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Modelling the Status of Land Degradation Neutrality, Ecosystem Service Value and Sediment Export of Rib Watershed, Upper Blue Nile Basin, Ethiopia.

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BAHIR DAR UNIVERSITY

FACULTY OF SOCIAL SCIENCES

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By

Melkamu Alebachew Anley

July 2024

Bahir Dar, Ethiopia

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Modelling the Status of Land Degradation Neutrality, Ecosystem Service Value and Sediment Export of Rib Watershed, Upper Blue Nile Basin, Ethiopia.

A Dissertation Submitted to

The Department of Geography and Environmental Studies, Faculty of Social Sciences, Bahir Dar University in Partial Fulfillment of the Requirement for the Degree of Doctor of Philosophy in Geography and Environmental Studies (Specialization in Environment and Natural Resource Management)

Melkamu Alebachew Anley

Advisor:

Amare Sewnet Minale (professor, PhD)

July 2024

Bahir Dar, Ethiopia

Declaration

I hereby declare that this Ph.D. dissertation entitled "Modelling the Status of Land Degradation Neutrality, Ecosystem Service Value and Sediment Export of Rib Watershed, Upper Blue Nile Basin, Ethiopia." is my work and has not been submitted to any other university for the award of any degree. Moreover, all the sources used in the study are properly acknowledged and cited.

Melkamu Alebachew ___________ 07/05/2024

BAHIR DAR UNIVERSITY

FACULTY OF SOCIAL SCIENSES

DISSERTATION APPROVAL

DEPARTMENT OF GEOGRAPHY AND ENVIRONMENTAL STUDIES

Approval of Dissertation for Defense

I hereby certify that, I have supervised, read and evaluated this dissertation entitled **“Modelling the Status of Land Degradation Neutrality, Ecosystem Service Value and Sediment Export of Rib Watershed, Upper Blue Nile Basin, Ethiopia.**” by Melkamu Alebachew prepared under my guidance. I recommend the dissertation can be submitted for oral defense.

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ABSTRACT

This study was targeted on Modelling the Status of Land Degradation Neutrality, Ecosystem Service Value and Sediment Export of Rib Watershed, Upper Blue Nile Basin, Ethiopia. between 2000 and 2020 years. The study employed, primary and secondary data including satellite images, soil maps, climatic data, and soil samples. The status of Land Degradation Neutrality (LDN) was assessed by integrating the three indicators (Land use land cover, Net primary product, and Soil organic carbon) and by employing one out all out framework. Images including Landsat 5 TM for 2000 and 2010, and Landsat 8 OLI_TIRS for 2020 years were classified by using supervised classification technique with a Maximum Likelihood Algorithm (MLA) in ERDAS Imagine 2014. The results showed that there was a net loss in cultivated land (123,977 ha), forest land (5623 ha), shrub lands (13984 ha), grass land (11,999 ha), water bodies (1056 ha) and settlement (1993 ha) from 2000 to 2020. The LDN status in the Rib River Watershed was in a net loss condition for the past two decades. The study also estimated the changes in ESVs and sediment export using the modified ecosystem service value coefficients and the Integrated Valuation of Ecosystem Services Tradeoff (InVEST) model respectively. The total ESVs of the watershed were estimated to be US$ 68.6 million in 2000, US$ 59.4 million in 2010, and US$ 59.3 million in 2020. The ESVs lost between the 2000 and 2020 years in the study watershed were approximately US$ 9.3 million (13.5%). Similarly, the sediment export increased from 6.54 t/ha/year to 11.05 t/ha/year in 2000 and 2020, respectively, and the average soil loss raised from 22.37 t/ha/year in 2000 to 33.38 t/ha/year in 2020. The highest rate of soil erosion was observed on cultivated land, which was increased from 40.86 t/ha/year in 2000 to 53.90 t/ha/year in 2020. The soil loss and sediment export rates in sub-watersheds three (SW-3) and five (SW-5) were the highest, accordingly 61.80 and 18.75 t/ha/year for SW-3 and 63.48 and 19.35 t/ha/year for SW-5. The least amount of soil loss occurs in sub-watershed twelve (SW-12) (2.56 t/ha/year). This is because SW-12 is situated in the lower parts of the watershed that experience less erosion. The result concluded that land managers and policymakers can use the status of LDN, ESVs, and sediment export together during decision-making processes.

Keywords: Ecosystem services, In-VEST model, Land Degradation Neutrality, Land use/land cover, Sediment export, Soil loss.

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ABBREVIATION AND ACRONYM

1OAO	One out All out
BD	Bulk Density
CS	Coefficient of Sensitivity
DEM	Digital Elevation Model
EMOWE	Ethiopia Ministry of Water and Energy
ESV	Ecosystem Service Values
GCPs	Ground Control Points
GIS	Geographic Information System
GPS	Global Positioning System
IDW	Inverse Distance Weighted Interpolation
ISRIC	International Soil Reference Information Center
InVEST	Integrated Valuation of Ecosystem Services Tradeoff
LDN	Land Degradation Neutrality
LPD	Land Productivity Dynamics
LULC	land Use/Land Cover
MODIS	Moderate Resolution Imaging Spectroradiometer
NDVI	Normalized Difference Vegetation Index
NPP	Net Primary Production
PBIAS	Percentage Bias Error
RRMSE	Residual Root Mean Square
RUSLE	Revised Universal Soil Loss Equation
SDG	Sustainable Development Goals
SDR	Sediment Delivery Ratio
SLM	Sustainable Land Management
SLSE	Soil Loss and Sediment Export
SLT	Soil Loss Tolerance
SOC	Soil Organic Carbon
TEEB	The Economics of Ecosystems and Biodiversity
USGS	US Geological Survey
USLE	Universal Soil Loss Equation

CHAPTER ONE

1. INTRODUCTION

1.1 Background of the Study

Land degradation (LD) is a critical environmental problem that negatively affects biodiversity, ecosystem services, and the lives of millions of people in the world by aggravating poverty (Susilowati & Syekhfani, 2015; Gashu & Muchie, 2018). Some studies on LD and influencing factors have been carried out in various areas (Malav et al., 2022). Globally annual land degradation cost is about USD 40 billion and it will remain an important issue for the 21st century due to its negative effects on natural resources (Adnan 2020; Megerssa and Bekere 2019). Therefore, halting land degradation is a prerequisite for sustainable development. Due to this reason, recently, the United Nations General Assembly introduced a new paradigm shift to tackle LD. The new concept is known as "Land Degradation Neutrality" (LDN), which is part of the Sustainable Development Goals (SDG) target15 article 3 (15.3). LDN refers to "a state whereby the amount and quality of land resources necessary to support ecosystem functions and services and enhance food security remain stable or increase within specified temporal and spatial scales"(Sciortino et al. 2020; Feng et al. 2022). Therefore, the ultimate objective of LDN is to avoid, reduce, and reverse land degradation and achieve a healthy, productive state of land resources without net loss.

The LDN is estimated by applying a conceptual and methodological scientific framework developed by the Convention to Combat Desertification (UNCCD) (Gonzalez-Roglich et al. 2019; Liniger et al. 2019). In this framework, the LD assessment employs integrating the three indicators including land cover (LC), Land Productivity Dynamics (LPD), and soil organic carbon (SOC) using a "one out all out (1OAO)" principle, where the degradation of any indicator means the degradation of LDN (Kapovi et al., 2018; Gichenje & Godinho, 2019; Sims et al., 2020). The research conducted by Kiani-Harchegani and Sadeghi (2020) looked into the LDN status of the Shazand watershed, in Iran. The study used satellite images, MODIS NPP, and soil samples for the assessment of the three sub-indicators of LDN from 2000 to 2016. The result of the combination of the study metrics showed that the LDN status of the watershed was in a net loss situation. The determination of the indicators serves as a basis for establishing the current state of the land, knowing the changes and trends over time, and monitoring the progress of degradation (Cowie et al., 2018; Erşahin, 2020).

The rural community in different parts of the world has changed the natural environment to obtain food, fresh water, medical products, and other essential materials for their survival. The amount and rate of human alterations of the land surface increased at an increasing rate over the last two centuries and accelerated over the last two decades (Egarter Vigl et al., 2017; Karki et al., 2018). Changes in land use land cover (LULC) have become an international concern due to their diverse environmental impacts (Minta et al., 2018; Bekele, 2019). Globally, expansions of cropland and grazing land at the cost of a forest, natural grassland, and savannas were observed between 1700-1990 (Lambin, Geist, and Lepers 2003). However, the direction of the LULC changes was not constant in all regions of the world. For example, in temperate regions, forests increased at the rate of 3×10^6 ha^{-1} yr^{-1} while in tropical regions it decreased at the rate of 12×10^6 ha^{-1} yr^{-1} (Mooney, 2005).

The primary environmental concern in Ethiopia is also LULC changes that favor the expansion of cultivated land at the expense of forest areas (Meshesha et al., 2016; Belay and Mengistu, 2019). Accordingly, the annual rate of deforestation in Ethiopia between 1990-2010 was at a rate of 1.4×10^5 ha^{-1} yr^{-1} (Nyssen et al., 2009). The primary factors that led to the notable LULC alterations in Ethiopia's highlands were early settlement and population pressure (Tewabe and Tolessa et al., 2017; Fentahun, 2020). However, the growth of the agricultural sector is not keeping up with rapid population growth (CSA, 2013; Getu et al., 2022). Such a dynamic tension between the increasing population and agricultural productivity has forced the continued expansion of cultivated land into increasingly steeply sloping landscapes under natural habitats (Nyssen et al., 2009; Haregeweyn, et al., 2017). LULC changes and evidence from the local communities affirm widespread deforestation from the highlands in search of new cultivated and grazing lands.

Changes in LULC are also the primary factors that drastically changed ecosystem services (Groot et al., 2012; Gashaw et al., 2018; Xuan & Rao, 2023). For example, the total worldwide Ecosystem Service Values (ESV) decreased due to LULC alteration from US$145 trillion to US$125 trillion in 2007 and 2011 respectively (Costanza et al. 2014). The continued degradation of ecosystems comes in many countries of Africa at the expense of the livelihood of future generations (Groot et al. 2012; Kubiszewski et al. 2017). The value of numerous ecosystem services in Ethiopia has decreased as a result of LULC change, as reported in Munessa-Shashemene landscape between 1986 and 2012 (Kindu et al. 2016), Afar region between 1972 and 2007 (Tsegaye et al., 2010) Chillimo forest between 1986 and 2015 periods (Tolessa et al, 2017) and Andasa watershed between 1985 and 2045 (Gashaw et al. 2018).

LULC changes also have an impact on the rate of soil erosion (Yesuph & Dagnew, 2019; Moisa, 2021; Bekele et al., 2022) and sediment yield (Haregeweyn et al., 2011; Shi et al., 2014; Tesema & Leta, 2020). For instance, the expansion of cultivated land and vegetation cover losses in the Megech watershed of Ethiopia between 2000 to 2020 (Getu et al. 2022), Three Gorge area in Chania between 1995-2005 (Shi et al. 2012) periods increased the rate of soil erosion. The conversion of vegetation cover into agriculture and grasslands over large areas of the Upper Blue Nile basin has also caused an increase of sediment yield by 147 x 10^6 t yr^{-1} between the years 1993-2009 (Gebremicael et al. 2013). Similarly, Gashaw et al., (2018) described the situation in the same basin as the expansion of cultivated land in the Andasa watershed contributed to the increased rate of sedimentation problems into the downstream part of the watershed.

1.2 Statement of the Problem

Land degradation has been becoming one of the most serious environmental problems, getting attention from both governments and global researchers. Land degradation involves multiple forms of environmental problems, requiring interdisciplinary and multidimensional investigation. Reversing land degradation is therefore a prerequisite for sustainable development. Due to this reason land degradation neutrality (LDN) was officially launched in 2017 as a standard quantitative method for determining degradation states in the framework of three sub-indicators viz. land cover, land productivity, and carbon storage (Cowie et al. 2018; Gichenje and Godinho 2019; Liniger et al. 2019). For instance, in the Shazad watershed, the result of the combination of the three metrics showed that the LDN status of the watershed was in a net loss situation between 2000 to 2016 years (Kiani-Harchegani and Sadeghi 2020). Therefore, the status of land degradation neutrality is imperative and such type of study was not conducted in the study Rib River watershed.

Ecosystem services are the direct and indirect contributions of ecosystems to human wellbeing and survival. Quantifying and analyzing changes in ecosystem service values (ESVs) are important tools to raise awareness, and formulate polices. As a result, interest in ecosystem service values has evolved rapidly in both the scientific communities and policy. The provision of ecosystem services is directly correlated to the situation of ecosystems, e.g., land use/land cover (LULC) types, in a given area. The dynamics of LULC can cause changes in the values of ecosystem services. As changes in ESVs differ depending on the direction, and/or magnitude of the LULC dynamics, most of the available studies were location-specific. For instance, Leh et al. (2013) revealed a general decline in ESVs while Wang et al. (2015) found the opposite, i.e. an increasing trend. Consequently, generalizing the results to other areas might lead to erroneous conclusions.

The study watershed indicated that the watershed has been experiencing human-induced land degradation due to LULC changes. Therefore, understanding the impacts of LULC changes on ecosystem service, soil erosion, and sediment export in this watershed is very important not only for watershed management planning measures and restoring the degraded watershed but also for preventing siltation of the Rib reservoirs. Despite this, in the study watershed, there are only a few studies that focused on quantifying the effects of LULC changes on soil erosion (Moges & Bhat, 2017; Teshome et al., 2020; Sinshaw et al., 2021) and sediment yield (Tsegaye & Bharti, 2021) but no research was done on the value of ecosystem services. As a result, investigating the impacts of LULC changes on ecosystem services in the study watershed is also indispensable to raising public awareness and indicating policy directions regarding the loss/gain in ecosystem services.

There are considerable scientific challenges in facilitating sustainable development while safeguarding natural resource degradation in most parts of Ethiopia highlands. Rapid LULC changes are fundamental environmental problems in Ethiopia. Mostly, in the highlands, there has been a continuous expansion of cultivation toward naturally vegetated and marginal landscapes. Several studies were carried out on the changed in LULC in Ethiopia (Tadesse et al., 2017; Guzha et al., 2018; Assfaw, 2020), soil erosion (Amsalu and Mengaw 2014; Meshesha et al. 2016; Molla and Sisheber 2017) and sediment yield (Degife et al., 2021; Gashaw, et al., 2021). The study watershed contributes a significant volume of water to Lake Tana. As a result, soil loss and sediment export are serious problems that affect the socioeconomic activity of farming communities. Therefore, this study was intended to fill the gaps taking the Rib River watershed as the case from 2000 up to 2020 in North West, Ethiopia.

1.3 Objectives

1.3.1 General Objective

The general objective of the study was to Modelling the Status of Land Degradation Neutrality, Ecosystem Service Value and Sediment Export of Rib Watershed, Upper Blue Nile Basin, Ethiopia.

1.3.2 Specific Objectives

- Examine the status of land degradation neutrality (LDN) in the Rib River watershed, North West, Ethiopia.
- Assess the impact of land use land cover change on ecosystem service values in River Rib watershed, North West, Ethiopia.
- Model the impact of Land use land cover change on the estimation of soil loss and sediment export using InVEST Model at the Rib River watershed of North West, Ethiopia.

1.3.3 Research Question

- How is examine the status of land degradation neutrality in the study, Rib River watershed.
- What is the impact of land use land cover change on the ecosystem service value of the study area?
- How is the change of soil loss and sediment export in response to land use land cover change in the Rib River watershed be modeled?

1.4 Empirical Evidences, Models and Framework of the Study

1.4.1 Land Degradation Neutrality Concepts

Land degradation (LD) is a serious environmental problem that harmfully affects ecosystem services, biodiversity, and the lives of millions of people in the world by promoting poverty. It can also be used to describe how sophisticated rain-fed farmland, irrigated cropland, or rangelands, grasslands, forests, and woodlands have become and how their biological or economic productivity has declined (Reith et al. 2021; Susilowati and Syekhfani 2015). However, due to the complexity and variety of the biophysical and socioeconomic factors that affect land resources, it is challenging to identify this phenomenon (Meseret, 2016; Lu et al., 2022). By integrating information about ecosystems and the mechanisms that produce degradation, numerous research have evaluated the phenomenon of LD at the international as well as national level. Due to the complexity, variety, and quantity of indicators employed in the research carried out during the past 30 years, the evidence is not similar throughout regions (Gashu and Muchie 2018; Lu et al. 2022). Furthermore, data was scarce, and the cost of repeatability and implementation of techniques makes them rarely practical at more local and regional scales (del Barrio et al., 2021; Malav et al., 2022).

Land degradation involves multiple forms of environmental problems, requiring interdisciplinary and multidimensional investigation. Reversing land degradation is therefore a prerequisite for sustainable development. The LD is rapidly creating a problem. This calls UNCCD to launch the LDN concept as one of the SDG. The notion of "Land Degradation Neutrality" (LDN), which is a component of one of the Sustainable Development Goals (SDG), target 15 article 3 (15.3), was recently introduced by the United Nations General Assembly as a novel approach to tackling land degradation (LD). A state in which the quantity and quality of land resources required to maintain ecosystem functions and services and enhance food security within particular temporal and spatial scales and ecosystems is referred to as LDN." and serves as a measurement of SDG 15.3 (Cowie et al. 2018). To reach a healthy, productive state for land resources with no net loss, land degradation must therefore be avoided, reduced, and reversed.

The LDN can assessed by using a methodological and conceptual scientific framework accompanied by the Convention to Combat Desertification (UNCCD) (Gonzalez-Roglich et al. 2019; Liniger et al. 2019). In this framework, using the "one out of all out (1OAO)" approach, the three indicators, such as Land Cover (LC), Land Productivity Dynamics (LPD), and Soil Organic Carbon (SOC) are combined in the assessment of LD. However, the decline of any indicator corresponds to the degradation of LDN. The choice of indicators provides a foundation for assessing the current state of the land, understanding changes and trends through time, monitoring the rate of degradation, and calculating the proportion of degraded land. (Cowie et al., 2018; Erşahin, 2020). In addition, UNCCD offers a global dataset to identify patterns of land degradation neutrality in a particular geographic area.

Some studies on LD and inducing factors have been performed in various areas (Gashu & Muchie, 2018; del Barrio et al., 2021). Yet, past research suggested that the LDN concept had only lately been introduced and taken into account. LDN was initially studied in dry areas by (Grainger 2015). They emphasized that the significance of researching LD in dry regions and meeting objectives for sustainable development goals. (Minelli et al. 2018) offered a basic outline of important worldwide decisions that contributed to the formation of the LDN conception in addition to explaining how to measure, monitor, and assess LDN. (Safriel 2017) studied on LDN has been designed with a focus on semi-arid areas, to neutralize LD and restore degraded lands following the UNCCD to accomplish the SDGs.

The finding of Dengiz, (2018) explored the possible impacts of land use changes on the dynamics of land productivity in semi-humid parts of the Gediz Watershed over 14 years (2001-2014) with a focus on the LDN concept. He used data from Landsat satellite images to detect changes in land use and cover. He collected 319 soil samples from all around the study catchment to evaluate SOC. The results showed that the watershed's total land productivity has dropped by 23%. (Kiani-Harchegani and Sadeghi 2020) looked into the LDN status of the Shazand watershed, in Iran. They used satellite images, MODIS NPP, and Soil samples for the assessment of the three sub-indicators of LDN from 2000 to 2016. The result of the combination of the study indicators showed that the status of LDN in the watershed was in a net loss situation. In Ethiopia context, the idea of LDN is not researched by scholars. For instance, in the study Rib watershed, no one is doing research on the assessment of LDN.

1.4.2 Indicators of Land Degradation Neutrality

1.4.2.1 Land Use Land Cover Change as Indicator of LDN

Land use and land cover change is one of the indicators of land degradation neutrality. Humankind activities have been modifying the natural environment to obtain food, fiber, fresh water, medical products, and other essential materials. The extent and pace of human alterations of the land surface increased rapidly over the last three centuries and accelerated over the last three decades (Degife et al. 2019; Venter et al. 2022). Changes in land use (human purpose or intent applied to biophysical attributes of the earth's surface) and land cover (biophysical attributes of the earth's surface) are key forms of human impacts on the natural environment driven by multiple interacting factors including demographic, social, economic, political, economic, technological and institutional variables (Hassen & Assen, 2017; Nelson & Geoghegan, 2002). The driving factors thereby LULC change vary in time and space depending on the specific human-environment conditions. Land use and land cover change is generally a concern due to its pervasive effects on loss of biodiversity, resource degradation, and a reduced ability of the landscape to sustain natural resources and ecosystem services.

In the past few decades, significant LULC change has been taking place in the Ethiopia highlands above 1500 m.a.s.l. However, the impact of LULC on land degradation neutrality was not investigated in detail. Several studies pointed out that deforestation and expansion of cultivated land into marginal areas are the principal forms of LULC change in most upland areas of the country (Kidane et al., 2019; Negese, 2021). Despite some authors (Zeleke and Hurni 2001) are skeptical about 40% forest cover of the Ethiopian landscape in 1900 and estimates of forest cover are inconsistent. Several research reports dealing with LULC changes and evidence from the local communities affirm widespread deforestation from the highlands in search of new cultivated and grazing lands.

In Ethiopia, numerous studies on LULC changes have been conducted and witnessed the massive LULC conversion (Birhanu et al. 2019; Moges and Bhat 2018). These studies indicated that the direction, pattern, and magnitude of LULC changes are heterogeneous across Ethiopia. For instance, Birhanu et al.(2019) in the Ethiopia highlands; Abebe et al. (2021) in the Gubalafito district, Northeastern Ethiopia; Abebe et al. (2021) in Gelda catchment, Lake Tana watershed, Ethiopia; Tadesse et al. (2017) in the Yezat Watershed, and Mariye et al. (2022) in the Ojoje watershed, reported a considerable expansion of cultivated land at the cost of forest, grassland and shrubland. Minta et al. (2018) also reported a decline in the forest land, bushland, and grassland, whereas cultivated land and bare lands have increased in the Dendi-Jeldu hilly-mountainous areas in the central Ethiopian highlands from 1957 to 2014.

Many studies in the different parts of the country are required for a profound understanding of the dynamics in the human-environment interactions at different spatial and temporal scales (Johansen et al. 2015; Shebelle 2020). This would be useful to make better "generalities" on patterns of LULC change and likely impacts on ecosystem functioning in Ethiopia. The study area, the Rib River watershed, is characterized by its high human and livestock population and cereal production, which is prone to land degradation, deforestation, and high erosion (Moges and Bhat 2018). Therefore, knowledge of the dynamics of LULC conversion, on land degradation neutrality is necessary to build appropriate environmental protection and land management approaches for the entire watershed.

1.4.2.2 Net Primary Product as Indicator of LDN

Land degradation is one of the most serious ecological and environmental problems affecting most countries on Earth. Sustainable development goals (SDGs) were implemented in January 2016 (Reith et al. 2021). SDG target 15.3 was proposed to combat desertification, restore degraded land and soil, including land affected by desertification, drought, and floods, and strive to achieve a land degradation-neutral world by 2030. An increased number of countries have begun to monitor indicator 15.3.1, i.e. the "proportion of land that is degraded over the total land area," to achieve SDG target 15.3 in 2030 (Lu et al. 2022). Thus, evaluating SDG 15.3.1 at the global scale has become an important recent focus.

Land productivity reflects the efficiency of solar energy conversion and land fixation, driven by plant photosynthesis that forms terrestrial vegetation cover. It can be quantified in terms of the net primary production (NPP). All other organisms (e.g. humans, other species of animals, bacteria, and fungi) depend directly and indirectly on this primary production for their health and well-being. Globally, humans appropriate a constantly increasing proportion of this NPP, affecting the structure and functioning of ecosystems; in many cases, this proportion exceeds the natural variability and dynamics of the ecosystems. Therefore, land productivity is an essential variable for detecting and monitoring active land transformations typically associated with land degradation processes. Trends in land productivity have thus been adopted by the United Nations Convention to Combat Desertification (UNCCD) as one of three biophysical progress indicators (Ryan et al., 2013; Gashu & Muchie, 2018). Trends in land productivity have been proposed as a sub-indicator for the global indicator to monitor progress toward achieving SDG target 15.3 for land degradation neutrality (LDN) (Dessie & Kleman, 2007; del Barrio et al., 2021).

Global land productivity monitoring currently relies on multi-temporal evaluations of long-term remotely sensed vegetation index time series computed from continuous spectral measurements of photosynthetic activity. The normalized difference vegetation index (NDVI) is the most commonly used vegetation index; other indices have been proposed and used for different scales, such as the enhanced vegetation index (EVI), leaf area index (LAI), and net primary productivity (NPP) (Sciortino et al., 2020; Xuan & Rao, 2023). These indices reflect different vegetation characteristics and have been reported to perform better than other indices under specific vegetation conditions (Peng et al. 2017; Yaekob et al. 2022); however, there is no consensus on the selection of appropriate indicators.

Retrieving meaningful metrics based on time series vegetation indices is another challenge for land degradation assessments owing to observations of highly variable land productivity between different years or vegetation growth cycles, even under stable conditions. The Joint Research Centre (JRC) developed a land productivity dynamics (LPD) dataset for land degradation and improvement assessments, which was adopted by the third edition of the World Atlas of Desertification (WAD3) and the UNCCD LDN Target Setting Program (Gonzalez-Roglich et al. 2019; Tsymbarovich et al. 2020). This LPD dataset defines five classes by combining three metrics, i.e. trends, states, and performance, based on the SPOT NDVI from 1999 to 2013. Here, trends reflect the significance of the magnitude and persistence of changes in land productivity over time, states compare the current productivity levels with the historical productivity levels for the same region, and performance compares the local productivity levels with the productivity levels for similar land units at a national scale. Although the state and performance metrics provide new important insights into land degradation, their effective determination faces many technical challenges. Therefore, the LPD class mainly depends on the objective trend metric in a real assessment (Cui and Li 2022).

1.4.2.3 Soil Organic Carbon as Indicator of LDN

The Ethiopia Highlands of the upper Blue Nile Basin support an extensive population of smallholder farmers who strongly rely on natural resources for their livelihood. However, the Blue Nile Basin is facing serious challenges of agricultural land degradation and loss of natural resources, contributing to low agricultural productivity (Yu and Song 2023), emissions of greenhouse gases, carbon dioxide (CO_2), and methane (CH_4) (Amanuel, Yimer, and Karltun 2018). Efforts have been made by different agencies to reduce this degradation, but success over the past decades has been limited. One reason for this is the lack of understanding of the long-term impacts of land use and management on soil and specifically organic carbon (SOC) dynamics.

Soil quality determines the capacity of the soil within a given ecosystem to sustain biological productivity, maintain environmental quality, and promote plant and animal health (Amanuel et al., 2018a; Yu & Song, 2023). Soil organic carbon (C) is one of the most important indicators of soil quality because it impacts key soil properties and shows a strong response to land use, land-use change, and land degradation (Winkler et al., 2019; Beatriz et al., 2020). The dynamics in SOC are reflected in soil fertility, nutrient supply, porosity, and erosion (Abegaz et al. 2016; Husein et al. 2019).

Soils represent an important terrestrial stock of carbon (C), and the SOC of agricultural lands comprises the main pool of terrestrial C (Kapovi et al. 2020; Yu and Song 2023). Therefore, small proportional changes in the SOC stock can strongly influence greenhouse gas concentrations in the atmosphere and have a high impact on global climate change (Cui & Li, 2022; Yu & Song, 2023). Soil also has the potential to be a major sink of C and it has been estimated that 89% of the greenhouse gas mitigation potential of agriculture relies on C sequestration (Feng et al. 2022).

The stock of SOC is influenced by soil characteristics (for example texture, pH, and drainage conditions), environmental factors (for example parent material, climate, vegetation, topographic position, and time), and human activities (for example land management and land-use change) (Emde et al. 2021; Prout et al. 2022). Soil characteristics and environmental factors have a long-term impact on the dynamics of SOC, while human activities can have a more immediate impact (X. Liu et al., 1994). Therefore, there is a growing interest in regulating land management and land-use strategies to increase SOC sequestration or reduce greenhouse gas emissions (Zeraatpishe & Khormali, 2012; Malla et al., 2022). Sequestration of SOC can be increased, for example, by adding a larger fraction of the produced biomass to the soil, or by increasing primary production in land-use systems (Zeraatpishe & Khormali, 2012; Malla et al., 2022). Furthermore, stored SOC can be managed using adaptation strategies that reduce soil erosion, conserve soil moisture, and diversify crop rotations (Martin et al. 2022). Increasing and managing SOC content improves the biophysical quality of the soil, providing further benefits in adaptation to climate change (Martin et al. 2022).

Many authors have estimated the total amount of C sequestered in the soils at a global scale and comprehensive data on C sequestration potential have been compiled at a global level under several climate regimes (Zeraatpishe and Khormali 2012). However, no localized land-use-based data is available within the upper Blue Nile Basin of the Ethiopian Highlands. Methodological tools for the evaluation of the consequences of different land use and changes in SOC at the country or regional level for varying land-use categories have been developed by the (Janusuary and Actaseion 2020), but it is widely accepted that such methodological tools are too general to provide localized information on the changes in management practices needed to increase SOC stocks (Abegaz et al., 2016; Amanuel et al., 2018).

Many of the earlier studies of land degradation in the Highlands of Ethiopia have assessed the land degradation that results from soil erosion (Akale et al., 2017; Assfaw, 2020). These studies did not explore temporal dynamics, providing only a snapshot of the current situation, and so may not support policy formulation for long-term sustainable management (Tripathi & Panda, 2010). More recent studies in the Highlands of Ethiopia have focused on the dynamics of SOC (Buruso 2020). By mapping land degradation prevalence, soil functional properties, and SOC stocks were assessed the spatial variability of SOC did not determine the long-term dynamics of SOC concerning different land uses. (Prout et al. 2022) suggest that exclosures used to reduce/eliminate grazing pressures are effective in restoring degraded lands and can potentially improve local communities' livelihoods beyond the rehabilitation of degraded lands if C stored in enclosures is traded. The study by (Martin et al. 2022) used a summary model to explore the effects of different farm management practices on the long-term dynamics of soil C on cultivated soils.

