ASSESSING THE IMPACT OF LANDUSE/LAND COVER CHANGE ON STREAM FLOW AND FUTURE PREDICTIONS OF LANDUSE/LAND COVER CHANGES OF BELES SUB-BASIN, UPPER BLUE NILE BASIN, ETHIOPIA

MSc THESIS

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HAWASSA UNIVERSITY, IOT,

HAWASSA, ETHIOPIA

JULY, 2023

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A THESIS SUBMITTED TO THE FACULTY OF BIO-SYSTEMS AND WATER RESOURCES ENGINEERING, DEPARTEMENT OF WATER RESOURCE AND IRRIGATION ENGINEERING

HAWASSA UNIVERSITY, INSTITUTE OF TECHNOLOGY
SCHOOL OF GRADUATE STUDIES
HAWASSA UNIVERSITY
HAWASSA, ETHIOPIA

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTERS OF SCIENCE IN WATER RESOURCE AND IRRIGATION ENGINEERING
(SPECIALIZATION: WATER RESOURCE ENGINEERING AND MANAGEMENT)

JULY, 2023

ADVISORS' APPROVAL SHEET

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This is to certify that the thesis entitled "Assessing the impact of landuse/land cover change on stream flow and future predictions of landuse/land cover changes of Beles Sub-Basin, Upper Blue Nile basin, Ethiopia" was submitted in partial fulfillment of the requirements for the degree of masters with specialization in water resource engineering and management, department of water resource and irrigation engineering, and it will be carried out by tsega moges id no. gpwremr/0012/13, under our supervision. therefore, we recommend that the student has fulfilled the requirements and hence hereby can submit the thesis to the department.

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As members of the Examining Board of the Final MSc Open Defense, we certify that we have read and evaluated the thesis prepared by Tsega Moges entitled “Assessing the impact of landuse/land cover change on stream flow and future predictions of landuse/land cover changes of Beles Sub-Basin, Upper Blue Nile basin, Ethiopia.”, and recommend that it be accepted as fulfilling the thesis requirement for the degree of Master′s of science in school of Water Resources and Irrigation Engineering with Specialization in Water Resource Engineering and Management.

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DECLARATION

I declare and confirm by my signature that this thesis entitled "Assessing the impact of landuse/land cover change on stream flow of Beles Sub-basin, Upper Blue Nile basin, Ethiopia" is my original work that has not been submitted to any other institution anywhere for the award of degree, diploma or certificate. Data analysis and preparation of this paper and that all the sources that I have used or quoted have been indicated and acknowledged.

Name: Tsega Moges Dereje

Signature:____________________

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ACKNOLOGIMENT

First and foremost, praises and thanks to God, the Almighty, for His showers of blessings throughout my research work to complete it successfully.

I am overwhelmed in all humbleness and gratefulness to acknowledge my advisors Dr. Tewodros Assefa and Dr. Tewodros Tesfaye for their endeavor consults and advice which I will hold onto for long. Also, Mr. Ermias Eyasu I am grateful for your help and constructive feed backs. Hawassa University, Institute of Technology (IOT) in particular for their admitting and serving me in all aspects during the study thank you for the opportunity of the study and the effort put to organize all.

I extend my appreciation and special thanks to Ministry of Agriculture for scholar and sponsoring me with financial support in order to finish thesis work.

My deep sincere gratitude goes to the National Metrological Agency of Ethiopia and Ministry of Water and Energy am very thankful for all the support, data, and humble communication.

I am extremely grateful for my family for their love, prayer, and care to support me in all I need. Also, am very thankful for my friends for their support to put this research idea in a more tangible form.

Dedication

This thesis is dedicated to my beloved father in heaven Moges Dereje and my family. He was always my biggest supporter, believed in me and encouraged me to follow my dreams, and although he did not get to see me finish this journey, I know he would have been proud.

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LIST OF ABBREVIATIONS AND ACRONYMS

CA	Cellular automata
DEM	Digital Elevation Model
DEW	Dew Point Temperature Calculator Program
DMC	Double Mass Curve analysis
DWSM	Dynamic Watershed Simulation Model
ENS	Nash and Sutcliffe simulation efficiency
ENVI	Environment for Visualizing Images
EROS	Earth Resources Observation and Science Center
ET	Evapotranspiration
FAO	Food and Agriculture Organization
ETM+	Enhanced Thematic Mapper Plus
GIS	Geographical Information System
GPS	Global Positioning System
GRASS	Geographic Resources Analysis Support System
HBV	Hydrologisika Bayraans Vattenbalans-avediling
HEC-HMS	Hydraulic Engineering Centre-Hydrologic Modeling System
HRU	Hydrologic Response Unit
HSPF	Hydrological Simulation Program–Fortran
HWSD	Harmonized World Soil Database
IHACRES	Identification of unit Hydrograph and Component flows from Rainfall, Evapotranspiration, and Streamflow
IHDM	Institute of Hydrology Distributed Model
ITCZ	Inter-Tropical Convergence Zone
KIA	Kappa Index of Agreement
LCM	Land Change Modeler
LULC	Land Use Land Cover
LULCC	Land Use Land Cover Change
MASL	Meters Above Sea Level
MLP	Multi-Layer Perception
NASA	National Satellite Agency of the United States of America
PcpSTAT	Program designed to calculate daily precipitation

PRMS	Precipitation Runoff Modeling System
QGIS	Quantum Geographic Information System
R2	Coefficient of Determination
SHE	Système Hydrologique Européen
SRTM	Shuttle Radar Topography Mission
SWAT	Soil and Water Assessment Tool
TM	Thematic Mapper
TOPLATS	Topographically-based LandAtmosphere Transfer Scheme
UNESCO	United Nations Educational, Scientific and Cultural Organization
USGS	U.S. Geological Survey
UTM	Universal Transverse Mercator
WATBAL	Water Balance
WGEN	Weather Generator
WGS	World Geodetic System

ABSTRACT

Landuse and land cover change drives changes that limit availability of products and services for human, and it can undermine environmental health. Studying impact of landuse/land cover changes on the stream flow is very important for proper basin management. Hence this study investigated the past and potential future land cover changes, and the impact of the past on the stream flow of Beles Sub-Basin using using the Soil Water Assessment Tool (SWAT). To analyze the change that in the study area, satellite images were downloaded for 1987, 2002, and 2019 years and processed using ERDAS Imagine 2014. Then using supervised image classification, the satellite images were classified to agriculture, wetland, forest, shrub land, and urban land. Accuracy assessment was done, and overall accuracy of 86.25%, 88.7% and 87.9%, were achieved for the classified images of 1987, 2002 and 2019 respectively. The net changes of landuse/land cover of the study area from 1987 to 2019 indicated that forest, shrub land and wet land decreased by 4.73%, 10.59%, and 1.10%, respectively, while Agriculture, and Urban, increased by 14.18%, and 2.24%, respectively. The future LULCs of 2035 and 2055 were projected by IDRISI (CA-Markov method), and the result indicated an increase of Agriculture 10.94%, Urban 44.04%, where as forest -12.63%, shrub land -11.35%, and wetland -43.61% decreased. Ten parameters identified to be sensitive for the stream flow. Model calibration was carried out using observed stream flow data from (1989-2010) and The validation was performed from (2011-2019). Both results showed good match between measured and simulated stream flow data with R^2 and ENS achieved 0.80, 0.74 for calibration and 0.64, 0.78 for validation respectively. Due to LULCC, the mean annual Stream flow increased by 3.04m^3/s from 1987-2002, and, 2.83m^3/s from 2002-2019 and seasonal flow increased by 12.05m^3/s, and 5.49m^3/s in the wet season, while increased and decreased by 2.13m^3/s and -2.78m^3/s respectively in the dry season. The surface runoff increased, while groundwater flow decreased from 1987 to 2002 and from the year 2002 to 2019 the mean monthly stream flow increased by 23.29m^3/s for the wet months while for the dry months decreased by 6.31m^3/s. The Stream flow change to different predefined study years indicates LULCC has significant impacts on the stream flow of the study area. To mitigate LULCC, local and national officials in the Beles Sub-Basin should be invited to develop and implement scientific and suitable planning and management plans.

Keywords: LULCC, LULCC Prediction IDRISI, SWAT, Stream Flow.

1. INTRODUCTION

1.1 Background

Humans have been reliant on land for food production and different forms of economic growth since the dawn of civilization, and this has resulted in a steady alteration of the world landscape (Weinzettel *et al*., 2013). The constant push to fulfill the requirements of an ever-increasing population, as well as demand-driven development activities has increased the stress on earth's land (Foley *et al*., 2005). In other words, one way or the other, human activities of survival depend mostly on the earth's surface (Rai *et al*., 2014). This implies that studies on land-use change of a particular watershed bear their importance. The term Land use usually refers to how, and the purposes for which, humans employ the land and its resources (Tadese *et al*., 2021) .

In the last few decades over half of the world's landscape is influenced by human activities or under some sort of anthropogenic development and since the historic past, many natural resources have been heavily used or even depleted in the worst cases (Goldewijk *et al*., 2011). The extent and diversity of landuse/land cover has been changing at an accelerating pace and this is due to the increasing human population, expansion of the agricultural sector, and the exploitation of natural resources at an alarming rate (Belay and Mengistu, 2019).

The use of land and the cover on the Earth's surface are important factors when studying the impact of human activities on the environment (Argaw and Sulaiman, 2011). Changes in land use and land cover, known as LULCC, result from a combination of natural and human factors. Understanding the relationship between land use, land cover, and water resources is crucial for managing water and ensuring sustainable development (Chilagane, 2018). LULCC has significant effects on various aspects, including land productivity, biodiversity, and hydrological processes. It can affect hydrological components such as infiltration, surface runoff, and groundwater recharge, which in turn modify soil properties and the atmosphere. Assessing the impact of LULCC on water resources management is essential for informed decision-making in environmental planning and management (Kenea *et a*l., 2021).

Different methods, such as modeling, statistical analysis, and experimental catchments, can be used to investigate the effects of LULCC on hydrological response. The choice of method depends on factors like scale, geographic location, and available resources. Models are commonly used to study the impact of human interference and watershed management, as they provide a comprehensive understanding of the causes and consequences of LULCC (Tankpa *et al*., 2020).

In Ethiopia, different researches have been conducted to understand what is behind the change in LULC and the actual driving force of the change is in a different part of the country. The landscape, the extent, and diversity of landuse/land cover of Ethiopia are constantly changing at an accelerating pace similar to the rest of the world due to rapid population growth, climate change, resettlement programs, expansion of the agricultural sector, and the exploitation of natural resources (Belay and Mengistu, 2019; Marchant *et al*., 2018). A study by Bekele (2019) reported that Ethiopia has truly passed noteworthy elements in LULC for numerous decades and still the LULCCs are expanding at a disturbing rate, playing a noteworthy part within the expanding rate of population. According to Belay and Mengistu (2019), Upper Blue Nile is one of the 12 river basins in Ethiopia; which is one of the most important and diverse river basin. The living style of the people in the basin is so dependent on small-scale irrigation and rain-fed agriculture (Seleshi *et al*., 2014).

The study area Beles Sub-Basin is one of the most potential river basins in Ethiopia, which is the main tributary for the upper Blue Nile it receives water from Lake Tana via the Tana-Beles interbrains transfer, which is to be used in a series of irrigation projects below the power plant (Ashebir, 2017). A study conducted by Woldesenbet *et al* (2017) on Tana and Beles Sub-Basin presented that the Beles Sub-basin is demonstrated to be an expansion of agricultural land area and the growth of farmland has expanded.

1.2. Statement of the Problem

Landuse/land cover change is a major global environmental change issue, and projecting changes are essential for the assessment of the environment (Abuelaish and Olmedo, 2016). The implications for landuse/land cover were: increased deforestation and intensified cultivation, as well as increased and accelerating soil and land degradation throughout the highlands of Ethiopia (Alemu *et al*., 2015; Motuma Shiferaw *et a.l*, 2021).

Beles Sub-basin becoming an investment and settlement hotspot for the last 30 years, As the establishment of roads and large commercial farms as of the year 2000 enhanced changes in many places in the basin, an increasing population density necessitates a more intensive pressure on the land use plus traditionally, and nowadays still in the majority, the shifting cultivation also involves frequent shifting of villages. Due to the increase in population, in response to the increasing number of towns and villages, deforestation, and the search for more land for agriculture, people have moved to cultivated forested areas and marginally unproductive land (Nyssen *et al.*, 2018).

Impacts of LULC on hydrology in the Beles Sub-Basin are poorly documented. To address this deficiency, this study applies an integrated approach of hydrological modeling to quantify the contribution of changes in each LULC class and projected changes of the basin to changes in hydrological components in Beles. Understanding the types and impacts of land use and land cover change is an essential indicator for resource base analysis and development of effective and appropriate response strategies for sustainable management of natural resources and also prediction of LU/LC using time series data is important for the future management plan of LULC in the country in general and at the study area in particular (Leta *et al*., 2021).

Land Cover is one of the most important products of remote sensing and it is a primary input of many hydrologic models. In this regard, different hydrological models can be used to represent a complex system in a simplified way namely TOPMODEL, Soil Assessment Tools (SWAT), HEC-HMS model, SHE, and Institute of Hydrology Distributed Model (IHDM) are just a few (Tegegne *et al.,* 2017). Among those SWAT model is chosen because of the foundational strength of SWAT as seen in different studies and in different environments their results revealed the dynamic nature of surface hydrological processes in response to LULCC (Belihu *et al.*, 2020; Tan *et al*., 2014), it is a versatile model that can be used to integrate multiple environmental processes, which support more effective watershed management and the development of better-informed policy decisions (Gassman *et al.*, 2007). Researchers around the globe have been devising and utilizing a wide variety of land use models, all of which are diverse in their formulations, objectives, and capabilities. There are whole landscape models, distributional landscape models as well as spatial landscape models (Singh, 2003). As pointed, some of the models are ERDAS, ENVI, QGIS, GRASS, and IDRISI are few of them and among those listed ERDAS provides some pretty powerful build-in models such as a land cover classifier and climate models, etc. which are attractive features if they fall within specific use-case. ERDAS is a better teaching/learning tool because it more explicitly connects remote sensing and GIS. For analyzing land cover changes is chosen because of its capability to analysis of the land use changes it gives a better understanding of the functions of the land use systems and the support needed for planning and policy making. Such models can also predict the possible future change and use of the land cover under different scenarios (Ahmed and Ahmed, 2012; Rai *et al*., 2014).

1.3. Objective

1.3.1. General Objective

The main objective of this study was to assess the impact landuse land cover change on stream flow of Beles Sub-Basin.

1.3.2. Specific Objective

The specific bejectives of this study were

- To assess the historical changes in Land use and Land cover occurring within Beles Sub-Basin between 1987 to 2019.
- To project future LULC changes for the future years from 2019 to 2035 and 2055.
- To investigate the effect of Land use/Land cover change on the stream flow.

1.4. Research Questions

To address the above objectives the following research questions were designed

- What are the trends of Land use/Land Cover Changes in the study area for the past 33 years?
- What will be the future LULC of the basin in 2035 and 2055?
- To what extent do the land use/land cover changes affect the Stream Flow of the study basin?

1.5. Significance of the Study

Assessing the Effects of landuse and land cover change on stream flow is important to understand the land use and land cover patterns and the hydrological processes of the watershed. Up to date LULC and future projection of LULC changes information that will be generated in the study could be used by natural resource managers, researchers, planers, and policy makers in the study landscape for resource inventory and designing appropriate innervations for improving the use and sustainable management of natural resources both in short and long-term. Further, it will contribute to a better understanding of how the LULC changes impacted the local community and coping strategies to counter the shocks exposed to them as a result of the changes (Munthali, 2020).

2. LITERATURE REVIEW

2.1. Concepts Landuse and Land cover (LULC) changes

Until recently there was no agreement worldwide, or even at national levels, on precisely what constitutes land use or land cover or how to define them (Mcconnell, 2002). There are many definitions and descriptions of land use land use land cover depending on the purpose of the application and the context of the study (Mengistu, 2009). It is hence necessary to define the definition and description of land use, land cover, and landuse/land cover change terms are used in this study.

Land use describes activities, arrangements, and inputs often associated with people that take place on the land and represent the current use of property or in other words land use is attributed to how humans exploit the land cover to serve their purposes and include features such as residential zones, agricultural farms, logging areas, etc. Land cover describes the natural and anthropogenic features that can be observed on the Earth’s surface, i.e., forests, tidal wetlands, developed/built areas, grasslands, and water (Kaul and Sopan, 2014). Land use influences the changes in land cover; therefore, LULC change can be defined as the modification of surface features on the earth's landscape which is realized by the difference in their surface appearance assessed at two different times (Tadese *et al*., 2021).

The current global condition of mass environmental change and sustainability issues explains the magnitude of LULC change detection research in different parts of the world. Though LULC changes entail both natural (e.g. weather, flooding, earthquake, etc.) and anthropogenic causes, the ever-increasing demand of the growing population has designated the anthropogenic influences like the most dramatic (Turner, 2007; Foley *et al*., 2011; Weinzettel *et al*., 2013). The undisturbed original areas cover less than 50% of the total earth's landscape; forest cover is only 30% which was around 50% some 8000 years ago (Lambin *et al*., 2003). Diverse and intense anthropogenic activities around the world are attributed to most of these LULC changes. For this reason, researches are conducted around the world to study this dynamic LULC alteration and devoted efforts are underway to explore its connection with the disturbances happening in the earth system. As a result, general statements about impacts of LUCC and land-water interactions need to be continuously questioned to determine whether they represent the best available information and whose interests they support in decision-making processes (Bewket and Sterk, 2005; FAO, 2002).

So all this will add up giving a comprehensive knowledge of LUCC which is useful for reconstructing past land use and land cover changes and for predicting future changes, and thus may help in elaborating sustainable management practices aimed at preserving essential landscape function (Hietel, 2004).

2.1.1. Land Use and Land Cover Change Studies in Ethiopia

The impact of Land Use/Land Cover (LULC) change in Ethiopia is a complex topic, with various perspectives and opinions (Bewket and Sterk, 2005). While there may be common agreements and disagreements, it's crucial to note that viewpoints can differ based on individual expertise and research (Alemu *et al.*, 2015).

One potential agreement is that LULC change in Ethiopia has contributed to significant environmental challenges, such as deforestation, soil degradation, and biodiversity loss (Seleshi *et al*., 2014). This viewpoint recognizes the negative consequences of land conversion for agriculture, urbanization, and other human activities. However, the extent to which these impacts are occurring and their severity can be a matter of disagreement. Some argue that LULC change is happening at an alarming rate, leading to irreversible damage to ecosystems, while others may believe that the impacts are being exaggerated or that natural regeneration can mitigate the adverse effects (Eweg *et al*., 1998).

Another potential agreement is the need for sustainable land management practices. Many organizations, experts, and policymakers agree that implementing land use strategies that prioritize conservation and restoration can help mitigate the negative impacts of LULC change in Ethiopia. Approaches like agroforestry, reforestation, and sustainable agriculture are often seen as beneficial solutions (Amare *et al.*, 2014).

However, disagreements may arise regarding the implementation of these practices and their effectiveness. Some might argue that traditional knowledge and local involvement are crucial for successful land management, whereas others may focus on technological advancements, such as remote sensing and precision agriculture (Argaw and Sulaiman, 2011). Overall, it's had been important to consider a wide range of perspectives when assessing the impact of LULC change in Ethiopia which was done by engaging interdisciplinary research, It can better understood the complexities of this issue and work towards sustainable solutions.

Land is a precious resource for the livelihood of developing countries particularly Ethiopia, and following the demand for land, LULCCs in Ethiopia have resulted in a decline of natural forests to human settlements, urban centers, farmlands, and grazing lands (Dadi *et al*., 2016). Recent studies indicated that land use/land cover change is increasing; predominantly, expansion of agricultural land at the expense of natural forest was observed in different parts of Ethiopia (Kindu *et al*., 2018; Minta *et al*., 2018).

Studies that have been carried out at different parts of Ethiopia show that there is a rapid change recognizable, due to the population pressure, resettlement programs, climate change, and other human and nature-induced driving forces. Similar to other countries, anthropogenic activities are the most significant factors adversely changing the natural status of the Ethiopian landscape; for instance Alemu *et al*., (2015); Hurni *et al*., (2005); Gashaw *et al*., (2017); Kassa and Forech, (2009); Bekele, (2019); Geremew, (2013). As pointed by Dibaba *et al*., (2020) factors such as biophysical, socioeconomic, institutional, technological, and demographic, contributed to LULCCs, which leads to a decline in the agricultural yield and a loss of biodiversity in the entire upper Blue Nile Basin, but significantly in the Finchaa sub-basin in the Oromia Regional State, Ethiopia. The authors also pointed out that extended aridity and persistent drought, land and soil degradation, as well as the decline of water resources in general, are the major consequences of LULCCs at the regional scale.

A study that was done on the Andassa watershed which is in the Upper Blue Nile Basin shows that there had been a tremendous change in the land use land cover due to the increase of built-up areas and cultivated lands and also the projected LU/LC changes continued soil loss will increase and putting pressure on the hydrology of the studied watershed (Gashaw *et al*., 2017). Another study at Blue Nile Basin done was on Muga watershed there was urbanization increased by 27% and cultivation with 12% while forest lands, grasslands, and shrubs declined and over all, there was a change in the hydrological regime (Belay and Mengistu, 2019).

2.1.2. Approaches In Landuse/Land Cover Change Detection

As pointed by Marcucci (2000) historical analysis is the basis of landscape evaluation. It is not possible to assess the present conditions of landscape mosaic without at least knowing the recent history; it is only by considering the evolution of landscape that is possible to understand the level of response to different conditions. Nowadays characterizing land cover classification has been a widely done research topic for a variety of applications (Liang *et al*., 2001). According to (EPA, 2007) to characterize land cover changes different approaches are available where each their known strength and weakness have. There are two major approaches to the classification of remotely sensed images for various applications

In remote sensing, there are various image classification methods, supervised, unsupervised and hybrid. Unsupervised classification is computer controlled and its limitation is that the user cannot control the computer's selection of pixels into clusters. In the case of a supervised image classification system, the user relies on her/his prior knowledge and skills and can select a group of pixels belonging to a particular LULC. In this system, the user is required to have good knowledge about the local conditions of the area under study, or clear field evidence to validate the classification. Supervised classification is the most common type of land use classification system and depends on prior information about the land use and land cover. It is also common to come across a third approach known to be a hybrid classification that combines both supervised and unsupervised classification techniques (Kenea *et al*., 2021).

2.2. Projection of land use land cover changes

Projection of LULC is important for the future management plan of LULC by using time series data (Gashaw *et al*., 2017). Moreover, the prediction of LULC changes has significant roles in the understanding of earth-atmosphere interaction, forest fragmentation, biodiversity loss (Mahmood *et al.*, 2010). And also the result acquired from the projection can be a guide for conservation planning, assisting decision-makers to improve land use management plans to balance development and conservation (Tadese *et al*., 2021). It also ensures the continuous supply of natural resources available for current and future generations (Bunyangha *et al*., 2021). Nevertheless, prediction of the effect of future change has hardly even started (Beven, 2020).

Projection change will be achieved by creating a transition probability matrix of LULC change from period one to period two (Hyandye and Martz, 2017). To do so a variety of models have been used in diverse LULC predictions across the world including Agent-based, Markov, cellular automata models, and CA-Markov, etc. are just a few (Veldkamp and Lambin, 2001).

I. **Agent-based model**: Agent-based modeling refers to a modeling concept that is closely linked to the modeling techniques of object orientation (OO). Object orientation is the use of objects and classes in analysis, design, and programming. `Slots' within the object and the procedures are called `methods' (Huigen, 2003). In the context of a LULCC model, an agent may represent a land manager who combines individual knowledge and values, information on soil quality and topography (the biophysical landscape environment), and an assessment of the land-management choices of neighbors (the spatial social environment) to calculate a land-use decision (Parker *et al*., 2001).

II. **Markov model:** The Markov chain is a model that uses the logic of applying the probability of transition to predict the next situation and all future situations depending on the current situation (Aksoy and Kaptan, 2021). In another word, it can be used for determining the future state of a system can be predicted purely based on the proximately preceding state (Tadese *et al*., 2021). The procedure determines exactly how much land would be expected to transition from the later date to the predicted date based on a projection of the transition potentials into the future and creates a transition probabilities file. The transition probabilities file is a matrix that records the probability that each land cover category will change to every other category (Mishra *et al*., 2014). But, Markov chain analysis has several issues as the methods only provide short-term projection (Sinha and Kumar, 2013) and for this model, the spatial parameters are weak and do not recognize the various types of land use changes in the spatial extents (Wickramasuriya *et al*., 2009).

III. **Cellular automata:** The approach in this model is 'bottom to top'. The final global structure emerges from purely local interaction among the cells. CA not only offers a new way of thinking for dynamic process modeling. It also provides a laboratory for decision-making processes (Torrens, 2003). They have a natural affinity with GIS and remotely sensed data(Torrens and Sullivan, 2001).

IV. **CA-Markov Model:** The Markov chain model can be integrated with the cellular automata model (or CA-Markov model), and these models have been widely used on different scales especially involve with modeling and predicting the land use change (Hua, 2017). The CA-Markov model is applied for the advantages of the combination of the stochastic aspatial Markov techniques with the stochastic spatial cellular automata method (Arsanjani *et* *al.*,2012). These include the prediction of two-way transitions among the availability of LULC classes.

