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Effect of Land Use/Land Cover Changes on Soil Ero- Sion and Sediment Yield Using Invest Model In Gate- No Watershed, Tekeze Upper Basin, Ethiopia

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BAHIR DAR UNIVERSITY

COLLEGE OF AGRICULTURE AND ENVIRONMENTAL SCIENCE

GRADUATE PROGRAM

ENVIRONMENT AND CLIMATE CHANGE

EFFECT OF LAND USE/LAND COVER CHANGES ON SOIL EROSION AND SEDIMENT YIELD USING INVEST MODEL IN GATENO WATERSHED, TEKEZE UPPER BASIN, ETHIOPIA

M.SC. THESIS

BY

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MSC THESIS

BY

BIRTUKAN SHEGE

A Thesis Submitted To the Faculty of the Graduate School of

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In Partial Fulfillment of the Requirements for the Degree of Master of

Science (M.Sc.) in Environment and Climate Change

Major Advisor: Temesgen Gashaw (PhD.)

Co Advisor: Getachew Bayable (PhD.)

August, 2025

Bahir Dar, Ethiopia

DECLARATION

This is to certify that the thesis prepared by Birtukan Shege (ID No 1500032), entitled: ―Effect of land use/land cover changes on soil erosion and sediment yield using InVEST model in Gateno watershed, Amhara region, Ethiopia‖ submitted in partial fulfillment of the requirements for the award of the degree of Master of Science in Environment and Climate Change to the Graduate Program of College of Agriculture and Environmental Sciences, Bahir Dar University is a record of original work carried out by me and has never been submitted to this or any other institution to get any other degree or certificates. The assistance and help during the investigation have been received during this exploration have been duly acknowledged.

Birtukan Shege		9/12/2025
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DEPARTMENT OF NATURAL RESOURCE MANAGEMENT

M.Sc. IN ENVIRONMENT AND CLIMATE CHANGE

Approval of thesis for defense

I hereby certify that I have supervised, read, and evaluated this thesis ―Effect of land use/land cover changes on soil erosion and sediment yield using InVEST model in Gateno watershed, Amhara region, Ethiopia‖ by Birtukan Shege prepared under my guidance. I recommend the thesis to be submitted for oral defense.

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As member of the Board of Examiners of the Master of Sciences (M.Sc.) thesis open defense examination, we have read and evaluated this thesis prepared by Mr. Birtukan Shege entitled "Effect of land use/land cover changes on soil erosion and sediment yield using InVEST model in Gateno watershed, Amhara region, Ethiopia". We hereby certify that the thesis is accepted for fulfilling the requirements for the award of the degree of Master of Sciences (M.Sc.) in Environment and Climate Change.

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iv

DEDICATION

I dedicated this thesis work to Asefa Asirat.

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ABBREVIATIONS AND ACRONYMS

AOI	Area of Interest
C –FACTOR	Cover Management
CSV	Coma Separated Value
DEM	Digital Elevation Model
ERDAS	Earth Resources Data Analysis System
ETM+	Enhanced Thematic Map
GIS	Geographical Information System
GPS	Global Positioning System
Ha	Hectare
HRUs	Hydrologic Response Units
	Initial Coin Offering Max Maximum
IDW	Inverse Distance Weighted
InVEST	Integrated Valuation Of Ecosystem Services And Tradeoffs
Kb	Kilobyte
K-FACTOR	Soil Erodibility
	Land Use Land Cover
LULCC	Land Use Land Covers Change
NMA	National Metrological Agency
OLI-TIRS	Operational Land Image Thermal Infrared Sensor
P –FACTOR	Support Practice
R-FACTOR	Rainfall Erosivity
RS	Remote Sensing
RUSLE	Revised Universal Soil Loss Equation
SDR	Sediment Delivery Ratio
SW	Sub Watershed
SWAT	Soil and Water Assessment Tool
USGS	United States Geological Survey
USLE	Universal Soil Equation
UTM	Universal Transverse Mercator
WSG	World Geodetic System

TABLE OF CONTENTS

Contents Page №

List of table

LIST OF FIGURES

LIST OF APPENDIX

ABSTRACT

Land use and land cover (LULC) changes are becoming more common in developing countries, mainly due to growing populations and expanding development. These changes can lead to increased soil erosion and sedimentation, which negatively affect both farming productivity and water quality. Despite this, the relationship between LULC change and soil erosion and sediment yield is not well studied in many watersheds. This research focused on the Gateno watershed in northeastern Ethiopia, aiming to understand how LULC changes from 2000 to 2024 have influenced soil erosion and sediment yield Landsat 7 and Landsat 8 satellite images were used to map LULC changes, while remote sensing and GIS tools supported the analysis. To this study, rainfall data (1995–2024) from the national meteorological institute, *soil maps from the Amhara Water Works Design Office, an ASTER digital elevation model (DEM) and satellite images from USGS, and watershed shape files were used. All spatial data were processed in ArcGIS 10.8.The InVEST Sediment Delivery Ratio (SDR) model was applied to estimate soil loss and sedimentation, and to identify erosion-sensitive areas within the watershed.The results showed that areas used for farming and built-up areas have grown a lot, while areas with bare land and shrubs have decreased. Correspondingly, soil loss rose from 31.4 to 56.17 tons per hectare per year, and sedimentation increased from 6.08 to 10.11 tons per hectare per year between 2000 and 2024.These findings indicate* a *strong link between LULC change and soil sediment yield in the study area. Understanding these impacts is crucial for planning sustainable watershed management and helping policymakers and local communities make informed decisions.*

Keywords: *Gateno Watershed, InVEST, Land use Land cover, Sediment yield, Soil erosion*

CHAPTER ONE: INTRODUCTION

1.1. Background of the study

Land use land cover (LULC) changes analysis is one of the most useful methodologies to understand how the land was used in the past years, what types of detections are to be expected in the future (Motuma *et al.*, 2021; Regasa *et al.*, 2021). Land and water are the two most valuable and vital resources essentially required not only for sustenance of life but also for the economic and social progress of the country throughout the world and it is strongly affected by anthropogenic influences (Temesgen *et al.*, 2021).The LULC change studies provide useful information for a better understanding of previous practices, current LULC patterns, and future LULC trajectory (Hagos *et al.*, 2015). A change in LULC is one of the major causes of changes in Earth‘s system functioning (Abebe *et al.*, 2022).

Land usage and land cover changes have an impact on global ecological processes, resulting in major environmental resource challenges of global significance (Mathias *et al.*, 2022). According to many studies, LULCC is a widespread and accelerating process that is primarily driven by natural phenomena (such as earthquakes and volcano eruptions) and human-caused changes, which in turn drive changes that harm natural ecosystems (Andrew *et al.*, 2018). Land cover has changed over the last attributable to human actions, for three centuries in general and agriculture, in particular, modifying or changing land-use activities (Hurtt *et al.*, 2006). These developments cover the most pressing environmental issues facing people today, such as climate change and water contamination, soils, and air.

Land use change in Africa accounts for a conversion of 75 thousands of hectares of woodland to agriculture and pasture between the years 1990 and 2010 (Mayes *et al.*, 2015). More significantly, over the same 20-year period, approximately 13 million hectares of original East African forest were destroyed, and the remaining forest is fragmented and continues to be at risk (Liya *et al.*, 2011). In sub-Saharan African countries, LULC change, particularly the conversion of natural land cover into agricultural land, is a continuous phenomenon primarily driven by anthropogenic activities (Näschen *et al.*, 2019). Like other sub-Saharan African nations, Ethiopia faces significant challenges due to human-induced conversion of natural land cover into cultivated land, where agriculture serves as the backbone of the economy (Mulatu *et al.*, 2019). A LULC shift toward the growth of cultivated land at the expense of wooded regions is also the root cause of Ethiopia's primary environmental crisis (Moges *et al.*, 2019). Human activity and population growth, socioeconomic factors, urbanization, and agricultural activities all have a significant impact on these dynamics. Changes in land use and cover have a direct impact on the condition of water resources, primarily through forest interception, evapotranspiration, runoff, surface infiltration, soil moisture status, and so on, influencing the process of watershed cycles of hydrology and water resources (Hasan *et al.*, 2020).

Furthermore, with the aforementioned issues, modifications to land use, and cover may result in a decrease in the availability of different products and services for humans, livestock, agricultural production, and damage to the environment as well (Hasan *et al.,* 2020). Similar to this, soil erosion caused by water is one of the largest issues impeding Ethiopia's ability to sustain agricultural production. It has both on-site and off-site implications. According to (Tegegne & Biniam, 2017), farming methods are directly responsible for the loss of agricultural soil due to runoff. The yield of sediment is determined by gross soil loss in the watershed as well as the transport of eroded material out of the watershed. The sediment yield is the overall sum of sediment delivered to the watershed's outlet. It is caused by erosion and deposition within a watershed (Jain & Das, 2010).

Because of the shift in surface roughness, soil infiltration rate, and hydraulic connectedness within watersheds, this has had a considerable impact on soil erosion and sediment export to rivers (Zhou *et al.*, 2019). Due to this, the pace of LULCCs has increased, which has an impact on overall ecosystem health (Munsi *et al.*, 2010). Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) Sediment Delivery Ratio (SDR) models are now very helpful for the assessment and evaluation of anthropogenic and natural impacts, land transformation planning and management, future land use change patterns prediction, and assisting natural resource managers to achieve sustainable environments.

The InVEST SDR model addresses the limitations of conventional erosion models like RUSLE by evaluating hydrological connectivity within watersheds (Sharp et al., 2018). Unlike RUSLE, the InVEST model provides a comprehensive assessment of soil loss and sediment export at watershed outlets across different land use types over time. Empirical erosion models, including InVEST, are widely used in large-scale studies due to their reliance on readily available soil, topographic, and forest data (Sharp *et al.*, 2018). Watershed models are very important tools for the planning and management of watersheds or river basins. Watershed models can integrate information over a large scale and a long period to simulate various watershed processes such as runoff, soil erosion, and transport of nutrients and pesticides.

Understanding soil erosion dynamics is essential for designing effective soil and water conservation strategies. However, current land management practices in many regions, including the study area, often fail to account for variations in erosion rates, climate, topography, soil types, and LULC factors. The Gateno watershed faces significant pressure from agricultural expansion, soil erosion, and sedimentation. Thus, evaluating the impact of LULC changes on soil erosion and sediment yield is crucial for developing sustainable land management strategies. This study focused on assessing the impacts of changes in land use and cover on soil erosion and sediment yield of Gateno watershed by using InVEST model, and GIS techniques.

1.2. Statement of the problem

Dramatic land use land cover change (LULCC) caused by the rapid population growth and economic development has affected the amount of soil loss and sediment export dynamics in a basin (Zhou *et al.*, 2019). Although several studies have examined the general relationship between LULCC and soil erosion, the effects of LULCC on soil erosion and sediment yield in the Gateno Watershed are not well documented. There is a lack of localized, empirical, watershed-specific studies that quantify these impacts using spatially explicit models such as InVEST. Therefore, this study aims to fill this knowledge gap by the effects of LULCC on soil erosion and sediment yield in the watershed from 2000 to 2024. Major issues on the watershed include significantly increased soil erosion and very high sediment yield in wetter seasons as a result of significant expansion of intensive agricultural practice and overgrazing (Gebiaw *et al.,* 2017). As a result of excessive soil erosion in the mountainous Ethiopian highlands, soil fertility has decreased and sedimentation in lakes and water storage reservoirs has occurred. Because of the shift in surface roughness, soil infiltration rate, and hydraulic connectedness within watersheds, this had a considerable impact on soil erosion and sediment export in a watershed (Zhou *et al.*, 2019).Changes in land use and land cover and their effect on soil loss and sedimentations are one of the major threats. Even though there are no studies regarding Changes in land use and land cover issues in the study area coordinate with soil erosion and sediment yield by using InVEST model integrated with geospatial technologies.

In the Waghimra zone the main causes of land-use class change were the land-use policy/strategy of various governments, population growth, clearing of forests, agricultural expansion, rural settlement expansion, and infrastructure (Alemu *et al.*, 2024). However, no previous studies on consequences of LULC changes on soil erosion and sediment yield have been conducted in the study area. Although the watershed area surrounding studies have examined the general effects of LULC change on soil degradation, there is a lack of detailed, watershed specific no studies using spatially explicit models such as InVEST to quantify and map these effects. Without this localized information, land use planning and soil conservation efforts remain inefficient and poorly targeted. If the ongoing trends of LULC change and unmitigated soil erosion continue, the Gateno Watershed could experience further environmental degradation, reduced agricultural productivity, and increased risk of food insecurity.

Therefore, it is essential to assess the effect of LULC change on soil erosion and sediment yield using the InVEST model in the Gateno Watershed. Rapid population growths, expansion of agricultural land, deforestation, and overgrazing have significantly altered the land cover over recent decades. These changes have intensified soil erosion, and reduced land productivity, threatening both livelihoods and ecosystem stability in the watershed. As a result, this study focused on assessing the impact of land use and land cover change on soil erosion and sediment yield in Gateno watershed from 2000 to 2024 because this watershed has no settlement before 2000 and they begin to settle 2005 because the increasing population of the surrounding community and the land has been allocated to young people for farming more than three times, but due to LULC, it has been converted from Shrub land into settlement and agricultural land. As a result, this study's objective is to quantify the decadal LULC type before and after settlement which facilitated human activities like deforestation, over grazing, population pressure on land resources and the like which accelerate soil erosion and sedimentation. In general, this research was carried out to fill the impact of LULC changes on soil erosion and sediment yield in Gateno watershed, Ethiopia.

1.3. Objectives

1.3.1. General objective

The overall objective of this study is effect of LULC changes on soil erosion and sediment yield using the InVEST model in Gateno Watershed, Amhara Region, Ethiopia.

1.3.2. Specific objectives

The specific objectives of this study were;

- To analyze the patterns and rates of LULC changes between 2000 and 2024
- To estimate the effects of LULC changes on soil erosion between 2000 and 2024
- To evaluate the effects of LULC changes on sediment yield between 2000 and 2024

1.4. Research question

1. What are the patterns and rates of LULC changes in Gateno Watershed in 2000 and 2024?

2. How have LULC changes on soil erosion in the watershed in 2000 and 2024?

3. What are the effects of LULC changes on sediment yield in the watershed in 2000 and 2024?

1.5. Significance of the study

Understanding the impacts of land use and land cover (LULC) changes on soil erosion and sediment yield is crucial for sustainable land and watershed management. This study, covering the period from 2000 to 2024, provides a detailed assessment of LULC dynamics and their effects on soil erosion and sediment yield in the Gateno Watershed over the past two and a half decades. The findings are expected to benefit multiple stakeholders: policy makers and government agencies can use the results to develop informed land use policies, soil and water conservation strategies, and sustainable agricultural plans; natural resource and environmental managers will gain spatially explicit information on erosion-prone areas and sediment yield hotspots to guide targeted interventions and watershed management; local farmers and communities can better understand the effects of land use changes on soil fertility and agricultural productivity, supporting the adoption of improved land management practices; researchers and academicians can utilize the datasets and methodological insights for future studies on LULC change, watershed processes, and ecosystem services modeling; and development organizations and NGOs can apply the results to design and implement sustainable development and conservation initiatives. Overall, this study contributes to a better understanding of LULC trends and their consequences on soil erosion and sediment dynamics, providing critical information for evidence-based decision-making and sustainable management of land and water resources in the Gateno Watershed.

1.6. Scope of the study

The scope of this study was spatially limited only to the Gateno watershed, northern Ethiopia. The study was focused on effect of land use cover change on soil erosion and sediment yield from 2000-2024 using the InVEST model in the study area.

1.7. Limitation of the study

This study is based on an InVEST SDR max model. So, the relative limitations of the study could be expressed as below the InVEST model relies on the RUSLE equation that is widely used with limited scope and represents only the rill/inter-rill erosion process that occurred in the watershed. Different types of soil erosion which are the sources of sediment yield like gully erosion, stream bank erosion, and landslides have not been covered within the result of the model. In addition to this lack of accurate data, transportation problems, network problems, lack of peace to work from place to place and finance was the most serious limitation of this study.

CHAPTER TWO: REVIEW OF RELATED LITERATURE

2.1 . Concept of LULC Change

Studies of LULC change do not always employ similar definitions of the principal terms Usage of land and land use change. Definitions and descriptions of these terms vary with the purpose of the application and the context of their use. The term "land cover" describes the biophysical cover that can be seen on the surface of the earth, such as water bodies, plant, soil, and hard surfaces whereas, land use is referring to the functional dimension that corresponds to the description of areas in terms of their socio-economic purposes like residential, industrial, commercial, farming, forestry, recreation, conservation, and so on (Motuma *et al.*, 2021).

Land cover change is the complete replacement of one cover type by another, while land use changes also includes modification of land cover types for example intensification of agricultural use without changing over all classification (Comber, 2008). Globally general land at local scales; particularly LULC changes generate many environmental problems such as biodiversity loss and release of greenhouse gases and land use pattern changes of regions (Folega *et al.,* 2019). LULC change can be classified into LULC conversions, and modification. Therefore, both conversion and modifications of LULC have important environmental consequences through their impacts on soil and water, biodiversity, and microclimate, hence, contributing to watershed degradation and getting global attention (Mitiku *et al.*, 2020).