1.4.3 Ecosystem Services

The benefits that people derive from the ecosystem are known as ecosystem services (Walter V Reid 2005). The services differ according to the type of ecosystem and its status (Tolessa, Senbeta, and Kidane 2016), and each ecosystem offers different services that cannot be substituted by others. For example, the forest ecosystem supplies a different service from aquatic ecosystems (Cover, 2020; Crespin & Simonetti, 2016). In addition, dense forests do not provide similar ecosystem services to that of degraded forests. The ecosystem services provided by a certain environment such as provisioning, regulating, supporting, and cultural services are essential for several key components of human well-being, such as personal security, basic materials needed for a good life, health, freedom, and choice, and good social relations (Deng et al., 2013; Ryan et al., 2013).

The value of ecosystem services has considerably declined over time and space, despite the immense contribution they provide to the sustainability of human well-being and survival as well as the functioning of the environment (Sutton et al., 2016; Yang & Lu, 2018; Schirpke et al., 2019). For example, the total global ESV in 2007 was $US145 trillion, however, it dropped to $US125 trillion in 2011 (Costanza et al. 2014). In terms of exposure to see the changes in the specific sites, the total ESV has reduced in Sanjiang Plain (China) between 1980-2000 (Wang et al. 2015), Menglun (China) between 1988-2006 (Hu et al. 2008), Zoige plateau (China) between 1980-2005 (Li et al. 2010) and Northern Thailand (Arunyawat and Shrestha 2016). In Ethiopia, studies were carried out in the central highlands of Ethiopia such as in the Munessa-Shashemene landscape (Kindu et al. 2016), Toke Kutaye District (Tolessa et al. 2016), and Chillimo forest (Tolessa et al., 2017) were shown reductions in the total ESV between 1986-2012, 1984-2014 and 1986- 2015 periods, respectively. It was also estimated that land degradation has lost about 17.7% of the country's total terrestrial ESV (Sutton et al. 2016).

The critical dependency of society on ecosystem services has been described by scientists (Yang & Lu, 2018; Shiferaw et al., 2021). Ecosystem services are the direct and indirect contributions of ecosystems to human well-being and survival (Hu et al., 2008; Costanza et al., 2014). The ecosystem services include not only provisioning (e.g. food production, raw material, and water supply), but also regulating (e.g. climate regulation, water purification, and disturbance regulation), supporting (e.g. nutrient cycling, pollination, and soil formation) and cultural services (e.g. aesthetic values) (Walter V Reid 2005). Because of their significance to society, these ecosystem services as well as their economic values have become focuses of interest over the last decade (Adem et al., 2020; Collins et al., 2020) and among one of the popular issues in ecological economics.

The change in LULC can cause changes in the values of ecosystem services (Paula et al., 2015; Balvanera et al., 2016; Temesgen et al., 2018). It may increase the provision of some services while decreasing others that affect the ability of biological systems to support human needs, indicating ecological degradation (Braat and Groot 2012), or vice versa. As changes in ESVs differ depending on the direction and/or magnitude of the LULC dynamics, most of the available studies were location-specific. For instance, Leh et al. (2013) revealed a general decline in ESVs while Wang et al. (2015) found the opposite, i.e. an increasing trend. Consequently, making direct use of such results in other areas might lead to erroneous conclusions. Nevertheless, because of population growth, economic pressure, and urban growth, many natural ecosystems are continuously been altered, destroyed, or transformed, especially during the last decades (Deng et al., 2019; Dube et al., 2019). Such ecosystem degradation threatened a continued supply of ecosystem services, while, at the same time, the demand for ecosystem services is increasing with human population growth (Tekle & Hedlund, 2000; Fedele et al., 2017). Globally, the Millennium Ecosystem Assessment found that over 60% of ecosystem services, such as wood, fresh water, air and water purification, and the regulation of local and regional natural hazards are being degraded in an unsustainable manner (Walter V Reid 2005).

One of the most important and quickly developing fields of study in environmental and ecological economics is the quantification of ESVs and analysis of their changes after the publication of (Costanza et al. 2014), who proposed a list of ecosystem service value coefficients of biomes (LULC types) based on the synthesis of past studies and estimates of global ESVs. Although the proposed global value coefficients have been criticized because of uncertainties (Gandhi et al., 2015; Fedele et al., 2017), many research was done in regions where data are scarce have used them through the benefit transfer method and paved the path to the science of ecosystem service valuation (Li et al., 2010; Wang et al., 2015; Lu et al., 2022). The benefit transfer approach, which is used when there is a lack of site-specific valuation information, involves estimating ESVs of other similar locations using existing values and other information from the original study site (Paula et al., 2015; Fu et al., 2020).

The growing body of literature on the valuation of ecosystem services includes studies on changes in ESVs (Kreuter et al. 2001), analyses of the effect of spatial scales on the valuation of ecosystem services (Hao et al. 2012), land use planning based on ecosystem service assessment (Paula et al. 2015), quantifying and mapping of multiple ecosystem service changes (Leh et al. 2013), bringing ecosystem services into economic decision making (Fu et al. 2020), and assessment of values of ecosystem services in nature reserve (Wang et al. 2015). Even though there have been many case studies on ESVs, not enough of them have focused on how ESVs evolve in response to LULC changes or how to increase the local validity of the available coefficients when estimating ESVs. Little attention has also been focused on the spatial visualization and mapping results of ESVs and their changes (Groot et al., 2012; Jacobs et al., 2016). When estimating and describing the values with statistical data, the majority of earlier economic valuations were non-spatial (J. Liu et al., 2007; Hu et al., 2008).

In recent years, remote sensing and GIS technologies were commonly applied in most of the studies during the spatially explicit ecosystem service estimation processes. The former offers opportunities to generate LULC types for a given area that can be utilized as proxies of measurements while the latter is used for estimating and mapping their distributions (Chen et al., 2020; Fu et al., 2020). Ecosystems and their services are spatially explicit, and this makes GIS very appropriate for the analyses. As primary datasets are costly, or sometimes scarce in some regions, secondary data consisting of spatial units, such as LULC classes, are also more often used as proxies for estimation (Kreuter et al. 2001; Wang et al. 2015). In addition, for the corresponding value coefficients, the Economics of Ecosystems and Biodiversity (TEEB) valuation database was also developed, mainly, based on the literature of case studies in different parts of the globe (Groot et al., 2012; Fedele et al., 2017). Thus, the ecosystem service value coefficients established by Costanza et al. (1997) for 16 biomes were employed in various studies to determine ESV for LULC categories However, this model is criticized due to its uncertainties and limited use at the local level.

1.4.3.1 Ecosystem Service Valuation Model

The ecosystem service valuation model was established by Costanza et al. (1997) for 16 biomes, and it was applied in various studies to decide ESV for LULC categories (Kreuter et al. 2001; Lu et al. 2022). However, this model is criticized due to its uncertainties and limited use at the local level (Braat & Groot, 2012; Wang et al., 2015; Kindu et al., 2016). Consequently, the values of ecosystem coefficients have been modified for 11 biomes and the modification was carried out based on the previous estimation by Groot et al. (2012) through a benefit transfer method, which refers to the process of using existing values and other information from the original study site to estimate ESV of other similar location in the absence of site-specific valuation method. However, the modified estimates given by Groot et al. (2012) are very general and, because of the scale effect, it did not clearly represent the context of a certain region.

Further estimation of global ecosystems was carried out by Groot et al. (2012) and Costanza et al. (2014). However, their estimates were also criticized because it overestimated some ecosystem services (Tolessa et al. 2016), and by any means, it did not actually represent a particular region. As a result, modifications of the ecosystem coefficients to a particular country were done. Previously, a modification was made in China using expert knowledge-based valuation methods (Ling-xing et al. 2019). Similarly, more conservative estimation coefficients for Ethiopia were developed by Kindu et al. (2016) for 11 biomes using expert knowledge of the study landscape conditions and other studies, mainly from the Economics of Ecosystems and Biodiversity (TEEB) valuation database (Costanza et al. 1997; Groot et al. 2012).

1.4.4 Soil Loss and Sediment Export

1.4.4.1 Soil Loss

Soil erosion is a two-phase process, which is the detachment of individual soil particles from the soil mass and their transport by erosive agents (Renard et al. 1991). In the majority of the world, it is a serious environmental issue (Uddin et al., 2018; Shaikh & Palanisamy, 2020). Nearly 2 billion hectares of land worldwide, or about one-third of agricultural soils, were damaged by soil degradation, with water and wind erosion causing 56% and 28%, respectively, of this harm (Shaikh and Palanisamy 2020). Only 10% of the world's agricultural area is estimated to be experiencing little erosion, whereas 80% of agricultural land worldwide experiences moderate to severe erosion (Zolotov et al. 2020). Soil erosion causes the loss of 10 million hectares of agriculture worldwide each year (Uddin et al. 2018). With increasing human population numbers, this figure is expected to be much higher today. In Africa, Asia, and Latin America, where the majority of the population is dependent on agriculture (Haregeweyn, et al., 2017; Hurni, 2020), soil erosion is a severe challenge for food production and the problem will continue to persist in the 21st century. Comparatively, Africa is more seriously influenced by soil erosion than Asia and Latin America, and of the one billion people affected globally, about 50% are found in Africa (Hall and Foster 2000; Nwaogu et al. 2018).

Ethiopia, like many of the highland mountainous countries such as Haiti, suffers from severe soil erosion (Haregeweyn et al., 2008; Aneseyee, et al., 2020). The previous estimate stated that Ethiopia's average annual soil erosion rate was 18 t ha^{-1} yr^{-1} (Hurni 1985). The problem is more serious in the highlands (Moges & Bhat, 2017; Yesuph & Dagnew, 2019), where steep topography, rapid deforestation, and early settlements were existent (Hurni 1983). Various studies report quite inconsistent figures about the rate of erosion in the highlands. For instance, (Hurni 1985) reported a soil erosion rate of 16-300 t ha^{-1} yr^{-1} in cultivated fields while (Zeleke and Hurni 2001) reported 130-170 t ha^{-1} yr^{-1} in a similar land use in the northwestern highlands of Ethiopia. The average rate of erosion from cultivated fields has been also reported 42 t ha^{-1} yr^{-1} (Hurni 2020).

The earlier estimate for the highlands of Ethiopia put the average rate of soil erosion at 35 t ha^{-1} yr^{-1} (Nyssen et al. 2009). However, recent studies by Bewket & Teferi, (2009) in the Chemoga watershed; Kebede, (2014) in the Chaleleka wetland watershed; Sewnet (2016) in the Koga watershed; Moges and Bhat (2017) found that the erosion rate above 35 t ha^{-1} yr^{-1} in the respective study sites. The reported figures are way beyond the tolerable soil loss (TSL) rate that influences the economic and high level of production (Freimund and Renard 1994; Witchmeier w m and Smith 1978). In terms of total soil loss, earlier assessments reported the annual loss of about 1.9 to 3.5 billion tons of topsoil from the highlands and as a result over 20,000-30,000 ha of cropland is taken out of production every year (Safari et al. 2021). On the other hand, Nut et al. (2021) reported the annual loss of 1.5 billion tons of topsoil in the same region, resulting in the reduction of about 1.5 million tons of grain from the country's annual harvest. Hence, despite the inconsistency of the estimates, the figures are clear signals of the seriousness of the problem in the highland regions. According to model predictions, if soil erosion in the highlands is not properly controlled, the country's potential land production capacity will decline by 30% between 2010 and 2030 (Schirpke, Meisch, and Tappeiner 2018; Uddin et al. 2018). Additionally, they predicted that the agriculture sector's value contributed per capita would drop from US$372 in 2010 to US$162 in 2030.

1.4.4.2 Soil Erosion Modeling and Assessment Approach

As was already described above, several natural and human causes both influence and cause soil erosion. Understanding the intricate relationships between rainfall, soil type, topography, and land cover is necessary to determine the causes and subsequence of this process. Prediction of soil loss from a given area needs spatial handling of all this information based on their contribution to the process (Paula et al., 2015; Ganasri & Ramesh, 2016). Such a task is done using the application of existing models which are developed based on the relationships of these interacting factors.

A model is a straightforward representation or abstraction of a complicated system that makes reality simpler (Freimund and Renard 1994). There are numerous models available for estimating how much soil will be lost from a specific location. Models differ from each other based on issues such as the process they are based on scale, input, and output. The difficulty in observing and measuring erosion processes during runoff or erosion events, owing to the time and spatial constraint at which the processes occur, perceives the use of erosion models for the prediction of erosion and sedimentation in catchments (Tadesse.,et al. 2017). Erosion models allow users to ascertain variations, identify various processes, and explore the possible impacts of remedial measures and the relative effectiveness of implementation strategies for erosion and sedimentation controls (von Maltitz et al. 2019). The practice of quantitatively characterizing soil erosion on land surfaces is known as modeling soil erosion. The goal of soil erosion models is to forecast how much soil will be lost in a particular area of land (Shaikh and Palanisamy 2020). In general, the models fall into three main categories such as conceptual, empirical, and physically based models.

Conceptual models lie somewhere between empirical and physically based models and aim to reflect the physical processes governing the system but describe them with empirical relationships (Hall and Foster 2000). Conceptual models tend to include a general description of catchment processes, without including the specific details occurring in the complex process interactions. Because parameter values are determined through data, conceptual models have limitations associated with the identification of the parameter values (Saavedra 2005).

Physically based models are based on the application of the physics of the erosion and sediment transport processes (Safari et al., 2021). In principle, they can be applied outside the range of conditions used for assessing and they can be measured directly and without the need for long hydro meteorological records (Saavedra 2005). A physically based model includes the Morgan-Morgan and Finney, Water Erosion Prediction Project and the Soil and Water Assessment Tool.

Empirical models are generally the simplest of the three model types. They are based primarily on defining important factors through field observation, measurement, experimentation, and statistical techniques relating erosion factors to soil loss (Landi et al. 2011). The computational and data requirements for such models are usually less than for conceptual and physically based models (Lu et al. 2022). They are particularly useful as a first step in identifying the sources of sediments. The Universal Soil Loss Equation (USLE) and its revised version RUSLE are two of the empirical models that have been most widely used and generally accepted by the natural resources community because they are relatively easy to use (Saavedra 2005). In this study, RUSLE was applied over other methods because the model was revised in Ethiopia condition.

1.4.4.3 Revised Universal Soil Loss Equation

The Revised Soil Loss Equation (RUSLE) model (Renard et al., 1991; Freimund & Renard, 1994) is often used to estimate soil erosion rate. RUSLE is an extension of the Universal Soil Loss Equation (USLE) model by adapting the input parameters to the local conditions (Renard 1996). Because of its clear and relatively simple computational inputs, RUSLE has been commonly applied in Ethiopia (Haregeweyn et al., 2015; Tolosa, 2018; Bekele et al., 2022) and elsewhere in the world (Shi et al., 2012; Hateffard et al., 2021). RUSLE (Freimund and Renard 1994) and its predecessor USLE (Witchmeier w m and Smith 1978) estimate mean annual soil loss (A) from sheet and rill erosion as a function of five factors .

1.4.4.4 The Use of Remote Sensing and GIS in Soil Loss Modelling

Several studies showed the potential utility of Remote Sensing (RS) and Geographic Information System (GIS) techniques for quantitatively assessing erosional soil loss (Jiru 2019). The advancements in RS and GIS technologies provide effective means in the modeling of soil erosion. Soil erosion is a spatial phenomenon, (Hazarika and Honda 2001; Zeghmar, et al; 2022). The potential utility of remotely sensed data in the form of aerial photographs and satellite sensors data is well recognized in mapping and assessing landscape attributes controlling soil erosion, such as physiography, soils, land-use/land cover, relief, soil erosion pattern (Seutloali, Dube, and Sibanda 2018). In a GIS environment, it is possible to link data generated from remote sensing with their spatial locations.

In general, the use of geo-information techniques offers fast and cost-effective estimates, possibilities to investigate larger areas, greater possibilities of continuous monitoring of these areas, and possibilities to refine the soil erosion model depending on the required output scale, i.e. rough global to more precise local scale. According to Ghosh et al., (2023), the use of digital elevation models and GIS offers possibilities to estimate topographical parameters that are useful in soil erosion modeling.

The basic fundamentals in remote sensing are the properties of electromagnetic radiation and their interaction with substances. Remote sensing has opened a new era in the planning and development of watershed management, as satellite imagery provides a fast and economic way to analyze large watersheds by their synoptic and repetitive coverage (Sanogo et al. 2023; Zeghmar et al. 2022). Thus, by using multispectral data, different ground features can be differentiated from each other and a thematic map depicting land use/land cover can be prepared. Satellite imagery has been well utilized in different studies for watershed characterization and management aims and to measure qualitative and quantitative terrestrial land-cover changes in a watershed (Jiru 2019). For soil erosion assessments in a watershed, RS has been used for both detecting erosion features and obtaining erosion model input data.

Remote Sensing can facilitate studying factors enhancing the processes, such as soil type, slope gradient, drainage, geology, and land cover. Multi-temporal satellite images provide valuable information related to seasonal land use dynamics. Digital Elevation Model (DEM) is one of the vital inputs required for soil erosion modeling that can be created by analysis of stereoscopic optical and microwave remote sensing data (Abebe et al. 2021; Adem et al. 2020).

1.4.4.5 Sediment Export

The amount of eroded material that is transferred from a plot, field, channel, or watershed is referred to as sediment export (Vigiak et al. 2012). Hence, soil erosion is the main source of sediment export, and there is no sediment export to any given point or a stream channel unless soil erosion has been taking place (Melaku et al., 2018; Collins et al., 2020; Yaekob et al., 2022). Despite this, none of the soil erosion that took place in the higher slope areas resulted in a downstream point for the sediment yield. This is because when the erosive agent has no sufficient energy to transport the eroded soil particles, some of them are deposited in the meantime before reaching the downstream point (Collins et al. 2020). Sedimentation, the deposition of sediment particles after separating from their origin (Owens, Petticrew, and van der Perk 2010), reduces the storage capacity of reservoirs (dams) and lakes. Therefore, Indicators of a higher soil erosion rate in the upland areas include higher sediment output and, ultimately, sedimentation of reservoirs and lakes (Tadesse et al., 2017a; Kulimushi et al., 2021).

Hence, it is clear that sediment yield is dependent on soil erosion, and sedimentation is determined by sediment yield (Ayalew & Bharti, 2022). The sediment yield is the sediment load at the last point of the slope length, in the channels, at the outlet or sediment basins. It is the sediment load normalized for the drainage area and is the net result of erosion and deposition processes within a watershed. Sediment yield is typically unavailable as a direct measurement in a watershed lacking adequately recorded sediment data. The accurate estimation of SDR coupling with spatial soil loss is an important and effective approach to predicting sediment yield. In different parts of Ethiopia high land, sediment yield is computed by superimposing the soil loss and SDR layers of the watershed (Ayele et al., 2021; Roba et al., 2021).

In the highlands of Ethiopia, equally worrisome to the soil loss is the annual sediment load from agricultural landscapes (Amsalu & Mengaw, 2014). Because of a large number of sediment loads from the upland areas, the water quality and storage capacity of natural lakes in the country have reduced drastically (Assfaw, 2020; Tesema & Leta, 2020). Nowadays, even though Lake Alemaya in the eastern highlands rehabilitated, it was already dried out due to uncontrolled erosion and sedimentation from the surrounding agricultural landscapes (Zewdu, 2012; Senti et al., 2014) . Other Lakes such as Abijata in Central Rift Valley region may dry out in the near future (Meshesha et al., 2012). Besides, a large amount of sediment loads from un-managed uplands has threatened water supply and power generation reservoirs in the country. Good examples of affected power generation reservoirs are Koka, Gilgel Gibe I, Aba Samuel, MelkaWakena; and water supply reservoirs are Angereb, Legedadi, Borkena and Adrako as well as several irrigation reservoirs in the northern highlands (Kebede, 2014). Similarly, in the East African region, the Sinnar, the Rosieres and the Khashm el Girba reservoirs in Sudan (Shahin, 1993; Mekuriaw, 2017) and the High Aswan reservoir in Egypt have lost substantial proportions of their planned storage capacities due to sedimentation (Shahin 1993).

1.4.4.6 InVEST Model

The InVEST sediment delivery model provides insight into how variations in LULC patterns affect the annual sediment output by estimating the relative contributions of sediment from each parcel of a landscape in a spatially explicit manner. It helps the integrated study of soil loss, and sediment export, in a given watershed as it is capable of determining the sediment pathways from hill slopes to water bodies. This is important to examine possible downstream impacts of the amount of sedimentation (Bouguerra and Jebari 2017; Zhou et al. 2019).

Although much research on SLSE has been conducted on a worldwide scale, the majority of them have concentrated on the use of refined tools and well-qualified experts in a data-rich atmosphere (Kulimushi et al. 2021; Xie et al. 2021). Such methods are less applied in developing nations, such as Ethiopia, where data is few and experienced specialists are scarce (Haregeweyn et al., 2012). The Revised Universal Soil Loss Equation (RUSLE) model is commonly used in Ethiopia to evaluate the sum of soil loss (Hurni 1985). However, the model is unable to estimate the sediment export of a given watershed. The RUSLE's limitations are addressed by the InVEST model, which allows for combined assessments of SLSE by characterizing a given watershed (Nelson et al., 2014). As a result, the InVEST model was used to take advantage of the model's thorough accurate estimation of SLSE at the Rib watershed in Upper Blue Nile Basin, Ethiopia.

Despite the limitations, the model still now provides an important assessment of how landscape scenarios may affect the annual delivery of sediment export. Besides, compared to other sophisticated and data-intensive models, the InVEST model was preferred due to its requirement of fewer input parameters, availability of the required input spatial data, and compatibility with various GIS data. Most importantly, the model uses the RUSLE and some of the input parameters of the RUSLE equation were calibrated for the Ethiopian context (Hurni 1985) which can readily be used in the model.

1.5 Conceptual Framework of the Study

A conceptual framework is a set of concepts that are used to guide the flow of research work and helps researchers to understand the relationships between different variables (dependent and independent) to answer a research question (Scholastica 2021). The LDN status in the study Rib Watershed was examined in the study area. Accordingly, the LUC, NPP, and SOC indicators (Independent variables) were used to examine the status of LDN (dependent variable).

The conceptual scientific framework developed by Cowie et al., (2018) was applied to evaluate the status of LDN in the study watershed. In this framework, the evaluation of land degradation uses the "one out all out (1OAO)" approach to integrate the three indicators, where the degradation of any indication results in the degradation of LDN status. According to this framework, if any of the three indicators displays considerable negative change, it is considered as degradation. Conversely, it is deemed an improvement of the land condition if at least one indicator shows a significant positive change and none shows a significant negative change.

In this study, ESVs value of the study watershed was quantified between 2000, 2010, and 2020 years concerning LULC using the modified ecosystem value coefficient. Therefore ESV is determined by LULC. This indicated that ESV is a dependent variable whereas LULC is an independent variable. Soil loss and sediment export were calculated in the study watershed using the InVEST model. Therefore soil loss and sediment export (dependent variable) depend upon by LULC (Independent variables). The overall conceptual framework of the study is displayed in (figure 1.1).

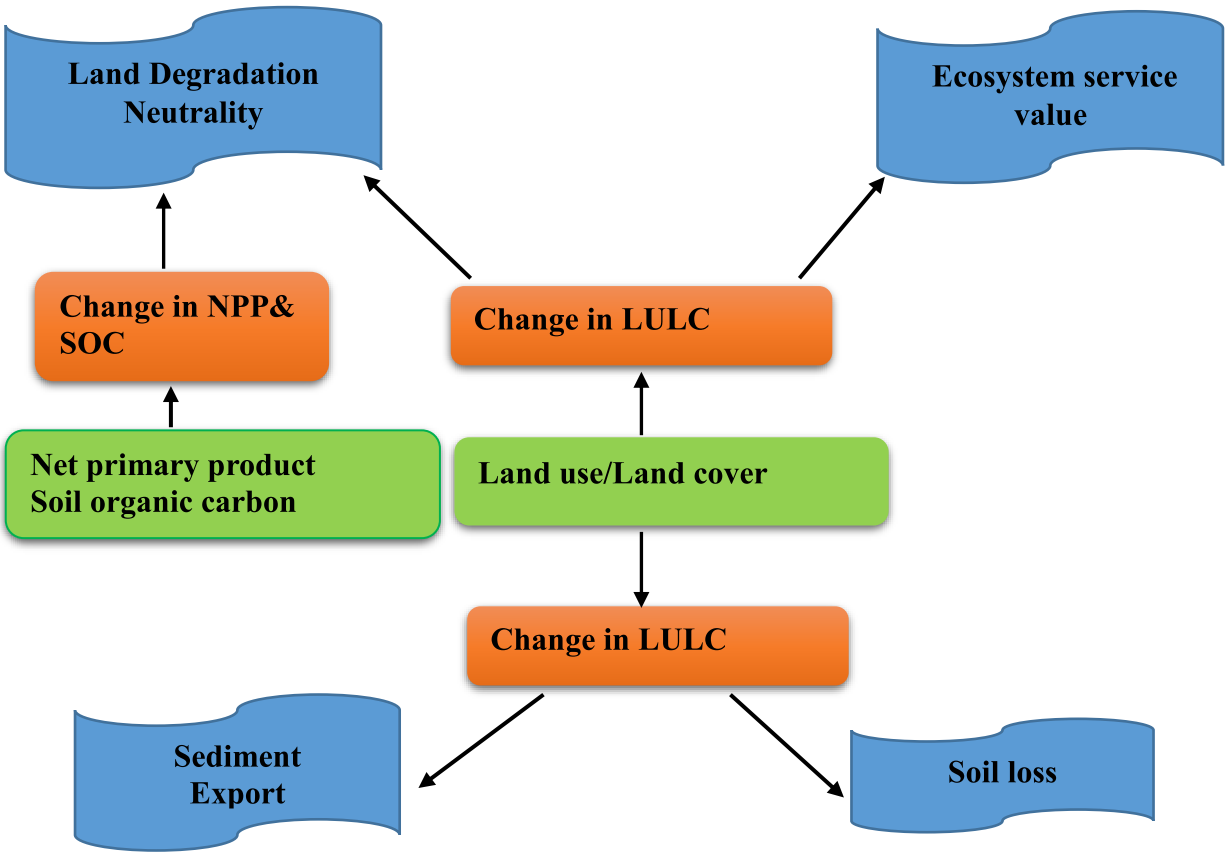


Figure 1.1 Conceptual framework of the study

1.6 Philosophical Perspective

In social science research, the term "paradigm" is used to refer to the philosophical assumptions that guide the worldview of the researcher. It is also described as "a way of thinking about and making sense of the complexities of the real world. Paradigms are conceptual and practical philosophies that are used to solve specific research problems. For this study pragmatism paradigm approach was employed as a philosophical perspective regardless of both subjective and objective data used.

Pragmatists believe that from an epistemological perspective at some stage during the research it takes an objective approach by not interacting with subjects, while at other stages it takes a more subjective approach by interacting with research subjects to construct realities (Abbato 2009). Here, a pragmatic approach allows researchers to be flexible enough to adopt the most practicable approach to address research questions. By doing this, both singular and multiple realities can derived from the quantitative and qualitative research (Dawadi, Shrestha, and Giri 2021).

Pragmatists believe that no truth is absolute and permanent as it is ever-changing from time to time and from place to place. Thus, their fundamental start is “change”. Whatever was true yesterday need not be true today. The philosophy of pragmatists is predetermined to those ideas and values which result in utility to mankind in a certain time, place, or circumstance rather than any predetermined of life.

1.7 Significance of the Study

This study is important for departments of natural resource conservation program of Debretabor, Ebnat, Addiszemen woredas, and non-governmental organizations that are engaged in agricultural development issues, to assess the impact of LULC on ecosystem service value, soil loss, sediment export, and the status of land degradation neutrality at Rib watershed of Upper Blue Nile Basin, Ethiopia.

Different stakeholders are highly concerned with ecosystem service value, sediment export, and LDN to take measures to maintain the existing natural resource bases. Such as the natural resource department of the above-mentioned woredas needs to understand the severity of the problem in the farming society. So, it can help them to develop appropriate intervention measures that promote the mitigation of ecosystem service value, sediment export, and the status of LDN. At each year massive work to control soil erosion was done by the coordinator of those woredas. So this research may help them to give due attention to high soil erosion and sediment export priority areas. In addition, this research also helps as a reference for other researchers who study about ecosystem service, soil erosion, sediment export, and the status of LDN. For the international academician, the following articles were produced from the PhD dissertation.

1. Melkamu Alebachew Anley & Amare Sewnet Minale, (2023) Examining the Land Degradation Neutrality (LDN) status of Rib watershed, Upper Blue Nile Basin,

Ethiopia, *Sustainable Environment,* 9:1, 2287906, https://doi.org/10.1080/27658511.2023.2287906

2. Anley, M. A., Minale, A. S., Ayehu, N. H., & Gashaw, T. (2022). Assessing the impacts of land use/cover changes on ecosystem service values in Rib watershed, Upper Blue Nile Basin, Ethiopia. *Trees, Forests and People*, *7*(3), 100212. https://doi.org/10.1016/j.tfp.2022.100212
3. Anley, M. A.,and Minale, A. S.(2024). Modeling the impact of land use land cover change on the estimation of soil loss and sediment export using InVEST model at the Rib River watershed of Upper Blue Nile Basin, Ethiopia. Remote Sensing Applications: Society and Environment 34 (2024) 101177. https://doi.org/10.1016/j.rsase.2024.101177
4. Anley, M. A., & Minale, A. S (2024). Evaluating Land Use and Land Cover Change and Shifting Index in Rib River Watershed of Upper Blue Nile Basin Ethiopia. *Trees, Forests and People, In Revision stage.*

1.8 Scope and Limitations of the Study

The study is delimited at the Rib River watershed of North West, Ethiopia. The study focused on" Analyzing the Status of Land Degradation Neutrality in the Rib Watershed, of the Upper Blue Nile Basin, Ethiopia. In this study, LULC datasets were used to facilitate the estimation of the change in ESV, soil loss, sediment export, and the status of land degradation neutrality. However, there are some limitations concerning the LULC datasets that were used. For instance, we are unable to use Landsat 7 images from USGS for image classification between 2000 and 2010, because the dataset is not free from the strip and hence, Landsat 5 images were used instead of Landsat 7. Additionally, the other limitation was the inability of the InVEST model to account for types of soil erosion and sediment export other than rill or inter-rill erosion (unable to measure gulley erosion).