2.3. Impact of Land use/Land cover Change on Stream Flow

Human-induced activities on land have significant effects or changes on land which is caused by factors such as deforestation, afforestation, and agricultural and urban development within the river basin and all this adversely puts pressure on stream flow (Galata *et al.*, 2020). It is researchers' interest to study the hydrological cycle and the stream flow or in genral the hydrological response of a catchment but the journey to do so has become very complex due to complicated inter-relationship between various hydrological components such as precipitation, evaporation, transpiration, infiltration, and runoff. land use change has adverse implications on the natural hydrologic system in terms of variation in the runoff regime, evapotranspiration (ET), subsurface flow, infiltration, etc..(Dwarakish and Ganasri, 2015). In other words, as stated by Kassa and Forech (2009) LULC has a direct impact on a basin's hydrological responses by sub-dividing rainfall between the atmosphere as evaporation and transpiration to return flow and flow to rivers and into the ground. And all this shows that it has to do with land use planning and management (Getu Engida *et al*., 2021). As a result to understand the complex relation between LULCC and hydrological response and come up with better planning and management different models can be applied, the development of hydrologic models that consider Spatio-temporal watershed characteristics helps in the accurate prediction of the dynamic water balance of a watershed (Dwarakish and Ganasri, 2015).

2.3.1 Previous studies on LULC change impact on stream flow in Ethiopia.

Understanding of LUCC has built up from individual case studies, using both remote sensing and ground-based data, and we will continue to rely on case studies as a means to gain the required knowledge. Studies have been carried out at different parts of Ethiopia to understand at a watershed level the impact of LULC on hydrological responses (Motuma *et al.*, 2021); To support effective watershed management, a thorough understanding of the hydrological processes occurring in the watershed is important. Numerous studies on land use change impact on hydrological parameters have been carried out at different sites (Belay and Mengistu, 2019; Belihu *et al*., 2020; Bewket and Sterk, 2005; Galata *et al*., 2020; Getu Engida *et al.*, 2021; Tadese *et al*., 2021; Tegegne *et al*., 2017; Woldesenbet *et al*., 2017).

A study that was done on Melka Kuntrie Sub-basin in Ethiopia by Getahun and Haj (2015) found that; the land use in 2003, which was mostly converted to agricultural land from forest, grass, or shrubland, showed increased streamflow in the main rainy season, while the streamflow in the dry or small rainy season. At the same time, there was a decrease in evapotranspiration in 2003 land use. The streamflow increased by the 2003 land use was 25% in June, 4% in July, 6% in August, and 9% in September that corresponded to 0.065 mm/day in June, 0.077 mm/day in July, 0.07 mm/day in August and 0.039 mm/day in September for the main rainy season as compared to the 1986 land use. Another study by Gashaw et al., (2017) on Andassa watershed, Blue Nile Basin Cultivated land was expanding from 62.7% in 1985 to 73.1% in 2000 and 76.8% in 2015. The area of built-up also slightly increased (0.1–1.1%) between the 1985 and 2015 periods. In contrast, forest, shrubland, and grassland were reduced from 3.5 to 1.9%, 26.2 to 15.3%, and 7.6 to 4.9% in the 1985 and 2015 periods, respectively. The increase of cultivated land and built-up area, and the withdrawing of forest, shrubland, and grassland were further continued in the 2030 and 2045 periods. Eventually in both cases agricultural expansion, population growth, shifting cultivation, fuelwood extraction.

The case for Majang Forest Biosphere Reserves of Gambella, Southwestern is no different Tadese *et al*.,(2021) it was identified that forestland, farmland, grassland, settlement, and water body. Farmland and settlement increased by 17.4% and 3.4%, respectively; while, forestland and grassland were reduced by 77.8% and 1.4%, respectively, from 1987 to 2017. (Predicted results indicated that farmland and settlement increased by 26.3% and 6.4%, respectively, while forestland and grassland decreased by 66.5% and 0.8%, respectively, from 2032 to 2047. Aklilu and Jan, (2007) indicated that an increase in agricultural land at the expense of natural vegetation in central highlands. On the other hand, Bewket and Sterk (2005) pointed out an increase in a woodland area in recent years due to afforestation efforts in the Blue Nile basin, North Ethiopia.

2.3.2. Hydrologic Models

Studying the hydrologic dynamics of land use in this basin requires the use of hydrologic modeling that serves as a valuable tool in water resources management for many years and is also used to predict the impacts of land use on a hydrological response (Tegegne *et al*., 2017). The hydrological model is an assemblage of mathematical descriptions of components of the hydrologic cycle (Kassa and Forech, 2009). Different hydrological models perform long-term simulations to assess impacts on hydrological processes and management options (Belihu *et al*., 2020). They have been developed for many different reasons and have many different forms. In general, they are designed to meet one of the two primary objectives; to get a better understanding of the hydrologic processes in a watershed and of how changes in the watershed affect the whole system and for hydrologic prediction and they are also providing valuable information for studying potential impacts of changes in land use and land cover (Kassa and Forech, 2009). The following are some of the hydrological models which are used to analyze the hydrological response of the watershed.

Lumped hydrologic models: Lumped models assume the complete basin as a homogenous system without considering the spatial distribution of processes (Famiglietti and Wood, 1994). Lumped hydrologic models do not vary spatially within the basin and thus, basin response is evaluated only at the outlet, without explicitly accounting for the response of individual sub-basins. The parameters often do not represent physical features of hydrologic processes and usually involve a certain degree of empiricism. The impact of spatial variability of model parameters is evaluated by using certain procedures for calculating effective values for the entire basin. The most commonly employed procedure is an area-weighted average. These models are not usually applicable to event-scale processes while for discharge prediction they can provide just as good simulations as complex physically-based models (Beven, 2020). Typical examples of lumped hydrological models include IHACRES, WATBAL, and TOPLATS.

Distributed models: Distributed modeling approach attempts to incorporate data concerning the spatial distribution of parameter variations together with computational algorithms to evaluate the influence of this distribution on simulated precipitation-runoff behavior. These models generally require large amounts of (often unavailable) data for parameterization in each grid cell. However, the governing physical processes are modeled in detail, and if properly applied, they can provide the highest degree of accuracy. Typical examples of these models include MIKE SHE, CASC2D, and CEQUEAU (Kassa and Forech, 2009).

Semi-distributed hydrologic models: models partially allow parameters to vary in space by dividing the basin into several smaller sub-basins. The main advantage of these models is that their structure is more physically based than the structure of lumped models and that they are less demanding on input data than fully distributed models. SWAT, HEC-HMS, HSPF, PRMS, DWSM, TOPMODEL, HBV are considered semi-distributed models. These types of models calculate flow contribution from separate sub-basins, considering that the sub-basins are homogenous (XU, 1998).

2.3.2.1 Model Selection

The choice of the hydrologic model may depend on several selection criteria, including the character (e.g., relevant spatial and temporal scale, acceptable level of error and uncertainty for alternative screening vs. detailed design) (e.g.,(Clark *et al*., 2008)) of the water resource management issue. In addition, the scale of variability in physical characteristics (e.g., land use, elevation, geology) that influences important hydrological processes (e.g., evapotranspiration, snow accumulation and melt, or groundwater recharge and discharge) can be a principal factor in selecting hydrologic models (Surfleet *et al.*, 2012). Finally, aspects of the individual models may influence its appropriateness for an application, including ease of use that includes pre-and post-processing, hardware requirements, rigor and comprehensiveness of modeled processes, availability and quality of required data, adaptability of source code, model availability, and cost (Novotny, 2016).

This study aims to assess the hydrological response of the Beles Sub-basin under historical and projected land use land cover so to assess the hydrological response is done with the hydrologic model which has the capability to:

- Represent variable land use/land cover throughout the catchment, and produce a full hydrograph response from each sub-area
- Simulate different components of the streamflow including surface runoff, lateral flow, and base flow
- Route hydrographs through different stream reach and identify principal runoff source areas at selected points of interest.
- Compute sub-area release rates, or provide travel time and peak flow information from which these release rates may be developed.
- Evaluate the impact of land use land cover changes on hydrology
- To be applied over a range of catchment sizes from small to large catchments
- Simulate continuous and long term impact
- Freely available

For this study, SWAT is a typical approach to be used to assess LULCC impacts on hydrological response particularly in watershed management. have proven the suitability of such a model in LULCC impact assessments on water resources SWAT is selected as an appropriate model to meet the simulation requirements set above using available soil, topography, land cover /land use, and weather data.

2.3.2.2 SWAT Model

The Soil and Water Assessment Tool (SWAT) was developed by the U.S. Department of Agriculture's Agricultural Research Service (Arnold and Fohrer, 2005). It is a physically-based, basin-scale, pseudo-distributed, continuous-time watershed model emphasizing surface processes. SWAT operates by taking a single watershed, gauged or ungagged, and breaking it into multiple sub-basins which are then further broken into multiple unique combinations of land use, soil, and slope known as Hydrologic Response Units (HRUs) (Wible, 2014). Calculations in SWAT are performed for each HRU and then scaled up to the sub-basin outlet by the percent area of the HRU within the sub-basin based on land cover and soil maps. Each HRU contains several water storage volumes: canopy, snow, soil profile, shallow aquifer, and deep aquifer. Precipitation falling on the HRU is reduced by canopy interception, which is modeled as a function of the reference evapotranspiration (ET), the maximum canopy storage, and the ratio between actual (Huisman *et al*., 2004). This approach results in the HRUs lacking the spatial relations typically seen in a fully distributed model, but yields a computationally efficient calculation scheme allowing for watershed simulation over large periods (Gassman *et al*., 2007). And also SWAT has been increasingly used to assess the impacts of land use change on hydrological processes and hydrological influenced ecosystem services (Arnold and Fohrer, 2005; Francesconi *et al*., 2016).

Many studies have successfully been used as a calibrated and validated model to estimate the impacts of LULC on the water budget. For example, Mengistu, (Mengistu, 2009), showed model potential through estimated impacts of LULC changes and management practices on watershed hydrological responses at Hare Watershed, Ethiopia. Homdee *et al*., (2011) used the SWAT model to assess the impacts of land cover changes on hydrological response at Chi river basin, Thailand. In all the studies, there is an adequate potential of the model to evaluate hydrological impacts of LULC changes. The following figure displays the pathways for water movement within SWAT2005.

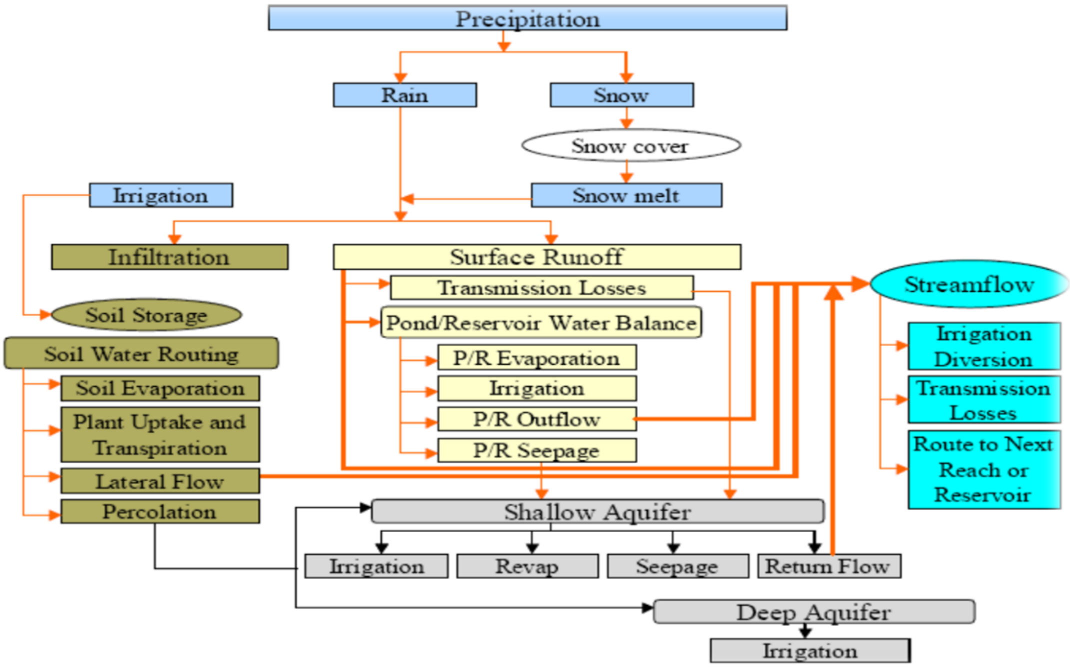

Figure 2. 1 Pathways for water movement within SWAT2005

Source: Adopted after ((Neitsch, Arnold, 2005)

3. MATERIAL AND METHODS

3.1 Description of the study area

3.1.1. Location

Beles Sub-Basin, which is in one of the major the sub-basins of Upper Blue Nile Basin. It is situated on the plateau of the north-western highlands and its adjacent lowlands of Ethiopia, in the southwestern direction of Lake Tana. Its geographic location between 10° 56' to 12° North latitude and 35°12' to 37° East longitude. It is located at a distance of around 698 Km from the capital city of Ethiopia Addis Abeba. The total area of the sub-basin is about 1358063.0 ha. Figure (3.1) shows the location of the study area.

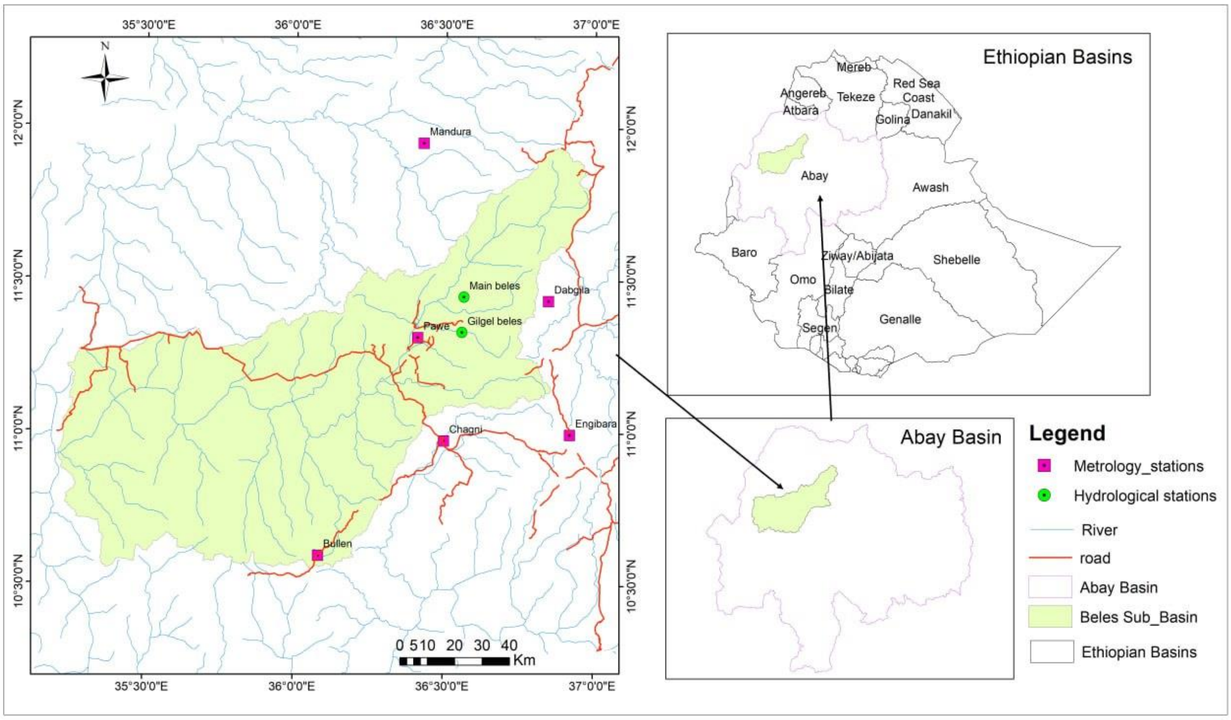

Figure 3. 1 : Location of Beles Sub-Basin

3.1.2 Topography

The study area generally has a complex topography with a significant elevation variation range from 990- 2725m. The Upper Beles sub-basin is bounded on the east and southeast by steep escarpment and the north and west by rolling to hilly terrain which separates it from the Dindir River drainage basin. The highest point in the sub-basin is 2,725 (masl) at the water divide between the Tana and Beles sub-basins and the mean elevation is about 1870 (masl). The central part of this area encloses the wide, gently undulating to flat plains of the Pawe area.

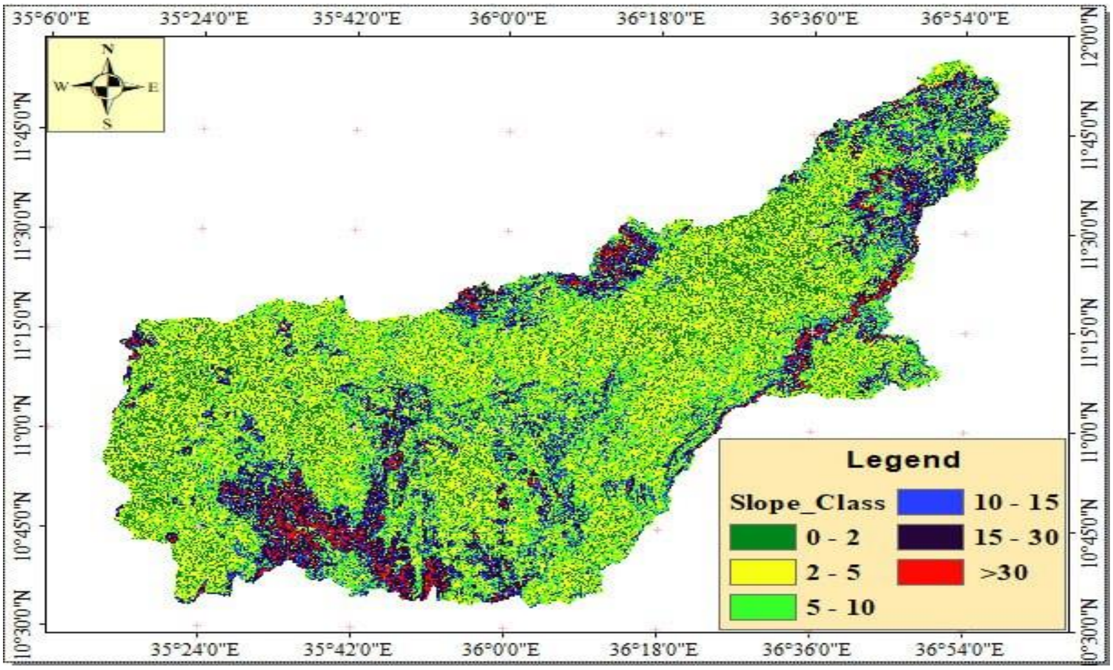

Figure 3. 2 : Slope map of Beles Sub-Basin.

The study area marked topographic variation. As shown in Table (3.3) and Figure (3.2) the dominant slope class between 2-5% which is called gently flat to undulating terrain which covers 27.9% of the study area and 5-10 % (Rolling terrain) topography with total coverage of 22.2%, whereas 0-2% is the third dominating slope with percentage of 19.6% from the total area and 10-15 % slope classes of hilly terrain cover 14.3% study area. Mountainous terrain and gently mountainous terrain topography covers only 10.4% of the study area.

Tabel 3. 1 :Slope classes and their area coverage in Beles sub-basin

Slope Class (%)	Slope Class Name	Area(ha)	Area (%)
0-2%	Flat to Almost flat terrain	266,180.35	19.60%
2-5%	Gentle flat to undulating terrain	378,899.58	27.90%
5-10%	Rolling terrain	301,489.99	22.20%
10-15%	Hilly terrain	194,203.01	14.30%
15-30%	Slope dissected to mountainous terrain	141,238.55	10.40%
>30%	Steep mountainous terrain	76,051.53	5.60%
Total		1,358,063.00	100.00%

Source: Adopted from (FAO, 2002)

3.1.3 Climate

The climate of the study area is characterized by a tropical climate and is dominated by its high altitude. The climate is also governed by the movement of the Inter-Tropical Convergent Zone (ITCZ). The climate in the study area is warm and subtropical. The annual mean yearly minimum and maximum temperature is ranging between 16.5ºC - 32.5 ºC (Pawe metro. station). Precipitation is moderately abundant in the upper Beles (about 1000 mm/year), even in years when other adjacent areas are very severely affected by drought (Yimer *et al.*, 2009). Rainfall increases with elevation in the study area. Annual potential evapotranspiration is about 1500 mm. Annual rainfall shows a unimodal distribution and is well over 1000 mm year−1 with a daily contrast that is stronger than the seasonal contrast. Global warming tends to lead to slightly increased rainfall over the basin by the end of the twenty-first century.

A. Rainfall

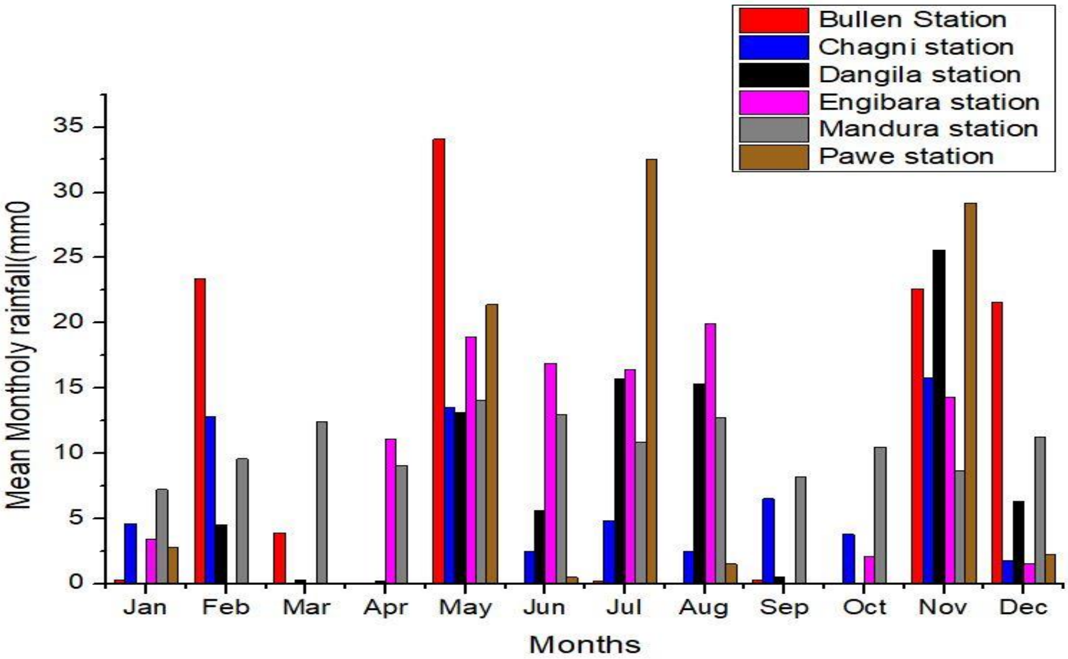

Figure 3. 3 : Mean monthly rainfall graph of selected meteorological stations in Beles Sub-Basin (1987-2019).

B. Temeprature

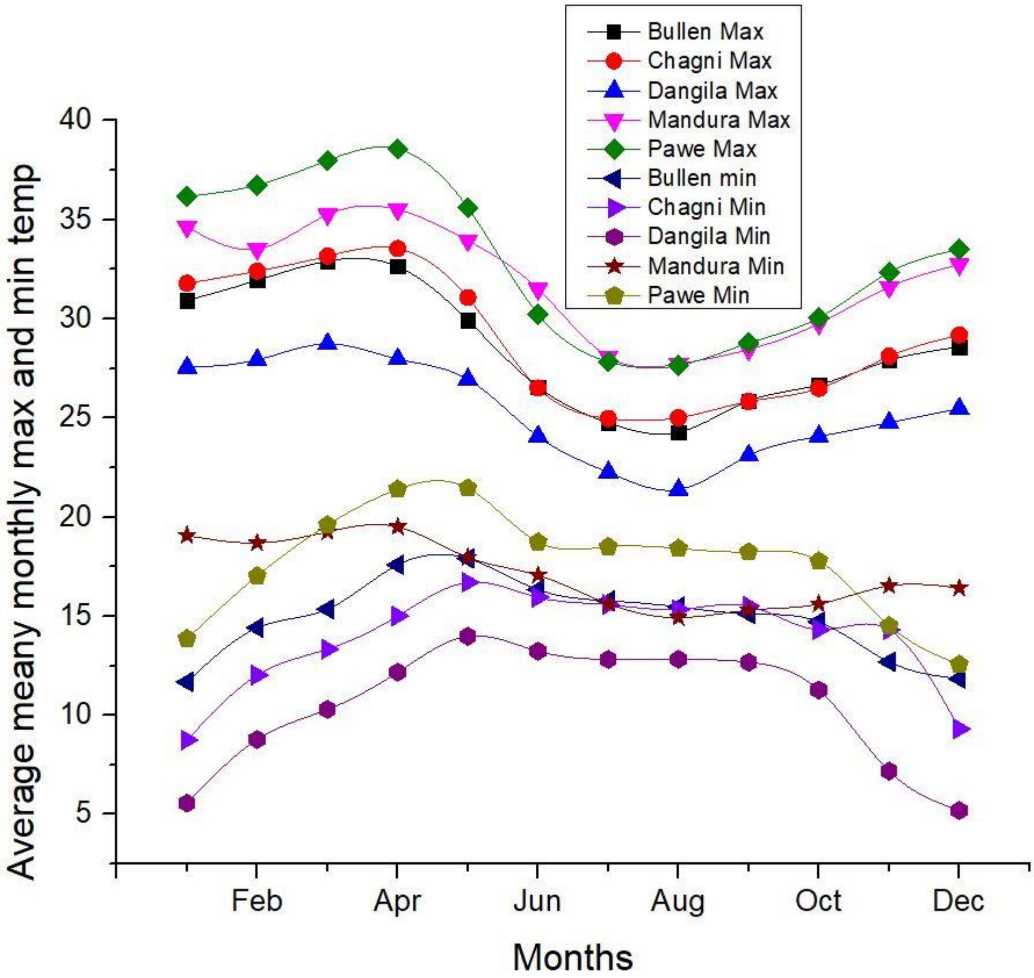

Figure 3. 4 : Average Monthly Max, Min and Mean Temp in the period of (1987-2019)

3.1.4 Soil

The Main Belles watershed is characterized by four major dominant soil types: Haplic Luvisols, Humic Nitisols, Eutric Vertisols, and Eutric Leptosols. Black clay soils are predominant in the Beles Sub-Basin and particularly in the north-western area. The Upper Beles sub-basin near Pawe plateau is more dominated by Chiromic Vertisols and Chiromic Luvisols which are more dominant at the upper part of the sub-basin (Gete, 2018).