2.2. Drivers of Land use and Land Cover Change

A change in land use has been showing the past of man's activities and the future of humankind. Therefore, a significant change has been determined by a variety of factors related to population growth, development, technology, and environmental dynamics (Schilke, 2014). In the case of Ethiopia, most LULC changes are caused by human drivers mainly due to population growth (Mulatu *et al.*, 2019). For example, the increase in population in the highlands from the mid to the turn of the 20th century accelerated deforestation and intensified cultivation (Hans *et al.*, 2005).

Demand for cultivable land, which mainly emanated from population growth, was also the fundamental driver of forest cover loss in the Upper Gilgel Abbay catchment (Rientjes *et al.*, 2011). In addition to the increase in human population number, institutional and policy factors were found the drivers of the reduction of forest and grassland and the increase of cultivated land, bare land, and shrub land in Geleda catchment during the 1957-2014 periods (Esa & Assen, 2017). Therefore, the major drivers of LULC changes in Ethiopia emanated mainly from population growth, which is manifested mostly through the expansion of cultivated lands, even in areas where cultivation is almost impossible, and urban expansions.

2.3. Concept of Soil Erosion and Sedimentation Yield

Despite the indispensable importance of soil for the survival of life on earth, soil erosion is a serious environmental problem in most parts of the world (Pimentel, 2006). Soil erosion is one of the most important ecological processes (Hurni *et al.*, 2016). Globally, about 10 million hectares of cropland have lost their productivity annually because of erosion (Pimentel, 2006). Soil erosion has not only a significant impact on the productivity of cultivated land, but also adversely affects chemical, physical and biological functions of soil leading to eutrophication of environmental and water resources pollution (Guzman *et al.*, 2013).

Soil erosion is a serious challenge particularly in Africa, Asia, and Latin America, where the highest number of their populations rely on agriculture for livelihoods (Pimentel & Burgess, 2013). Soil erosion is causing extreme onsite (e.g., loss of fertile soil and crop productivity) and offsite (sedimentation of water infrastructures) negative externalities particularly in the highland regions of Ethiopia due to its rugged topography and intense rainfall (Temesgen *et al.*, 2021).

The severe soil erosion and its environmental and socioeconomic impacts warrant investigating different land and water management practices that may reduce soil erosion. Such practices include intensive cultivation, extensive cultivation, filter strip, tracing, stone or soil bund, agro-forestation and area enclosure (Betrie *et al.*, 2011). Soil erosion and sedimentation remains globally the major threats for sustainability of the food production (Nyssen *et al.*, 2009). The problem is particularly severe in Africa, Asia, and Latin America, with Africa being the most affected continent (Tully *et al.*, 2015). Soil erosion is the primary source of sediment production, and without soil erosion, there is no sediment yield to any point or stream channel (Dutta, 2016).

In the Ethiopian highlands, soil erosion, flooding and sedimentation have often been accelerated by improper agricultural practices, and particularly by the failure to implement appropriate soil and water conservation (SWC) strategies such as: agronomic conservation practices, mechanical conservation measures and runoff control structures (Nyssen *et al.*, 2009). Assefa *et al.* (2015) found that about 50 % of the highlands of Ethiopia were already significantly eroded. 4% was beyond reclamation, and soil erosion causes severe decline in agricultural land productivity at the rate of about 2.2%. Land degradation in Ethiopia accounts for 8% of the global total (Gizachew & Yihenew 2015).

In the Ethiopian highlands, approximately 1.5 billion tons of top soil have been lost annually through soil erosion which can add about 1.5 million tons of grain to the country‘s annual harvest (Tamene & Vlek, 2008). The accumulation of large volumes of sediment on water bodies can cause severe problems resulting in the loss of various functions in the hydraulic projects. Thus, it is very important to determine the rate of soil loss and sediment sources in watersheds, which can provide a good basis to facilitate soil erosion control and river basin management (Shimelis *et al.*, 2010).

Several studies have indicated that the soil erosion and sediment loss have been reduced significantly in the Ethiopian highlands by land use changes as well as the construction of reservoirs, flood-control structures, and water diversions (Nyssen *et al.*, 2009). Sedimentation is a process of depositing eroded particles of rock through transportation mainly by moving water relatively from higher elevation to lower elevation (Cook *et al.*, 2016)**.** The sediment rate in the reservoir shows how much erosion has taken place in a watershed upstream and the sediment trap is considered as the efficiency of the reservoir (Morgan, 2009). Sediment yield refers to a part of eroded material originating from either erosion or soil erosion processes, which is transported beyond a point of reference in the catchment (Catari, 2010). The sediment sources include upland inter rill erosion, gullies, stream banks, channels, construction sites and the relative magnitude of these potential sources depends on factors that include slope steepness and length, soil types, land use and rainfall characteristics (Catari, 2010). Sediment yield is the net results of soil erosion and sediment deposition processes (Nyssen *et al.*, 2009).

In Ethiopia, rates of soil erosion are alarmingly high and sedimentation in reservoirs, lakes and rivers is a serious problem (Haregeweyn *et al.*, 2006). Soil erosion causes not only on-site degradation of land resources but also off-site problems such as downstream sedimentation and deposition in fields, plains and water bodies (Zeleke & Hurni, 2001). Soil erosion and sedimentation can significantly reduce agricultural yields, which enhances the conversion of forest ecosystems to agricultural land (Bewket & Sterk, 2005).

2.4. Soil Erosion Rate

Soil erosion is a common phenomenon in the East African highlands, where it causes wide-spread soil degradation. Especially in East Africa, where Ethiopia shows the highest erosion rates (Lanckriet *et al*., 2014). The annual soil loss rate by water ranges from 16 to 300 t $ha^{-1}year^{-1}$ in Ethiopia, mainly depending on the degree of slope gradient, intensity, and type of land cover and nature of rainfall intensities (Tesfaye *et al*., 2014). Land degradation in Ethiopia is especially severe in the high lands where the annual soil loss from farmland is estimated to 100 to 300 t $ha^{-1}yr^{-1}$. It has been estimated that out of 60 million hectares of agriculturally productive land, about 27 million hectares are significantly eroded and 2 million hectares of land have already been irreversibly lost from productive uses. Loss of arable land due to soil erosion is a widespread phenomenon in the highlands which accounts for about 45% of Ethiopia‘s total land (Gizachew & Mersha, 2015). The soil loss rates were grouped in the following scales of priority: low (5-11 t $ha^{-1}yr^{-1}$), moderate (11-30 t $ha^{-1}yr^{-1}$), high (30-50 t $ha^{-1}yr^{-1}$) and very high (> 50 t ha t $ha^{-1}yr^{-1}$), which was adapted from (Tamene *et al.*, 2017) .For example, recent research showed that the mean annual soil erosion rate in a watershed that is located in the northwestern Ethiopian highlands is 55 t $ha^{-1}yr^{-1}$ (Gashaw *et al.*, 2019). Other studies in the Ethiopian highland showed a higher estimate. According to Arega *et al.* (2021) the mean annual erosion rate from Lake Hawassa was estimated to be 37 t $ha^{-1}yr^{-1}$. The estimated erosion rate was greater than the maximum tolerable erosion limit in Ethiopia (2-18 t $ha^{-1}yr^{-1}$).

2.5. Soil Erosion Model

Soil erosion models are mathematical tools that simulate erosion processes by relating key parameters such as terrain characteristics, soil properties, land use/land cover, and weather variables (Merritt *et al.*, 2003). Parameters involved include terrain characteristics, soil properties, land use/land cover, and weather variables (Jetten *et al.*, 2003). Soil erosion models describe detachment, transport, and deposition phases, which comprise the soil erosion process (Merritt *et al.*, 2003). Soil erosion models serve as important tools for planning because they enable the prediction of soil loss (Benavidez *et al.*, 2018). Above all, models create a clear understanding of the entire soil erosion phenomenon and the resulting impacts (Benavidez *et al.*, 2018). However, the choice of appropriate models for a particular soil erosion study is based on the objectives, catchment characteristics, and data availability on the model‘s efficiency (Keesstra *et al.*, 2014). Generally, soil erosion models have been categorized into three types based on the physical processes to be simulated, algorithms that describe such processes, and data dependence by the model (Sujatha & Sridhar, 2018).

2.5.1. Physically based models

Physically based models have wide applications in soil erosion modeling (Malleswara *et al.*, 2005). Physical models are known to describe a catchment‘s soil erosion process by providing solutions to fundamental physics equations (Roshani *et al.*, 2013). Physical models have been widely applied by different researchers to study water quality problems and erosion processes (Benavidez *et al.*, 2018). the following physical models have been developed and applied in different parts of the world: European Soil Erosion Model (EUROSEM) , Areal Nonpoint Source Watershed Environment Response Simulation model (ANSWERS) (Beasley *et al.*, 1980), Water Erosion Prediction Project model (WEPP) (Laflen *et al.*, 1991), Griffith University Erosion System Template model (GUEST) (Misra & Rose, 1996), and Productivity, Erosion and Runoff, Functions to Evaluate Conservation Techniques model (PERFECT) (Littleboy *et al.*, 1992).

2.5.2. Conceptual models

Conceptual models typically represent a catchment like a string of internal storage (Merritt *et al.*, 2003). Such models define the broad mechanisms behind the interchange of water and sediment between these storages (Merritt *et al.*, 2003). Sediment-producing parameters, notably rainfall and runoff, serve as the system‘s input and sediment yield as the output (Chandramohan *et al.*, 2015). Here, underlying transfer mechanisms that involve generation of sediment and runoff are incorporated in the model where f low paths within the catchment are represented as storages in a series form where the dynamic behavior of each requires some characterization (Merritt *et al.*, 2003). Some good examples of conceptual models include Chemical Runoff and Erosion from the Agricultural Management Systems (CREAMS) model (Knisel, 1980) and Large-Scale Catchment Model(LASCAM) (Fistikoglu & Harmancioglu, 2002).

2.5.3. Empirical models

Empirical Models are category of soil erosion models that utilize inductive logic, some experiences, and results from an experiment and have the advantage that they are quite simple in their use (Ayinla & Jona, 2018). Empirical models have wide application because of the fewer computations involved and the fewer amount of data required (Asadi *et al.*, 2017). However, empirical models are quite expensive in addition to being involved especially during calibration exercises where much time is required to obtain the much-needed data. Moreover, detailed experiments are necessary so as to collect important data to facilitate calibration. Some common examples include Universal Soil Loss Equation (USLE) (Wischmeier, 1978), Modified Universal Soil Loss Equation (MUSLE) (Williams & Berndt, 1977), sediment delivery ratio (SDR) **(**Young *et al.*, 1989**)**, Agricultural Nonpoint Pollution Source (AGNPS) (Young *et al.*, 1989), Sediment Delivery Distributed (SEDD) (Ferro & Porto, 2000), and Revised Universal Soil Loss Equation (RUSLE) (Renard, 1997).

2.5.4. InVEST model

InVEST is a set of Geographic Information Systems models that predict the provision and value of ecosystem services and habitat provision given land use / land cover maps and related biophysical, economic, and institutional data for the study region. It is a model used for analysis of carbon storage, soil erosion regulation (sediment retention), water quality, habitat provision, and agricultural production. It also describes the data used to estimate the value of timber production and urban development (Redhead *et al.*, 2016). It used to assess the impacts of changes in different ecosystem services due to LULC changes for calculating results annually based on LULC information. It needs the input data in the form of a raster or vector shape file and a biophysical table containing coefficients for each LULC type for providing the results at a local, regional or global scale (Lüke & Hack, 2017). According to Delelegne *et al.* (2017), the soil loss algorithm is used by InVEST SDR to first calculate annual soil loss, and then the SDR is calculated as a function of the catchment's hydrologic connectivity (Lestrelin *et al.*, 2012). The SDR values represent the percentage of soil loss from each pixel that reaches the stream (Marques *et al.*, 2021).The InVEST SDR model was applied in many areas of the world and provides reasonable estimates (Lestrelin *et al.*, 2012). Therefore, this study has used the InVEST SDR model to provide reasonable sediment rate estimation. The input data required to run the model are DEM, rainfall erosivity (R), soil erodibility (K) factor, LULC, watershed boundary map, biophysical table, threshold flow accumulation, drainage raster (optional), barselli kb parameter, barselli Ico parameter and SDR max value.

2.6. Effect of land use land cover change on soil erosion

Land use is one of the vital factors in estimating soil erosion over an area. Significant changes in spatiotemporal land use distribution might lead to water runoff which causes soil erosion events (Samsudin *et al.*, 2020). Land use land cover change has resulted in severe land degradation in the form of soil erosion, loss of biodiversity and soil fertility depletion, which in turn impeded agricultural and ecological sustainability (Moges *et al.*, 2018). Besides, due to natural phenomena and various anthropogenic activities, rapid land use/land cover is happening in the earth (Thomas *et al.*, 2019). This land use and land cover change is a major cause of soil loss at watershed, regional and global scales (Moges *et al.*, 2018). Among all LULC, cultivated land is experiencing an increasing trend in soil loss, i.e., the soil loss is increased from 74.3 ton/ha/year in the year 1986 to 83.7 ton/ha/year and 87.6 ton/ha/year, 2003 and 2020, respectively (Teshome *et al.*, 2022). Substantial studies have been reported that LULC change and type significantly influence soil erosion (Borrelli *et al.*, 2017). After cultivated land, Shrubs land experienced the highest soil loss.

2.7. Effect of land use land cover on sediment yield

Sediment yield is the end product of erosion or wearing away of the land surface by the action of water, wind, ice and gravity. The total amount of onsite sheet, rill, and gully erosion in a watershed is known as the gross erosion. Sediment yield refers to the amount of sediment exported by a basin over a period of time, which is also the amount that will enter into a reservoir (Dereje *et al.*, 2015). The sediment sources include upland inter rill erosion, gullies, stream banks, channels, construction sites and the relative magnitude of these potential sources depends on factors that include slope steepness and length, soil types, land use and rainfall characteristics (Gusman, 2014). Sediment yield is the net results of soil erosion and sediment deposition processes (Sewnet, 2015).

The continuous increase of the mean SDR in the study area is generally due to the expansion of non vegetated LULC types and the dwindling of the vegetated class. On the other hand, the higer SDR obtained in cultivated compared with vegetated LULC coversin the watershed stud y is reasonable because the probability of eroded materials reaching the nearest stream channe l from the nonvegetated covers is higher than that from the vegetated LULC (Tesfayeetal.201 4). Studies in the upper Blue Nile basin, such as those in the Andassa watershed (Gashaw *et al.*, 2021), have consistently shown cultivated land to be the primary contributor to maximum sediment yield.

2.8. Sensitivity Analysis

Sensitivity analysis determines the sensitivity of the input parameters by comparing the output variance due to the input variability This is useful not only for model development but also for model validation and reduction of uncertainty (Lüke & Hack, 2017). Sensitivity analysis has been used in this study to pinpoint the InVEST model's sensitive parameters. By changing parameter values and observing how the model responds, the sensitivity analysis is carried out If a small change in a given parameter value results in a remarkable change in the model output, the parameter is said to be sensitive to the model.

2.9. Satellite Image

Satellite imagery is the most popular tool in the modern world to assess and analyze a large piece of earth‘s surface. Satellite imagery has emerged as a pivotal resource in understanding and analyzing Earth's surface, offering a wealth of information for various applications, including environmental monitoring, urban planning, disaster management, and resource allocation. By providing a bird‘s-eye view of extensive geographical regions, satellite imagery enables researchers and policymakers to observe, analyze, and classify land use and land cover (LULC) changes with precision. These classifications are critical for identifying environmental changes, monitoring urban growth, conserving natural habitats, and addressing climate-related challenges (Gudmann *et al.*, 2020). There are two primary methods to detect land cover. The first approach is to detect land cover using Global Positioning System (GPS) and the second approach is to extract land cover information from the satellite images using image processing techniques. For the reason that detection of land cover using GPS is time-consuming and costly depending on the area of the survey region, most of the studies are examined on satellite image processing (Thwal *et al.*, 2019).

Land Use and Land Cover (LULC) classification involves categorizing the Earth‘s surface into distinct types, such as forests, agricultural lands, urban areas, and water bodies. Manual classification of such data, while accurate, is time-consuming and impractical when working with large-scale images. The advent of machine learning, especially deep learning, has revolutionized this field by automating the process, reducing time, and enhancing accuracy (Helber *et al.*, 2019). Land use and land cover (LULC) is a crucial spatial data because it is an essential input for most analysis and prediction tasks. Presently, LULC is obtained more easily and more quickly than was in the past due to the rapid progress in remote sensing, geographic information systems, and machine learning technologies. For this reason, the satellite images data are processed to classify land use.

This method has advantages over conventional field surveys at the actual area in various aspects, such as time and cost-saving. However, processing of LULC data from the low-resolution satellite images has some limitations; its results are of lower accuracy than when doing it from high-resolution satellite images (Puttinaovarat *et al.*, 2025). The most researches for land resource management are focused on satellite image processing. Most changes are caused by artificial processes and some changes are caused by natural disasters. The land cover change, also called land change, is a generic term for the human modification of the earth‘s surface (Ellis & Pontius, 2007). There are commonly two main categories in land cover change namely conversion (a change of land cover class to another e.g. from forest to shrub land) and modification (a change within one land cover category e.g. from rain fed cultivated area to irrigated cultivated area) (EUROST, 2001).