1.9 Structure of the Thesis

The thesis is organized into six chapters. The first chapter introduces the background, statements of the problem, and objectives. Chapter two consists of an assessment of the status of land degradation neutrality in the study Rib River Watershed. Chapter three contain the second specific objective of our work entitled on the impact of land use land cover change on ecosystem service values in the study area.Chapter Four contain modelling the impact of land use land cover change on the estimation of soil loss and sediment export at the Rib River watershed,North West Ethiopia. Chapter Five consists of evaluation of land use land cover change and shifting index in Rib River watershed of,North weast Ethiiopa. The last chapter (Chapter Six) concludes and Recommends by considering the major findings of the study.

1.10 Definition of Terms

Baseline	The initial estimated value of each of the indicators used to monitor progress in the achievement of LDN for each land type.
Ecosystem services	the benefits that people obtain from ecosystems.
Land cover class	a category of land cover differentiated by a combination of diagnostic attributes based on a nationally refined application of an International standard such as the FAO Land Cover Classification System.
Land degradation	the deterioration or loss of the productive capacity of the soils for the present and future.
Land degradation neutrality	A state whereby the amount and quality of land resources necessary to support ecosystem functions and services and enhance food security to remain stable or increase within specified temporal and spatial scales and ecosystems.
Land improvement	any type of alteration to the land to make it more usable.
Metrics of LDN	Metrics are variables that reflect a process of interest.
Net primary product	the amount of biomass or carbon produced by primary producers per unit area and time.
One-out, all-out	a conservative approach that combines different indicators/metrics to assess the status of land degradation neutrality.
Soil loss	Soil relocated on or removed from a given site by the forces of erosion and the redeposit of the soil at another site on land and measured by ton per hectare per year.

Soil erosion	the gradual process that occurs when the impact of water or wind detaches and removes soil particles, causing the soil to deteriorate.
Sediment export	the amount of onsite sediment source actually reaching the catchment outlet.
Soil organic carbon	a measurable component of soil organic matter.
Watershed	An area or ridge of land that separates waters flowing to different rivers.

CHAPTER TWO

2. Examining the Land Degradation Neutrality (LDN) Status of Rib River Watershed, North West, Ethiopia.

Based on Publication:

Melkamu Alebachew Anley & Amare Sewnet Minale, (2023) Examining the Land Degradation Neutrality (LDN) status of Rib watershed, Upper Blue Nile Basin, Ethiopia, *Sustainable Environment*, 9:1, 2287906, https://doi.org/10.1080/27658511.2023.2287906

Abstract

Land degradation because of the overutilization of natural resources is a suitable strategy for many countries of the world. This crucial strategy hasn't been introduced or implemented widely enough. The present study intended to examine the status of Land Degradation Neutrality (LDN) for the study Rib Watershed which covers an area of 1585 km^2 and is situated in the Upper Blue Nile Basin, Ethiopia. For the past two periods between 2000 and 2020, three indicators, such as Land Cover/Use Changes (LULC), Soil Organic Carbon (SOC), and Net Primary Productivity (NPP) metrics were primarily used to assess the LDN status of the study site. A total of 80 soil sample were then collected from the top 15 cm for six different types of LULC, including cultivated land, forest land, shrub lands, grassland, settlement, and water body. Consequently, Land uses land cover matrices, NPP metric, and SOC metrics were also obtained using Landsat images, soil samples, and MODIS satellite images respectively for three periods of 2000, 2010, and 2020. Lastly, by integrating the three indicators and using one out all out framework, the status of LDN in the study area was evaluated. The combined findings of the study measurements showed that there was a net loss in cultivated land (123,977 ha), forest land (5623 ha), shrub lands (13984 ha), grassland (11,999 ha), water body (1056 ha) and settlement (1993 ha) for the past two decades (2000 to 2020). For the past two decades LDN status of the Rib Watershed was generally in a net loss condition. The information delivered by the three sub-indicators is important for experts for the good recognition of their spatial distribution and types of land degradation to attain the LDN targets.

Keywords: Land Degradation Neutrality, Land use/cover, Net primary product, Soil organic carbon

2.1 Introduction

Land degradation (LD) is a serious environmental problematic issue that harmfully affects ecosystem services, biodiversity, and the lives of millions of people in the world by promoting poverty and migration (Gashu and Muchie 2018; Meseret 2016; Susilowati and Syekhfani 2015). LD can indicate the decline of biological or economic productivity in rain-fed farmland (Reith et al. 2021; Susilowati and Syekhfani 2015). However, due to the complexity and variety of the biophysical and socioeconomic factors that affect land resources, it is challenging to identify this phenomenon (Lu et al. 2022; Meseret 2016). By integrating information about ecosystems and the mechanisms that produce degradation, numerous research has evaluated the phenomenon of LD at the international as well as national levels. Due to the complexity, variety, and quantity of indicators employed in the research carried out during the past 30 years, the evidence is not similar throughout regions (Gashu and Muchie 2018; Lu et al. 2022). However, data was scarce, and the cost of repeatability and implementation of techniques makes them rarely practical at more local and regional scales (Adnan 2020; del Barrio et al. 2021; Malav et al. 2022).

The Sustainable Development Goal (SDG), goal 15 article 3 (15.3), includes the idea of "Land Degradation Neutrality" (LDN), which was recently presented by the UN General Assembly as a creative way to address land degradation (LD). LDN is a state that refers to the amount and quality of land resources needed to preserve ecosystem services and functions and improve food security within specific temporal and spatial scales. Therefore, land degradation needs to be avoided, controlled, and reversed in order to return land resources to a healthy, productive state with no net loss.

The LDN can be assessed by using a methodological and conceptual scientific framework accompanied by the Convention to Combat Desertification (UNCCD) (Gonzalez-Roglich et al. 2019; Liniger et al. 2019). In this framework, using the "one out of all out (1OAO)" approach, the three indicators, such as Land Cover (LC), Land Productivity Dynamics (LPD), and Soil Organic Carbon (SOC) are combined in the assessment of LD. However, the decline of any indicator corresponds to the degradation of LDN. The choice of indicators provides a foundation for assessing the current state of the land, understanding changes and trends through time, monitoring the rate of degradation, and calculating the proportion of degraded land. (Cowie et al. 2018; Erşahin 2020; Quatrini and Crossman 2018). In addition, UNCCD offers a global dataset to identify patterns of land degradation neutrality in a particular geographic area (Gonzalez-Roglich et al. 2019).

Some studies on LD and inducing factors have been performed in various areas (del Barrio et al. 2021; Gashu and Muchie 2018; Malav et al. 2022; Susilowati and Syekhfani 2015). Yet, past research suggested that the LDN concept had only lately been introduced and taken into account. LDN was initially studied in dry areas by (Grainger 2015). They emphasized the significance of researching LD in dry regions and achieving the objectives for sustainable development goals. (Minelli et al. 2018) offered a basic outline of important worldwide decisions that contributed to the formation of the LDN conception in addition to explaining how to measure, monitor, and assess LDN. (Safriel 2017) studied on LDN has been designed with a focus on semi-arid areas, to neutralize LD and restore degraded lands following the UNCCD to accomplish the SDGs. (Dengiz 2018) explored possible impacts of land use changes on the dynamics of land productivity in semi-humid parts of the Gediz Watershed over 14 years (2001-2014) with a focus on the LDN concept. He used data from Landsat satellite images to detect changes in land use and cover. He collected 319 soil samples from all around the study catchment to evaluate SOC. The results showed that the watershed's total land productivity has dropped by 23%. (Kiani-Harchegani and Sadeghi 2020) looked into the LDN status of the Shazand watershed, in Iran. They uses satellite images, MODIS NPP, and Soil samples for the assessment of the three sub-indicators of LDN from 2000 to 2016. The result of the combination of the study indicators showed that the status of LDN in the watershed was in a net loss situation.

In Ethiopia's context, the idea of LDN is not researched by scholars. For instance, in the study Rib watershed, no one is doing research on the assessment of LDN. Therefore, this research intends to fill the knowledge gap by taking the Rib watershed of the Upper Blue Nile basin as a case site for the past two decades. Hence, this study was targeted at examining the LDN status in the study watershed using three determinant variables (land use/land cover change, net primary productivity, and soil carbon content) from 2000 up to 2020. The objective of the present study was to (1) Examine the land use land cover change for the past two decades (2000 up to 2020), (2) Detect the trend of net primary productivity in the study area from the time series of the (MODIS) NPP data (2000–2020). (3) Assess soil organic carbon change in the study Rib watershed, (4) determine the status of LDN in the Rib watershed of Upper Blue Nile Basin, Ethiopia from the period 2000 to 2020.

2.2 Material and Method

2.2.1 Description of the Study Area

The research was done in the Rib watershed of Upper Blue Nile Basin, Ethiopia, which extends from Mountain Guna to Lake Tana in the eastern direction and is considered the principal source of water for the Blue Nile. It is situated under the Lake Tana basin of northwestern Ethiopia and has an absolute location between 10°43' - 11° 53' N and 35^0 - 37° 47' E. The elevation of the study watershed ranges from 1785 - 4049 above sea level and has a catchment area of 1583 km^2 (Figure 2.1). The watershed's terrain is extremely hilly, with a steep mountain range on its southern border and sparsely spaced hills and their escarpments on its center and northern sides (Sinshaw et al. 2021). The watershed is the main source of water for Lake Tana. The major river in the watershed is the Rib River. Woredas, such as Ebnat, Farta, Libo Kemkem, and Fogera are all intersected by the river. Rib Dam is under construction since 2008 and cost $ 40 million. It has a reservoir storage capacity of 234 million m^3. The dam is targeted to use for irrigation purposes at Fogera plain of Amhara regional state and is proposed to supply 14,000 ha of land to serve more than 28,000 households (Annys et al. 2020). The rice granary and demonstration location for national rice research are both located in Fogera Plain, which is part of the Fogera woreda.

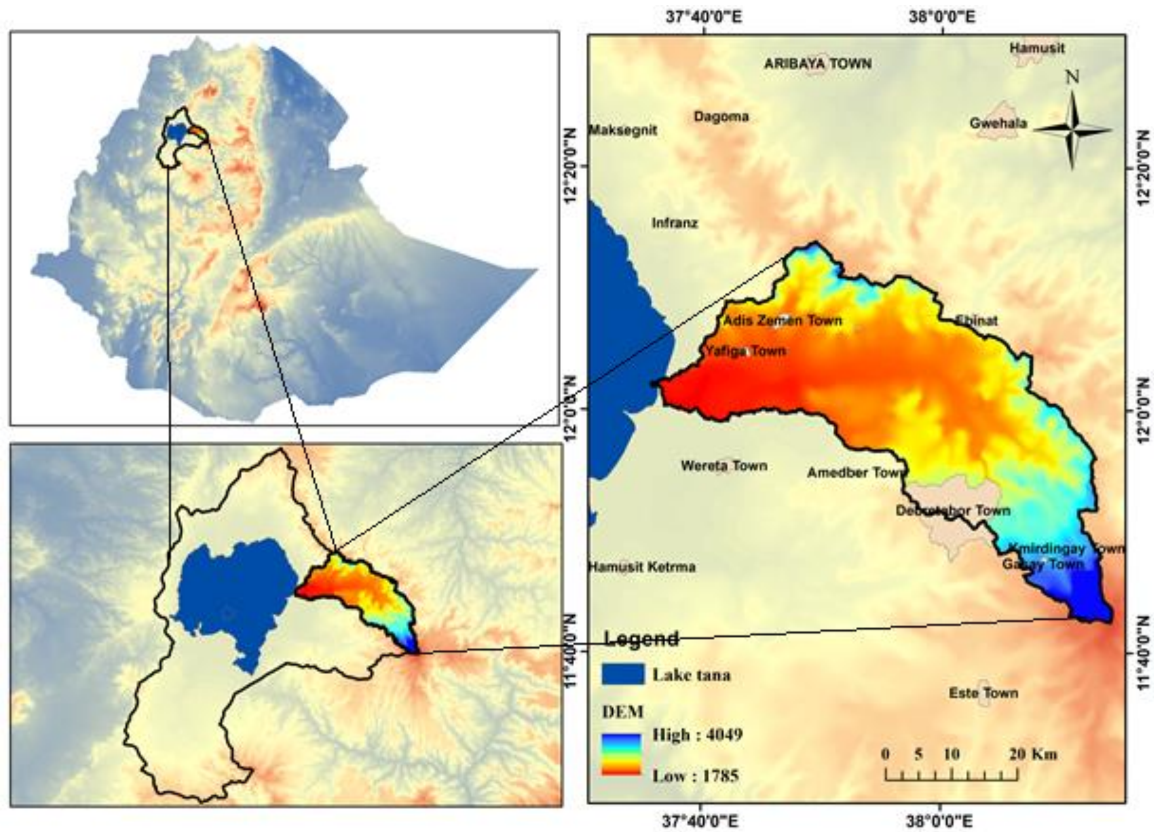


Figure 2.1 Map of the study area

According to projected Central Statistical Authority (Central Statistical Agency 2014), 878,261 people are living within the watershed, with 89.7% of them living in rural regions and relying primarily on agriculture. According to (Anley et al. 2022), the land use land cover of the watershed consists of Agriculture (123,977 ha), Forest land (5623 ha), Shrub land (13984), Grassland (11,999 ha), and waterbody (1056 ha). Among those land use, agriculture is the primary economic activity in the study area and is used as the source of livelihood for the rural community. On one side, a variety of agricultural products are grown, and on the other, animals are reared for both market and domestic consumption in the study watershed. Rainfall is a major factor in crop productivity; it mostly falls between June and September. As a result, farming can only be done during the remaining months of dry weather, which is uncommon in the watershed. However, only a small portion of the farming community employs irrigation to harvest maize and onions. The community in the study watershed depends largely on the rearing of cattle for their survival. Four types of soils derived from weathering of basaltic rocks were known in the study area, including Luvisols (34%), Leptosols (28%), Vertisols (23%), and Regosols (15%) (Ayalew and Bharti 2022).

The climatic zone of the Rib watershed is highly dominated by subtropical (traditionally, woina dega), statistically 2% (alpine), 64.4% (sub-tropical), and 33.6% (temperate). Weather record data for the past two decades indicated the annual average rainfall (1550.5 mm) and temperature (15.4 °C) of the study watershed. Over 70% of rainfall occurs during the summer season. Little or no rainfall data was recorded in the remaining months.

2.2.2 Measurement of LDN Metrics

The LDN status in the study Rib Watershed was examined using the Scientific Conceptual Framework (SCF) developed by (Cowie et al. 2018). Accordingly, the LUC, NPP, and SOC indicators for the study area throughout the periods of 2000–2010, 2010–2020, and 2000–2020 were used to examine the LDN status (Figure 2.2). The existing approach for evaluating and assessing LDN consists of the use of site-based data to measure the quantitative value of the sub-indicators resulting from Earth observation and geospatial information. For those indicators, the baseline data was determined. This would involve the preparation of baseline data on the land cover that builds on existing land cover ontologies, as well as establishing baselines for soil organic carbon and land productivity in the research area.

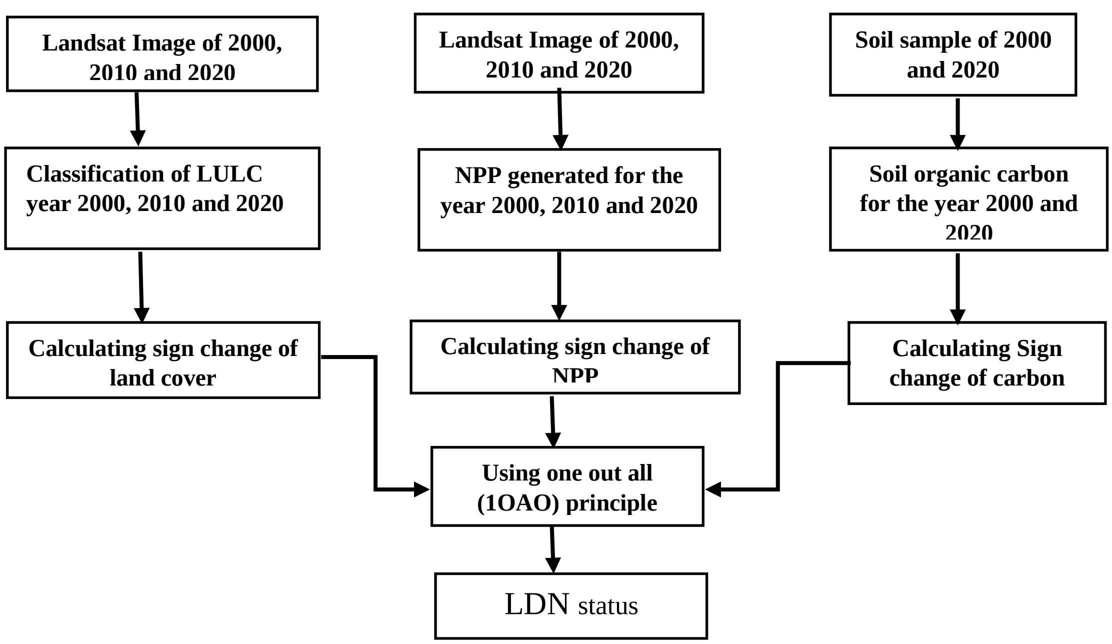


Figure 2.2 Methodological framework of LDN metrics.

After the baseline data was prepared, change detection for each sub-indicator was done to identify the area subject to change and mostly where the change in two or three indicators overlap spatially. Lastly, the methodological and conceptual scientific framework conducted by (Cowie et al. 2018) was applied to evaluate the status of LDN in the study watershed. In this framework, the evaluation of LD uses the "one out all out (1OAO)" approach to integrate the three indicators, where the degradation of any indication results in the degradation of LDN (Fig 2). According to this framework, if any of the three indicators displays considerable negative change, it is considered as degradation. Conversely, it is deemed an improvement of the land condition if at least one indicator shows a significant positive change and none shows a significant negative change. The change of each sub-indicator of LDN between years was calculated using analysis of variance in SPSS software version 23.

2.2.2.1 Land Use/Land Cover

The term "land cover" describes the (bio) physical cover that can be seen on the earth's surface (Egarter Vigl et al. 2017; Karki et al. 2018; Tolessa et al. 2017; Willemen et al. 2018). One of the most frequently used markers for influences on ecosystems caused by humans or by the environment is land cover (Arunyawat and Shrestha 2016; Meshesha et al. 2014). This indicator of LDN can detect the change in time series and may show degradation or the improvement (Recovery) of the land condition in a certain geographical territory.

Time-series multispectral Landsat imagery taken in three different years (2000, 2010, and 2020) were utilized in the study area to set the baseline land cover and identify land cover changes (Table 2.1). The images were kindly downloaded from the United States Geological Survey (USGS) (https://www.usgs.gov). The raw images were free from clouds because they were taken during the drier season. Therefore, all satellite images were taken in February with less cloud cover.

By utilizing the fundamental image preparation techniques, satellite image data were prepared and processed using the ERDAS IMAGINE 14 software. Pre-processing methods for the satellite images included color composite, layer stacking, and sub-setting were done. To increase image quality, Landsat images were then rectified geometrically and radiometrically. Finally, a projection to the Universal Transverse Mercator (UTM) was applied. The satellite image from the years 2000, 2010, and 2020 were classified using the supervised image classification method with a maximum likelihood classification algorithm. Finally, Six LULC classes such as cultivated land, grazing land, forest, shrub land, waterbody, and settlement were identified in the research area.

Table 2.1 Description of imagery data.

Acquisition date	Data type	Spatial resolution	Path and raw	Source
02/07/2000	Landsat 5 TM	30 m	169/52	USGS*
01/31/2010	Landsat 5 TM	30 m	169/52	USGS
01/26/2020	Landsat 8 OLI	30 m	169/52	USGS
01/20/20	Ground truth point	-	169/52	Ground survey

* Refers to United States Geological Survey

Google Earth, interviews with elder people, and expert knowledge were utilized to classify images for 2000 and 2010. Field observation was carried out and ground control points (GCPs) were acquired using a Garmin GPS device to perform accuracy assessments for each land-use class to gather the training sample for 2020. According to (ERDAS Inc., 2008), at least 50 GPS points per land-use type are advisable for land cover classification. In this study, to increase the accuracy, on average 100 GPS points at each land use type were taken. Therefore, a total of 600 GCP training samples for supervised land cover classification were collected for all land use/land cover classes. The area proportion of the land uses was used to determine the number of GCPs for each class. Therefore, a proportional sampling technique was employed to take GCP points (314 points for cultivated land, 33 for forest land, 59 for shrubland, 53 for grassland, 19 for waterbody, and 22 for settlement). For accuracy assessment, 100 GCP points were collected in the study watershed. The GCP points were taken in proportion to land use land cover classes of the study area (59 points for cultivated land, 7 for forest land, 13 for shrubland, 11 for grassland, 4 for waterbody, and 6 for settlement).

The number of GCPs at each class was determined using the areal extent of each land use. By contrasting the sample LULC class of the classified layer to the reference layer, the classification accuracy assessment of the LULC layers of satellite images was explored. To determine the degree of accuracy error, the overall accuracy and Kappa statistics were analyzed. Lastly, the area in hectares was calculated. LULC is one of the indicators of LDN. The change of each LULC has its contribution to determining the status of LDN in the study Rib watershed. According to (Orr, 2017), the expansion of agricultural land and settlement, along with the loss of natural and semi-natural land cover types (forest, shrubs, grasslands, and waterbodies), indicated that the degradation (loss) of the land condition, and the inverse is true for the improvement (gain) of the land. Hence this standard was applied to examine the impact of LULC on the status of LDN in the study area.

2.2.2.2 Net primary Productivity (NPP)

The difference between total photosynthesis and total plant respiration in an ecosystem is also known as land productivity. It is a measure of above-ground net primary productivity (NPP) and is considered as the total amount of new organic matter produced over a certain period (De La Fuente et al. 2020). Tones of dry matter per hectare per year are used to measure NPP (t DM/ha/year). Primary productivity of plants indicates the distinct change over varied temporal scales; daily variability because of the position of the sun, intra-annual variability because of seasonal effects, and inter-annual variability because of dynamics in land use(Liu et al. 2022; Xuan and Rao 2023). Therefore, the land productivity of the study watershed was disaggregated by type of land cover. The spatial and temporal resolution of remote sensing data may give ongoing and synoptic information to determine the influence of natural and human stresses on the status and trends of the land's productive potential (Cui and Li 2022; De La Fuente et al. 2020).

In the Rib Watershed, the NPP distribution was examined in six LULC classes, including cultivated land, grazing land, forest, shrub land, waterbodies, and settlement, within the node years of 2000, 2010, and 2020. The NPP estimation image at the watershed level was downloaded from the USGS with 30m spatial resolution. Finally, Arc GIS 10.3 software was used to extract the NPP of each land cover type and SPSS 23 software was used to check whether there is a significant difference or not between the years of each LULC class.

2.2.2.3 Soil Organic Carbon

The residual plant and animal matter that bacteria produce and decomposes in response to environmental factors including temperature, moisture, and soil conditions is what makes up soil organic carbon (Abegaz et al. 2016; Amanuel, et al. 2018). Depending on natural factors (temperature, soil parent material, land cover and/or vegetation, and topography), as well as human-induced factors (land use, management and degradation), the annual rate of loss of organic matter can vary significantly. Soil organic carbon (SOC) is the largest carbon pool on Earth's surface, and it plays an important role in global carbon cycling. In fact, the SOC pool is 3-fold larger than the atmospheric pool and 4.0-fold larger than the biotic pool (Amanuel et al., 2018a; Yu & Song, 2023). SOC is an important indicator of soil quality and can improve the soil aggregate content and increase soil porosity and water holding capacity. Moreover, SOC is one of the sub indicator of land degradation neutrality. Therefore, Understanding the spatial patterns and change of SOC is essential for the achievement of land degradation neutrality.

The soil samples were collected in late January and February 2020. Accordingly, 80 soil samples were ultimately taken from the entire watershed (Table 2.2) considering the proportion of six different land cover types (i.e. grazing land, cultivated land, shrub land, forest land, waterbody, and settlement). The sample sites were properly located using a global positioning system (GPS). Each sample of soil was taken by inserting a core sampler for bulk density and an auger for carbon up to a depth of 15 cm.

Table 2.2 Soils Samples from the Rib River watershed.

Sampled site	Soil organic carbon	Bulk density	Total	Functions
Stable LULC Type	20	20	40	Represent the baseline data (2000)
Changed LULC type	20	20	40	Represent the target year data (2020)
Total	40	40	80	

Two types of soil samples were collected in the field (Table 2.3 & 2.4). From the first groups, twenty soil samples for bulk density and another twenty soil samples for organic carbon were collected from the types of land cover which was unchanged (stable) for the past two decades. These types of soil sample represent the baseline carbon stock data for the year 2000.

Table 2.3 Soil organic carbon result for the year 2000.

ID	LULC_2000	X	Y	Bulk density g/cm^3	SOC in %	t/c/ha
1	Cultivated land	37.85	12.07	1.72	2.91	75.15
2	Cultivated land	37.64	12.03	1.78	2.78	74.32
3	Cultivated land	37.59	12.03	1.81	2.73	74.32
4	Cultivated land	37.83	12.21	1.75	2.81	73.98
5	Cultivated land	37.79	12.22	1.70	2.94	75.13
6	Grass land	37.79	12.03	1.63	4.59	112.31
7	Grass land	37.64	12.01	1.65	4.42	109.64
8	Grass land	37.89	12.03	1.61	4.61	111.52
9	Grass land	38.23	11.72	1.69	4.32	109.68
10	Forest	38.17	11.79	1.13	8.93	151.4
11	Forest	37.91	12.15	1.19	8.22	146.87
12	Forest	37.61	12.00	1.21	8.25	149.9
13	Forest	37.97	12.13	1.15	8.92	154.03
14	Settlement	38.01	11.86	1.47	4.53	100.10
15	Settlement	37.71	12.00	1.45	4.66	101.45
16	Settlement	38.13	11.79	1.42	4.59	97.84
17	Shrub land	37.87	12.09	1.36	5.89	120.3
18	Shrub land	37.69	12.11	1.32	6.23	123.48
19	Shrub land	37.81	12.19	1.35	5.70	115.49
20	Shrub land	38.23	11.72	1.31	6.10	120.02

From the second group, twenty soil samples for bulk density and twenty soil samples for organic carbon were collected from the types of land cover which were changed to other land use for the last two decades. This soil sample represents the soil carbon stock of the target year (2020). The soils were immediately placed in polythene bags to maintain their field moisture and then taken to the Amhara agriculture center soil laboratory. The samples were dry in an oven to calculate the bulk density (BD) using the cold method. The Walkley and Black method was finally used to compute the percentage of SOC.

Table 2.4 Soil organic carbon result for the year 2020.

I.D	Changed LULC From	To	X	Y	Bulk density g/cm^3	SOC in %	t/c/ha
1	Agriculture	Settlement	37.94	12.03	1.62	3.01	73.35
2	Agriculture	Forest	37.96	11.96	1.38	4.53	93.77
3	Agriculture	Settlement	38.23	11.71	1.53	3.63	83.30
4	Agriculture	Forest	37.79	12.22	1.49	3.75	83.81
5	Grass land	Cultivated	37.88	12.03	1.72	3.39	87.46
6	Grass land	Settlement	37.63	12.00	1.53	4.89	112.4
7	Grass land	Cultivated	37.83	12.21	1.68	3.56	89.71
8	Grass land	Settlement	37.61	12.00	1.52	4.92	112.38
9	Forest	Settlement	37.88	12.03	1.33	7.49	149.5
10	Forest	Cultivated	37.96	12.13	1.46	3.31	72.64
11	Forest	Shrub	37.62	12.02	1.25	8.14	152.63
12	Forest	Shrub	37.67	12.10	1.28	7.67	147.36
13	Forest	Grass	38.1	12.06	1.34	5.65	113.7
14	Forest	Cultivated	38.11	12.04	1.40	3.12	65.63
15	Shrub land	Cultivated	37.85	12.16	1.51	2.97	67.37
16	Shrub land	Settlement	37.81	12.21	1.37	5.51	113.35
17	Shrub land	Cultivated	38.02	11.87	1.52	2.82	64.48
18	Shrub land	Grass	38.06	11.87	1.48	5.28	117.36
19	Shrub land	Grass	38.10	11.92	1.42	5.14	109.62
20	Waterbody	Cultivated	37.09	12.08	1.71	2.79	71.62

Finally, SOC maps for the years 2000 and 2020 were developed for the Rib River watershed using the IDW method of interpolation in ArcGIS 10.3 software. Information on the grids was individually extracted to form SOC map in the years 2000 and 2020 for each land cover type in the study site. In the next step, SOC amounts for the years 2000 and 2020 were computed using Eqs. (2.1) and (2.2). Lastly, a proper database was ready for SOC in Excel and the crucial statistical analyses were made in SPSS software packages. Using the following equation, the SOC density for each sampling site (SOCD in t C ha^{-1}) was calculated (Husein et al., 2019).

$$SOCD = \Sigma SOC \times BD \times D \quad (2.1)$$

Where SOC refers to SOC content in percent, BD refers to the bulk density in g cm^{-3}, and D indicates the depth of the soil surface layer at 15 cm. The total SOC storage in the study region, TSOC (t C), was expressed in this regard as follows.

$$TSOC = \Sigma \; ASOCD * S \quad (2.2)$$

Where, ASOCD refers to the average SOC density (t/C/ ha), S indicates the area of different land covers (ha).

2.2.3 Statistical analysis

SPSS 23.0 statistical software was used to conduct all statistical analyses. To compare the means of measurements for LUC, NPP, and SOC, a one-way analysis of variance (ANOVA) was employed during the periods of 2000–2010, 2010–2020, and 2000–2020. Finally, using the three metric values, LDN statuses were investigated throughout periods at a statistically significant level of $P < 0.05$. One-way analysis of variance was important to check whether there is a significant difference between the baseline years (2000) and targeted years (2020). According to Cowie et al., 2018), a significant increment and stability of the indicator shows the improvement of the land condition (Positive impact for LDN) and the significant reduction of those indicators shows the reduction of the land condition (negative LDN).

2.3 Results

2.3.1 Analysis of Indicators of Land Degradation Neutrality

2.3.1.1 Land Use Land Cover Change as Indicator of LDN

One of the most crucial indicators to evaluate the status of LDN in the study watershed was land use and land cover. Six LULC classes, including cultivated land, forestland, shrubland, grassland, waterbody, and settlement, were found in the study area. According to Anleye et al., (2022), the overall accuracy assessment for the years 2000, 2010, and 2020 was 80.11 %, 82.7 %, and 84.8 %, respectively (Table 2.5). This confirms the suggested and recommended value by (Olofsson et al. 2014). Thus, the data was used for the assessment of LDN in the study Rib watershed.

