid climate change pose significant challenges to sustaining stream flow in the region. There hasn't been much research done on the detection of changes in the land use and land cover (LULC) of the Kulfo river watershed using integration of hydrological models with remote sensing, which is an essential source of information for various decision support involving water resource management, sustainable development, and land conservation. The objective of this study was to evaluate impact of land use land cover changes on stream flow which is essential for implementing effective land management strategies to conserve water resources and ensure the long-term sustainability of River and its catchment by integrating SWAT model with geographical information system.

1.3 Objectives

1.3.1 General objective

General objective of this study was to assess basin hydrologic (stream flow) response under land use and land cover changes in Kulfo watershed using SWAT model.

1.3.2 Specific objectives

✓To determine the land use land cover changes over the last 22 years, it is important to analyze and compare satellite imagery or other remote sensing data from multiple time periods spanning the last 22 years which in turn allows to determine what changes in land use have occurred in the catchment during last two decades.

✓To estimate stream flow of Kulfo River which involves using hydrological models to simulate stream flow under different LULC conditions which is further important to compare each flow outputs to quantify the impacts of LULC change.

✓To evaluate the effects of land use/land cover change on stream flow in order to evaluate the response of watershed for LULC changes.

1.4 Research questions

- ✓ How the land use/land cover has changed over the past 22 years from 2000 to 2022?
- ✓ How much is stream flow of study watershed for each land use land cover maps
- ✓ How stream flow changed with change in land use/land cover?

1.5 Scope and limitations of study

The scope of this study limited to assess how land use and land cover change of Kulfo watershed has changed for last 22 years (2000-2022) only and to evaluate its impact on water resources of Kulfo River. Future prediction of land use and land cover change of study area has not be addressed in the study. It is better to assess the performance of several hydrological models in order to obtain accurate rain fall runoff modeling and various image classification techniques. However, it takes a lot of time and work to assess the performance of numerous models and come in to conclusion in a single study. For these reasons, the scope of this study is restricted to ERDAS for image processing and classification and Soil and Water Assessment Tool (SWAT) model for rainfall-runoff modeling.

1.6 Significance of study

Assessment of Land use and land cover change impact on water resources of the basin/watershed scale is essential for watershed conservation policy makers by providing tangible results how water resources of specific area are strictly dependent on its land use features. The result of study is important for governmental and non-governmental organizations which take part in Integrated Watershed Management implementations for environmental policies like woreda agriculture offices, Managing Environmental Resources to Enable Transitions (MERET) project, World Food Program (WFP), Ministry of Agriculture (MoA),Ministry of water and Energy, German Agency for International Cooperation(GIZ), The Marine Conservation Society, The Worldwide Fund for Nature (WWF).Furthermore, Planning and managing water resources effectively for both current and future consumptions requires an understanding of spatial and temporal availability of water resources and its dependability on land use and land cover change. Therefore, the outcome of this study is important for future water resources project development in area as a scenario in predicting stream flow by using model.

2. LITERATURE REVIEW

2.1 Land use land cover change

Worldwide, the term "land use/land cover change" (LULCC) refers to the alteration of Earth's surface caused by human activity (Zhou et al., 2008). Although humans have been altering land for thousands of years to support themselves and get other necessities, the scope, severity, and rate of LULCC are significantly higher today than they were in the past. These shifts are causing previously unheard-of changes in ecosystems and environmental processes at the local, regional, and global levels. As a result, LULC modifications are crucial to the research and analysis of the current worldwide altered picture since the information on these changes is necessary to support future environmental planning and ecological management decisions specially for water resources(El-Kawy et al., 2011). Researchers from a wide range of fields discovered via empirical investigations that variations in land use and land cover are now crucial for a wide range of applications, including forestry, agriculture, ecology, geology, and hydrology(Deribew & Dalacho, 2019; Garg et al., 2019; Nagendra et al., 2004; Negese, 2021; Poyatos et al., 2003)

2.2 Land use and land cover change studies in Ethiopia

Land use and land cover changes have been recognized as one of the major drivers of hydrological changes, including alterations in stream flow. This literature review aims to provide an overview of studies investigating the impact of land use and land cover changes on stream flow in Ethiopia, Rift valley and Kulfo catchment, Ethiopia.

In Ethiopia, land is utilized for farming, building new structures and roads, as well as growing of grasses for making food for animals. The majority of the land in the nation is used for subsistence farming. Only some portion of land in the country has remained as forest and shrub land. There is deforestation for increased output due to population growth, slow technological adoption that can improve productivity, conversion of forest to agricultural land, and the spread of urban populations (Kassaye, 2024; Wassie, 2020).

Studies carried out in several regions of Ethiopia have demonstrated significant shifts in the land cover and use of the nation. According to the majority of these research, croplands have grown to the extent of native vegetation, such as forests and shrub lands. As indicated in results of those studies, there has been significant increase in urbanization along different basins of countries.

Regasa et al. (2021) reviewed land use land cover change studies in Ethiopian basins and mentioned basic reasons behind land cover changes as population pressure, resettlement programs, climate change, and other human and nature-induced driving forces. Many studies in sub basin and watershed scale are also conducted in different studies. For instance, over a 35-year period in Birr River Watershed, Abay Basin, Ethiopia, Malede et al. (2023), indicated a rise in agricultural land cover and a decrease in wild vegetation. The author summarized that, these changes in land use are primarily driven by population growth, agricultural expansion, urbanization, increasing energy and food demands, and changes in lifestyle and socio-economic conditions in the area.

Review conducted by (Negese, 2021) was aimed to view previous studies in Ethiopia that quantify the change in the rate of soil erosion and hydrological responses as a result of the change in land use and land cover in the country. From past studies in the country, reviewers indicated that, over the past forty years, Ethiopia's mean rate of soil erosion, sediment output, surface runoff, mean wet monthly flow, and mean annual stream flow has all increased due to the country's growth of cultivated land at the expense of forest, shrub, and grassland areas. However, the country's evapotranspiration (ET), groundwater flow and recharge, and dry average monthly flow have all decreased as a result of the change.

Specific studies are also conducted to find LULC impact on hydrological components of sub basin For instance, Getachew and Manjunatha (2022) came in to conclusion about significant increase of the lake Tana sub-basin's mean annual water yield and surface runoff and decrease of evapotranspiration and lateral flow due to an expansion of agricultural and built-up lands and a decrease in shrub lands and grasslands. The study by (Getahun & Van Lanen, 2015) aimed in evaluating the impact of land use and cover changes on surface and ground water quantity of Melka Kuntrie watershed and came in to conclusion that there is increase in stream flow in the main rainy season and inconsistency of stream flow in dry or small rainy season from month to month due to expansion of agriculture in the area.

Overall, the LULCC studies conducted Ethiopian river basins have provided important insights into the linkages between land use changes and water resources, which are crucial for sustainable land and water management in the country. These studies have also highlighted the need for integrated land use and water resources planning to mitigate the adverse impacts of LULCC on the hydrological regime and water quality in these basins

2.3 Land use and land cover change studies in rift valley basin

A study by Mekonnen (2017) examined the impact of land use change on stream flow in the Rift Valley catchment. The results indicated that conversion of natural vegetation to agriculture and urbanization significantly reduced the stream flow during dry seasons. Changes in land cover were found to increase surface runoff and decrease groundwater recharge, leading to reduced stream flow. Kiprotich (2021)investigated the influence of climate and land use change on stream flow in the Rift Valley catchment. They found that land use change, particularly deforestation for agricultural purposes, was a major driver of decreased stream flow. The study also highlighted the importance of considering both land use change and climate variability in hydrological modeling to obtain accurate predictions of stream flow.

In a study conducted by Reta (2021), impact of land use changes on stream flow dynamics in the Rift Valley catchment was examined . Findings suggested that conversion of forested areas to agroforestry systems resulted in increased stream flow during wet seasons. However, excessive grazing and deforestation were found to decrease stream flow during dry seasons. The study emphasized the need for sustainable land management practices to mitigate the negative effects of land use changes on stream flow. Kuma et al. (2021) investigated the effects of land use and climate change on stream flow in the Rift Valley catchment. The study employed a hydrological model to simulate stream flow under different land use and climate scenarios. The results indicated that land use change had a significant impact on stream flow, with urbanization and agriculture expansion leading to increased peak flows and decreased base flows. Climate change exacerbated these effects, resulting in further alterations to stream flow patterns.

Land use and land cover changes and their effects on the landscape of Abaya-Chamo Basin, southern Ethiopia was studied by Wankie (2015). According to the study, the basin's increasing trend of landscape fragmentation and LULC alterations exacerbated soil erosion, surface runoff volume, and sediment transport, which in turn impacted the levels and water quality of the lakes located in the rift floor. Moreover, the reduction of wild flora and animals that were once common in the basin was caused by the destruction and fragmentation of natural grasslands and shrub lands. The above literature review slightly demonstrates that land use and land cover changes have a substantial impact on stream flow in the Ethiopian watersheds. Conversion of natural vegetation to agriculture or urban areas leads to reduced stream flow, while changes in forest cover and grazing patterns can affect stream flow dynamics. It is evident from the reviewed studies that a holistic approach considering both land use change and climate variability is necessary for accurately predicting and managing stream flow in the study area.

2.4 Land use and land cover change impacts on Kulfo river catchment

Wankie (2015) conducted a study in the Kulfo catchment to assess the impact of land use and land cover changes on stream flow using hydrological modeling. The findings revealed that conversion of forests and grasslands into croplands and settlements significantly reduced stream flow, leading to increased water scarcity in the catchment. It is examined that the changes in land use and land cover over a period of three decades (1985-2005) in the Kulfo catchment and its impact on stream flow. Researcher observed a significant increase in cropland expansion and urbanization, which led to a decline in stream flow due to increased surface runoff and reduced infiltration.

Similar study was also conducted in study area by Anja (2021).The researcher used Google Earth Engine to detect land use land cover changes of study area and Soil and Water Assessment Tool (SWAT) to simulate stream flow for each LULC change maps. It is concluded from the study that, there is a noticeable change in the LULC of the Kulfo catchment over the past decades which caused significant change on stream flow. In the study performance evaluation of hydrological model was confirmed after examining objective functions for each LULC maps which is non-reasonable to compare the changes. In assessing impact of LULCC on hydrological event as stream flow, calibration and validation of model has be to examined by using single LULC map and the same obtained results have to be examined and analyzed by changing only LULC map of different years(Aredehey et al., 2020; Barkhordari, 2003; Deribew & Dalacho, 2019; Getahun & Van Lanen, 2015; Mikias, 2015).

In above mentioned studies, soil data from FAO which is coarse resolution having limitations of indicating small watershed characteristics is used. But, as recommended by the same studies in various watersheds, it boosts the accuracy of study if soil map which has fine spatial resolution is utilized in the study (Cavazzi et al., 2013; Terribile et al., 2011; Van Zijl et al., 2016; Ye et al., 2011). In this study, land use and land cover change impact on stream flow, Kulfo catchment using soil map data from Ethiopian geospatial agency which represents the properties of small watershed has been used. In addition, all studies were limited to surface runoff studies. Impact of land use land cover change on base flow and other hydrological components of watershed are disregarded.

2.5 Techniques of land use land cover change study

Numerous techniques have been developed and used for change detection to monitor changes in LULC by making use of remotely sensed data for instance image differencing. post-classification comparison (PCC), vegetation index differencing and principle components analysis (PCA) (Hassan et al., 2016). Numerous studies have indicated that post-classification comparison is the most accurate method among them since it provides an indication of the type of changes that are occurring. It detects changes in land cover by comparing classifications of independently produced images taken at different periods (Civco et al., 2002; Manandhar et al., 2009; Peiman, 2011).

The most popular techniques for evaluating, displaying, and identifying LULCC patterns are satellite remote sensing and geographic information systems (GIS), due to their precise geo referencing methods, digital formats that are appropriate for computer processing, and capacity for repeated data collection(Hassan et al., 2016; Rahman et al., 2012). It has been used widely for determination and/or description of the prevalent changes in LULC properties based on multi-temporal remotely sensed data. This data's capacity to detect unusual changes between two or more dates is the primary use case for change detection. Numerous investigators have tackled the issue of precise LULCC monitoring across various settings due to quality of satellite images (Rahman et al., 2012; Tahir et al., 2013).

2.6 The role of ERDAS imagine in LULC studies

ERDAS Imagine is a powerful software package widely used for processing, analyzing, and interpreting satellite imagery in LULC studies. It offers various tools and functionalities that aid researchers in extracting valuable information from remote sensing data. Land use and land cover change (LULCC) studies conducted using the ERDAS (Earth Resources Data Analysis System) software in various river basins of Ethiopia have provided valuable insights into the dynamics of land cover changes and their implications for environmental management.

A study by Adugna et al. (2016) used Landsat imagery from 1986, 2000, and 2014 to detect land cover changes in the basin by using ERDAS Imagine. They found significant conversions of forest and grassland to cropland and urban areas, leading to increased surface runoff and decreased groundwater recharge.

Another study by Gessesse et al. (2015) employed ERDAS to analyze LULCC patterns in the Akaki sub-basin of the Awash River Basin between 1973 and 2010. They observed a decline in natural vegetation cover and an increase in agricultural and built-up areas, which had negative impacts on water quality and quantity.

Bewket and Abebe (2013) used ERDAS to analyze land cover changes in the Lake Tana sub basin between 1957 and 2008, revealing a significant increase in cropland and a decrease in natural vegetation. These changes were associated with reduced groundwater recharge and increased soil erosion. Dessie and Bewket (2013) employed ERDAS to quantify LULCC in the Gumara watershed of the Lake Tana Basin between 1957 and 2008. They found a substantial conversion of forests and grasslands to cropland, leading to increased sediment loads and water quality degradation.

A study by Rientjes et al. (2011) utilized ERDAS to map land cover changes in the Gilgel Abbay watershed of the Upper Blue Nile Basin between 1973 and 2001. They observed a significant decline in forest cover and an increase in cropland, which had implications for water resources and ecosystem services. Garede and Minale (2015) employed ERDAS to analyze LULCC in the Rib River watershed, a sub-basin of the Upper Blue Nile, between 1973 and 2011. They found a substantial conversion of natural vegetation to agricultural and built-up areas, leading to increased surface runoff and soil erosion.

Overall, the LULCC studies conducted using ERDAS in various river basins in Ethiopia have evaluated performances of model for similar studies and provided valuable insights into the spatial and temporal dynamics of land cover changes and their implications for water resources, ecosystem services, and environmental management. These studies have highlighted the need for sustainable land use planning and integrated water resources management to address the challenges posed by LULCC in these important river basins.

2.7 Hydrological Modeling

2.7.1 Introduction

All Rainfall-Runoff (R-R) models and, in the broader sense, hydrologic models are simplified characterizations of the real-world system. They are mostly employed for understanding the hydrologic processes taking place in the watershed and for hydrologic forecast (Sorooshian et al., 2008). Rainfall-runoff models are classified based on model input and parameters and the extent of physical principles applied in the model. It can be classified as lumped and distributed model based on the model parameters as a function of space and time and deterministic and stochastic models based on the other criteria (Devia et al., 2015).

Hydrological modeling is crucial for water resources studies as it helps in predicting and managing water availability. By simulating the behavior of rainfall, river flow, groundwater recharge, and evapotranspiration, models provide valuable insights into the quantity and quality of water resources. These models allow for assessing the impact of various factors such as climate change, land use changes, and human activities on water availability. This information is essential for making informed decisions regarding water resource management and planning. Hydrological models also help in understanding the hydrological processes occurring within a watershed or river basin. They assist in identifying areas prone to flooding or droughts, which can aid in developing strategies to mitigate potential risks.

The integration of hydrological modeling with other disciplines such as ecology, agriculture, and engineering enhance our understanding of the complex interactions between water resources and these sectors. It provides a comprehensive approach to address issues related to irrigation planning, environmental conservation, hydropower generation, etc. Furthermore, hydrological modeling plays a significant role in supporting decision-making processes related to infrastructure development projects like dams or reservoirs. It enables assessing their potential impacts on downstream flows and ecological systems before implementation. Overall, hydrological modeling is indispensable for studying water resources as it allows us to predict future scenarios accurately while considering various influencing factors. Such understanding aids effective management strategies that ensure sustainable use of our precious water resources.

Although many watershed models are available now a day to asses water resources of large and small basin they have their own unique properties (Devia et al., 2015). During past decades there has been dramatic increase development and use of hydrologic models for simulation of complex hydrological process (Xu & Singh, 2004). The selection of model should be ultimately depended on objective of study and availability of resources and data and time scale of analysis (Brannan Kevin et al., 2003). The degree to which a model accurately captures the hydrological processes and describes the watershed is what determines the model's capacity to replicate hydrological processes (Zhang et al., 2020).

2.7.2 Applications of hydrological models for LULC studies

The land use land cover change studies in Ethiopian river basins have typically employed a combination of remote sensing, GIS, and hydrological modeling techniques (Gebrehiwot et al., 2019). The SWAT model has been the most widely used hydrological model in these studies, due to its ability to simulate the complex interactions between land use, hydrology, and water quality (Dile et al., 2016; Alemayehu et al., 2017). Other models, such as HSPF and HEC-HMS, have also been used to complement the SWAT model or to address specific research questions for LULC studies (Edossa et al., 2019; Mengiste et al., 2019). The studies have used a variety of data sources, including satellite imagery, land use and land cover maps, climate data, and observed stream flow and water quality data, to parameterize and calibrate the hydrological models (Gashaw et al., 2018; Ayele et al., 2017).

Overall, the LULCC studies conducted in Ethiopian river basins using hydrological models have contributed significantly to our understanding of the complex interactions between land use, hydrology, and water resources in the region. These insights can aid in the development of sustainable water and land management strategies to address the pressing environmental challenges facing Ethiopia.

2.7.3 Soil and Water Assessment Tool (SWAT)

2.7.3.1 Model description

The SWAT model is a physically based semi-distributed model that divides a catchment into sub-catchments and then further into hydrological response units (HRUs) for which a land phase water balance is calculated(Arnold et al., 2012). Runoff from each HRU (i.e. combinations of land use, soil and slope) is aggregated at sub-catchment level and then routed to the main channel for which the catchment water balance is calculated.

It is physically based requiring specific information about soil, topography, weather, and land management practices within the watershed. Each watershed is first divided into sub basins and then in hydrologic response units (HRUs) based on the land use and soil distribution. SWAT is a useful tool because watersheds that do not have any monitoring data can be modeled. It also can simulate large watersheds in a relatively short period of time (Arnold et al., 2011). SWAT model considers many parameters impacting on hydrology and simulates the flow and the transport of sediments or polluting elements. It has been developed to predict the impact of land management practices on water, sediment and agricultural chemical yields in large, complex watersheds with varying soil, land use, and management conditions over long periods of time (Dile et al., 2016). Detail simulation process of model is briefly described by Arnold et al. (2011). The Simulation of the hydrology of a watershed is done in two separate divisions. One is the land phase of the hydrological cycle that controls the amount of water and sediment loadings to the main channel in each sub watershed. Hydrological components simulated in land phase of the hydrological cycle are canopy storage, infiltration, redistribution, evapotranspiration, lateral subsurface flow, surface runoff, ponds, tributary channels and return flow. The second division is routing phase of the hydrologic cycle that can be defined as the movement of water and sediments through the channel network of the watershed to the outlet. the watershed was partitioned in to hydrologic response units (HRU), which are unique occurrence of soil type, land cove and slope class combinations within the watershed to be modelled.

2.7.3.2 SWAT model sensitivity analysis

Sensitivity analysis is an important step in the SWAT modeling process to identify the most influential parameters on model outputs. Several studies have been conducted to assess the sensitivity of SWAT parameters. For example, Nair et al. (2011) performed a global sensitivity analysis of the SWAT model for a watershed in Texas, USA. They used the Latin hypercube one-at-a-time (LH-OAT) method to identify the most sensitive parameters for stream flow, sediment, and nutrient predictions.

Several studies have been conducted to assess the sensitivity of SWAT parameters in Ethiopian watersheds. For example, Bitew and Beyene (2011) performed a global sensitivity analysis of the SWAT model for the Gilgel Abbay watershed in the Upper Blue Nile Basin, Ethiopia. They used the Latin hypercube one-at-a-time (LH-OAT) method and found that the curve number, soil available water capacity, and groundwater delay time were the most sensitive parameters for stream flow simulation (Bitew & Beyene, 2011).

Similarly, Worqlul et al. (2015) conducted a sensitivity analysis of the SWAT model for the Choke Mountain watershed, also in the Upper Blue Nile Basin. They used the Sobol' method and identified the curve number, soil available water capacity, and groundwater "revap" coefficient as the most sensitive parameters for stream flow, sediment, and nitrate predictions (Worqlul et al., 2015).

2.7.3.3 SWAT model Calibration and validation

Calibration involves adjusting model parameters within reasonable ranges to minimize the discrepancy between simulated and observed data. Validation then tests the calibrated model against an independent dataset to evaluate its predictive performance. Calibration and validation are essential steps to ensure the SWAT model accurately represents the watershed being studied in Ethiopia. Several studies have reported on SWAT model calibration and validation for Ethiopian watersheds

Dessu and Melesse (2012) calibrated and validated the SWAT model for the Mara River Basin, which straddles the border between Kenya and Tanzania. They used a combination of manual and automatic calibration techniques and achieved satisfactory model performance, with Nash-Sutcliffe efficiency (NSE) values of 0.75 for stream flow and 0.68 for sediment (Dessu & Melesse, 2012).Dile and Srinivasan (2014) also calibrated and validated the SWAT model for the Awash River Basin in Ethiopia. They used the Sequential Uncertainty Fitting (SUFI-2) algorithm for calibration and obtained good model performance, with NSE values of 0.82 for stream flow and 0.72 for sediment (Dile & Srinivasan, 2014).

In summary, studies conducted on swat model calibration and validation in Ethiopian watersheds reveled the potential of SWAT model to simulate water, sediment and nutrient with reasonable accuracy. However, accuracy of model predictions depends on specific watersheds properties and quality of data used in simulation processes. Sensitivity analysis, calibration and validation have been used to improve model performances and used to provide valuable insight for water resources manage in the region.

2.7.3.4 SWAT model performance evaluation

Evaluating the performance of the SWAT model is crucial to determine its suitability for a particular application in Ethiopia. Common performance metrics used to evaluate SWAT model performance include the Nash-Sutcliffe efficiency (NSE), coefficient of determination (R^2), and percent bias (PBIAS). For instance, Setegn et al. (2010) assessed the performance of the SWAT model in simulating stream flow and sediment load for the Lake Tana Basin in Ethiopia. They reported NSE values of 0.80 for stream flow and 0.72 for sediment, indicating good model performance (Setegn et al., 2010).

Abebe and Foerch (2006) also evaluated the SWAT model's performance in simulating stream flow and water quality for the Alemaya watershed in eastern Ethiopia. They obtained NSE values ranging from 0.65 to 0.85 for different water quality constituents, demonstrating the model's reliability in predicting hydrology and water quality in the study area (Abebe & Foerch, 2006).

Overall, these studies conducted in Ethiopia demonstrate the importance of sensitivity analysis, calibration, validation, and performance evaluation in the SWAT modeling process to ensure the model's reliability and accuracy in simulating hydrology and water quality in various Ethiopian watersheds..

2.7.3.5 Application of SWAT Model for LULC studies

In recent years, the trend of assessing impact of LULC on water resources of basin by integrating Soil and water assessment tool (SWAT) with GIS and RS technology and other advanced technologies like ERDAS and Google Earth Engine has become ideal approach across all over the world (Brook et al., 2015; de Oliveira Serrão et al., 2022; Geremew, 2013; Kiros et al., 2015) to list some of studies. Worku et al. (2017) applied the model to evaluate LULC impact on water and sediment yield of in the Beressa watershed and revealed its successful performance in estimating stream flow and sediment yield with various LULC dynamics. Tadele and Förch (2007) used the SWAT model to analyze the effects of land use and land cover change on stream flow in the case of the Hare River watershed, Ethiopia, and proved the model's acceptance in hydrological performance. All of the studies conducted in different basins of country depicted good performance of SWAT model in order to simulate stream flow and strongly recommend to use model for further LULC studies.

According to review conducted by Awasthi et al. (2021), Soil & Water Assessment Tool (SWAT) model is one of the remarkable distributed hydrological models which has been extensively used in hydrological research and to predict the future stream flow of rivers and sediment flow and agricultural production.