CHAPTER THREE: MATERIALS AND METHODS

3.1. Descriptions of the study watershed

3.1.1. Location

Gateno watershed located in Sekota Woreda within the Tekeze River Basin Ethiopia experiences a semi-arid climate. It is situated 720 km north of Addis Ababa and is approximately 15 km southeast of Sekota town adjacent to the Sekota-Lalibela highway. The study was conducted in Woleh Keble of Sekota district Wag-Himra administration zone in Ethiopia. It lies approximately 720 km north of Addis Ababa and about 15 km southeast of Sekota town, adjacent to the Sekota Lalibela highway. Geographically, the watershed extends from 12°30′30″ to 12°31′00″ N and 39°00′30″ to 39°01′00″ E (Figure 3.1). The watershed covers about 5234.9 ha of land from Tekeze River Basin.

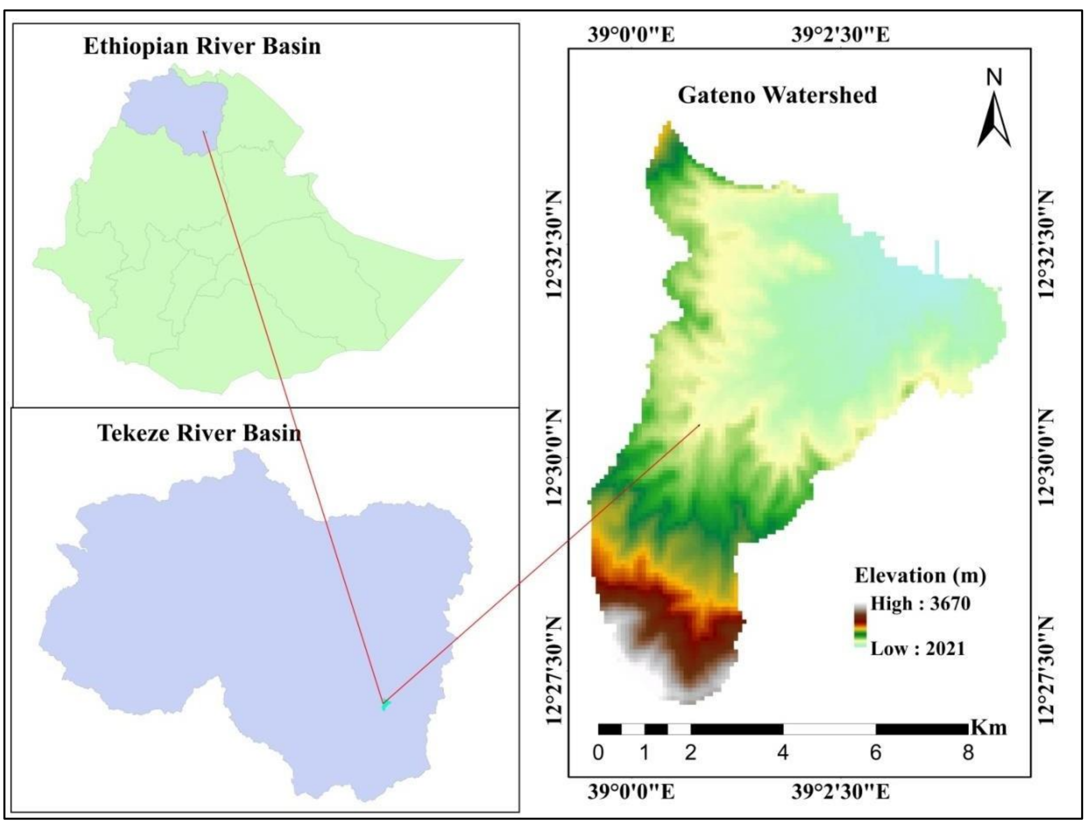

Figure 3.1: Map of the study area

3.1.2. Climate

The study area was characterized by a unimodal rainfall pattern, which extends from late June to late August or early September, where crops are cultivated in the summer season. As shown in climate data obtained from the National Meteorology Agency, indicate that the study area has a mean annual rainfall of 632 mm and the mean minimum and maximum annual temperatures are 10°C and 22°C, respectively. Rainfall patterns are highly variable, leading to frequent droughts or short, intense rain events that can cause soil erosion. The altitude of this study area ranges from 2021 to 3670 m.a.s.l. According to Dejene (2003) the climatic zone classifications in Ethiopia are based on the altitude, rainfall, average annual temperature, and length of growing season; the study area belongs to dry semi-arid lowland.

3.1.3. Land use Land cover Classes and Human Practices in Study Area

The study area is characterized by diverse (LULC) patterns shaped by both natural and human activities. The major LULC classes include cultivated land, forest land, shrub land, bare land, and settlements. Cultivated land is primarily used for rain fed subsistence agriculture, with productivity highly dependent on seasonal rainfall. Due to limited irrigation and farming on steep slopes without soil conservation, the area experiences significant soil erosion. Forest land is scarce and found mainly on steep slopes, threatened by fuel wood collection, charcoal production, and agricultural expansion. Shrub lands, dominated by drought-resistant species, are located in degraded zones and heavily exploited for firewood and fodder. Bare lands result from prolonged cultivation, erosion, and deforestation, leaving little forest and degraded soils. Human-induced drivers such as agricultural expansion, deforestation, traditional farming, and overgrazing are the main contributors to these LULC changes. These LULC changes are largely driven by human practices such as agricultural expansion to meet food demands, deforestation for energy and construction needs, unsustainable traditional farming methods, overgrazing due to unmanaged communal grazing systems. The cumulative effect of these practices has accelerated land degradation, soil erosion, and ecological imbalance in the region.

3.2. Research Design

To assess the effect of LULC change on soil erosion and sediment yield, this study has used both quantitative and qualitative research approaches or mixed approaches. Because, the study used a quantitative approach for estimating soil loss and sediment yield class area in hectare and in percent and the sensitivity of each sub-watershed with LULC types of the study area. The qualitative research approach is used to answer questions related to LULC types and level of soil loss and sediment yield class like very severe, severe, moderate, slight and very slight.

3.2.1. Data sources

This study used both primary and secondary data sources.

3.2.1.1. Primary data sources

The primary data sources have been collected during the field survey or observation. The primary data were collected from the field using GPS point and Google earth engine for image classification validation.

3.2.1.2. Secondary data sources

The secondary data sources were obtained from different data sources. Such as satellite images of Landsat-7 (2000) and Landsat-8 (2024) for path 169 and row 051 from the website of the United States Geological Survey (USGS) http://www.earthexplorer.usgs.gov.downloaded. Rainfall data (1995-2024) were collected from the National Meteorological Service Agency. A soil-type map with a 1:20,000 scale was obtained from the Amhara Water Works Design and Supervision Enterprise. Published journals, articles, and related works of literature have been used for this study.

Table 3.1: Satellite data types and their characteristics

No	Satellite Data	Source	Sensor	Path/Row	Date of Acquisition	Resolution	Cloud Cover
1	Landsat 7	USGS	ETM+	169/051	1/3/2000	30m	0
2	Landsat 8	USGS	OLI_TIRS	169/051	1/21/2024	30m	0
3	DEM	USGS	ASTER	N11E37	2/23/2024	30m	0
4	Rainfall data	EMI	-	-	1/15/2025	-	-
5	Soil Data	ARADSA	-	-	-	1:20,000	-

Table 3.2: Types, models, and purposes of software‘s

Types of Software	Models /Versions	Purposes
Arc GIS	10.8	Analyze data, Mapping, and Display Results
ERDAS Imagine	2015	Preprocessing, classification of Images, and scan line correction
Arc SWAT	_	Delineating sub watersheds
InVEST	3.10	Estimate soil erosion and sediment yield
Endnote	21	Citing references
Hand Held GPS	Garmin	Collecting field data

3.2. Methodology

3.2.1. Satellite image

Satellite image classification is a strong method to extract information from a large number of satellite images. Therefore, for this study, Landsat images of Landsat 7 (ETM+) and Landsat 8 (OLI-TIRS) were used. The making of LULC maps of the study area in periods 2000 and 2024 was based on supervised image classification techniques.

3.2.1.1. Image pre-processing

Pre-processing satellite images is a crucial step before change detection and has the distinct goal of establishing a closer connection between the observed biophysical phenomena and the data collected. The data has been pre-processed in ERDAS imagine 15 for geo-referencing, layer stacking, and sub-setting of images based on area interest. Landsat satellite imagery data received from satellites need to be corrected before being used. Landsat images of (Landsat 7 ETM+, 2000, and Landsat 8 OLI-TIRS 2024) were used and the satellite images of each band in each year (2000 and 2024) would be a pixel in ERDAS 15 within the interpreter main icon utilities with layer stacked function. Then, from the stacked satellite image of the study area, images have been extracted by clipping the Area of Interest (AOI) layer of the study area shape file by Geographic Information System in Arc-GIS 10.8 software.

3.2.1.2. LULC classification

There are numerous classification systems for LULC. However; they have not been internationally recognized and designated as a standard because they have lacked in fulfilling those requirements and different perspectives in the classification processes. Hence, LULC classifications are based on the available satellite images of the study area. The classification of satellite images is to categorize pixels on an image into LULC categories. The Landsat 7 ETM+ and Landsat 8 OLI-TIRS images have undergone pre-processing, and post-processing stages to ultimately get the LULC maps of the study area for the two time periods of 2000 and 2024 respectively. Generally, the most significant procedures that were used in this study are showing the following.

3.2.1.3. Image restoration

Before the use and classification of any image data received from satellites, radiometric and scan line corrections have been corrected. Furthermore, to be able to work in a GIS environment similar to overlaying maps, the images must be linked to coordinate systems and a projection of the globe. In this study, the images for the years of (Landsat 7 ETM+, 2000, and Landsat 8 OLI-TIRS 2024) were projected using the UTM projection type WGS1984 spheroid and in the northern hemisphere direction 37 zones.

3.2.1.4. False color composite (FCC) image preparation

Different color composite images have been prepared, to select the best band combination, which enhances the raw satellite images for the identification of the different land cover classes in the study area. In this study, the false-color composite image made using Land sat 8 bands 5-4-3(R-G-B) OLI/TIR sensors launch on January 21,2024, and Land-sat 7 ETM+ bands 4-3-2 (R G-B) launch on January 3, 2000, has been founded to be best for the identification of main land cover classes in the study area.

3.2.1.5. Supervised classification

In supervised classification; training areas were manually digitized for each class. Based on prior knowledge of the study area and the use of Google Earth, Google maps, and topographic maps as references, four and five LULC classes were classified in the study area for the two satellite images of 2000 and 2024 respectively. The LULC classes such as forest, shrub land, bare land, and cultivated land in 2000 and forest, shrub land, bare land, built up and cultivated land in 2024.

According to Chan *et al.* (2015), there are three basic steps in supervised classification namely; the training stage, the classification stage, and the output stage. Therefore, this study used training areas with the use of polygon creation and region-growing tools in the Area of Interest (AOI). Then this classification has been used to define the original pixels that contain similar spectral classes representing certain land cover classes. The Visual interpretation and the guidance of Google earth were used to classify the images for the years of 2000 and 2024 classes.

Lastly, five land-use/land-cover (LULC) classes: cultivated land, forest land, shrub land, bare land, and built-up areas were represented by representative ground control points (GCPs) used in this study. A total of 320 GCPs were used: 180 in 2024 and 140 in 2000. Because of the increased geographical heterogeneity and growth of farmed and built-up regions in 2024, more samples were needed to maintain classification accuracy, which accounts for the change in the number of GCPs between the two years. For the 2000 image, GCPs were indirectly generated from historical reference sources, such as topographic maps, high-resolution Google Earth images, and local expert knowledge; for the 2024 image, all GCPs were gathered during fieldwork using a handheld GPS and digital camera.

3.2.1.6. Maximum likelihood classification algorithms

This classification determines the likelihood that a given pixel belongs to each class by assuming that the data from each class in each band are normally distributed. Maximum likelihood classification determines the likelihood that a given pixel belongs to a certain class by assuming that the statistics for each class in each band are normally distributed. All pixels are categorized unless a probability threshold is chosen. Each pixel is categorized into the class with the highest likelihood (that is, the maximum likelihood). The pixel stays unclassified if the highest likelihood is less than the threshold you select (Anderson *et al.*, 2011).

3.2.1.7. Accuracy assessment

In order to understand and quantify the changes accurately, accuracy assessment is a significant and essential component of studying image classification and, consequently, LULCC detection (Cheruto *et al.*, 2016a). It demonstrates the degree of agreement between actual conditions and classification outcomes. According to Cheruto *et al.* (2016a), if the generated data are to be relevant in change detection analysis, it is crucial to be able to determine accuracy for individual categorization. According to Weng and Qihao (2007), the most common accuracy assessment elements include overall accuracy, producers, users, and kappa coefficient. Accuracy assessment is important to derive accuracy for individual classification if the resulting data are to be useful in change detection analysis. In this study, accuracy assessments would be done on classified Landsat-7 for ETM+ and Landsat-8 for OLI-TIRS satellite images which the ground truth data likely equates. The overall accuracy assessments were calculated by dividing the sum of the correctly classified sample units by the total number of sample units.

3.2.1.8. Kappa coefficient and overall accuracy

The agreement or accuracy between the classification map obtained from remote sensing and the reference data, as indicated by the major diagonals, and the chance agreement, as indicated by the row and column totals, is measured using the kappa statistic (Rwanga & Ndambuki, 2017). The percentage of agreement left over after subtracting the percentage of agreement that could be expected to happen by chance is known as the Kappa coefficient (Li *et al.*, 2020). A value >0.80 (80%) strong agreement, a value between 0.40 and 0.80 (40 to 80%) represents moderate agreement, and a value < 0.40 (40%) represents poor agreement

(Yetnayet *et al.*, 2017). Therefore, the image classification accuracy of the study area was encountered/meets these requirements are strong agreement. The Kappa factor is given by the formula (Rwanga & Ndambuki, 2017).

$$\text{Overall Accuracy} = \frac{\text{Number of correctly classified samples}}{\text{Total number of samples}} * 100$$

OA = (Σ Xii) / N × 100

Xii = the observation along the diagonals

N = Total number of samples

$$\text{Producer Accuracy} = \frac{Number\ of\ correctly\ classified\ pixels\ in\ a\ class}{Total\ number\ of\ pixels\ classified\ in\ that\ class} * 100$$

PA = Xii / (Σ Xref) × 100

Xii = the observation along the diagonal

Xref = are the observations for reference data

$$\text{User Accuracy} = \frac{Number\ of\ correctly\ classified\ pixels\ in\ a\ class}{Total\ number\ of\ pixels\ classified\ in\ that\ class} * 100$$

UA = Xii / (Σ Xref) × 100

Xii = the observation along the diagonals

Xref = are the observations for reference data

$$\text{k} = \frac{N\ Xii -}{N2 -}\frac{\text{Xclass} * \text{Xref}}{\text{Xclass} * \text{Xref}}$$

Where, N=is the total number of observations

X Class = are the observations for classified data

X ref = are the observations for reference data

Xii = the observation along the diagonals

3.2.2. Land use and land cover rate of change

It is useful in various applications related to LULC changes in watershed areas. The study area has been defined to have five LULC categories based on the supplemented field observations and the land use/land cover dynamics in the sub-watershed were classified into various LULC classes. The LULC rate of change needs prior classification of an image using a maximum likelihood classifier and the accuracy assessment of the classification ought to be good enough to meet this requirement (Manandhar *et al.*, 2009). The change detection was performed on the post-classification of the images for 2000 and 2024 in the study area. The percentages of LULCCs are calculated using the following formula (Moonrut *et al.*, 2021).

$$\%\text{ of LULCC} = \frac{Area\ of\ Final\ Year - Area\ of\ Initial\ Year}{Area\ of\ Initial\ Year} * 100$$

Positive values indicate an increase whereas negative values show a decrease in the extent of LULC.