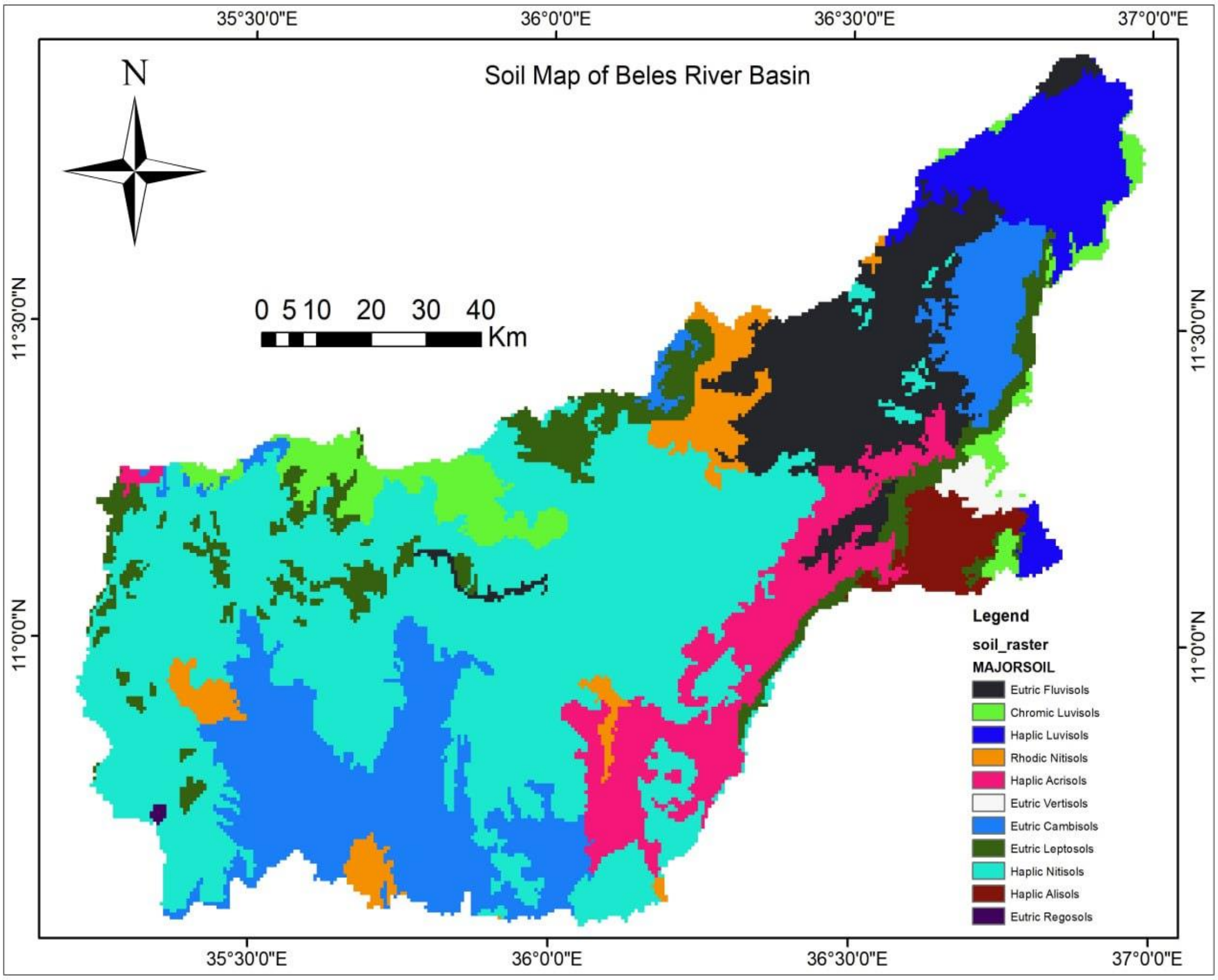

Figure 3. 5 : Soil map of Beles Sub-Basin

3.1.5 Land Use Land Cover

The Land use/cover types of the Beles basin are classified as Agricultural land, Wet Land, Forest Land, Shurb Land and Urban. The whole area is dominated by Shurb Land and Agricultural Land starting from Past to upto present. The southern half of the basin is characterized by wood-land savannah composed of various species of acacia, figs, and associated small trees.

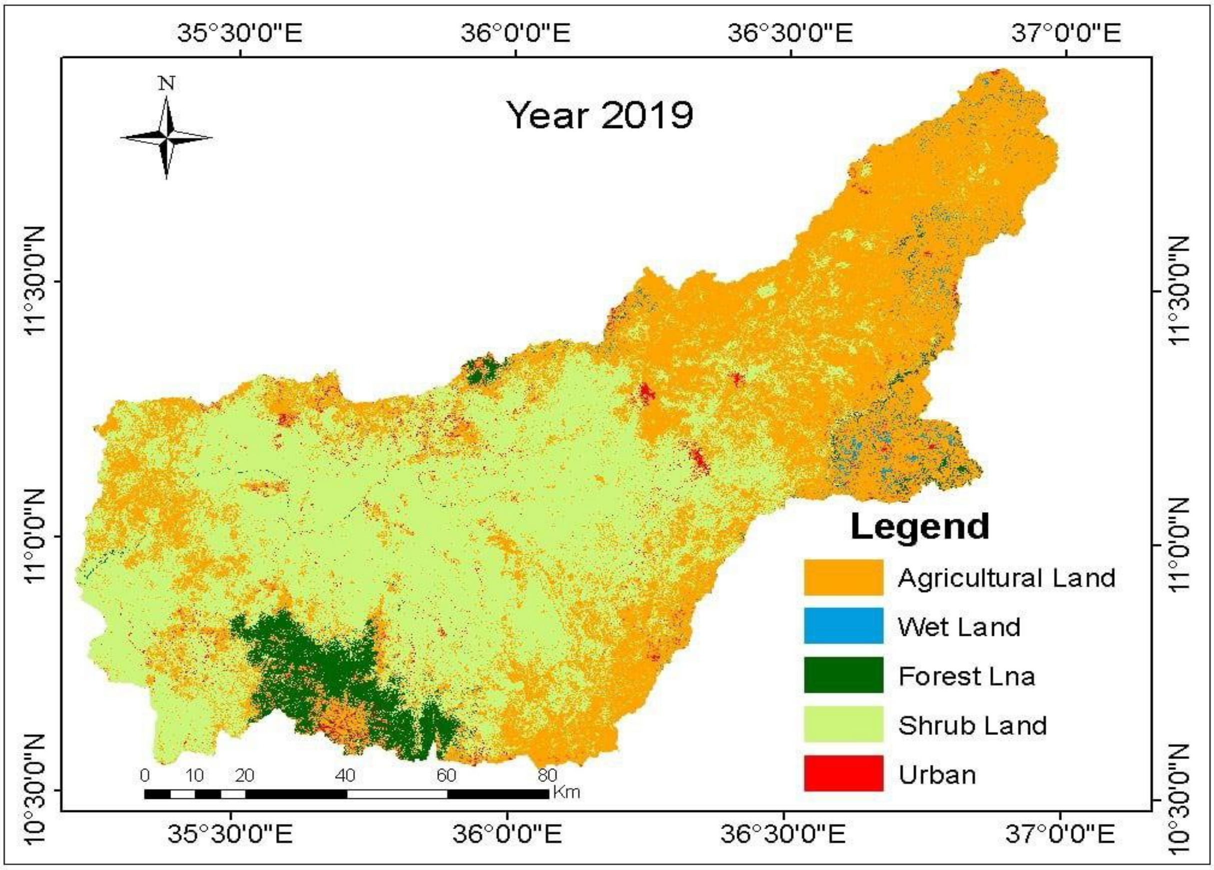

Figure 3. 6 : Land Use Land Cover of Beles Sub-Basin

3.2. Data Collection and Analyes

3.2.1 Assesement of Land use Land cover Change of the Past Years

This assessment was based on the analysis of satellite imagery of the study area. Therefore, the first and foremost task was the selection of satellite sensors and associated images. During this process, the prior considerations were the purpose of the study, objects to be identified, and the availability of images. Landsat satellite images were selected for this study for many reasons such as: for long-term change detection, Landsat data are available since 1972 (Siddhartho, 2013).

This property of this sensor has increased the flexibility of data selection, especially when cloud cover is a major limitation in satellite data selection and Last but not least, Landsat data are freely available and it was a huge support to this assessment. After selecting the satellite sensor, the next task was to collect the necessary landsat imagery for this study

(Hemati *et al*., 2021). Since this study aims to detect the LULC changes in Beles Sub-Basin from 1987 to 2019 where the years were chosen based on the basin becoming an investment and settlement hotspot for the last 30 years as the establishment of roads and large commercial farms as of the year 2000 enhanced changes in many places in the basin, political change in the country, quality of the available images, and compatibility with the metrological and hydrological available data in the study area.

After considering all of these factors, three landsat images were selected for analysis and download from the data warehouse of USGS Earth Resources Observation and Science Center (EROS): For 1987 Landsat 5 TM imagery, for 2002 Landsat 7 ETM and 2019 Landsat 8 OLI. Detailed information's about the collected satellite images are indicated in the table below (Table3.2).

Tabel 3. 2: Satellite images with their dates of acquisition, path/row, and resolution

Satellite ID	Sensor ID	Path/Row	Date of Acquisition	Spatial Resolution
Landsat 5	TM	170/52 170/53 171/52 171/053	Jan 18, 1987	30m*30m
Landsat 7	ETM+	170/52 170/53 171/52 171/053	Jan 12, 2002	30m*30m
Landsat 8	OLI	170/52 170/53 171/52 171/053	Dec 30, 2019	30m*30m

In addition to a satellite image, the other data which was crucial for landuse/land cover quality assessments are ground control points. This data can be obtained from different sources such as georeferenced thematic maps, aerial photographs, and global position system, and Google Earth. Depending on the availability of data, time and cost, google earth was chosen as the source of ground control points for this study

3.2.1.1 Image Classification

Image classification and enhancement for this study were performed using ERDAS Imagine. ERDAS Imagine was also used for preparation of land use land cover data . This model uses for Data acquisition, image processing and classification of the land use and land cover image of the catchment which is used for further analysis and interpretation of the result. The landsat data image of the catchment which shows the landuse/land cover for three different years of 1987, 2002 and 2019 were downloaded and used for ERDAS Imagine for further image enhancement, processing and re-classification. Layer staking of the different bands of downloaded satellite images were done for all the data on ERDAS Imagine. then mosaic(groping of multiple images to single imagery) Afterwards, sub setting or extraction of the watersheds satellite image were done for simplification and time saving of image classification on ERDAS Imagine using the watershed's shape files which was derived from delineation.

The images was classified using a supervised classification algorithm the remotely sensed satellite image was used for accurate signature development. This method is used to cluster pixels in a data set into classes corresponding to a user-defined area of interest training classes which are selected as representative areas to be mapped in the output. Historical information has been integrated to minimize complete reliance on spectral information and solve the mystery of spectral similarity of different land cover classes to improve classification accuracy.

The main objective of classifying satellite images is to categorize pixel values automatically and transform them directly in to the classes or forms of land use

3.2.1.2 Accuracy assessment

All classification procedures were produce different classified images but which one is the most correct. One way to assess the accuracy of the classification output is to directly compare the classified pixels to known, Google Earth. Therefore, this study intend to examine the accuracy of Landuse land cover classification using Google Earth in the case of Beles Sub-Basin.

Google Earth is free to the public is a good source of imagery including satellite images and air photos. Google Earth (http://earth.google.com) provided by Google Inc. Google earth high-resolution imagery is an important accuracy assessment by comparing of point-by-point basis. A random set of points generated for the area and then identified using Google Earth the value for each point (Tilahun, 2015). To quantitatively assess the accuracy, statistical methods like overall accuracy and kappa value will be applied. Kappa were used as a measure of agreement between model predictions and reality (Congalton, 2014). Kappa was computed using Equation 3.1

Kappa Index of Agreement (KIA)

$$KIA= \frac{N \sum x_{11} - \sum x_1 * x_2}{N^3 - \sum x_1 * x_2} \dots \dots \dots \dots \dots \dots \dots \dots .. (3.1)$$

x_{11} = number of combinations along the diagonal

x_1 = total obs in row i

x_2 = total obs in column i

N = total number of cells

Kappa analysis is a discrete multivariate technique used in accuracy assessments. According to (Badura et al., 2011) the acceptable ranges of the kappa coefficient are presented in the table below.

Tabel 3. 3: Table Kappa statics recommended Range.

SNO	Kappa Statistic	Strength of agreement
1	<0.00	Poor
2	0.00-0.2	Slight
3	0.21-0.4	Fair
4	0.41-0.6	Moderate
5	0.61-0.8	Substantial
6	0.81-1	Almost perfect

The kappa coefficients of the classified images were calculated by equation (3.2) which was recommended by (Congalton., 1991).

$$K = \frac{[N \sum_{i=1}^{r} X_{ii} - \sum_{i=1}^{r} (X_{i+} X_{i+1})]}{N^2 - \sum_{i}^{r} (X_{ii+} X_{i+1})} \dots \dots \dots \dots \dots \dots .. (3.2)$$

Where K is the kappa coefficient, $_{i=1}$

r = number of rows and column in the error matrix,

Xii = observations in a row, i and column i,

Xi+ = the marginal totals of row i,

X+i = the marginal totals of column i, and

N = total number of observations.

3.2.1.3 LULC Change Analysis

LULCC finding is the process of identifying differences in the state of an object or phenomenon by observing it at different times. Essentially, LULCC recognition involves the ability to quantify temporal effects using multi-temporal data sets. The general approach of LULCC is based on the post-classification comparison method, which is commonly employed in land cover change detection studies. In this method, after two images from different dates were independently classified, post-classification comparison of independently classified and developed landuse/land cover maps of 1987, 2002 and 2019 years were conducted, after their accuracy assessment was cheeked.

LULCC detection is the process of finding differences in the state of landuse/land cover by observing it at different times. LULCC detection involves the ability to quantify temporal effects using multi-temporal data sets. In the supervised classification technique, images with different dates were independently classified, to the pre-defined landuse/land cover types, and compared to each other. Landuse/land cover change comparison matrix gives general information about major changes in the landuse/land cover classes between two periods. To recognize the major land cover gain and loss of cover classes, the conversion matrix for each period was analyzed. The conversion matrix of consecutive years was computed by using intersect functions in the GIS and the intersected area was computed, then the attribute table was exported to excel and the conversion matrixes were determined

The annual rate of change for individually landuse classes was calculated by the difference between a final year to initial year which represents the magnitude of change between corresponding years was divided by the number of study years, i.e 1987-2002, 2002-2019 and 1987-2019 (33 years) respectively using the following equations.

$$\text{Total gain or loss} = [\text{Area of the final year} - \text{Area of thr intial year}] \dots\dots\dots\dots\dots\dots\dots . (3.3)$$

$$\text{PRECENTAGE CHANGE} = \left[\frac{\text{FINAL YEAR AREA} - \text{INTIAL YEAR AREA}}{\text{INTIAL YEAR AREA}}\right] \times 100 \ldots\ldots\ldots.(3.4)$$

$$\text{ANNUAL RATE OF CHANGE} = \left[\frac{\text{FINA YEAR AREA} - \text{INTIAL YEAR AREA}}{\text{No Of YEARS}}\right] \ldots\ldots\ldots\ldots\ldots(3.5)$$

3.2.2 Projection of the Future Land use Landcover

To predict future LULC changes for the study site, IDRISI software (CA-Markov model) was used. Combination of Cellular Automata(CA) models, the Markovian model, Cellular Automata models were used for simulating spatial distributions and Markov Chain models were used for simulating temporal changes so the combination of those is a robust approach for predicting land-use change estimates the quantity of change (Tadese *et al*., 2021). Based on the suitability maps that were generated, it was possible to proceed to the final step of the Markov-CA model, "change the allocation," and the prediction maps for the year 2035 and 2055. That was the probability of each land cover category changing to another category. In the second step, a set of conditional probability images one for each land cover class was produced. These maps express the probability that each pixel belong to the designated class in the next period. They are called conditional probability maps since this probability is conditional on their current state. In this study Landuse/land cover of 2002 and 2019 were used to predict the future landuse land cover of the study area.

To identify the land use/land cover change dynamics for any study area depending on the previous or current land cover condition in CA-MC model, used was mathematically computed as

$$S(t+1) = Pij * S(t) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.(3.6)$$

Where, S (t), S (t +1) are the system status at the time of t or t +1;

Pij is the transition probability matrix in a state which is calculated as show

$$Pij = \begin{bmatrix} P11 & P12 \ldots & P1n \\ P21 & P22 \ldots & P2n \\ Pn1 & Pn2 \ldots & Pnn \end{bmatrix} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(3.7)$$

Where, P is the Markov probability matrix, and P ij stands for the probability of converting from current state i to another state j in next time period.

3.2.2.1 CA – Markov model validation

For model validation, the simulated land use/cover map for 2019 was used in the model validation. Markov model validation was achieved by comparing the simulated LULC map of 2019 based on the kappa variation. Kappa variation was also generated from VALIDATE module. The validating LULC map of 2019 was used as a basis to predict LULC changes for 2035 and 2055 under the CA-Markov prediction module in the LCM of IDRISI using markovian transition area, transition suitability images and a standard cellular automate filter (Bunyangha *et al*., 2021). The Kappa Index for a valid model is >70% If the model has the Kappa Index less than 70% then the suitability map for the land covers and filter used repeated based on several considerations (Chilagane, 2018).

$$Kappa = \left[\frac{Po - Pc}{1 - Pc} \dots \dots \dots \dots \dots \dots \dots \dots (3.8)\right]$$

Where, Po is the proportion of correctly simulated cells; Pc is the expected proportion correction by chance between the observed and simulated map. The study according to (Arsanjani *et al.*, 2012) represents that a kappa value of 0 illustrates the agreement between actual and simulated map (equals chance agreement), the upper and lower limit of kappa is +1.00 (when there is total agreement) and -1 (it's happen when agreement is less chance

3.2.2.2 MLP-NN Performance Evaluation and Sensitivity Analysis

The transition potentials tab in the LCM TerrSet image processing toolset is used for testing parameters and conducting model performance evaluation, as well as performing sensitivity analysis using the MLP (Multi-Layer Perceptron) model. In this context, various sensitivity analysis parameters are employed to evaluate the skill measure.

Three specific sensitivity analysis techniques mentioned are: Forcing a single independent variable to be constant: This involves holding one independent variable at a constant value while allowing the other variables to vary. By observing the effect of changing the other variables while keeping one constant, the sensitivity of the model to that particular variable can be assessed, Forcing all independent variables except one to be constant: This technique involves fixing all independent variables at constant values except for one. By varying a single independent variable while keeping others constant, the impact of that specific variable on the model can be examined and Backward stepwise constant forcing mechanism: This method involves systematically removing independent variables from the model and assessing their individual contributions. Starting with all variables included, one variable is removed at a time, and the model's performance is evaluated each time. This allows for understanding the sensitivity of the model to the exclusion of specific variables.

These sensitivity analysis techniques help evaluate how the model's performance and results are influenced by changes in the independent variables, enabling a deeper understanding of the model's behavior and robustness

Figure 3.8 summarizes the entire process chain for both the historical and projected Land Use Land Cover change

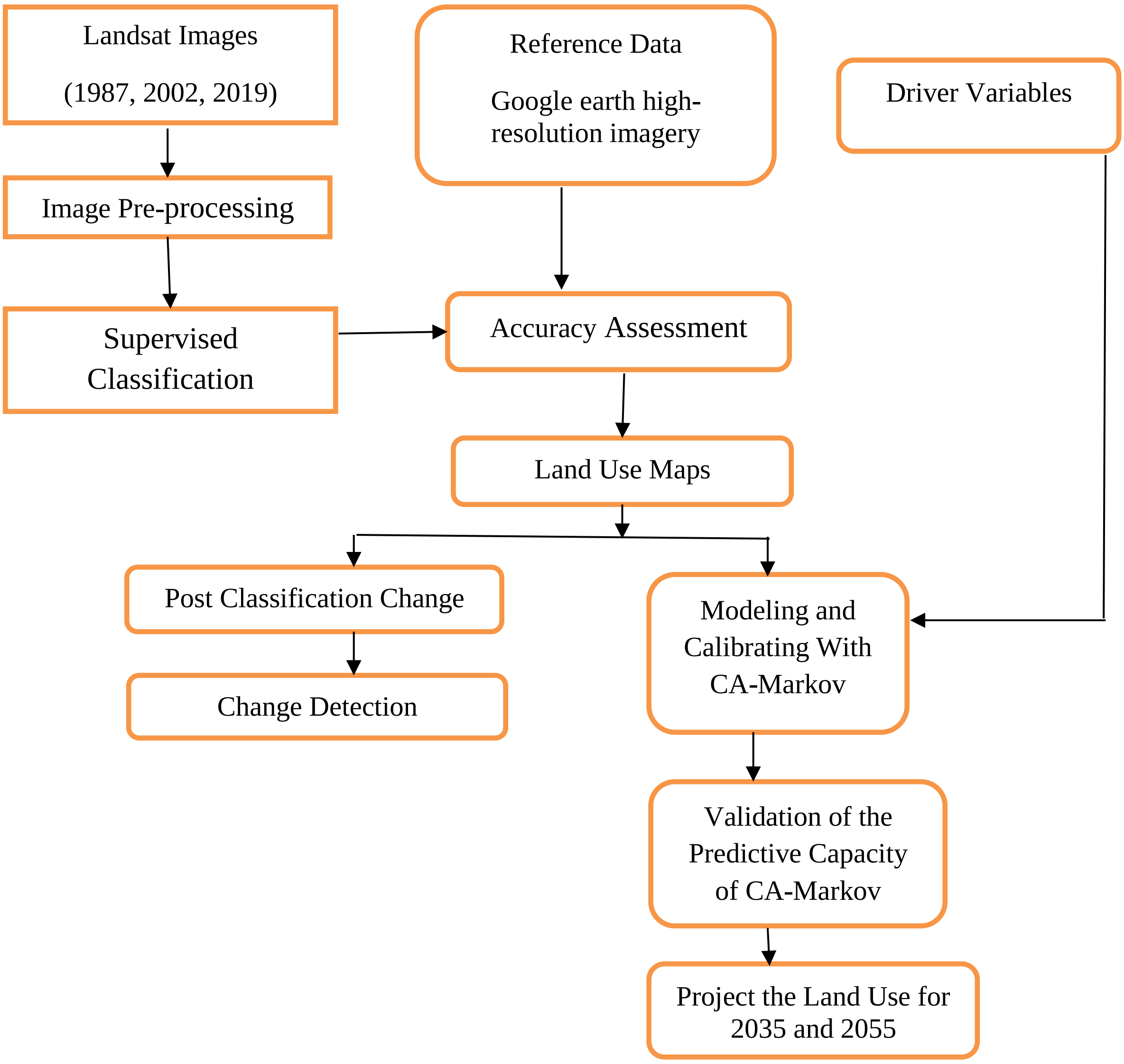

Figure 3. 7: Flow Chart of Land use land covers analysis procedure

3.2.3 Analyzing the impact of Change in LULC on stremflow

3.2.3.1 SWAT Model Input Data Collection and processing

To analyze the hydrological response to the change in the LULC SWAT model was used and the specific data's and information needed about the watershed such as soil properties, weather data, Land use and Land cover, and other land management practices. These data was collected from different sources and databases. (Geremew, 2013). The data that were analyzed are presented in the next sub-sections

3.2.3.2 Digital Elevation Model

This research used Digital Elevation Model (DEM). The 30-meter Shuttle Radar Topographic Mission (SRTM) data which was obtained from the USGS website (https:/www.usgs.gov/). The data then projectd to Universal Transverse Mercator (UTM) on the spheroid of WGS84 zone 37N. was processed for the extraction of flow direction, flow accumulation, stream network generation and delineation of the watershed and sub-basins. The topographic parameters of the study watershed, such as terrain slope, channel slope or reach length was also derived from the DEM (Mengistu, 2009).