SWAT model has got great acceptance for assessing water resources potential of basin and catchment and evaluating Impact of LULC change on it. This is due to:

- ✓ It can forecast how changes to soil, land use, and land cover may affect watershed hydrologic response (Zhang et al., 2020).
- ✓ Only a little direct calibration is required for SWAT model to obtain good hydrologic predictions (Devia et al., 2015).
- ✓ Uses readily available inputs (Arnold et al., 2012).

- ✓ The model is capable of simulating major watershed hydrologic processes (Singh et al., 2005)
- ✓ Computationally efficient to operate on large basins in reasonable time (Arnold & Fohrer, 2005; Van Griensven et al., 2012).
- ✓ The model contains a community of creators and users who support one another for greater comprehension.
- ✓ An accuracy predictive capacity of SWAT model depends on accuracy of input data which is a major problem in developing countries like Ethiopia(Setegn et al., 2010; Zewde et al., 2024).

3. MATERIALS AND METHODS

3.1 Descriptions of the study area

3.1.1 Location

The Kulfo River originates in the Guge highlands, which are located on the western escarpment of the Main Ethiopian Rift in southern Ethiopia. Chamo Lake is encircled by the Guge and Amaro Mountains. The Kulfo river is the primary source of water for Lake Chamo (Timotewos et al., 2020). The Kulfo River generally drains into Lake Chamo; however, after heavy rains, it can also flow to Lake Abaya via a bifurcation immediately southwest of Arba Minch airport. The total area of Kulfo catchment at new bridge monitoring station is 380 square kilometers This study has been conducted in the Kulfo river watershed of the Southern Ethiopian Rift Valley, situated around 5^0 54'N' and $6^0$15'N latitude and $37^0$21'0" and $37^0$31'30"E longitude.

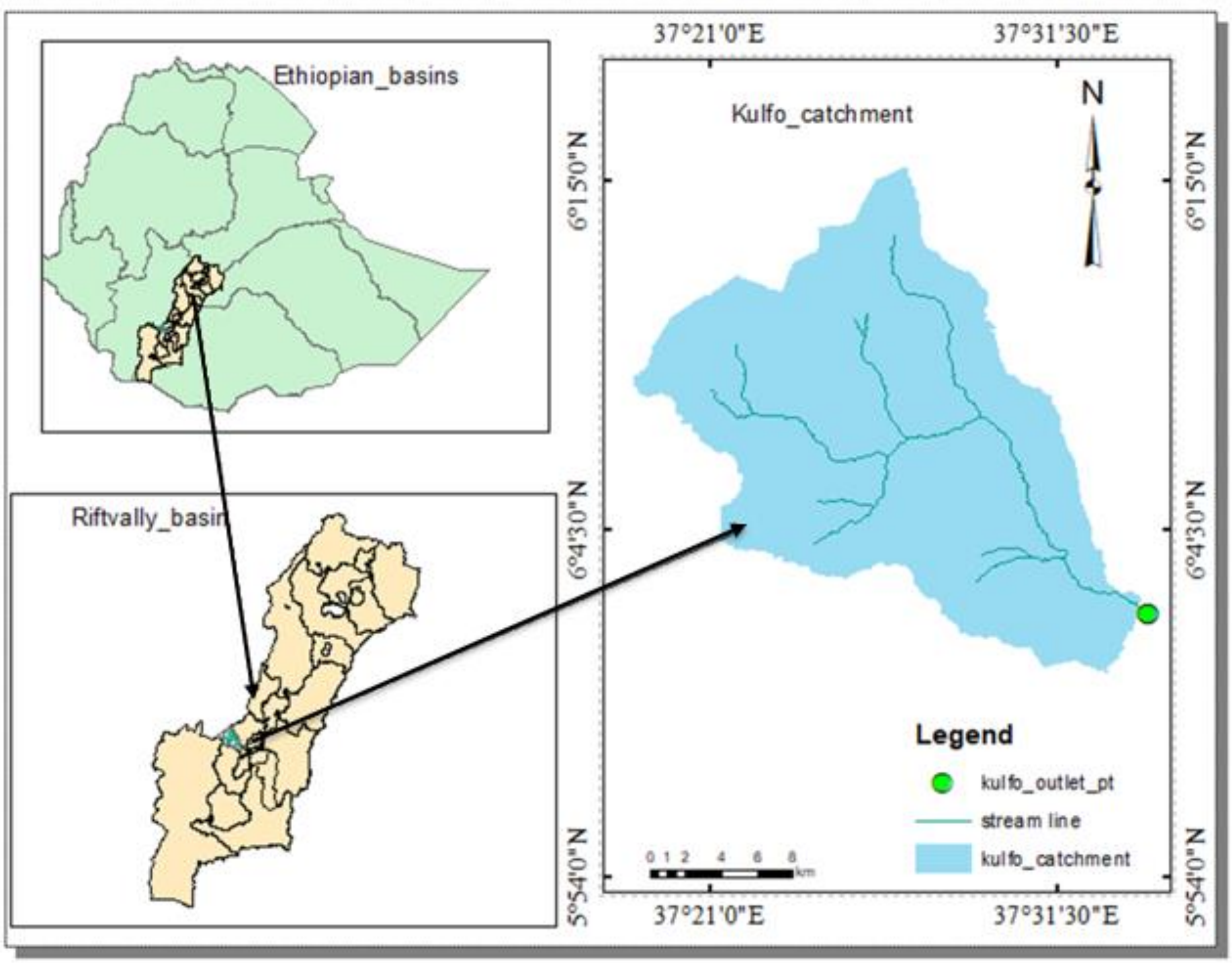


Figure 3. 1 Location map of study area.

3.1.2 Climate

Daily series metrological data of four stations in and near the watershed that contribute for study area are analyzed. According to daily precipitation analyzed from station, the study has bimodal distribution of precipitation with mean annual precipitation of 509mm to 1028mm. The catchment's four main months with the greatest recorded precipitation records are April, may, September and October. The Chancha station records the highest annual precipitation whereas the Geresse station of the area show lower annual precipitation. Maximum temperatures of study area ranges between 38°C to 18.5°C recorded at Arbaminch and Chancha stations respectively. Minimum temperature of Kulfo watershed ranges between 11.2°C to 18.5°C.

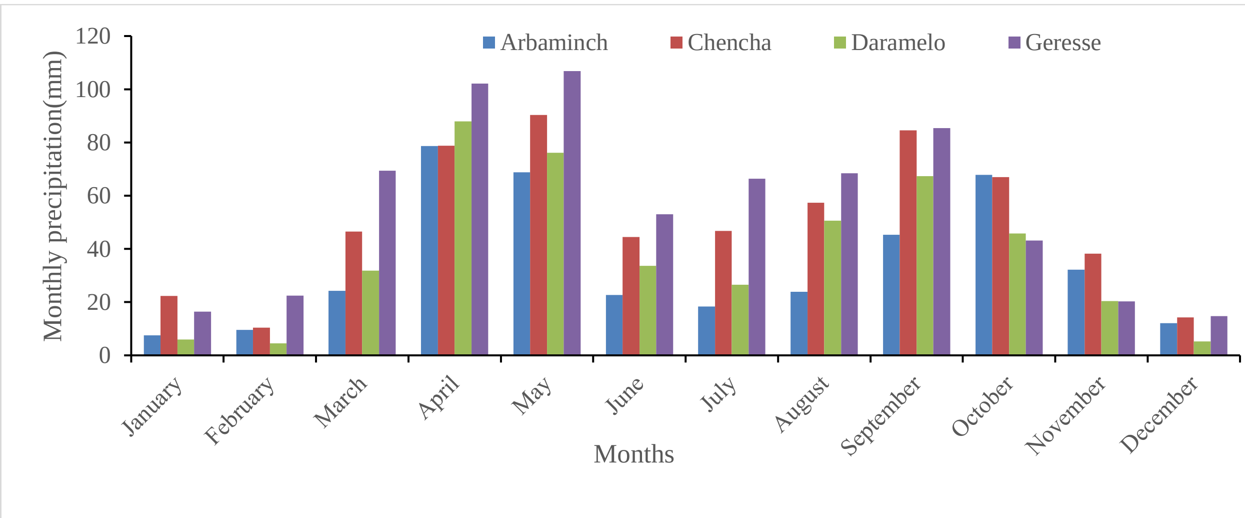


Figure 3. 2 Mean monthly precipitation of stations

3.1.3 Topography

The amount of surface flow and subsurface flow that enters the stream is determined by topography. A free digital elevation model with a spatial resolution of 30 meters was obtained from USGS (United States Geological Survey) to model the topography and elevation variations within the river basin. It helps to capture the flow pathways and drainage network, which play a crucial role in water flow simulations. The region's topographic height ranges from 3545 masl near Guge highlands to 1215 meters above sea level at the outlet of the Kulfo River near new bridge. Slope of watershed which determines generation of surface runoff or infiltration in to soil is generated from DEM. Accordingly, the slope of watershed ranges from 0 degree to 81degrees.

3.1.4 Land use land cover

Land Use Land Cover Data: Accurate and up-to-date land use land cover data is essential for the SWAT model. It helps to understand the changes in land use patterns over time, which directly affect soil infiltration, vegetation evapotranspiration, and surface runoff. Although there are some minor changes between years, pasture and agricultural land account for the majority of the Kulfo watershed's land use and land cover, accounting for over 29% and 46%, respectively. The remaining land use and land cover types of Kulfo watershed listed from higher areal coverage to lower are Forest, shrub land, settlement and water body.

3.1.5 Soil type

Detailed soil information, including soil type, texture, organic matter content, and hydraulic properties, is essential for accurate hydrological modeling. Accurate hydrological modeling requires consideration of these factors as they directly impact various processes such as rainfall-runoff transformation, evapotranspiration rates, groundwater recharge estimation, flood prediction models, nutrient cycling dynamics through leaching processes etc. Without detailed knowledge about these parameters specific to each location within a watershed or catchment area being modeled accurately there will be uncertainties leading to potential errors in predictions which may result in improper management decisions regarding land use planning practices like irrigation scheduling optimization plans adaptation strategies related flooding risk assessment etc

Soil type of study area is classified in to seven soil group categories. Majority of the area (almost 70%) is covered with orthic Acrisols. Other soil types in the area are; chromic Vertisols(2.1%), dystric Luvisols(9.5%), dystric nitisols(14.5%), Eutric Fluvisols(0.3%), Eutric nitisols(2.4%) and Luvisols(1%).Soil type map of Kulfo watershed obtained from Ethiopian Geospatial Agency is depicted in figure below.

Table 3. 1 Soil type characteristics of study area

Soil type	SWAT-code	Area	Percentage	Soil group	Texture
Chromic Vertisols	CVSL	8.08	2.14	D	Clay-loam
Dystric Fluvisols	DVSL	35.78	9.47	D	Clay-loam
Dystric Nitisols	DNSL	54.84	14.52	C	Sandy-clay
Eutric Fluvisols	EFSL	1.17	0.31	C	Loam
Eutric Nitisols	ENSL	9.25	2.45	D	Clay-loam

Luvisols	LUSL	3.68	0.97	C	Loam
Orthic Acrisols	OASL	264.92	70.14	C	Clay

3.1.6 Land sat images

Remote sensing images which are downloaded from USGS were used for image classification. Produce land use/cover map. The quality of the image, particularly for those with little or no cloud cover, and the need to avoid seasonal variations in the amount of vegetation covered, played a role in the selection of the Landsat satellite image periods. The selection of the Landsat satellite images dates was influenced by the quality of the image especially for those with limited or low cloud cover. Each Landsat was georeferenced to the WGS_84 datum and Universal Transverse Mercator Zone 37 North coordinate system. As a result, the images have to be nearly cloud-free and captured the same time of year. In addition, in order to compare and contrast the changes in land use land cover change spatial resolution of set of images has to be similar. General characteristics of used land sat images (Images at Appendix) for image classification are depicted in table below.

Table 3. 2 Land sat image characteristics

Date acquired	Spacecraft ID	Cloud cover	Number of bands	Pixel size
2000-01-26	LANDSAT_5	0.00	7	30m
2010-01-30	LANDSAT_5	0.01	7	30m
2022-01-30	LANDSAT_8	0.03	11	30m

Landsat 5 used the Thematic Mapper (TM) sensor, while Landsat 8 uses the operational land imager (OLI) and thermal infrared sensor (TIRS). The OLI has improved sensor performance, including greater radiometric resolution, increased sensitivity in the blue wavelength range, and a wider spectral range. Spectral Bands: Landsat 5 had seven spectral bands covering visible to thermal wavelengths. On the other hand, Landsat 8 has eleven spectral bands with enhanced capabilities such as two additional coastal aerosol bands to monitor shallow water bodies. As new satellite technology improves with each new mission launch, newer sensors like OLI on Landsat-8 usually offer superior image quality compared to older sensors like TM on Landstat-5. Both datasets are freely available through USGS earth explorer. However, as Landstat-5 reached its end-of-life phase in june-2013 after serving nearly three decades; thus, availability has limited its usage compared to more recent missions like Landstat-8 which was launched in february-2013 and continues operations today.

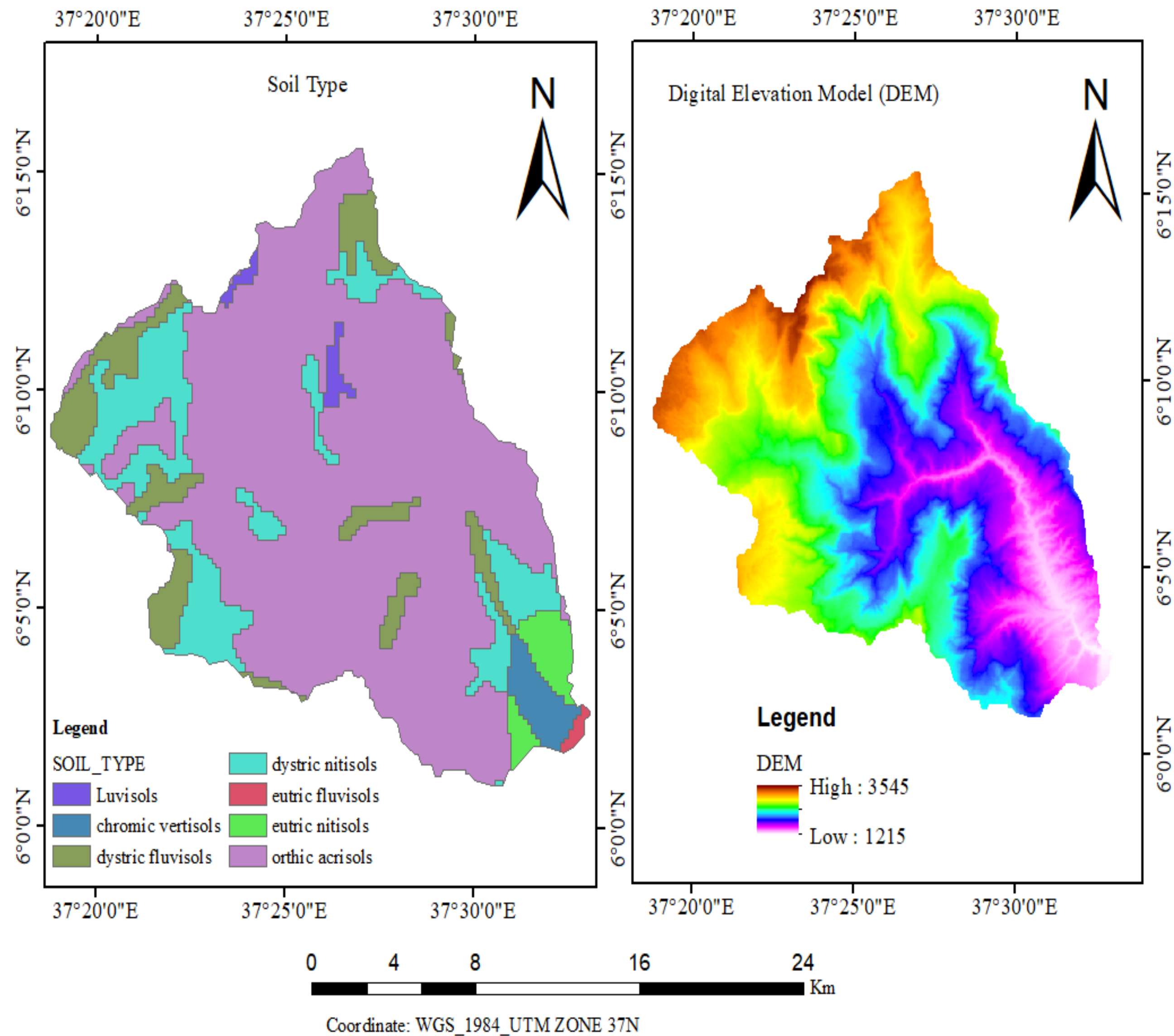


Figure 3. 3 soil type and digital elevation model of study area

3.2 Data collection and analysis

3.2.1 Data collection

In order to assess impact of land use land cover change on stream flow, set of spatial and temporal data series are important. For the study, weather time series of daily series of precipitation, temperature (maximum and minimum), solar radiation, relative humidity, and wind speed data recorded by the weather stations in and near of catchment as well as spatial data, including topography, land cover, and soil information have been used. Stream flow which is monitored from gauging station near Arba Minch has been utilized to calibrate and validate simulated stream flow by Soil and Water Assessment Tool. The model's primary input are rainfall and temperature, and the model's ability to simulate and forecast the future is greatly influenced by the locations of stations. The temporal and spatial distribution of precipitation and other weather data will affect the modeling of surface and groundwater in a watershed. Consequently, using prevalent patterns of rainfall at the watershed size is preferred. Based on data availability, contribution to the catchment, and data quality, four weather stations are included in the study procedure.

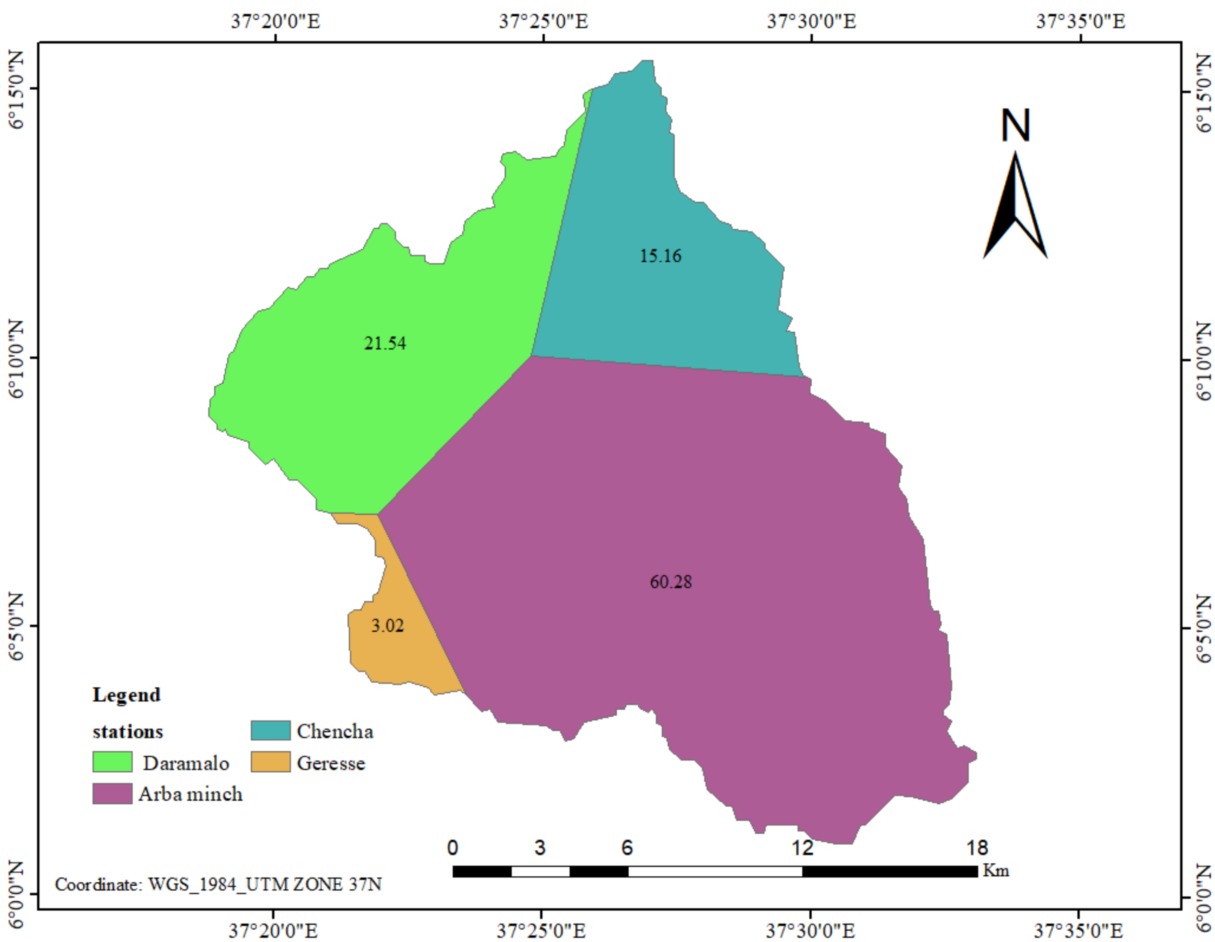


Figure 3. 4 The contributions of meteorological stations to the research area

In order to improve the accuracy of the study, long-term data from recent times was collected in order to evaluate the evaluate impact of land use and land cover change on stream flow of Kulfo watershed using GIS and hydrological models. Thus, precipitation and temperature data of stations for 22 years (2000-2022) are obtained from National Metrological Agency (NMA) of Ethiopia.

Moreover, the remaining meteorological time series data that are essential inputs for the SWAT model are only accessible from Arba Minch station. SWAT weather generator is used to fill in the series for the remaining stations that are lacking wind speed, solar radiation and relative humidity.

For the purpose of calibrating and validating stream flow generated through the Soil and Water Assessment Tool (SWAT), hydrological data of stream flow, was used. Daily stream flow data monitored at Kulfo River at new bridge station (2000 -2015) covering area of 377 Km^2 was collected from Ethiopian ministry of water and energy, hydrology department. It is true that researching and evaluating hydrology would yield more accurate results if current hydro-meteorological data were used. If data availability does not preclude its use, hydrological data from the same year as the metrological data used for simulation should be utilized to calibrate model performance. Given that the study's examined simulation period runs from 2000 to 2022, it could be better if the calibration was based on the observed stream flow for that year.

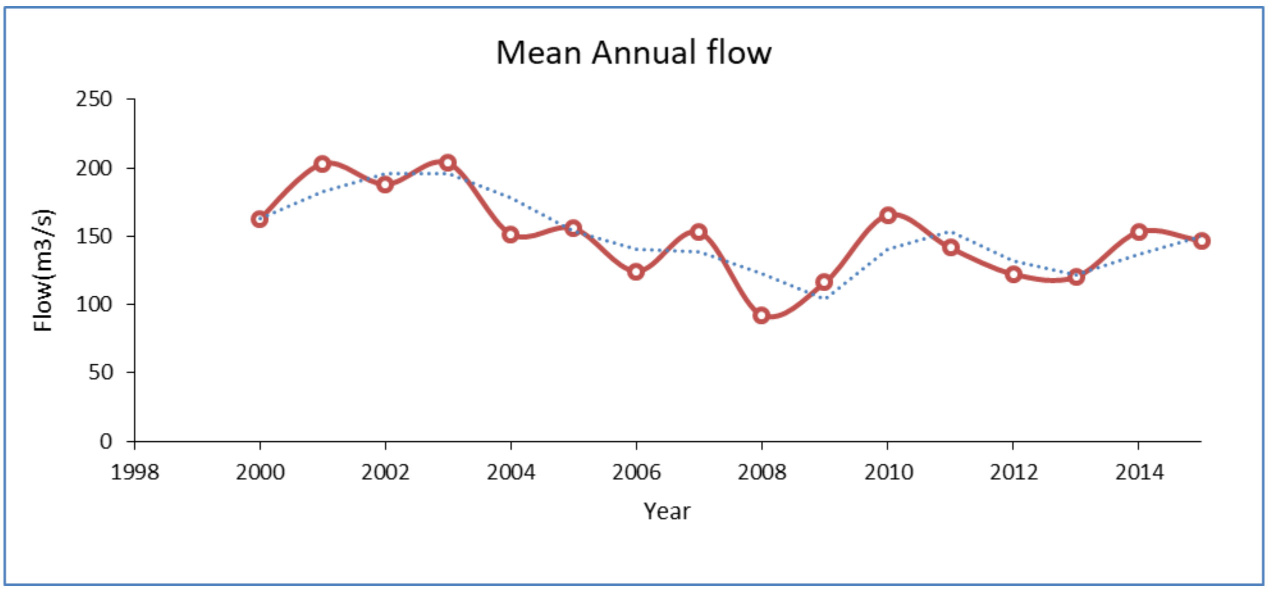


Figure 3. 5 Annual stream flow of Kulfo River

3.2.2 Data analysis

3.2.2.1 Preparation of data's

Before using any hydro-meteorological data's, it is necessary to first check their continuity and consistency. Continuity of data's may be broken due to presence of missing data due to damage or fault in measuring instruments, missing in observations of monitored data and misinterpretation of collected data(Subramanya, 2008). The longer data period of recent time would have been more useful to minimize uncertainties associated with model development. However, it is assumed that shorter and relatively older data period would not reduce the usefulness of the present modeling work(Kusre et al., 2010). Furthermore, this work is applied to demonstrate applicability of GIS and hydrological models to asses impact of land use change on stream flow, collection of long period data's of recent time has been tried to increase accuracy of work.