Table 2.5 The accuracy assessment report.

LULC class	2000		2010		2020	
	User accuracy	Producer accuracy	User accuracy	Producer accuracy	User accuracy	Producer accuracy
Cultivated land	78.3	80	83.4	83.2	87.2	85.1
Forest	82.1	81.3	83.3	84.7	85.5	85.6
Shrubland	81.4	82.8	82.4	83.6	83.1	84.9
Grassland	78.9	78.6	81.2	82.5	84.7	83.4
Waterbody	80.1	79.3	83.3	79.6	85.6	86.6
Settlement	79.8	79.5	81.9	80.6	83.9	84.7
Overall accuracy	80.1		82.7		84.8	
Kappa coefficient	0.78		0.80		0.82	

Statistically, cultivated land has increased by 23% in the last two decades. Whereas forest land decreased by 8.9% from (2000 to 2010), 41% (2010 to 2020), and 46.5% (2000 to 2020). Shrub land decreased by 27.1% from 2000 to 2010 and 24% from 2010 to 2020. The total reduction of shrubs was 44.5% from 2000 to 2020. Grassland decreased by 20%, 27%, and 41.5% from 2000 to 2010, 2010 to 2020, and 2000 to 2020 respectively. Waterbody decreases considerably between 2000 to 2010 but showed an incredible expansion between 2010 and 2020 (Table 2.6, Figure 2.3). The expansion in the waterbody is probably caused by the building of the Rib irrigation dam. According to Cowie et al., (2018), natural and semi-natural land cover types (forest, shrubs, grasslands, waterbody) change to agricultural land and settlement, indicate the degradation of the land condition and the inverse is true for the improvement (Recovery) of the land. Hence this standard was applied to this study.

Table 2.6 The LULC map of Rib River watershed for the years 2000, 2010 and 2020.

LULC Class	Areal extent (ha)	change between years in ha	The status of metrics between 2000 and 2020

	2000	2010	2020	2000-2010	2010-2020	2000-2020	
Cultivated	101,038	112,351	123,977	11,313	11,626	22,939*	Sig +ve change
Forest	10460	9523	5623	- 937	- 3900	- 4837*	Sig –ve change
Shrub land	25182	18360.9	13984	- 6821.1	- 4376.9	- 11,198*	Sig –ve change
Grass land	20524	16497	11999	- 4027	- 4498	- 8525*	Sig –ve change
Waterbody	586	220.1	1056	- 365.9	835.9	470*	Sig +ve change
Settlement	843	1679.9	1993	836.9	313.1	1,150*	Sig –ve change
	158630	158630	158630				

* refers to significant differences at $P < 0.05$ between the studied years,-ve and +ve indicate positive and negative respectively.

As depicted above in table 2.6, there was a significant change in cultivated and settlement areas between 2000 and 2020. Therefore, the expansion of cultivated land and settlement has a negative effect on the status of LDN (Cowie et al. 2018). Additionally, there was a significant reduction in forest, shrubs, and grassland. This significant reduction in land use has also a negative impact on the status of LDN. Whereas waterbody showed a significant increment over the past two decades. This shows that the increment of the water body has a positive impact on the status of LDN.

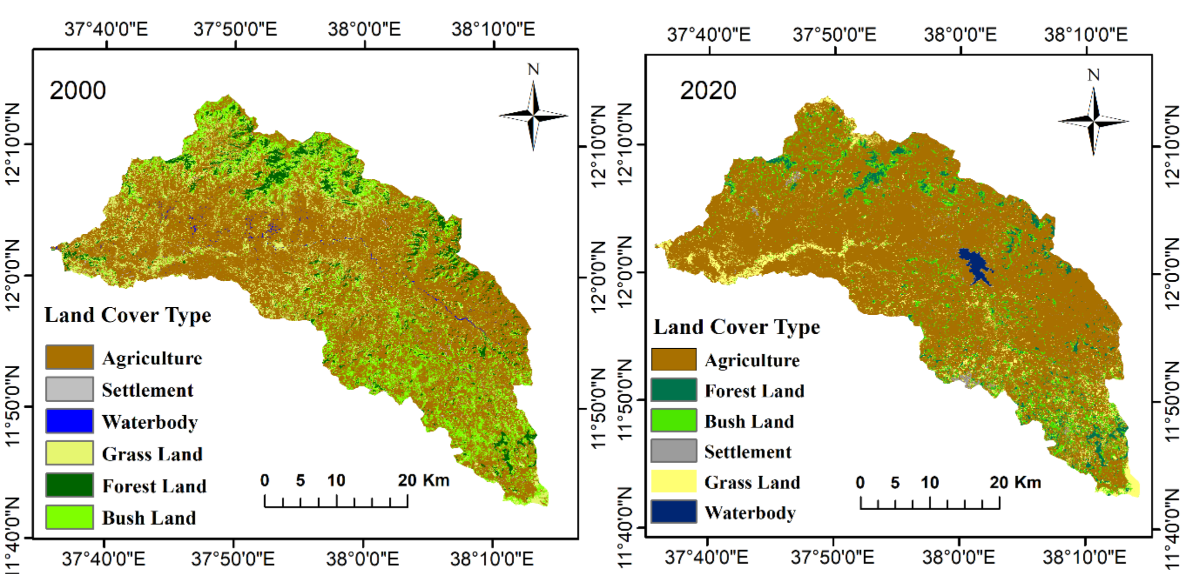


Figure 2.3 Land use and land cover map of Rib River watershed for 2000, and 2020.

2.3.1.2 Land Productivity Change as Indicator of LDN

The intricate processing of space-based data provides an evaluation of the dynamics of land production, which is a proxy indicator of the status of sustained land quality. An excellent indicator of Earth's potential to continue providing ecosystem services is the dynamics of its biomass. An approximation of a metric for the general productivity levels of the land environment system is to evaluate variations in NPP dynamics. Land users take advantage of this land productivity to harvest biological goods with a profit (Cui and Li 2022; Sciortino et al. 2020). A decline in total land productivity might be expected to show degradation (loss) of the land quality, whereas an increment of NPP shows improvement (gain) of the land condition in a certain geographical territory. According to (Cowie et al. 2018), a significant negative trend of NPP over the analysis period shows productivity decline (loss), whereas a significant positive trend leads to an increase in NPP, hence improvement (gain) of the land condition.

The land productivity change for each land use cover was extracted using Arc Map 10.3 software. The gain or loss of biomass, which reflects the LPD, is significantly influenced by the land use/land cover and average NPP. Table 2.7 indicated that there was a significant positive change in NPP between 2000 and 2020 for forest land, shrubland, and grassland. These increments have a positive impact on the status of LDN in the study watershed. Whereas the Average NPP of waterbody indicated significant negative change, this situation has a negative impact on the status of LDN. Furthermore, the NPP value of cultivated land and settlement was stable for the past two decades in the study watershed.

The Landsat image NPP time series was used to calculate the trend of net primary productivity for the years 2000 to 2020. These data were produced at a spatial resolution of 30 m USGS. The Landsat NPP product is estimated from atmospherically corrected bi-directional surface reflectance that has been masked for water, clouds, heavy aerosols, and cloud shadows (Liu et al. 2022; Quatrini and Crossman 2018; Sciortino et al. 2020; Yu and Song 2023). The average annual NPP was calculated for every pixel using MODIS NPP data from 2000 to 2020. The average annual was calculated as the arithmetic mean of the NPP values within each year.

The change in NPP value of cultivated land, forest land, shrub land, settlement, and Grassland indicated a positive change for the year 2000 to 2020. But the NPP value of waterbody indicated a negative change (Figure 2.4). Statistically, Table, 2.7 indicated that cultivated land and settlement increased by 259.61 t/DM/ha and 343.52 t/DM/ha respectively for the past two decades. These changes are stable with no significant change at $p < 0.05$. Whereas forest land increased by 914.47 t/DM/ha, Shrub land by 487.10 t/DM/ha, Grassland by 555.65 t/DM/ha and their change was a significant positive change from 2000 to 2020.

Table 2.7 NPP of the years 2000 and 2020 and implication for LDN.

LULC type	2000	2010	2020	2000-2010	2010-2020	2000-2020	The status of metrics Between 2000 and 2020
Cultivated	7330.69	6403.44	7590.30	- 927.25	1186.86	259.61	Stable, no sign change
Forest land	9205.63	8424.12	10120.10	- 781.51	1695.98	914.47*	Sig + ve change
Shrub land	8934.20	7860.14	9421.30	-1074.06	1561.16	487.10*	Sig + ve change
Settlement	7507.10	7031.43	7850.62	- 475.67	819.19	343.52	Stable, no sign change
Grass land	7986.82	7148.27	8542.47	- 838.55	1394.20	555.65*	Sig + ve change
Waterbody	5555.75	5093.66	2778.13	-462.15	-2315.53	-2777.62*	Sig - ve change

* shows the significant difference at $P < 0.05$

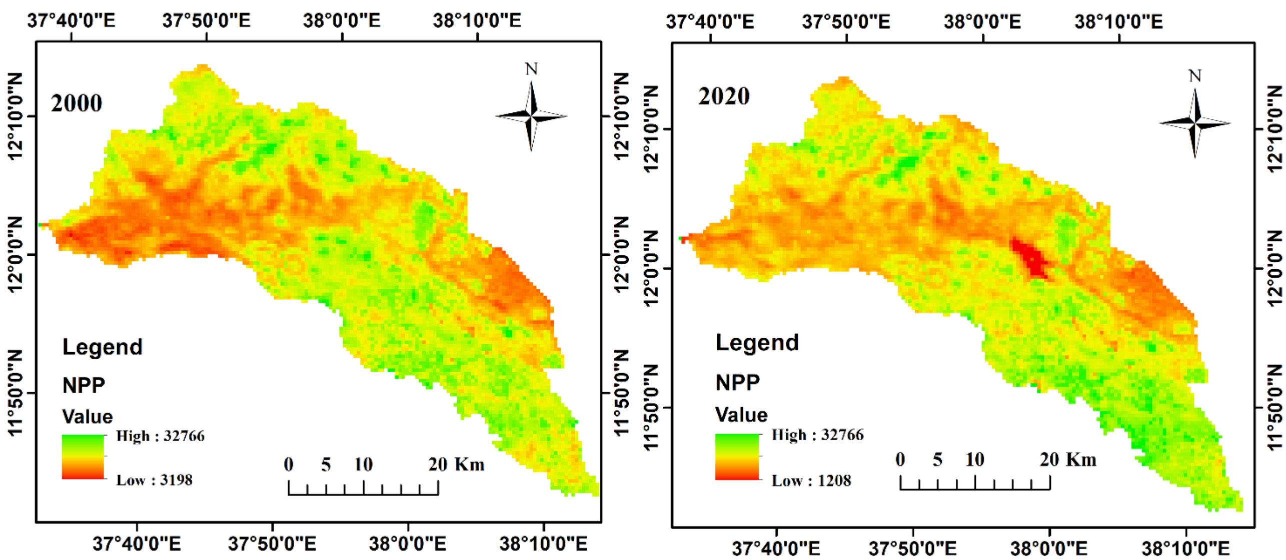


Figure 2.4 NPP for the years 2000 and 2020.

2.3.1.3 Soil Organic Carbon as Indicator of LDN

The largest concentration of carbon is found in soils, which are also used as a proxy indicator for LD assessments in particular geographic regions (Amanuel, et al. 2018b; Husein et al. 2019), but there is a shortage of quality data about carbon stocks in different land use land cover types (Sims *et al*., 2019). The SOC concentration indicated the major difference with land cover types ($p < 0.05$; Table 2.8, Figure 2.5). The overall average SOC concentration was higher under forest land and lower under cultivated land compared with other land uses in 2000 as well as 2020. In contrast, for the year 2020, the lowest average SOC stock of cultivated land was 76.98 t/c/ha and the highest was for forest land at 125.27 t/c/ha.

Table 2.8 Mean soil organic carbon of each land use and the status of metrics.

LULC type	2000	2010	2020	2000 to 2010	2010 to 2020	2000 to 2020	The status of metrics between 2000 and 2020
Cultivated land	77.63	79.52	75.05	- 2.58	- 4.47	- 2.58	Stable, no sign change
Forest land	128.60	127.15	125.27	- 1.45	-1.88	- 3.33	Stable, no sign change
Shrub land	121.32	121.51	119.05	0.19	- 2.46	- 2.27	Stable, no sign change
Settlement	107.80	114.39	113.88	5.59	- 0.51	6.08*	Sign + ve change
Grass land	112.22	111.35	108.07	0.87	- 5.28	- 4.15	Stable, no sign change

Waterbody	106.61	109.76	114.92	18.31	15.16	8.31*	Sig + ve change

In this study site average SOC stock of the agricultural field was reduced by - 2.58 t/c/ha from 2000 to 2020. This showed that there is no significant difference between the changes in carbon stock for the past two decades in the study area in the surface layer (0–15cm). The same is true for other land cover types, such as forest land reduced by (-3.33), Shrub land by (- 2.27), and grassland by (- 4.15) from 2000 to 2020. The change of SOC for the above-mentioned land use was non-significant at $p < 0.05$. In the study Rib watershed comparison among different land use showed that SOC declined by 3.32% in cultivated land, 2.58% in forest land, 0.02% in shrub land, and 3.69% in grassland land compared between 2000 to 2020. Whereas the average SOC of settlement and waterbody increased by 6.08t/ha (5.64%) and 8.31(7.79%) t/ha respectively for the past two decades. Those land covers showed a significant difference in the change of SOC between 2000 and 2020 (Table 2.8, Figure 2. 5). This positive change of SOC in settlement and waters body has a positive impact on the status of LDN in the study watershed.

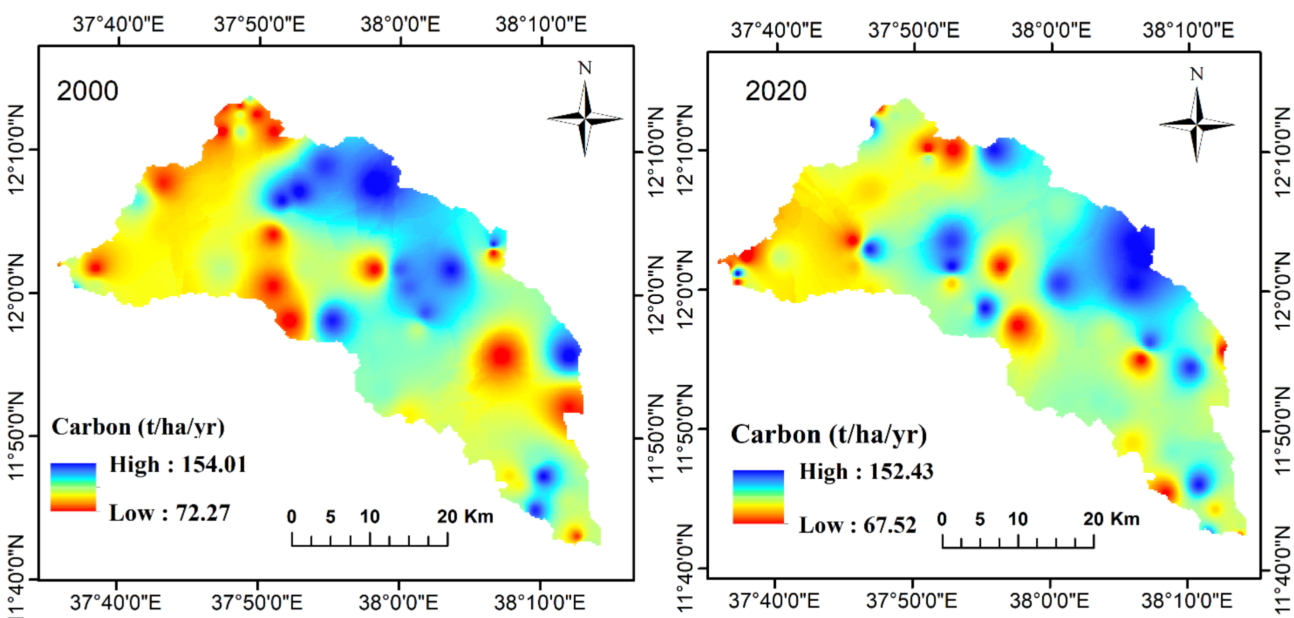


Figure 2.5 Soil organic carbon stock of 2000 and 2020

2.3.2. Analysis of the LDN Status

The years between 2000 and 2020 were then examined for the three primary LDN metrics of LC, NPP, and SOC. For this aim, the maps in the changes of metrics were prepared in the pixel size as shown in (Figures. 2.3, 2.4, 2.5) and précised (Table 2.9). Then, one-way analysis of variance (ANOVA) was used to compare measures' mean values for the period 2000–2020. The metrics of each data of different years of 2000, 2010, and 2020 were obtained from Land sat image, MODIS NPP, and soil samples. Lastly, the value of each metrics data of the watershed as well as each land cover type was then extracted from Arc GIS 10.3 using a spatial analysis tool. Finally, databases of each metric (LC, NPP, and SOC) were prepared in Excel 2016 for SPSS software to check whether there is a significant difference between metrics or not.

Table 2.9 LDN status of the Rib River Watershed.

LULC	Metrics	2000	2020	Change in metrics between 2000 & 2020	Status of metrics	LDN Status
Cultivated land	LUC	101,038	123,977	22,939*	Sig +ve change	
	NPP	7330.69	7590.30	259.61	Stable, no sign change	Loss (Degradation)
	SOC	77.63	75.05	- 2.58	Stable, no sign change	
Forest land	LUC	10460	5623	- 4837*	Sig –ve change	
	NPP	9205.63	10120.10	914.47*	Sig + ve change	Loss (Degradation)
	SOC	128.60	125.27	- 3.33	Stable, no sign change	
Shrub land	LUC	25182	13984	- 11,198*	Sig –ve change	
	NPP	8934.20	9421.30	487.10*	Sig + ve change	Loss (Degradation)
	SOC	121.32	119.05	- 2.27	Stable, no sign change	
Settlement	LUC	843	1993	1,150*	Sig –ve change	
	NPP	7507.10	7850.62	343.52	Stable, no sign change	Loss (Degradation)
	SOC	107.80	113.88	6.08	Sign + ve change	
Grass land	LUC	20524	11999	- 8525*	Sig –ve change	
	NPP	7986.82	8542.47	555.65*	Sig + ve change	Loss (Degradation)
	SOC	112.22	108.07	- 4.15	Stable, no sign change	

Waterbody	LUC	586	1056	470*	Sig +ve change	
	NPP	5555.75	2778.13	-2777.62*	Sig - ve change	Loss (Degradation)
	SOC	106.61	114.92*	8.31	Sign + ve change	

The indicator was quantified by estimating changes in the sub-indicators over time, to determine the spatial extent of land that is degraded over total land area. To determine whether this area was improving or degrading over time, the extent of degradation assessed in each sub-indicator for the targeted periods (2020) was compared to the extent of degradation measured in the baseline period (2000). The baseline determines the benchmark extent of degradation against which changes towards achieving SDG target 15.3 and LDN status was evaluated in the study watershed. The 1OAO concept was therefore used in the calculating procedure, and changes in the sub-indicators are shown as Positive (improving), Negative (declining), and Stable. (Unchanging). If one of the sub-indicators is significantly declining then LDN status degradation will occur for a particular land unit.

There was a positive significant change in cultivated land between 2000 to 2020 at $P < 0.05$ (Table 2.9). The expansion of cultivated land is considered the cause of degradation (Cowie et al. 2018). The remaining metrics, NPP and SOC observed that there was no significant change (Stable) for the past two decades. As can be seen, using the 1OAO rule, the calculated LDN metrics show a degradation trend of cultivated land in the study Rib watershed.

As can be seen from Table 2.9, the three metrics of forest land and shrub land showed the Sig –ve change, Sig + ve change, and Stable (no sign change) respectively for the past two decades. This indicates that the LDN status of both forest land and shrubland was under degradation (loss) in the study watershed. The status of metrics for settlement was Sig –ve change for LUC, Stable, no significant change for NPP and Sign + ve change for SOC from the year 2000 to 2020. The change of metrics for settlement for the past two decades showed a degradation in the status of LDN. In the same vein, grassland showed Sig –ve change, Sig + ve change, and Stable, with no significant change for LUC, NPP, and SOC respectively. This situation implies the degradation (loss) of grassland. The last type of land cover was waterbody. The change of tree metrics for waterbody was Sig +ve change for LUC and again Sig +ve change for SOC at $P < 0.05$. However, NPP showed the Sig - ve change for the past two decades. In general, the output of the above-mentioned land cover type indicated that a net loss (degradation) occurred from 2000 to 2020 at the Rib watershed of the Upper Blue Nile Basin, Ethiopia.

2.4 Discussion

2.4.1 Trends of LULC, NPP, and Soil Organic Carbon Changes

The decline of the forest, shrubland, grassland, and the increase of cultivated and settlement in the Rib watershed during the study period (2000–2020) is consistence with the findings of several studies in Ethiopia (Meshesha et al. 2014; Minta et al. 2018; Tolessa et al. 2017). The expansion of cultivated land in Ethiopia is mostly credited to the country's policy. For instance, in the existing Ethiopian government, the land ownership policy is specified in the constitution, with land as the belongings of the state (Mengesha et al. 2022). This allowable them to use the land but not to sell it. Due to the state's ownership of resources related to land, rural residents were easily able to transform grazing, shrub, and forest land into cultivated land.

An evaluation of the dynamics of land productivity, which is a proxy statement of the status of sustained land quality, is produced through the complex processing of routine space-based observation. The change in the Earth’s biomass cover is an important expression of its capacity to supply ecosystem services. Assessing the dynamics in vegetative cover change is an approximation of a measure for general productivity levels of the land. Land users take advantage of this land productivity to produce biological products of economic value (Lal et al. 2012). The change in NPP value of cultivated land, forest land, shrub land, settlement, and Grassland indicated a significant positive change in land productivity for the year 2000 to 2020. The finding of our result was in line with the conclusion of other papers (Wang et al., 2021; Tian et al., 2022). Whereas the change in settlement and waterbody showed stable and negative changes in land productivity in the study watershed respectively.

The SOC concentration indicated that there is a significant difference within land use types ($p < 0.05$; Table 4). The total mean SOC concentration was higher under forest and lower under cultivated land compared with other land uses which is similar with other studies such as (Abegaz et al. 2016; Amanuel et al. 2018b; Soleimani et al. 2019). The cause for more soil carbon stock in the soil of forest is due to the minimum disturbance in soil and a slow amount of SOC decomposition which result in higher carbon accumulation, whereas low SOC stock in agricultural land is due to intensive cultivation practices which results in larger soil disturbance, and increase rate of SOC decomposition (Mancinelli et al. 2010; Sainju et al. 2008; Yimer et al. 2007).

This study showed that the change in land cover could have an effect on how much carbon is stored in the soil. To increase the SOC content, efforts should be made to use appropriate land use management practices, such as applying organic manure. In addition to helping to increase soil carbon, land use management is a crucial step in protecting the soils organic carbon. Based on the type of land use or cover, the study found considerable variations in the amount of organic carbon in the top 15 cm of soil. The results showed the average reduction of organic carbon from cultivated land (2.58t/c/ha), forest land (3.33), shrub land (2.27), and grassland (4.15) for the past two decades at Rib watershed. These results highlight the important role that land use plays in influencing soil carbon levels and the need for prudent land-use procedures to maintain soil health and maintain soil carbon levels. This decline is a result of the removal of above-ground biomass from cultivated and grassland areas for livestock feed. In addition, tillage and site preparation activities disrupt the soil, which exposes organic matter to breakdown and causes quick losses of soil organic carbon. The decomposition, leaching, and soil erosion can contribute to the decreased soil organic carbon storage. Poor farm management and post-harvest grazing may also be to impact soil organic carbon storage (Yu and Song 2023). After harvest, there may be a large loss of topsoil and organic matter, especially in regions with high levels of precipitation and rapid rates of erosion, like the Rib watershed.

2.4.2 The Status of Land Degradation Neutrality

The result of the tree indicator indicated that a net loss (degradation) occurred from 2000 to 2020 at the Rib watershed of Upper Blue Nile Basin, Ethiopia. In this regard, the results are consistence with (Akhtar-Schuster et al. 2017), who highlighted the change in land use change, continuous expansion of degraded land, and avoiding the prospect of ever achieving a stable state of LDN. The LDN status was under degradation state in the Rib Watershed of Upper Blue Nile Basin for the year 2020. This study provides decision-makers with key information on the LDN status in different LULCs of the Rib Watershed. The output of the study is vital to apprise policy development on land management mostly, specifically on how to design for the implementation and monitoring of LDN by 2030. In this concern, (Akhtar-Schuster et al. 2017; Grainger 2015), and (Gichenje et al.2019) stressed the evaluation of LDN and restoring degraded lands, improving national land use planning systems, and establishing national monitoring capacities. The outcomes for the LDN were also compared with those for the LDN approach, as published by (Bobushev and Sultanaliev 2020; Gichenje and Godinho 2019; Gichenje et al. 2019; Kust, Andreeva, and Lobkovskiy 2020; von Maltitz et al. 2019; Sims et al. 2019; Teich et al. 2019; Zolotov et al. 2020) dealing with LDN approach.

2.5. Conclusion

The goal of the current study was to evaluate the current LDN status by using the LDN approach in the Rib Watershed of the Upper Blue Nile Basin. To plan and manage the many compartments in a watershed ecosystem adequately, managers and planners require information on the LDN status for at least 10 years. To assess the LDN status in the Rib Watershed, the metrics provided by UNCCD, including changes in land cover, NPP, and SOC, were employed. Different land uses were classified as being in a state of degradation (sign - ve change), improvement (sign +ve change), or stability (no change) based on the analysis of the trend in each metric. In order to prevent, decrease, and stop degradation in the settlement, waterbody, and cultivated land in the study watershed, appropriate managerial actions might be planned using the research's findings.

As one of the determinant factors LDN of in the research area, various conservation agricultural land management strategies can also be recommended to increase the organic matter contents of the soil. Therefore, managers and planners must take into account the capability and potential of the lands in diverse ecosystems given the LDN status in various types of land use in the Rib Watershed. Meanwhile, it is essential to put suitable managerial and developmental plans into place to prevent interventions or changes in land use that would worsen land degradation in the research area. In conclusion, experts are suggested to take managerial actions to avoid the degradation of different types of land use.

CHAPTER THREE

3. Impact of Land Use/Cover Changes on Ecosystem Service Values in Rib River Watershed, Upper Blue Nile Basin, Ethiopia.

Based on Publication:

Anley, M. A., Minale, A. S., Ayehu, N. H., & Gashaw, T. (2022). Assessing the impacts of land use/cover changes on ecosystem service values in Rib watershed, Upper Blue Nile Basin, Ethiopia. *Trees, Forests and People*, *7*(3), 100212. https://doi.org/10.1016/j.tfp.2022.100212

Abstract

This study was aimed to assess the impact of land use/land cover (LULC) changes on ecosystem service values (ESVs) in the Rib watershed of the Upper Blue Nile Basin between the 2000 and 2020 periods. Image classifications were carried out using Landsat 5 TM for 2000 and 2010, and Landsat 8 OLI_TIRS for 2020 periods following the supervised classification technique with a Maximum Likelihood Algorithm (MLA) in ERDAS Imagine 2014. The study estimated the effects of LULC changes on ESVs using the modified ecosystem service value coefficients. The LULC result indicated that, a reduction of forest (46 %), shrubland (44 %), grassland (42%), and an increase of cultivated land (23 %), settlement (137%), and waterbody (80 %) during 2000 and 2020 periods. The total ESVs of the watershed were estimated to be US$ 68.6 million in 2000, US$ 59.4 million in 2010, and US$ 59.3 million in 2020. The ESVs lost between 2000 and 2020 periods in the study watershed was about US$ 9.3 million (13.5%). The observed LULC changes during this period have also affected the individual ecosystem services The reduction of ESVs through 2000 to 2020 periods indicates the effects of LULC changes on ecological degradation. Hence, it is suggested that land managers and policymakers can use LULC change and ESVs together for good decision-making processes.

Keywords: Ecosystem services values, Land use/land cover, modified ecosystem value coefficient.

3.1 Introduction

Scientific investigations indicated that land use land cover (LULC) changes can alter provision of ecosystem services. Our earth provides a vast range of ecosystem services that vary in quality and quantity depending on the type and status of ecosystem (Fetene Admasu et al., 2020; Marzec, 2018; Mooney, 2005). For instance, tropical forest land was found to be different in service provision compared to grassland (Costanza et al., 1997, 2014; de Groot et al., 2012), and hence, it is clear that ecosystem provide different services that could not be substituted by another (Gashaw et al., 2018; Kindu et al., 2018). Ecosystem services contribute to human well-being and survival, either directly or indirectly. (Sch¨agner &, Luke et al., 2013; Costanza et al., 2014; Marzec, 2018). However, when an ecosystem is managed for providing a single service others ecosystem services are negatively affected (Braat & de Groot, 2012). As a result, quantitative analysis on the changes in ecosystem service values (ESVs) is important for decision-makers to allocate resources (Barral et al., 2015; Guo et al., 2010), and policy design to formulate policy related to ecosystem services (Schagner et al.,2013).

Throughout the world, the total net reduction of ecosystem service has been estimated at USD 20.20 trillion per year from 1997 up to 2011 as a result of LULC changes (Costanza et al., 2014). However, estimation of ESVs change at a regional scale from the global study might lead to erroneous conclusions; in fact, a regional study of a country often results in a different yield due to various approaches and classifications. Many regions of Africa are facing rapid and profound transformations economically, socially, and environmentally a transformation that is already endangering the long-standing conservation of its substantial natural heritage and biodiversity (Babalola & Borokini, 1988). As a result, many parts of the continent are experiencing persistent ecosystem degradation at the expense of future generations' well-being (de Groot et al., 2012; Kubiszewski et al., 2017), which is especially true for Ethiopia, which lost roughly 17.7% of its ESVs owing to LULC change (Sutton et al., 2016).

In Ethiopia, LULC changes are a common phenomenon where agricultural activities dominate rural landscapes affecting ecosystem services. Combining LULC and ecosystem service valuation data can help identify the area most vulnerable to changes in ecosystem services at the landscape level and provide an entry point for land management opportunities in the future (Tolessa et al., 2017). Therefore, recognizing and estimating the effects of LULC changes on global, regional, and local ESVs is a practical approach to evaluating the costs and benefits of sustainable land management decisions (Deng et al., 2013; Liu et al., 2008; Xu et al., 2018). It also aids in the advance of a land-use planning framework that is compatible with the long-term sustainability of land resources. (Cabral et al., 2017; Jacobs et al., 2016; Temesgen et al., 2018).