3.2.3. Soil erosion and sediment rate of change

The rate change of both soil erosion and sediment rate has been calculated based on the following formula:

$$\%\text{ of Soil loss} = \frac{Area\ of\ Final\ Year - Area\ of\ Initial\ Year}{Area\ of\ Initial\ Year} * 100$$

$$\%\text{ of Sediment rate} = \frac{Area\ of\ Final\ Year - Area\ of\ Initial\ Year}{Area\ of\ Initial\ Year} * 100$$

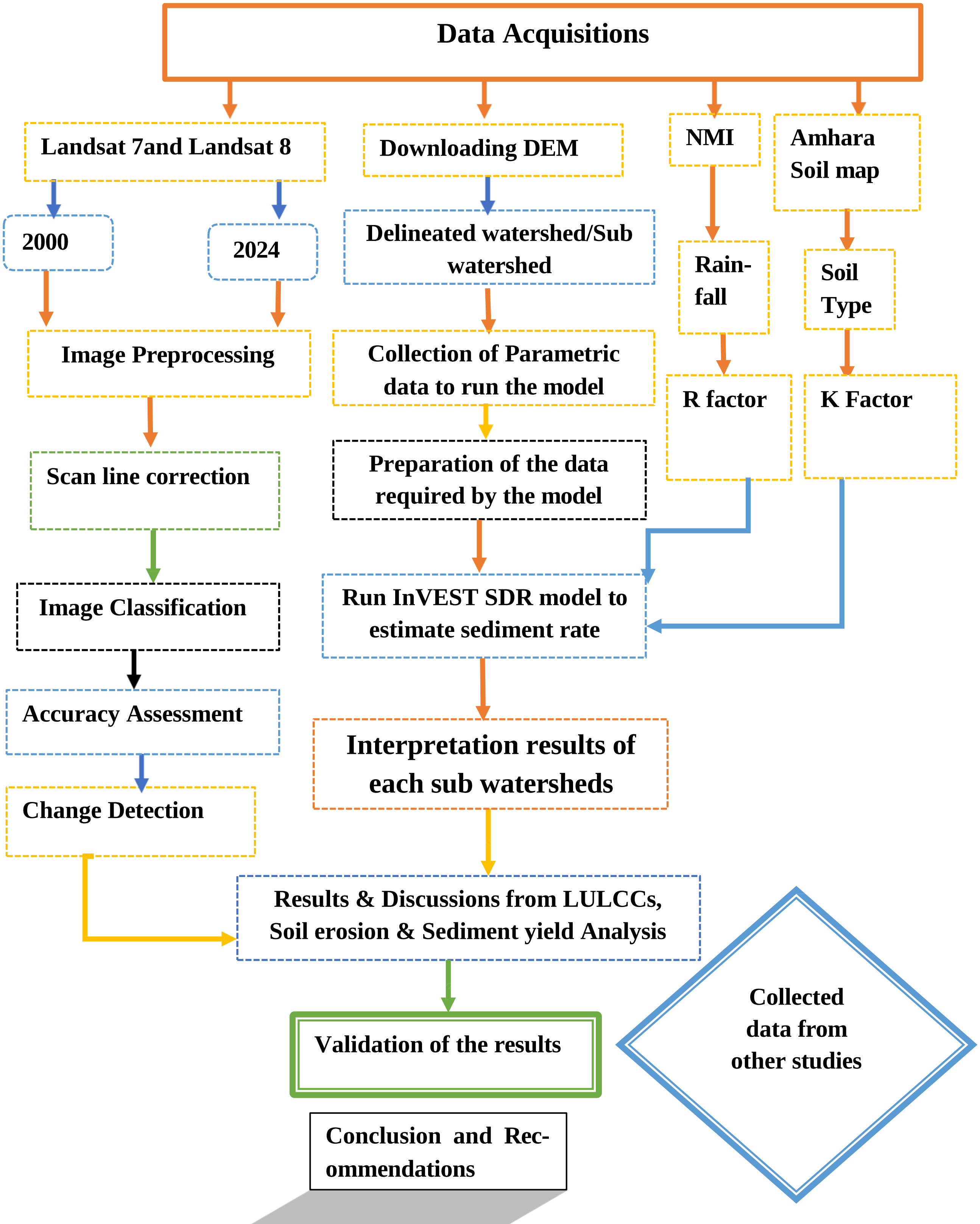

Figure 3.2: Methodological flow chart of the stud

3.2.4. Watershed delineation

The study watershed boundary was divided into 13 sub-watersheds and each sub-watershed was into Hydrologic Response Units (HRUs), which are the unique combinations of land use and soil type within each sub-basin. Five sections make up Arc SWAT's watershed delineation interface: DEM set up, stream definition, outlet, and inlet, definition, watershed outlet(s) selection and definition, and calculation of sub-basin parameters. To delineate the network's sub-basins, the minimal drainage area needed to create a stream's origin has to meet a key threshold value. The whole watershed was divided into 13 sub-watersheds after the initial sub-watershed delineation; the generated stream network can be edited and refined by the inclusion of sub-watershed outlets.

3.3. Parameterization of InVEST model inputs

InVEST is used to quantify and map ecosystem services having a set of different models within it. It is an open-source, stand-alone software developed by the natural capital project and aims at the assessment of LULC changes in large watersheds to point out their influence on ecosystem service. These functions are considered the simplifications derived from a common hydrological relationship (Meraj *et al.*, 2022). Out of the total model functions of the InVEST, the SDR model is used for estimating the sediment rate and its delivery to the stream overland surface (Ougougdal *et al.*, 2020). Therefore, it was selected to meet the purpose of this study.

To run the model the nine types of data are compulsory to be prepared locally to obtain reliable output as far as practicable. The required input data are as follows:

3.3.1. Digital elevation model

An ASTER Digital Elevation Model (DEM) for the study area, with a resolution of 30 m by 30 m, was downloaded from the United States Geological Survey (USGS) website (http://www.earthexplorer.usgs.gov. It needs the DEM to be filled to remove the sink to obtain good results that were performed by using ArcGIS10.8 fill tool. The size of the DEM was made enough to be a bit larger than that of the watershed boundary for appropriate function having units in meters. Finally, the DEM was extracted by mass by the extent of the study area shape file.

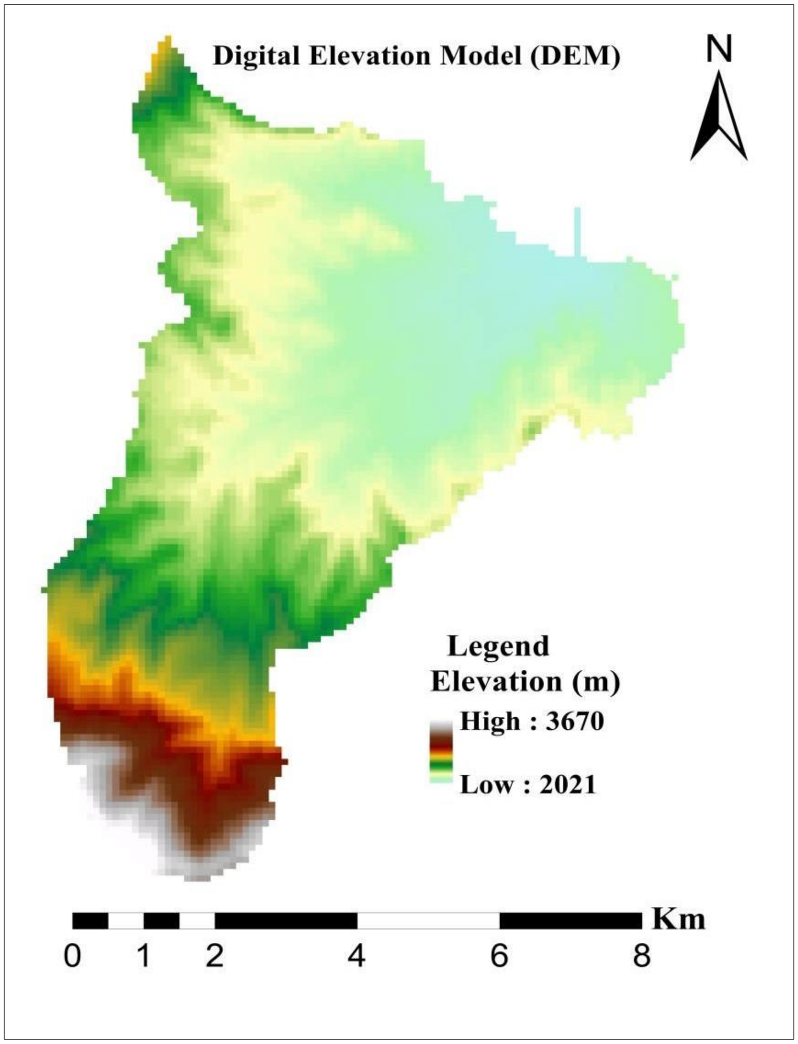

Figure 3.3: DEM of the study area

3.3.2. Rainfall erosivity factor (R)

The model needs the rainfall erosivity index (R factor) in the raster format of the study area. It is the factor of rainfall and runoff with a geographic location to show erosion potential (Parveen & Kumar, 2012). The R factor acts as the force for sheet and rill erosion without protection (Biswas & Pani, 2015). It works based on the rainfall amount and intensity of a particular location (Koirala *et al.*, 2019). However, the values of the R-factor for this study were estimated according to the equation adopted by (Gizachew & Yihenew 2015) for Ethiopian conditions.

R= -8.12+ (0.562xP)...(1)

Where; R is the Rainfall Erosivity factor, and P is the Mean Annual Rainfall in Millimeters per Year (mm/yr).

To compute the R-factor, the mean annual rainfalls of over 30 years were used from five stations such as: Sekota, Lalibela, Tsitsika, and Maychew. Rainfall data (1995-2024) were collected from Ethiopia Meteorological Institute, and these data were interpolated from a given station using IDW (Inverse Distance Weighted) methods in Arc-GIS 10.8 software because IDW method of interpolation was used for data shortage or scarce area and use the shortest distance of the station. It is relatively worthy to recognize the annual rainfall distribution over the area.

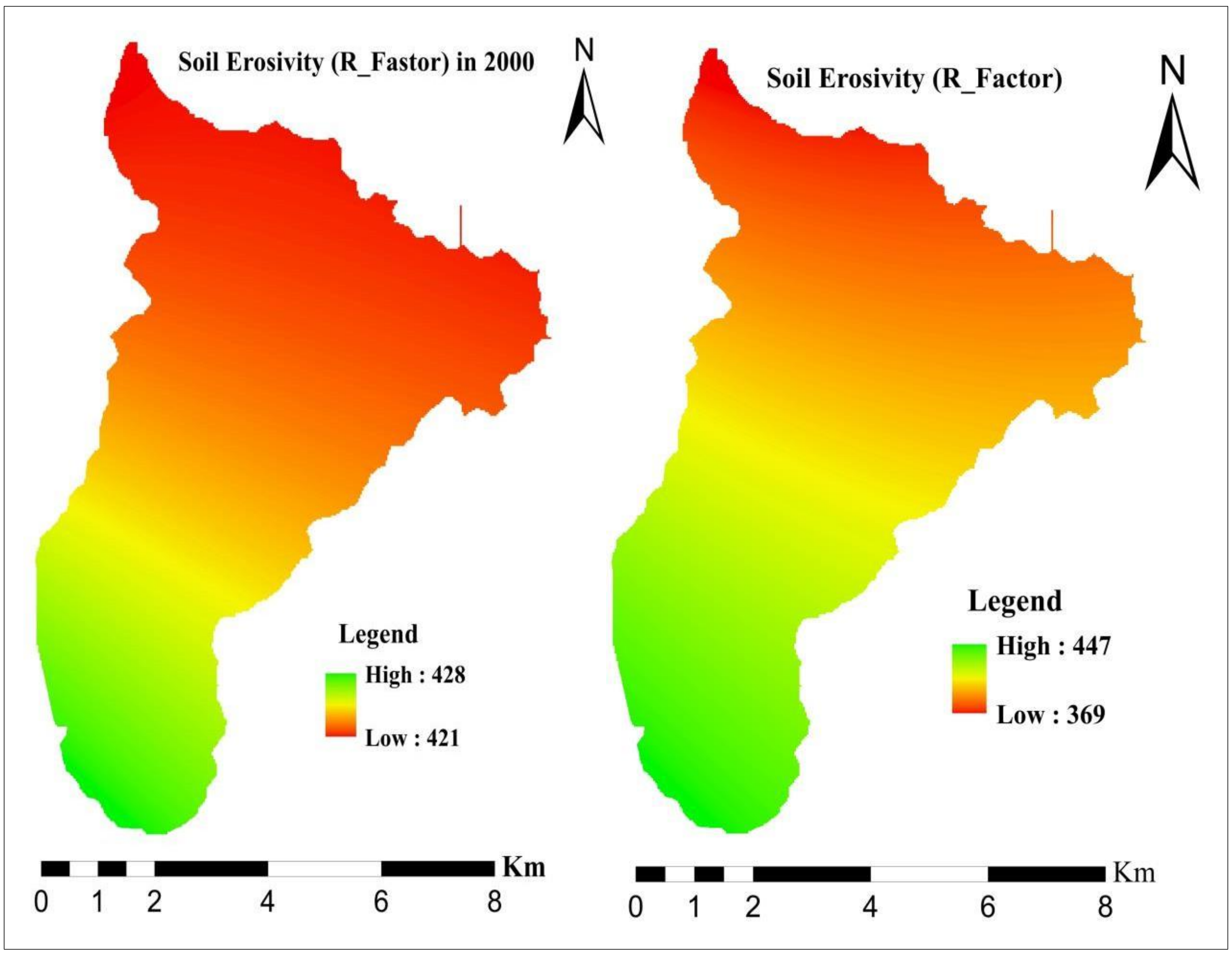

Figure 3.4: Rainfall erosivity (R) factor of the study area

3.3.3. LULC

Land use is one of the most critical factors influencing runoff, evapotranspiration, and soil erosion in a watershed. Accurate LULC data are essential inputs for the InVEST SDR model, as they help determine watershed characteristics and allow for assessing the impact of land use changes on stream flow and sediment yield. For this study, LULC maps and associated datasets for the years 2000 and 2024 were obtained from USGS Earth Explorer. The original spatial resolution of the Landsat images was 30 m for the multispectral bands of both Landsat 7 ETM+ (2000) and Landsat 8 OLI/TIRS (2024). All classified LULC maps were resampled to a uniform 30 m resolution in raster format to ensure compatibility with other input datasets of the InVEST model. Resampling to a consistent grid size is necessary for accurate pixel-level calculations of runoff and sediment yield. Each land cover type was assigned a unique integer code, as illustrated in Figure 4.1.

3.3.4. Soil erodibility factor (K)

Soil erodibility factor (K) expresses the soil susceptibility to detachment and move soil fragments (grains or crumbs), under an amount and rate of runoff for a specific rainfall, measured under a standard plot (Aksu *et al.,* 2022). The resistance of soil to detachment and transport by rainfall and discharge by water erosion is referred to as erodibility.

It depends mainly on the texture of the soil and the erodibility varies with soil, a property which involves texture, aggregate, stability, shear strength, infiltration capacity, organic matter and chemical contents of the soil is also a contributor of factors. Because soil colors have long been the best-known characteristics and easily identifiable part of the soil properties since they show mainly the kind, amount, and distribution of organic matter and mineral substances of the soil (Cattle *et al.*, 2020). Furthermore, for this study, the erodibility of soils has been used by (Gizachew & Yihenew 2015) in adaption to Ethiopian conditions deliberates that soil color has a relation with erodibility even though others consider soil texture and structure to determine the value of soil erodibility factors.

The K factor values were added in the attribute field of the corresponding soil types of the soil map. As the model needs the K-factor in raster format, the soil map (vector file) was converted into a raster image assigning those K values by using the 'polygon to raster' tool (available in Arc GIS 10.8) for the site with 30m resolution to be suited for the model.

Table 3.3: Major soil types of the study area

Major soil types	K_Factor	Area in ha	Area in %	Sources
Alisols	0.25	600.8	11.5	(Habtamu & Amare 2016)
Exposed	0.37	5.5	0.1	(Habtamu & Amare 2016)
Fluvisols	0.3	1090.9	20.8	(Temesgen *et al.*, 2017)
Leptosols	0.25	2805.2	53.6	(Temesgen *et al.*, 2017)
Luvisols	0.3	677.2	12.9	(Mengesha *et al.*, 2018)
Regosols	0.33	55.2	1.1	(Mengesha *et al.*, 2018)
Total		5234.9	100.0	

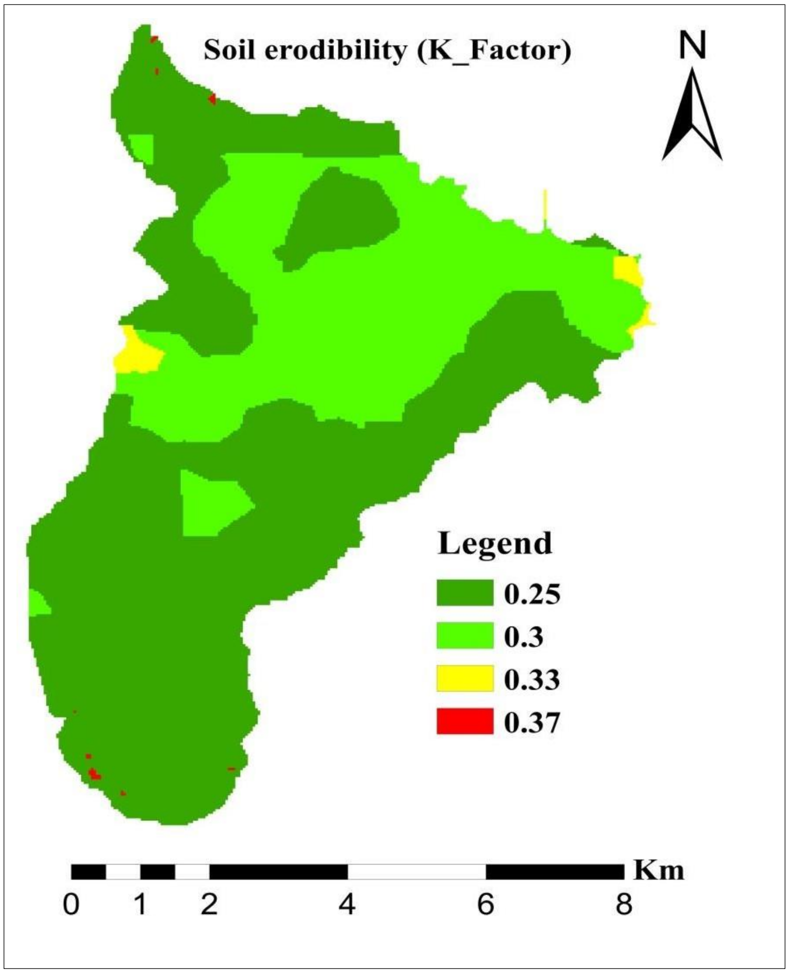

Figure 3.5: Soil Erodibility (K) factor of the study area

3.3.5. Watershed shape file

The delineated sub-watersheds boundary map was coded with an integer field named WS_ id values for each sub-watersheds having vector shape file format.