3.2.2.2 Filling Missing data's

All weather stations may not have fulfilled observation data because some weather stations may have instrumental error or failures and others have lack of record observers. Therefore, it should be necessary to estimate or fill in this missing record. Relatively, Arba Minch station has minimum missing precipitation and temperature data compared to other three stations. The table below shows percentage of missing data of stations in the study area.

Table 3. 3 Percentage of missing metrological data of stations

Station	Metrological data	% missing
	Precipitation	4.6
	Temperature	2.8
Arba Minch	Relative Humidity	9.4
	Sunshine hour	21.1
	Wind speed	8.9
Chancha	Precipitation	6.3
	Temperature	9.6
Geresse	Precipitation	14.3
	Temperature	8.9
Dara Malo	Precipitation	9.2
	Temperature	5.3

The missing precipitation and temperature records of metrological station has been estimated from the observation of data at some other station as close to as evenly space around station with the non-missing record as possible. However, relative humidity, sunshine hour and wind speed data's of Arbaminch station was filled from historical records of station itself by using multiple imputation method in which many researches recommend to use if there is/are no surrounding station/s to fill missed data(Hamzah et al., 2021; Patrician, 2002; Sinharay et al., 2001). Spatial distribution of four stations is not uniform. Due to this reason Arithmetic average method to fill missing data has been dis regarded. Missed metrological data in gauging station is conducted by using the normal ratio and inverse distance approaches, depending on the availability of data from nearby stations. Those methods have got great acceptance among many researchers due to their simplicity, adaptability and their accuracy (Hamzah et al., 2021; Paulhus & Kohler, 1952).

3.2.2.3 Outlier test

Values that depart from the norm in observations that appear to be lower or higher than other records are known as outliers. Outliers in the observation lead to inaccurate output results. For hydrological and meteorological data, one aspect of quality management is the detection of outliers. In particular for small sample sizes, the retention or removal of these outliers can have a considerable impact on the magnitude of statistical parameters generated from the data before conducting the outliers test (Chow, 2010). According to the Lach (2018), the major errors (outliers) should be eliminated from the sample before evaluating data analysis since they could considerably alter the results of the analysis and result in an incorrect interpretation.

It is not necessary for any of these all approaches to assume that the mean or variance is known or independently assessed. They are therefore self-contained in that the conclusion is based only on the sample data and does not require knowledge of the parameter values(Tietjen & Moore, 1972). Detecting outlier observations with the Grubbs test (Grubbs, 1950) is given by

$$G = \max \left| \left(\frac{X_i - \overline{X}}{S} \right) \right|$$

X_i is the ith observation and $\overline{X}$ is the sample mean, s is the sample standard deviation

Multiple Grubb's-beck test is a generalization of Grubb's beck test, it is used for detecting the multiple discordant that is based on the extremes value distribution or approximate normal distribution (Tiwari & Tripathi, 2022).

Because of its robustness and adaptability, this inquiry uses the multiple Grubb's-beck test with XLSTAT to find outliers(Dahmen & Hall, 1990; Silva et al., 2007). Each time, a significance threshold of 0.05 was taken into consideration, and the premise that each observation in the sample comes from the same normal population was assessed. Outliers are detected by using monthly stream flow of Kulfo River. All outliers detected are removed and filled by taking them as missing records.

3.2.2.4 Data consistency

Stations may be relocated over their life of operation. Record adjustment may be necessary to accommodate reasonable analyses and comparisons. If the conditions relevant to the recording of rain gauge stations have undergone a significant change during the period of record, inconsistency would arise in the rainfall data of that station s in the same region. To check a given weather station data time series observational data is relatively consistent and homogeneous and the periodic data are proportional to an appropriate simultaneous period. The double mass curve technique is a reliable procedure for checking the consistency of a precipitation record, e.g., when a station is moved(Dahmen & Hall, 1990; Searcy & Hardison, 1960). This technique compares long-term annual or seasonal precipitation of a group of comparison stations to the station being evaluated. To obtain more precise findings when analyzing hydro metrological data from multiple stations, the cumulative value of one variable is plotted against the cumulative value of the other stations. One station's average seasonal record and the average seasonal data for all stations are sorted in reverse chronological order, with the newest data at the top and the oldest at the bottom. Graph of cumulative of one quantity versus cumulative of other quantity during the result will be straight line all over the period if data is proportional and consistent. The constant proportionality between two quantities will be provided by the slope. Break in slope shows the occurrence of inconsistency in records and it is corrected by following relationship (Subramanya, 2008).

$$p_{cx} = p_x \frac{M_c}{M_a}$$

Where p_{cx} and p_x are corrected precipitation and original recorded precipitation and M_c , M_a are correct slope of the double mass curve and original slope of double mass curve respectively.

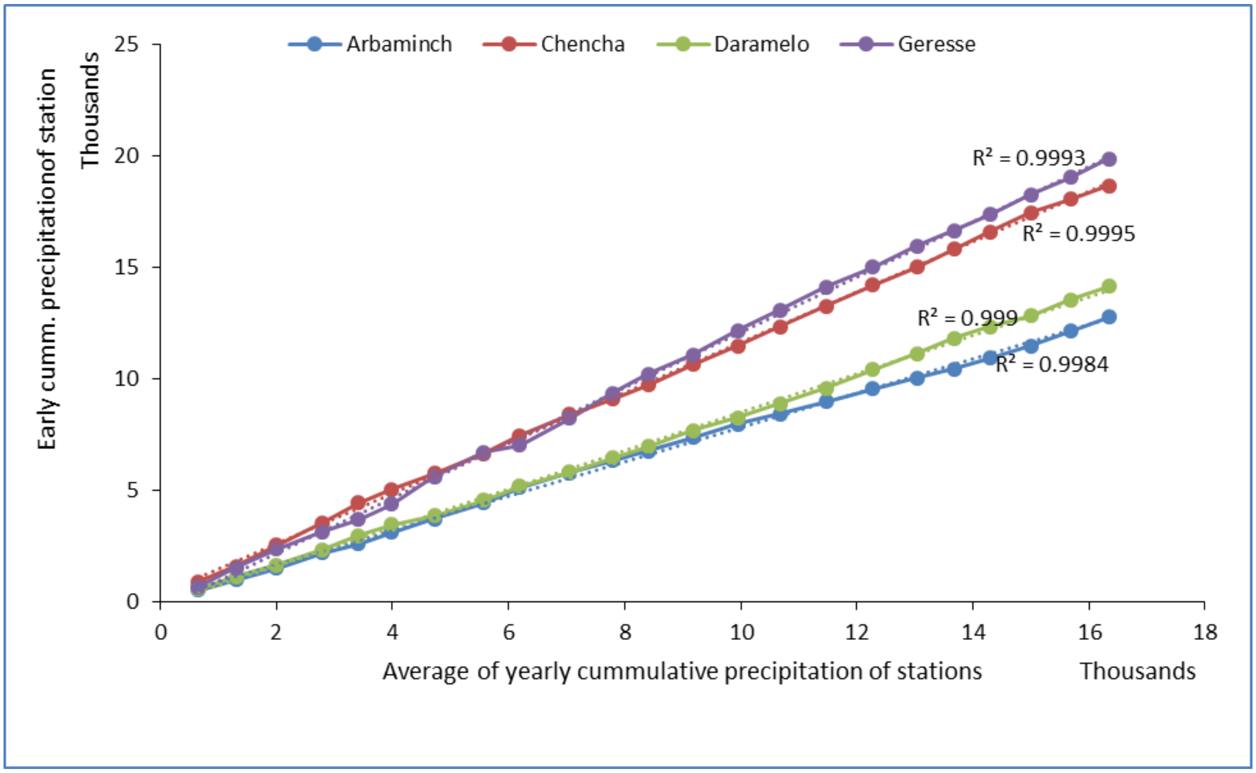


Figure 3. 6 consistency test of metrological stations

As shown in figure above, , the graph of cumulative precipitation of a single station and the average cumulative precipitation of the all station (used as base station) is straight line showing consistency of stations.

When it comes to hydrological data, the double-mass test cannot be used to stream-flow records since there are typically insufficient adjacent stream-gauging stations to allow for data comparison. Because of this, a single-mass curve analysis is frequently used to assess the consistency of the yearly flow records(Dahmen & Hall, 1990). This technique entails graphing the cumulative annual flows versus time, often as ordinates and abscissa. Again, a straight line representing the obtained representation indicates that the records are consistent. As shown in figure below, stream flow records of Kulfo river is consistent as the graph between cumulative annual flows versus time is straight line.

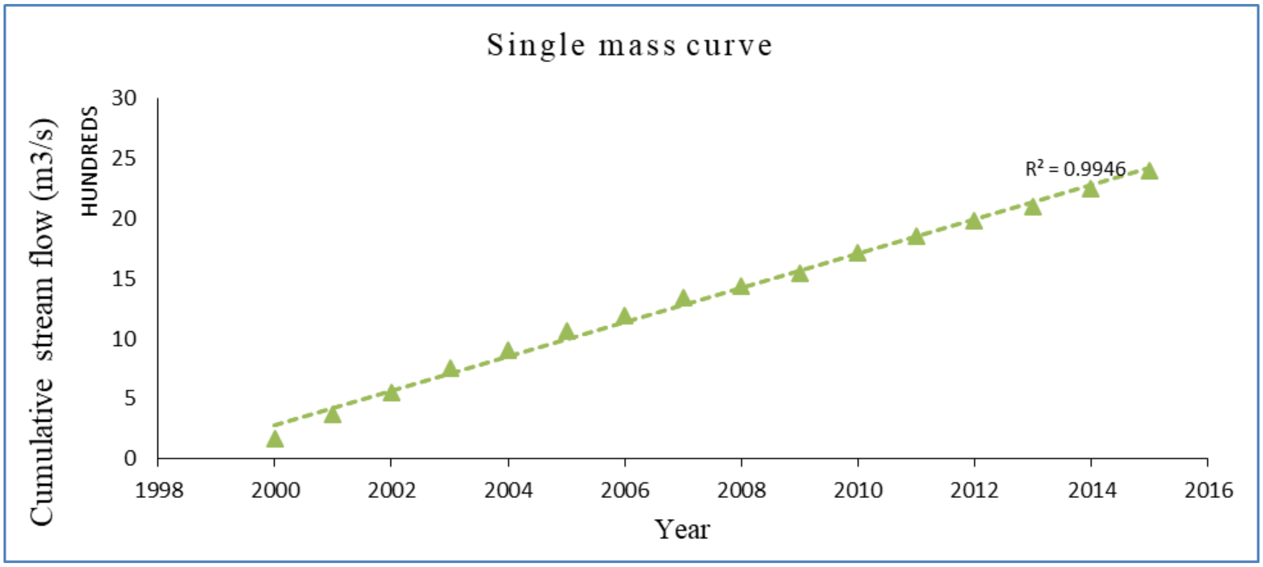


Figure 3. 7 Consistency of stream flow

3.2.2.5 Homogeneity test

Homogeneity is an important issue to detect the variability of the data. In general when the data is homogeneous, it means that the measurements of the data are taken at a time with the same instruments and environments(Kang & Yusof, 2012). However, handling rainfall data is challenging because there are constantly variations in measuring methods and observational standards, environmental features and structures, and station locations.

In this study Non-Dimensional parameterization (NDP) simple but effective method to test homogeneity was used. In this method, non-dimensional parameter (p_i) which is ratio of average monthly precipitation for stations (p_i^-) and average yearly precipitation of the station (P^-) is plotted with month and finally its trend is observed to check homogeneity.

$$p_i = \left[\frac{p_i^-}{P^-}\right] \times 100$$

As shown in figure below, it clear that the stations which have bi-modal distribution of precipitation are homogenous.

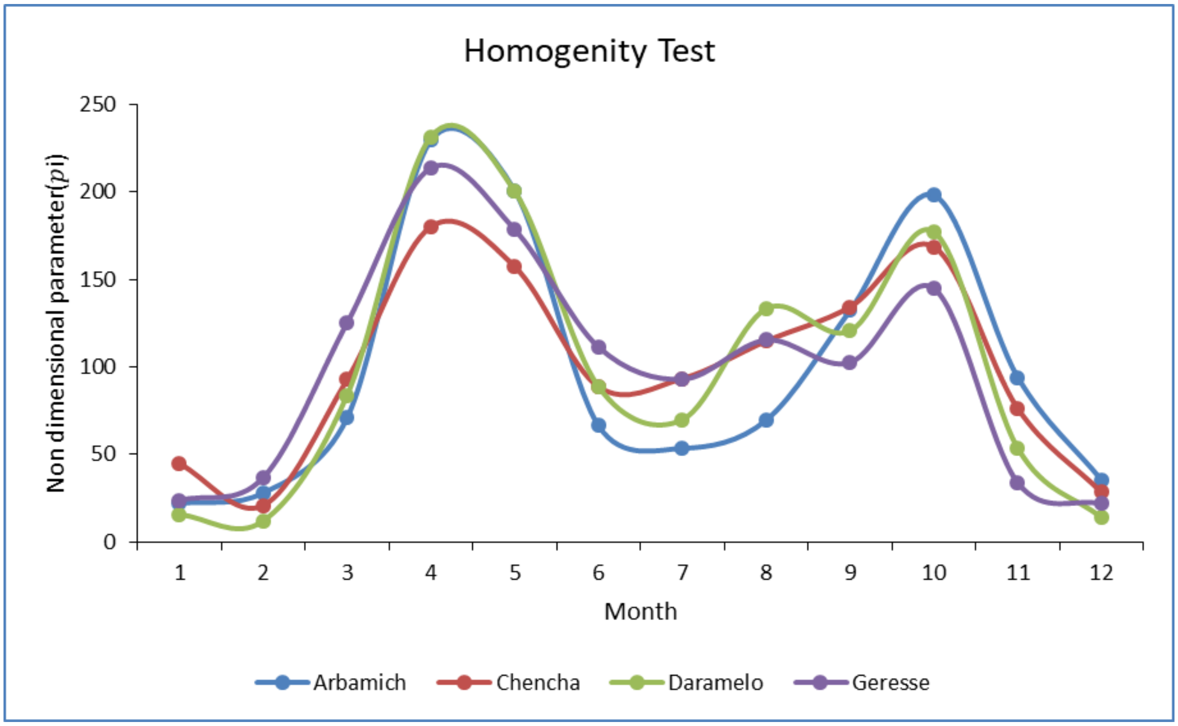


Figure 3. 8 Homogeneity test

3.2.2.6 Trend test

Using hydro metrological data for hydrological modeling needs detail and effective analysis of trends. Trend analysis is a quantitative review data's what happens over a period of time.

One of the most widely used non-parametric trend test methods for hydro metrological data quality assessments is the Mann-Kendall test (Hu et al., 2020; Likinaw et al., 2023; Seenu & Jayakumar, 2021; Wang et al., 2020). This test is simple, very accurate, depending on distribution, and flexible enough to adjust for data outliers. The Mann-Kendall method is unaffected by irregularities in the timing of the measurement points and is independent of the duration of the time series data.

In Mann-Kendall trend test, the alternative hypothesis (H1) in this test was that there has been a trend (increasing or decreasing) in precipitation over time, while the null hypothesis (H0) stated that there has been no trend in precipitation over time. Mathematical equation to estimate Mann-Kendall Statistics S, $V(S)$ and standardized test statistics Z are given in equation below(Ijaz Ahmad et al., 2015):

Where n is number of data points and x_j & x_i are data values in time series i and j respectively and sgn is sign function and it is function of equation

$$\operatorname{sgn}(x_j - x_i) = \begin{cases} +1 & \text{if } (x_j - x_i) > 0 \\ 0 & \text{if } (x_j - x_i) = 0 \\ -1 & \text{if } (x_j - x_i) < 0 \end{cases}$$

Variance is computed when $n \geq 10$ by equation

$$\operatorname{var}(s) = \frac{n(n-1)(2n+5) - \sum_{i=1}^{m} t_i(t-1)(2t_i+5)}{18}$$

$$Z = \begin{cases} \frac{s-1}{\sqrt{\operatorname{var}(s)}} & \text{if s>0} \\ 0 & \text{if s=0} \\ \frac{s+1}{\sqrt{\operatorname{var}(s)}} & \text{if s<0} \end{cases}$$

The total number of equal observations for extend I at a given date is represented by the symbol m, which is used to denote a collection of data points with the same data value. A tied group is a collection of sample data that have the same value. Z values that are positive suggest an upward trend while those that are negative imply a downward trend. To ascertain if the dataset shows an upward or downward trend, a significance value is also computed. The MK test's null hypothesis is that there is no trend, and its alternative hypothesis assumes that the time-series exhibits a monotonic trend. At the test significance level of α , the null hypothesis can only be rejected when $p < \alpha$. The selected significance level for this study is 0.05. The Mann-Kendall non-parametric trend test technique is now included in Excel via XLSTAT. In this study monthly series of stream flow data are used for trend analysis and procedure is doe through XLSTAT.

3.3 Method

3.3.1 General

General methodological frame work study which consists of three basic components (Image processing and land use land cover classification, Hydrological modeling and evaluation of LULC changes on stream flow) is illustrated in figure below.

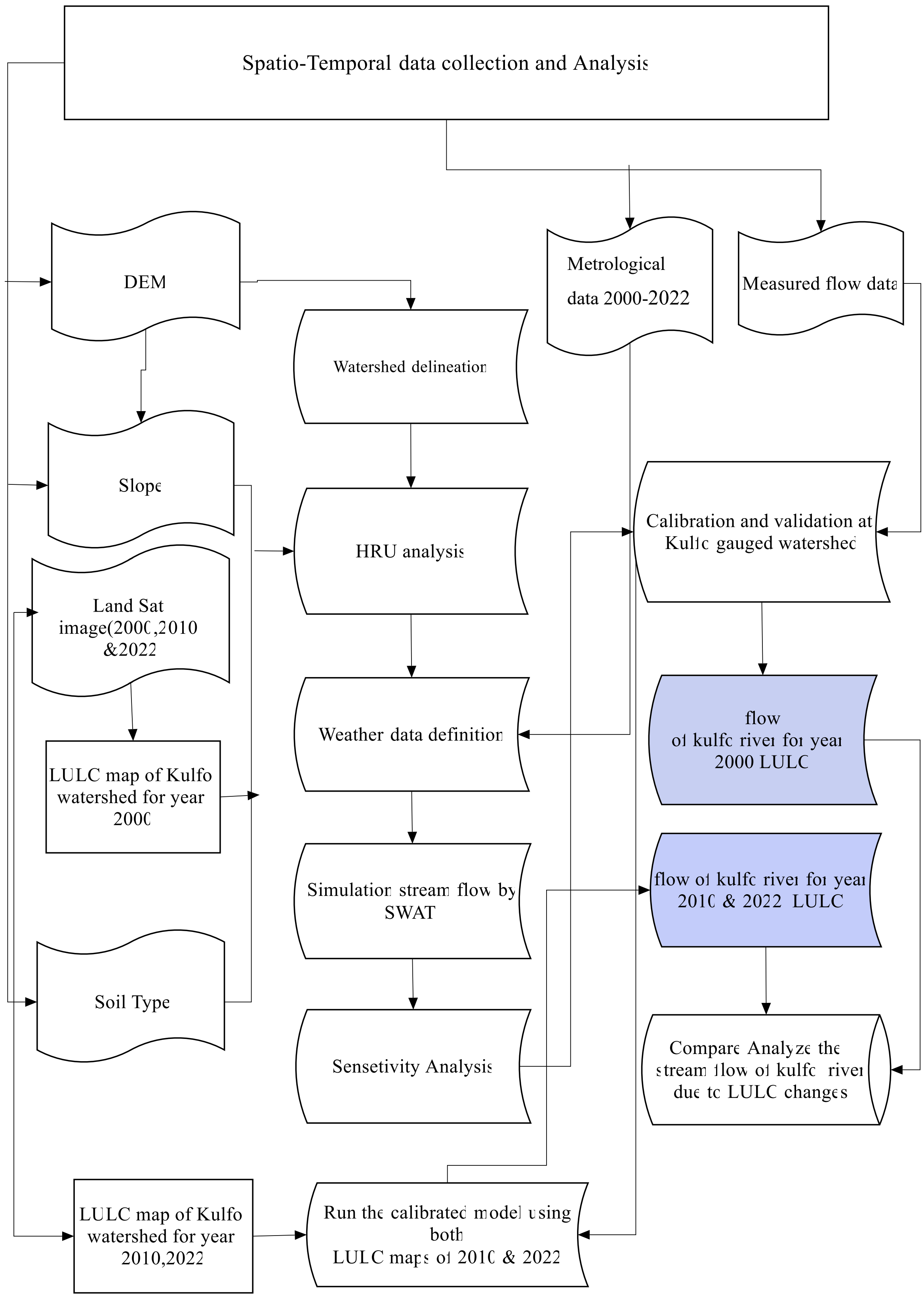


Figure 3. 9 Methodological frame work of the study

3.3.2 Image processing and land use and land cover map development

Satellite Landsat images (5 and 8) of the area which are downloaded from USGS were used for LULC classification. This has been conducted by using ERDAS IMAGINE software via Google earth. Satellite images available freely on online sources are subjected to distortion and cloud contaminations(Li et al., 2020). Therefore, Image preprocessing to improve the quality of images and thus boost them for analysis and further processing for land use land cover classification is essential. Some powerful image preprocessing techniques include layer stacking, noise reduction, contrast enhancement, image resizing, color correction, segmentation, feature extraction, etc (Phillips, 1994).

There are several image classification techniques used in remote sensing. Unsupervised, supervised and hybrid. Supervised classification uses a collection of training data to classify individual pixels in an image. The training examples are chosen by manually from the image and placed into the appropriate land cover classes. The remaining pixels in the image are then classified by the algorithm using this training set of data.

In unsupervised classification, pixels with similar spectral features are automatically grouped into groups by the method of classification. This technique is used in remote sensing. The method does not require any training data from the user. Rather, the program examines the image's spectral characteristics and finds pixel clusters that share comparable spectral characteristics.

For land use land cover classification, majority of researchers frequently used supervised image classification technique due to its accurate and efficient result for further analysis (Chughtai et al., 2021; Devi & Baboo, 2011; Regasa et al., 2021; Urgessa & Lemessa, 2020). The basic sequence operations followed on supervised classification to obtain LULC map of Kulfo watershed were summarized as follows;

Satellite imagery of different bands for Kulfo watershed has been obtained from USGS. Furthermore, ground truth data, which are actual samples of different land cover types from the field that can be used to validate the accuracy of map later are collected from filed by using GPS and additional samples were also obtained from Google Earth.

By importing satellite imagery into ERDAS Imagine 2015, radiometric and atmospheric corrections on the images has been performed. Finally, the areas designated as training grounds for each land cover class were identified. Usually, the digital features that are displayed on screen are used for this. Areas of Interest (AOI) are the features that have been built. The regions that could be easily recognized in all image sources were used to determine which training sites to use. Total of two hundred training sites were found in this investigation. After the establishment of training classes, the supervised classification was implemented. A certain class was represented by one or more training areas. The whole Signature editor was chosen to be applied on the classification process during the supervised classification procedure. Next, the classify/supervised option was chosen from the editor menu bar.

3.3.3 LULC classification accuracy assessment

An essential phase in the land use land cover classification process is accuracy assessment. The aim of this procedure is to ascertain, by quantitative means, the degree to which pixels in the examined area were correctly classified into feature classes. Through a comparison of the classified map and sample GCP points which were collected from easily accessible watershed parts by using GPS, existing land use land cover maps as well as observed features via Google earth, the accuracy of the image classification process was estimated.