The four basic categories of ecosystem services provided by a certain geographical area are provisioning, regulatory, supporting, and cultural services (Braat & de Groot, 2012; Kindu et al., 2016; Costanza et al., 2017; Marzec, 2018). However, LULC changes are tightly tied to each ecosystem service, and they change across time and space. (Costanza et al., 2014; Sutton et al., 2016; Schirpke et al., 2017; Xu et al., 2018). For example, studies show that the conversion of forest to cropland increases food production while it reduces the regulating services supplied by the forest (Fedele et al., 2018; Foley et al., 2005; Rodríguez et al., 2006). Since the changes in ESVs are different depending on the pattern and magnitude of LULC changes, most of the available studies were location-specific. For instance, some studies reveal an overall increase ESVs (Temesgen et al., 2018; Wang et al., 2015) while others confirm a decreasing trend of the majority of the individual ecosystem services (Gashaw et al., 2018; Leh et al., 2013; Tolessa et al., 2017).

This study was conducted in the Rib River watershed of North West, Ethiopia where expansions of cultivated land and a reduction of the forest land were undertaken at an increasing rate. Those expansions and reduction of LULC cannot be properly managed by land planners. In addition, the impact of each LULC on ecosystem service is not well understood by experts and communities. For instance, the building of a dam in the watershed increases the percentage share of a waterbody. Hereafter it increases ecosystem service of the watershed supplied by waterbody. As a result, examining the impact of LULC changes on ESV in the study watershed is crucial for raising public awareness and guiding policy on ecosystem service. In the Ethiopian context, LULC changes have been widely studied by (Belay & Mengistu, 2019; Birhanu et al., 2019; Meshesha et al., 2016; Minta et al., 2018; Tolessa et al., 2016) but no attempts have been made for its impact for ecosystem service.

Therefore, this study aims to fill the gap taking the Rib River watershed of North West Ethiopia as a case site covering the period from 2000 to 2020.

This study was targeted on estimating the loss of ESVs due to the LULC changes undertaken in the past two decades using the modified ecosystem service value coefficients. The modified ES value coefficient which was developed by (Kindu et al., 2016). The modified ecosystem coefficient was developed by a review of the previous studies, expert opinion, and dataset available from the Economics of Ecosystem and Biodiversity database. The LULC change versus ecosystem service interaction in the Rib watershed was the central point of the study. Therefore, land managers in the study area can use the result of the study during their decision-making processes. Hence, the main objectives of the study were 1) to quantify the amount and rate of LULC changes undertaken during the past two decades and (2) to estimate the loss of ESVs from 2000 to 2020 periods because of the LULC changes.

3.2 Material and Method

3.2.1 Description of the study Area

The research was conducted in the Rib River watershed that extends from Mountain Guna to Lake Tana at the source of the Blue Nile. Rib watershed is found eastern part of the Lake Tana basin with locations between 10°43’ - 11° 53’ N and 35^0 - 37° 47’ E (Figure 5.1). The watershed is one of the major sources of water for Lake Tana. The major river in the watershed is the Rib River which extends within the districts of Ebnat, Farta, Libo Kemkem, and Fogera.

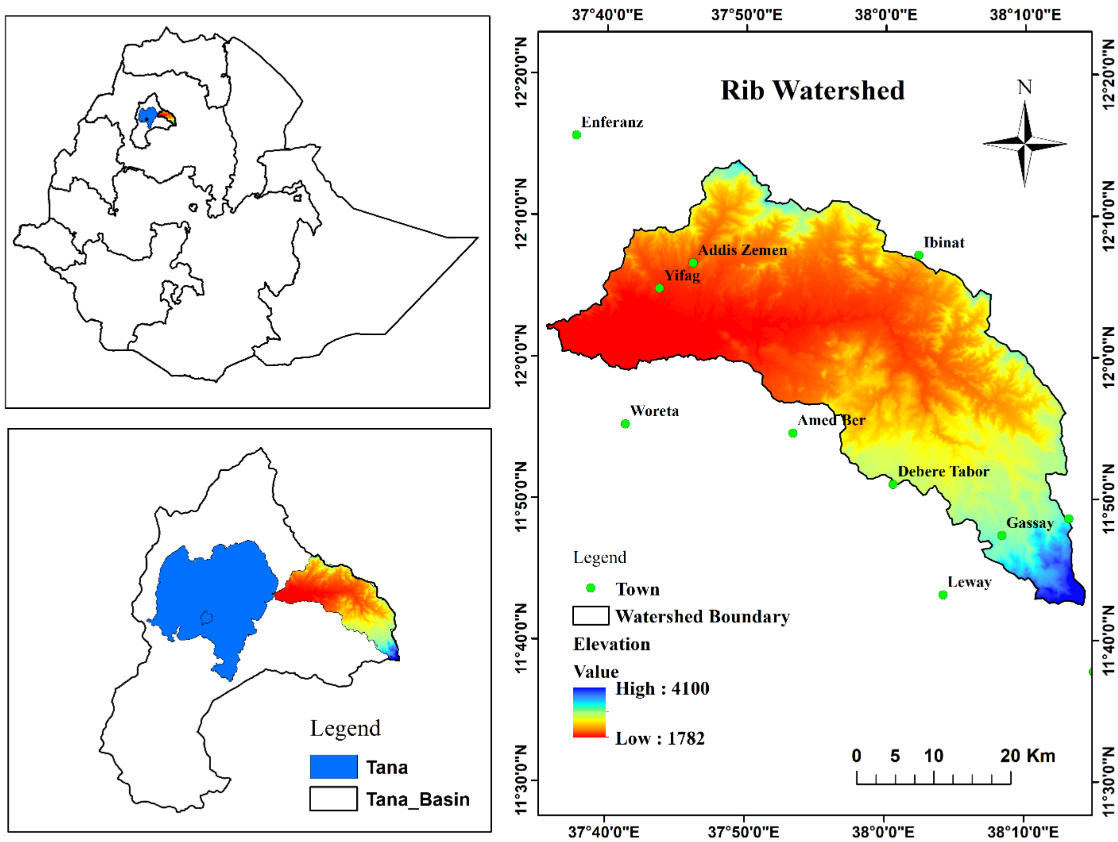


Figure 5.1 Map of Rib River watershed.

3.2.2 Topography

The elevation of the study watershed ranges from 1785 - 4049 masl and has a total area of 1583 km^2 (Figure 5.2). The watersheds has diverse terrain types including hills, with a steep mountain range on its southern border and sparsely scattered hills and their escarpments on its center and northern sides (Sinshaw et al., 2021). According to the slope classification of FAO, and derived from 30m resolution DEM, about 32% of the study area constitutes gently slope gradient (>5^0), 20% moderate sloping (5-15^0), and 43% steep slope (15^0-30^0) and the remaining 15% are very steep sloping above 30^0(Figure 5.2). The topography of the study watershed is suitable for agricultural production. The soils were developed from volcanic ashes and reworked materials from tertiary volcanic eruptions as well as sedimentation processes. Four types of soils derived from weathering of basaltic rocks were known in the study area, including Luvisols (34%), Leptosols (28%), Vertisols (23%), and Regosols (15%) (Ayalew & Bharti, 2022).

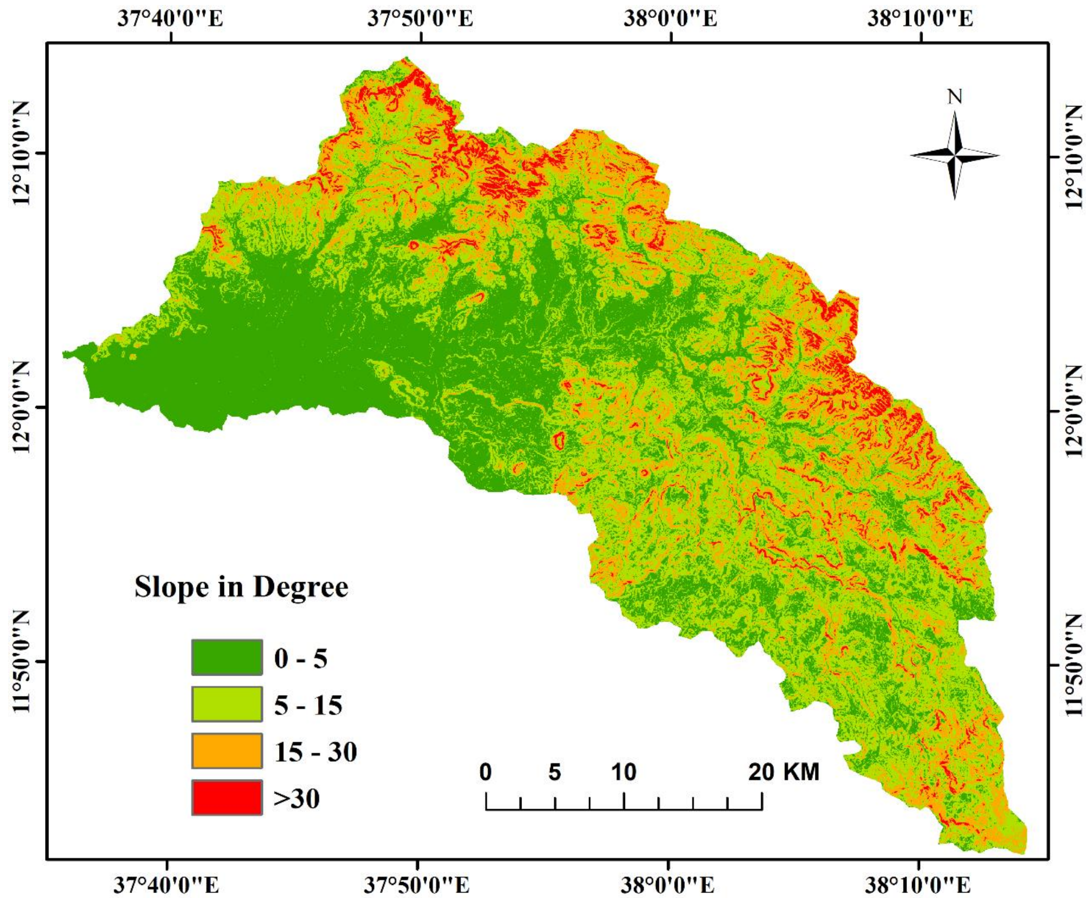


Figure 5.2 Slope classification of the study area

3.2.3 Socio Economies

According to the projection of Central Statistical Authority (2014), about 878,261 people are living within the watershed, with 89.7% of them are living in rural areas and relying primarily on agriculture. According to (Anley et al., 2022), the land use land cover of the watershed consists of agriculture (123,977 ha), forest land (5623 ha), shrub land (13984), grassland (11,999 ha), and waterbody (1056 ha). Agriculture is the primary economic activity in the study area and is used as the main source of livelihood for the rural community. Furthermore, the community is also rearing animals for both market and domestic consumption in the study watershed.

Agriculture is the major economic activity and main source of income for the local community in the study area. The communities practice mixed farming, growing crops, and rearing animals as means of livelihood. The commonly grown crops in the study area include; Potato (*Solanum tuberosum*), teff (*Eragrostis tef*), rice (*Oryza galberrima*), beans

(*Phaseolus vulgaris L*), barley (*Hordeum vulgare*), maize (*Zea mays L*), and wheat (*Triticum Vulgare*) are the main types of agricultural products grown in the research region. Rib Dam has been under construction since 2008 and cost $ 40 million. It has a reservoir storage capacity of 234 million m^3. The dam is targeted to be used for irrigation purposes at Fogera plain of Amhara regional state and is proposed to supply 14,000 ha of land to serve more than 28,000 households (Annys et al., 2020). The rice granary and the demonstration location for national rice research are both located in Fogera Plain, which is part of the Fogera woreda.

3.2.4 Climate

The climate types of the region are markedly influenced and controlled by altitude and regional/global weather systems. The climatic zone of the Rib River Watershed is highly dominated by subtropical (traditionally, Woina Dega), statistically 2% (Alpine), 64.4% (Sub-Tropical), and 33.6% (Temperate). Weather record data for the past two decades in the watershed indicated the annual average rainfall (1550.5 mm) and temperature (15.4 °C) (Figure 3.3). Over 70% of rainfall occurred during the summer season while little or no rainfall data was recorded in the remaining months. Rainfall, which primarily occurs between June and September, plays a significant role in crop productivity. This means that cultivation is limited to the remaining months of dry weather, which is unusual for the watershed. However, only a small portion of the farming community employs irrigation to harvest maize and onions.

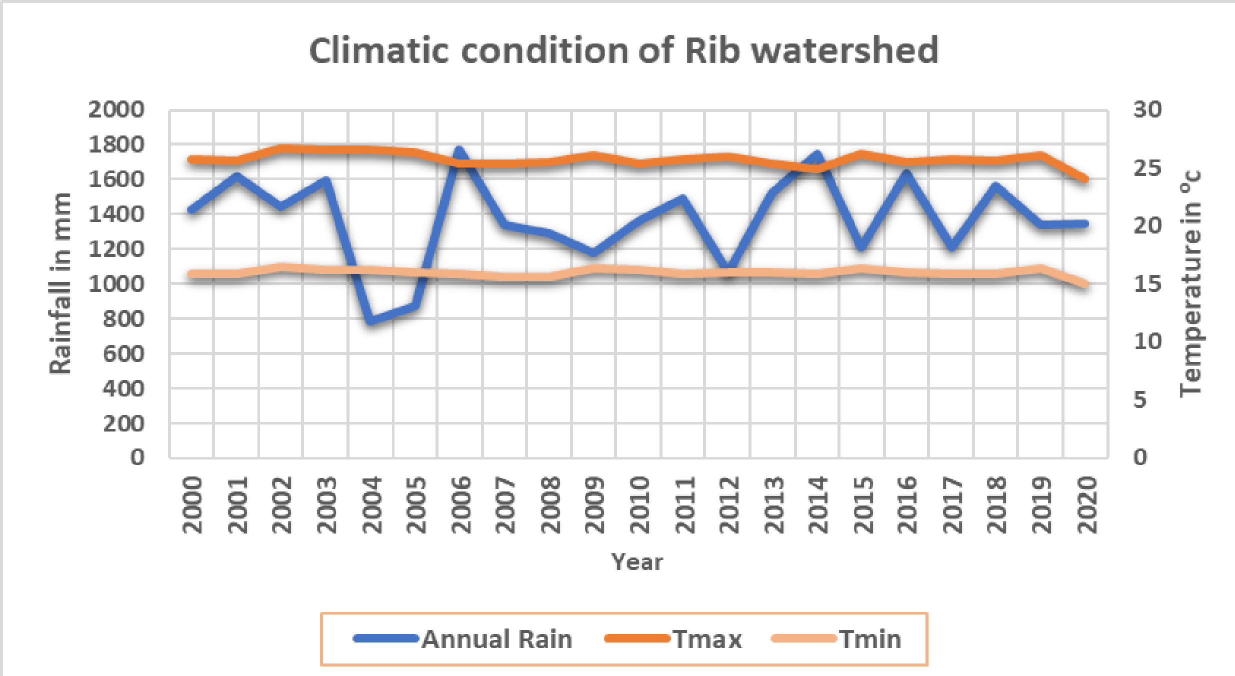


Figure 5.3 Annual mean rainfall and temperature of Rib River watershed from 2000 to 2020.

3.3 Satellite Images Pre-Processing and LULC Classifications

The study used time-series multispectral Landsat imageries to quantify the LULC changes and to estimate the associated loss of ESVs (Landsat 5 TM, and Landsat 8 OLI) during 2000, 2010, and 2020 periods (Table 3.1). All of the raw images were taken in the same season and were nearly free of cloud since they were taken during the dry season. To prevent the effect of seasonal fluctuations at each LULC, satellite images taken during the dry season and without clouds are essential. (Belay & Mengistu, 2019; Birhanu et al., 2019; Johansen et al., 2015). Therefore, all the satellite images were taken in January and February with a cloud cover of less than 10%. The Millennium development goal related to land resource and ecosystem service was launched in 2000, thus the year 2000 was used as an initial (benchmark) time for the analysis of LULC and ESV.

Table 3.1 Descriptions of the Landsat images.

Imagery date	Imagery type	Spatial resolution	Path and raw	Source
02/07/2000	Landsat 5 TM	30 m	169/52	USGS*
01/31/2010	Landsat 5 TM	30 m	169/52	USGS
01/26/2020	Landsat 8 OLI	30 m	169/52	USGS

* Refers to United States Geological Survey

ERDAS imagine 14 software was used for preprocessing and processing satellite image data by applying the basic image preprocessing techniques starting from image enhancement, image classification, and accuracy assessment. The pre-processing of the images such as layer stacking, color composite, and sub-setting was done. Then, geometrically and radiometrically Landsat images correction were done to improve image quality, and a Universal Transverse Mercator map projection system was also performed. The satellite images of 2000, 2010, and 2020 were classified using a supervised image classification technique with a maximum likelihood classification algorithm. Based on the criterion of FAO, the Rib watershed was classified into six LULC classes such as cultivated land, forest, shrubland, grazing land, waterbody, and settlement (Table 3.2). ArcMap 10.3 and Erdas Imagine 2014 software were used for image classification and mapping of ESVs, respectively.

Table 3.2 The LULC classes of Rib River watershed and their descriptions.

LULC types	Descriptions
Cultivated land	Land under cultivation
Forest	An area dominated by trees with dense canopy cover
Shrubland	land with isolated small trees always with a lower range of grass.
Grassland	Landscape under grass cover but highly influenced by grazing and browsing of domestic animals.
Waterbody	Area covered by rivers, lakes
Settlement	A land dominated by houses and huts

For image classification, expert knowledge, elder people interview, and Google earth were used for the years 2000 and 2010. Field observation was carried out to collect training samples for 2020. Ground control points (GCPs) were also collected using a GPS device to perform classification accuracy assessments for each land-use class for the 2020 classification year. Ground control points for accuracy assessment were independent of those used as training samples. According to (ERDAS Inc., 2008), at least 50 GPS points per land-use type are advisable for land cover classification. In this study, to increase the accuracy, on average 100 GPS points at each land use type was being taken.

Therefore, a total of 600 GCPs training samples for supervised land cover classification were collected for all land use/land cover classes. The area proportion of the land uses was used to determine the number of GCPs for each class. By comparing the sample LULC class of the classified layer to the reference layer, the classification accuracy of the LULC layers of satellite image was investigated. To determine the degree of classification accuracy of the error, the overall accuracy and Kappa analysis were computed (Table 4.4). The Kappa coefficient represents the difference between the actual agreement of the classified map and the chance agreement of the random classifier when compared to reference data. It was also calculated as follows (Eq 3.1).

$$K_{hat} = \frac{N \sum_{i=1}^{K} Xab - \sum_{i=1}^{k} (Xa * Xb)}{N2 - \sum_{i=1}^{k} (Xa * Xb)} \qquad (3.1)$$

where:

Khat = Kappa coefficient; N is the total number of values; $\Sigma_{i=1}^{k} X_{ab}$ is observed accuracy, and $\Sigma_{i=1}^{K}(Xa*Xb)$ is chance accuracy.

3.4 Methods of Estimating the Impacts of LULC Changes on ESVs

The overall approach was estimating the changes of ESVs between 2000, 2010, and 2020 years with concern to LULC. The LULC map was classified and the areal extent of each type was calculated. Using the modified ecosystem value coefficient, the total ESV and their changes to each LULC type were calculated between 2000, 2010, and 2020 (Figure 3.2). In this study, we examined the possible LULC changes in the Rib watershed of Upper Blue Nile Basin of Ethiopian highlands covering the period for the past two decades (2000 – 2020) using spatially explicit GIS and Remote sensing-based software.

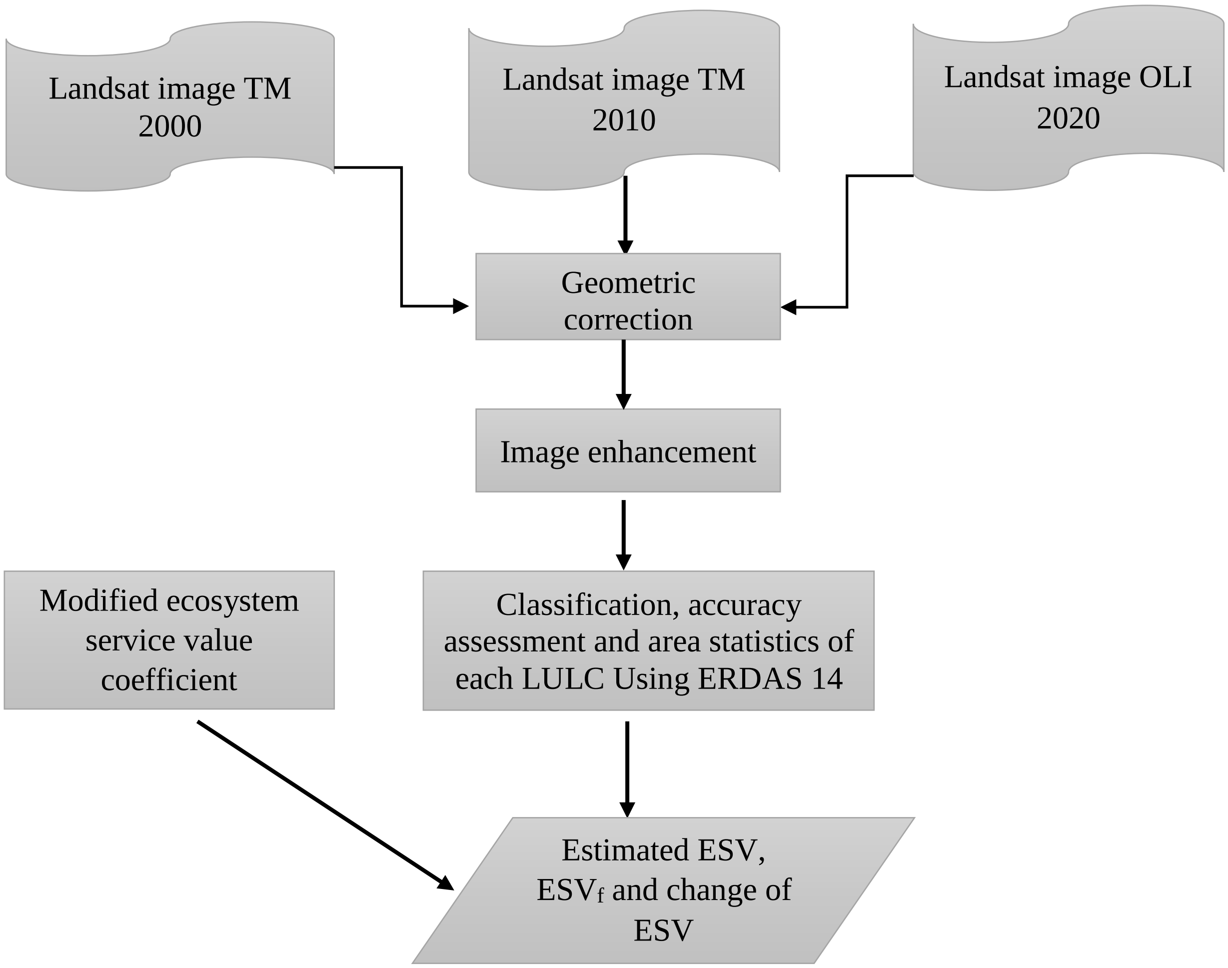


Figure 3.2 The methodological approaches.

In this study, ESV of six LULC categories was calculated using a modified ecosystem service value coefficient developed by (Kindu et al., 2016, 2018) for 11 biomes for Ethiopia conditions. The modified ecosystem coefficient was developed by a review of the previous studies, expert opinion, and dataset available from the Economics of Ecosystem and Biodiversity database. Therefore, LULC types of Rib watershed were associated with the corresponding representative biomes, and their ecosystem service coefficient (US \$ ha^{-1} yr^{-1}) are as follow: 1) cropland for cultivated land (225.56), 2) tropical forest for forest and shrubland (986.69), 3) rangeland for grassland (293.25), and 4) settlement for the built-up area (0), 5) Waterbody for rivers and lakes (8103.5). The modified ecosystem service value coefficient which was employed in this study is displayed in Table 3.3.

Table 3.3 Coefficients (US \$ ha^{-1} yr^{-1}) of the modified ecosystem service valuation (Kindu et al., 2016) for the represented biomes

Ecosystem services	Biome				
	Cropland	Tropical forest/shrub	Grassland	Urban	Waterbody
Provisioning services					
Water supply		8			2117
Food production	187.56	32	117.45		41
Raw materials		51.24			
Genetic resources		41			
Regulating services					
Water regulation		6	3		5445
Climate regulation		223			
Disturbance regulation		5			
Gas regulation		13.68	7		
Biological control	24		23		
Erosion control		245	29		
Waste treatment		136	87		431.5
Supporting services					
Nutrient cycling		184.4			
Pollination	14	7.27	25		
Soil formation		10	1		
Habitat/refuge		17.3			
Cultural services					
Recreation		4.8	0.8		69
Cultural		2			
Sum	225.56	986.69	293.25	0	8103.5

The value coefficients were given to each LULC type developed by (Kindu et al., 2016, 2018) during the ecosystem service value calculation procedure (Table 3.3). After that, by multiplying the hectare area of each LULC type by the value coefficients for each LULC type, the total ESV for each LULC type was computed. The value of LULC type was summed to estimate the total ESV of the landscape for each year (2000, 2010 and 2020). The total ESV in the study landscape for 2000,2010 and 2020 were obtained following the methodology used by (Hu et al., 2008; Li et al., 2010) E.q 3.2:

$$ESV=\Sigma\,(AK \times VC_k) \qquad (3.2)$$

Where ESV = estimated ecosystem service value, AK = area in hectare (ha) and VC_k = value coefficient (US \$ $ha^{-1}yr^{-1}$) for LULC category k (Table 3.3). To evaluate change in ESV, the variance between the estimated ESV for each LULC category between 2000, 2010, and 2020 was calculated.

Additionally, the effect of change on each 17 specific ESV in the study area was evaluated to estimate LULC change effects on the overall ESV (Table 3.3). The following empirical equation 3.3 was employed to calculate the value of each ecosystem service used by (Kindu et al., 2016):

$$ESVf = \Sigma\ (AK \times VCfk) \tag{3.3}$$

Where ESVf = the estimated ESV of function f, Ak = the area (ha), and VCf_k = the value coefficient of function f (US $\$ha^{-1}yr^{-1}$) for LULC category k.

Sensitivity analysis was done to estimate the change in ESVs for change in the value coefficient (Li et al., 2010). Accordingly, the modified ESV coefficients for cultivated land, forestland, shrubland, grasslands, waterbody, and settlement were each adjusted by 50%, and the corresponding coefficient of sensitivity (CS) was calculated using Eq. (3.4) as in (Kreuter et al., 2001).

$$CS = \frac{ESVj - ESVi\ /\ ESVi}{VCjk - Vcik/\ VCik} \tag{3.4}$$

Where CS = Coefficient of Sensitivity, ESV_i and ESV_j are initial and adjusted total estimated ESV respectively. VCj_k and VCi_k refer to adjusted and initial value coefficients (US $\$$ $ha^{-1}yr^{-1}$) for LULC type ‘k’ respectively.

3.5 Results

3.5.1 Analysis of Spatiotemporal LULC Changes

Six LULC classes were identified in the study area, such as cultivated land, forestland, shrubland, grassland, waterbody, and settlement. The user and producer accuracy of the classified image was calculated and depicted in (Table 3.4). The user's accuracy essentially tells us how often the class on the map will be present on the ground and calculating by taking the total number of correct classifications for a particular class and dividing it by the row total. Whereas producers’ accuracy shows how often are real features on the ground correctly shown on the classified map. It is also the number of reference sites classified accurately divided by the total number of reference sites for that class (ERDAS, 2009). The overall accuracy assessment for the years 2000,2010 and 2020 was 80.11%, 82.7%, and 84.8% respectively with Kappa statistics 0.78 for 2000,0.80 for 2010, and 0.82 for 2020 (Table 3.4). This confirms the recommended and suggested value by (Olofsson et al., 2014). Thus, the data was used for the estimation of ESV for different LULC types.

The types of LULC that increased progressively for the past two decades were cultivated land and settlement. For example, cultivated land was increased by 11.2% from (2000 up to 2010), 10.3% (2010 to 2020) and 22.7 % (2000 to 2020). Besides, settlement was increased by 99.9% from 2000 to 2010 and 19.6% from 2010 to 2020. The overall increment of settlement from 2000 to 2020 was 136.5%. On the other hand, forest, shrubland, and grassland were decreased progressively from 2000 to 2020 (Table 3.5, Figure 3.3).

Statistically, forest cover has been decrease by 8.90% from (2000 to 2010), 40.90% (2010 up to 2020) and 46.24% (2000 to 2020). Shrubland decreased by 27.08% from 2000 to 2010 and 23.83% from 2010 to 2020. The total reduction of shrub was 44.46% from 2000 to 2020.Grassland decreased by 19.62%, 27.26%, and 41.53% from 2000 to 2010, 2010 to 2020, and 2000 to 2020 respectively. Waterbody decreases considerably between 2000 to 2010 but showed a tremendous increase between 2010 and 2020 (Table 3.5, Figure 3.3). The increase in a waterbody is probably due to the construction of the Rib dam in the watershed.

Table 3.5 The patterns and rates of LULC changes during 2000-2020.