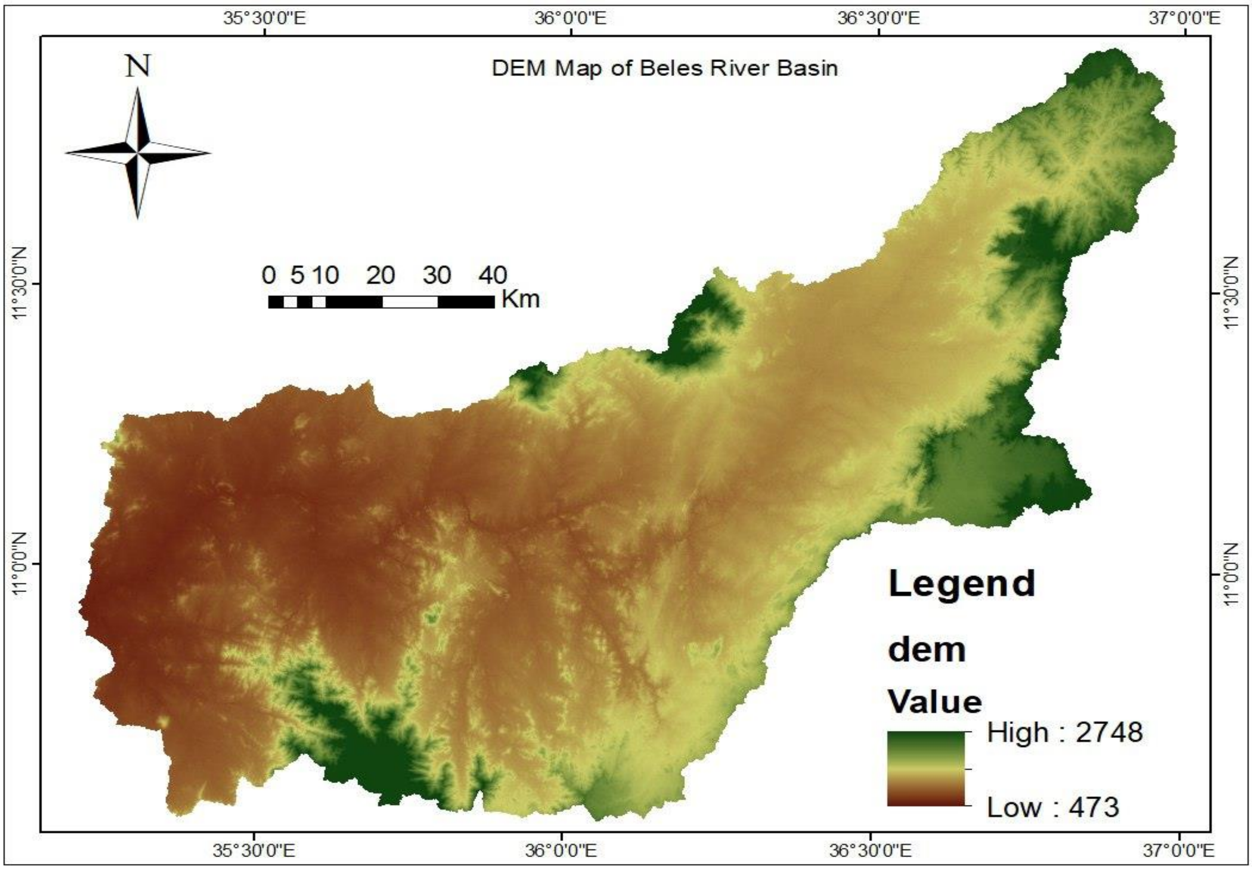

Figure 3.8 : DEM of Beles Sub-Basin.

3.2.3.3 Slope

The slope was derived from DEM input so that the model used this slope for the development of the Hydrological Response unit in addition to land use and soil input parameters. Based on the FAO slope classification the slope of the study area was classified (Asitatikie, 2019).

3.2.3.4 Soil Data

Soil data needed to determine the hydrological parameters of the sub-watershed and the Hydrological Response Unit (HRU). The SWAT model of input soil layers was obtained from the Harmonized World Soil Database (HWSD). Soil physicochemical and hydrological properties was then obtained from various sources like FAO-UNESCO soil databases. Accordingly, a user-defined soil database which was uprepared for each soil layer and added to the SWAT user soil database (Mengistu, 2009).

3.2.3.5 Weather Data

Daily climatic data is an important input data required by the Arc SWAT model to simulate streamflow. The data include daily precipitation, maximum and minimum temperature, relative humidity, wind speed, and solar radiation. These data then obtained from the National Meteorology Agency of Ethiopia for the study area. The climatic data were used for this study covered years from January 1987 to December 2019 which is 33 years of duration.

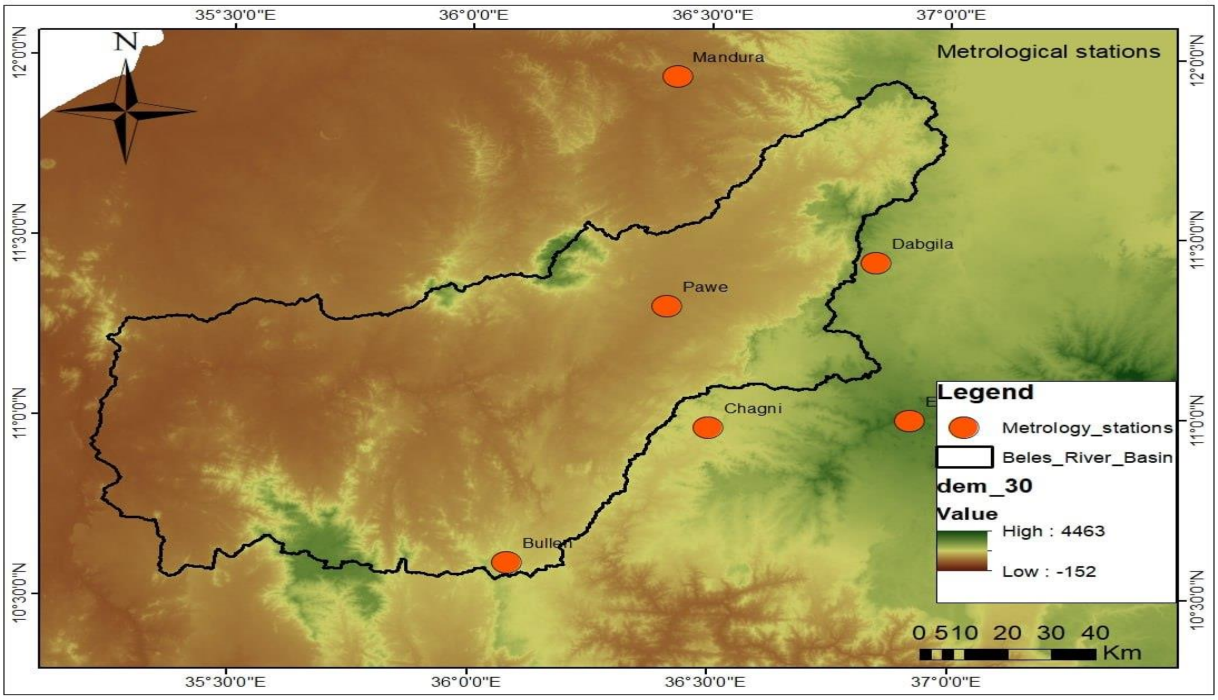

Figure 3. 9 : Location of meteorology stations

3.2.3.5.1 Filling missing data for the selected stations

The table below shows the chosen metrology stations and their percent of missing data.

Tabel 3. 4 : Geographic information of the selected weather stations.

Id	Station name	Lat(^{0})	Lon(^{0})	Preci	Tem	Rh	Suhr	Ws	(%) of missing Data
1	Bullen	10.5959	36.082	X	X	X	X	X	1.6
2	Chagni	10.974	36.499	X	X	X	X	X	8.6
3	Dangila	11.4337	36.846	X	X	X	X	X	3.2
4	Enjibara	10.9954	36.9193	X	-	-	-	-	5.5
5	Mandura	11.95	36.426	X	X	-	-	-	4.2
6	Pawe	11.31227	36.41017	X	X	X	X	X	2.8

Some stations have short breaks in the records because of the absence of the observer or because of instrumental failures. It is often necessary to estimate or fill in this missing record. For representing the climate in the basin.

There are different methods to fill in missing data. Among these, the normal ratio method was used in this study depending on an average annual precipitation in the neighboring gauges that is greater than 10% of the gauge under consideration. As a result, the Normal Ratio method was used to compute the missing rainfall data for this study (Eq 3.6). If any nearby gauge's normal annual precipitation exceeds 10% of the gauge under consideration, this method is used.

$$Px = \frac{Nx}{m}\left[\frac{P1}{N1} + \frac{P2}{N2} + \frac{P3}{N3} - \frac{Pn}{Nn}\right] \ldots\ldots\ldots\ldots\ldots\ldots\ldots.\ldots..(3.9)$$

Where: Px = the missing precipitation for any storm at the interpolation station x,

Pi = the precipitation for the same period for the same storm at the ith station of a group of index stations.

Nx = the normal annual precipitation for station x,

Ni = the normal annual precipitation value for the i^{th} station.

3.2.3.5.2 Checking the Consistency of Data

Checking for inconsistency of the record was done by the double-mass curve technique which is the most common method of checking the inconsistency of climatic records. The principle of double mass analysis is to plot accumulated values of the station under investigation against accumulated values of another station, or accumulated values of the average of other stations, over the same period. A change in the proportionality between the measurements at the suspect station and those in the region is reflected in a change in the scope of the trend line of the plotted points. The inconsistent data series will be adjusted to consistent values by proportionality. Accordingly, a double mass curve plot was made for the selected. the gradient and was corrected as (Eq 3.7)shows (Geremew, 2013):

$$PCX = \frac{Px * Mc}{Ma} \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots . (3.10)$$

Where Pcx = correct precipitation at any time $t1$ at station x

Px = original record precipitation at any time $t1$at station x

Mc = correct slope of the double mass curve

Ma = original slope of double mass curve

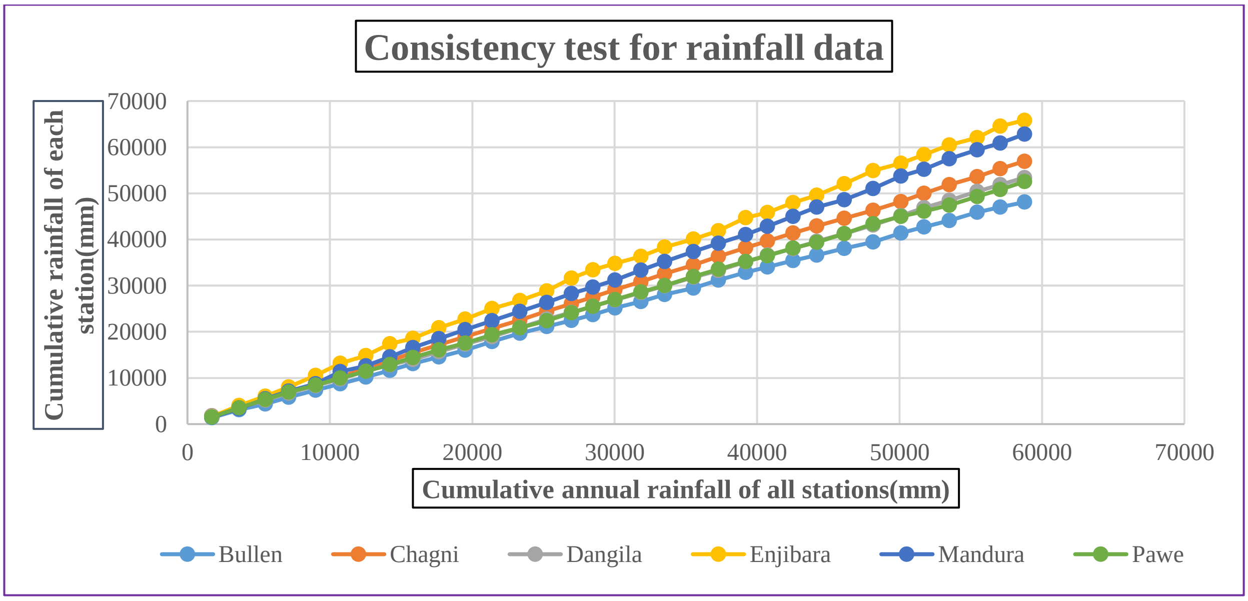

Figure 3. 10: Double mass analysis representing data consistency of stations on the Beles Sub-Basin

3.2.3.5.3 Homogeneity Test of Rainfall Data.

The homogeneity of parameters analysis is important to the variation of the statistical properties of the time series. To select the representative meteorological station for the analysis of rainfall estimation, checking the homogeneity of group stations is important. The homogeneity was tested using RAINBOW. In RAINBOW the test for homogeneity is based on the adjusted partial sums or cumulative deviations from the mean

$$S_k = \sum_i (x_i - \bar{x}) \qquad k = 1, \dots n \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots .. (3.11)$$

Where, Xi the records of the partial duration series X1, X2….Xn and $\bar{X}$ the mean

For a homogeneous record one may expect that the Sk's fluctuate around zero since there is no systematic pattern in the deviations of the Xi's from their average value. In RAINBOW the rescaled cumulative deviations, obtained by dividing the Sk's by the sample standard deviation value (αx). A statistic which is sensitive to departures from homogeneity is,

$$Q = MAX \left|\frac{S_x}{\alpha_x}\right|, K = 0, \dots, n \dots \dots \dots \dots \dots \dots \dots \dots .. (3.12)$$

High values of Q are an indication for a change in the mean level. Another statistic which is used for homogeneity is the range, given as below

$$R = MAX \left|\frac{S_x}{\alpha_x}\right| - MIN \left|\frac{S_x}{\alpha_x}\right|, K = 0, \dots, n \dots \dots \dots \dots \dots \dots \dots \dots (3.13)$$

In RAINBOW the maximum cumulative deviation (Q) and the range (R) are used to decide whether or not to reject the homogeneity of the data. According to the test the flow is homogeneous.

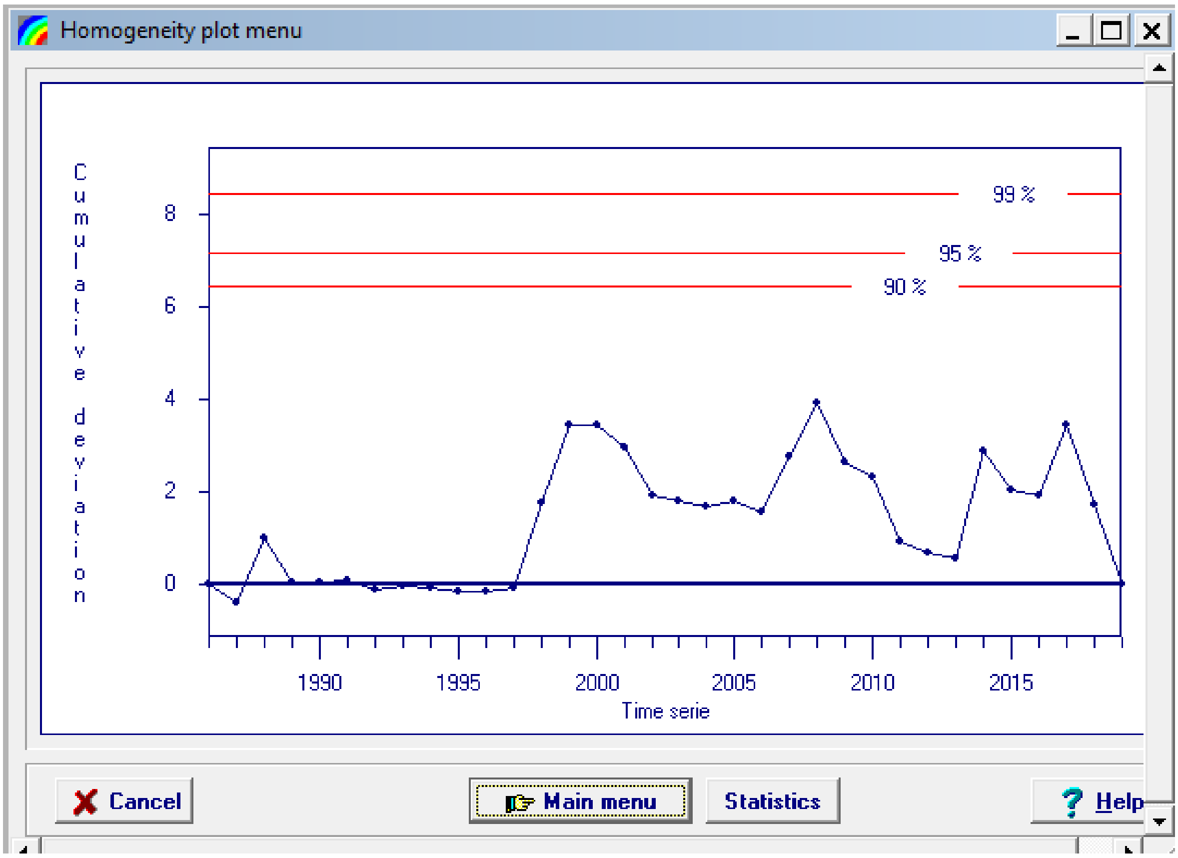

Figure 3. 11 : Homogeneity test by Rainbow software

3.2.3.6 Hydrological Data

The streamflow data of the study area is needed for the calibration and validation of the SWAT model. Accordingly, the daily streamflow data (1987-2019) of the gauging station Gilge Beles was collected from the Ministry of Water, Irrigation, and Energy of Ethiopia (Mengistu, 2009).

3.2.3.7 Land use and Land cover maps

LULC maps were one of the main input data that were used to describe and define the Hydrological Response Units (HRUs) of the watershed. The Arc SWAT model normally has predefined four-letter codes for each land use category. These codes were used to associate the land use and land cover map of the study area to the SWAT model land use database embedded in the model. While preparing the land use lookup-table, the land use types were made compatible with the input format needed of the model.

3.2.3.8. SWAT Model set up, and hydrological response analysis.

SWAT operates on a daily time step is designed to predict the impact of landuse and management on water. The model is process-based, computationally efficient, and capable of continuous simulation over long periods. Major model components include weather, hydrology, soil temperature and properties, plant growth, nutrients, pesticides, bacteria and pathogens, and land management. In SWAT, a watershed is divided into multiple subwatersheds, which are then further subdivided into hydrologic response units (HRUs) that consist of homogeneous landuse, management, topographical, and soil characteristics. Alternatively, a watershed can be subdivided into only sub-watersheds that are characterized by dominant landuse, soil type, and management.

SWAT simulates the hydrological cycle based on the water balance equation as shown in Equation (3.14) (S.L. Neitsch *et al*.., 2011)

$$\mathrm{SWt} = \mathrm{SWO} + \sum (\mathrm{Rday} - \mathrm{Qsurf} - \mathrm{Ea} - \mathrm{Wseep} - \mathrm{Qgw})\ \mathrm{ti} = 1 \dots\dots\dots\dots\dots\dots\dots.. (3.14)$$

Where: SWt =is the final soil water content (mm);

SWo = is the initial water content (mm)

t =is the time (days)

Rday =is the amount of precipitation on a day i (mm)

Qsurf= is the amount of surface runoff on a day i (mm)

Ea= is the amount of evapotranspiration on a day i (mm)

Wseep=is the amount of water entering the vadose zone from the soil profile on the day i (mm)

Qgw= is the amount of return flow on a day i (mm).

Surface runoff volumes and peak runoff rates for each HRU. The SCS curve number method was used to estimate surface runoff by equation (2.2). The SCS curve number equation is:

$$\mathrm{Qsurf} = \frac{(\mathrm{Rday} - 0.2\mathrm{S})^2}{(\mathrm{Rday} + 0.8\mathrm{S})} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots.. (3.15)$$

Where: Qsurf is the accumulated runoff or rainfall excess (mm), Rday is the rainfall depth for the day (mm), S is the retention parameter (mm).

The retention parameter S can be calculated by using equation (2.3)

$$S = \left(\frac{1000}{CN} - 10\right) \ldots\ldots \quad (3.16)$$

Where, CN is the curve number for the day and its value is the function of land use practice, soil permeability, and soil hydrologic group.

3.2.3.9 Watershed Delineation

At first, the Arc SWAT model was set up the project of the study area. The watershed delineation process generally consists of five major steps, i.e., DEM setup, stream definition, outlet and inlet definition, watershed outlets selection, and definition and calculation of sub-basin parameters. Consequently, watershed and subwatershed delineation were performed using the SRTM 30 m by 30m resolution DEM data using the watershed delineation tool embedded in the model (Fulaji, 2015). Therefore, using the watershed delineation tool, the study area was delineated into sub-basins having an estimated total area, and the default area threshold value was also suggested by the Arc SWAT interface (Naschen *et al*., 2019).

The topographic parameters like elevation and slope of the study area was also generated from the DEM data. After watershed delineation is done, the slope classification had been carried out based on the DEM of the study area as a pre-requirement for the definition of hydrologic response units. Therefore, the slope value of the study area was reclassified in percent. The stream definition and the size of sub basins at Beles Sub-Basin were delineated into 35 sub basins having an estimated total area of 1358063.0ha.

3.2.3.10 Analysis of Hydrologic Response Units

After the delineation of the watershed is completed, sub-watersheds were divided into different hydrologic response units (HRUs) through the assignment of threshold values for soil, land use, and slope. This helps to eliminate minors or insignificant portions of the watershed area as suggested by (Gassman *et al.*, 2007). By loading land use and land cover and soil maps into the set project, HRUs were created. Promptly two common options were provided in the model to define the HRUs. The first thing that was done was by assigning a single HRU and the other with multiple HRUs options. In this study, therefore, the multiple

HRUs options was employed aiming at obtaining reliable results of simulation (Choto & Fetene, 2019). Then, as per the recommendation of the SWAT user's manual for most modeling applications, a 20 % land use/land cover threshold, a 10 % soil threshold and a 20 % slope threshold are 36 will be adopted (Eitsch *et al.*, 2002). Due to this the Beles Sub-Basin was divided into 80 HRUs, each has a unique land use and soil combinations.

3.2.3.11 Weather Generator

The weather generator model just requires the daily data of all climatic variables from measured data or generated values using monthly average data. Accordingly, measured data for the climatic variables of the study area including daily rainfall, maximum and minimum temperature, relative humidity, wind speed, and solar radiation was collected for the study period and used in this study. To generate the climatic data, weather parameters was developed by using the pcpSTAT01 program and the dew point temperature calculator program (DEW02). Both the programs are often used with SWAT modeling as an alternative to easily obtain required parameters for the user weather database by using monthly climatic data. For this study the pcpSTAT01 program calculates statistical parameters of average daily precipitation data was used by SWAT in the userwagen.dbf.. The daily prepared weather variables from the selected meteorological stations was used to generate the weather database for the simulation process which is also suggested by other similar studies (Sharpley and Williams, 1990). Finally before a SWAT simulation started, all of the input files were written as required by SWAT and produced from the preprocessed data from Arc SWAT were carried out. After preprocessing of the required input for the SWAT model, flow simulation was performed for years of recording periods starting from 1987 through 2019 the first two years of which will be used as a warm-up period

3.2.3.12 Sensitivity Analysis Model Calibration and Validation

I. Sensitivity Analysis

Sensitivity analysis is a method of minimizing the number of parameters to be used in the calibration step by making use of the most sensitive parameters largely controlling the behavior of the simulation process. This helps to reduce the uncertainty in the model outputs. Sensitivity analysis is hence important to identify and rank parameters that have a significant impact on the specific model outputs of interest (Griensven *et al.*, 2006). The SWAT-CUP application was employed to conduct the sensitivity analysis. In the sensitivity analysis process, selected parameters was later on entered for the analysis with the default lower and upper parameter bound. A t-test is then used to identify the relative significance of each parameter. The global sensitivities estimates of the average changes in the objective function resulting from changes in each parameter, while all other parameters are changing. This gives relative sensitivities based on linear approximations and, hence, only provides partial information about the sensitivity of the objective function to model parameters. T-stat provides a measure of sensitivity (larger in absolute values are more sensitive), p-values determined the significance of the sensitivity (A value close to zero has more significance).

II. Model Calibration and Validation

Model calibration was done to obtain optimum values. a single set of parameters claiming to represent the best simulation. The stochastic approach which recognizes the errors and uncertainties in modeling works tries to capture the lack of understanding of the processes in natural systems. The model was calibrated using a sequential uncertainty fitting (SUFI-2) algorithm which was founded in the SWAT-CUP computer program. Calibration is an alteration of model parameters by checking results against observations to check a similar response over time. This involves comparing the model outcomes, entered with the use of observed stream flows data. During model calibration, manual and automatic calibration methods were applied.