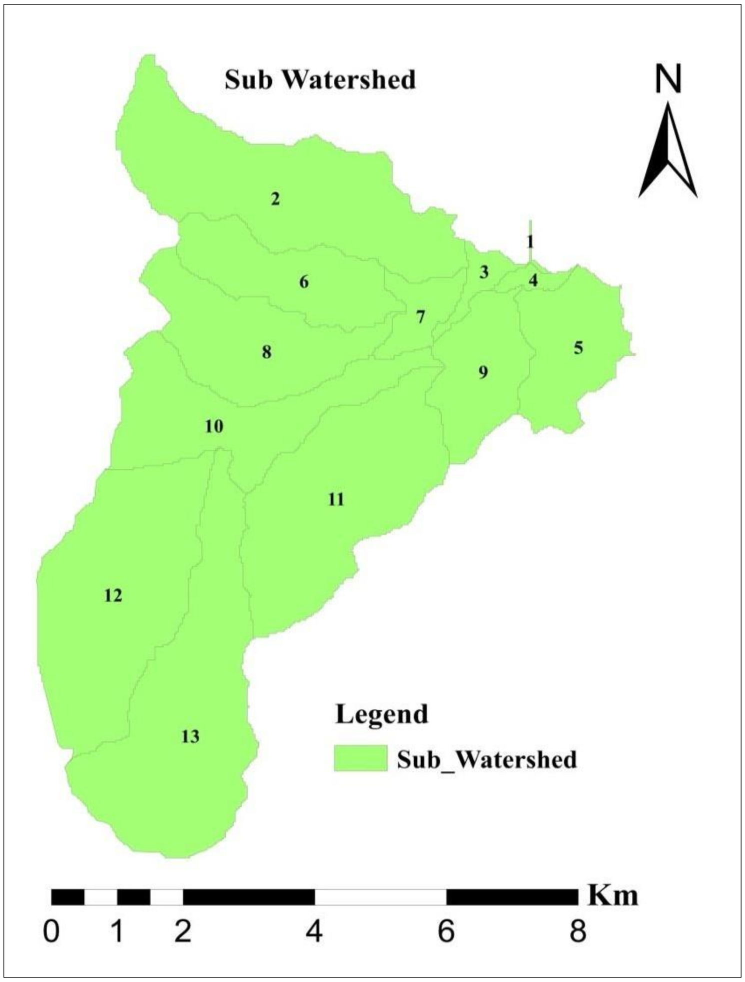

Figure 3.6: Sub watershed of the study area

3.3.6. Biophysical table

This table needs to be in CSV (Comma separated values) format having at least three field values such as Lucode, usle_c-factor, and usle_p-factor.

Lucode**:** It needs a unique integer for each LULC class having a corresponding lucode value in the biophysical table. The obtained LULC maps were prepared with unique integer lucode enough to be used for the model.

Usle C- factor: It is a cover management factor (c- factor) that needs to be in a floating-point value between 0 and 1. The value of the c-factor depends on the forest types, stage of growth, and percentage of cover. Its higher value means no cover effect, whereas lower values mean a very strong cover effect resulting in no erosion at that management status of the crop. So, it is also explained as a crop management factor (Koirala *et al.*, 2019).

Usle P- factor**:** It is a support practice factor that needs to be a floating point value between 0 and 1. It is considered a control practice to decrease the erosion potential caused by the influence of runoff on drainage patterns, its concentration, velocity, and hydraulic forces exerted by runoff on the soil surface (Sahli *et al.*, 2019). As the image classification approach requires very high-resolution remote sensing datasets and some experimental results (Panagos *et al.*, 2015) that are currently unavailable for the study area, the c-factor and p-factor values were prepared by referencing different relevant sources of literature review adopted by previous researchers in their studies with incorporating local condition to have a biophysical table to run the model with reliable output.

Table 3.4: Biophysical table (C and P values) of the study area

LULC Classes	**Lucode**	**Usle_C factor**	**Sources**	**Usle_P factor**	**Sources**
Forest	1	0.001	(Chadli, 2016)	0.9	(Kim, 2006)
Shrub Land	2	0.01	(Koirala *et al.*, 2019)	0.8	(Morgan *et al.*, 2005)
Bare Land	3	0.05	(Panagos *et al.*, 2015)	0.73	(Morgan *et al.*, 2005)
Built up Area	4	0.1	(Panagos *et al.*, 2015)	0.73	(Panagos *et al.*, 2015)
Cultivated Land	5	0.01	(Panagos *et al.*, 2015)	0.5	(Panagos *et al.*, 2015)

3.3.7. Threshold flow accumulation

It is requisite that the number of upstream cells flows into a cell before it is considered the part of a stream used to classify the stream from the DEM. It is also known as threshold flow accumulation for the model. Though its value can vary generally depending on DEM resolution, local climate, and topography, and the stream derived from the DEM does not exactly match the real world but just comes to be as close as possible. So, its good integer value is '1000' to start the model with no comma or period that has been given as the default value for this parameter (Carpenter *et al.*, 2017). Hence this study has used 1200 threshold values as input data to run the model because in the study area there are no closely networked streams. In the simplest form, the flow accumulation is the number of upslope cells that flows into a specific cell whereas its threshold value could be applied to define the stream networks of the watersheds (Band, 1986).

3.3.8. Kb and IC0

These two parameters are required to determine the shape of the relationship that shows hydro logically the degree of connection from patches of land to the stream. These are also known as Barseli parameters (Band, 1986). The default values for the Kb and IC0 have been given as 2 and 0.5 respectively for the model (Koch *et al.*, 2004). According to Hamel *et al.* (2015), Kb was only the parameter used for calibration. Hence, the value of the Kb parameter was selected as 1.5 to minimize the relative difference between predicted and observed values for 2000 and 2024.

3.3.9. SDR max value

It is known as the fraction of topsoil particles finer than coarse sand i.e. 1000 micrometers (Lestrelin *et al.*, 2012). It could be used for calibration in advanced studies. The default value for this parameter has been given as 0.8.

3.3.10. Drainage layer

This layer is optional to use in raster format for the model that corresponds to the pixels to be artificially connected to the stream. Using this layer has to stop flow routing before reaching the stream network and having assumption with exported sediment to be reached the catchment outlets (Curbelo *et al.*, 2017).

3.4. Sediment delivery ratio (SDR)

The measurement of the sediment deposit, the sediment rating curve, and other empirical methods are a few ways to determine how much soil has been eroded (Verstraeten & Poesen, 2002). During a rainfall event, only some of the eroded soil is routed to the basin channels and the outlet. The ratio between the basin sediment yields at the basin outlet to the total soil erosion over the basin is described as SDR. It is a measurement of sediment transport efficiency that takes into account the ratio of the total amount of soil that is detached and eroded above the channels or the outlet point to the amount of sediment that is transported from the eroding sources to the catchment channels and outlet (Lewoye & Rishikesh, 2021). Therefore, this study SDR could be determined from the stream channel slopes of the watershed using the following equation.

SDR = 0.627 SLP… .... (2)

When there are insufficient sediment data for a watershed, a realistic result for SDR estimation using steam channel slopes is produced (Alemu *et al.*, 2020).

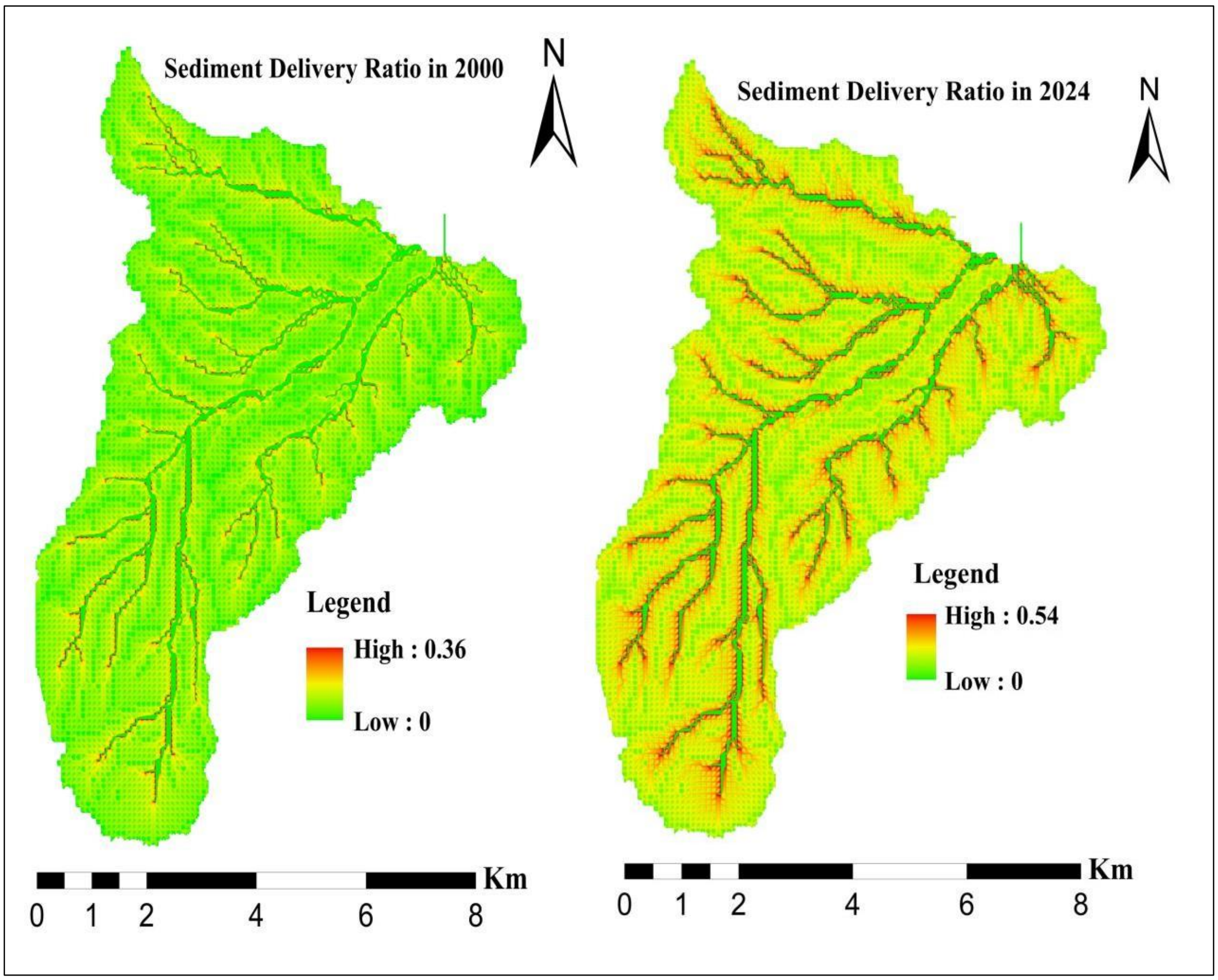

Figure 3.7: SDR values of the study area in 2000 and 2024

CHAPTER FOUR: RESULT AND DISCUSSION

4.1. LULC Classifications

The result of temporal and spatial LULC classification based on the 2000 land sat 7 ETM+ images of the study area, cultivated land is the dominant LULC class which covers 2047.93 ha (39.12%) followed by shrub land which cover 1493.19 ha (28.52%), bare land covers 1296.72 ha (24.77%) of the study area, and the forest area covers 397.06ha (7.58%) of the study area. Whereas, LULC classification based on the 2024 Landsat 8 satellite image of the study area, the proportion of land allocated for cultivated land is the dominant LULC class which covers 3811.9 ha (72.8%) followed by shrub land which covers 859.5 ha (16.4%) of the total area, forest land 274.6 ha (5.2%) of the study area, and bare land covers 185.3 ha (3.5%) of the study area. The built-up area which is due to the increasing population of the surrounding community and the land has been allocated to young people covers 103.6 ha (2.0%) of the total area (Table 4.1 and Figure 4.1). Throughout the years 2000-2024, the amount of built-up area and farmed land has also increased. This result was comparable with the finding of Argaw *et al.* (2017); who noted that the cultivated land was expanding from 62.7% in 1985 to 73.1% in 2000 and to 76.8% in 2015. The area built up also slightly increased (0.1-1.1%) between 1985 and 2015 periods in Andassa watershed.

In contrast, this result showed a decrease in bare land, forest land, and shrub land over these in 2000 to 2024. This result agrees with Alemu and Abegaz (2024), who reported that in the LULC change results from 1990 to 2021 showed decrease of 12.2%, 1.2%, and 15.4%, in forest, shrub land, and bare land respectively in the Upper Tekeze Basin, Ethiopia. Between 2000 and 2024, the proportion of cultivated land in study area increased significantly from 39.12% (2047.93 ha) to 72.8% (3811.9 ha), while the amount of bare land decreased from 24.77% (1296.72 ha) to 3.5% (185.3 ha). These changes were driven by government land allocation programs, population growth, and agricultural expansion into previously unsuitable areas, reclamation of degraded land through soil conservation, and the conversion of marginal or unused lands into cultivated land. Bare lands are frequently transformed into agricultural or populated regions as a result of fast population growth. Therefore, as farmers expand cultivation into previously marginal or bare areas, the apparent drop may represent land-use change rather than ecological recovery. You might verify whether agricultural land or towns grew where bare land decreased by looking at your classified land-use maps.

Table 4.1: LULC Results of the study area in 2000 and 2024

LULC Type	2000		2024	
	Area in ha	Area in %	Area in ha	Area in %
Forest	397.06	7.58	274.6	5.2
Shrub Land	1493.19	28.52	859.5	16.4
Bare Land	1296.72	24.77	185.3	3.5
Cultivated Land	2047.93	39.12	3811.9	72.8
Built up Area	0	0	103.6	2.0
Total	5234.9	100	5234.9	100

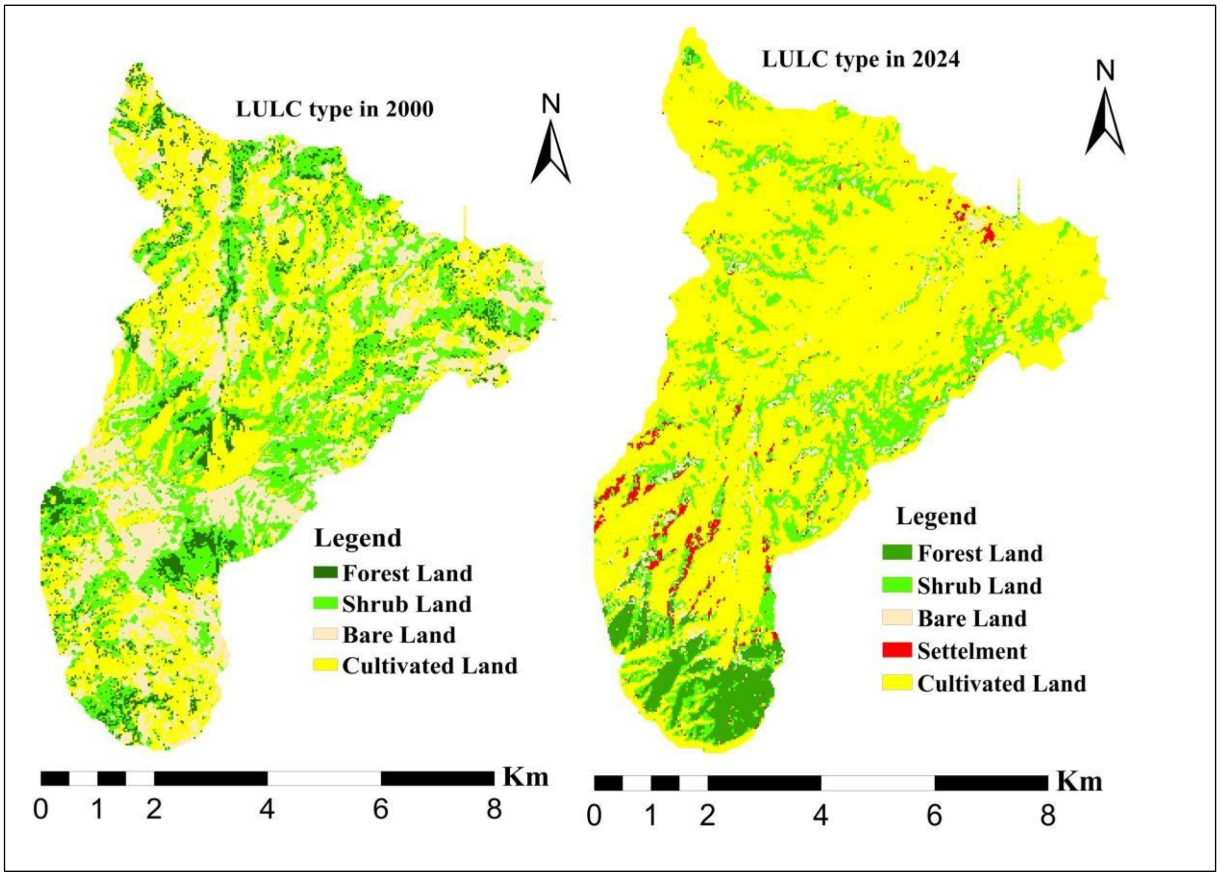

Figure 4.1: LULC of the study area in 2000 and 2024

4.1.1 Accuracy Assessment

To ascertain whether the classified image is accurate, accuracy assessment is utilized. This study uses the ground control points taken for each of the different classes to assess the accuracy of the 2000 and 2024 classified images for four and five LULC classes. For example, in 2000 there were 30, 50, 30, and 30 each of forestland, shrub land, bare land, and cultivated land; in 2024 there were 30, 40, 30, 30, and 50 each of forestland, shrub land, bare land, built-up area, and cultivated land, respectively. Tables 4.2 and 4.3 below display the resulting error matrix.