LULC class	Area coverage (ha)			Cover change between periods (%)		
	2000	2010	2020	2000	2010	2020
Cultivated	101,038	112,351	123,977	11	10	23
Forest	10460	9523	5623	- 8.9	- 41	- 46.5
Shrubland	25182	18360.9	13984	- 27.1	- 24	- 44.5
Grassland	20524	16497	11999	- 20	- 27	- 41.5
Waterbody	586	220.1	1056	- 62	380	80
Settlement	843	1679.9	1993	99	19	136.5
Sum	158,630	158,630	158,630			

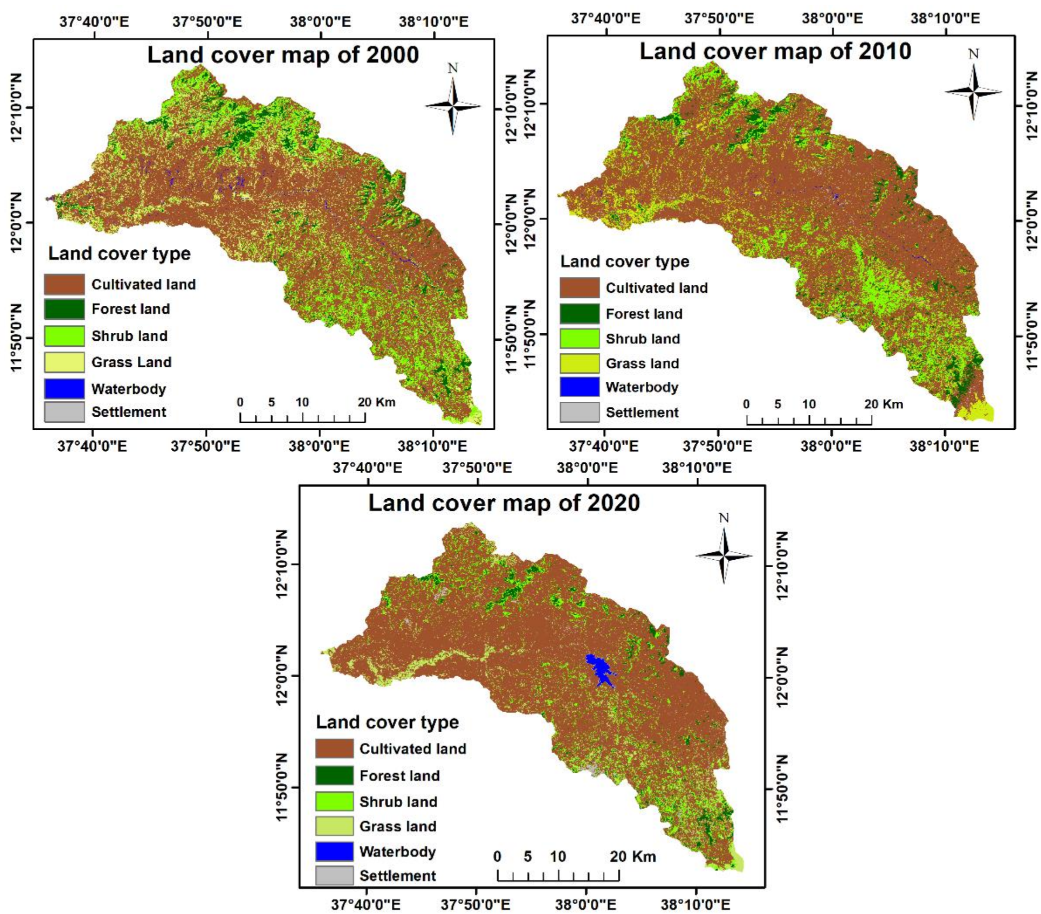


Figure 3.3 LULC map of Rib watershed 2000, 2010 and 2020

3.5.2 Impact of LULC Changes on ESVs

The ecosystem value between 2000, 2010, and 2020 periods for each LULC were mapped, evaluated, and classified (Figure 3.2). As a result, ESV for cultivated land and waterbody increased between 2000 and 2020 periods at the Rib River watershed. On the contrary, the ESV of forestland, shrubland, and grassland over these periods has been reduced (Table 3.6, Figure 3.4).

Table 3.6 The estimated ESVs (US$ in millions) of each LULC types during 2000-2020 periods

LULC class	ESV (US$ million)			ESV (US$ million) change		
	2000	2010	2020	2000-2010	2010-2020	2000-2020
Cultivated	22.8	25.3	28	2.5(10.9%)	2.5(9.9%)	5.2(22.8%)

Forest	10.3	9.4	5.5	- 0.9(-8.7%)	-3.8(-40.4%)	-4.8(-46.6%)
Shrubland	24.8	18.1	13.8	- 6.7(-27%)	-4.3(-23.7%)	-11(-44.3%)
Grassland	6.0	4.8	3.5	- 1.2(-20%)	-1.3(-27%)	-2.5(-41.6%)
Waterbody	4.7	1.8	8.5	- 2.9(-61.7%)	6.8(377.7%)	3.8 (80.8%)
Settlement	0	0	0	0	0	0
Sum	68.6	59.4	59.3	- 9.2(13.4%)	-0.1(0.2%)	-9.3(-13.5%)

Consequently, the total ESV has reduced from US$ 68.6 million in 2000 to US$ 59.40 million in 2010 and US$ 59.30 million in 2020. It was found that the major contributor to these changes was the change in shrubland. The next major contributor factor to the dimensioned of total ESV in the study years was the reduction of forest land cover (Table 3.6: Figure 3.4). The net ESV was radically reduced over the study period. It is also observed that the LULC occurred over 2000 to 2020 years have lost US$ 9.30 million ESV (Table 3.6). In other words, the ecosystem value of the Rib River watershed was reduced by 13.50% from 2000 to 2020.

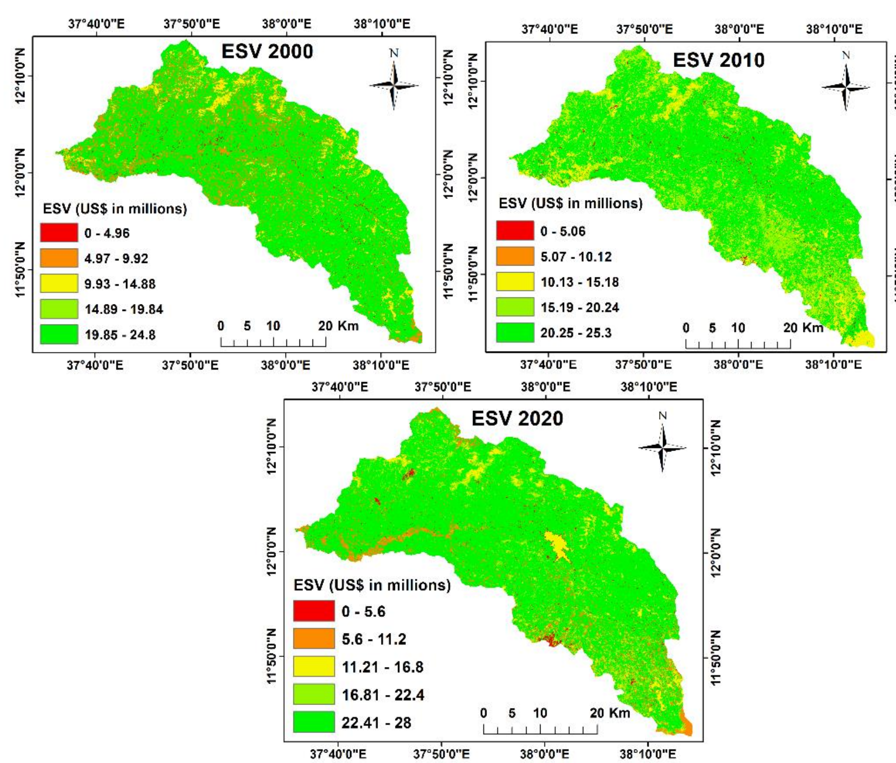


Figure 3.4 Ecosystem value of Rib River watershed (US$ in millions).

The effect of LULC on each specific ecosystem service was displayed in (Table 3.7). The result revealed that there exist diverse effects of LULC changes in the various ecosystem services; it increased some ecosystem service while others were reduced. For instance, food production was increased by US$ 2.80 million and Biological control also raised by 0.35 million from 2000 to 2020 due to the expansion of cultivated land. Also, Water supply and Water regulation were raised by US$ 0.87 million and US$ 2.43 million between 2000 to 2020 respectively. These increments were directly associated with the construction of a Rib dam in the watershed. However, in the remaining specific ecosystem service loss was observed. The decline of most ecosystem services is highly associated with the reduction of shrub land, forest and grass land (Table 3.7).The overall service was reduced by US$ 9.30 million in the watershed.

Table 3.7 The estimated specific ESVs (ESV_f in US $ million per year) in the Rib River watershed

No.	Ecosystem services	ESV across periods (US$ in millions)			Overall change
		ESV_f 2000	ESV_f 2010	ESV_f 2020	2000-2020
1.	Provisioning services				
	Water supply	1.53	0.69	2.40	0.87
	Food production	22.53	23.91	25.33	2.8
	Raw materials	1.83	1.42	1.00	-0.83
	Genetic resources	1.46	1.14	0.8	-0.66
2.	Regulating services				
	Water regulation	3.47	1.4	5.9	2.43
	Climate regulation	7.95	6.22	4.4	-3.55
	Disturbance regulation	0.18	0.14	0.1	-0.08
	Gas regulation	0.49	0.49	0.35	-0.14
	Biological control	2.9	3.06	3.25	0.35
	Erosion control	9.34	7.31	5.10	-4.24
	Waste treatment	6.88	5.31	4.15	-2.73
3.	Supporting services				
	Nutrient cycling	6.58	5.14	3.61	-2.97
	Pollination	2.18	2.19	2.17	-0.01
	Soil formation	0.37	0.29	0.20	-0.17
	Habitat/refuge	0.61	0.48	0.33	-0.28

4.	Cultural services				
	Recreation	0.23	0.16	0.17	-0.06
	Cultural	0.07	0.05	0.04	-0.03
	Sum	68.6	59.4	59.3	-9.3

For the outcomes of the analysis to be reliable, coefficients of sensitivity (CS) were done. The Coefficient of sensitivity was used to evaluate the overall ESV of the Rib watershed presented in (Table 3.8). The result showed that the coefficient of sensitivity of these analyses was less than one in all cases. CS ranged from a low of 0.05 – 0.08 for grassland to a high of 0.42 – 0.47 for cultivated land, when the value coefficients were adjusted by 50% (Table 3.8). The CS for cultivated land was the highest due to the highest service value coefficient and significantly larger geographical extent. If CS exceeds one, the projected ecosystem value is elastic with that coefficient. If CS is less than one, then the predicted ecosystem value is inelastic. The use of the ESV coefficient becomes more important when the proportionate change in the ESV is compared to the proportionate change in the valuation coefficient. The total ecosystem values assessed for the research area were generally inelastic regarding the ecosystem value coefficients, implying that the ecosystem value evaluation was fair and resilient.

Table 3.8 Coefficient of sensitivity (CS) after adjusting ecosystem services valuation coefficient (VC) at Rib watershed.

	2000		2010		2020	
	Percent	CS	Percent	CS	Percent	CS
Cultivated land VC ± 50%	16.61	0.33	21.29	0.42	23.60	0.47
Forest land VC ± 50%	7.5	0.15	7.91	0.16	4.63	0.09
Shrub land VC ± 50%	18.07	0.36	15.23	0.30	11.63	0.23
Grass land VC ± 50%	4.37	0.08	4.04	0.08	2.95	0.05
Waterbody VC ± 50%	3.42	0.06	1.15	0.03	7.16	0.14

3.6 Discussion

3.6.1 Spatiotemporal LULC Changes

The LULC analysis showed that, the reduction of forest cover, shrubland, grassland, and expansions of cultivated, settlement during the study period (2000–2020). This confirms with many LULC studies shown in Ethiopia. For instance Beressa watershed Northcentral Ethiopia (Meshesha et al., 2016) and other research mentioned here (Gashaw et al., 2018; Hassen & Assen, 2018; Karki et al., 2018; Minale & Kameswara Rao, 2012; Tewabe & Fentahun, 2020). The increase of cultivated land in Ethiopia increases at an increasing rate. This expansion is directly attributed to the country’s policy. For instance, in the current Ethiopian People Revolutionary Democratic Front government (1991up to present), the land ownership policy is stipulated in the constitution, with land as the property of the state (EPRDF, 2003). This allowed them to use the land but not to sell it. As a result of the state's ownership of land-related resources, rural people were able to readily convert woodland, shrubland, and grazing land into cultivated areas. The government also adopted the Agricultural Development Led Industrialization (ADLI) policy in the 1990s which assures that agriculture is a major engine for the growth of the Ethiopian economy (Dube et al., 2019). From this context increase in cultivated land is expected in a certain rural community in Ethiopia.

3.6.2 Effects of LULC Changes on ESVs

The LULC alterations are nonlinear and have been identified as a key driver of change in ecosystem services. The overall ESV of the Rib River watershed was found to be diminished due to the reduction of forest land, shrubland, and grassland which is in line with other findings elsewhere such as Chillimo forest of central highland Ethiopia (Tolessa et al., 2016), Munessa–Shashemene landscape of Ethiopian highlands (Kindu et al., 2016), Andasa watershed of Upper Blue Nile Basin (Gashaw et al., 2018), Bilate Alaba Sub-watershed of Southern Ethiopia's (Markos et al., 2018), and dry Afromontane Forest of Northern Ethiopia's (Solomon et al., 2019). The detail on the areal extent, year of study, ESV (US$ in millions), and trends of ESV for the above-mentioned studies are available in (Table 3.9). However, the raised in ESV was observed in cultivated land between 2000–2020 may be attributed to the following reason, firstly in the study Rib River watershed for the past five years rural land administrations distribute a large amount of grazing land for rural youth unemployed, so this grazing land was changed into cultivated land. Secondly different types of LULC, such as forest, shrublands, and grazing lands are the property of the government, thus farmer converts those LULC in to agricultural land illegally.

Table 3.9 Trends of ESV for selected studies in different parts of Ethiopia

Study area	Area in (ha)	Years	ESV (US$ in millions)	Trends of ESV	Selected studies
Gojeb watershed south Ethiopia	701595	1986	2520.5	Decreasing	(Shiferaw et al., 2021)
		2016	1969.3		
Andasa watershed of upper blue Nile basin Northern Ethiopia	58,761	1985	26.83	Decreasing	(Gashaw et al., 2018)
		2000	22.58		
		2015	21.00		
		2030	17.94		
		2045	15.25		
Afar region Ethiopia's	6,667,647	1986	3109.7	Decreasing	(Shiferaw et al., 2019)
		2017	2997.7		
Bilate Alaba Sub-watershed Southern Ethiopia's	40,269.4	1972	35.23	Decreasing	(Markos et al., 2018)
		1986	33.61		
		2008	27.91		
		2017	25.87		
Chillimo forest of central highland Ethiopia	7687.26	1986	7.66	Decreasing	(Tolessa et al., 2017)
		2001	6.40		
		2015	5.37		
Munessa–Shashemene landscape of Ethiopian highlands	103,675	1986	118.5	Decreasing	(Kindu et al., 2016)
		2000	114.8		
		2012	111.1		

When segregated individual ecosystem services, among the seventieth specific ecosystem services all of them, were reduced in our study area except Water supply, Food production, and Biological control, which confirms with other findings (Hu et al., 2008; Hao et al., 2012; Markos et al., 2018). The extension of the cultivated area during the study periods is undoubtedly responsible for the ongoing increase in food production and biological control.

On the other hand, the loss of shrubland is strongly linked to the deterioration of most ecosystem services over the research period (Table 3.9). Similar to this finding a decrease in forest lands, shrubland, and grazing land between 1985 to 1945 periods at Andasa watershed of upper Blue Nile basin, Ethiopia, has resulted in a decrease in the value of climate regulation, and gas regulation (Gashaw et al., 2018). The increase of water supply service was due to the expansion of waterbody in the watershed from 2000 to 2020, which is in line with the findings of an increase of water supply and water regulation between 1986 to 2015 years at Gedeo Abaye south-eastern escarpment Ethiopia (Temesgen et al., 2018). The ESV was determined to be reliable in a sensitivity analysis conducted to verify the robustness of the study, which was similar to the findings of (Kindu et al., 2018; Temesgen et al., 2018; Tolessa et al., 2017).

3.6.3 Implications of the LULC Changes on Land Degradation Neutrality

Change in LULC appears the most important indicator for the status of land degradation neutrality (LDN). The LDN is the new aspirational target of sustainable development goal intended to assure sustainable delivery of ecosystem services for the coming generation. LULC is one of the indicators of LDN. Trends in LULC showed that, the reduction of forest cover, shrubland, grassland, and expansion of cultivated land, settlement, and waterbodies between 2000 and 2020 periods (Table 3.5). According to (Orr et al., 2017), the increase of forest, shrubland, grasslands, and waterbodies has a positive (good) impact on the status of LDN, whereas the reduction of the previously mentioned LULC has a negative impact. Changes in land cover may be characterized as positive or negative when contextualized with local information. Some critical changes are generally considered as negative, for instance, the reduction of natural or semi natural land cover classes (i.e. deforestation), as well as expansion of cultivated land and settlements. The inverse is true for positive impact for LDN (Orr et al., 2017).

Using the above-mentioned criterion, the LULC change impact on LDN was assessed and depicted in (Table 3.10). The LULC change between 2000 to 2010 revealed that, expansion of cultivated land, settlement, and reduction of the remaining other land cover. As a result, those expansions and reduction of LULC contribute to negative effects for the achievement of LDN. From 2010 up to 2020, the increment of waterbody had a positive effect whereas, the remaining LULC contributes negatively to the achievement of LDN.

Generally, for the former two decades between 2000 to 2020, even if cultivated land expands and has provision service, its effect for LDN was negative. In the remaining land cover, expansion of settlement and reduction of forest, shrub, and grassland displayed a negative impact on the status of LDN which was similar to the result of (Cowie et al., 2019; Orr et al., 2017). The only land cover type that showed a positive effect for LDN was the expansion of the waterbody in the study watershed. The expansion of the water body has water supply and water regulation services. Generally, all LULC types showed a negative effect on the status of LDN except waterbody.

Table 3.10 The LULC changes in Rib River watershed between 2000 and 2020 and its effect on land degradation neutrality

LULC class	Change between periods						Effect on LDN		
	2000-2010	%	2010-2020	%	2000-2020	%	2000-2010	2010-2020	2000-2020
Cultivated	11313	11.2	11626	10.34	22,939	22.7	-	-	-*
Forest	-936.7	-9.0	-3900.2	41	-4837	46.24	-	-	-
Shrubland	-6820.8	-27.0	-4376.9	23.8	-11197.7	-44.46	-	-	-
Grassland	-4027	-19.6	-4498.1	27.3	-8525.1	-41.53	-	-	-
Waterbody	-366.2	-62.4	835.6	379.6	469.4	80.06	-	+	+ **
Settlement	837.4	99.4	313	18.6	1150.4	136.54	-	-	-

* Negative effect and ******positive effect for LDN.

3.6.4 Limitation of the Study

In this study, LULC datasets were used to facilitate the estimation of the change in ESV. However, there are some limitations concerning the LULC datasets that were used. For instance, we are unable to use land sat 7 images from USGS for image classification between 2000 to 2010, because the data set is not free from the strip as a result land sat 5 images were employed. Additionally, although the overall accuracy (82.28%) and land cover dataset can be considered acceptable, there are still uncertainties in the accuracy of LULC change analysis and consequently in the estimation of ESV.

The biomes used for the land cover types are not perfectly similar in every case, as has been the case in previous studies (Kindu et al., 2016; Tolessa et al., 2017). For example, the shrubland may include sparse grassland. This implies that this land cover type in some areas may contain not only shrubland but also sparse grassland of little value, thus leading to overestimation of the ESV of this land cover type. Moreover, the collection of primary data in developing nations is affected by financial constraints, thereby using the modified ESV model which was employed by (Kindu et al., 2016) in the Ethiopia context is the only feasible option. Additionally, land degradation neutrality is a new paradigm shift of land degradation, which was launched by the UN. However, LDN related article was not done in the study Rib watershed as a result, a lack of literature was also considered as the challenge of the article.

3.7 Conclusions

Land use land cover change is a single parameter used to analyze ecosystem service value estimation. The importance of such estimations at the local, regional, and global levels influencing decision-making processes through the modification of national accounting systems to reflect the true worth of ecosystem services. This estimation also ultimately be used for the sustainable development of ecosystem service. Besides, land-use planners, experts, and communities will have awareness of the impact of each land cover conversion on the total ecosystem value and the status of land degradation neutrality.

The study illustrates that the enlargement of cultivated land, waterbody, and settlement by 22.70%, 80.06%, and 136.54% respectively. The remaining land cover shows a significant reduction for the past two decades from 2000 to 2020. As a result, the overall ESV decreased by 13.50%. Among the specific ecosystem services identified Water supply (0.87 US$ in millions), Food production (2.80 US$ in millions) and Biological control (0.35 US$ in millions) had positive ecosystem service value which is very small as compared to other ESVs, while the remaining services had negative values indicating a decrease in those ecosystem service values. This result shows that total ESV was lost in the study area. Finally, we concluded that the reduction in ESVs reflected the effects of ecological degradation at the Rib watershed and it is also suggested that land managers and policymakers can use LULC change and ecosystem service value together during their decision-making processes.

In this study, CS shows the estimation ESVs was robust regarding all the values for each LULC less than one. For the study periods, the CS for cultivated land use is the greatest of all land uses, indicating the greatest size and greater ESV for cultivated land use. The finding of this study will be an important milestone for future research related to the change of ESV in response to LUL

CHAPTER FOUR

4. Modeling the Impact of Land Use Land Cover Change on the Estimation of Soil Loss and Sediment Export Using Invest Model at the Rib River Watershed of Upper Blue Nile Basin, Ethiopia.

Based on Publication

Anley, M. A.,and Minale, A. S.(2024). Modeling the impact of land use land cover change on the estimation of soil loss and sediment export using InVEST model at the Rib River watershed of Upper Blue Nile Basin, Ethiopia. Remote Sensing Applications: Society and Environment 34 (2024) 101177. https://doi.org/10.1016/j.rsase.2024.101177

Abstract

Information on soil loss and sediment export is essential to identify vulnerable area of soil erosion and to inform conservation interventions in a given watershed. The goal of this study was to analyze the changes in soil loss and sediment exports in the Rib watershed of Ethiopia's Upper Blue Nile Basin. The study used spatial data by using a variety of data sources, including topographic maps, soil maps, meteorological data, and satellite images. Cultivated land, forests, grazing areas, shrubs, water bodies, and settlements were all identified in the study watershed. Soil loss and sediment export were calculated using the Integrated Valuation of Ecosystem Services and Tradeoff (In-VEST) model. The model was calibrated using the sediment yield data gathered in the sample watersheds. The results reveal that while the equivalent sediment export grew from 6.54 t/ha/year to 11.05 t/ha/year in 2000 and 2020, respectively, the average soil loss increased from 22.37 t/ha/year in 2000 to 33.38 t/ha/year in 2020. The largest rate of soil erosion was seen on cultivated land, which increased from 40.86 t/ha/year in 2000 to 53.90 t/ha/year in 2020. This relates to the expansion of the agricultural land. The soil loss and sediment export rates in sub-watersheds three (SW-3) and five (SW-5) were the highest, at 61.80 and 63.48 t/ha/year and 18.75 and 19.35 t/ha/year, respectively. The least amount of soil loss occurs in sub-watershed twelve (SW-12) (2.56 t/ha/year). This is because SW-12 is situated in the watershed's lower reaches Fogera plain parts of the watershed experiencing less erosion. The result concluded that prioritizing those sub-watersheds is important for informed decision-making processes.

Keywords: GIS, In-VEST model, Remote sensing, Soil loss, Sediment export.

4.1 Introduction

Due to its promotion of poverty and migration, land degradation (LD) is a major environmental concern that negatively impacts biodiversity, ecosystem services, and the lives of millions of people worldwide (Gashu & Muchie, 2018; Meseret, 2016; Susilowati & Syekhfani, 2015). However, due to the complexity and variety of the biophysical and socioeconomic factors that affect land resources, it is challenging to identify this phenomenon (Lu et al., 2022; Meseret, 2016). It can also be used to describe how sophisticated rain-fed farmland, irrigated cropland, or rangelands, grasslands, forests, and woodlands have become and how their biological or economic productivity has declined (Reith et al., 2021; Susilowati & Syekhfani, 2015). Therefore Land uses and land cover change is one of the indicators of land degradation (LULC). Through the integration of knowledge regarding LULC and the processes leading to degradation, a number of studies have assessed the phenomena of LD both nationally and internationally.

Land use and land cover change (LULC) are major causes of soil loss in highland watersheds around the world, especially in Sub-Saharan Africa (Abduljelil, 2020; Nwaogu et al., 2018). Soil erosion is a worldwide environmental problem that disturbs the provisioning and management of ecosystem services. It is influenced by precipitation (R factors), soil characteristics (K factors), topographic factors (LS factors), land cover management (C Factor), and conservation practices (P Factors) in a certain geographic territory (Meshesha et al., 2016; Sinshaw, Belete, Mekonen, Wubetu, et al., 2021). Soil erosion initiated by running water is the most prevalent reason for soil loss and accounts for the majority of the world's soil degradation (Comino et al., 2015; Owens, 2020).

Various scientific investigations indicated that forest areas have the lowest amounts of soil loss (the sum of soil that is eroded in a watershed) and sediment export (the amount of soil that is transferred to streams and reaches a watershed's exit) and highest cultivated due to factors of soil erosion (Tadesse et al., 2017; Tolessa et al., 2016). Many investigations also indicated that LULC change consequences that the increment of soil loss and sediment export (SLSE) in various watersheds in Ethiopia. For example, according to Aneseyee et al.(2020), Winike watershed of Omo Gibe Basin, the amount of soil loss raised by 176.35 thousand tons between 1988 to 2018 while sediment export increased by 3.85 thousand tons for the same period. Tully et al.(2015), also investigated that because of soil erosion more than 66% of cultivated land degradation and the resulting production loss in Africa. Meanwhile, Degife et al. (2021), show that In the Central Rift Valley of Ethiopia, erosion and the deposition of silt from nearby farmlands caused Lake Cheleleka to disappear and the surrounding wetlands to deteriorate.

All soil loss in a certain watershed cannot reach the outlet; a sizable portion is left behind at intermediate locations. According to Fang (2021); Jian et al.(2022); Ning et al.(2021); Pessoa et al.(2022), 10% of the whole soil erosion is touches the outlet of the watershed and exported to water bodies. This eroded soil provides downstream sediment deposition effects on lakes siltation and hydroelectric dams (Degife et al., 2019). For example, Egypt's Aswan Dam has lost 4% of water storing potential in 48 years, Sudan Khashm el-Girba Dam has lost 53% of its storing potential in 46 years; Sinnar reservoir of Sudan has lost 85% of its storing potential in 85 years and due to sedimentation problem, Ethiopia's Angereb reservoir has lost 46% of its ability to store water in 19 years (Degife et al., 2019). This indicates how sedimentation is a serious problem in Ethiopia. As a result, calculating and distinguishing the levels of soil erosion as well as sediment export at a watershed level is critical for effective water resource management (Yesuph & Dagnew, 2019).

Although much research on SLSE has been conducted on a worldwide scale, the majority of them have concentrated on the use of refined tools and well-qualified experts in a data-rich atmosphere (Ayele et al., 2021; Kulimushi et al., 2021; Xie et al., 2021). Such methods are less applied in developing nations, such as Ethiopia, where data is few and experienced specialists are scarce (Haregeweyn et al., 2012). The Revised Universal Soil Loss Equation (RUSLE) model is commonly used in Ethiopia to evaluate the sum of soil loss (Hurni, 1985). However, the model is unable to estimate the sediment export of a given watershed. The RUSLE's limitations are addressed by InVEST model, which allows for combined assessments of SLSE by characterizing a given watershed (Nelson et al., 2014). As a result, the InVEST model was used to take advantage of the model's thorough accurate estimation of SLSE at the Rib watershed in Upper Blue Nile Basin, Ethiopia.

The frequent heavy rains and mountainous topography present substantial soil erosion threats in most high-land watersheds, which call for increased consideration in land use planning for the future (Zhu et al., 2019). Using the InVEST model, we were explain how land use changes have caused a change in SLSE. Despite the significant contributions of past studies, Ethiopian researchers are still paying little attention to research that integrates estimates of SLSE, as well as their geographic variation related to LULC change spatially and temporally. Most importantly, some studies were done in the study area on soil loss as well as sediment export using SWAT, RUSLE models, and GIS software (Admas et al., 2022; Ayalew and Bharti, 2022; Moges and Bhat, 2017, 2018; Sinshaw et al., 2021). But no research was done in the study area using InVEST model. Therefore, this was our research gap. In the study area, there is a scarcity of input data to do research. Hence, InVEST model was chosen for this study over other complex (data-intensive) models due to its restriction of fewer input parameters, accessibility of input geographical data, and compatibility with different GIS data. The distinctive characteristic of InVEST model is its capability to examine SLSE from individual land use types and quantify the extent of sediment export reached to the water bodies. This is the main advantage of the model over other models, like RUSLE, and SWAT. Additionally, no one also investigates soil loss and sediment export at a sub-watershed level. This is also the other research gap that we intended to achieve taking the Rib watershed of the Upper Blue Nile basin as a case site covering the year 2000 to 2020.

The study watershed is one of the key hydrological systems that contributes a significant volume of water to Lake Tana. In this watershed, SLSE is a serious problem that affects the socioeconomic activity of farming communities. For these reasons, the key purpose of the research was to determine the extent of soil erosion and sediment export for landscape management at the Rib watershed. Identifying the main sources of sediment is a necessary first step in overcoming the sedimentation challenge in downstream reservoirs. Hence the core objectives of the study are to (1) Examine the changes in LULC related to SLSE between 2000 and 2020; (2) Identify the major contributor factors of SLSE from the changes in individual LULC types between 2000 to 2020 (3) to estimate the spatial and temporal variation of SLSE at the sub-watershed level of Rib watershed Upper Blue Nile Basin Ethiopia.

4.2 Material and method

4.2.1 Description of the Study Area

One of Ethiopia's major watersheds, the Rib watershed stretches from the western portions of Guna Mountain to the eastern side of Lake Tana. (Figure 4.1). Spatially, the watershed is situated between 11° 40′ up to 12° 20′ N and 37° 30′ up to 38° 20′ E. The study watershed's highest and lowest elevations are 4084 and 1785m above sea level respectively with an area extent of 1583 km^2 (Figure 4.1). The drainage networks flowing towards Lake Tana were generated by the watershed's hills and peaks features.