Automated model calibration requires that the uncertain model parameters are systematically changed, the model is run, and the required outputs (corresponding to measured data) are extracted from the model output files. The simplest way of handling the file exchange is through text file formats.

The graphical and statistical approaches were used to evaluate the SWAT model performance many iterations were conducted until the acceptable values were obtained for surface runoff and base flow independently. The flow calibration procedure made by SWAT developers was carefully followed the observed flow of the Beles River (1987-2019) was used for calibration and validation. From total available flow data (33 years) the two years data were used for a warm-up purpose, two-third of the available flows at gauging stations flow data were used in the calibration of the swat model.

The purpose of model validation is to check whether the model can predict flow for another range of periods or conditions than those for which the model was calibrated. Model validation involves rerunning the model using input data independent of data (meteorological data) used in calibration (by the different periods of a simulation) but keeping the calibrated parameters unchanged. Like model calibration, the model performance evaluation parameters were calculated and checked whether the model performed very well or not. In this study one-third of the available streamflow) data, Gilgel Beles gauging station was used for the validation purpose

3.2.3.13 Model Performance Indicators

Models have always been useful with their limitations which are observed in terms of performance. Therefore, this step is necessary to evaluate the model outputs against the observed data. Among the various methods of evaluating model performance during the calibration and validation periods, this study employed the commonly used methods namely, the coefficient of determination (R^2), Nash and Sutcliffe simulation efficiency (ENS) (Gassman *et al.*, 2007; Pereira *et al.*, 2018). The above methods will be calculated as follows The coefficient of determination (R^2) describes the magnitude of the linear relationship between the observed and the simulated values. It ranges from 0 to 1, with the higher value indicating less error variance. The value of R^2 which is greater than 0.6 is considered sufficient and acceptable for hydrological modeling.

$$R^2 = \frac{\left[\sum_i (Q_m - \overline{Q}_m)(Q_s - \overline{Q}_s)\right]^2}{\sum_i (Q_m - \overline{Q}_m)^2 \sum_i (Q_s - \overline{Q}_s)^2} \dots\dots\dots\dots\dots\dots\dots\dots (3.17)$$

Where,Qm = measured value (m3/s)

Qm= average measured value (m3/s)

Qs= simulated value (m3/s) and

Qs= average simulated value (m3/s)

Similarly, the Nash–Sutcliffe simulation efficiency (ENS) indicates that how well the plots of observed versus simulated data fit. The values of ENS range from negative infinity to 1. And, a value of greater than 0.5 is generally considered acceptable (Moriasi *et al*., 2015).

Nash and Sutcliffe simulation efficiency (ENS) given by the following formula

$$\text{ENS} = 1 - \frac{\sum_i^n (Q_m - Q_S)^2}{\sum_i^n \left(Q_m - \overline{Q}_m\right)^2} \ldots\ldots\ldots\ldots\ldots\ldots\ldots..(3.18)$$

Where,

Q_m = measured value

Q_s = simulated value and

Qm = average observed value

Tabel 3. 5 : General performance ratings for recommended statistics for a monthly time step

Performance rating	ENS	R2
Very god	.75 < NSE < 1.00	R2>0.8
Good	0.65 < NSE < 0.75	0.7<R2<0.8
Satisfactory	0.50 < NSE < 0.65	0.6<R2<0.7
Unsatisfactory	NSE < 0.50	<0.6

Source: Adopted From (Moriasi *et al.*, 2015).

The major working procedure for the model setup and model calibration is summarized in the workflow diagram (Figure3.12**)**

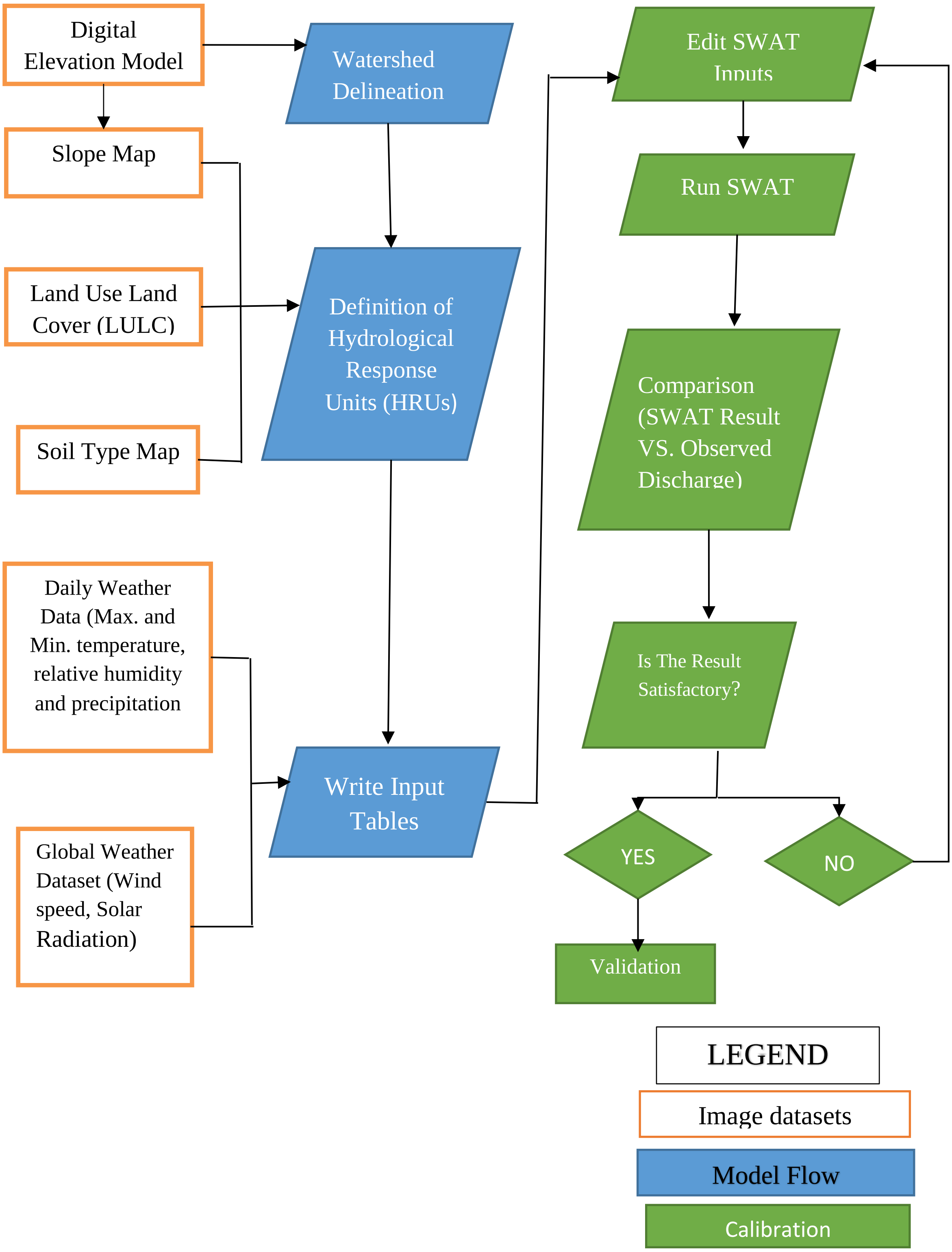

Figure 3.12 : Flowchart of Arc SWAT processing procedures

4. RESULTS AND DISCUSSION

4.1. Landuse/Land Cover Classification and Accuracy Assessment

The satellite images of 1987, 2002 and 2019 years were downloaded from USGS. During image classification, five landuse/land cover classes were identified based on band reflectance of the remote sensing data and the historical knowledge about the study area. The landuse types of the study area include Agriculture, Forest, Shrub land, Urban area and Wet land. The results of the supervised classification satellite images were evaluated using the general precision and the kappa coefficient values. An accuracy evaluation test was performed using a confusion matrix with 133 randomly selected points for the 2019 land cover, with 80 randomly selected points for the 2002 and with 80 randomly selected points for the 1987 land cover land cover and the accuracy of the data was compared by linking the online Land Sat image to the Google Earth Pro Win program18.82, as shown in Figure (4.1). After classification of land use land cover types, 133,80 and 80 Random Points were generated in Arc GIS and converting random points to KML in order to open in Google Earth. The correctness of the LULC 1987, 2002, and 2019 land sat images was assessed in an original way by tying ERDAS IMAGINE 2014 and Google Earth Pro Win 18.82 together by time adjustment at the same Acquisition Date of each land sat image.

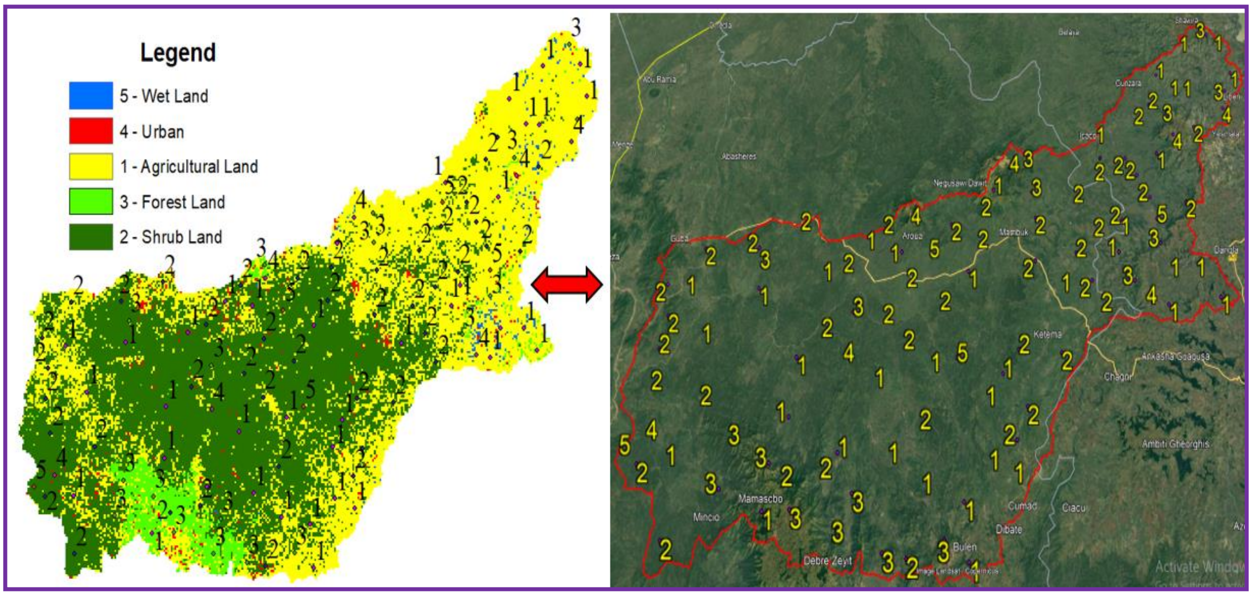

Figure 4. 1: 2019 accuracy check points in LULC with google earth

Figure (4.1) displays the landuse/ land cover of 2019 and points imported in KML format from historical Google Earth images and ARCGIS referenced points as a reference. Selected points were compared with the relevant classification . The validation of the images from 1987, 2002, and 2019 is done using 80, 80, and 133 points, respectively, for the accuracy assessment of the classified image. A confusion matrix for the three Land sat images may be found in the three successive Tables 4.1, 4.2, and 4.3 below.

Tabel 4. 1: The Confusion Matrix for LULC Classification 1987

1987 LULC ACCURANCY ASSESSMENT REFERENCE DATA							
Land use types	Agricultural	Forest	Shrub Land	Wet Land	Urban	Total	UA
Agricultural Land	13	0	0	1	1	15	86.6
Forest	2	13	1	0	0	16	81.25
Shrub Land	0	1	14	1	0	16	87.5
Wet Land	1	0	1	14	0	16	87.5
Urban	1	0	1	0	15	17	88.23
Total	17	14	17	16	16	80	
PA	76.47	92.8	82.35	87.5	93.75		
Overall accurancy = 86.25%							
Kappa coffient (K) = 82.8%							

Tabel 4. 2: The Confusion Matrix for LULC Classification 2002

2002 LULC ACCURANCY ASSESSMENT REFERENCE DATA							
Land use types	Agricultural	Forest	Shrub Land	Wet Land	Urban	Total	UA
Agricultural Land	13	0	0	0	1	14	92.8
Forest	0	14	1	2	0	17	82.3
Shrub Land	0	1	15	1	0	17	88.2
Wet Land	1	0	1	14	0	16	87.5
Urban	1	0	0	0	15	16	93.7
Total	15	15	17	17	16	80	
PA	86.6	93.3	88.2	82.3	93.7		
Overall accurancy = 88.7%							
Kappa coffient (K) = 85.9%							

Tabel 4. 3: The Confusion Matrix for LULC Classification 2019

2019 LULC ACCURANCY ASSESSMENT REFERENCE DATA							
Land use types	Agricultura l	Fores t	Shrub Land	Wet Land	Urba n	Total	UA
Agricultural Land	33	0	2	1	1	38	86.8
Forest	0	15	1	2	0	18	83.3
Shrub Land	0	1	39	1	0	44	88.6
Wet Land	0	3	1	25	0	28	89.2
Urban	0	0	0	0	5	5	100. 0
Total	33	19	43	29	6	133	
PA	100	78.9	90.6	86.2	83.3		
Overall accurancy = 87.9%							
Kappa coffient (K) = 84%							

The overall classification accuracy was calculated as the ratio of all correctly identified pixels to all reference pixels, and it was 86.25%, 88.7%, and 87.9% for the categorized images from 1987, 2002, and 2019, respectively. Kappa statistics for the 1987, 2002, and 2019 maps were 82.8%, 85.9%, and 84%, respectively. According to the study's findings gathering data using Google Earth for accuracy assessment is quite effective, with an acceptable Kappa (K) value of 77.02% and an overall accuracy of land use and land cover of 82.00%. Kappa values greater than 0.80 are deemed to indicate strong classification performance.When the Kappa value is less than 0.40, the classification performance is bad, and when the value is between 0.40 and 0.80, the classification performance is moderate (Fichera *et al.*, 2012). According to this study's accuracy assessment, there is excellent agreement within classified land use kappa coefficients.

4.2. Landuse/land Cover change analysis

4.2.1. Trend of landuse/land covers change.

The LULC maps of Beles Sub-basin of the considered year are shown in Figure 4.2. The area coverage of the main land use/land cover types shown on the maps indicates that there have been around 33 years of LULC changes from 1987-2019. Five major classes are shown in Figure 4.2: urban land, forest cover, agricultural land, shrub land, and wetlands.

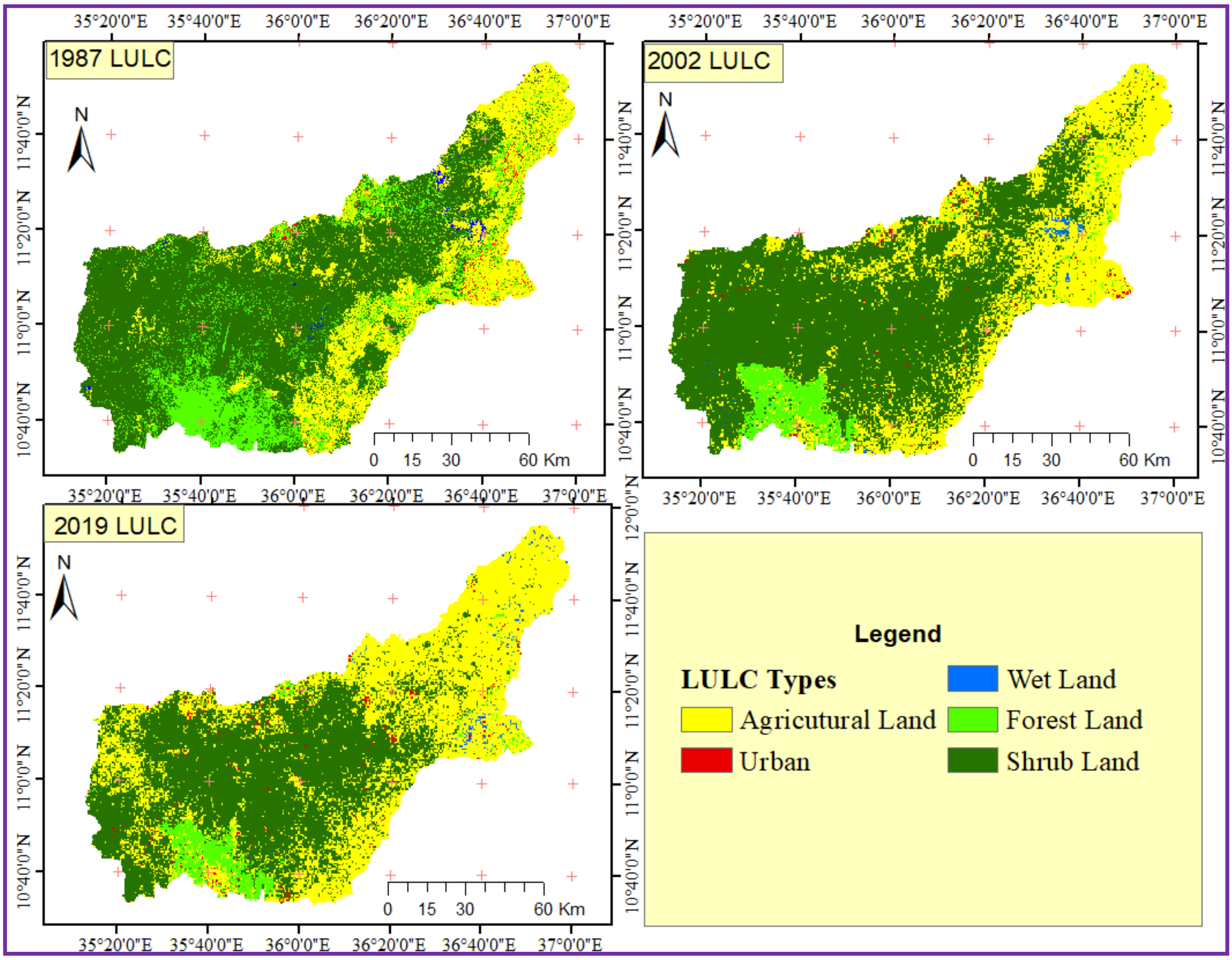

Figure 4. 2: : LULC map of 1987 (A), 2002 (B), 2019 (C), in Beles Sub-Basin

In the years 1987, 2002, and 2019, in which agricultural and urban land use indicates counitinuosly increasing which showed a greater annual rate expansion per hectare as a result of the rapidly growing population, the demand for fuel wood, grazing pasture, and farmlands but the remaining three landuse/land covers were decreasing. As shown in Table 4.4. in the year 1987 the dominating land use which accounts for 51.99% of the total area, is shrub and the second dominant land use, agricultural land, accounts for 29.70% of Beles of the total area, forest, wet land, and urban area shares were placed in the following order: 15.81%, 1.78%, and 0.71%.

The two main changes in land use and land cover in Beles sub-basin in 2002 were an increase in agriculture coverage of area by 4.68% (from 29.70% to 34.38%) and a decrease in shrub land by 2.77% (from 51.99% to 49.22%). In contrast, urban area grew by 1.87% in 2002, while forest and wetland decreased by 3.19% and 0.58%, respectively.

The same trend, which has persisted over the last past 17 years from 2002 to 2019, has seen the land use coverage of agriculture, and urban areas increase by 9.51%, (34.38% to 43.89%), and 0.37%, (2.58% to 2.95%) respectively, while the remaining three land use/land cover types shrubs, forests, and wet land constantly contract by 7.82%, 1.54%, and 0.52%, respectively. As shown in Table 4.4, the agricultural land trend shows a 0.42 annual rate change, which indicates a greater rate expansion per hectare due to the rapidly rising population growth, which is believed to be the main cause of the decline in other types of LULC due to the rising demand for new agricultural production land parcels. The study findings of Nigusie & Dananto, (2021) reported that the decline of grass and shrubs suggests that the primary anthropological factors influencing LULC changes in the watershed are the rapidly increasing population demand for agricultural products, the worst land degradation, and the expansion of residential and industrial zones.

The gain and loss of each land use category was discovered in the study region with the use of the land change module. According to Figure 4.3, which shows the increase and decrease in land uses and land cover between 1987 and 2002, agricultural land increased (29.70% to 43.89%) and urban area increased (0.71% to 2.95%), but shrub land decreased (51.99% to 41.40%), forest cover decreased (15.81% to 11.08%), and wet land also decreased (1.78% to 0.68%) between 1987 and 2019. The graph on the left represents a decline in land use, whereas the one on the right, in a similar manner, indicates an increase in land use. The largest growth and losses in land use/cover between 1987 and 2002 were on agricultural land and shrub land, respectively. This demonstrates that agricultural land is the primary receiver inland use loss, whereas shrub land is a significant contributor to land use growth.

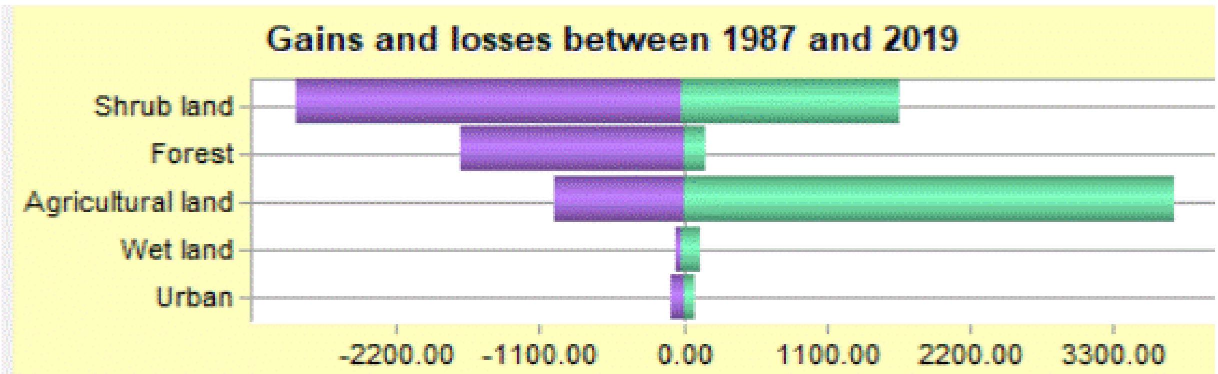

Figure 4. 3: Gains and loss (sq km) from 1987-2019.

Tabel 4. 4: LULC change trend between 1987 and 2019 in Beles Sub-Basin

Net change (gain and loss in %) between 1987-2019									
LULC change (1987-2019)		area (ha)		area (100%)			Net change (1987-2019)		Annual rate change
land use types	1987	2002	2019	1987	2002	2019	gain	Loss	
Agricultural Land	403405.71	466895.04	596032.22	29.70	34.38	43.89	14.18		0.42
Forest Land	214722.57	171355.77	150529.80	15.81	12.62	11.08		4.73	-0.14
Shrub Land	706063.34	668458.20	562196.68	51.99	49.22	41.40		10.59	-0.31
Urban	9701.38	35018.58	40092.59	0.71	2.58	2.95	2.24		0.07
Wet Land	24170.02	16335.42	9211.72	1.78	1.20	0.68		1.10	-0.03
Grand Total	1358063.01	1358063.01	1358063.01	100.00	100.00	100.00			

Tabel 4. 5: Land Use Land Cover change Transition Matrix between 1987 and 2002.

	2002 LULC 100%						
	LULC types	Agricultura l Land	Forest Land	Shrub Land	Urban	Wet Land	Grand Total
1987 LULC 100%	Agricultural Land	16.9	0.2	12.3	0.2	0.1	29.7
	Forest Land	6.0	4.4	5.2	0.1	0.0	15.8
	Shrub Land	11.1	7.9	30.2	2.1	0.7	52.0
	Urban	0.3	0.0	0.0	0.0	0.3	0.7
	Wet Land	0.1	0.0	1.4	0.2	0.1	1.8
	Grand Total	34.4	12.6	49.2	2.6	1.2	100.0

Tabel 4. 6: Land Use Land Cover change Transition Matrix between 2002 and 2019 .

	2019 LULC 100%						
	LULC types	Agricultural Land	Forest Land	Shrub Land	Urban	Wet Land	Grand Total
2002 LULC 100%	Agricultural Land	24.1	0.7	8.9	0.3	0.3	34.4
	Forest Land	1.4	10.0	1.1	0.0	0.0	12.6
	Shrub Land	17.7	0.3	30.6	0.5	0.0	49.2
	Urban	0.4	0.0	0.1	2.1	0.0	2.6
	Wet Land	0.2	0.0	0.6	0.0	0.3	1.2
	Grand Total	**43.9**	**11.1**	**41.4**	**3.0**	**0.7**	**100.0**

4.2.3. Net Change in land use land cover.

The net change, as estimated by the LCM's change analysis module, represents the percentage gain or loss in each land use category over the course of a specific perspective year period. In the year between 1987 and 2019, as shown in Figure 4.4, net changes within the relevant study period were acquired in the LCM change analysis module.