Currently, the literature on accuracy assessment focuses on the confusion matrix among different various methods. Comparing the mapped class label to that found in the ground. The utilization of ground or reference data for a sample of cases at designated locations gives a clear basis for assessing accuracy. In fact, the confusion matrix offers the foundation for characterizing errors and describing classification accuracy, which could help towards enhancing the classification or estimates generated from it(Foody, 2002).

The most popular approach for figuring out the accuracy level is the contingency method, often known as the contingency matrix (confusion matrix). There are three types of information in the contingency matrix: producer accuracy, overall accuracy, and kappa accuracy. The estimators of overall accuracy are the accuracy of the producer and the user. The accuracy of the map as perceived by the user is known as the producer's accuracy, while the accuracy as seen by the user is known as the user's accuracy(Islami et al., 2022).

The overall accuracy of the classified image compares how each of the pixels is classified versus the definite land cover conditions obtained from their corresponding ground truth data. Producer’s accuracy measures errors of omission, which is a measure of how well real-world land cover types can be classified. User’s accuracy measures errors of commission, which represents the likelihood of a classified pixel matching the land cover type of its corresponding real-world location (Rwanga & Ndambuki, 2017).

$$Users\ accuracy = \frac{Number\ of\ correctly\ classified\ pixeles\ \text{in}\ each\ catagory}{Total\ \text{number of}\ reference\ pixeles\ \text{in}\ that\ catagory(row\ total)}$$

$$Producer\ accuracy = \frac{Number\ of\ correctly\ classified\ pixeles\ \text{in}\ each\ catagory}{Total\ \text{number of}\ reference\ pixeles\ \text{in}\ that\ catagory(column\ total)}$$

$$Overall\ accuracy = \frac{Total\ Number\ of\ correctly\ classified\ pixeles\ \text{(diagonal)}}{Total\ \text{number of}\ reference\ pixeles}$$

One most popular way to represent classification accuracy is Kappa coefficient (KC), from which a number of descriptive and analytical statistics can be obtained(Stehman & Foody, 2009; Van Vliet et al., 2011). By evaluating the degree of agreement between the prediction model and a collection of field surveyed sample points, it is utilized to calculate the accuracy of predictive models(Moriasi et al., 2007). KAPPA analysis yields a Khat statistic (an estimate of KAPPA) that is a measure of agreement or accuracy(Rwanga & Ndambuki, 2017). The Khat statistic (K) is computed as;

$$K = \frac{N\sum_{i-1}^{r} X_{ii} - \sum_{i=1}^{r}\left(x_{i+} \times x_{+i}\right)}{N^2 - \sum_{i=1}^{r}\left(x_{i+} \times x_{+i}\right)}$$

r = number of rows in error matrix, N = total number of observations (pixels)

Xii = the number of observations in row i and column i

Xi+ = marginal total of row i, and X+i = marginal total of column

Here under is detail procedure followed to estimate kappa statistics to measure the accuracy of model. Mostly adopted rating criteria for kappa statistics to measure the accuracy of model is indicated in Table below.

Table 3. 4 Rating criteria for kappa statistics (Landis & Koch, 1977)

S.No	Kappa statistics	Strength of agreement
1	<0.00	Poor
2	0.00-.0.20	Slight
3	0.21-0.40	Fair

4	0.41-0.60	Moderate
5	0.61-0.80	Substantial
6	0.81-1.00	Almost perfect

Observations features from Google earth and field data from easily accessible parts of watershed are used for the accuracy assessment process for the year 2022 for the classification results of the landsat-8 satellite image. To ensure the validity and precision of the classification results, a total of 130 random points (20 from field data and 110 from Google earth) have been used. To ensure the validity and precision of the classification results of map 2000 and 2010, a total of 217 random points (20 samples from interview from old peoples around Arba Minch town and 197 from Google earth by adjusting its historical image viewer) has been used. The following table depicts some sample ground truth points from Google earth and additional samples taken from ground by using hand Gps.

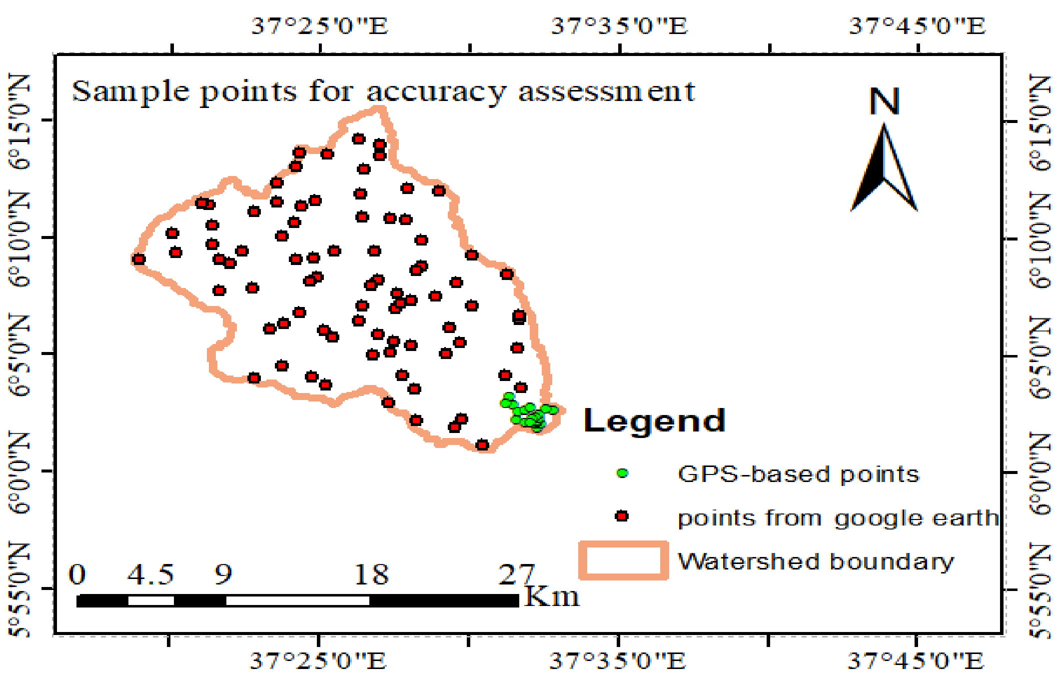


Table 3. 5 Sample points for accuracy assessment

3.3.4 Land use land cover change detection

In order to find which land-use class is shifting from one features to the others over study years, classified land cover maps of 2000,2010 and 2022 have been imported in to ERDAS. Post classification change detection method based on the matrix laboratory compiler (MLC) algorithms has been used in the study to determine land cover changes. Each types of land cover's covered areas over the different time periods had compared. Next, each type of land cover's alterations' directions positive or negative were identified. The following equation is used to calculate degree of changes (C_i) for each classes.

$C_i = L_i - B_i$

The change in class is divided with the coverage area base year and again multiplied by 100.the calculations was used to estimate percentage changes (C%) which is calculated by following formula

$$\mathrm{Pi} = \frac{\mathrm{Li} - \mathrm{Bi}}{\mathrm{Bi}} * 100$$

The number of class in the images is indicated by i. Ci indicates how much class i has changed and Pi is percentage change of class i.Li means basic image during comparison.

3.4 Hydrological modeling using SWAT

3.4.1 Model setup and stream flow simulation

Evaluation of impact of land use land cover changes on stream flow requires hydrological models in order to predict stream flow at un-gauged water courses. In this study SWAT model has used to simulate stream flow for different land use land cover maps. The modeling procedure includes SWAT project setup, Watershed delineation, and HRU Analysis, write input tables, edit swat input and SWAT simulation. Using 30 m resolution DEM data and the Arc SWAT model watershed delineation function, the watershed and sub watershed delineation was carried out.

By establishing threshold values for soil, slope percentage, land use, and land cover, the sub watersheds were divided into HRUs. Unlike employing a single slope approach, the multiple slope classes' technique was applied to account for the various slopes that present within the area. In the study, a more accurate estimate of the components of runoff is obtained by using the HRU definition with several alternatives considerations of 10% land use, 20% soil, and 10% slope for overlay analysis as recommended by (Arnold et al., 1998). Once HRU analysis is defined in SWAT the next step is weather generator. SWAT model needs set of precipitation and temperature data from all stations. In addition, at least one station has to be synoptic station with sufficient relative humidity, sunshine hour and wind speed. For remaining stations, it is possible to generate those data's by using weather generator program in SWAT. In this study, Arbaminch station has all important data for SWAT input and to generate climatic variables for other stations.

3.4.2 Sensitivity analysis

Sensitivity analysis is used to show how various sources of variation in the model input can be linked to differences in the model output. Sensitivity analysis aids in the calibration of the SWAT model by revealing a number of parameters. The aim of sensitivity analysis is to estimate the rate of change in the output of a model with respect to changes in watersheds that result in a clear difference in hydrologic sensitivity. The sensitivity analysis tool is helpful to model users in identifying parameters that are most influential in governing stream flow response Sufi-2 algorithm of SWAT-CUP software package was used to for sensitivity analysis, calibration and validation. Parameter estimation through calibration is concerned with the problem of making inferences about physical systems from measured output stream flow (Abbaspour et al., 2017).

For the sensitivity analysis, stream flow recorded at Kulfo Gauging Station between 2000 and 2015 periods was used. Global sensitivity analysis of 16 flow parameters gathered from several articles conducted in and near of the study area(Ayalew et al., 2022; Ayele et al., 2016; Meaza et al., 2019; Mikias, 2015; Yifru et al., 2021) was conducted by using SWAT-Cup using SUFI-2. The ranking of the sensitive parameters is determined by the global sensitivity analysis's p-value and t-statistic. The greatest absolute value of the t-stat, which is used to identify a measure of sensitivity for each parameter, and a p-value used to assess significance of sensitivity that is close to zero are both indicators of greater sensitivity. Parameters having P value less than 0.05 are considered as most sensitive parameters(Abbaspour et al., 2017)

3.4.3 Calibration and validation

Model calibration is the process of finding the best fit between measured data and model predictions by varying input parameters within a tolerable range. According to Abbaspour (2015), model validation is the process of verifying the calibrated model by contrasting the observed data with the model predictions while keeping all input parameter values constant. Calibration and validation procedures are used to assess the performance of Watershed models. With the aid of software known as SWAT-CUP, the performance of the model has been assessed. In this study utilizing measured data from Kulfo river station near Arbaminch from 2000-2015.

Because calibration is by nature entirely subjective, it is closely related to the uncertainty of the model's output. The challenge of deriving conclusions about physical systems from measurable model output variables such as river discharge, sediment concentration, nitrate load, etc. is known as parameter estimation by calibration. This is appealing since it is typically less applicable, expensive, time-consuming, and tedious to directly measure the characteristics characterizing the physical system. The majority of measurements have some mistake, models are oversimplifications of reality, and inferences are often statistical in character. These factors all contribute to uncertainty(Abbaspour et al., 2017). Additionally, no calibration can result in a single parameter set or output because one can only measure a finite number of data and because continuous equations are typically used to simulate physical systems. Putting another way, there will be numerous models if only one fulfills the measurements.

3.4.4 Performance evaluation

Performance of the model was checked by statistical tests that can be used to judge the SWAT model. According to Coffey et al. (2013), the statistical tests that are used to judge the SWAT model including R^2, NSE, root mean square error (RMSE), nonparametric tests, t-test, objective functions, autocorrelation, and cross-correlation. For this study, Nash– Sutcliffe efficiency (NSE), percent bias (PBIAS), and coefficient of determination (R^2) which are recommended by(Moriasi et al., 2012) are used for performance evaluation.

The Nash–Sutcliffe efficiency (Weick & Sutcliffe, 2001) indicates how well the plot of observed versus simulated data fits the 1:1 line. It generally ranges from - ∞ to 1. The higher value of NSE indicates better accuracy of model prediction whereas lower NSE indicates poor model prediction and if it is 0.5 the model is satisfactory. NSE is computed as shown below:

$$NSE = 1 - \frac{\sum_{t=1}^{T=t}\left(Q_o^t - Q_m^t\right)^2}{\sum_{t=1}^{T}\left(Q_o^t - \overline{Q_o}\right)^2}$$

Where Q_o^t is observed value of stream flow, Q_m^t is the simulated value of stream flow, and $\overline{Q_o}$ is the average of the observed values of stream flow.

Percent of Bias (PBIAS) measures the average tendency of the simulated data to be larger or smaller than their observed counterparts. The optimal value of PBIAS is 0.0, with low magnitude values indicating accurate model simulation. Positive values indicate model underestimation bias, and negative values indicate model overestimation bias (O'connell et al., 1970) PBIAS is, generally, expressed in percentage and is calculated using Equation Below.

$$PBIAS = \frac{\sum_{i=1}^{I=n} V_o - \sum_{i=1}^{n} V_e}{\sum_{i=1}^{n} V_o} \%$$

Where V_o and V_e are respectively the observed and simulated volumes of water for day *i.*

The root means square error (RMSE) and the standard deviation of observed flow (σ_o) can be expressed as a ratio (RSR). RSR is calculated using equation.

$$RMSE = \frac{RMSE}{\sigma_o} = \frac{\sqrt{\sum (Q_{oi} - Q_{ei})^2}}{\sqrt{\sum \left(Q_{oi} - \overline{Q_o}\right)^2}}$$

Table 3. 6 Performance evaluations for stream flow simulation

performance	NSE	PBIAS	R^2
Unsatisfactory	$NSE \leq 0.5$	$PBIAS \geq \pm 25$	$R^2 < 0.50$
Satisfactory	$0.5 < NSE \leq 0.65$	$\pm 15 \leq PBIAS < \pm 25$	$0.50 < R^2 < 0.70$
Good	$0.65 < NSE \leq 0.75$	$\pm 10 \leq PBIAS < \pm 15$	$0.70 < R^2 < 0.800$
Very good	$0.75 < NSE \leq 1$	$PBIAS < \pm 10$	>0.80

The process of verifying that a particular site-specific model is capable of performing sufficiently realistic simulations which can vary depending on project goals is known as validation(Arnold et al., 2012). Without making any additional adjustments to the parameters, it is used to test the calibrated parameters using a different set of data. It is used to build confidence on calibrated parameters. The analyst is required to do one iteration with the same number of simulations as in the last calibration iteration. Similar to calibration, validation results are also quantified by the p-factor, r-factor, and the objective function value(Abbaspour et al., 2017). The measured data of average monthly stream flow from 2010-2015 at Kulfo river gauging station at new bridge near Arba Minch was used for model validation.

The choice between daily or monthly calibration for a SWAT (Soil and Water Assessment Tool) model depends on several factors, including the availability and quality of data, the specific objectives of the study, and computational resources. Daily data may provide more detailed information about hydrological processes, such as rainfall patterns, evapotranspiration rates, or stream flow dynamics(Arnold et al., 2012; Thampi et al., 2010). However, obtaining reliable daily data can be challenging in some regions or for certain variables. In such cases, monthly data may be more readily available. Another criterion for using daily or monthly basis for evaluation of model performance is objectives of the Study: If study aims to investigate short-term variations in hydrological processes or simulate events with high temporal resolution (e.g., floods), daily calibration might be more suitable. On the other hand, if study focus is on long-term trends or average conditions over a longer period (e.g., annual water yield), monthly calibration could be sufficient(Wang et al., 2011; Ye et al., 1997).

3.5 Effect of land use land cover change on stream flow

This is the main objective of study. Once land use land cover change of Kulfo watershed is assessed and stream flow of river for those various LULC maps is simulated, final procedure has been to assess impact of those land use land cover changes on stream flow. The study is conducted for three different periods(2000,2010 and 2022).As depicted in methodological frame work, stream flow simulation of river is conducted by using land use land cover map of 2000 and the result has been well calibrated and validated through procedures entailed above. Well-calibrated and validated parameters are used to simulate stream flow by imputing land use land cover maps of 2010 and 2022. Finally, simulated stream flow by using three land use land cover maps has been compared to see effect of land use change on simulation outputs.

4. RESULTS AND DISCUSSIONS

4.1 Land use land cover change in Kulfo watershed

4.1.1 Land use land cover map of Kulfo Watershed

The spatial analysis had carried out to describe land cover change patterns and overall land-use changes with time. Land use and land cover maps of study area is conducted by supervised classification of satellite images for three different periods(2000,2010 and 2022) by ERDAS Imagine 2015. The main ERDAS-based classified land use and land cover groups of Kulfo watershed are described in table below.

Table 4. 1 Main land use land cover types of Kulfo watershed

S.No	Land use land cover class	Description
1	Crop land	Crop fields and fallow lands
2	Settlements	Settlement areas of residential buildings
3	Forest	Area covered with dense trees including mixed forest and plantation forest
4	Pasture	Area of land covered with grasses
5	Shrub land	Woody vegetation's and plants
6	River	Part of land which is covered with flowing water.

Land use land cover change analysis of Kulfo watershed for 22 years was conducted in order to evaluate impact of changes on stream flow. Merely 44.25% of the watershed was covered in crops in 2000, while about thirty percent of the area was pasture (grass-covered land).Approximately 58.51km^2 of land, or 15.49% of the total area, were covered in forest this year. In 2010, it is observed from results that, there was slight increment of shrub lands in watershed from 2000 to 2010. This change again reduced during 2022 due to expansion of agricultural activities in the area.

As results of image classification indicates, during 2000, upper portion and lower portions of watershed were covered with grasses latterly changed in to agricultural land. Due to expansion of Arba Minch town, the lower areas of the watershed around the town which were covered in agricultural land in 2010 are subsequently transformed into settlements in 2022.

According to the most recent LULC map for the year 2022 and the percentage coverage of each land cover class (Table 4.2 and Figure 4.1), the watershed consists of a total of 21.34% grassland, 11.65% forest land, 8.52% shrub land, 57.47% agricultural land, and 0.55% of settlement area. Some areas of grass lands and shrub lands were reduced and primarily replaced by agricultural land in this most recent land use map. Recent expansion of Arba Minch Town has resulted in the conversion of a small section of agricultural land into settlements.

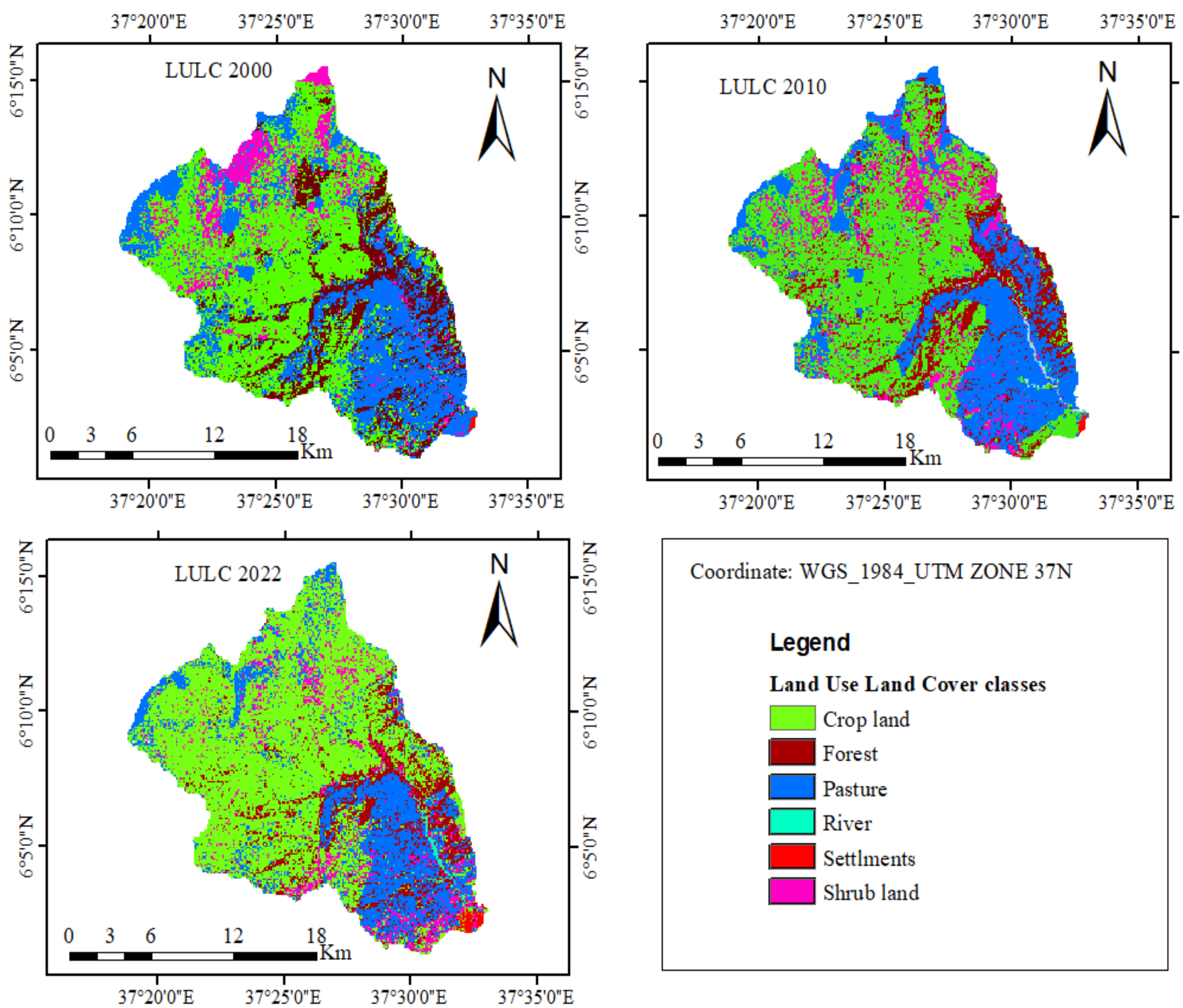


Figure 4.1 LULC maps of Kulfo watershed for different years

Generally, results of study revealed significantly increasing the amount of agricultural land throughout the catchment which is also supported by study conducted by (Wankie, 2015). Furthermore, it is disclosed that there is occasionally a minor depreciation of forest land due to expansion of agricultural expansion and overgrazing in area. Summary of areal coverage of land use land cover categories of study area over study years is depicted in table below.

Table 4. 2 Spatial coverage of LULC class

S.No	LULC Type	2000		2010		2022	
		Area(Km^2)	%	Area(Km^2)	%	Area(Km^2)	%
1	Water body(River)	1.80	0.48	1.92	0.51	1.77	0.47
2	Forest	58.51	15.49	49.02	12.98	44.00	11.65
3	Crop land	167.12	44.25	174.22	46.13	217.04	57.47
4	Shrub land	37.06	9.81	42.68	11.30	32.16	8.52
5	Pasture	113.59	30.08	109.38	28.96	80.58	21.34
6	Settlements	0.34	0.09	0.48	0.13	2.08	0.55

4.1.2 Accuracy Assessment

For LULC maps to be used more effectively and appropriately for analysis, users must be aware of the classification accuracy level. The accuracy assessment is used to ascertain the land use classification's accuracy results. As per reference Anderson (1976), a lower than 80% interpretation accuracy of land use and land cover change is prohibited.

Table 4. 3 Calculation of land use land cover map 2022 accuracy assessment.

LULC classes	Water Body	Forest	Crop land	Shrub land	Pasture	Settlements	Total	User accuracy
Water Body	3	0	0	0	0	0	3	100.00
Forest	0	9	1	1	0	0	11	81.82
Crop land	0	1	34	2	2	0	39	87.18
Shrub land	0	1	2	13	1	0	17	76.47
Pasture	0	0	4	4	32	0	40	80.00
Settlements	0	0	0	0	0	20	20	100.00
Total	3	11	41	20	35	20	130	**85.38**
Producer accuracy	100.00	81.82	82.93	65.00	91.43	100		

Kappa coefficient is calculated by using mathematical expression given in equation is K=81.5%

Table 4. 4 Calculation of land use land cover map 2010 accuracy assessment.

LULC classes	Water Body	Forest	Crop land	Shrub land	Pasture	Settlements	Total	User accuracy
Water Body	4	0	0	0	0	1	5	80.00
Forest	0	11	0	2	1	0	14	78.57
Crop land	0	0	84	6	10	0	100	84.00
Shrub land	0	8	8	54	4	0	74	72.97
Pasture	0	0	4	3	18	0	25	72.00
Settlements	0	0	0	0	0	3	3	100
Total	4	19	96	65	33	4	217	**80.18**
Producer accuracy	100.00	57.89	87.50	83.08	54.55	75		

Kappa coefficient (K)= 80.43

Similar procedures have been conducted to assess accuracy of land use land cover map for year 2000. 219 sample points from historical Google earth image viewer were used for error matrix formation to estimate accuracy of classification.