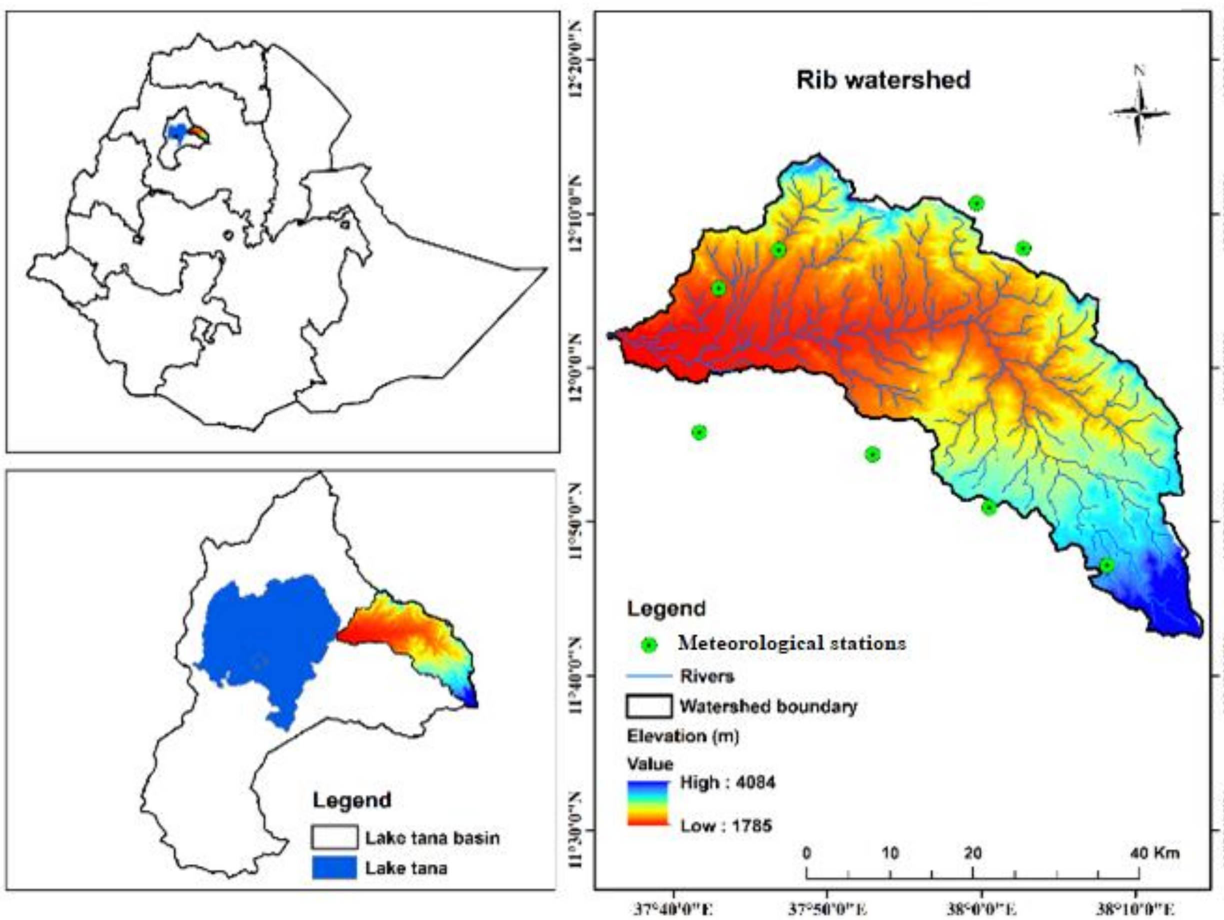


Figure 4.1 Map of Rib River watershed.

The climatic zone of the Rib watershed is highly dominated by subtropical, statistically 2% (alpine), 64.4% (sub-tropical), and 33.6% (temperate). The following meteorological stations provided their weather records data, such as (Addis Zemen, Agere Genet, Amed Ber, Debere Tabor, Ibinat, Kimir Dingay, Leway, Woreta, Yifag, Wolela Bahir, Gassay and

Enferanz) for the past two decades showed that the annual average rainfall (1550.5 mm) and temperature (15.4 °C) of the study watershed. The major rainy season, which lasts from June through September, sees over 70% of rainfall, with the remaining months seeing little to no precipitation. Tertiary and quaternary basalts, as well as alluvial deposits, make up the watershed's geology (Adego et al., 2019; Adem et al., 2020).

The study area's main economic activity is agriculture, which provides the rural community's main source of income. On one side, a variety of agricultural products are grown, and on the other, animals are raised for both market and domestic consumption. Potato (*Solanum tuberosum*), teff (*Eragrostis tef*), rice (*Oryza galberrima*), beans (*Phaseolus vulgaris L*), barley (*Hordeum vulgare*), maize (*Zea mays L*), and wheat (*Triticum Vulgare*) are the main types of agricultural products grown in the research region. Rainfall is a major factor in crop productivity. It mainly falls between June and September. As a result, farming can only be done during the remaining months of dry weather, which is uncommon in the watershed. However, a small portion of the farming population employs irrigation to harvest maize and onions. The community in the study watershed depends largely on the rearing of cattle for their survival. The Central Statistical Agency (2013), projected that there will be 181,900 households residing in the watershed in 2014. Four types of soils derived from weathering of basaltic rocks were well-known in the study area, including Luvisols (34%), Regosols (15%), Vertisols (23%), and Leptosols (28%) (Anley et al., 2022).

4.2.2 Data Sources

All data used for land cover classification, soil loss, and sediment export are described on (Table 4.1). As depicted from figure 4.3, the rainfall erosivity (R) factor was quantified using Eq. (4.5), spatial regression analysis in Ethiopian highlands as calculated by (Hurni, 1985,), based on existing average annual rainfall of the study watershed. The soil erodabliry (K-factor) map was calculated using Eq. (4.6 and 4.7) (Witchmeier and Smith, 1978).Using the formula, the K value of the study area was extracted and prepared using ArcGIS 10.3 for InVEST model (Figure 4.4). For this study, the LS factor was calculated from DEM (SRTM) with 30m spatial resolution using equation 8 developed by (Hamel et al., 2015). The LS-value was calculated for the assessment of SLSE in the study area (Figure 4.5). The mean C-value was quantified based on the Normalized Difference Vegetation Index (NDVI) value

Following Durigon et al.(2014) formula Eq. (4.11,4.12,4.13,4.14,4.15), and (4.16).The P-factors were taken from research done in the upper Blue Nile basin. Finally using Borselli parameters SLSE of the study area was quantified (Figure 4.2).

Table 4.1 Data used for land cover classification, soil loss, and sediment export.

Acquisition date	Data type	Spatial resolution	Path and raw	Source
02/07/2000	Landsat 5 TM	30 m	169/52	USGS*
01/31/2010	Landsat 5 TM	30 m	169/52	USGS
01/26/2020	Landsat 8 OLI	30 m	169/52	USGS
03/23/2020	DEM	30 m	169/52	USGS
02/14/2020	Soil map	1:100,000	169/52	ABMPSD**
01/20/20	Ground truth point	-	169/52	Ground survey
2000-2020	Precipitation	-	169/52	ENMSA***
2000-2008	Sediment data	-	169/52	EMOWE****

* Refers to United States Geological Survey: **Refers to Abay Basin Master Plan Soil Database *** Refers to Ethiopia national metrology and satellite agency: **** Ethiopia ministry of water and energy

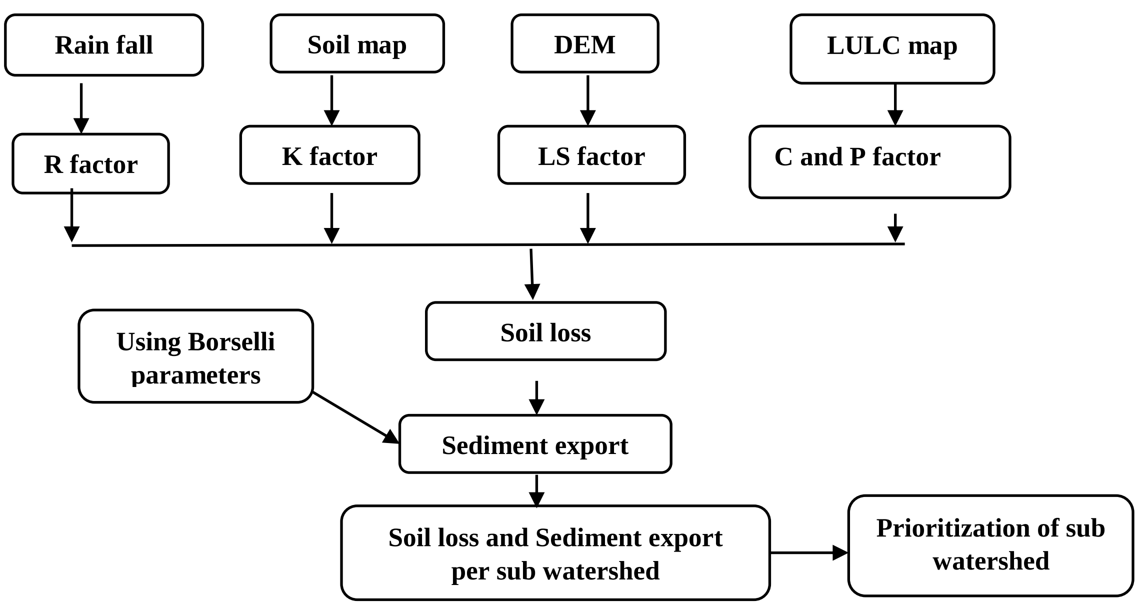


Figure 4.2 Methodological framework of the study.

In this study, both primary and secondary data sources were utilized. The former include (elder people interviews, expert knowledge, Field observation, and GCP points) and the latter such as Google Earth and FAO criterion for LULC classification were used in the study watershed. For historical image classification, Google Earth, elder people interview, and expert knowledge was used for the year 2000 and 2010. Field observation was performed to collect training samples for 2020. For the 2020 classification year, ground control points (GCPs) were gathered using a Garmin GPS device to complete accuracy assessments for each land-use class. The ground control points used for accuracy assessments were separate from the training samples. According to ERDAS Inc (2005), at least 50 GPS points for individual land-use types are advisable during image classification. In this study, to increase the accuracy, on average 100 GPS points at each land use type were taken. Therefore, a total of 600 GCPs training samples for supervised land cover classification were collected from the whole LULC class. The number of GCPs at each class was calculated using the area proportion of the land uses. For accuracy assessment, 100 GCP points were collected in the study watershed. The GCP points were taken in proportion to land use land cover.

4.2.3 Satellite Images Pre-processing, LULC Classifications and Mapping

The study used time-series multispectral Landsat imagery (one for each year) to detect land cover changes, and to quantify SLSE which were acquired in three separate years: 2000, 2010, and 2020 (Table 5.1). The raw images were almost completely cloud-free because they were taken during the dry season. To avoid the consequence of seasonal fluctuations at each LULC, satellite images taken during the winter season and without clouds are essential (Alam et al., 2020; Muleta et al., 2021; Roba et al., 2021; Sewnet et al., 2016). Therefore, all the three satellite images were taken in January and February with less than 10% of cloud cover for the year 2000, 2010 and 2020. The land resource-related sustainable development goal was initiated in 2000, thus this year was used as a starting time for the assessment of LULC.

ERDAS Imagine 14 software was employed for preprocessing and processing satellite image data by applying the fundamental image preprocessing techniques. The satellite images were pre-processed using techniques like color composite, layer stacking, and sub-setting. Then, geometrically and radiometric Landsat images correction were done to increase image quality and projected to Universal Transverse Mercator (UTM) map projection system also performed. Using a maximum likelihood classification algorithm of supervised image classification, the satellite images from the years 2000, 2010, and 2020 were classified. In the study area, six LULC classes were found, including cultivated land, grazing land, forest, shrub land, waterbody, and settlement.

In this study, Ground control points (GCPs) were also collected using a GPS device to perform classification and accuracy assessments for each land-use class for the 2020 classification year. Ground control points for accuracy assessment were independent of those used as training samples. For image classification, expert knowledge, elder people interview, and Google earth were used for the years 2000 and 2010. Field observation was carried out to collect training samples for 2020. Ground control points (GCPs) were also collected using a GPS device to perform classification accuracy assessments for each land-use class for the 2020 classification year. Ground control points for accuracy assessment were independent of those used as training samples. According to (ERDAS Inc., 2008), at least 50 GPS points per land-use type are advisable for land cover classification. In this study, to increase the accuracy, on average 100 GPS points at each land use type were taken. Therefore, a total of 600 GCPs training samples for supervised land cover classification were collected for all land use/land cover classes. The area proportion of the land uses was used to determine the number of GCPs for each class. Therefore, a proportional sampling technique was employed to take GCP points. For accuracy assessment, 100 GCP points were collected in the study watershed. The GCP points were taken in proportion to land use land cover classes of the study area.

By contrasting the sample LULC class of the classified layer to the reference layer, the classification accuracy assessment of each LULC layer of satellite images was examined. To determine the degree of classification accuracy of the error, the whole accuracy, and Kappa analysis were assessed. The Kappa coefficient was calculated as follows Eq 4.1:

$$\text{Khat} = \frac{N\sum_{i=1}^{K} Xab - \sum_{i=1}^{K}(Xa \times Xb)}{N2 - \sum_{i=1}^{K}(Xa \times Xb)} \qquad \text{Eq (4.1)}$$

Where:

Khat = Kappa coefficient; N refers to the total number of values; $\sum_{i=1}^{K} Xab$ is observed accuracy, and $\sum_{i=1}^{K}(Xa \times Xb)$is chance accuracy.

After image classification, all LULC maps were clipped to a common area using the ArcMap GIS 10.4. The vector data was rasterized using 30 m cell size and Zonal statistics in ArcGIS Spatial Analyst's tool was used to compute change in the area by cross tabulating pairs of time intervals i.e. 2000 and 2010 and 2020. Transitions between different land use/land covers were evaluated to measure areas converted among the different land uses. Quantified values of the changes between the different LULC classes were used for statistical analysis to reveal the extent of the changes in the study areas. The percentage of change within the same LULC class between two time points is calculated using Eq 4.2:

$$\text{Change (\%)} = \frac{Atn - Atn{-}1}{Atn{-}1} * 100 \qquad \text{Eq (4.2)}$$

Where:

Atn - area of specific land use land cover class at time tn

Atn^{-1} - area of the same land use land cover class at time tn^{-1}

Change (%) - percent change in the area of specific land use land cover class between times tn and tn^{-1}

A "land use and land cover shift index (LUSHI)" was calculated to assess LULC type contributing most to specific LULC class expanded remarkably. The index is calculated from the following equation 4.3:

$$\text{LUSHI} = \frac{\Delta LCi{-}j}{Mean\ \Delta LC} \qquad \text{Eq (4.3)}$$

Where:

LUSHI = land use shift index

ΔLCi = area of land use land cover class i converted to land use land cover j in period between time 1 and time 2, i.e., period between target reference years

Mean ΔLC = mean of areas of all land use land cover types converted to land use land cover type j in period between time 1 and time 2

Note: Land use land cover types contributing most to the expansion of land use land cover j have LUSHI > 1 while less preferred ones have LUSHI < 1.

4.2.4 Description of InVEST Model

The InVEST model provides how changes in LULC patterns influence the annual SLSE by estimating the relative contributions of soil and sediment from individual parcels of a landscape. Combining the study of soil loss with sediment export in a particular watershed is vital because it allows for the identification of sediment transport routes from the watershed to water bodies. This is significant to study possible downstream impacts of sedimentation (Collins et al., 2020; Kruczkowska et al., 2021). The model also offers a valuable valuation of how landscape scenarios may impact annual sediment export. Additionally, the InVEST model was chosen for this study over other complex (data-intensive) models due to its restriction of fewer input parameters, accessibility of input geographical data, and compatibility with different GIS data. The RUSLE equation is mostly employed in the model, and some of its input factors have been calibrated for Ethiopian conditions (Hurni, 1985), making them enthusiastically usable in the model. Most importantly, InVEST model has only been used in a very small number of studies in Ethiopia and most likely none at all in the Rib watershed. The quantity of SLSE at the watershed and sub-watershed levels were assessed using the InVEST model. Studies have shown that the model is an efficient tool for helping decision-makers identify the most crucial places where they should take action to preserve soil and water resources (Nelson et al., 2014).

The InVEST model was used to classify erosion severity and priority areas for intervention measures. The distinctive characteristic of InVEST model is its capability to examine SLSE from individual land use types and quantify the extent of sediment export reached to the water bodies. This is the main advantage of the model over other models, like RUSLE, and SWAT.

To employ the model the necessary parameters are the watershed shape file, RUSLE factors, sub-watershed shape file, Maximum Sediment delivery ratio (SDR), Borselli parameters (calibration parameters that define the shape of the sediment delivery ratio (SDR) and connectivity index(IC) relationship), flow accumulation, and the biophysical table. The overall flow chart of the study is displayed in (Figure 4.2). To combine the datasets and run the model, all input data were set to the same geographic resolution, projection, and reference system. All other data had the same cell size and reference system as the DEM and Landsat image, which had 30 m cell sizes. After the input data had been prepared and organized by ERDAS IMAGIN 2014 and Arc GIS 10.3, the amount of SLSE were evaluated using the InVEST 3.9.0 model.

The result from the InVEST model consists of the amount of SLSE in the watershed by each LULC from the year 2000 to 2020. These results are crucial for determining the LULC's regulatory capability for the soil erosion and sediment conservation services provided by the watershed, as well as for the management of the Rib Dam and Lake Tana. Finally, maps and tables were used to show the amount and spatial distribution of the estimated mean annual SLSE. Several intensity classes and ranges of soil loss and sediment export were classified from the calculated result using (Haregeweyn et al., 2017). Each parameter was prepared following the InVEST modeling standards of data format.

4.2.4.1 Soil Loss

The RUSLE equation Wischmeier and Smith (1978) was utilized as the basis for the InVEST model, which was used to simulate probable soil loss in the study watershed utilizing six parameters. (Eq. 5.4). The Revised Universal Soil Loss Equation (RUSLE) model was used to calculate soil loss in the study watershed (Hurni, 1985). RUSLE is a part of the Universal Soil Loss Equation (USLE) model by familiarizing the input factors to the local conditions (Negese, 2021; Nut et al., 2021). RUSLE has been used commonly in Ethiopia due to its simple and transparent computational inputs (Bewket & Teferi, 2009; Ayalew, 2015a; Sewnet et al., 2016). The mean annual soil loss rate (A) from sheet and rill erosion is quantified by RUSLE (Hurni, 1985) and USLE (Witchmeier and Smith, 1978) as a function of six parameters (Eq. 4.4).

$$\mathrm{A} = \mathrm{R} \times \mathrm{K} \times \mathrm{LS} \times \mathrm{C} \times \mathrm{P} \qquad (4.4)$$

Where A is average soil loss (t /ha/ year); R is rainfall-runoff erosivity factor (MJ mm/ ha/ h/ year); K is soil erodibility factor (t /ha /MJ/ mm), LS is slope length and steepness factor (dimensionless), C is crop and management factor (dimensionless) and P is conservation practice factor (dimensionless). The detail description of each parameter are as follow:

Rainfall erosivity factor (R)

The rainfall erosivity (R) factor was quantified using (Eq 4.5), spatial regression analysis in Ethiopian highlands as calculated by (Hurni, 1985,), based on existing average annual rainfall (P). Twenty-year data of monthly rainfall were acquired taken from the following meteorological stations in the study watershed (Addis Zemen, Agere Genet, Amed Ber, Debere Tabor, Ibinat, Kimir Dingay, Leway, Woreta, Yifag, Wolela Bahir, Gassay and Enferanz)(Table 4.2). To construct the spatial raster map, Inverse Distance Weighted Interpolation (IDW) was utilized for InVEST model (Ayalew, 2015) (Figure 4.3).

$$R = 0.562\,P - 8.12 \tag{4.5}$$

Where Erosivity factor represent by R and the mean annual rainfall in mm/year represent by P.

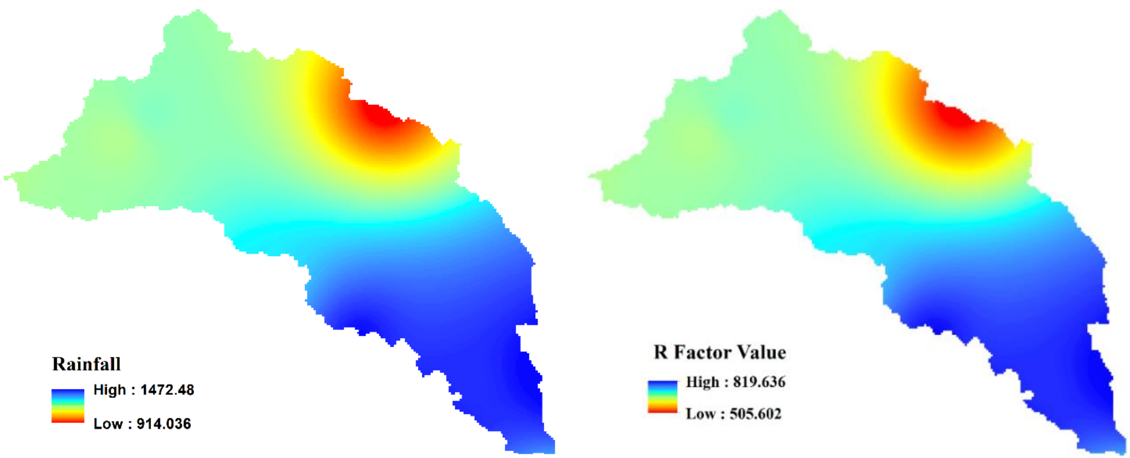


Figure 4.3 Map of precipitation and R factor value.

Table 4.2 Mean annual rainfall and R factor of different stations

Stations	Location		Mean annual rainfall (2000 up to 2020)	R factor
	Latitude	Longitude		
Addis Zemen	12.11	37.77	1243	690.45
Agere Genet	11.80	38.29	1597	889.39
Amed Ber	11.91	37.89	1301	723.04
Debere Tabor	11.85	38.01	1468	816.9
Ibinat	12.12	38.04	913	504.99
Kimir Dingay	11.81	38.22	1472	819.14
Leway	11.72	38.07	1574	876.47

Woreta	11.92	37.69	1200	666.28
Yifag	12.08	37.73	1205	669.09
Wolela Bahir	11.63	38.25	1045	579.17
Gassay	11.79	38.14	1448	805.65

Soil Erodibility Factor (K)

One of the required parameters for the InVEST model is soil erodibility data. According to (Witchmeier and Smith, 1978) the K-factor, which is affected by the physical and chemical characteristics of the soil, is a measurement of how easily soil particles in uplands can detach during storm events. For instance, Sand soils are difficult to transport due to their high rates of infiltration and hence low runoff generation, whereas clay soils are highly resistant to detachment. Conversely, silt soil is easily detachable, and transportable (Bekele et al., 2022). The soil map of the Rib watershed was obtained from the International Soil Reference Information Center (ISRIC) database. The map identifies four soil types of soil (Lithosol, Luvisol, Nitosol, and Vertisol).

The soil's physicochemical properties are important to determine the K-factor. However, complete soil data, which are required to calculate the K-factor, are unavailable in the study watershed. On the other hand, determining these soil properties by collecting soil samples is expensive, particularly for large areas. In cases where complete soil physicochemical properties are unavailable, (Hurni, 1985) suggested K-values based on the soil colors to the Ethiopian condition. Due to the absence of soil properties-related data, the suggested method has also been employed in several studies (Gelagay & Minale, 2016; Getnet & Mulu, 2021;Molla & Sisheber, 2017). But this method was the oldest one to determine k value of the watershed.

For this study, the soil erodiblity (K-factor) map was calculated using Eq. (4.6 and 4.7) (Witchmeier and Smith, 1978). Soil physical and chemical property data for the upper layer (0–15cm) such as clay, sand, silt, and soil organic matter contents at 250 m spatial resolution were obtained from the International Soil Reference Information Center (ISRIC) database (Hengl et al., 2017). The derived K-factor map from the soil physicochemical properties data was resampled into a 30 m resolution grid. Lastly using the formula, the K value of the study area was extracted and prepared using ArcGIS 10.3 for InVEST model (Figure 4.4, Table 4.3).

$$K = \frac{2.1M^{1.14}\times 10^{-4}(12-OM)}{7.59} \tag{4.6}$$

Where K refers to soil erodibility, OM refers to soil organic matter content (%), and M calculated as

$$\%\,Silt + \%\,Sand\ \times 100 - \%\,Clay \tag{4.7}$$

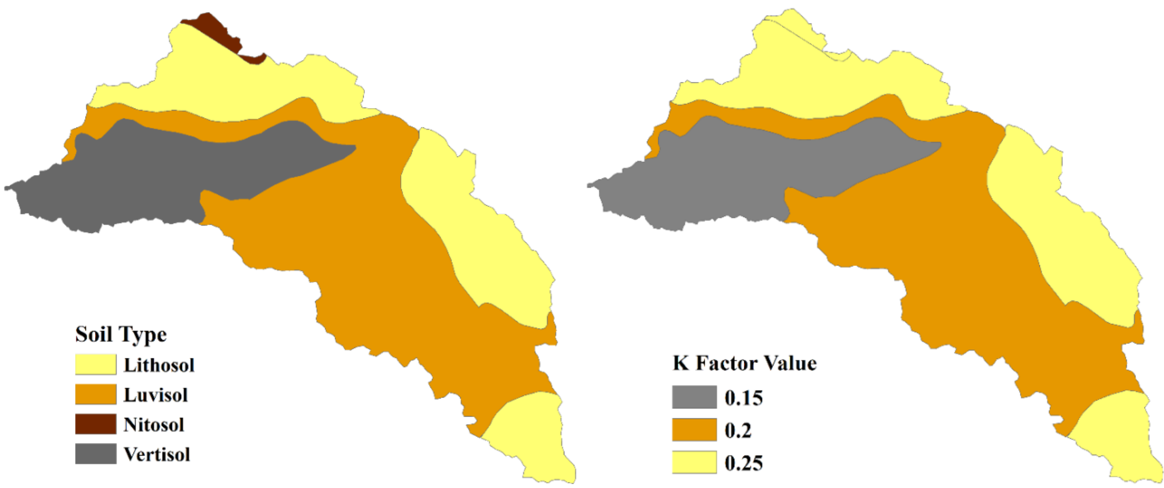


Figure 4.4 Types of soil and their erodibility value

Table 4.3 Types of soil corresponding to k value of the study area

Soil type	K value
Lithosol	0.22
Luvisol	0.21
Nitosol	0.24
Vertisol	0.16

Slope Length and Slope Gradient (LS) Factors

A DEM with 30 m spatial resolution was employed as key data to the InVEST model to quantify slope length (L) and slope gradient (S) in sediment delivery estimates. One of the parameters for the RUSLE equation was the LS factor. The LS factor is a combined factor that shows the influence of slope length and slope gradient and controls the velocity and volume of runoff and the transport of soil particles (Thapa, 2020). The amount of soil erosion in a certain geographic area depends on the slope's steepness and length. (Moges & Bhat, 2017; Gashaw, et al., 2021), through a greater accumulation of runoff (Witchmeier and Smith, 1978). According to Renard et al. (1991) the LS factor compares the consistent loss from a "typical" 9 percent slope steepness on a 22.13 m long plot to the soil loss per unit area on a spatial area. The LS factor depends on slope length and slope gradient. The velocity and erosive force of runoff will therefore increase as the amount of the LS factor increases (Renard et al., 1991; Witchmeier and Smith, 1978). For this study, the LS factor was calculated from DEM (SRTM) with 30m spatial resolution. As indicated by (Hamel et al., 2015), it is challenging to make direct field measurements to decide the LS factor in difficult topography, the InVEST model can compute the LS factor from DEM using equation 4.8 developed by (Hamel et al., 2015). Finally, the LS-value was calculated for the assessment of SLSE in the study area (Figure 4.5).

$$LS = \left(\frac{\text{Acc} * \text{Cell size}}{22.13}\right) 0.4 * \left(\frac{Sin\ \theta * 0.01745}{0.0896}\right) 1.3 * 1.4 \tag{4.8}$$

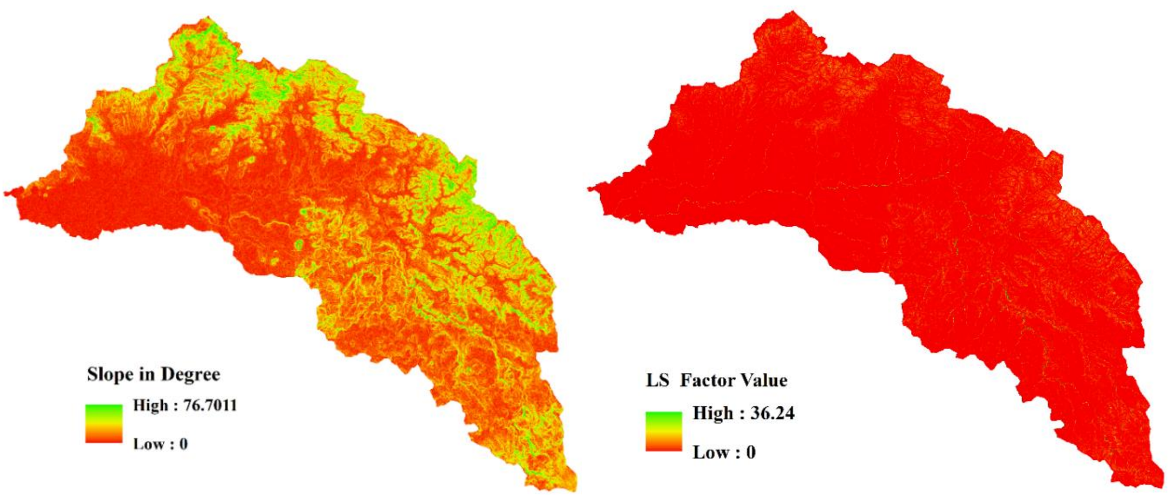


Figure 4.5 Slope in degree and LS factors of Rib River watershed.

Cover management and Conservation practice (C and P factors)

The biophysical table is one of the parameters of InVEST model consisting of cover management (C) and conservation practice (P) factors (Thapa, 2020). For the computation of SLSE in the study watershed, a ".csv" format database consisting of P and C factors corresponding with each LULC class was necessary. The rows were LULC classes, the columns were support practice and cover management factors. Data preparation for cover management and conservation practice for the biophysical table are described at (Table 4.4).