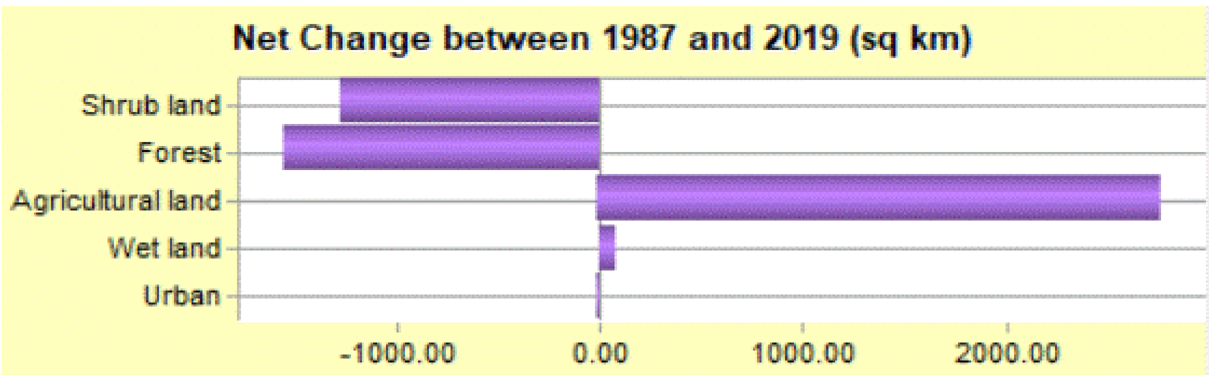

Figure 4. 4: Net change graph from 1987-2019.

In the year between 1987 and 2019 the graphical value in the figure 4.6 indicates the net gain in the area by percentage of agricultural land (14.18%), and urban area gained (2.24%) and in the same year the largest losses also occurred in the percentage of shrub (-10.59%) which gain and loss indicates forest lands are the largest contributors to agriculture, forest cover (-4.73) and (-1.10) wet land in the year.

4.2.4. Main Contributors to Net Change.

When land use and land cover types are contributed to or change from one land use type to another in an area that has already been occupied over the course of a year, the LCM change analysis model can be used to determine the contributors to net changes. Agricultural land and urban area experienced the biggest percentage increases, while three remaining land category, shrub land, wet land and forest land cover, frequently contributes to two expanding land use categories in the watershed. In the overall year between 1987 and 2019 contributers to net change indicated in figure (4.5A). According Land Use Lan/Cover change Transition Matrix table (4.5 and 4.6) the highest increase of agricultural land contributed by 11.1% and 17.7% by shrub land between 1987- 2002 and 2002-2019 respectively. The same gain of agricultural land again contributed 6.0% and 1.4% by forest land between 1987-2002 and 2002- 2019 respectively. The result indicates that shrub and forest cover highly shrinking land use type but agricultural land and urban area are replacing land use types shown in the Figure 4.5C.

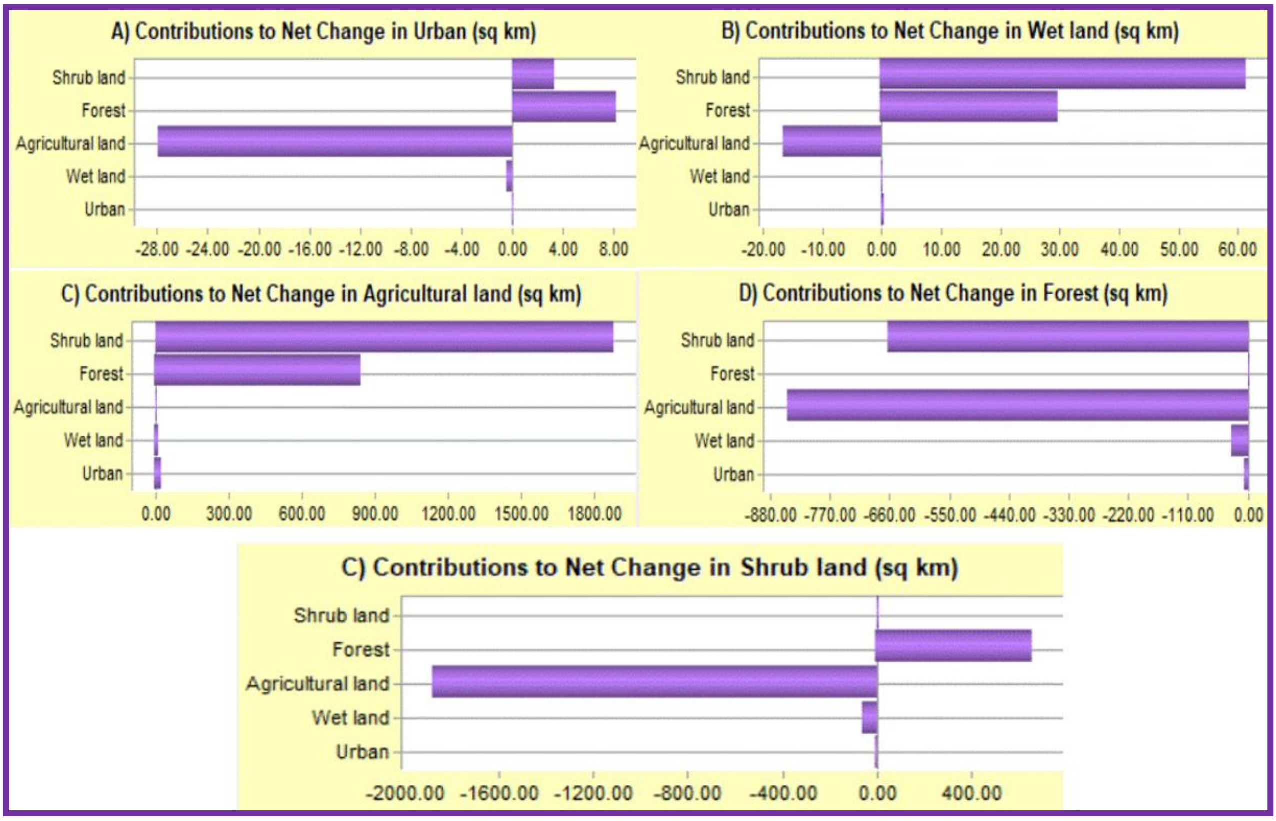

Figure 4. 5: Contributors graph to net change LULC category from 1987 to 2019.

The transformation map in the figure generally shows a decline in shrub and forest cover over the entire study period (1987-2019) but a rapid expansion of agricultural land and urban areas, which indicates anthropological changes to land use and land cover that were primarily brought on by the study's rapidly rising population rate. According to study findings by (Girma *et al*., 2022) overall, agricultural land has increased the most, while shrub and forest cover have continued to decrease.

4.3. Prediction of the Future LULCC with MLP NN-CA- MC Model

4.3.1 Driver Variables Used in MLP NN CA_MC Model

Predictions of future land use and land cover must consider important independent factors relating to anthropogenic, topographic, infrastructure, and water body proximity (Birhane et al., 2019).

Elevation, slope, road, and river distance (water body proximity) are the main factors taken into account in this study to predicting future land use and land cover in 2035 and 2055 represented in Figure 4.6. To create the Potential transition map in the (LCM) function of TerrSet software, all the driving variable data sets were created by ArcGIS and converted to

ACSII raster format (input for Terrset program). All of the taken into account driver variables, as suggested by Leta *et al*., (2021). They were used in predicting the future 2035 and 2055 LULC change.

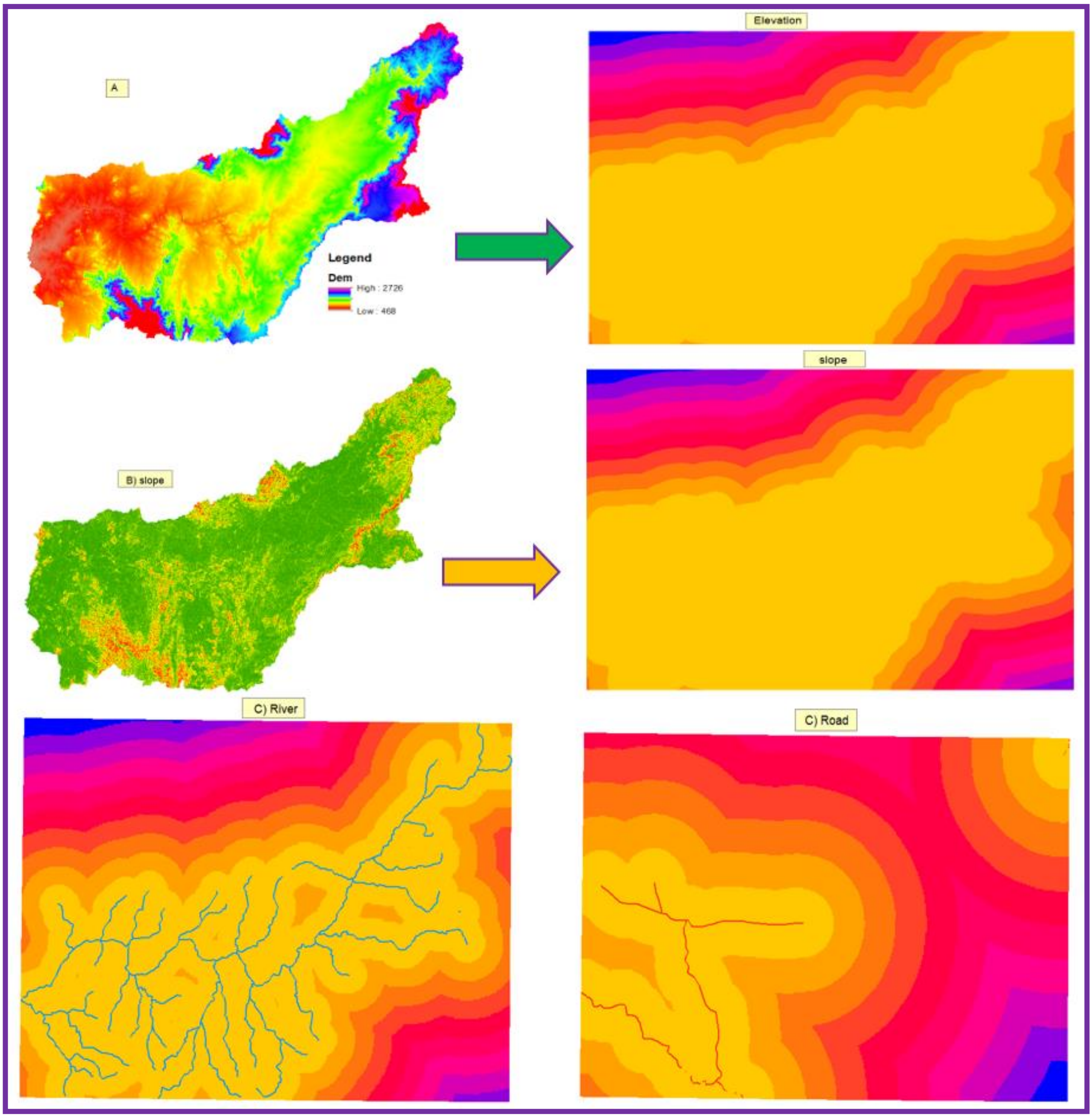

Figure 4. 6: Driver variables used for future LULC prediction

4.3.2. General Model Information and MLP_NN Model Performance Evaluation and Sensitivity Analysis.

4.3.2.1 MLP-NN skill measure

A machine learning method called MLP-NN can simulate complicated patterns and behavior (Gharaibeh *et al*., 2020). In this study 10,000 iterations were used to statistically analyze each driver variable's effect and influence order on the MLP-NN skill. The MLP-NN skill measure of driver variable influence was statistically tested using 10,000 iterations, and 10000 requested samples per class. The appendix table (1) shows the observed training RMS (0.364) and testing RMS (0.364), respectively. The model's overall skill measure (with all variables) 0.6571% and accuracy (78.86%) are much above the acceptable level, and the driver forces help the model more accurately predict future LULC change (Gharaibeh *et al*., 2020; Girma *et al*., 2022).

Tabel 4. 7: Input Files

Independent variable 1	Elevation
Independent variable 2	river
Independent variable 3	slope
Independent variable 4	road

According to a single variable to be constant table (4.7) shows that Variable 1 (Elevation) constant is the most influential parameter with poor model accuracy (49.61%) and skill measure of 0.542. The study according to (Girma *et al*., 2022) revealed that holding evidence the most influential constant significantly generates poor model accuracy (28%) and skill measure than other least influential variables and inversely least influential variable generates a good accurancy and skill measure.

4.3.2.2 Sensitivity of Model to Forcing Independent Variables to be Constant

1) Forcing a Single Independent Variable to be Constant

Model	Accuracy (%)	Skill measure	Influence order
With all variables	78.86	0.6571	N/A
Var. 1 constant	49.61	0.542	1 (most influential)
Var. 2 constant	57.8	0.621	2
Var. 3 constant	72.8	0.657	3
Var. 4 constant	82.86	0.687	4 (least influential)

2) Forcing All Independent Variables Except One to be Constant

Model	Accuracy (%)	Skill measure
With all variables	78.86	0.6571
All constant but var. 1	49.61	0.542
All constant but var. 2	57.8	0.621
All constant but var. 3	72.8	0.657
All constant but var. 4	82.86	0.687

3) Backwards Stepwise Constant Forcing

Model	**Variables included**	**Accuracy (%)**	**Skill measure**
With all variables	All variables	78.86	0.6571
Step 1: var.[1] constant	[2,3,4]	74.80	0.6243
Step 2: var.[1,2] constant	[3,4]	68.24	0.5765
Step 3: var.[1,2,3] constant	[4]	58.40	0.5264

4.3.3 Validation of CA-Markov Model

Comparing the most recent classified land use land cover in the present with two simulated classified land uses in two successive decades served as the benchmark before predicting future land use and cover to assess model-based kappa index performance. While creating the map of the simulation of land use and land cover in 2019, the classified land use and land cover from 1987 and 2002 were once more employed. In order to validate the LULC forecast provided by the CA-Markov model, the simulated land use areas were used to compare the actual present land use areas. The performance of the model was then assessed using the kappa index by comparing the observed LULC 2019 with the simulated LULC 2019. The results show 97.99%, 91.88%, 97.58%, 74.70%, and 100% of agricultural land, forest, shrubs land, urban area, and wet land, respectively, to come to an agreement on the accuracy percentage of each land use map in simulated and classified compared in area coverage. The urban area had the least area fitness, with 74.70% accuracy and a 1% difference in simulated and classified land use land cover, whereas agricultural land had an area fitness comparison between simulated and classified images of 97.99% almost fit. A specific model's performance for prediction should be accepted or rejected based on the kappa coefficient between simulated and observed area coverage in addition to the percentage of statistically determined accuracy. Statistically determined kappa value between 2019 actual and 2019 simulated land use positive value (+1) indicates that CA-Markov model totally agreed to predict future land use land cover(Gemmechis, 2022). As a result, using the CA-Markov model with in a Table 4.8 kappa coefficient value to simulate the future in order to accurately predict future land use and land cover is best suggested.

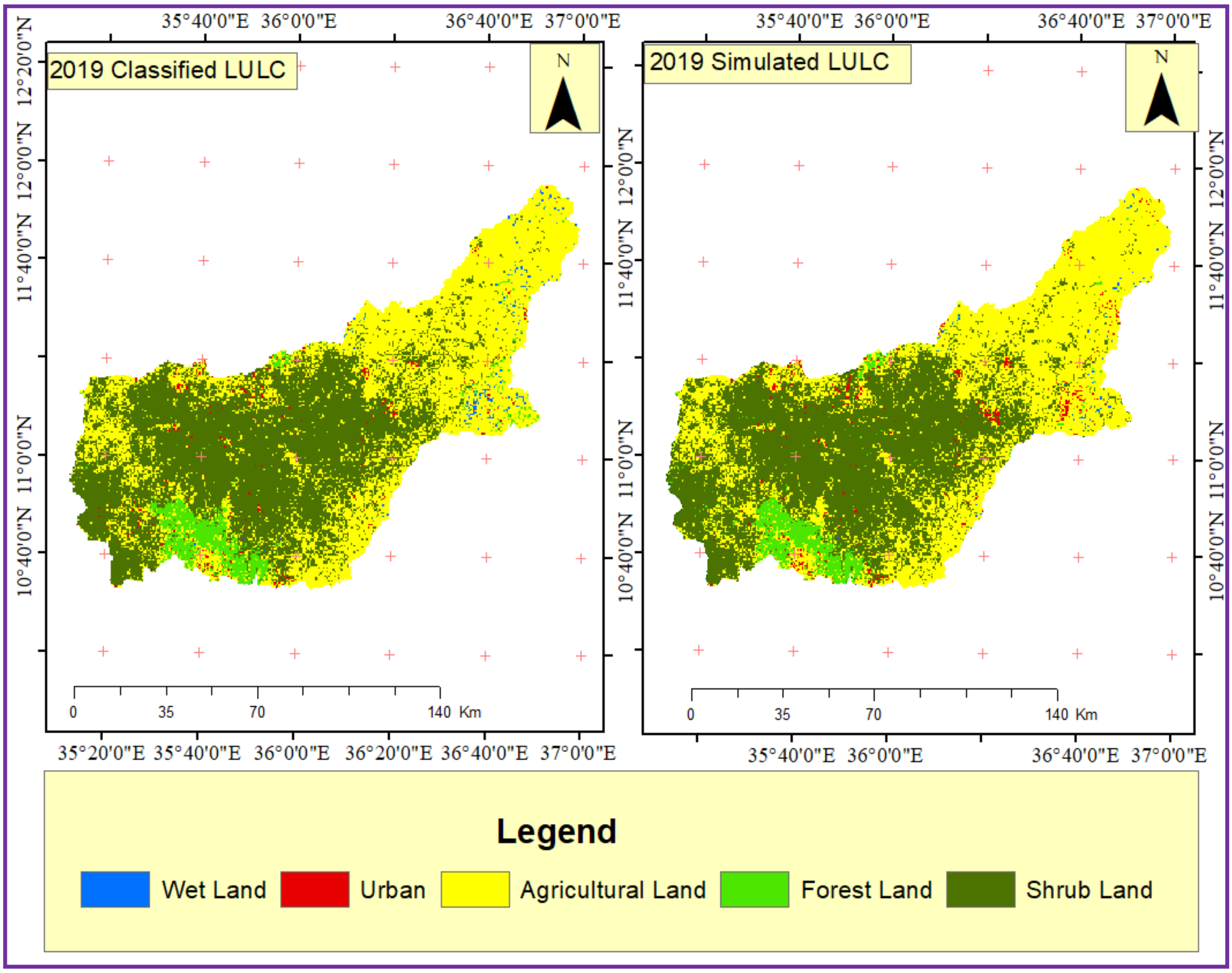

Figure 4. 7: classified (A) and simulated (B) LULC Map of 2019

Tabel 4. 8: Comparison of actual and projected LULC 2019.

Year	Classified LULC 2019		Simulated LULC 2019		% of accuracy
LULC types	Area ha	Area %	Area (ha)	Area %	
Agricutural Land	596032.22	43.89	608254.79	44.79	97.99
Forest Land	150529.80	11.08	138307.23	10.18	91.88
Shrub Land	562196.68	41.40	548616.05	40.40	97.58
Urban	40092.59	2.95	53673.22	3.95	74.70
Wet Land	9211.72	0.68	9211.72	0.68	100.00
Total area	1358063.01	100.0	1358063.01	100.0	100.00

4.4. Predicted future Land Use Land Cover.

Terrset's geospatial monitoring and modeling system uses classification and year-interval time series to estimate future land use and land cover (LCM). The 2002 LULC earlier land cover image and the 2019 LULC later land use cover image are used in the change analysis. To put the transition model into practice, transition submodels and the appropriate structures were created upon performing a change analysis on the transition matrix potentials.

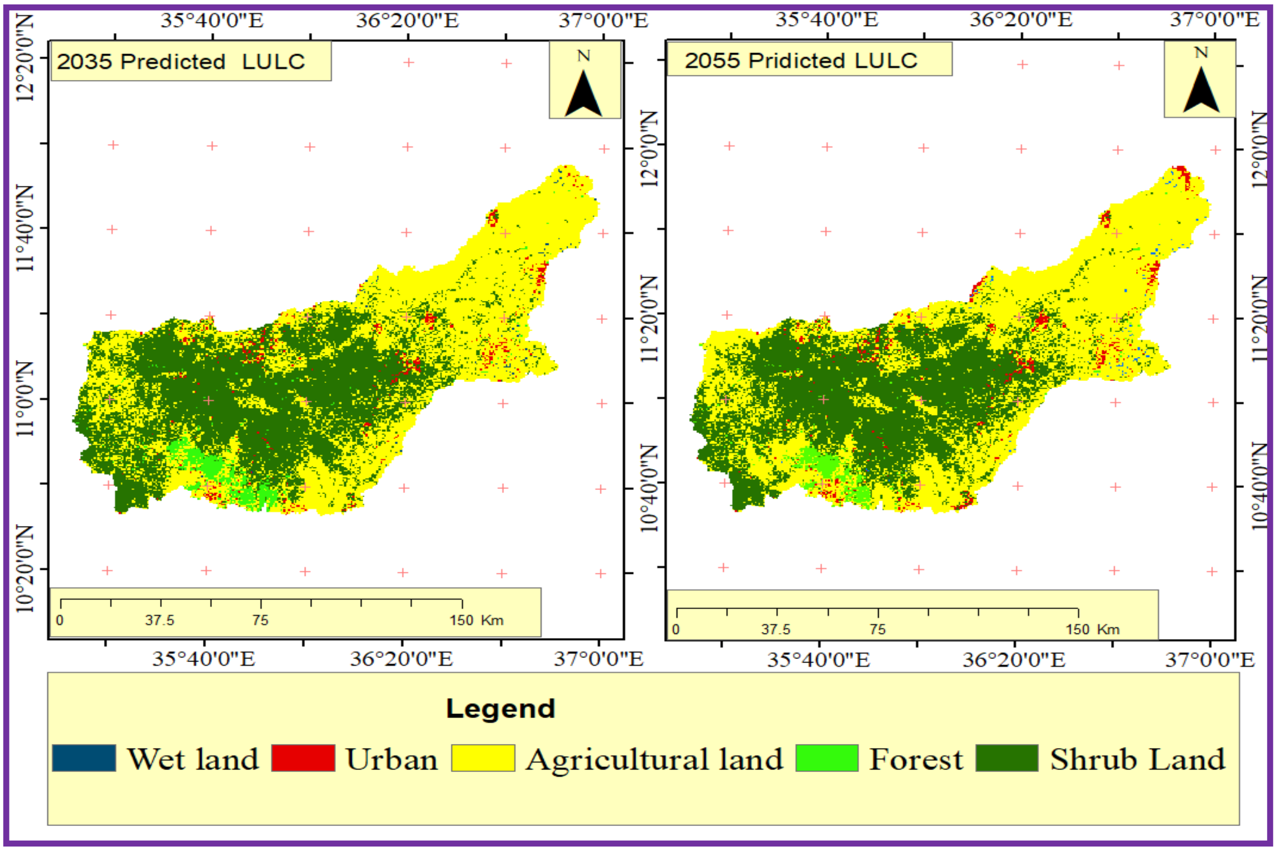

Figure 4. 8: Predicted LULC Map of the year 2035 (left) and 2055 (right)

The 2002 and 2019 LULC images were used as a baseline to forecast future land use coverage, and the 2035 and 2055 LULC images in Figure (4.7), respectively, demonstrate the outcomes of the prediction.

Tabel 4. 9: 2019-2055 Predicted LULC percentage of change and rate of change**.**

LULC (2019-2055)		Area (ha)			Area (%)			Percentage of change			Rate of change in ha/year	
Study Period		2019	2035	2055	2019	2035	2055	2019-2035	2035-2055	2019-2055	2019-2035	2035-2055
	Agricutural	596032.2	633936.7	661219.2	43.8	46.6	48.6	6.36	4.30	10.94	2229.68	1604.85
	Forest Land	150529.8	136364.0	131516.9	11.0	10.0	9.68	-9.41	-3.55	-12.63	-833.28	-285.13
	Shrub Land	562196.6	528577.7	498367.7	41.4	38.9	36.7	-5.98	-5.72	-11.35	-1977.59	-1777.06
	Urban	40092.59	42849.00	57747.41	2.95	3.16	4.25	6.88	34.77	44.04	162.14	876.38
	Wet Land	9211.72	16335.42	9211.72	0.68	1.20	0.68	77.33	-43.61	0.00	419.04	-419.04

Comparing area transformation from actual LULC, which is classified land use, and expected LULC change from 2019 to 2055, it can be seen that between 1987 and 2019, there was a quick pace of transformation. Nevertheless, the predicted land use change rate was more slow. Nonetheless, a trend of shrinkage that was comparable to the actual LULC change was present in all wet land, forest, and shrub land. Another way to put it is that between 2019 and 2035, and again between 2035 and 2055, agricultural land, and urban area land use/land cover, are consistently increasing by 6.36%, 6.88%, and 4.30%, and 34.77%, respectively.

From 2019 to 2035, agriculture land and urban areas increased by 2229.68 ha/year and 162.14 ha/year, respectively and from 2035 to 2055, they increased by 1604.85 ha/ year and 876.38 ha/year, respectively

Shrub land and forest have also changed, with annual rates between 2019 and 2035 predicted to be -1977.6 ha/year and -833.28 ha/year, respectively, and between 2035 and 2055 predicted to be -1777.06 ha/year and -285.13 ha/year. These changes are related to decreasing land use types, which assist expanding land use.