Table 4.2: Accuracy assessment error matrix of 2000 LULC classes

LULC Type	Ground truth data					
	Forest	Shrub Land	Bare Land	Cultivated Land	Row total	User Accuracy
Forest	**23**	2	2	1	28	82%
Shrub Land	1	**44**	4	2	51	86%
Bare Land	2	2	**24**	1	29	83%
Cultivated Land	4	2	0	**26**	32	81%
Column total	30	50	30	30	140	
Producer accuracy	77%	88%	80%	87%		
Overall accuracy = 84%						
Kappa Coefficient =81%						

Table 4.3: Accuracy assessment error matrix of 2024 LULC classes

LULC Type	Ground truth data						
	Forest	Shrub Land	Bare Land	Built up Area	Cultivated Land	Row total	User Accuracy
Forest	**25**	2	1	1	2	31	81%
Shrub Land	2	**34**	3	1	2	42	81%
Bare Land Area	1	1	**23**	3	2	30	77%
Built up Area	1	1	1	**24**	1	28	86%
Cultivated Land	1	2	2	1	**43**	49	88%
Column total	30	40	30	30	50	180	
Producer accuracy	83%	85%	77%	80%	86%		
Overall accuracy = 82%							
Kappa Coefficient = 80%							

The above result was used for the evaluation of overall accuracy, overall K statics as well as producer's and user's accuracy for each LULC class. The ranges obtained for producer's accuracy for individual LULC were found as 77% - 88% and 77% - 86% whereas the ranges of user's accuracy were found to be 81% - 86% and 77% - 88% respectively for the classification of 2000 and 2024 land sat images. Hence, for this study overall accuracy assessment for the Land sat image of 2000 was 84%, which has been achieved with a kappa coefficient of 81% and an overall accuracy for the Land sat image of 2024 was 82% with 80% Kappa Coefficients respectively. This result was almost similar to Zemenu (2022), who found that land use classification of 1990, 2000, 2010, and 2021 was achieved with an overall accuracy of 81.25%, 80%, 81.25% and 85% was obtained with the Kappa coefficient of 80%, 73%, 81.25% and 80% for the four scenes respectively in Tul Watershed, Upper Blue Nile Basin, Ethiopia.

The overall accuracy assessment is similar to the average accuracy with each accuracy weight ed by the proportion of test samples for that class in the total training. In general, the overall accuracy assessment provides a more reliable and representative measure of classification accuracy. A value >0.80 (80%) strong agreement, a value between 0.40 and 0.80 (40 to

80%) represents moderate agreement, and a value < 0.40 (40%) represents poor agreement (Tr avis *et al.*, 2015). Therefore, the image classification accuracy of the study area was met to these requirements are strong agreement.

4.1.2. LULC rate of changes

Many studies needed LULC to have accurate and updated information for detailed ecosystem studies having hydrological modeling (Muhammad *et al.*, 2015). In this study, the result on LULC rate of changes (Table 4.4 and Figure 4.1) showed that, cultivated land and built up area coverage increased by 1764 ha (86.1%) and 103.6 ha (2%) respectively which studied that, increasing human population leads to convert other land use into intensive agriculture in order to fulfill their demands.

This result was similar to other findings the major changes were expansion of cropland at the expense of other LULC classes at the rate of 29.56% in 1978, 38.91% in 1987, 46.62% in 2001 and 52.74% in 2015 (Melku *et al.*, 2020) in Gojeb River Catchment, Omo Gibe Basin, Ethiopia. In the other study, cropland has increased from 34.1% in 1986–2000 to 46.3% between 1986–2020, which is linked to population growth, settlement, and expansion of farmlands (Mehari *et al.*, 2022) in Ojoje watershed, Southern Ethiopia. On the other hand, bare land, shrub land and forest land have decreased by 1111.4 ha (85.7%), 633.7 ha (42.4%) and 122.5 ha (30.8%) respectively. This result coincides with the findings of other studies: 20.04% in 1986 and 7.24% in1986 decreased 15.28 % in 2019 and 3.89% in 2019 for forest and Shrub land respectively (Kassahun *et al.*, 2024) in the Baro-Akobo Basin, Southwestern Ethiopia.

Table 4.4: LULC rate of change from 2000 to 2024

LULC Class	2000 Area in ha	Area in %	2024 Area in ha	Area in %	2000-2024 change of Area in ha	Rate of change in %
Forest	397.1	7.6	274.6	5.2	-122.5	-30.8
Shrub Land	1493.2	28.5	859.5	16.4	-633.7	-42.4
Bare Land	1296.7	24.8	185.3	3.5	-1111.4	-85.7
Cultivated Land	2047.9	39.1	3811.9	72.8	1764	86.1
Built up Area	0	0	103.6	2	103.6	----
Total	5234.9	100	5234.9	100		

4.1.1. Land Use and Land Cover (LULC) Transition Analysis (2000–2024)

The (LULC) transition matrix for the period 2000 to 2024 reveals substantial spatial and temporal changes within the study area, which covers a total of 5,234.9ha Table 4.5. The matrix demonstrates how each land cover category in 2000 was converted to other types by 2024, indicating pronounced dynamics associated with human activity and natural processes.

Cultivated Land was the most dominant and dynamic land cover class. In 2000, it accounted for 2,047.93 ha, and by 2024 it had expanded to 3,851.9 ha, recording a substantial increase of 1,803.97 ha (88.1%). The major sources of this expansion were Bare land (926.69 ha), Shrub land (1,109.30 ha), and Forest land (270.79 ha). Despite some losses to other classes, including 65.4 ha to bare land, 269.25 ha to Shrub land, and 143.79 ha to Forest land, the overall gain indicates a strong agricultural expansion across the landscape. The growth of cultivated areas can be attributed to increased demand for agriculK8tural land and settlement expansion into previously natural areas. Settlement areas covered 103.60 ha in 2024. However, the matrix shows that new built-up land was gained from several other categories: 35.41 ha from Bare land, 24.37 ha from Cultivated land, 9.02 ha from Forest land and 34.80 ha from Shrub land.

Bare land Transition In 2000, bare land occupied approximately 1,296.72 ha of the total area. By 2024, this category had drastically declined to 185.30 ha, showing a net loss of 1,111.42

ha, which represents about 85.7% reduction over the study period. The transition analysis shows that about 926.69 ha of bare land were converted to cultivated land, 220.41 ha to Shrub land, 66.45 ha to Forest land and 35.41 ha to Settlement, while only 47.76 ha remained unchanged. This indicates that previously barren or unused areas were largely reclaimed for agriculture and vegetation growth, reflecting intensive land use and environmental rehabilitation efforts. The Forest land category covered 397.06 ha in 2000 but declined to 277.75 ha by 2024, resulting in a net loss of 119.31 ha (30%). The analysis indicates that approximately 270.79 ha of forest were converted into cultivated land and 85.47 ha into Shrub land, while 66.45 ha were gained from bare land and 44.81 ha from Shrub land. Although there was some natural regeneration, the overall reduction suggests continued deforestation and vegetation degradation, likely associated with agricultural expansion and wood extraction activities. In 2000, Shrub land covered 1,493.19 ha, making it one of the dominant classes in the area. By 2024, its extent decreased to 816.35 ha, showing a total loss of 676.84 ha (42.4%). The largest conversions were observed toward Cultivated land (1,109.30 ha), indicating that shrub areas were significantly cleared for agricultural purposes. In addition, 63.06 ha of Shrub land were converted into bare land, 44.81 ha into Forest land and 34.80 ha into Settlement, while 241.22 ha persisted as Shrub land. This pattern demonstrates substantial land transformation from semi-natural vegetation to human-modified uses.

Table 4.5: Transition area matrix (ha) between 2000 and 2024

		LULC in 2024					
	LULC change	**Bare Land**	**Cultivated Land**	**Forest Land**	**Settlement**	**Shrub Land**	**Grand Total**
LULC in 2000	Bare Land	47.76	926.69	66.45	35.41	220.41	1296.72
	Cultivated Land	65.40	1545.12	143.79	24.37	269.25	2047.93
	Forest Land	9.08	270.79	22.70	9.02	85.47	397.06
	Shrub Land	63.06	1109.30	44.81	34.80	241.22	1493.19
	Grand Total	185.30	3851.90	277.75	103.60	816.35	5234.90

4.2. Effect of LULC Changes on Soil Erosion from 2000 to 2024

The study watershed was classified into four LULC classes in the year 2000 and five LULC classes in the year 2024 and it has significant changes. Each LULC change has its own effects on the potential of soil erosion and sediment yield variation within the study area (Table 4.5 and figure 4.2). In addition, it also has effects on Sediment delivery ratio (SDR) variations during the study periods (Figure 4.3). Among all LULC cultivated land area is experiencing an increasing trend in soil loss i.e. the soil loss is increased from 31.4 t/ha/year to 56.17 t/ha/year, 2000 and 2024, respectively. The reasons were the area of cultivated land increased from (2047.9 ha) in 2000 to (3811.9 ha) in 2024 implied that the mean annual soil erosion rate increased from cultivated land and shrub land (13.28 and 7.96 t/ ha/yr in 2000 to 40.8 and 9.22 t/ ha/yr in 2024) respectively so increased soil erosion rate estimated from other LULC types. Meanwhile the area of the shrub land decreased from (1493.2 ha in 2000 to 859.5 ha in 2024. In contrast, the mean annual soil loss rate in bare land and forest land decreased from (7.78t/ha/yr and 2.38t/ha/yr) in 2000 to (1.99t/ha/yr and 1.95t/ha/yr) in 2024 respectively. Due to decreased bare land and forest from 1296.7 ha and 397.1 ha in 2000 to 185.3 ha and 274.6 ha in2024 (Table 5).This study was in line with Tamire *et al.* (2022) who reported that the mean annual soil loss was 13.06t/ha/yr to increase 31.26 t/ha/yr in 1991 and 2021 respectively. The soil loss rates were grouped in the following scales of priority: very slight (0-5), slight (5-11 t/ha/yr), moderate (11-30 t/ha/yr), severe (30-50 t/ha/yr), and very severe (>50 t/ha/yr) which was adapted from (Temesigen *et al.*, 2019).

Table 4.6: Mean annual sediment yield and soil erosion each LULC

Mean annual soil erosion rate		Cultivated land	Forest land	Settlement land	Shrub land	Grand total
Soil loss (t/ha/yr)		13.28	2.38	0	7.96	31.4
Sediment yield (t/ha/yr)		2.38	0.46	0	1.73	6.08
Soil loss (t/ha/yr)	1.99	40.8	1.95	2.12	9.22	56.08
Sediment yield (t/ha/yr)		7.36	0.53	0.2	1.66	10.11

Based on the result, the highest mean annual soil erosion in the year 2000 is very low severity which covers 4144.7 ha (79.2%) followed by low severity which covers 559.4 ha (10.7%) of the total study area. Moderate soil erosion severity covers 326.8 ha (6.2%) of the study area whereas, high severity and very high severity covers 136.7 ha (2.6%) and 67.4 ha (1.3%) of the study area respectively as shown (table 4.6). Due to LULC type change from the year

2000 to 2024, the severity of erosion also changed as follow: Based on this, the result indicated that, the highest mean annual soil erosion in the year 2024 is very low severity class which covers 3671.3 ha (70.1%) followed by low severity class which covers 682.7 ha (13.0%) of the study area and moderate soil erosion severity covers 542.8 ha (10.4%) of the study area. whereas, high soil erosion severity and very high soil erosion severity class covers 252.6 ha (4.8%) and 85.5 ha (1.6%) of the study area respectively as shown (table 4.7 and figure 4.2).

Table 4.7: Soil erosion rate of change from 2000 to 2024

	2000		2024		2000-2024 Change	Rate of Change (%)
Severity class	Area in ha	Area in %	Area in ha	Area in %	Area in ha	
Very Slight	4144.7	79.2	3671.3	70.1	- 473.4	-11.4
Slight	559.4	10.7	682.7	13.0	123.3	22.0
Moderate	326.8	6.2	542.8	10.4	216	66.1
Severe	136.7	2.6	252.6	4.8	115.9	84.8
Very Severe	67.4	1.3ክ2	85.5	1.6K8	18.1	26.9
Total	5234.9	100.0	5234.9	100.0	-----	-----

As shown above (table 4.7) in this study, the effect of LULC changes on soil erosion rate of change shows that only very low erosion severity has decreased from 4144.7 ha to 3671.3 ha which accounts for 473.4 ha (11.4%). The other severity class has been increased from 2000 to 2024. When we look one by one low severity class increased from 559.4 ha (10.7%) to 682.7 ha (13.0%) with the rate of change 123.3 ha (22.0%), moderate erosion severity class increased from 326.8 ha (6.2%) to 542.8 ha (10.4%) with the rate change of 216 ha (66.1%), high erosion severity class increased from 136.7 ha (2.6%) to 252.6 ha (4.8%) with the rate change of 115.9 ha (84.8%), and very high erosion severity class also increased from 67.4 ha (1.3%) to 85.5 ha (1.6%) with the rate change of 18.1 ha (26.9%). Another study stated that soil loss, as the main sediment source, but limited by the scope of land use change and fluctuates with land use cover change (Borselli *et al.*, 2008).

This shift can be linked to LULC transitions on steeper slopes, where protective forest or shrub cover was replaced by crop land or settlement, reducing surface stability. The changes in rainfall patterns such as more intense, short duration storms likely accelerated runoff and erosion rates has been the main cause. Poor soil management practices, including over cultivation and inadequate conservation structure. In addition, the expansion of agriculture into marginal lands with soils and higher gradients increased susceptibility to erosion amplifying the observed severity shift. This finding was similar to the report of Liyew *et al.* (2024), who reported Severity from 2002 to 2023: very low severity class decreased from 15604.2 ha (83.17 %) to 14563.89 ha (77.60 %), low erosion severity increased 1750.86 ha (9.33%) to 2273.5 ha (12.11%) moderate erosion severity class increased from 679.95 ha (3.62 %) to 859.14 ha (4.58%), high erosion severity class increased from 326.61 ha (1.74%) to 451.17 ha (2.40%), and very high erosion severity class also increased from 399.69 ha (2.13%) to 568.89 ha (3.03%)in Dondor Watershed, Blue Nile Basin, Northwestern Ethiopia