Table 4. 5 Calculation of land use land cover map 2000 accuracy assessment.

LULC classes	Water Body	Forest	Crop land	Shrub land	Pasture	Settlements	Total	User accuracy
Water Body	2	0	0	0	0	1	3	66.67
Forest	0	9	0	4	1	0	14	64.29
Crop land	0	0	66	6	13	0	85	77.65
Shrub land	0	8	6	54	4	0	72	75.00
Pasture	0	0	4	6	36	0	46	78.26
Settlements	0	0	0	0	0	3	3	100
Total	2	17	76	70	54	4	219	**77.63**
Producer accuracy	100.00	52.94	86.84	77.14	66.67	75		

Kappa coefficient (K)= 80.18

The aforementioned tables show that image classification for mapping land use and cover varies from substantial to almost perfect ranges. The findings suggest that a map of classified land use and land cover is accurate and can be used to study the impact of LULC changes on stream flow. When we compare the image classification of current years with older ones, we find that both the overall accuracy and the Kappa coefficient decrease. This is because satellite image quality has improved from time to time, making it possible to see exact and precise features(Mishra et al., 2016). The use of ground truth points for verification of image processing and classification contributed for improvements in Kappa coefficient and overall accuracy factors. The table below is a summary of the accuracy assessment factors for each LULC class for each study year.

The confusion between forest and shrub land as well as crop land and pasture are understandable since these areas of land cover share similar spectral characteristics in satellite images. Forests and shrub lands can have similar vegetation characteristics, such as dense vegetation cover and similar tree/shrub species composition, which can make it challenging to differentiate between them based purely on visual interpretation. In addition, there may be fragmented landscapes with mixed patches of forests, shrubs, crops, and pastures occurring in close proximity. These complex patterns make it difficult to accurately delineate boundaries between different land use/cover types. Throughout the whole image classification period, certain mistakes were made in agricultural surfaces. Due to significant spectral similarities across features, similar issues are probably expected(Getachew & Melesse, 2012).

Table 4. 6 Summary of the accuracy evaluation

Year	Overall Accuracy (%)	Kappa Coefficient (%)
2022	87.23	82.30
2010	80.13	80.43
2000	77.63	80.18

4.1.3 Land use and land cover change detection

As displayed in the following figures over the previous 22 years, there has been some changes in the land cover and land use of the Kulfo watershed. The figure below depicts some notable changes in the area's land cover and land use over the span of three classification periods. During the year 2010, there is some shifts from crop land to shrub land and pasture. It is also revealed that the area's land cover and land use changed significantly between 2000 and 2010: from crop land to pasture and from crop land to shrub land. This may be due to plantation of eucalyptus trees and ever green vegetation in the area. In a contrary, there is also significant class change from pasture to crop land between the periods. Almost 27Km^2 area of land which was pasture during 2000 has been shifted in to crop land in 2010. Summary of LULC class changes between 2000 and 2010 is depicted in figure below.

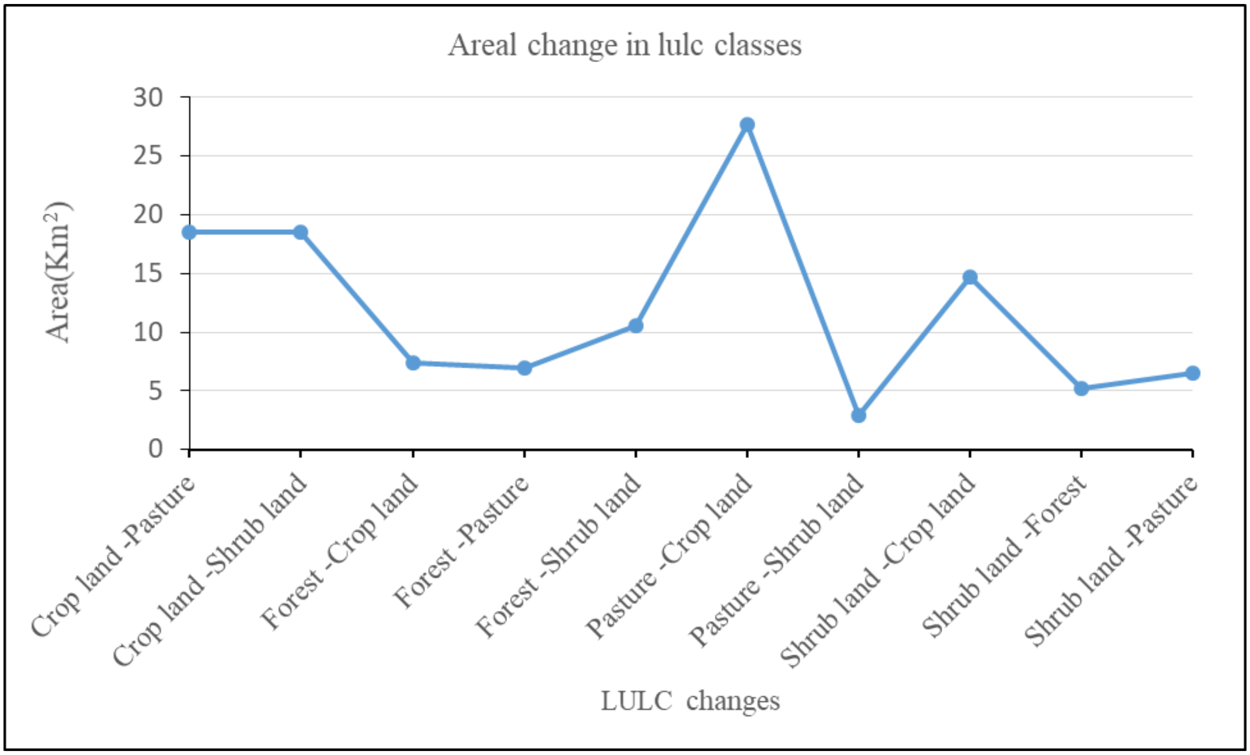


Figure 4. 2 LULC class changes from 2000 to 2010

Significant changes in land use and land cover have also observed between years of 2010 and 2022. One of the major changes noticed during this period is conversion of agricultural land in to settlements. More than 1.6Km^2 of agricultural land was changed in to urban area due to expansion of Arba Minch town towards south direction. Significant interchangeable conversion of land use class from crop land to pasture is also noticed within 12 years of periods. 46km^2 of pasture land was changed in to agricultural land where as 37Km^2 of crop land was converted in to pasture. Land cover change from crop land to shrub land has been also seen as one of occurred events between those years.

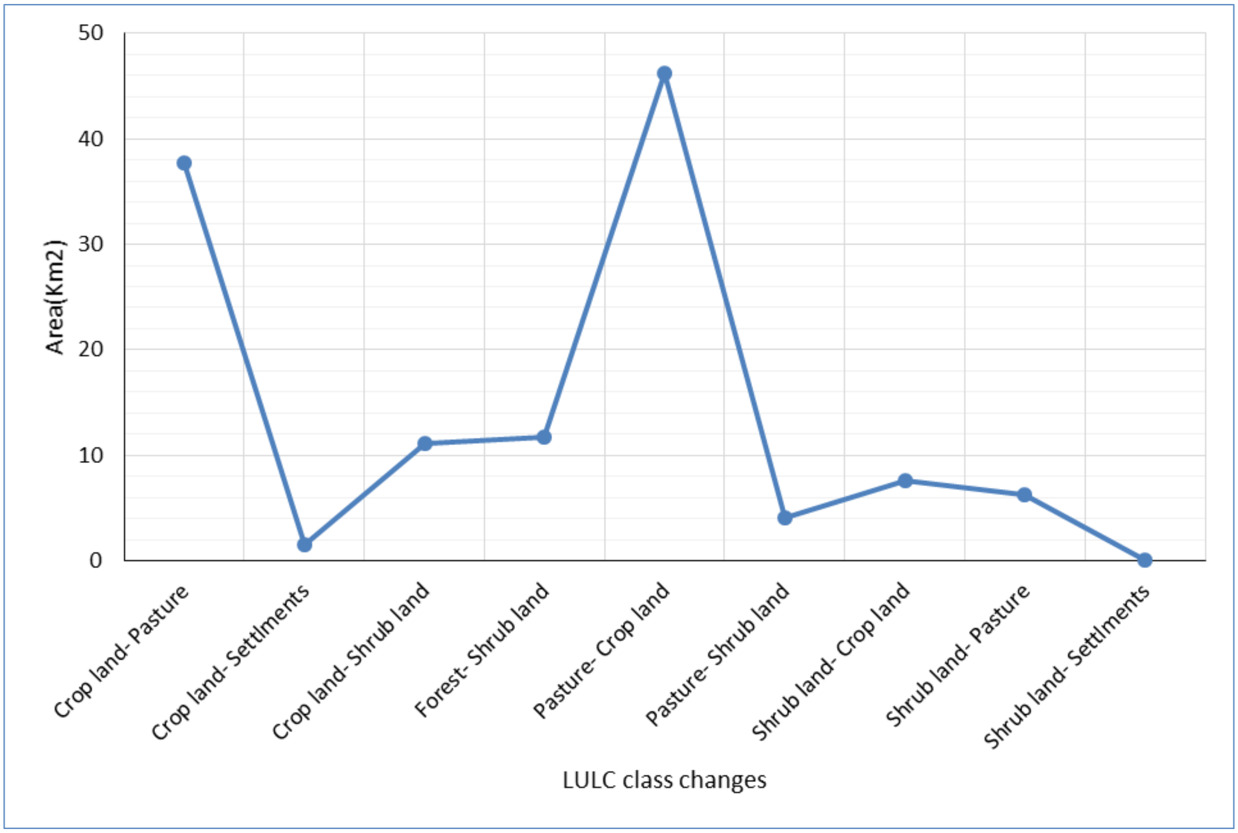


Figure 4.2 LULC class change from 2010 to 2022

Interchangeable conversion of pasture land and agricultural land was the main observed event in the years 2010 and 2022. This feature's interchangeability could indicate that local farmers are employing contemporary farming techniques to interchange pasture land and agricultural land which are vital for better agricultural efficiency. It has been revealed by different studies that overgrazing and related activities have been becoming main issues in the study area that changed land use and land cover dynamics of Kulfo watershed(Tunkala et al.; Yirgu et al., 2020). The figure below illustrates the general LULC type conversion from one class to another.

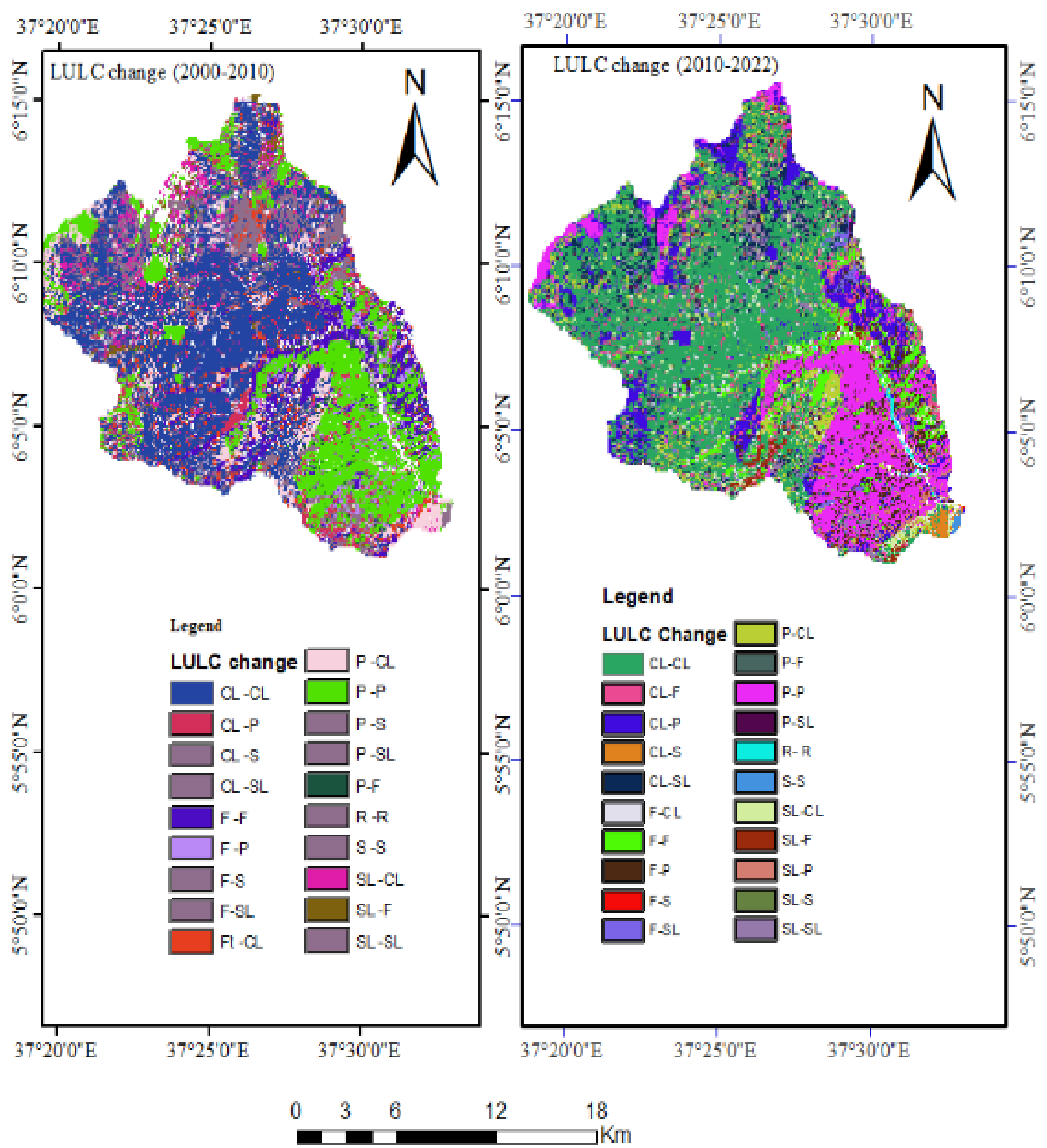


Figure 4. 4 LULC changes of Kulfo watershed

CL	Crop land	SL	Shrub land	R	River
P	Pasture	F	Forest	S	settlements

LULC change detection in the Kulfo watershed revealed that agricultural land and settlement areas increased from 2000 to 2022 while pasture land and shrub land has shown little decrement in areal coverage. This is a result of population growth driving up demand for agricultural land, which in turn drives up agricultural expansion. The results of study are similar with other findings conducted in Kulfo watershed and other neighboring watersheds. For instance study by Mekuria et al. (2021) revealed expansion of farmlands, has occurred at the expense of grasslands, forestlands and shrub lands in rift valley basin between 1973 and 2005 . Multi-temporal Land Use/Land Cover Change Detection for the Batena Watershed, Rift Valley Lakes Basin, Ethiopia was conducted by Ayele et al. (2016). The study's findings showed that overall forest cover and shrub land had decreased while agricultural lands increased by more than 41.7% between years 1973 and 2008. The study aimed to assess land use and land cover changes (LULCC) effects on stream flow of the upper Gidabo Watershed, Ethiopia was conducted by Belihu et al. (2020). The researchers concluded that urbanization and agricultural areas were escalating at the expense of grasslands, shrub land and forests.

4.2 Stream flow simulation by SWAT

4.2.1 Sensitivity analysis

Out of 16 parameters, 10 parameters listed in table below with P-stat value less than 0.05 were selected as highly sensitive which affect model output.

Table 4. 7 Parameters used for sensitivity analysis.

Parameter	Parameter Name	t-stat	P-stat	Rank
V_CN$_2$.mgt	SCS runoff curve number	30.4	0.00	1
V-RCHRG_DP.gw	Deep aquifer percolation fraction	26.7	0.00	2
V_CH_K$_2$.rte	Effective hydraulic conductivity in main channel alluvium	19.8	0.00	3
R_OV_N.hru	Manning's "n" value for overland flow	24.3	0.01	4
V__ALPHA_BF.gw	Base flow alpha factor (days)	24.6	0.01	5
R_SOL_BD(..).sol	Moist bulk density of soil	12.2	0.02	6
V_GWQMN.gw	Threshold depth of water in the shallow aquifer required for return flow to occur (mm)	-10.80	0.02	7
R_SOL_AWC(..).sol	Available water capacity of the soil layer	-5.60	0.03	8
V_SURLAG.bsn	Surface runoff lag time	-1.37	0.03	9
V-ESCO.hru	Plant uptake compensation factor	-1.27	0.05	10
R_SOL_Z(..).sol	Depth from soil surface to bottom of layer.	1.08	0.08	11

V_GW_DELAY.gw	Groundwater delay (days)	1.06	0.09	12
V_REVAPMN.gw	Threshold depth of water in the shallow aquifer for "revap" to occur (mm	1.06	0.246	13
R_EPCO.bsn	Plant uptake compensation factor.	0.53	0.59	14
V_CH_N2.rte	Manning's "n" value for the main channel.	-1.26	0.7 1	15
V_GW_REVAP.gw	Threshold depth of water in the shallow aquifer for "revap" to occur (mm)	-0.065	0.83	16

The CN_2 parameter, which represents the initial moisture content of the soil profile, was found to be highly sensitive to changes in the model predictions. is most sensitive parameter that highly affects simulated output of the model. This rank is expected due to reason that SWAT model uses internally embedded soil conservation service (SCS) curve method to compute stream flow. Most of studies conducted in SWAT-based simulation of stream flow identified CN2 as most sensitive parameter among others (Ashenafi & Hailu, 2014; Belihu et al., 2020; Kebede, 2019; Leta et al., 2022; Mengistu et al., 2022). The rate at which surface runoff is generated is influenced by CN_2, which is a function of soil permeability, land use/cover, and the antecedent soil moisture. Despite having little effect on minimum flow, an increase in CN_2 will result in an increase in peak stream flow.

The RCHRG_DP.gw parameter, which represents the groundwater "revap" coefficient, has been also found to be highly sensitive. Adjusting this parameter impacted the rate of movement of water from the shallow aquifer to the overlying unsaturated zone. Increasing RCHRG_DP.gw resulted in more water being drawn from the shallow aquifer, which improved the simulation of baseflow contributions to the stream.

The CH_K_2.rte parameter, which controls surface runoff, was also identified as a sensitive parameter. This parameter impacts the partitioning of precipitation into surface runoff, infiltration, and other hydrologic processes. Adjustments of CH_K_2.rte allowed the model to better simulate the surface runoff response to rainfall events.

Moist bulk density of soil and threshold depth of water in the shallow aquifer required for return flow to occur are also sixth sensitive parameters that affect SWAT output. Moist bulk density of soil is an indicator of soil compaction. This parameter affects the infiltration rate of rainfall into the soil profile and the storage capacity of the soil, and small changes in its value can significantly impact the recharge rate of the groundwater system(Zemke et al., 2019). The SURLAG parameter, which represents the surface runoff lag time, was found to be sensitive. Adjusting this parameter altered the timing of the surface runoff response to precipitation events, which in turn affected the shape of the simulated stream flow hydrograph.

Lastly, the ESCO parameter, which represents the soil evaporation compensation factor, was identified as a sensitive parameter. This parameter influenced the partitioning of precipitation into evapotranspiration and other hydrologic processes, and calibrating it helped to improve the water balance simulation

Most of parameters identified as sensitive in watershed are consistent with other studies conducted in rift valley. For instance, study conducted by Belihu et al. (2020) listed sensitive parameters as CN2.mgt, ALPHA_BF.gw, GW_DELAY.gw, GWQMN.gw and EPCO.bsn. Other study aimed to estimate of runoff and Sediment Yield katar watershed of rift valley Using SWAT Model, revealed threshold water depth in shallow aquifer and SCS runoff curve number as top leading sensitive parameters next to Saturated Hydraulic conductivity of soil.

4.2.2 Calibration and validation

Calibration of stream flow has been performed depending on observed flow measurements of kulfo river from 2000 to 2010. In the process identified model parameters are altered within optimum range until model output matches with observed stream flow. The goodness of fit between observed and simulated stream flow was assessed by objective functions of NSE,R^2,RMSE and PBIAS. Final adjusted calibrated parameters values for stream flow are shown below.

Table 4. 8 Sensitive parameters and fitted values

Parameter	Parameter description	Fitted	Min	Max
V_CN_2.mgt	SCS runoff curve number	74	30	100
V-RCHRG_DP.gw	Deep aquifer percolation fraction	0.21	0	1
V_CH_K_2.rte	Effective hydraulic conductivity in main channel alluvium	0.38	0	1
R_OV_N.hru	Manning's "n" value for overland flow	0.03	0	1
V__ALPHA_BF.gw	Base flow alpha factor (days)	0.6	0	1
R_SOL_BD(..).sol	Moist bulk density of soil	1.6	0.9	2.5

V_GWQMN.gw	Threshold depth of water in the shallow aquifer required for return flow to occur (mm)	667	0	5000
R_SOL_AWC(..).sol	Available water capacity of the soil layer	0	0	1
V_SURLAG.bsn	Surface runoff lag time	13.5	1	24
V-ESCO.hru	Plant uptake compensation factor	0.36	0	1

An independent measured dataset is subjected to the calibrated parameter ranges for validation procedures, without any additional modifications by using average monthly stream flow from 2011 to 2015.

The statistical objective function outcomes for calibration and validation indicated "very good" efficiency during calibration and validation. In addition to objective functions, performance of hydrological model has to be measured by using p and t factors. These measurements are within the simulation uncertainty of our model; hence, they are simulated well and accounted for by the model. Subsequently, (1-p-factor) represent the measured data not simulated well by the model, in other words, (1-p-factor) is the model error. R-factor is a measure of the thickness of the 95PPU band and is calculated as the average 95PPU thickness divided by the standard deviation of the corresponding observed variable. During the calibration phase, the Nash-Sutcliffe efficiency (NSE), correlation coefficient (R^2), root mean square error (RMSE) and percent of bias (PBIAS) were all 0.81, 0.83, 0.12 % and -0.1 respectively. During validation, showed better performance with those objective functions as 0.84, 0.86, 0.01 % and 0.03 respectively.