Tabel 4. 10: 2035 predicted Land Use/Land Cover change Transition Matrix.

2019 LULC (100%)	2035 Predicted LULC (100%)						
	land use types	Agricultural	Forest	Shrub Land	Urban	Wet Land	Grand Total
	Agricutural Land	29.8	0.9	12.0	0.9	0.2	43.9
	Forest Land	0.7	8.0	2.3	0.0	0.0	11.1
	Shrub Land	15.5	1.1	24.0	0.1	0.6	41.4
	Urban	0.3	0.0	0.5	2.1	0.0	3.0
	Wet Land	0.3	0.0	0.0	0.0	0.3	0.7
	Grand Total	46.7	10.0	38.9	3.2	1.2	100.0

Shrub land shrinks more than forest and wet land in two of the expected LULC areas, which is why agricultural land and urban areas have increased despite the higher cost of shrub land than other types of land represented in the table (4.10 and 4.11). Expansion of agricultural and urban land at the expense of a bigger area from shrub and forest lands is represented in the change transition matrix restriction table.

Tabel 4. 11: 2055 predicted Land Use/Land Cover change Transition Matrix

2035 LULC (100%)	2055 Predicted LULC (100%)						
	land use types	Agricultural	Forest	Shrub Land	Urban	Wet Land	Grand Total
	Agricutural Land	29.8	0.7	14.6	1.2	0.3	46.7
	Forest Land	0.9	7.0	2.1	0.0	0.0	10.0
	Shrub Land	16.8	1.9	19.2	0.9	0.0	38.9
	Urban	0.9	0.0	0.1	2.1	0.0	3.2
	Wet Land	0.2	0.0	0.6	0.0	0.3	1.2
	Grand Total	48.7	9.7	36.7	4.3	0.7	100.0

In general, proper management methods are needed to reduce the rates of future forest and shrub land loss, including reducing overgrazing, area closure, afforestation, planning to modernize agricultural practices in existing agricultural land, and other integrated productive agroforestry.

The same study according to (Tewabe & Fentahun, 2020) in lake tana basin north western Ethiopia reported that in the last 32 years period, agricultural land and residential areas had significantly increased by 15.61% and 8.05% respectively in the basin. Therefore, proper land management practices, integrated watershed management, and active participation of the local community should be advance to protect undesirable LULC change in the basin.

4.5. Impact of LULC on stream flow

4.5.1. Sensitivity Analysis.

Sensitivity analysis was helpful to rank and identify the most sensitive parameters based on significant impact for each parameter. The most sensitive parameter corresponds to greater change in output response. This information is important during model calibration. SWAT on daily time steps with observed data of the Beles River on Gilgel Beles gauging station. For this analysis all SWAT parameters were considered and only 10 parameters were identified for both (SWAT-CN & SWAT-WB) to have significant influence in controlling the stream flow in the river basin. In this study, we have evaluated the relative sensitivity values found in the parameter estimation process for SWAT-WB. The most sensitive parameters for SWAT-WB were: Base flow Alpha Factor (days) ALPHA_BF, threshold depth of water in the shallow aquifer for “revap” to occur (REVAPMN. gw) [mm H2O] [days], soil evaporation compensation factor (ESCO), Initial soil depth (SOL_Z), available water capacity (Sol_Awc) [mm WATER/mm soil], threshold depth of water in the shallow aquifer for return flow to occur (GWQMN. gw) [mm H2O] and soil hydraulic conductivity (SOL_K). These sensitive parameters were considered. The important aim of parameter sensitivity analysis is to provide opportunities to reduce the number of input parameters there by reducing the computation time for model calibration. Out of 19 parameters which govern the hydrology in SWAT sensitivity analysis was carried out and the most 10 most sensitive parameters Tabel 4.12 were chosen for calibrating the model.

Tabel 4. 12: The main parameter use For Beles Sub-Basin

N0	Parameter	Description	Range Value
1	CN	SCS Runoff Curve Numbers	0.25 – 25
2	Alpha_BF	Base Flow Alpha Factor	0 – 1
2	Esco	Soil Evaporation Compensation Factor	0 – 1
3	So_AWC	Available water content of soil	0 – 1
4	GW_Delay	Groundwater delay	0 – 500
5	Epco	Plant uptake compensation factor 0	0 -1
6	Soil_k	Saturated hydraulic conductivity(mm/hr) 0	0 – 2000
8	CH_CN2	Manning’s “n” value for the main 0	0,0250 - 250
9	GW_REVAP	Groundwater revap coefficient	0.02 - 0.2
10	Revamp	Threshold depth of water in the shallow	0 – 500

Tabel 4. 13: Sensitive Flow Parameters, their rank and fitted value

	Parameters		t-stat	P-Value	Rank
1	R__CN2.mgt	Initial SCS CN II value	0.097	0.925	1
2	V__GW_DELAY.gw	GW Delay	0.155	0.866	2
3	R_Epco.bsn	Plant uptake compensation factor	0.355	0.737	3
4	V-Sol_AWC	Available water capacity (mm)	-0.657	0.533	4
5	V__ALPHA_BF.gw	Base flow alpha factor [days]	-0.862	0.421	5
6	V__CH_K2.rte	Saturated hydraulic conductivity [mm/hr]	2.063	0.0852	6
7	V__GWQMN.gw	depth of water in shallow aquifer	2.566	0.042	7
8	V__ESCO.hru	Soil evaporation compensation factor	-6.800	0.00023	8
9	V__GW_REVAP.gw	Groundwater "revap" coefficient	-0.780	0.00033	9
10	V__CH_N2.rte	Manning's n value for main channel	-0.880	0.00043	10

Note: A, indicates add the fitted value to the existing value, V implies replace the existing value with the fitted value; R indicates multiply the existing value with (1+ the fitted value).

The t-value measures the size of the difference relative to the variation in the sample data and P-value is the probability of observing a test statistic at least as large as the one calculated assuming the null hypothesis is true. Ranking of sensitivity of parameters was determined by the absolute values of t-stat and P-value. The parameter having the highest absolute value of t-stat and the minimum P-value, would take the first rank of sensitivity. Which indicate any value change on this parameter would was most significantly affecting the dynamics of flow compared with other parameters. Base on the sensitivity analysis done for this watershed the most sensitive parameter found was Curve Number 2(CN2).

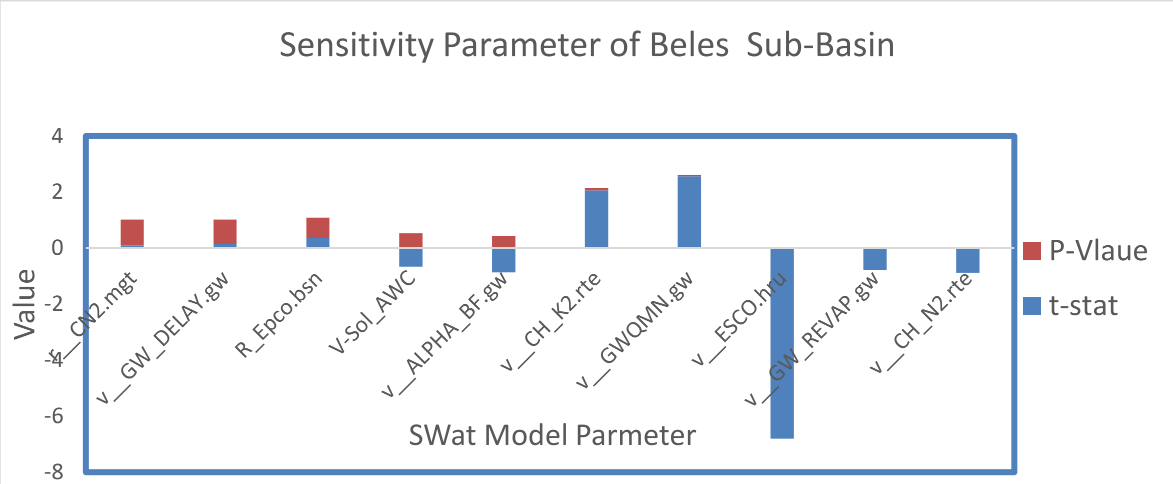

Figure 4. 9: Graphical representation of sensitivity analysis with t-test and p-value

4.5.2 Calibration and Validation of Model

The model calibration was conducted after the sensitive parameters were identified. The monthly flow of the Beles Sub-Basin from 1989 to 2010 was used for calibration purposes, from these observed flows the two years (1987 and 1988) data were used as a model warm-up purpose. Then by using the sensitive parameter the calibration were done for (1989-2010). The default simulation outputs were compared with the observed stream flow data of the catchment. The result of calibration for monthly flow shows that there is a good agreement between the measured and simulated average monthly flows with Nash-Sutcliffe simulation efficiency (NSE) of 0.74 and coefficient of determination (R^2) of 0.80. Similarly, on the findings of the study that was done on upper blue nile and where the calibration was also done on Gilgel beles (Woldesenbet *et al.*, 2017) found that the correlation cofficent R^2= 0.82 and the Nash-sutcliff simulation (NSE= 0.79) and also on another study the findings (Fenta Mekonnen *et al.*, 2018) was found that the correlation coefficient (R^2=0.80) and the Nash – Sutcliffe simulation efficiency (NSE =0.70) showed a very good agreement between observed and simulated for upper Blue Nile River basin during the calibration period. Using the three different years classified images of the study area three calibration graphs and results were generated as summarized s below and also The figure below indicates the scatter plot of the simulated and observed flow of the study area for calibration as the result shows the simulated and observed data have good distributions this indicates the observed and simulated value have a strong correlation for calibration.

The validation was performed for nine years, period from (2011-2019). The result of Coefficient of determination and Nash-Sutcliff Efficient indicates acceptable accuracy for the model to predict the catchment response. Based on the model performance evaluation parameter numerical values of determination coefficient (R^2 = 0.64) and Nash-Sutcliff's simulation efficiency (ENS = 0.78) assures that the model shows a good performance during validation so as to able to simulate the stream flow in the study area. (Woldesenbet *et al*., 2017) finding indicate that the model performance show a good correlation and agreement between the monthly measured data and simulated (ENS= 0.80 and R^2=0.81) that was done on upper Blue Nile and those specific result was on the Beles Basin for validation period. The linear regression of the scattering plot of observed stream flow and validation stream flow for each classified LULC (1987,2002 and 2019) will be shown in the next sections.

4.5.2.1 Calibration and Validation for Land cover 1987

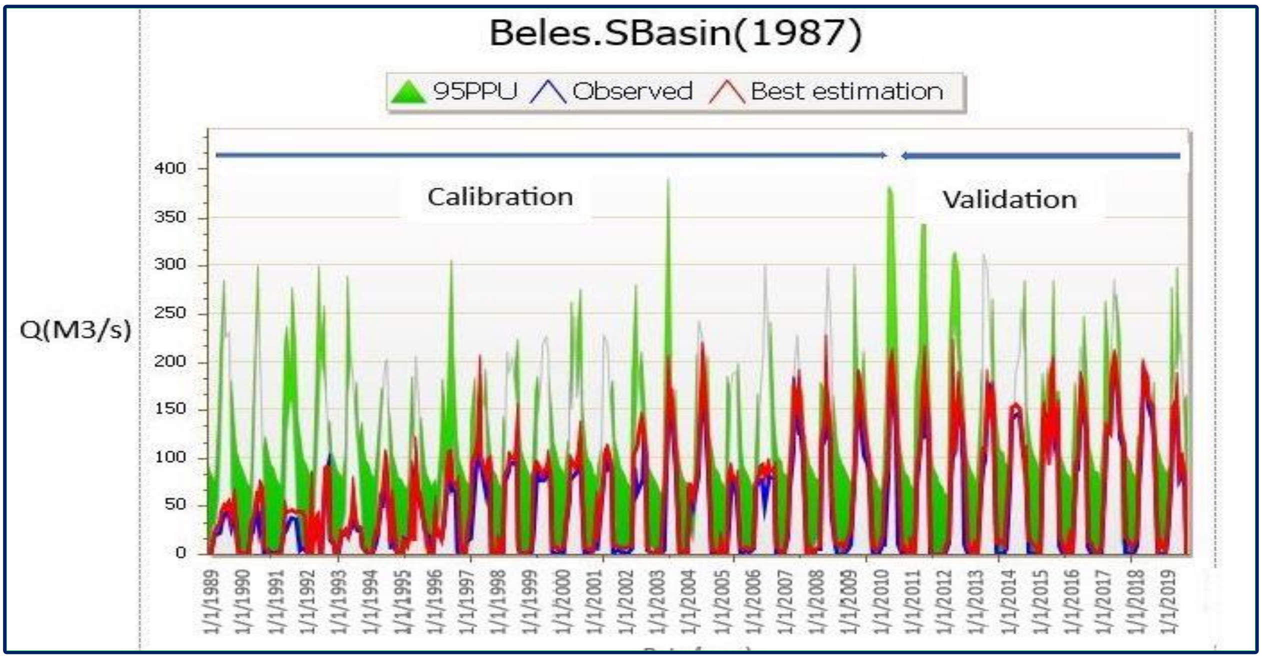

Figure 4. 10: Model calibration and validation using 1987 land cover of Beles Sub-Basin

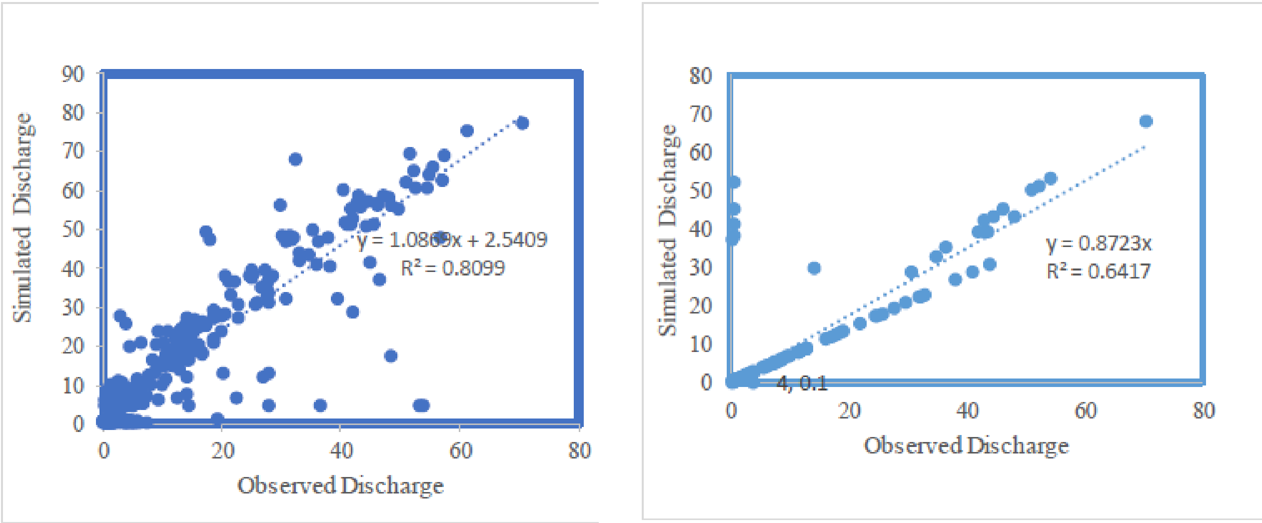

Figure 4. 11: Scatter plot of the observed and simulated monthly average flow (m3 /s) in the calibration (left) and validation (right) period for 1987 LULC.

4.5.2.2 Calibration and Validation for Land cover 2002

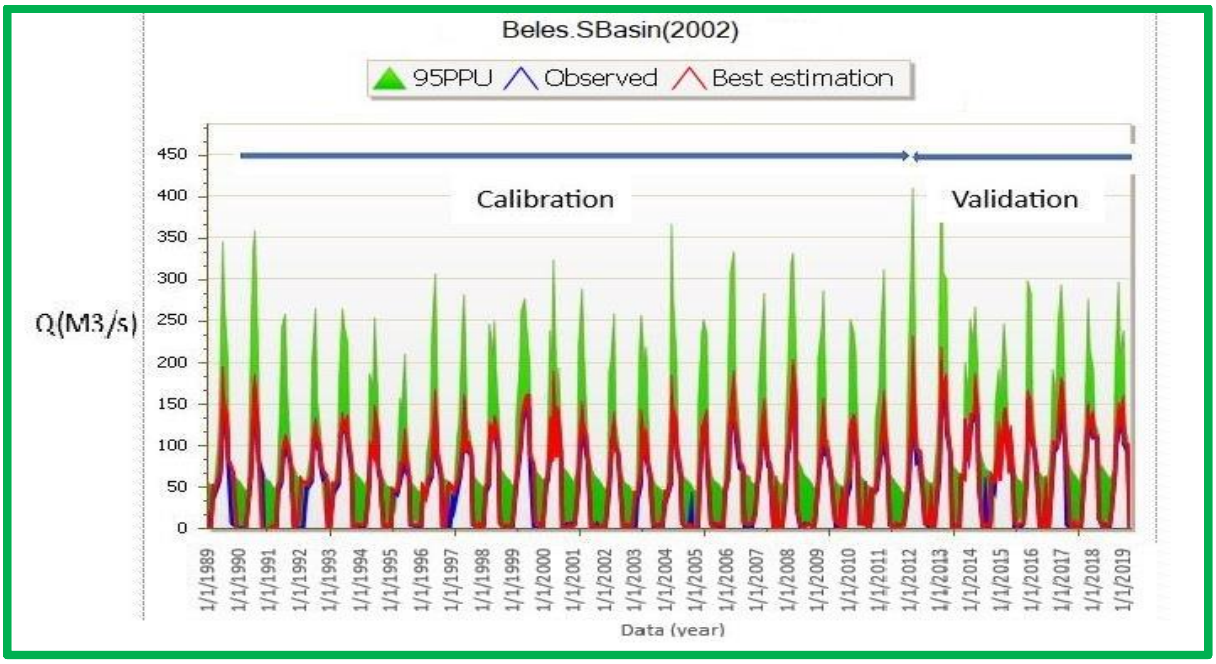

Figure 4. 12 : Model calibration and validation using 2002 land cover of Beles Sub-Basin

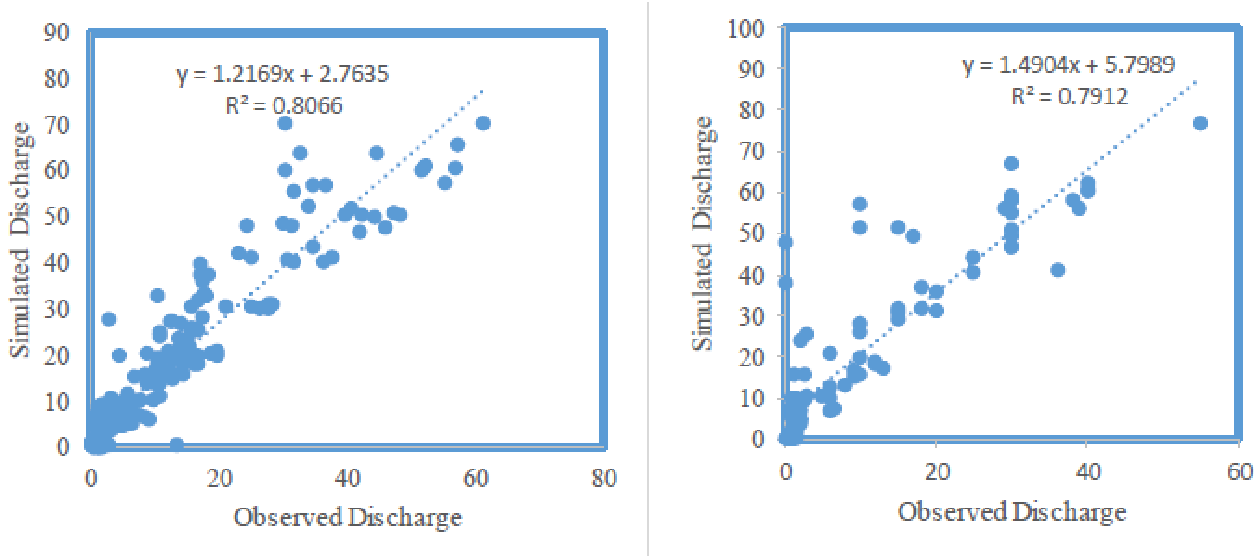

Figure 4. 13: Scatter plot of the observed and simulated monthly average flow (m3 /s) in the calibration (left) and validation (right) period for 2002 LULC.

4.5.2.3 Calibration and Validation for Land cover 2019

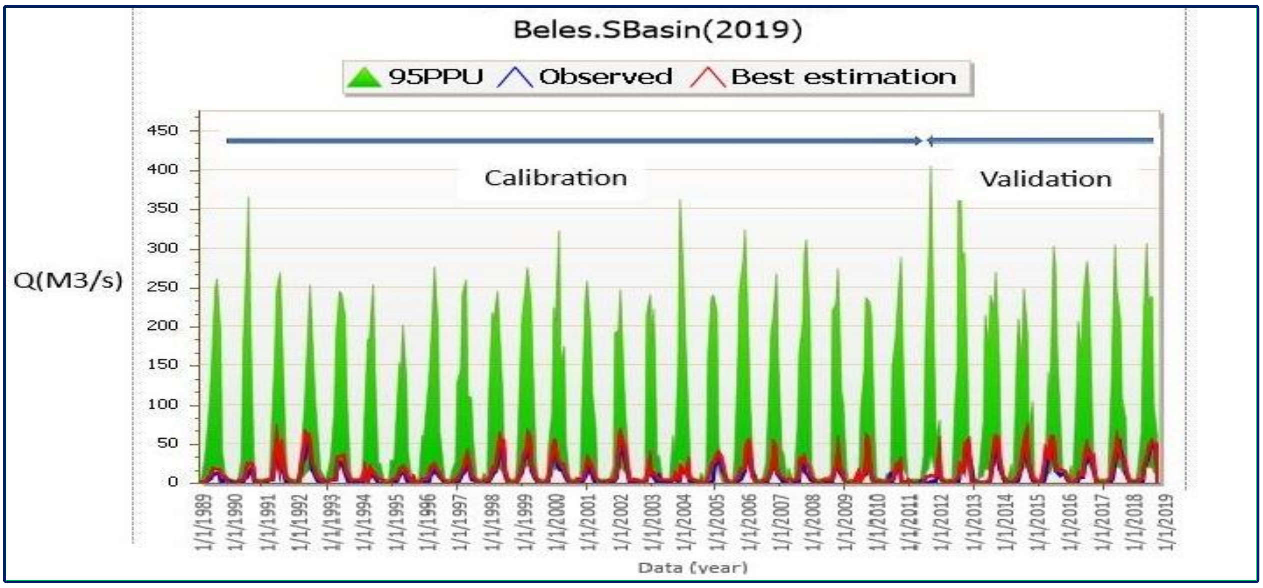

Figure 4. 14: Simulated and Observed stream flow using 2019 land cover of Beles Basin for calibration period

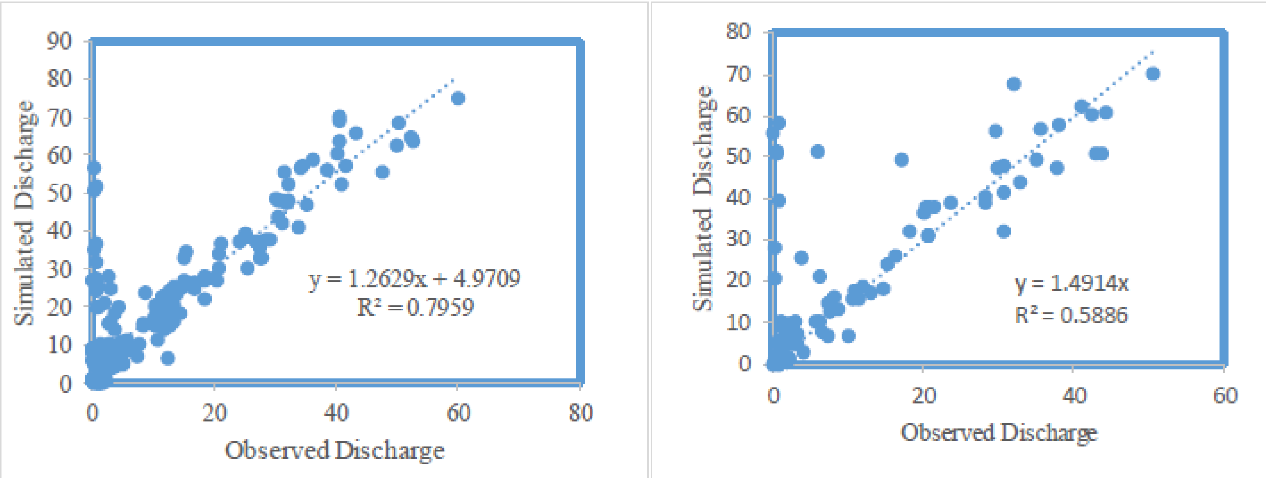

Figure 4. 15 : Scatter plot of the observed and simulated monthly average flow (m3 /s) in the calibration (left) and validation (right) period for 2019 LULC

The table below shows the summary of the SWAT model performance evaluations for calibration and validation.