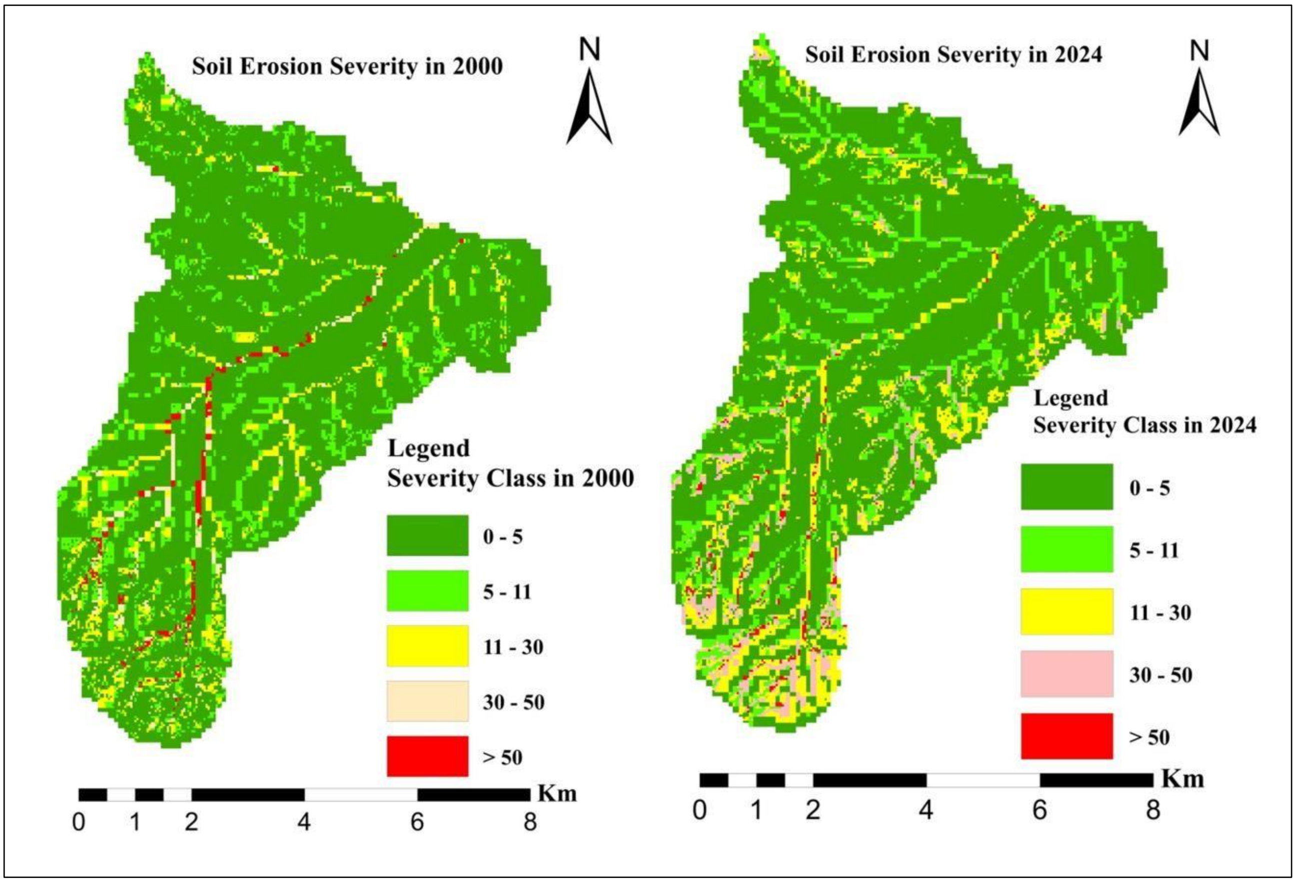

Figure 4.2: Soil erosion rate changes in 2000 and 2024

4.3. Effect of LULC Changes on Sediment Yield from 2000 to 2024

The effects of LULC changes on sediment yield dynamics in the Gateno watershed are increasing. Because the LULC drastically changed from forest, bare land and shrub land to agricultural land and built up areas. The sediment yield was grouped into five scales of priority, which was adapted from (Tamene *et al.*, 2017; Temesgen *et al.*, 2019). These are very slight (0–5 t ha^{-1} yr^{-1}), slight (5–11 t ha^{-1} yr^{-1}) moderate (11–18 t ha^{-1} yr^{-1}), severe (18–25 t ha^{-1} yr^{-1}) and very severe (>25 t ha^{-1} yr^{-1}). In this study, the result obtained from running the In-VEST model showed that the mean annual sediment yield of the Gateno watershed was increasing from the rate of 6.08 (t/ha/yr) to 10.11 (t/ha/yr) for the years 2000 and 2024 respectively. The mean annual sediment yield increased from forest land and settlement land (0.46 and 0 t/ ha/yr in 2000 to 0.53 and 0.2 t/ ha/yr in 2024) respectively but lower than the sediment yield estimated from cultivated land. Cultivated land increased 2.38 t/ha/yr in 2000 to 7.36 t/ha/yr in 2024.and the other LULC type decreased bare land and shrub land 1.5 t/ha/yr and 1.73 t/ha/yr in 2000 to 0.36 t/ha/yr and 1.66 t/ha/yr 2024(Table 4.8).This finding coincides with the previous research conducted Teshome *et al.* (2022) the mean sediment yields of the study area is estimated to 7.8 ton/ha/year in 1986, and later increased to 10, and 10.2 ton/ha/year in 2003, and 2020, respectively. Results revealed that the steep slope areas with crop land experience considerable soil loss, with mean soil loss increasing over all study period in Muger Sub-basin and Zemenu (2022), the expansion of cultivated land and built up area was caused to increase the mean annual sediment yield increased from 9.07 (t/ha/yr) in 1990 to 15.74 (t/ha/yr) in 2000 in the Tul watershed. Therefore; the visible factors that caused an increase in sediment rate from 2000 to 2024 were reduced forest land, shrub land and bare land cover and an increasing rate of cultivated land and a built-up area within the study watershed **(**Table 10). According to other studies, forest lands allow minimum erosion and low flow velocity, and the contribution of such areas to sediment yield is small and the highest sediment yield in cultivated land as compared to forest lands was reported (Diyabalanage *et al.*, 2017).

Other findings stated that a higher rate of soil loss means to have a greater amount of sediment to be retained by the existing forest and anti-erosive activities (Barhoumi *et al.*, 2019).

Table 4. 8 Sediment yield of the study area

Severity class	2000		2024		2000-2024 Area in ha	Rate of Change (%)
		Area in %	Area in ha	Area in %		
Very Slight		94.29	4857.76	92.80	-78.11	1.58
Slight	197.95	3.78	256.91	4.91	58.96	-29.78
Moderate		0.99	65.77	1.26	14.06	-27.19
Severe	24.70	0.47	26.48	0.51	1.78	-7.21
Very Severe		0.47	27.96	0.53	3.31	-13.43
Total		100	5234.9	100		

As shown above (table 4.8 and figure 4.7) in this study, the effect of LULC changes on sediment yield of change shows that only very slight sediment export severity has decreased from 4935.87 ha to 4857.76 ha which accounts for 78.11 ha (1.58%). The other severity class has been increased from 2000 to 2024. When we look one by one slight severity class increased from 197.95 ha (3.78%) to 256.91 ha (4.91%) with the rate of change 58.96 ha (29.78%), moderate sediment export severity class increased from 51.71 ha (0.99%) to 65.77 ha (1.26%) with the rate change of 14.06 ha (27.19%), severe class increased from 24.70 ha (0.47%) to 26.48 ha (0.51%) with the rate change of 1.78 ha (7.21%), and very severe class also increased from 24.65 ha (0.47%) to 27.96 ha (0.53%) with the rate change of 3.31 ha (13.43%).

The conversion of forest and shrub land to cropland and settlements, particularly on steep slopes where surface stability is diminished, is the main factor influencing the change in the severity of sediment export. Erosion and runoff have been further accelerated by intense, brief rainfall events. Sediment export severity has been exacerbated by poor soil management practices, such as over cultivation and inadequate conservation measures, as well as agricultural expansion into marginal lands. These practices have reduced sediment retention and increased sediment delivery. This finding was similar to the report of (Mersha *et al.*, 2025), who reported Severity from 1993 to 2023: very slight severity class decreased from 86652.00 ha (69 %) to 77330.00 ha (61%), slight severity increased 11645 ha (9%) to 18934 ha (15%) moderate severity class increased from 16503 ha (13%) to 18412 ha (15%), severe severity class increased from 11443 ha (9%) to 13012 ha (10%), and very severe severity class also increased from 3010 ha (2 %) to 5151 ha (4%) in the Borkena watershed.

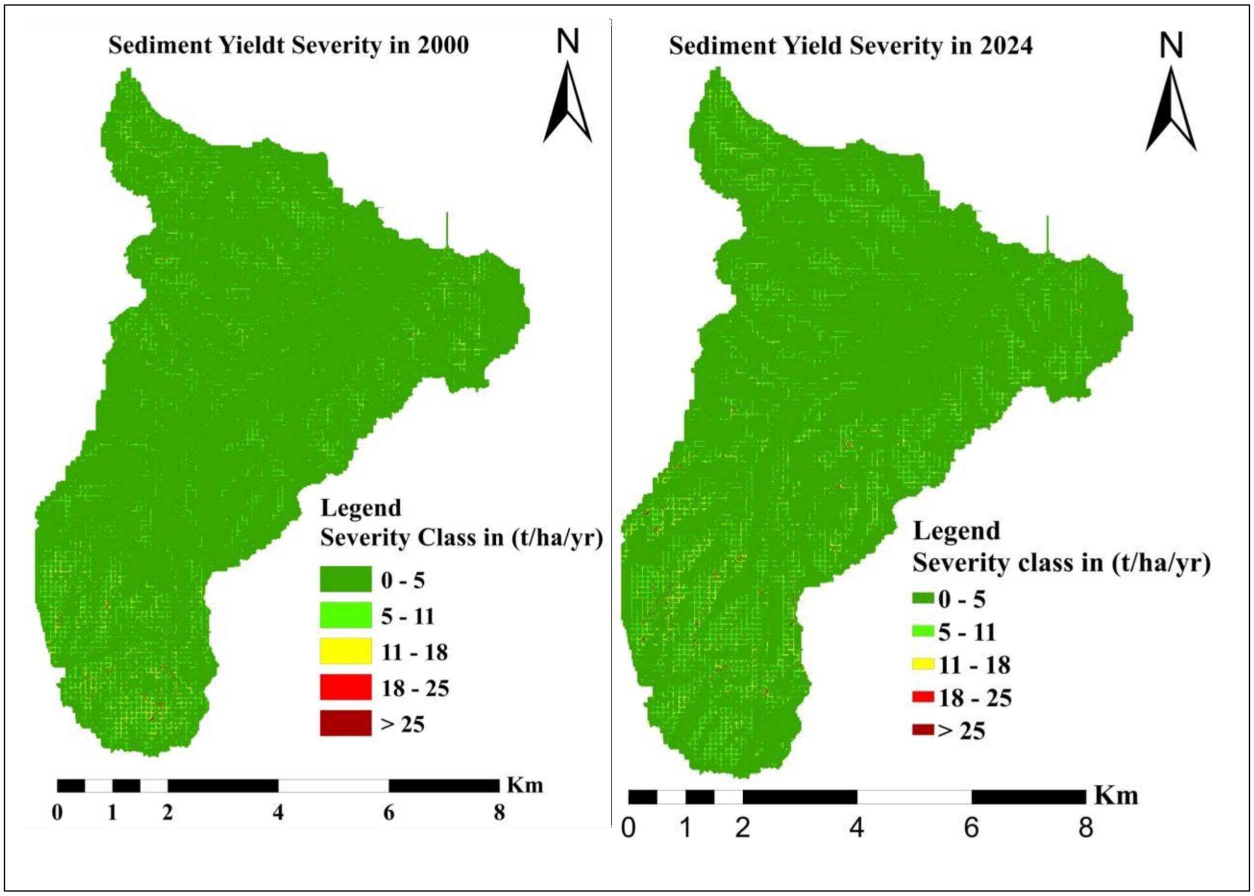

Figure 4.3: Sediment yield severity classes from 2000 – 2024

4.3.1 Most sensitive sub-watersheds based on sediment yield

The result of estimation of sediment export and potential soil loss in terms of ton per year per sub-watershed was obtained as an absolute value from running the InVEST SDR_{max} model. Hence, to examine the status of each sub-watershed for sedimentation phenomena this model result was converted into ton per hectare per year per sub-watershed.

Table 4.9: Mean annual sediment yield and soil erosion at sub-watershed level in 2000 and 2024

Sub-watershed ID	Sediment Export 2000 (t/ha/yr)	Soil Loss 2000 (t/ha/yr)	Sediment Export 2024 (t/ha/yr)	Soil Loss 2024 (t/ha/yr)
SW_01	0	0	0.00	0.00
SW_02	0.53	2.74	3.75	20.83
SW_03	0.01	0.05	0.01	0.06
SW_04	0.03	0.16	0.08	0.44
SW_05	0.18	0.93	0.49	2.72
SW_06	0.15	0.78	0.44	2.44
SW_07	0.03	0.16	0.04	0.22
SW_08	0.22	1.14	0.51	2.83
SW_09	0.21	1.09	0.31	1.72
SW_10	0.25	1.29	0.47	2.61
SW_11	0.83	4.29	0.74	4.11
SW_12	2.16	11.17	1.22	6.78
SW_13	1.47	7.6	2.05	11.39
Total	6.08	31.4	10.11	56.17

The results for 2000 and 2024 have been presented in (Table 4.9) respectively. As a result, out of the total 13 sub-watersheds, the highest contributor for sediment yield or export SW_12 which has 2.16 t/ha/yr followed by SW_13 which has 1.47 t/ha/yr in 2000 whereas SW_02 (3.75 t/ha/yr followed by SW_13 (2.05 t/ha/yr) in 2024 as shown (Table 13 and figure 4.4). According to many studies, the change in land use and its management affects the sediment rate in a watershed (Misganaw & Aramde, 2019; Tang *et al.*, 2005). Therefore, this study results approved that there were changes in LULC and their management effects on the sediment rate. Other studies related to this issue show that the sediment export in watersheds changes over time and that function of change depends on watershed management, land use type, and slope (Lutz *et al.*, 2016; Yan *et al.*, 2013). So, this study results have a close relationship with the previous study for the cause of variation in sediment export in 2000 and 2024.

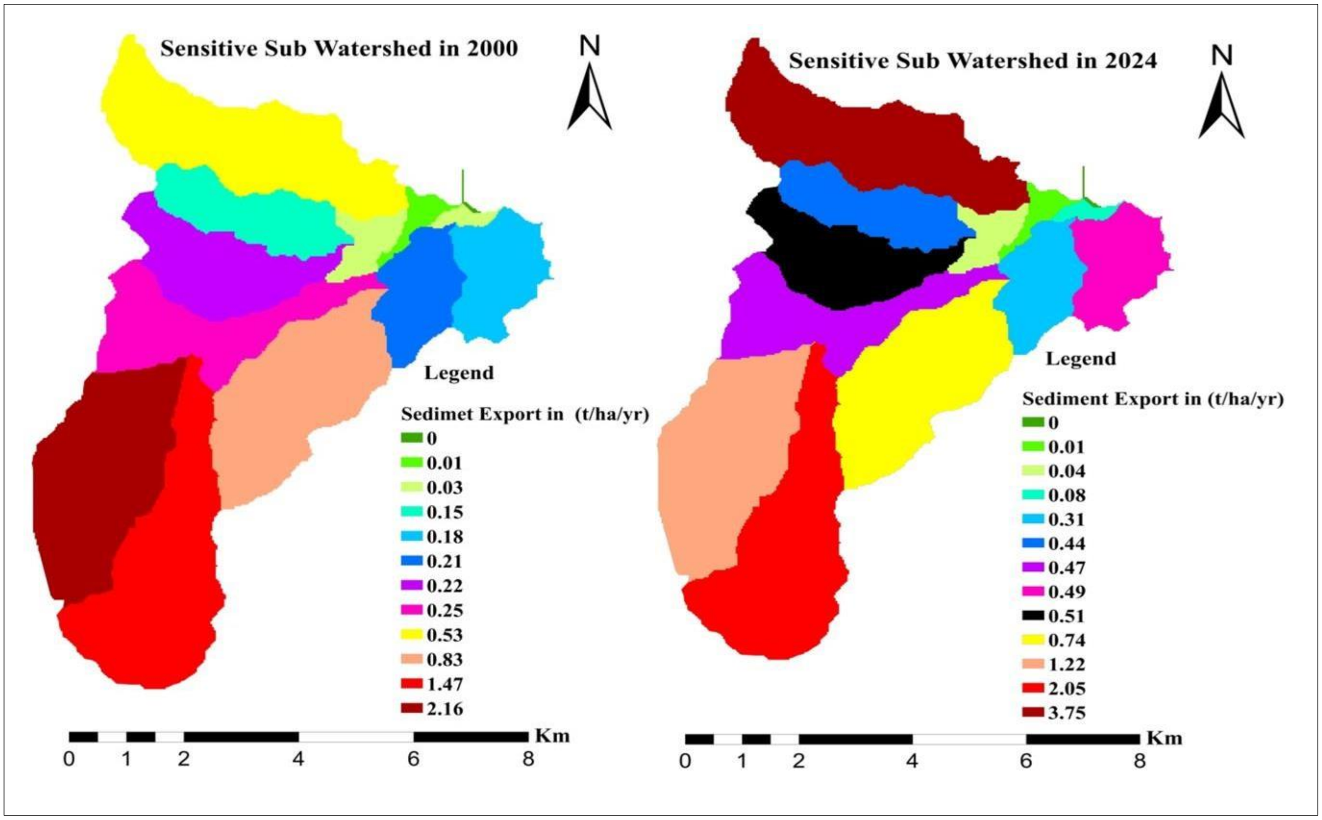

Figure 4.4: Sensitive sub watersheds in 2000 and 2024

In similar way, the SW_12 was the most contributor for mean annual potential soil erosion (11.17 t/ha/yr) followed by SW_13 (7.60 t/ha/yr) and SW_11 (4.29 t/ha/yr) in 2000 and SW_02 (20.83 t/ha/yr) followed by SW_13 (11.39 t/ha/yr) and SW_12 (6.78 t/ha/yr) in 2024 as shown (Table 4.9). Hence, as indicated in the results they have observed very high soil loss in the upper-stream mountainous and the steepness parts of the sub-watershed of the study area. In addition, this study has similar results to other study findings. As (Abaci & Papanicolaou, 2009; Restrepo & Syvitski, 2006), concluded that the changes in land use and their management effects are variations in soil erosion rate where no best management practice can increase the erosion rate and ultimately enhance sediment rate or yield. This is due to depending on the area covered in the watershed, amounts of forest coverage, and types of slopes in each sub-watershed.

4.4. Validation of Model Results

The absence of data for validating the model outputs is perhaps one of the InVEST SDR max mode land soil erosion models' weaknesses. As Temesgen *et al.* (2021b) indicated that, validating the soil erosion and sediment yield rates estimated by the InVEST SDR max model is difficult because of the lack of easily available measured soil loss and sediment records, especially in data-sparse regions. A comparison of soil erosion and sedimentation yield measured in the watershed with the obtained predicted sediment rate by the model is a means of validating the obtained result (Hamel *et al.*, 2017).