Table 4. 9 Calibration and validation results of average monthly observed and simulated flow

Phase	Objective functions				
	NSE	R^2	RMSE (%)	PBIAS	Evaluation
Calibration(2000-2010)	0.81	0.83	0.12	-0.1	*Very Good*
Validation(2011-2015)	0.84	0.86	0.01	0.03	*Very good*

The comparison between the observed and simulated mean annual flow provides valuable insights into the performance of the SWAT model in Kulfo catchment. Overall, the results of the calibration and validation showed that SWAT model has performed effectively in simulating stream flow of

Kulfo River. The figure below illustrates further diagrammatical comparison of simulated and observed monthly stream of Kulfo river

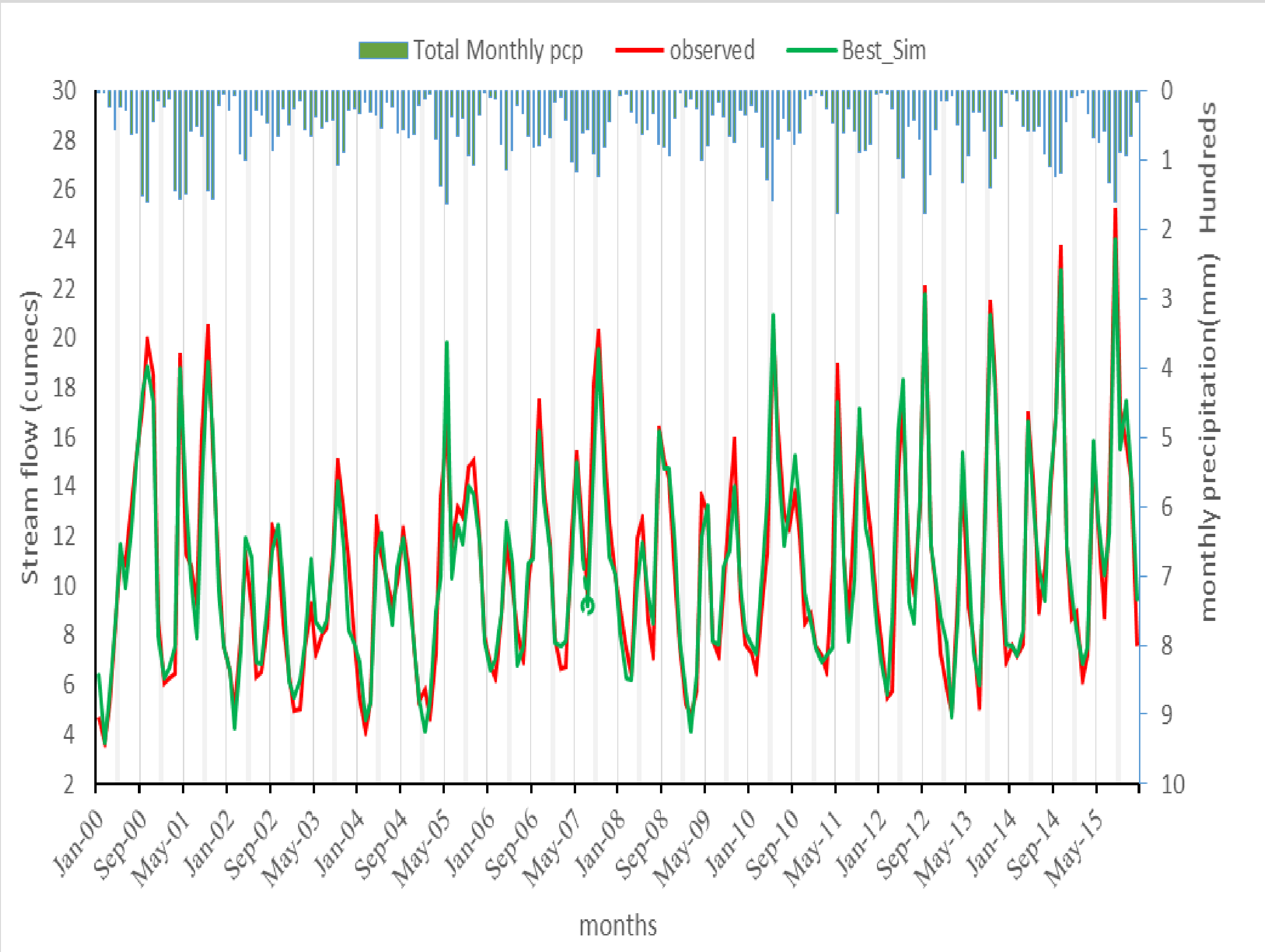


Figure 4.3 Observed versus simulated flow during calibration

During calibration periods with peak flow, SWAT model has underestimated stream flow. This is expectedly explained as limitations of model which could be partly because days that have intense weather events cannot be reliably predicted by the existing curve number technique which is embeded in SWAT model. Some articles on the subject have also examined this SWAT model weakness(Zhao et al., 2013). When repeated storms occur in a single day, the runoff curve number and soil moisture content of each storm are distinct in reality. However, SCS-CN methods consider all the rain that falls in a given day as be single rainfall event, which could lead to an underestimate of runoff(Chow et al., 1988). As shown in figure above ,it seems that SWAT over estimated stream flow and failed to cupture observed stream flow during periods of low flow. This is due to reduction in stream flow records at flow monitoring station as the results of water abstraction and detentions for irrigation,water supply and other demostic activites in the watershed. Those activies in the watershed which are common during dry seasons have not been accounted in SWAT-based simulation of stream flow. Corresponding corrlation of simulated stream flow with observed one is depicted in figure below.

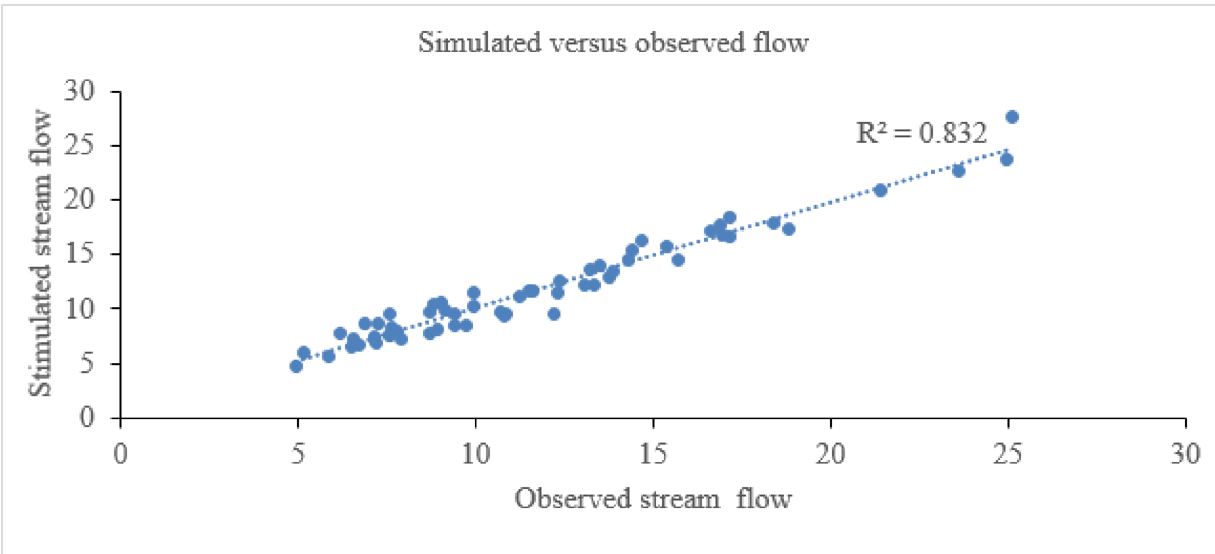


Figure 4.4 Scatter plot of observed and simulated flow

The R^2 value of 0.83 indicates a strong correlation between the observed and simulated stream flow data, with the model explaining 83% of the variability in the observed data. This suggests that the SWAT model was able to capture the overall trends and patterns in the stream flow dynamics within the study area.

The validation results also showed a PBIAS value of 0.03, indicating a slight bias in the forward direction. This means that, on average, the simulated values are slightly higher than the observed values. However, the magnitude of the bias is relatively small, suggesting that the model is still able to provide reliable predictions. The validation results revealed an R^2 value of 0.86, indicating a strong relationship between the observed and simulated values. This suggests that the model is able to capture a significant portion of the variability in the data, with minimal residual errors. As a whole , SWAT performed well in tracking the observed minimum and maximum streamflow during validation.

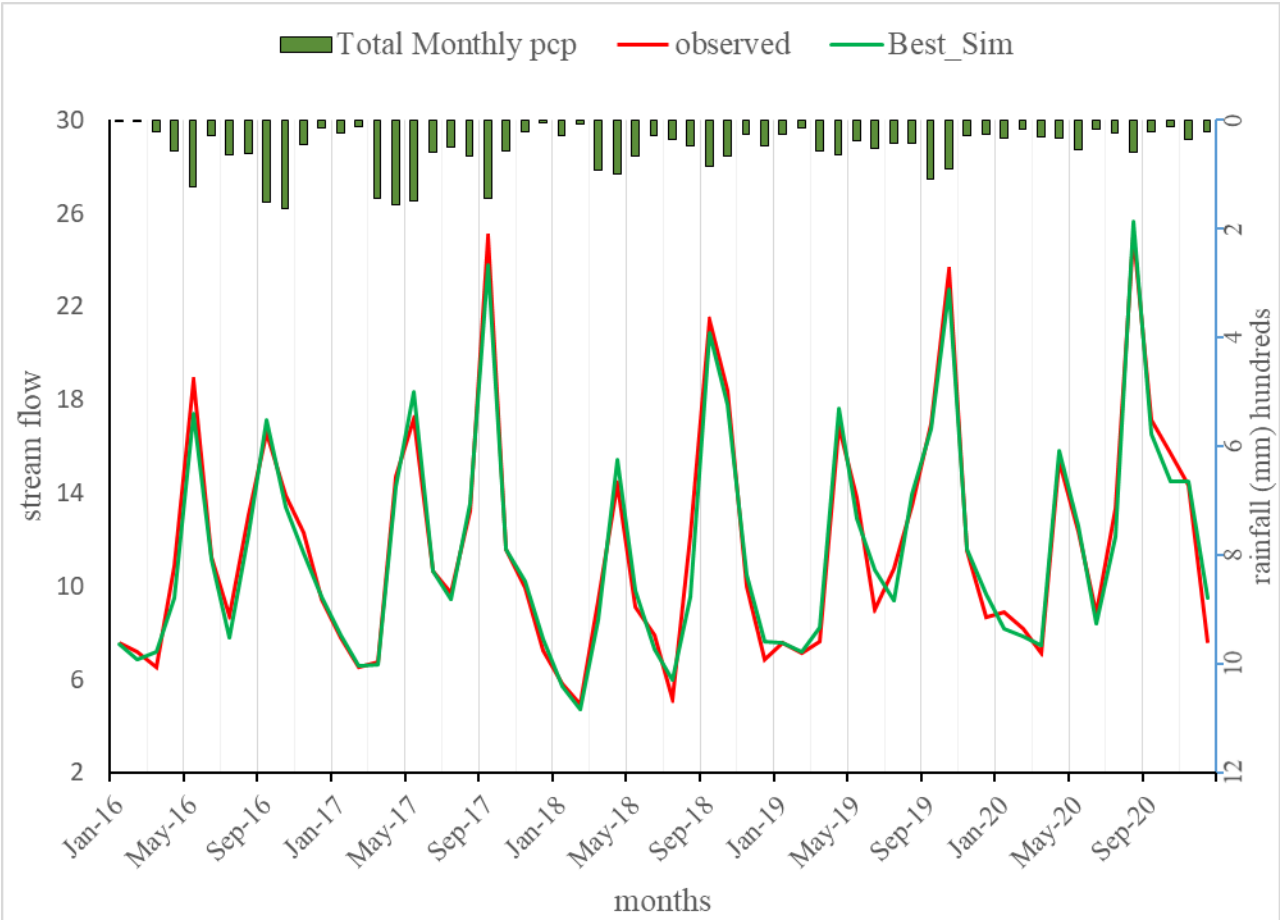


Figure 4.5 Observed and simulated flow during validation

The combination of these performance metrics during calibration and validation demonstrates the overall effectiveness of SWAT model in simulating the stream flow dynamics within the study area. The strong R^2, high NSE, low RMSE, and near-zero PBIAS suggest that the model has been calibrated and validated successfully, and can be confidently used for further study, analysis and decision-making related to land use land cover change impact on stream flow of study area.

4.3 Evaluation of impact of LULC change on stream flow

A comparison of the land use/cover maps from the 2000, 2010 and 2022 revealed that there is some non-exaggerated land use/cover change over time. In order to assess the variability of stream flow due to changes in land use and land cover between study periods, three independent simulation runs were carried out on a monthly basis by using three land use and land cover maps for the period of 2000,2010 and 2022, keeping all well calibrated input parameters and weather data's constant.

Changes in seasonal monthly flow and mean annual flow due to variations in land use and land cover map were assessed and comparison have been made on surface runoff and ground water flow contributions to stream flow based on three simulation outputs.

Accordingly, study results revealed presence of some non-exaggerated alterations on stream flow due to land use and land cover changes in the area. All monthly and mean yearly stream flows were found to be considerably higher in the simulations performed using the most recent LULC map (LULC map 2022). Mean annual stream of Kulfo river at considered monitoring station has been estimated as 142.3m^3/s while it was estimated as 130.8 and 121.2m^3/s using LULC maps of 2010 and 2000 respectively.

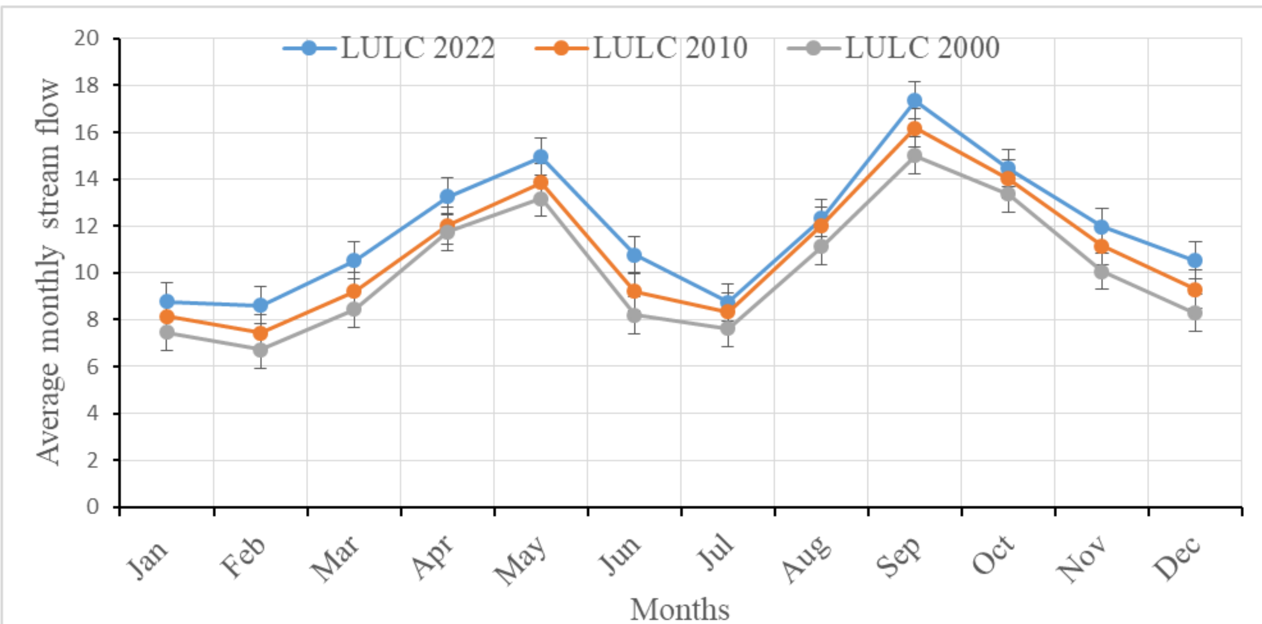


Figure 4. 6 Monthly flow of Kulfo watershed for different LULC maps

LULC	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Total
2022	8.77	8.62	10.52	13.26	14.96	10.77	8.75	12.32	17.36	14.45	11.98	10.53	142.29
2010	8.14	7.43	9.20	12.02	13.86	9.20	8.32	12.01	16.19	14.01	11.16	9.30	130.84
2000	7.45	6.73	8.44	11.75	13.18	8.19	7.61	11.11	15.00	13.37	10.07	8.28	121.19

The annual mean stream flow simulated using the LULC map from 2010 differs from the one with 2000 by 9.65m^3/s. In a comparable vein, stream flow increased from 130.84 to 142.29 m^3/s (increased by 11.45) in simulations conducted using LULC maps 2010 and 2022. These variations in stream flow result from the conversion of pasture to cropland, shrub land to agricultural land, and the ensuing increase in agricultural activity at the expense of the loss of forest and shrub land. Although area of land converted from agricultural land in to settlements is too small, it is expected to have its own impact on increments in surface flow. This is because even minor alterations from other earth features to urban areas will cause an unexpectedly large impact on stream flow(Bulti & Abebe, 2020; Negash et al., 2023). Mean monthly wet and dry month stream flow simulation and their variability with different land use land cover is also shown in figure below.

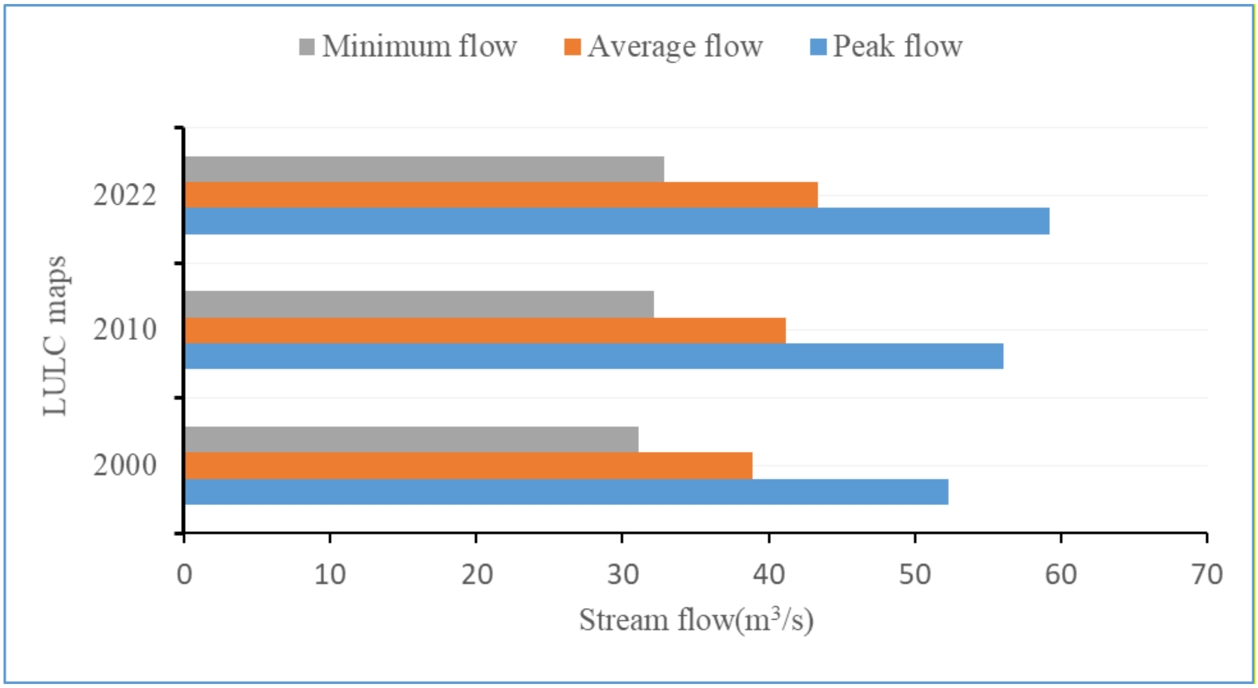


Figure 4. 7 Seasonal surface runoff of Kulfo watershed for different LULC maps

Results indicated in table above slightly verifies significant impact of LULC change has more influence in wet season stream flow(April, may, September and October) than that of dry season(January, February, July and December).This result is also concurrent with other studies conducted in similar topic at different watersheds(Anja, 2021; Aredehey et al., 2020; Ayalew et al., 2022). Impact of LULC change in ground water flow contribution for Kulfo River is shown in figure below.

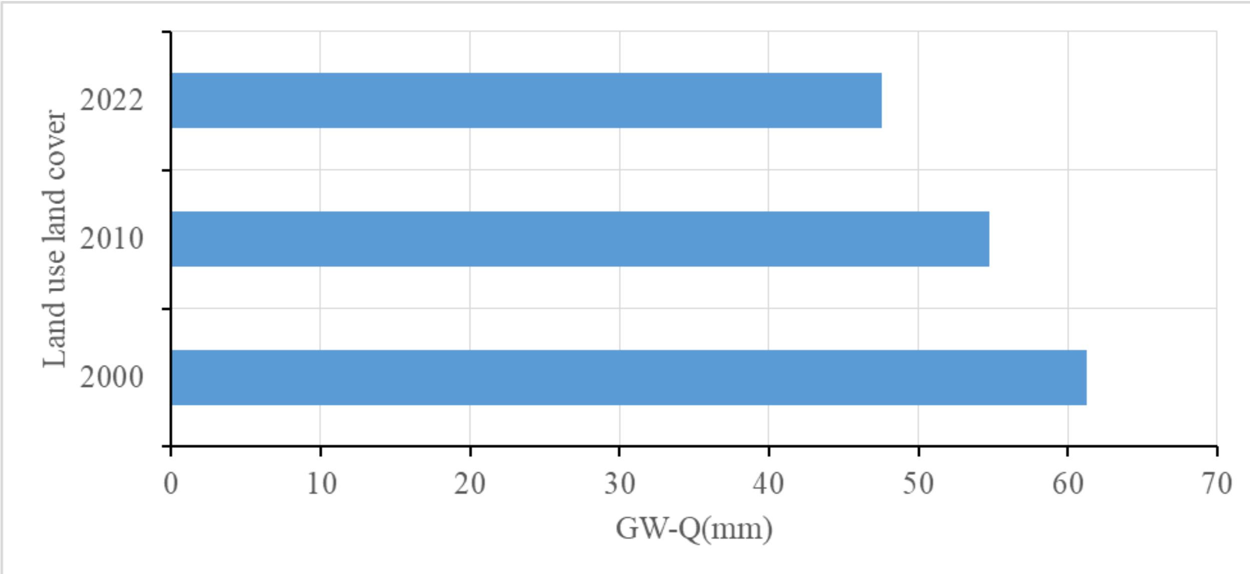


Figure 4. 8 Variation of ground water flow with LULC

As depicted in figure above, LULC changes occurred in Kulfo watershed have become causes for ground water flow reduction. This is a result of urbanization and agricultural land development at the expense of declining grass, forest, and shrub lands, which limits soil infiltration rate.

5. CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

LULC change has become a significant issue in Ethiopia, a nation renowned for its diverse topography, as a result of the country's agriculture focus economic policies and quickly growing population. Developing and carrying out long-term plans for the management of land and water resources requires a knowledge how changes in land use and land cover affects stream flow of watershed. This study is aimed in evaluating impact of land use land cover change on stream flow of Kulfo River. In the study, detection of land use land cover changes of watershed and its impact on stream flow has been analyzed. ERDAS IMAGINE and SWAT model coupled with GIS have been used for land use land cover change detection and stream flow simulation respectively. Accordingly, Land use land cover change over 22 years (2000 to 2022) has been analyzed by dividing periods in to three (2000,2010 and 2022). Accordingly.it is revealed that there is increasing trend in agricultural land and urbanization at the expense of decrease in grass land, shrub land and forest. It is observed from study results that, area of Kulfo watershed covered with crop and shrub (vegetation) has been increased from 44% to 46% and 9.8% to 11.3% respectively between study periods of 2000 and 2010. In contrary, there is declining trend of earth features covered with forest and grass land from 15.5% to 13% and 30% to 28.9% respectively between those years. Similarly, between periods 2022 and 2010,forest cover, shrub land and grass land of area have decreased to 11%,8.5% and 21% respectively whereas land covered with crop land has been increased in to 57.5% as well as settlement area increased during the times, rising from 0.13% to 0.55%.

Accuracy of SWAT model to simulate stream flow of Kulfo watershed was evaluated by using historical stream flow records from 2000-2015 monitored at Kulfo river near Arba Minch. Goodness of simulated stream flow with measured has been evaluated by using objective functions of NSE, R^2, RMSE and PBIAS of SUFI-2 algorithm. Results indicated very good performance of model during calibration and validation. During calibration, those objective functions have been determined as 0.81, 0.83, 0.12 and -0.1% respectively. During validation, those objective functions have been estimated as 0.84, 0.86,-0.01 and 0.03 respectively.

By altering the LULC maps while keeping the other SWAT inputs unchanged, an analysis was carried out using SWAT to determine the influence of those changes on stream flow. The result showed slight impact on surface flow and ground water contribution of Kulfo River during wet and dry seasons. The modeled yearly average stream flow with LULC map of 2010 was 9.65 m^3/s more than that of 2000 one. Similarly, the modeled yearly average stream flow with LULC map of 2022 was 11.45 m^3/s more than that of 2010. The results of study also revealed slight decrement in ground water contribution as the result of expansion of agriculture and urbanization which turn decreases infiltration capacity of soil. The study shows that there is some impact associated with land cover change on stream flow, even if excessive variation of stream flow with land use land cover changes was not observed due to the small study area. In conclusion, both methodologies applied here and results obtained in the study could be a useful support for governmental and non-governmental decision makers which take part in integrated watershed management, planning and implementations for environmental protection.

5.2 Recommendations

It is evaluated by the study through calibration and validation that SWAT can simulate stream flow of un-gauged catchments accurately. However, it is highly recommended to use multiple models, evaluating their performances and finally choosing the best model for watershed scale to come in to decisions to improve accuracy of the study. Therefore, further investigators are recommended to use multiple models like HEC-HMS, HSPF and WBM and evaluate the performance of each model then finally apply best performing model for watershed simulations.

In this study climate changes over study period has been disregarded. For future investigations it is also recommended to apply methodologies to combine its impact by considering climate changes in addition to corresponding land use land cover change impacts.

REFERENCES

Abbaspour, K. C., Vaghefi, S. A., & Srinivasan, R. J. W. (2017). A guideline for successful calibration and uncertainty analysis for soil and water assessment: a review of papers from the 2016 international SWAT conference. *10*(1), 6.

Abbaspour, K. C. J. A. u. m. (2015). SWAT calibration and uncertainty programs. *103*, 17-66.