Tabel 4. 14: Model performance statistics for the calibration and validation period

Parameter	Model Performance Evaluation Criteria					
	Calibration (1989-2010)			Validation (2011-2019)		
	1987 Land cover	2002 Land cover	2019 Land cover	1987 Land cover	2002 Land cover	2019 Land cover
R^2	0.80	0.80	0.79	0.64	0.79	0.58
ENS	0.74	0.67	0.80	0.78	0.69	0.78
RVE %	10	13	11	11.1	12	9

4.6. Evaluation of Stream Flow due to Land Use and land Cover Change

The main obejective of the study was to evaluate the impact of land use and land cover changes on Beles Sub-Basin. The evaluation was done in terms of the impact of land use and land cover changes on annual and seasonal stream flow and variations on the major components of stream flow during the period (1987 – 2019).

The results of detecting changes in land use and land cover using satellite images from three separate years indicated that these changes had an impact on the watershed's stream flow. Table 4.15 displays the calibrated and verified annual average stream flow simulation results for the land uses in 1987, 2002, and 2019. The findings revealed that stream flow increased throughout both the calibration and validation periods.

Tabel 4. 15: Mean annual stream flow results for the calibration and validation period

years	1987	2002	2019	Change Detection		
	Simulated	simulated	simulated	1987-2002	2002-2019	1987-2019
Calibration	133.26	150.47	141.80	17.21	-8.67	8.54
Validation	134.68	137.72	140.55	3.04	2.83	5.87

The stream flow results for the different years were compared based on the validated values (Table 4.15). Stream flows showed a higher increase in the first period (3.04m^3/s) than the second period (2.83m^3/s). Generally speaking stream flows has increased throughout the study period for over 33 years period with a magnitude of 5.87m^3/s. These tremendous changes of stream flow were due to the land cover changes of the sub-basin (an increase of Agriculture land trough study Period).

4.6.2. Change in the Seasonal Stream Flows

After calibrating and validating of the model using the three land use and land cover maps for their respective periods of 1987 to 2002 and 2002 to 2019 respectively, SWAT was run using the three land cover maps (1987, 2002 and 2019 maps) for the period of 1987 to 2019 while putting the other input variables the same for all the simulations to quantify the variability of stream flow due to the changes of land use and land cover. This process gave the discharge outputs for the three land use and land cover patterns. The effect of landuse/land cover change on stream flow was investigated at different seasons in this study area. In our country (Ethiopia) the season classification is based on rainfall patterns. According to NMSA, (1996) , there are three major seasons, Kiremt (main rainy season from June to September), Belg (small rainy season from February to May), and Bega (dry season from October to January). However, this is not true for overall the country. The study area has different spatial and temporal characteristics with bimodal rainfall patterns have four seasons, considering that for this specific study months January, February and March were considered as a dry period, and months June, July and August were also taken as wet period for detecting the change of stream flow

Table 14.16 and Table 4.17 presents the mean monthly wet and dry month's stream flow for 1987,to 2002 and 2002 to 2019 land use and land cover maps respectively

Tabel 4. 16: Mean monthly wet and dry month's stream flow and their variability (1987-2002)

Mean Monthly Flow Discharge				Mean Monthly flow change	
Land Use/Cover Map of 1987		Land use/Cover map of 2002			
Wet Months (Jun, Jul, Aug)	Dry Months(Jan, Feb,Mar)	Wet Months (Jun,Jul, Aug)	Dry Months(Jan, Feb,Mar)	Wet	Dry
260.37	17.54	272.42	19.67	12.05	2.13

As can be indicated in the table 16, the mean monthly stream flow for wet months had increased by 12.05 m3/s while the dry season increased by 2.13 m3/s during the 1987-2002 periods due to the land use and land cover change.

Tabel 4. 17: Mean monthly wet and dry month's stream flow and their variability (2002-2019)

Mean Monthly Flow Discharge				Mean Monthly flow change	
Land Use/Cover Map of 2002		Land use/Cover map of 2019			
Wet Months (Jun, Jul, Aug)	Dry Months(Jan, Feb,Mar)	Wet Months (Jun,Jul, Aug)	Dry Months(Jan, Feb,Mar)	Wet	Dry
272.42	19.67	277.91	16.89	5.49	-2.78

As can be indicated in the table 4.17 the mean monthly stream flow for wet months had increased by 5.49 m^3/s while the dry season decreased by -2.78 m^3/s during the 2002-2019 periods due to the land use and land cover change.

In general, for over the 33 years period (1987 – 2019) stream flows has showed an increase (+17.54m3/s) during the wet season due to an increase of cultivated land, which implies that agricultural lands increased surface runoff (peak runoff). On the other hand, stream flows has showed a decreasing trend in the dry season period with a magnitude of (-) 0.65m^3/s, which has reflected that base flow has decreased with an intense agricultural expansion

To assess the change in the contribution of the components of the stream flow due to the land use and land cover change, analysis were made on the surface runoff (SURQ) and ground water flow (GWQ). Table 4.18 and Table 4.19 presents the SURQ and GWQ of the stream simulated using 1987, 2002 and 2019 land use and land cover map.

Tabel 4. 18: . Surface runoff and Ground water flow of the stream simulated using 1987 and 2002land use/cover map

Land Use/Cover map of 1987		Land Use/Cover map of 2002		Change of SURQ AND GWQ	
SURQ (mm)	GWQ (mm)	SURQ(mm)	GWQ (mm)	SURQ (mm)	GWQ (mm)
40.85	48.68	47.06	45.40	+6.21	-3.28

Tabel 4. 19: Surface runoff and Ground water flow of the stream simulated using 2002 and 2019 land use/covermap.

Land Use/Cover map of 2002		Land Use/Cover map of 2019		Change of SURQ AND GWQ	
SURQ (mm)	GWQ (mm)	SURQ (mm)	GWQ (mm)	SURQ (mm)	GWQ (mm)
47.06	45.40	56.08	40.43	+9.02	-4.97

As the above tables showed the SURQ and GWQ components of the stream simulated using the 1987 land use and land cover map were 40.85 mm and 48.68 mm while using 2002 land use and land cover map were 47.06 mm and 45.40 mm, and while using 2019 land use and land cover map were 56.08mm and 40.43 mm respectively. For the years from 1987 to 2002 the contribution of surface runoff has increased from 40.85 mm to 47.06 mm whereas the ground water flow has decreased from 48.68 mm to 45.40 mm and the same trend followed for the year 2002 to 2019 surface runoff has increased from 47.06 mm to 56.08 mm whereas the ground water flow has decreased from 45.40 mm to 40.43 mm which is due to the land use and land cover change occurred between those periods. This is because of the expansion of agricultural land over forest that results in the increase of surface runoff following rainfall events which can be explained this in terms of the crop soil moisture demands. Crops need less soil moisture than forests; therefore the rainfall satisfies the soil moisture deficit in agricultural lands more quickly than in forests there by generating more surface runoff where the area under agricultural land is extensive. And this causes variation in soil moisture and groundwater storage. This expansion also results in the reduction of water infiltrating in to the ground. Therefore, discharge during dry months decreases, whereas the discharge during the wet months increases. These results demonstrate that the land use and land cover change have a significant effects on infiltration rates, on the runoff production, and on the water retention capacity of the soil.

Different studies have been conducted in different parts of the country to evaluate the effects of land use and land cover changes on stream flow (Nigusie & Dananto, 2021; Regasa, 2021; Tenagashaw et al., 2022; Yohannes et al., 2018) introduced that the surface runoff increased and the base flow decreased due to the expansion of agricultural land and declined of forest land it was also reported that due to the replacement of natural forest in to farmland and settlements, the mean monthly discharge for wet months had increased while in the dry season decreased. In the study of, and the large volume of surface runoff occurs during the storm events since the area under forest cover decreased.

5. SUMMARY AND CONCLUSION

5.1 Summary

An integrated approach of GIS and remote sensing with a hydrological model tools were used to map different land cover classes and to detect and analyses spatiotemporal land cover changes on different period of time. These techniques were applied to enable and asses of the land cover change effects on the stream flow for this study. The impacts of the land cover change on stream flow was analyzed statistically using the hydrological model, SWAT.

This study investigated the impact of landuse land cover change on the stream flow of the Beles Sub-Basin. To accomplish the research different data, such as climatic, hydrological, and spatial data were collected and analyzed. So as to fill the missing datas the normal ratio method was used to compute the missing rainfall data for this study, afterward checking for inconsistency of the record was done by the double-mass curve technique

The satellite image of 1987, 2002, and 2019 provided by Landsat 5 TM, Landsat 7 EMT+, and Landsat 8 OLI sensor were downloaded from USGS, to investigate the landuse land cover change in the Beles Sub-Basin. Then ERDAS imagine 2014 software used during landuse/land cover classification and mapping. After satellite images were classified to the pre-defined landuse/land cover type, the accuracy assessment was done to check the quality of the classified image. The overall accuracy values 86.25%, 88.7% and 87.9% and Kappa coefficients of 82.8%, 85.9% and 84% of 1987,2002 and 2019 were founded respectively. So the founded kappa coefficient indicated the image classification performed in the perfect range of kappa coefficients as recommended.

In the following decades 1987, 2002, and 2019, respectively, in which agricultural and urban land use cover trendes indicates counitinuosly increasing but remaining three land use/land covers were decreasing. However, Two land use/land cover types, such as settlement and agricultural areas, show a greater annual rate expansion per hectare as a result of the rapidly growing population, the demand for fuel wood, grazing pasture, and farmlands. The dominating land use in the study area, which accounts for 51.99% of the total area, is shrub and the second dominant land use, agricultural land, accounts for 29.70% of the total area in 1987. In the river basin in 1987, forest, wet land, and urban area shares were placed in the following order: 15.81%, 1.78%, and 0.71%, followed by shrub land and agricultural land.

The two main changes in land use and land cover in in Beles sub-basin in 2002 were an increase in agriculture coverage of area by 4.68% (from 29.70% to 34.38%) and a decrease in shrub land by 2.77% (from 51.99% to 49.22%). In contrast, urban area grew by 1.87% in 2002, while forest and wetland decreased by 3.19% and 0.58%, respectively.

The same trend, which has persisted over the last past 17 years from 2002 to 2019, has seen the land use coverage of agriculture, and urban areas increase by 9.51%, (34.38% to 43.89%), and 0.37%, (2.58% to 2.95%) respectively, while the remaining three land use/land cover types shrubs, forests, and wet land constantly contract by 7.82%, 1.54%, and 0.52%, respectively. the agricultural land trend shows a 0.42 annual rate change, which indicates a greater rate expansion per hectare due to the rapidly rising population growth, which is believed to be the main cause of the decline in other types of LULC due to the rising demand for new agricultural production land parcels. decline of grass and shrubs suggests that the primary anthropological factors influencing LULC changes in the watershed are the rapidly increasing population demand for agricultural products, the worst land degradation, and the expansion of residential and industrial zones.

The future landuse land cover was also projected based on the historical landuse land cover conditions of the study area. For prediction of two future land use change consider important independent factors relating to anthropogenic, topographic, infrastructure, and water body proximity Elevation, slope, road, and river distance (water body proximity) are the main factors taken into account in this study to predicting future land use and land cover in 2035 and 2055, The result of the change analysis 2035 and 2055 indicates there were the same trends in future LULCC as historical landuse land cover change.

Soil and Water Assessment Tool was used for hydrological modeling purposes in this study during the investigation of the impact of landuse/land cover change on the stream flow of the study area. In which spatial input data (land use, soil and slope) and metrological input data (precipitation, temperature, solar radiation, humidity and sunshine) were used for simulation.

Model sensitivity analysis was made and ten sensitive parameters were selected from the parameter considered during sensitivity analysis Then, using SWAT-CUP version 2019 calibration and validation of simulated streamflow the model were performed, and the following result was obtained: R^2 0.80 for calibration, 0.64 for validation, and Nash Sutcliff efficiency (NSE) values of 0.74 and 0.78 for calibration and validation respectively therefore SWAT model can be used or suitable for predicting the rainfall-runoff relationships as well as simulating discharge in the Beles sub-Basin and was used for evaluating the impact of land cover change in the Study area. model calibration and validation have showed that the SWAT model simulated the flow quit satisfactorily. Performance of the model for both the calibration and validation watershed were found to be reasonably

Following calibration and validation of the model, impacts of the land use and land cover change on stream flow was carried out. Land use and land cover changes recognized to have major impacts on stream flow and aslo on runoff and groundwater flow. The result of model for all periods of land use and land cover (1987, 2002 and 2019) indicated that anually Stream flows showed a higher increase in the first period (3.04m^3/s) than the second period (2.83m^3/s) stream flows has increased throughout the study period for over 33 years period with a magnitude of 5.87m^3/s. during the wet season, the mean monthly flow for 2002 land cover was increased by 12.05 m^3/s relative to that of 1987 land cover and for 2019 land cover period was increased by 5.49 m^3/s relative to 2002 land cover while the mean monthly flow increased by 2.13 m^3/s during the dry season from 1987 to 2002 and decreased by -2.78 from 2002 to 2019. The surface runoff increased from 41 mm to 47 mm to 56 mm, while the ground water decreased from 49 mm to 45 mm to for the 1987, 2002 and 2019 land cover maps respectively.

Generally, the study on change in stream flow with respect to the land use and land cover change within Beles Sub-Basin showed that the flow characteristics have changed, with increase in surface flow and reduction of base flows through the selected period of study.

5.2. Conclusion

Based on the finding of the landuse land cover change analysis and its impacts on the strean flow the following conclusions were reached.

- There was a continuous expansion of agricultural land and built-up in the study area, this was due to the increase of population in the sub-basin from time to time so the farmland-dependent families spatially in ruler area increase their agricultural land from time to time, in contrast to agricultural and built up, there was a continuous decrease of forest, shurbland and wet land in all the study periods.
- The result of LULC the change prediction of 2035 and 2055 presented a significant change in landuse/land cover in the same trends as the historical landuse land cover change.
- The landuse/land cover change has a great impact on the seasonal streamflow, surface runoff and ground water of the sub-basin. The seasonal stream flows indicate highly decreasing from in the dry season due to the landuse land cover change in the study area because of the expansion of agricultural and built up, as the cost of decreasing forest, shurbland and wetland.
- Adopting a holistic approach to manage water resources that considers the interactions between land use, water availability, and ecosystem health. This involves coordination among various stakeholders and the integration of water-related policies and practices.
- This condition requires great consideration because increasing streamflow in the worst case was the major problem in planning and running the existing water resource project.

5.3 Recommendation

Based on the result obtained during landuse/land cover change analyses, its impacts on the stream flow of the study, and the conclusion reached, the following recommendations are suggestions.

- The study was done by considering the impacts of the landuse/land cover change on the stream flow of the Beles Sub-Basin due to time and budget constraints, the effect of climate change did not consider during the investigation of the effect of landuse/land cover on the stream flow of Beles Sub-Basin. From this point of view, it can be recommended that research have a better result if the effect of climate change is included for further study.
- The reference point used in this study was taken from the google earth .due to time and budget constraints, however it is better if the GPS points to cheek the accuracy assessment of the classified satellite image.
- As the future predicted landuse/land cover of the study area indicated the change will continued in the future The predicted conditions in this study particularly the negative impacts of LULC changes may be overturned through the implementation of integrated local and regional scale policies and strategies toward efficient resource utilization, land use, and physical and human environmental protection. In line with this, practicing effective soil and water conservation measures, climate-resilient agricultural activities, periodic afforestation, and reforestation programs will tackle the adverse impacts emanating from the LULC changes. It is recommended that future studies undertake multisource data, more variables (spatial and socioeconomic), and models to evaluate and predict LULC changes, and provide sound information in the entire sub-basin (Beles Sub-Basin) and other basins.
- Landuse/land covers of the study indicated the expansion of Agricultural land and built-up area as the other landuse/land covers such as, Forest, Wet land and Shurb Land decreased from time to time, this condition causes the increase of surface runoff by reducing the infiltration rate in the wet season and decreasing base flow in the dry season, so the concerned stakeholder of the study area should be practiced the idea of integrated water resource management
- The hydro metrological data available in this study was not good enough, for their availability and quality. So it is better if more investigation is as well as establish the

additional modernized gauging stations. This task helps to have reasonable hydro metrological data for longer temporal and spatial scales, which reduce the uncertainties and increase the performance of the modeling in the study area.

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APPENDICES.

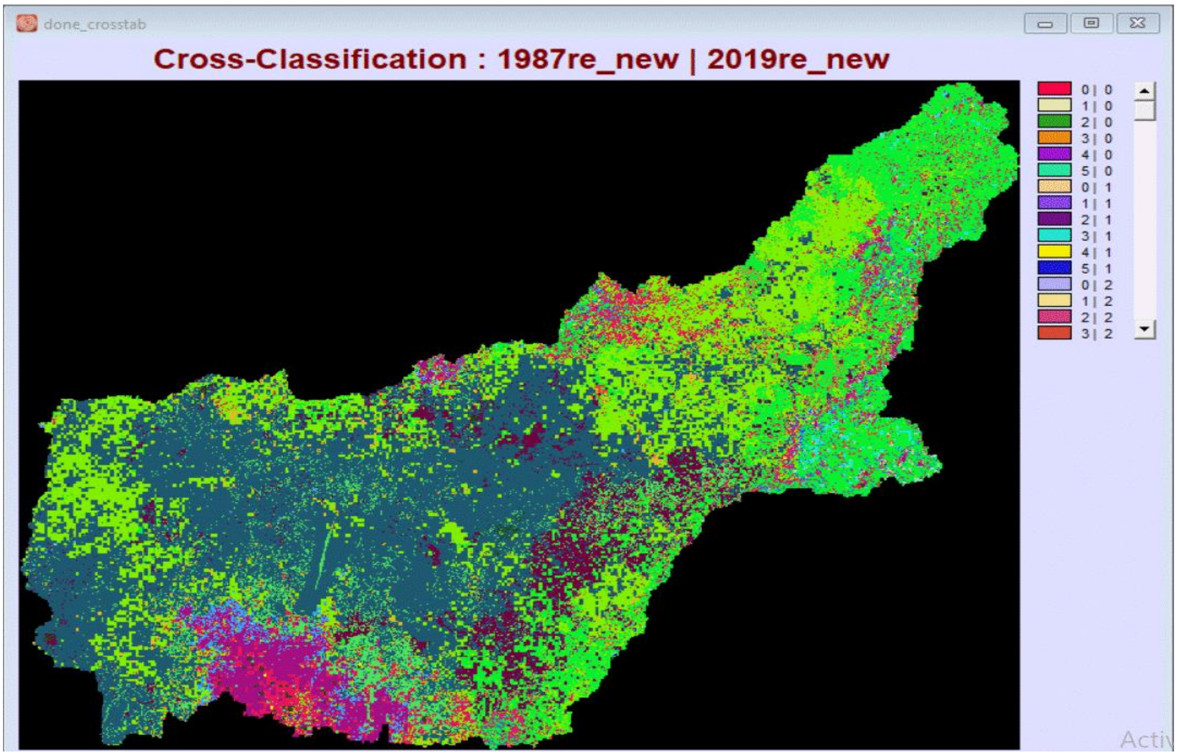
Appendix Table 1: MLP_NN Model Performance

Input layer neurons	4
Hidden layer neurons	3
Output layer neurons	2
Requested samples per class	10000
Final learning rate	0.0010
Momentum factor	0.5
Sigmoid constant	1
Acceptable RMS	0.01
Iterations	10000
Training RMS	0.3640
Testing RMS	0.3615
Accuracy rate	82.86%
Skill measure	0.6571

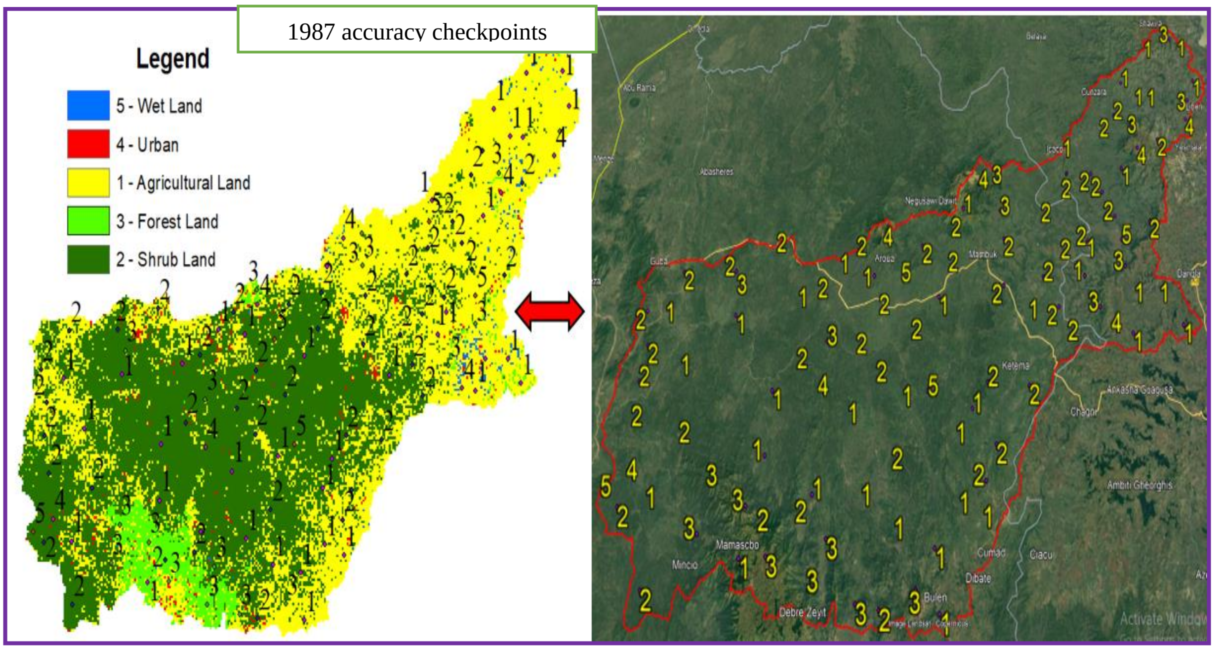
Appendix Table 2: Annual rainfall of stations around Beles Sub-Basin (cum).

Year	Bullen	Chagni	Dangila	Enjibara	Mandura	Pawe	Average
1987	1366.9	1755.874	1762.8	1580.5	1481.1	1527.7	1695.812
1988	3121.4	3511.474	3529.6	3978.1	3287.5	3525.6	1913.133
1989	4375.173	5236.174	5175.8	6034.4	5436.7	5332.856	1856.238
1990	5830.562	6836.662	6738.738	8024.7	7121.6	6881.343	1640.417
1991	7298.843	8503.293	8310.672	10535.08	8704.425	8419.934	1873.108
1992	8716.598	10259.19	9793.398	13138.3	11379.85	9992.85	1734.655
1993	10188.56	11981.53	11509	14850.15	12632.76	11440.25	1803.678
1994	11636.67	13697.3	12826.9	17387	14578.84	12846.42	1678.48
1995	13075.29	15426.32	14011.5	18547.68	16538.88	14375.3	1633.64
1996	14533.97	17158.86	15666.2	20843.4	18501.33	16077.03	1817.636
1997	16007.66	18892.95	17333.4	22711.94	20451.64	17517.65	1839.075
1998	17853.06	20733.63	18904.28	25020.26	22414.37	19340.52	1891.814
1999	19653.64	22506.48	20863.68	26751.25	24360.8	20869.2	1956.488
2000	21117.62	24457.18	22759.38	28828.99	26309.01	22389.42	1892.758
2001	22471.65	26089.08	24170.48	31621	28251.48	24134.63	1729.454
2002	23714.15	27497.4	25520.28	33384.94	29688.06	25497	1493.917
2003	25138.15	29080.6	26889.68	34797.84	31155.76	26941.62	1566.971
2004	26573.15	30818.4	28517.58	36287.26	33316.61	28631.02	1806.728
2005	28052.78	32552.7	29922.98	38298.78	35229.79	29996.63	1683.275
2006	29460.75	34466.43	31791.98	40053.13	37365.54	31938.77	2005.489
2007	31171.45	36306.46	33270.68	41886.39	39136.94	33554.52	1758.306
2008	32869.75	38219.86	35128.78	44686.6	41006.64	35243.02	1921.369
2009	34058.65	39618.46	36583.38	45827.67	42814.34	36436.82	1530.778
2010	35453.45	41404.47	37979.86	47992.61	44962.14	38146.13	1799.889
2011	36614.45	42892.77	39579.06	49548.01	46975.85	39394.84	1644.388
2012	38020.16	44543.97	41219.46	52056.84	48578.52	41253.85	1944.636
2013	39448.16	46299.53	43140.24	54939.37	51038.88	43372.45	2027.64
2014	41397.96	48178.33	45148.44	56480.8	53704.26	44969.84	1956.833
2015	42678.56	49966.03	46879.44	58386.98	55153.78	46125.67	1601.804
2016	44111.2	51881.83	48474.94	60476.77	57495.85	47439.22	1781.559
2017	45885.3	53618.96	50378.14	62078.75	59397.48	49320.53	1966.559
2018	46976.1	55291.96	51856.24	64516.67	60852.47	50847.49	1610.296
2019	48079.62	56950.76	53406.64	65827	62801.76	52524.41	1708.21

Appendix Figure 1:Lulc predition cross–classification transition in five land use types.



Appendix Figure 2: 1987 LULC accuracy reference points.



Appendix Figure 3: 2002 LULC accuracy reference points.