According to Hamel *et al.* (2015), available predicted data on sedimentation yield and understanding of the local soil loss and sediment budget for a given watershed is key to improved confidence in the model result. The result of the soil loss and sedimentation yield predicted by InVEST model in a studied watershed 31.4 t/ha/yr and 6.08 t/ha/yr in 2000 and t/ha/yr 56.17 and 10.11t/ha/yr) for 2024 respectively were relatively close to each other in quantity but with similar increasing trends in their respective year. However, the data for 2024 was found to be a relatively far increasing amount to that of 2000. The increase of soil erosion and sediment yield in the study watershed through the 2000-2024 periods is generally due to the increase of cultivated land and built-up area. Therefore, the values of soil erosion and sediment yield predicted by InVEST SDR max model in Gateno watershed have a significant relationship with low positive values to the measured and predicted soil loss and sediment yield results of other studies. This shows that the result of the InVEST SDR max model has been found in the right **direction within its limitations.**

Table 4.10: Mean annual soil loss results of previous studies in Northern Ethiopian

Location	Model applied	Mean annual soil loss in ton/ha/year	References
Tekeze basin	RUSLE	34.75	(Alemu Eshetu & Abegaz, 2024)
Chereti Watershed	RUSLE	38.71	(Ajanaw *et al.*, 2021)
Agewmariyam watershed	USLE	25	(Gebrehana *et al.*, 2020)
Laelaywukro catchment	RUSLE	45	(Lulseged *et al.*, 2017)
Medego Watershed	USLE	35.43	(Gebreyesus & Mekonen, 2009)

Table 4.11: Mean annual sediment yield results of previous studies in Northern Ethiopian

Watershed	Model applied	Mean annual sediment yield (t /ha/ yr)	References
Gumera watershed	SWAT	21.6	(Asres & Awulachew, 2010)
Fakisi watershed	SDR	27.2	(Tsegaye *et al.*, 2024)
Anjeni-Gauged watershed	SWAT	24.6	(Setegn *et al.*, 2010)
Tekeze basin	SWAT	15.17	(Welde & Gebremariam, 2017)

CHAPTER FIVE: CONCLUSION AND RECOMMENDATIONS

5.1. Conclusion

This study assessed the impacts of land use/land cover (LULC) changes on soil erosion and sediment yield in the Gateno watershed, Amhara Region, Ethiopia, for the period 2000–2024, using Landsat satellite imagery, geospatial techniques, and the InVEST Sediment Delivery Ratio (SDR) model. The findings clearly demonstrate that the watershed has undergone substantial transformations in land cover over the past two decades, primarily driven by rapid population growth, agricultural expansion, settlement development, and unsustainable land management practices.

The result revealed that cultivated land and built up area coverage was increased from 2000 to 2024 whereas the other LULC forest land, shrub land and bare land area coverage has been decreased. These shifts in LULC composition had a profound effect on soil erosion and sediment yield. The estimated mean annual soil loss increased from 31.4 t/ha/yr to 56.17 t/ha/yr in 2000 and 2024 respectively whereas the mean annual sediment yield from 6.08 t/ha/yr to 10.11 t/ha/yr in 2000 and 2024 respectively. From the total 13 sub watershed SW_12 is the most sensitive for sediment export and soil loss in 2000 whereas SW_02 is the most sensitive sub watershed in 2024 for both sediment export and soil loss.

The evidence from this study confirms a strong and direct link between anthropogenic land cover changes and the acceleration of soil erosion and sediment yield. If these trends persist unchecked, the Gateno watershed will face worsening land degradation, declining agricultural productivity, and increased sedimentation in reservoirs and rivers, threatening both livelihoods and ecosystem integrity.

In conclusion, urgent, integrated watershed management interventions are needed combining reforestation, sustainable agricultural practices, and effective soil and water conservation measures to halt further degradation. Restoring vegetative cover, enforcing land-use planning regulations, and promoting climate-resilient farming systems will be essential to safeguard the watershed‘s ecological balance and ensure the long-term well-being of its communities.

5.2. Recommendations

Based on the results of this study, the following actions are suggested to improve land use and land cover (LULC) analysis, estimate sediment production, and manage erosion risks in the study area:

- This research was conducted focusing on the impact of LULC dynamics on soil erosion and sediment yield. But the impact of climate change should also be taken under consideration for future research.
- This study used the InVEST model to estimate sediment export and soil loss variation. But this model doesn‘t estimate Gully erosion so in the future should use other models to estimate Gullies erosion like SWAT models.
- Setup geospatial monitoring systems to accurately and continuously track LULC changes. This involves routinely examining satellite imagery to track changes over time and pinpoint regions where land degradation is occurring..
- Appropriate management options for LULC dynamics have to be emphasized to reduce the source of soil erosion and sediment yield problems in Gateno watershed.
- Soil erosion and sediment yield reduction methods like terracing, contouring, grassed waterway, and filter strip must be taken into consideration to reduce sedimentation problems in the watershed area.

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APPENDIX

Appendix 1: Ground Control points for accuracy assessment of image 2000 classifications

CID	Easting	Northing	LULC Type	CID	Easting	Northing	LULC Type
1	500796	1388691	Forest	71	502993	1379808	Shrub
2	500652	1388757	Forest	72	503103	13802491	Shrub
3	501164	1388023	Forest	73	500126	1379558	Shrub
4	501939	1387858	Forest	74	500751	1378949	Shrub
5	501230	1387606	Forest	75	501977	1378824	Shrub
6	501691	1387595	Forest	76	499684	1378149	Shrub
7	501511	1386807	Forest	77	500226	1377499	Shrub
8	503364	138582	Forest	78	500951	1377465	Shrub
9	502506	1385055	Forest	79	501026	1376673	Shrub
10	502284	1383182	Forest	80	502002	1377115	Shrub
11	503535	1384667	Forest	81	501029	1388649	Bare
12	504150	1383411	Forest	82	500787	1388253	Bare
13	504835	1383025	Forest	83	500409	1387693	Bare
14	505347	13838888	Forest	84	502039	138858	Bare
15	506064	1384526	Forest	85	500897	1387448	Bare
16	502668	1385188	Forest	86	501802	1387388	Bare
17	506419	1385709	Forest	87	501179	1386632	Bare
18	507920	1384946	Forest	88	503463	1385559	Bare
19	506927	1384561	Forest	89	502749	1385179	Bare
20	507347	1383249	Forest	90	502526	1383417	Bare
21	505527	1383438	Forest	91	503673	1384367	Bare
22	504075	183976	Forest	92	503803	1383647	Bare
23	504476	1382575	Forest	93	504669	1382954	Bare
24	503608	1382002	Forest	94	505473	1383627	Bare
25	501526	1383051	Forest	95	505840	1384656	Bare

26	503502	1388534	Forest	96	505840	1385229	Bare
27	501893	1380391	Forest	97	506578	1386382	Bare
28	499442	1381225	Forest	98	507453	1385377	Bare
29	500668	1378365	Forest	99	506626	1384449	Bare
30	500809	1376715	Forest	100	507099	1383450	Bare
31	500843	1389047	Shrub	101	505251	1383379	Bare
32	500556	1388356	Shrub	102	503803	1383657	Bare
33	501670	1387894	Shrub	103	504140	1382480	Bare
34	501661	1387890	Shrub	104	503537	1381812	Bare
35	501230	1387505	Shrub	105	500984	1385951	Bare
36	501970	1387580	Shrub	106	503336	1380967	Bare
37	501383	1386894	Shrub	107	502443	1380800	Bare
38	503711	1385864	Shrub	108	499909	1381484	Bare
39	502487	1385271	Shrub	109	500768	1378824	Bare
40	502389	1383300	Shrub	110	501635	1376698	Bare
41	50336464	1384118	Shrub	111	500984	1388847	Crop
42	503751	1383391	Shrub	112	500939	1388113	Crop
43	504628	1383063	Shrub	113	500477	1387526	Crop
44	505112	1383869	Shrub	114	501814	1387762	Crop
45	505964	1384538	Shrub	115	501263	1387199	Crop
46	55662	1385111	Shrub	116	502033	1387154	Crop
47	506502	13859031	Shrub	117	501221	1386561	Crop
48	507772	1384804	Shrub	118	503777	1385605	Crop
49	506880	1384680	Shrub	119	502498	1385075	Crop
50	507311	1383503	Shrub	120	502395	1383155	Crop
51	505458	1383455	Shrub	121	503626	1384269	Crop
52	504057	1383757	Shrub	122	5002678	1383725	Crop
53	504228	1382528	Shrub	123	5049976	1382989	Crop
54	503454	1382067	Shrub	124	505077	1383698	Crop
55	501335	1383101	Shrub	125	505869	1384236	Crop
56	502694	1382769	Shrub	126	505644	1385087	Crop

57	501418	1381809	Shrub	127	506602	1386110	Crop
58	503110	1383760	Shrub	128	5076660	1385105	Crop
59	503669	1382142	Shrub	129	506213	1384384	Crop
60	504361	1383168	Shrub	130	507229	1383308	Crop
61	503836	1381008	Shrub	131	505122	1383231	Crop
62	501676	1380917	Shrub	132	503702	1383722	Crop
63	502602	1380508	Shrub	133	504447	1382510	Crop
64	503361	1381678	Shrub	134	503418	1381177	Crop
65	501793	1379950	Shrub	135	501343	1382718	Crop
66	501418	1381842	Shrub	136	503161	1381301	Crop
67	500459	1382484	Shrub	137	502919	1381175	Crop
68	499667	1381292	Shrub	138	500161	13813902	Crop
69	500351	1380350	Shrub	139	501084	1378857	Crop
70	501076	1379916	Shrub	140	501551	1377290	Crop

Appendix 2: Ground Control points for accuracy assessment of image 2024 classifications

CID	Easting	Northing	LULC Type	CID	Easting	Northing	LULC Type
1	500778	1388742	Forest	91	502998	1380618	Bare
2	506501	138581	Forest	92	501580	1381002	Bare
3	505740	1385698	Forest	93	500400	1380618	Bare
4	505515	1384968	Forest	94	501402	1379863	Bare
5	505773	1383303	Forest	95	499506	1378677	Bare
6	504810	1383121	Forest	96	500994	1378172	Bare
7	502280	1382608	Forest	97	501926	1377540	Bare
8	503428	1382697	Forest	98	501300	1376747	Bare
9	503096	1382432	Forest	99	500649	1377034	Bare
10	503679	1381921	Forest	100	501130	1378135	Bare
11	502280	1382574	Forest	101	500805	1389062	Crop

12	502800	1381731	Forest	102	500554	1388215	Crop
13	500888	1381540	Forest	103	501751	1388020	Crop
14	501578	1379859	Forest	104	500685	1387841	Crop
15	500389	1380535	Forest	105	501585	1387860	Crop
16	499401	1379852	Forest	106	501235	1387513	Crop
17	500229	1379930	Forest	107	501984	1387501	Crop
18	501581	1379855	Forest	108	505597	1385629	Crop
19	500031	1379448	Forest	109	506126	1385817	Crop
20	499288	1379006	Forest	110	505707	1385010	Crop
21	501114	1378847	Forest	111	506914	1384959	Crop
22	499578	1378815	Forest	112	507891	1385429	Crop
23	500640	1378464	Forest	113	507707	1384131	Crop
24	501939	1378280	Forest	114	507024	1383381	Crop
25	500045	1377905	Forest	115	505505	1383483	Crop
26	500962	13778003	Forest	116	504192	1384404	Crop
27	502193	1377767	Forest	117	501772	1374488	Crop
28	500796	1376861	Forest	118	503066	1384150	Crop
29	501057	1377608	Forest	119	502728	1383456	Crop
30	501214	1378107	Forest	120	504951	1383296	Crop
31	500461	1387865	Shrub	121	505186	1384462	Crop
32	52210	1387681	Shrub	122	503366	1382209	Crop
33	501536	1387308	Shrub	123	500327	1383166	Crop
34	502571	1386798	Shrub	124	501809	1382622	Crop
35	503489	1387653	Shrub	125	503197	1382218	Crop
36	503046	1385971	Shrub	126	503863	1381055	Crop
37	506577	1386157	Shrub	127	502541	1380886	Crop
38	504953	1384977	Shrub	128	502475	1380099	Crop
39	507958	1385141	Shrub	129	501519	1381449	Crop
40	506101	1384437	Shrub	130	499249	1381187	Crop
41	507583	1383886	Shrub	131	500693	1381327	Crop
42	506403	1383481	Shrub	132	501453	1380653	Crop

43	504455	1383582	Shrub	133	501912	1379911	Crop
44	504903	138294	Shrub	134	499765	1379376	Crop
45	502003	1383946	Shrub	135	500573	1378981	Crop
46	500605	1383225	Shrub	136	502307	1378889	Crop
47	502062	1382207	Shrub	137	502329	1378476	Crop
48	502915	1381924	Shrub	138	500878	1378198	Crop
49	501880	1380636	Shrub	139	499979	1378046	Crop
50	503001	1381278	Shrub	140	500924	1377692	Crop
51	503283	1380585	Shrub	141	502067	1377094	Crop
52	499405	1381236	Shrub	142	501175	13377388	Crop
53	500979	1380553	Shrub	143	500393	1377232	Crop
54	502259	1379923	Shrub	144	500987	1377119	Crop
55	500886	1379849	Shrub	145	501193	1376574	Crop
56	502152	1379545	Shrub	146	500414	1376800	Crop
57	500157	1386163	Shrub	147	501692	1382533	Crop
58	500408	1379694	Shrub	148	501231	1382774	Crop
59	501630	1379497	Shrub	149	502060	1383270	Crop
60	500387	1378712	Shrub	150	501035	1383538	Crop
61	499682	1378296	Shrub	151	500304	1387623	Settlement
62	500630	1378285	Shrub	152	501363	138787	Settlement
63	502131	1379021	Shrub	153	502359	1387051	Settlement
64	499716	1378491	Shrub	154	501002	1386871	Settlement
65	500516	1379008	Shrub	155	505074	1386253	Settlement
66	500077	1377663	Shrub	156	506074	1385522	Settlement
67	501339	1377745	Shrub	157	507115	1384447	Settlement
68	502025	1377530	Shrub	158	503585	1384950	Settlement
69	501033	1376579	Shrub	159	506116	1384230	Settlement
70	501353	1379184	Shrub	160	505140	1383834	Settlement
71	507191	1384847	Bare	161	502401	1383457	Settlement
72	506531	1385760	Bare	162	501150	1382944	Settlement
73	505529	1385864	Bare	163	502814	1382205	Settlement

74	505096	1385190	Bare	164	501406	1381875	Settlement
75	50640	1384437	Bare	165	500581	1382162	Settlement
76	500668	1388659	Bare	166	501415	1381654	Settlement
77	501563	1388108	Bare	167	502093	1381097	Settlement
78	501475	1386891	Bare	168	503301	1381393	Settlement
79	502133	1384858	Bare	169	501241	1381537	Settlement
80	503105	1384258	Bare	170	499768	1381006	Settlement
81	505194	1383302	Bare	171	500440	1379382	Settlement
82	504629	1385810	Bare	172	501405	1379245	Settlement
83	501609	1383513	Bare	173	502136	1379403	Settlement
84	502712	1383017	Bare	174	501398	1378741	Settlement
85	504608	1382769	Bare	175	499923	1378520	Settlement
86	500190	1382497	Bare	176	51529	1378044	Settlement
87	501881	1382352	Bare	177	502095	1377569	Settlement
88	503681	1382396	Bare	178	50073	1376846	Settlement
89	503260	1381605	Bare	179	501364	1376743	Settlement
90	501750	1381503	Bare	180	501672	1376943	Settlement

Appendix 3: The mean annual rainfall and locations of the stations

Station	Easting	Northing	Rainfall 2000	Rainfall 2024
Sekota	502274	1396416	766	632
Tsitsika	477522	1411606	642	802
Amdework	484182	1373028	798	932
Lalibela	505564	1329825	834	872
Maychew	558339	1413092	745	790

BIOGRAPHICAL SKETCH

Birtukan Shege was born in 1998 in Sekota Woreda, located in the Wag Himra Zone of the Amhara Region, Ethiopia. She began her formal education in 2007 at Kafa Elementary School, where she studied from 2007 to 2013. She then continued her secondary education from 2014 to 2017 at Wag Siyum Adimasu Wesen General Secondary School and Sekota Preparatory School in Waghimra Zone. Showing a strong passion for her education; Birtukan joined Wolaita Sodo University in October 2018. After nearly three years of dedicated study, she graduated in August 2021 with a Bachelor of Science (BSc) degree in Natural Resource Management (NaRM).Following her graduation, she began her professional career in September 2022 by joining Wolaita Sodo University as a Graduate Assistant. During her time there, she actively engaged in teaching and academic support services, laying the foundation for her future in academia and environmental research. With a desire to advance her knowledge and make a greater impact in the field of environmental science, she enrolled at Bahir Dar University in October 2023 to pursue her postgraduate studies. She joined the Department of Environment and Climate Change under the College of Agriculture and Environmental Sciences, where she continues to develop her academic and professional expertise**.**