Abd El-Kawy, O., Rød, J., Ismail, H., & Suliman, A. J. A. g. (2011). Land use and land cover change detection in the western Nile delta of Egypt using remote sensing data. *31*(2), 483-494.

Ahmad, I., Tang, D., Wang, T., Wang, M., & Wagan, B. J. A. i. M. (2015). Precipitation trends over time using Mann-Kendall and spearman's rho tests in swat river basin, Pakistan. *2015*.

Anderson, J. R. (1976). *A land use and land cover classification system for use with remote sensor data* (Vol. 964): US Government Printing Office.

Anja, A. (2021). Evaluating the Land Use and Land Cover Change Impact on Streamflow, Kulfo Catchment. *Thesis*.

Aredehey, G., Mezgebu, A., & Girma, A. J. C. E. S. (2020). The effects of land use land cover change on hydrological flow in Giba catchment, Tigray, Ethiopia. *6*(1), 1785780.

Arnold, J. G., & Fohrer, N. J. H. P. A. I. J. (2005). SWAT2000: current capabilities and research opportunities in applied watershed modelling. *19*(3), 563-572.

Arnold, J. G., Moriasi, D. N., Gassman, P. W., Abbaspour, K. C., White, M. J., Srinivasan, R., . . . Van Liew, M. W. J. T. o. t. A. (2012). SWAT: Model use, calibration, and validation. *55*(4), 1491-1508.

Arnold, J. G., Srinivasan, R., Muttiah, R. S., & Williams, J. R. J. J. J. o. t. A. W. R. A. (1998). Large area hydrologic modeling and assessment part I: model development 1. *34*(1), 73-89.

Ashenafi, Y., & Hailu, D. J. Z. J. (2014). Assessment of the use of remotely sensed rainfall products for runoff simulation in the Upper Blue Nile basin of Ethiopia. *31*, 1-9.

Ayalew, A. D., Wagner, P. D., Sahlu, D., Fohrer, N. J. E. M., & Assessment. (2022). Land use change and climate dynamics in the Rift Valley Lake Basin, Ethiopia. *194*(11), 791.

Ayele, G. T., Demessie, S. S., Mengistu, K. T., Tilahun, S. A., Melesse, A. M. J. L. D., soils, & climates, h. p. i. v. (2016). Multitemporal land use/land cover change detection for the Batena Watershed, Rift Valley Lakes Basin, Ethiopia. 51-72.

Barkhordari, J. (2003). Assessing the effects of land use change on the hydrologic regime by RS and GIS.

Bekele, S., & Hailemariam, A. J. E. E. R. (2010). Population dynamics and environment in Ethiopia: an overview. (1).

Belihu, M., Tekleab, S., Abate, B., & Bewket, W. J. H. (2020). Hydrologic response to land use land cover change in the Upper Gidabo Watershed, Rift Valley Lakes Basin, Ethiopia. *3*, 85-94.

Berihun, M. L., Tsunekawa, A., Haregeweyn, N., Meshesha, D. T., Adgo, E., Tsubo, M., . . . Yibeltal, M. J. L. u. p. (2019). Exploring land use/land cover changes, drivers and their implications in contrasting agro-ecological environments of Ethiopia. *87*, 104052.

Brannan Kevin, M., Saied, M., & Cho, J.-P. J. J. o. K. S. o. R. P. (2003). Predicting runoff and sediment yield on a forest dominated watershed using HSPF and SWAT models. *9*(4), 59-64.

Bulti, D. T., & Abebe, B. G. J. S. A. S. (2020). Analyzing the impacts of urbanization on runoff characteristics in Adama city, Ethiopia. *2*, 1-13.

Cavazzi, S., Corstanje, R., Mayr, T., Hannam, J., & Fealy, R. J. G. (2013). Are fine resolution digital elevation models always the best choice in digital soil mapping? *, 195*, 111-121.

Chala, M. (2022). Review of Pesticide Use in Vegetable Farms and Its Consequences in Ethiopia's Central Rift Valley. *Journal of Agricultural Research Pesticides, 3*(3).

Cheruto, M. C., Kauti, M. K., Kisangau, D. P., & Kariuki, P. C. (2016). Assessment of land use and land cover change using GIS and remote sensing techniques: a case study of Makueni County, Kenya.

Chughtai, A. H., Abbasi, H., Karas, I. R. J. R. S. A. S., & Environment. (2021). A review on change detection method and accuracy assessment for land use land cover. *22*, 100482.

Civco, D. L., Hurd, J. D., Wilson, E. H., Song, M., & Zhang, Z. (2002). *A comparison of land use and land cover change detection methods.* Paper presented at the ASPRS-ACSM Annual Conference.

Coffey, R., Dorai-Raj, S., O'Flaherty, V., Cormican, M., Cummins, E. J. H., & Journal, E. R. A. A. I. (2013). Modeling of pathogen indicator organisms in a small-scale agricultural catchment using SWAT. *19*(1), 232-253.

Daba, M. H., Ayele, G. T., & You, S. J. A. i. M. (2020). Long-term homogeneity and trends of hydroclimatic variables in Upper Awash River Basin, Ethiopia. *2020*, 1-21.

Dahmen, E., & Hall, M. J. (1990). *Screening of hydrological data: tests for stationarity and relative consistency*: ILRI.

De Silva, R. P., Dayawansa, N., & Ratnasiri, M. (2007). A comparison of methods used in estimating missing rainfall data.

Deribew, K. T., & Dalacho, D. W. J. E. S. R. (2019). Land use and forest cover dynamics in the North-eastern Addis Ababa, central highlands of Ethiopia. *8*(1), 1-18.

Devi, M. R., & Baboo, S. S. J. I. J. C. S. E. T. (2011). Land use and land cover classification using RGB&L based supervised classification algorithm. *2*(10), 167-180.

Devia, G. K., Ganasri, B. P., & Dwarakish, G. S. J. A. p. (2015). A review on hydrological models. *4*, 1001-1007.

Dibaba, W. T., Demissie, T. A., & Miegel, K. J. W. (2020). Watershed hydrological response to combined land use/land cover and climate change in highland Ethiopia: Finchaa catchment. *12*(6), 1801.

Fang, Z., Ding, T., Chen, J., Xue, S., Zhou, Q., Wang, Y., . . . Yang, S. J. S. o. t. T. E. (2022). Impacts of land use/land cover changes on ecosystem services in ecologically fragile regions. *831*, 154967.

Foody, G. M. J. R. s. o. e. (2002). Status of land cover classification accuracy assessment. *80*(1), 185-201.

Garedew, E., Sandewall, M., Söderberg, U., & Campbell, B. M. J. E. m. (2009). Land-use and land-cover dynamics in the central rift valley of Ethiopia. *44*, 683-694.

Garedew, E., Sandewall, M., & Soderberg, U. J. E. M. (2012). A dynamic simulation model of land-use, population, and rural livelihoods in the Central Rift Valley of Ethiopia. *49*, 151-162.

Garg, V., Nikam, B. R., Thakur, P. K., Aggarwal, S. P., Gupta, P. K., & Srivastav, S. K. J. H. (2019). Human-induced land use land cover change and its impact on hydrology. *1*, 48-56.

Gebresamuel, G., Singh, B. R., Dick, Ø. J. A. A. S. S. B. S., & Science, P. (2010). Land-use changes and their impacts on soil degradation and surface runoff of two catchments of Northern Ethiopia. *60*(3), 211-226.

Getachew, B., & Manjunatha, B. R. J. G. C. (2022). Impacts of Land-Use Change on the Hydrology of Lake Tana Basin, Upper Blue Nile River Basin, Ethiopia. *6*(8), 2200041.

Getachew, H. E., & Melesse, A. M. J. I. J. o. W. S. (2012). The impact of land use change on the hydrology of the Angereb Watershed, Ethiopia. *1*(6).

Getahun, Y. S., & Van Lanen, H. J. H. C. R. (2015). Assessing the impacts of land use-cover change on hydrology of Melka Kuntrie subbasin in Ethiopia, using a conceptual hydrological model. *6*(3), 1.

Grubbs, F. E. J. T. A. o. M. S. (1950). Sample criteria for testing outlying observations. 27-58.

Hailemariam, A. J. A. s. p. I. s. o. a. d. d. (2017). The second biggest African country undergoing rapid change: Ethiopia. 53-69.

Hamza, I., Iyela, A. J. E. J. o. E. S., & Management. (2012). Land use pattern, climate change, and its implication for food security in Ethiopia: A review. *5*(1), 26-31.

Hamzah, F. B., Hamzah, F. M., Razali, S. M., & Samad, H. J. C. E. J. (2021). A comparison of multiple imputation methods for recovering missing data in hydrological studies. *7*(9), 1608-1619.

Han, J., Hayashi, Y., Cao, X., Imura, H. J. J. o. U. P., & Development. (2009). Evaluating land-use change in rapidly urbanizing China: Case study of Shanghai. *135*(4), 166-171.

Hassan, Z., Shabbir, R., Ahmad, S. S., Malik, A. H., Aziz, N., Butt, A., & Erum, S. J. S. (2016). Dynamics of land use and land cover change (LULCC) using geospatial techniques: a case study of Islamabad Pakistan. *5*, 1-11.

Hu, Z., Liu, S., Zhong, G., Lin, H., & Zhou, Z. J. H. S. J. (2020). Modified Mann-Kendall trend test for hydrological time series under the scaling hypothesis and its application. *65*(14), 2419-2438.

Ijaz Ahmad, I. A., Tang DeShan, T. D., Wang TianFang, W. T., Wang Mei, W. M., & Bakhtawar Wagan, B. W. (2015). Precipitation trends over time using Mann-Kendall and Spearman's rho tests in Swat River Basin, Pakistan.

Islami, F., Tarigan, S., Wahjunie, E., & Dasanto, B. (2022). *Accuracy assessment of land use change analysis using Google Earth in Sadar Watershed Mojokerto Regency.* Paper presented at the IOP Conference Series: Earth and Environmental Science.

Kang, H. M., & Yusof, F. J. I. J. C. M. S. (2012). Homogeneity tests on daily rainfall series. *7*(1), 9-22.

Kassaye, M. L. (2024). Review of the Historic Trajectory of Deforestation, its Drivers and Implications in Ethiopia.

Kebede, A. B. J. J. o. S. E. (2019). Influence of soil type in stream flow and runoff modeled for the upper didessa catchment southwest ethiopia using SWAT model. *4*(4), 444-457.

Khawaldah, H., Farhan, I., Alzboun, N. J. G. J. o. E. S., & Management. (2020). Simulation and prediction of land use and land cover change using GIS, remote sensing and CA-Markov model. *6*(2), 215-232.

Kiprotich, P. (2021). Assessing the Impact of Land Use and Climate Change on Surface Runoff Response Using Gridded Observations and SWAT+. *MDPI*.

Kuma, H. G., Feyessa, F. F., & Demissie, T. A. (2021). Hydrologic responses to climate and land-use/land-cover changes in the Bilate catchment, Southern Ethiopia. *journal of water and climate change* 12.

Kusre, B., Baruah, D., Bordoloi, P., & Patra, S. J. A. E. (2010). Assessment of hydropower potential using GIS and hydrological modeling technique in Kopili River basin in Assam (India). *87*(1), 298-309.

Lach, S. (2018). *The application of selected statistical tests in the detection and removal of outliers in water engineering data based on the example of piezometric measurements at the Dobczyce dam over the period 2012-2016.* Paper presented at the E3S Web of Conferences.

Leta, M. K., Ebsa, D. G., Regasa, M. S. J. A., & Science, E. S. (2022). Parameter Uncertainty Analysis for Streamflow Simulation Using SWAT Model in Nashe Watershed, Blue Nile River Basin, Ethiopia. *2022*.

Li, J., Wu, Z., Hu, Z., Zhang, J., Li, M., Mo, L., . . . Sensing, R. (2020). Thin cloud removal in optical remote sensing images based on generative adversarial networks and physical model of cloud distortion. *166*, 373-389.

Likinaw, A., Alemayehu, A., & Bewket, W. J. C. (2023). Trends in Extreme Precipitation Indices in Northwest Ethiopia: Comparative Analysis Using the Mann–Kendall and Innovative Trend Analysis Methods. *11*(8), 164.

Malede, D. A., Alamirew, T., Kosgie, J. R., Andualem, T. G. J. E., & Indicators, S. (2023). Analysis of land use/land cover change trends over Birr River Watershed, Abbay Basin, Ethiopia. *17*, 100222.

Manandhar, R., Odeh, I. O., & Ancev, T. J. R. S. (2009). Improving the accuracy of land use and land cover classification of Landsat data using post-classification enhancement. *1*(3), 330-344.

Mansour, S., Al-Belushi, M., & Al-Awadhi, T. J. L. u. p. (2020). Monitoring land use and land cover changes in the mountainous cities of Oman using GIS and CA-Markov modelling techniques. *91*, 104414.

Martinuzzi, S., Rivera, L., Politi, N., Bateman, B. L., DE LOS LLANOS, E. R., Lizarraga, L., . . . Radeloff, V. C. J. E. C. (2018). Enhancing biodiversity conservation in existing land-use plans with widely available datasets and spatial analysis techniques. *45*(3), 252-260.

Meals, D., Spooner, J., Dressing, S., & Harcum, J. J. D. f. U. E. P. A. b. T. T., Inc., Fairfax, VA. (2011). Statistical analysis for monotonic trends, Tech Notes 6, November 2011. *23*, 2016-2005.

Meaza, H., Frankl, A., Demissie, B., Poesen, J., Zenebe, A., Gebresamuel, G., . . . Jacob, M. J. J. o. H. R. S. (2019). Water balance components of the potential agricultural grabens along the Rift Valley in northern Ethiopia. *24*, 100616.

Mekonnen, Z. (2017). Land use and land cover changes and the link to land degradation in Arsi Negele district, Central Rift Valley, Ethiopia. 5.

Mekuria, W., Diyasa, M., Tengberg, A., & Haileslassie, A. J. L. (2021). Effects of long-term land use and land cover changes on ecosystem service values: An example from the central rift valley, Ethiopia. *10*(12), 1373.

Mengistu, A. G., Woldesenbet, T. A., Dile, Y. T. J. E., & Hydrobiology. (2022). Evaluation of observed and satellite-based climate products for hydrological simulation in data-scarce Baro-Akob River Basin, Ethiopia. *22*(2), 234-245.

Meshesha, D. T., Tsunekawa, A., Tsubo, M. J. L. d., & development. (2012). Continuing land degradation: cause–effect in Ethiopia's Central Rift Valley. *23*(2), 130-143.

Meyer, W. B., Turner, B. L. J. A. r. o. e., & systematics. (1992). Human population growth and global land-use/cover change. *23*(1), 39-61.

Mikias, B. M. J. A. J. o. A. R. (2015). Land use/land cover dynamics in the central rift valley region of Ethiopia: Case of Arsi Negele District. *10*(5), 434-449.

Mishra, V. N., Rai, P. K., Kumar, P., & Prasad, R. (2016). *Evaluation of land use/land cover classification accuracy using multi-resolution remote sensing images.* Paper presented at the Forum geografic.

Mohamed, A., & Worku, H. J. U. C. (2020). Simulating urban land use and cover dynamics using cellular automata and Markov chain approach in Addis Ababa and the surrounding. *31*, 100545.

Moriasi, D., Wilson, B., Douglas-Mankin, K., Arnold, J., & Gowda, P. J. T. o. t. A. (2012). Hydrologic and water quality models: Use, calibration, and validation. *55*(4), 1241-1247.

Moriasi, D. N., Arnold, J. G., Van Liew, M. W., Bingner, R. L., Harmel, R. D., & Veith, T. L. J. T. o. t. A. (2007). Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. *50*(3), 885-900.

Nagendra, H., Munroe, D. K., Southworth, J. J. A., Ecosystems, & Environment. (2004). From pattern to process: landscape fragmentation and the analysis of land use/land cover change. In (Vol. 101, pp. 111-115): Elsevier.

Näschen, K., Diekkrüger, B., Evers, M., Höllermann, B., Steinbach, S., & Thonfeld, F. J. S. (2019). The impact of land use/land cover change (LULCC) on water resources in a tropical catchment in Tanzania under different climate change scenarios. *11*(24), 7083.

Negash, E. D., Asfaw, W., Walsh, C. L., Mengistie, G. K., & Haile, A. T. J. S. W. R. M. (2023). Effects of land use land cover change on streamflow of Akaki catchment, Addis Ababa, Ethiopia. *9*(3), 78.

Negese, A. (2021). Impacts of land use and land cover change on soil erosion and hydrological responses in Ethiopia. *2021*, 1-10.

Neitsch, S., Arnold, J., Kiniry, J., Srinivasan, R., & Williams, J. J. T., Texas, USA. (2002). Soil and water assessment tool—user's manual 2002.

Nikolaou, G., Neocleous, D., Christou, A., Kitta, E., & Katsoulas, N. J. A. (2020). Implementing sustainable irrigation in water-scarce regions under the impact of climate change. *10*(8), 1120.

O'connell, P., Nash, J., & Farrell, J. J. J. o. h. (1970). River flow forecasting through conceptual models part II-The Brosna catchment at Ferbane. *10*(4), 317-329.

Pandey, P. C., Koutsias, N., Petropoulos, G. P., Srivastava, P. K., & Ben Dor, E. J. G. I. (2021). Land use/land cover in view of earth observation: Data sources, input dimensions, and classifiers—A review of the state of the art. *36*(9), 957-988.

Patel, S. K., Verma, P., Shankar Singh, G. J. E. m., & assessment. (2019). Agricultural growth and land use land cover change in peri-urban India. *191*, 1-17.

Patrician, P. A. (2002). Multiple imputation for missing data. *25*(1), 76-84.

Paulhus, J. L., & Kohler, M. A. J. M. W. R. (1952). Interpolation of missing precipitation records. *80*(8), 129-133.

Peiman, R. J. I. j. o. r. s. (2011). Pre-classification and post-classification change-detection techniques to monitor land-cover and land-use change using multi-temporal Landsat imagery: a case study on Pisa Province in Italy. *32*(15), 4365-4381.

Phillips, D. (1994). *Image processing in C* (Vol. 724): R & D Publications Lawrence.

Poyatos, R., Latron, J., Llorens, P. J. M. r., & development. (2003). Land use and land cover change after agricultural abandonment. *23*(4), 362-368.

Rahman, A., Kumar, S., Fazal, S., & Siddiqui, M. A. J. J. o. t. I. S. o. R. S. (2012). Assessment of land use/land cover change in the North-West District of Delhi using remote sensing and GIS techniques. *40*, 689-697.

Regasa, M. S., Nones, M., & Adeba, D. J. L. (2021). A review on land use and land cover change in Ethiopian basins. *10*(6), 585.

reta, m. (2021). Impact of Land Use/Land Cover Change on Stream Flow in the Shaya Catchment of Ethiopia Using MIKE-SHE Model. *researchGate*, 5.

Rwanga, S. S., & Ndambuki, J. M. J. I. J. o. G. (2017). Accuracy assessment of land use/land cover classification using remote sensing and GIS. *8*(04), 611.

Sattari, M.-T., Rezazadeh-Joudi, A., & Kusiak, A. J. H. R. (2017). Assessment of different methods for estimation of missing data in precipitation studies. *48*(4), 1032-1044.

Searcy, J. K., & Hardison, C. H. (1960). *Double-mass curves*: US Government Printing Office.

Seenu, P., & Jayakumar, K. J. A. J. o. G. (2021). Comparative study of innovative trend analysis technique with Mann-Kendall tests for extreme rainfall. *14*(7), 1-15.

Setegn, S. G., Srinivasan, R., Melesse, A. M., & Dargahi, B. J. H. P. A. I. J. (2010). SWAT model application and prediction uncertainty analysis in the Lake Tana Basin, Ethiopia. *24*(3), 357-367.

Singh, J., Knapp, H. V., Arnold, J., & Demissie, M. J. J. J. o. t. A. W. R. A. (2005). Hydrological modeling of the Iroquois river watershed using HSPF and SWAT 1. *41*(2), 343-360.

Sinharay, S., Stern, H. S., & Russell, D. J. P. m. (2001). The use of multiple imputation for the analysis of missing data. *6*(4), 317.

Sorooshian, S., Hsu, K.-l., Coppola, E., Tomassetti, B., Verdecchia, M., & Visconti, G. (2008). *Hydrological modelling and the water cycle: coupling the atmospheric and hydrological models* (Vol. 63): Springer Science & Business Media.

Sreenivasulu, G., Jayaraju, N., Pramod Kumar, M., Lakshmi Prasad, T. J. I. J. o. S., & Publications, R. (2013). An analysis on land use/land cover using remote sensing and GIS–a case study in and around Vempalli, Kadapa District, Andhra Pradesh, India. *3*(5), 1-4.

Stehman, S. V., & Foody, G. M. J. T. S. h. o. r. s. (2009). Accuracy assessment. In (pp. 297-309): Sage Publications, Ltd., London, United Kingdom.

Subramanya, K. (2008). *Engineering hydrology*: McGraw-Hill.

Subramanya, K. J. N. d. (2008). Engineering Hydrology. 7 West Patal Nagar. *110*(008).

Tadele, K., & Förch, G. (2007). *Impact of land use/cover change on streamflow: the case of Hare River Watershed, Ethiopia.* Paper presented at the Catchment and lake research, proceedings 2nd Lake Abaya research symposium (LARS), Arba Minch, Ethiopia.

Tahir, M., Imam, E., Hussain, T. J. C. E., & Software. (2013). Evaluation of land use/land cover changes in Mekelle City, Ethiopia using Remote Sensing and GIS. *3*(1), 9.

Te Chow, V. (2010). *Applied hydrology*: Tata McGraw-Hill Education.

Te Chow, V., Maidment, D. R., & Mays, L. W. (1988). *Applied hydrology*.

Terribile, F., Coppola, A., Langella, G., Martina, M., Basile, A. J. H., & Sciences, E. S. (2011). Potential and limitations of using soil mapping information to understand landscape hydrology. *15*(12), 3895-3933.

Tewabe, D., & Fentahun, T. J. C. E. S. (2020). Assessing land use and land cover change detection using remote sensing in the Lake Tana Basin, Northwest Ethiopia. *6*(1), 1778998.

Thampi, S. G., Raneesh, K. Y., & Surya, T. J. W. R. M. (2010). Influence of scale on SWAT model calibration for streamflow in a river basin in the humid tropics. *24*, 4567-4578.

Tietjen, G. L., & Moore, R. H. J. T. (1972). Some Grubbs-type statistics for the detection of several outliers. *14*(3), 583-597.

Timotewos, M. T., Reddythota, D. J. J. o. W. R., & Science, O. (2020). Kulfo river stream impact on the sustainability of aquatic life in Chamo lake at Arba minch. *9*(2), 48-55.

Tiwari, V., & Tripathi, P. (2022). Outlier detection in a few catchments of the Godavari river basin: A case study.

Tunkala, A. A., Geletu, M. H., & Gemeda, D. O. J. G. o. R. A. i. S. S. R. GIS and Remote Sensing Technique to Assess Land Use Land Cover Change in Upper Kulfo Watershed, South West Ethiopia.

Urgessa, T., & Lemessa, D. J. E. (2020). Spatiotemporal landuse land cover changes in Walmara District, Central Oromia, Ethiopia. *9*(1), 32-37.

van Dijk, A. I., Keenan, R. J. J. F. e., & management. (2007). Planted forests and water in perspective. In (Vol. 251, pp. 1-9): Elsevier.

Van Griensven, A., Ndomba, P., Yalew, S., Kilonzo, F. J. H., & Sciences, E. S. (2012). Critical review of SWAT applications in the upper Nile basin countries. *16*(9), 3371-3381.

van Vliet, J., Bregt, A. K., & Hagen-Zanker, A. J. E. m. (2011). Revisiting Kappa to account for change in the accuracy assessment of land-use change models. *222*(8), 1367-1375.

van Zijl, G. M., van Tol, J. J., Riddell, E. S. J. D. s. m. a. p., scales, & boundaries. (2016). Digital soil mapping for hydrological modelling. 115-129.

Wang, F., Shao, W., Yu, H., Kan, G., He, X., Zhang, D., . . . Wang, G. J. F. i. E. S. (2020). Re-evaluation of the power of the mann-kendall test for detecting monotonic trends in hydrometeorological time series. *8*, 14.

Wang, Q., Pagano, T., Zhou, S., Hapuarachchi, H., Zhang, L., & Robertson, D. J. J. o. H. (2011). Monthly versus daily water balance models in simulating monthly runoff. *404*(3-4), 166-175.

Wankie, T. J. A. o. H. I. o. L.-u. C. i. K. R. W. U. S. (2015). Assessment of Hydrologic Impacts of Land-use Change in Kulfo River Watershed Using SWAT.

Wassie, S. B. J. E. s. r. (2020). Natural resource degradation tendencies in Ethiopia: a review. *9*(1), 1-29.

Wei, T. C. (1973). *Reciprocal Distance Squared Method, A computer technique for estimating areal precipitation* (Vol. 8): US Department of Agriculture, Agricultural Research Service, North Central ….

Weick, K. E., & Sutcliffe, K. M. (2001). *Managing the unexpected* (Vol. 9): San Francisco: Jossey-Bass.

WoldeYohannes, A., Cotter, M., Kelboro, G., & Dessalegn, W. J. L. (2018). Land use and land cover changes and their effects on the landscape of Abaya-Chamo Basin, Southern Ethiopia. *7*(1), 2.

Worku, T., Khare, D., & Tripathi, S. J. E. e. s. (2017). Modeling runoff–sediment response to land use/land cover changes using integrated GIS and SWAT model in the Beressa watershed. *76*, 1-14.

Xu, C.-Y., & Singh, V. P. J. W. r. m. (2004). Review on regional water resources assessment models under stationary and changing climate. *18*, 591-612.

Ye, W., Bates, B., Viney, N., Sivapalan, M., & Jakeman, A. J. W. R. R. (1997). Performance of conceptual rainfall-runoff models in low-yielding ephemeral catchments. *33*(1), 153-166.

Ye, X., Zhang, Q., & Viney, N. J. H. p. (2011). The effect of soil data resolution on hydrological processes modelling in a large humid watershed. *25*(1), 130-140.

Yifru, B. A., Chung, I.-M., Kim, M.-G., & Chang, S. W. J. J. o. H. R. S. (2021). Assessing the effect of land/use land cover and climate change on water yield and groundwater recharge in East African Rift Valley using integrated model. *37*, 100926.

Yirgu, T., Yihunie, Y., Assele, A., Wogayehu, T. J. J. o. G., Environment, & International, E. S. (2020). Land Use/Land Cover Dynamics and its Environmental Impacts in Kulfo Watershed, Gamo Highlands, SoutWestern Ethiopia. 1-11.

Young, K. C. J. M. W. R. (1992). A three-way model for interpolating for monthly precipitation values. *120*(11), 2561-2569.

Zemke, J. J., Enderling, M., Klein, A., & Skubski, M. J. G. (2019). The influence of soil compaction on runoff formation. A case study focusing on skid trails at forested andosol sites. *9*(5), 204.

Zewde, N. T., Denboba, M. A., Tadesse, S. A., & Getahun, Y. S. J. E. C. (2024). Predicting runoff and sediment yields using soil and water assessment tool (SWAT) model in the Jemma Subbasin of Upper Blue Nile, Central Ethiopia. *14*, 100806.

Zhang, H., Wang, B., Li Liu, D., Zhang, M., Leslie, L. M., & Yu, Q. J. J. o. H. (2020). Using an improved SWAT model to simulate hydrological responses to land use change: A case study of a catchment in tropical Australia. *585*, 124822.

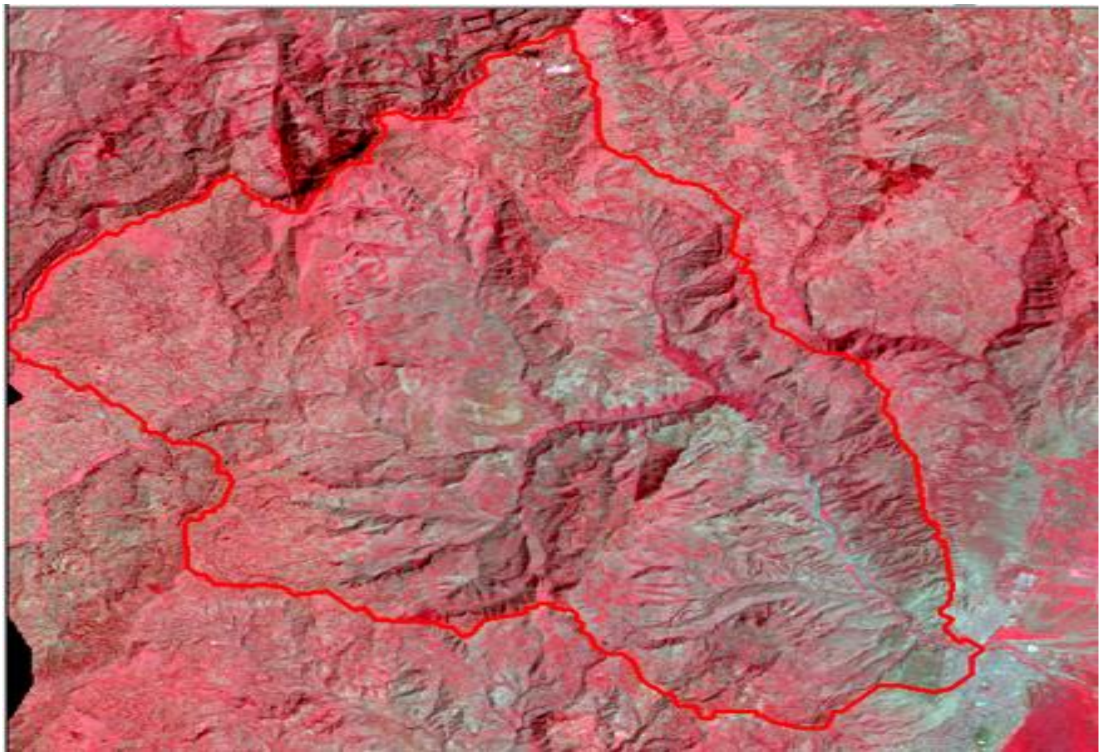
Zhao, W. J., Sun, W., Li, Z. L., Fan, Y. W., Song, J. S., & Wang, L. R. J. A. M. R. (2013). A review on SWAT model for stream flow simulation. *726*, 3792-3798.

Zhou, W., Troy, A., & Grove, M. J. S. (2008). Object-based land cover classification and change analysis in the Baltimore metropolitan area using multitemporal high resolution remote sensing data. *8*(3), 1613-1636.

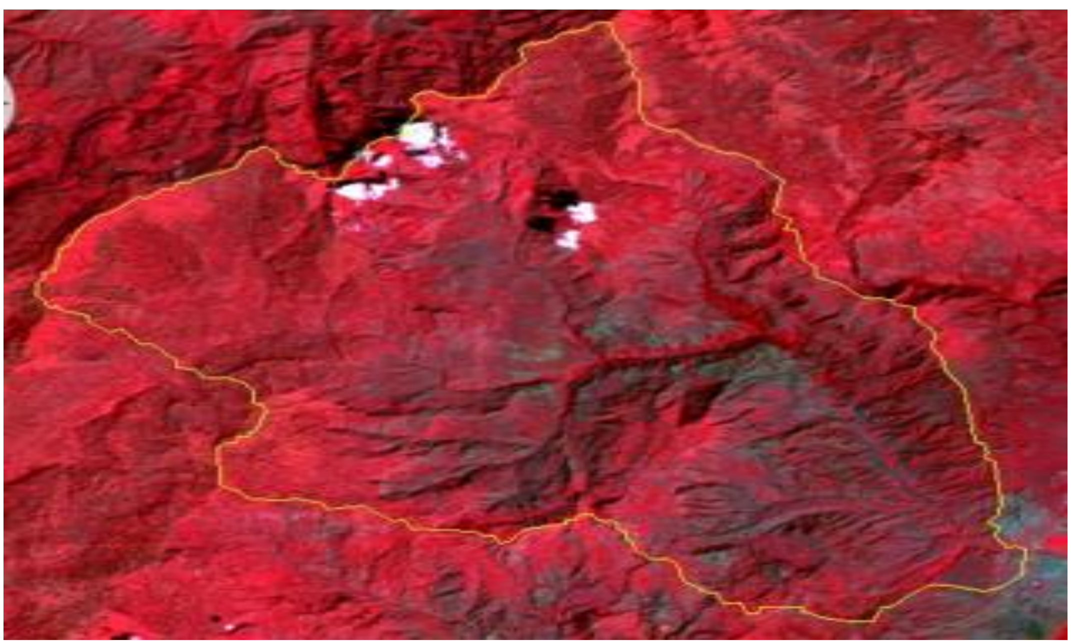
APPENDIXES

A. Land sat images used for LULC classification

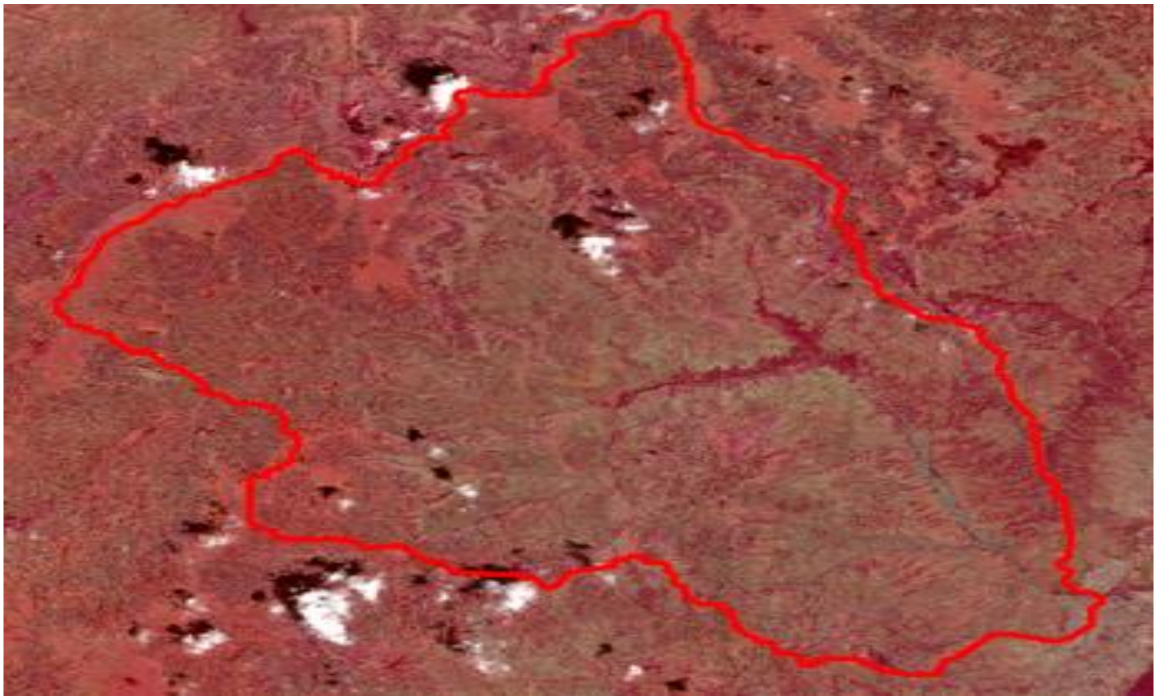
A. Land sat image 2000



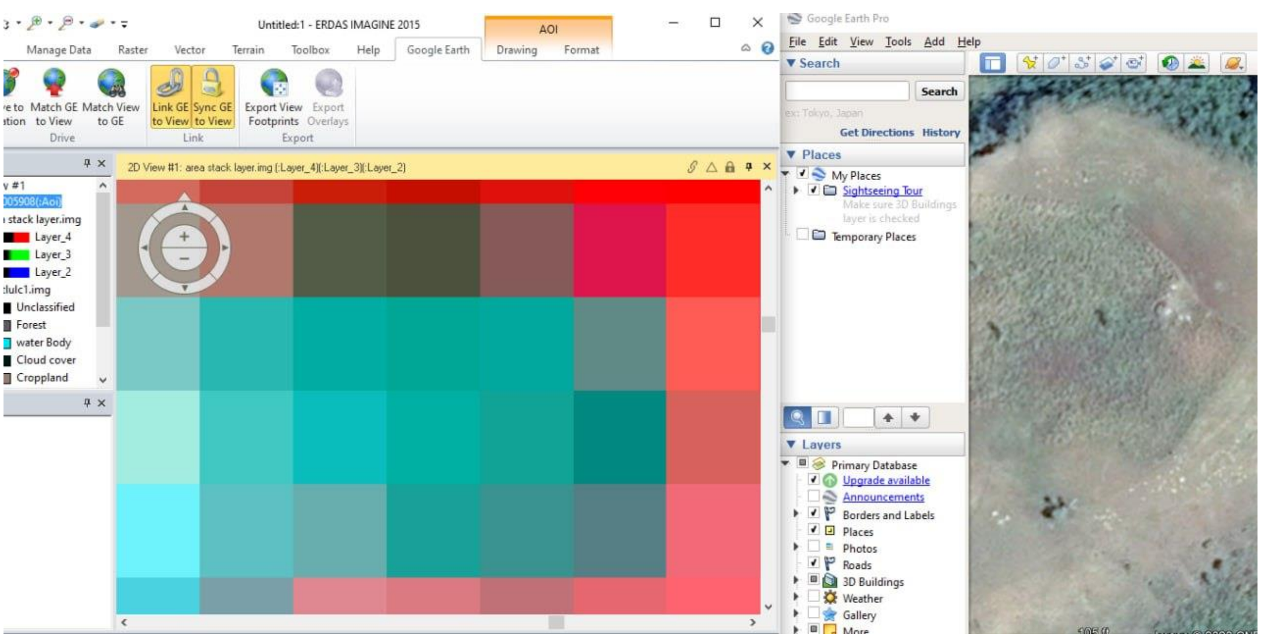
B. Land sat image 2010



C. Land sat image 2022



D. Using ERDAS Imagine with Google earth for LULC classification



E. Hydro Metrological Data's

A. Mean monthly flow of Kulfo river

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2000	3.76	3.63	3.35	8.56	11.36	10.87	13.28	15.20	17.18	19.87	18.52	8.59
2001	6.08	5.29	6.49	19.23	11.28	10.81	9.25	16.25	20.41	15.60	10.60	7.60
2002	6.58	5.98	9.84	11.30	9.20	6.30	6.50	8.36	12.41	11.53	9.50	7.55
2003	7.97	7.03	7.52	10.23	7.22	8.00	8.26	11.36	15.00	13.00	10.99	7.64
2004	6.46	6.14	6.32	12.69	11.23	10.14	7.23	10.14	12.23	10.87	7.53	6.36
2005	6.81	6.51	8.26	13.65	16.36	11.58	13.16	12.77	14.78	15.03	11.86	7.98
2006	6.77	6.24	8.87	11.76	9.93	8.21	7.02	10.14	11.66	17.42	13.94	11.65
2007	7.89	6.65	5.70	12.26	15.32	12.14	10.65	18.21	20.19	15.53	12.54	10.40
2008	9.03	7.47	6.39	11.93	12.69	7.52	7.17	16.28	15.15	14.36	10.24	7.57
2009	6.22	6.00	5.77	13.62	12.91	6.85	7.19	9.79	13.21	15.85	9.47	7.65
2010	7.29	6.54	9.30	11.29	20.36	16.24	12.93	12.30	13.73	11.93	8.47	8.90
2011	7.58	7.21	6.54	10.87	18.85	11.25	8.73	13.06	16.59	13.90	12.32	9.42
2012	7.78	5.51	5.74	14.70	17.18	10.68	9.72	13.23	24.97	11.61	9.93	7.25
2013	5.85	4.92	9.41	14.40	9.12	7.91	5.15	12.22	21.40	18.38	9.97	6.89
2014	7.59	7.16	7.66	16.88	13.78	9.02	10.79	13.47	16.95	23.59	11.52	8.69
2015	8.92	6.18	7.16	15.40	12.36	8.82	13.33	25.10	17.14	15.73	14.32	7.59

B. Mean monthly precipitation of stations

Year	1	2	3	4	5	6	7	8	9	10	11	12
2000	0.04	0.00	0.22	2.98	1.66	0.67	0.85	0.80	2.27	4.68	1.81	0.65
2001	1.06	0.26	1.15	4.59	3.41	1.71	0.67	1.39	2.62	4.00	0.92	0.18
2002	0.36	0.51	1.29	1.47	1.82	0.31	0.75	0.40	1.15	2.83	0.58	1.88
2003	0.44	0.36	1.15	4.71	2.22	0.81	0.65	1.62	1.29	1.79	0.83	0.46
2004	0.75	0.56	0.56	4.18	1.89	0.35	0.72	1.47	3.33	2.10	2.49	1.03
2005	0.18	0.10	1.73	6.46	5.21	0.55	0.93	0.72	1.98	3.89	1.08	0.14
2006	0.15	0.52	1.75	3.72	4.18	1.30	0.79	1.33	0.58	3.94	2.02	2.29
2007	0.37	0.50	0.55	3.56	3.66	2.06	1.88	1.63	3.36	2.12	2.01	0.00
2008	0.02	0.29	1.31	4.35	1.62	1.53	0.80	0.77	2.21	3.37	1.05	0.00
2009	0.75	0.35	0.91	2.43	2.42	0.48	0.05	0.52	1.35	3.02	0.89	0.56
2010	0.70	1.30	2.43	4.18	3.38	1.48	0.85	1.09	2.48	1.64	0.15	0.27
2011	0.00	0.12	0.65	0.99	6.96	0.94	1.05	0.81	1.86	2.27	2.73	0.48
2012	0.00	0.07	0.98	2.37	2.19	0.73	0.92	1.31	3.09	1.30	0.99	1.08
2013	0.51	0.25	1.52	4.55	2.30	0.58	0.43	1.06	1.87	3.09	1.53	0.25
2014	0.28	0.80	1.34	1.85	3.84	1.16	0.49	1.28	2.40	3.27	1.31	0.05
2015	0.00	0.19	0.69	2.60	2.36	1.82	0.63	0.61	1.22	3.97	1.74	0.38
2016	0.11	0.31	1.01	4.60	1.21	0.61	0.56	0.24	1.23	1.58	1.22	0.22

2017	0.02	0.80	0.60	1.04	4.40	0.09	0.88	0.65	2.25	3.60	1.55	0.00
2018	0.00	0.51	0.36	3.90	3.62	1.18	0.17	0.19	2.15	3.59	0.93	0.57
2019	0.00	0.24	0.40	3.97	4.15	1.40	1.40	1.12	1.15	3.26	2.60	1.27
2020	0.85	0.36	1.81	3.94	1.61	1.27	0.50	3.70	2.68	1.74	1.95	0.08
2021	0.33	0.42	1.06	3.42	2.99	0.99	0.80	1.04	1.97	2.95	1.40	0.53
2022	0.72	1.17	0.15	2.62	3.12	1.31	1.20	0.37	1.40	2.77	1.58	0.03

a) Arba Minch

b) Daramalo

Year	1	2	3	4	5	6	7	8	9	10	11	12
2000	0.00	0.00	0.41	2.19	2.81	1.07	2.33	0.99	2.20	3.91	0.66	0.10
2001	0.43	0.18	1.69	5.15	3.95	1.64	1.03	2.05	3.33	2.96	0.15	0.08
2002	0.11	0.07	3.86	3.85	2.14	0.81	0.76	1.62	3.25	2.00	0.82	0.47
2003	0.56	0.81	1.25	3.40	0.92	2.13	1.39	1.04	2.27	1.19	0.74	0.27
2004	0.55	0.33	1.36	2.79	1.07	0.34	1.25	1.77	1.63	0.97	0.60	0.48
2005	0.78	0.19	2.04	3.41	5.55	1.36	2.52	0.85	2.47	2.39	0.87	0.00
2006	0.15	0.37	2.25	3.97	1.76	0.42	1.39	2.14	2.30	2.18	1.99	1.21
2007	0.64	0.18	1.56	2.01	4.15	1.31	1.05	3.06	4.51	1.14	0.71	0.00
2008	0.08	0.06	0.53	2.72	2.60	2.77	1.00	4.41	2.47	2.50	1.11	0.13
2009	0.16	0.15	0.78	3.81	1.82	1.16	0.67	2.02	1.88	2.59	0.92	0.93
2010	0.27	0.63	2.54	4.08	5.64	2.11	1.32	2.36	2.54	1.00	0.32	0.18
2011	0.15	0.08	0.81	1.43	4.79	2.60	0.41	1.72	3.91	0.99	1.24	0.10
2012	0.00	0.00	0.71	4.20	3.95	1.38	0.89	2.98	4.62	0.85	1.47	0.07
2013	0.20	0.18	1.65	5.15	1.95	0.64	2.07	1.43	5.42	2.50	0.57	0.00
2014	0.00	0.08	1.49	5.88	4.69	1.39	1.53	3.01	3.33	4.62	0.63	0.04
2015	0.20	0.00	0.64	4.32	3.58	1.67	0.05	4.55	3.06	3.15	2.31	0.41
2016	0.00	0.08	1.56	5.99	4.32	1.40	0.55	1.75	2.05	3.19	0.57	0.37
2017	0.00	0.00	0.06	3.11	3.77	2.26	0.79	2.18	3.66	0.99	0.00	0.00
2018	0.60	0.46	1.32	4.75	1.83	1.74	0.42	1.64	0.00	1.24	2.06	0.00
2019	0.00	0.00	1.04	4.05	5.45	1.41	0.96	3.95	4.12	0.47	1.05	0.03
2020	0.00	0.35	0.87	4.43	3.81	1.03	0.82	2.30	4.76	0.00	0.96	0.20
2021	0.37	0.50	0.55	3.56	3.66	2.06	1.88	1.63	3.36	2.12	2.01	0.00
2022	0.52	1.10	0.18	2.62	3.23	1.45	1.20	0.37	1.40	2.77	1.58	0.03

Year	1	2	3	4	5	6	7	8	9	10	11	12
2000	0.04	0.05	1.55	5.21	3.18	1.00	2.89	4.20	7.34	2.21	1.92	0.64
2001	0.83	0.79	6.20	5.30	3.53	2.42	3.18	2.95	4.17	2.66	0.99	0.14
2002	2.30	0.14	3.67	4.36	2.43	1.64	1.99	2.46	3.92	1.60	1.15	2.31
2003	1.48	0.25	3.04	2.77	0.54	2.20	2.16	1.36	1.95	0.96	1.17	1.78

2004	1.80	0.64	1.10	6.01	2.24	1.01	0.25	2.59	0.53	3.55	3.04	0.60
2005	0.23	0.30	3.07	3.43	5.01	1.82	2.86	2.20	4.50	4.05	1.53	0.00
2006	0.62	0.31	3.46	3.32	2.33	0.38	0.96	2.89	4.99	1.57	2.10	3.14
2007	0.70	0.25	1.90	4.26	3.58	2.47	2.44	4.10	4.08	4.66	1.55	0.00
2008	0.71	0.18	1.04	3.73	3.44	1.15	1.48	2.36	3.19	3.08	1.64	0.07
2009	1.36	0.73	0.88	3.43	3.44	1.83	0.91	1.00	3.04	1.56	0.95	1.93
2010	1.18	0.98	2.85	4.09	6.23	3.29	1.64	2.32	2.49	3.22	0.71	0.22
2011	0.10	0.60	1.00	2.01	5.38	2.40	1.03	3.15	2.82	5.08	3.47	0.00
2012	0.04	0.31	0.76	2.84	6.00	2.83	2.17	2.57	2.63	4.71	3.10	0.22
2013	0.60	0.28	1.64	3.19	4.76	1.65	0.51	3.22	6.33	3.94	2.97	0.00
2014	0.19	0.57	2.14	1.76	6.77	2.41	1.10	2.52	6.19	3.59	2.40	0.80
2015	0.54	0.11	1.77	3.43	6.14	2.14	2.47	0.66	4.28	1.95	2.19	0.81
2016	0.82	0.65	1.01	4.74	5.28	2.28	2.46	1.43	3.15	2.60	0.99	0.21
2017	0.93	0.72	2.08	1.56	6.75	1.75	1.82	3.52	2.57	2.40	0.94	0.00
2018	0.00	0.48	0.47	1.71	5.01	4.34	3.60	1.73	2.79	3.24	3.56	1.17
2019	1.77	0.41	0.52	2.31	2.22	1.74	2.34	2.09	2.92	2.76	0.19	0.00
2020	1.69	0.42	0.54	2.32	2.23	1.75	2.28	2.02	3.01	2.52	0.20	0.00
2021	0.97	0.45	2.02	3.43	3.93	1.93	2.03	2.50	3.68	2.91	1.66	0.62
2022	0.21	0.40	3.08	3.11	5.11	1.52	2.22	2.58	4.10	4.05	1.53	1.80

c) Chancha