The C-factor indicated the effect of cover management practices in each LULC class on reducing soil loss (Ayalew, 2015b). Following Durigon et al.(2014) formula Eq. (4.9), and (4.10), the mean C-value of each LULC class for the years (2000, 2010, and 2020) was quantified based on the Normalized Difference Vegetation Index (NDVI) value. The NDVI is a practical method for identifying vegetated and non-vegetated areas in the watershed. Following Gandhi et al. (2015), three C factors were calculated by processing Landsat images for 2000, 2010, and 2020 in ERDAS IMAGINE 14 software and ArcGIS was employed to extract NDVI for individual LULC of the reference's year. The greater the NDVI values, the more vegetation is there, and vice versa. The well-established relations between NDVI and soil loss indicated that higher soil loss is associated with low NDVI values (low vegetation cover), and conversely, low NDVI, is indicated to high soil loss.

$$C = \frac{(-NDVI+1)}{2} \tag{4.9}$$

$$NDVI = \frac{NIR-RED}{NIR+RED} \tag{4.10}$$

Where NIR refers to the surface spectral reflectance in the near-infrared band and RED refers to the surface spectral reflectance in the red band.

Table 4.4 Types of LULC corresponding to C and P factor values.

LULC Type	C factor			P factor
	2000	2010	2020	
Cultivated land	0.45	0.47	0.43	0.8
Forest land	0.34	0.36	0.37	0.7
Shrub land	0.40	0.41	0.39	0.8
Grazing land	0.39	0.43	0.40	0.8
Water body	0.29	0.33	0.40	0.0
Settlement	0.47	0.47	0.44	0.9

The P-factor indicates the contribution of erosion control practice in decreasing soil erosion rate during raindrops in the uplands area (Witchmeier and Smith, 1978). Hurni (2020), showed that there are insufficient substantial soil and water conservation strategies in the Ethiopian highlands. The LULC classes' P-factors were taken from research done in the upper Blue Nile basin such as (Ali & Hagos, 2016; Haregeweyn, et al., 2017; Molla & Sisheber., 2017). Therefore, for the years 2000, 2010, and 2020, three P-factor maps were prepared.

4.2.4.2 Sediment Export

The sediment export indicates the fraction of soil loss arriving at the nearby waterbody (Wenng et al., 2021). InVEST model quantifies the sediment exported load based on the work by (Borselli et al., 2008). Since the valuation of SDR at each pixel is depend on the upslope area and downslope flow path, the model first calculates the connectivity index (*IC*) which is given by the following equation 4.11:

$$IC = Log10\left(\frac{Dup}{Ddn}\right) \tag{4.11}$$

Dup = upslope component and given by equation 4.12:

$$Dup = CS\sqrt{A} \tag{4.12}$$

Where C refers to the mean *C* factor of the upslope contributing area; S refers to the mean slope gradient of the upslope contributing area; and *A* refers to the upslope contributing area in m^2, which the model delineates based on the D infinity flow algorithm in accordance to (Aneseyee, et al., 2020; Gashaw et al., 2021) equation 4.13.

$$Ddn = \sum_i \frac{di}{ci\ si} \tag{4.13}$$

Where *di* refers to the length in a meter of the flow path of the i^{th} cell based on the steepest downslope direction; ***Ci*** refers to the *C* factor whereas ***Si*** represents the slope gradient of the i^{th} cell. The model is determined by the downslope flow path using the D-infinity flow algorithm derived by (Borselli et al., 2008). Then, the model calculates the SDR ratio for a single pixel from the connectivity index (IC) based on (Vigiak et al., 2012). The calculation of the connectivity index (IC) for each pixel is used to calculate the Sediment Delivery Ratio (SDR), as a function of the upslope area (Ud) and downslope flow path (Dd) to the streams based on DEM (Borrelli et al., 2012), which influences the severity of hydrological connectivity of a pixel per area to the stream using eq (4.14). The USGS data site was used to download a digital elevation model (DEM) with a 30 m resolution.

$$SDRi = \frac{SDR\ max}{1+exp\left(\frac{IC0-ICi}{K}\right)} \tag{4.14}$$

Where SDR max refers to the highest hypothetical SDR, set to a mean value of 0.8 (Vigiak et al., 2012), and *k* and *IC*0 refer to the calibration values that depend on the shape of the SDR-IC relation (Gashaw, et al., 2021). The value of IC0 was set to 0.5 based on recommendations in the literature (Hamel et al., 2015; Vigiak et al., 2012) . Finally, the sediment export of each pixel i, *Ei* (*t /ha/ yr*) is given by equation 4.15:

$$Ei = RUSLEi \times SDRi \tag{4.15}$$

The total sediment export from the watershed, *E* (*t/ha/ yr*) calculated using the following equation 4.16:

$$E = \sum_{\mathrm{i}} \mathrm{Ei} \tag{4.16}$$

4.2.5. Model Performance Validation

Model performance was evaluated using statistics recommended by (Boskidis et al., 2010; Yuemei et al., 2008). A comparison of the findings from the simulations and the data from the observations is crucial to determining the applicability and dependability of the models that have been used. By contrasting the annual simulated data with observed data (t/ha/year), the InVEST model's validity was investigated. The observed data (t/ha/year) from the gauging station the study watershed were found from the Ministry of Water, Irrigation, and Electricity, Ethiopia (MOWIE). Utilizing the Average Percentage Bias Error (PBIAS), Coefficient of Determination (R^2), and Residual Root Mean Square (RRMSE), the InVEST model's performance was evaluated (Zhu et al., 2019). If the PBIAS is < ± 10% and the R^2 and RMSE values are > 0.75, the model is performing very well. The model is inapplicable if the PBIAS is greater than 25% and the R^2 and RMSE are less than 0.50. (Nelson et al., 2014; Zhu et al., 2019).

4.3 Results

4.3.1 Land Use/ Cover Change (2000 to 2020)

Landscapes of the study site have experienced a marked change in land use and land cover over the last two decades (Table 4.5, Figure 4.6). Six LULC classes were identified in the study area, such as cultivated land, forestland, shrubland, grassland, waterbody, and settlement. The user and producer accuracy of the classified image was calculated and depicted in (Table 4.5). The user's accuracy essentially tells us how often the class on the map can be present on the ground and calculated by taking the total number of correct classifications for a particular class and dividing it by the row total. Whereas producers' accuracy shows how often are real features on the ground correctly shown on the classified map. It is also the number of reference sites classified accurately divided by the total number of reference sites for that class (ERDAS 2009). The overall accuracy assessment for the years 2000,2010 and 2020 was 80.11%, 82.7%, and 84.8% respectively with Kappa statistics of 0.78 for 2000,0.80 for 2010, and 0.82 for 2020 (Table 4.5). This confirms the recommended and suggested value by (Olofsson et al. 2014). Thus, the data was used for the analysis of different LULC classification and change detection analysis.

Table 4.5 The accuracy assessment (user and producer) report (in percent) of the classified LULC maps.

LULC class	2000		2010		2020	
	User accuracy	Producer accuracy	User accuracy	Producer accuracy	User accuracy	Producer accuracy
Cultivated land	78.3	80	83.4	83.2	87.2	85.1
Forest	82.1	81.3	83.3	84.7	85.5	85.6
Shrubland	81.4	82.8	82.4	83.6	83.1	84.9
Grassland	78.9	78.6	81.2	82.5	84.7	83.4
Waterbody	80.1	79.3	83.3	79.6	85.6	86.6
Settlement	79.8	79.5	81.9	80.6	83.9	84.7
Overall accuracy	80.1		82.7		84.8	
Kappa coefficient	0.78		0.80		0.82	

Land-use/land-cover classification maps for the years 2000, 2010, and 2020 are given in Figure 4.6. The spatial distribution of land-use/land-cover categories of the study area during the period 2000, 2010, and 2020 shows that cultivated land, waterbody, and settlement areas have increased, while the extent of forest, shrub, and grassland declined continuously from 2000 to 2020. A comparison of different land-use/land covers during these years is shown in Table 4.6. As per the land-use/land-cover classification map of 2000, cultivated land cover 63.7% of the total area (101,038 ha), However, analysis of three-time periods revealed progressive expansion of cultivated land during periods between 2000 and 2010, and became a dominant land use type for the past two decades (Figure 4.6). While forest land, shrub land, grassland, waterbody, and settlement covered 6.8% (10460 ha), 15.8% (25182 ha), 12.9% (20524 ha), 0.3% (586 ha) and 0.5% (843ha) of the total area respectively for the year 2000. Currently, in 2020 the watershed consists of 78.2% (123,977 ha) of cultivated land, 3.5% (5623 ha) of forest land, 8.8% (13984 ha) of shrub land, 7.6% (11999 ha) of grassland, 0.6% (1056 ha) of waterbody, and 1.3% (1993 ha) of settlement. The areal extent of each LULC and its percentage share from the total watershed are tabulated below under table 4.6.

Table 4.6 Area of land use and land cover (LULC) classes in (ha) for the year 2000, 2010 and 2020.

LULC Class	2000		2010		2020	
	Areal (ha)	%	Areal (ha)	%	Areal (ha)	%
Cultivated land	101,038	63.7	112,351	70.8	123,977	78.2
Forest	10460	6.8	9523	6.0	5623	3.5
Shrub land	25182	15.8	18360.9	11.6	13984	8.8
Grass land	20524	12.9	16497	10.4	11999	7.6
Waterbody	586	0.3	220.1	0.1	1056	0.6
Settlement	843	0.5	1679.9	1.1	1993	1.3
	158630	100	158630	100	158630	100

Statistically, cultivated land has increased by 23% over the last two decades. Whereas forest decreased by 8.9% from (2000 to 2010), 41% (2010 up to 2020), and 46.5% (2000 to 2020). Shrub land decreased by 27.1% from 2000 to 2010 and 24% from 2010 to 2020. The total reduction of shrubs was 44.5% from 2000 to 2020. Grassland decreased by 20%, 27%, and 41.5% from 2000 to 2010, 2010 to 2020, and 2000 to 2020 respectively. Waterbody decreases considerably from 2000 to 2010 but showed an incredible increase between 2010 and 2020 (Table 4.7, Figure 4.6). The increase in the areal extent of the waterbody is due to the building of the Rib irrigation dam.

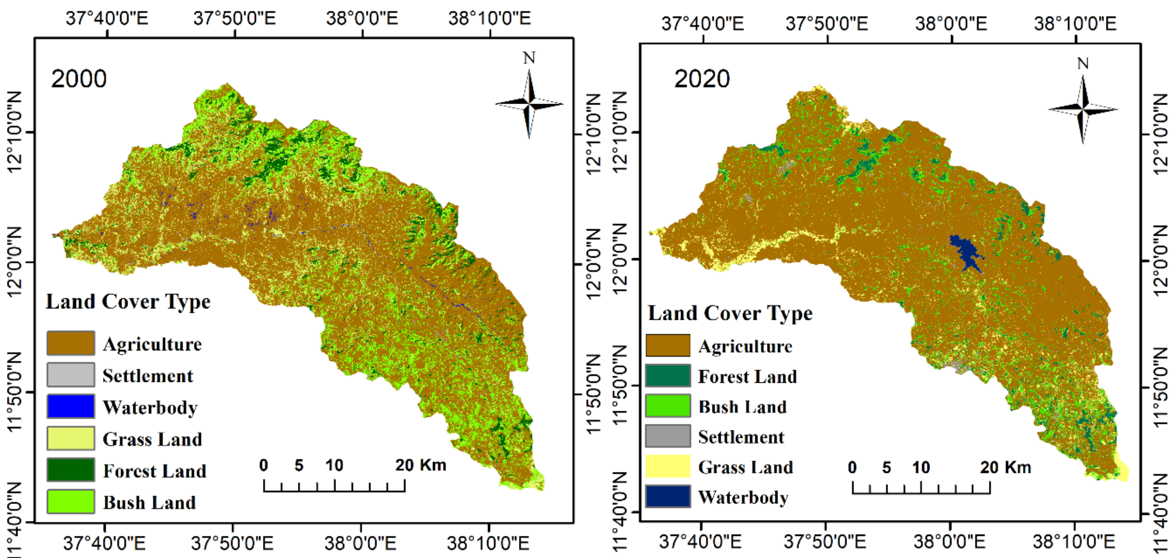


Figure 4.6 Land use and land cover map of Rib River watershed for the year 2000, and 2020.

The rate and trend of changes varied markedly between land uses, and intervals of the study period. Cultivated land expanded at a rate of 1.12 %, 1.03% and 1.15% per annum between 2000 to 2010, 2010 to 2020 and 2000 to 2020 respectively. For the past two decades (2000 to 2020), Forest land, Shrub land and Grass land showed a decreased rate of 2.3%, 2.2% and 2.2% respectively. Whereas water body increased at a rate of 4% per annum. This increment of waterbody is directly associated with the construction of Rib Irrigation dam in the study area. and settlement expanded at a rate of 6.8%.Coparatively, settlement area increased sustainably with rates exceedingly higher than any other land use and land cover type in the same time periods (Table 4.7).This increment is directly associated with the expansion of urban area in the study watershed.

Table 4.7 Land use and land cover (LULC) changes and annual rate for the year 2000–2010, 2010–2020 and 2000–2020.

LULC Class	Net change in Area (%)			Annual rate of change (%) per annum		
	2000-2010	2010-2020	2000-2020	2000-2010	2010-2020	2000-2020
Cultivated land	11.2	10.3	23	1.12	1.03	1.15
Forest	- 8.9	- 41	- 46.5	- 0.89	- 4.1	- 2.3
Shrub land	- 27.1	- 24	- 44.5	- 2.71	- 2.4	- 2.2
Grass land	- 20	- 27	- 41.5	- 2.0	- 2.7	- 2.2
Waterbody	- 62	380	80	- 6.2	38	4.0
Settlement	99	19	136.5	9.9	1.9	6.8

4.3.1.1 Trends in Transitions Between Land Uses and Land Cover

The conversions taken place from one LULC category to another during 2000-2010, 2010-2020 and 2000-2020 periods are presented in Table 4.8. The diagonals of the matrix from the tables are the persistence while the off-diagonals are the conversions from one category to the others. The change detection analyses indicated the significant conversions in LULC in both periods.

In the study watershed, from 2000 to 2010, 2761 ha, 12238 ha, 10021 ha, 389 ha and 49 ha of cultivated land were converted from forest, shrubland, grassland, waterbody and settlement area, respectively. While a significant area of cultivated land was also reverted to forestland, shrubland, grassland, and waterbody and settlement area (Table 4.8). During these times, some area of settlement was also converted from cultivated land (903 ha), forestland (21), shrubland (79 ha), grassland (83 ha). Although it is a small proportion, 49 ha, 6 ha, 72ha, 118ha and 2 ha of the settlement area were also in reverse converted to cultivated land, shrubland, grassland, and waterbody respectively. Gains and losses in forest, shrubland and grassland were also taken place during these periods (Table 4.8). For example, 12238 ha of Cultivated land, 658 ha of forest, 4758 ha grassland, 1 ha of waterbody and 79 ha settlement area were altered from shrubland. In reverse, a considerable area of shrubland was also reverted from cultivated land (6644 ha), forest (540 ha), grassland (3653 ha), waterbody (0) and settlement (72 ha).

Table 4.8 Transitions between major land use and land cover in (ha) between 2000, 2010 and 2020 for Rib River watershed.

2000			**2010**				
LULC	**CL**	**FL**	**SL**	**GL**	**WB**	**ST**	**Total (ha)**
CL	**86,893**	**1944**	**6644**	**4648**	**6**	**903**	**101,038**
FL	**2761**	**6,791**	**540**	**345**	**2**	**21**	**10460**
SL	**12,238**	**655**	**7,451**	**4758**	**1**	**79**	**25182**
GL	**10,021**	**123**	**3653**	**6624**	**20**	**83**	**20524**
WB	**389**	**4**	**0**	**4**	**189**	**0**	**586**
ST	**49**	**6**	**72**	**118**	**2**	**596**	**843**
Total (ha)	**112,351**	**9523**	**18360**	**16497**	**220**	**1679**	**158630**
2010			**2020**				
LULC	**CL**	**FL**	**SL**	**GL**	**WB**	**ST**	**Total (ha)**
CL	**102896**	**737**	**2216**	**5168**	**841**	**493**	**112,351**
FL	**2514**	**3260**	**3595**	**133**	**2**	**19**	**9523**
SL	**9865**	**1534**	**6,089**	**771**	**83**	**18**	**18360**
GL	**8215**	**81**	**1937**	**5689**	**25**	**552**	**16497**
WB	**101**	**9**	**2**	**3**	**105**	**0**	**220**
ST	**386**	**2**	**145**	**235**	**0**	**911**	**1679**
Total (ha)	**123,977**	**5623**	**13,984**	**11999**	**1056**	**1993**	**158630**
2000			**2020**				
LULC	**CL**	**FL**	**SL**	**GL**	**WB**	**ST**	**Total (ha)**
CL	**89093**	**303**	**5585**	**4697**	**579**	**781**	**101,038**
FL	**3394**	**4,790**	**1826**	**146**	**3**	**301**	**10460**
SL	**19595**	**401**	**3844**	**1057**	**4**	**280**	**25182**
GL	**11468**	**123**	**2653**	**6004**	**151**	**125**	**20524**
WB	**234**	**2**	**3**	**27**	**318**	**2**	**586**

ST	**193**	**4**	**73**	**68**	**1**	**504**	**843**
Total (ha)	**123,977**	**5623**	**13,984**	**11999**	**1056**	**1993**	**158632**

Note: CL = Cultivated land; FL = Forest land; SL = Shrub land; GL = Grass land; WB = Waterbody; ST = Settlement

The conversion matrix from 2010 to 2020 indicated that, 9865 ha, 1534 ha, 771 ha, 83 ha, and 18 ha of shrubland were converted to cultivated land, forest, grassland, waterbody and settlement, respectively. About 8215 ha, 81 ha, 1937 ha, 25 ha and 552 ha of grassland were also reverted to cultivated land, forest, shrubland, waterbody and settlement area, respectively. An estimated 2514 ha, 3595 ha, 133 ha, 2ha and 19 ha of forest were also converted to cultivated land, shrubland, grassland, waterbody and settlement respectively. Similarly, shrubland, forest, grassland, waterbody and settlement were also converted from other LULC categories (Table 4.8). In these periods, a significant area of cultivated land was converted from shrubland (9865 ha), grassland (8215 ha), forest (2514 ha), waterbody (101 ha) and settlement area (386 ha). In reverse, there was also a considerable conversion of cultivated land to other categories.

As depicted from the above table 4.6, between 2000 and 2020 forestland, shrubland and grassland experienced a remarkable decline by 46.5%, 44.5% and 41.5%, while cultivated land, waterbody and settlement area grew by 23%, 80% and 136.5% respectively for the past two decades. Transitions between LULCs constitute the replacement of one type by the other. In the study watershed, 3394 ha of forest land, 19595 ha of shrubland, 11468 ha of grass land, 234ha waterbody and 193 ha of settlement were changed to cultivated land. Relatively, conversion of shrubland and grassland to cultivated land was significant at a conversion index ≥1compared to other LULC types (Tables 4.8 and 4.9). The conversion index of shrubland were 2.4 (between 2000 to 2010), 2.34 (2010 to 2020) and 2.8 (2000 to 2020).Thus, the conversion index of grass land were 1.97,1.95 and 1.64 between 2000 to 2010, 2010 to 2020 and 2000 to 2020 respectively. Therefore, shrubland and grassland were highest contribution for the expansion of cultivated land in the study area.

Table 4.9 Area converted to cultivated and Index of different land use and land cover (LULC) conversion to cultivated land in years 2000 to 2010, 2010 to 2020, and 2000 to 2020.

LULC	2000-2010	2010-2020	2000-2020
	Area converted to cultivated land (ha)		
Forest land	2761	2514	3394
Shrub land	12238	9865	19595
Grass land	10021	8215	11468
Waterbody	389	101	234
Settlement	49	386	193
Mean [a]	5091.6	4216.2	6976.8
	Indexes of different LULC conversion to cultivated land		
Forest land	0.54	0.6	0.5
Shrub land	2.40	2.34	2.8
Grass land	1.97	1.95	1.64
Waterbody	0.07	0.02	0.03
Settlement	0.01	0.09	0.02

4.3.2 Soil loss and Sediment Export Dynamics

4.3.2.1 Soil Loss Change

The maximum soil loss estimation in each pixel was 174.20, 228.31, and 291.70 tons per pixel in 2000, 2010, and 2020 years respectively (Figure 4.7). The calculated average annual soil loss from the watershed was 22.37 t/ha/year in 2000, 23.68 t/ha/year in 2010 and 33.38 t/ha/year in 2020. Between the years 2000 and 2020, the watershed's estimated total soil loss increased from 3,548,553.1 tons to 5,295,069.4 tons.

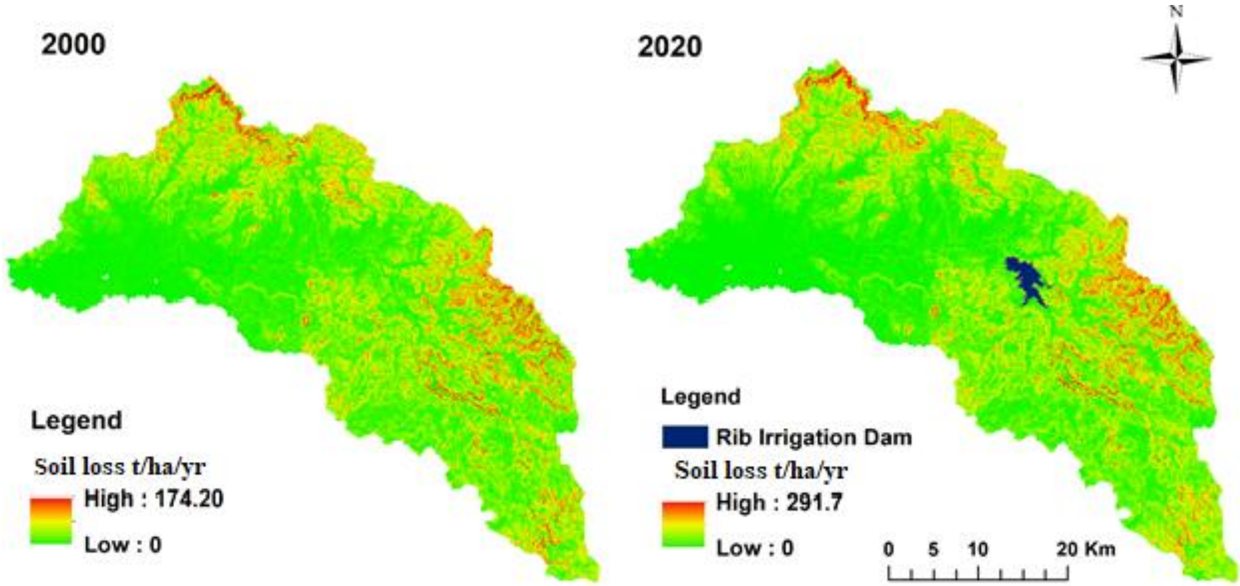


Figure 4.7 Soil loss (t/ha/yr) map of Rib watershed for the years 2000 and 2020.

Cultivated land experienced the highest soil loss among the LULC types, with losses ranging from 40.86 t/ha/year in 2000 to 53.90 t/ha/year in 2020. (Table 4.10). Shrub land follows, with soil loss ranging from 29.80 t/ha/year in 2000 to 50.01 t/ha/year in 2020. The data showed that due to poor cultural practices, particularly the cultivation of steep slopes (>30 degrees) without the proper conservation measures, cultivated land had the greatest impact on the overall soil loss in the watershed. For the past two decades, soil loss from forest land, grassland, and settlement increased by 17.61, 7.36, and 7.87 t/ha respectively (Figure 4.7, Table 4.10).

Table 4.10 Soil loss and Sediment export (t/ha/year) for the past two decades.

LULC	2000		2010		2020	
	Soil loss	Sediment export	Soil loss	Sediment export	Soil loss	Sediment export
Cultivated land	40.86	10.43	42.61	13.17	53.90	21.22
Forest land	22.76	8.01	22.14	8.49	40.37	13.12
Shrub land	29.80	8.82	37.03	10.06	50.01	15.43
Grass land	23.62	6.86	22.96	7.91	30.98	10.31
Waterbody	0.00	0.00	0.00	0.00	0.00	0.00
Settlement	17.21	5.14	17.37	4.84	25.03	6.22
Total	22.37	6.54	23.68	7.49	33.38	11.05

4.3.2.2 Sediment Export Change

Utilizing the RUSLE equation and InVEST model was used to calculate the amount of sediment exported to the stream. This integration made it potential to quantify the amount of sediment export that is moved in the watershed. Between 2000 and 2020, the proportion of sediment export increased by 4.51 t/ha/year. In other words, the data indicated a raised trend in sediment export. In 2000 and 2020, the watershed's average rate of sediment export was 6.54 t/ha/year and 11.05 t/ha/year, respectively. The sum of sediment export was 1,037,440.2 tons in 2000 and 1,752,861.5 tons in 2020. (Table 4.10). The sediment export showed significant differences with LULC. According to the InVEST model, the results shown that the maximum role in the total sediment export was from cultivated land (21.22 t/ha/year) which was followed by shrubland (15.43 t/ha/year) (Table 4.10, Figure 4.8). The lowest contribution to the sum of sediment export was from the waterbody area (0.00 t/ha/year) for the year 2020.

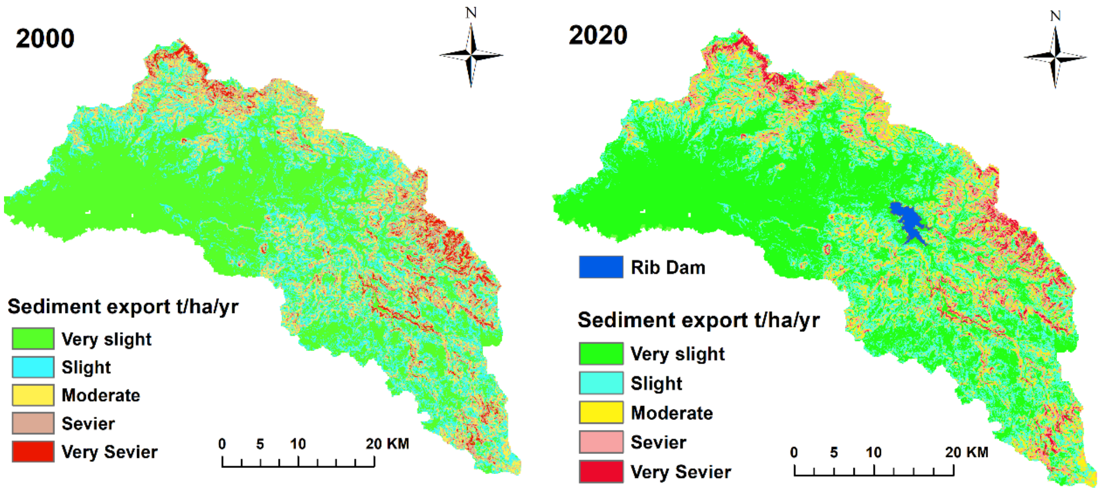


Figure 4.8 Sediment export class limit map of the study watershed between the years 2000 and 2020.

For the past two decades, all land cover showed increased sediment export. For instance, sediment export from cultivated land increased by 10.79 t/ha/year and shrub by 6.61 t/ha/year. Similarly, between those years forest, grass, and settlement land increased by 5.11, 3.45, and 1.08 t/ha/year respectively. This situation has an impact on the Rib irrigation dam exposed to siltation. This may eventually jeopardize the longevity of the dams in the watershed. In the study Rib watershed, the highest share of sediment export was located in the Easter and northern direction of the watershed. The maximum sediment export is directly related to enlargement in cultivation in these upland plateaus. The lowest sediment export was found at the central and Western parts of the Rib watershed due to the plain topography of the area.

4.3.3 Priority Sub-Watershed

The susceptibility of soil erosion varies significantly amongst sub-watersheds. In the study Rib watershed, fifteen sub-watersheds were identified to examine the spatial variation of the mean annual SLSE in each sub-watershed. Erosion severity level was rated as Very slight (< 5 t/ha/year), Slight (5–15 t/ha/year), Moderate (15–30 t/ha/year), Sevier (30 – 50 t/ha/year), Very Sevier (> 50 t/ha/year) and sediment export rated as Very slight (< 2 t/ha/year), Slight (2–5 t/ha/year), Moderate (5–10 t/ha/year), Sevier (10 – 15 t/ha/year), Very Sevier (> 15 t/ha/year) following (Haregeweyn, et al., 2017)(Table 4.11, Figure 4.9).

Table 4.11 Soil loss and sediment export (t/ha/year) result and erosion severity of sub watershed in 2020

Sub Watershed	Area (ha)	Soil loss (t/h/y)	Sediment export (t/h/y)	Erosion severe class
SW_1	13,521.4	36.69	12.13	Sevier
SW_2	9910.6	42.09	13.44	Sevier
SW_3	9996.5	61.80	18.75	Very Sevier
SW_4	8520.5	38.55	11.99	Sevier
SW_5	11618.7	63.48	19.35	Very Sevier
SW_6	12501.2	33.30	10.40	Sevier
SW_7	8124.6	26.59	9.33	Moderate
SW_8	9385.5	44.44	13.70	Sevier
SW_9	7257	36.41	11.65	Sevier
SW_10	9144.5	17.30	6.09	Moderate
SW_11	9467.1	19.86	7.07	Moderate
SW_12	7104.7	2.56	5.34	Very slight
SW_13	12623.9	27.36	9.61	Moderate
SW_14	14859.8	43.66	13.83	Sevier
SW_15	12516.5	5.33	3.21	Slight
Average value		**33.28**	**11.05**	

Using the above erosion severity class, severe susceptibility to soil loss was detected in the sub-watersheds (SW) three and five (SW-3, and SW-5) are accounts for about 21,615.2 ha of the whole watershed and experienced above 50 t /ha /year soil loss rate (Table 4.11, Figure 4.9). The average soil loss of SW-3 and SW-5 were 61.80 t/ha/year and 63.48 t/ha/year respectively. Sediment export of those sub-watersheds was 18.75 t/ha/year for SW-3 and 19.35 t/ha/year for SW-5. These sub-watersheds are located in the upland plateau where cultivated land use is the main LULC type. While the level of soil loss classes in the following sub-watersheds such as SW-1,2,4,6,8, 9, and SW-14 are from 30-50 t/ ha/ year (Figure 4.9). Four sub-watersheds such as (SW-7, SW-10, SW-11, and SW-13) are acquired annual soil loss rates of 15-30 t/ha/year. The average soil loss of SW-15 was from 5–15 t/ha/year. The remaining sub-watershed (SW 12) experienced below 5 t/ha/year in 2020. The factors for spatial variations of soil loss are credited to cultivations of a steep slope in the study areas.

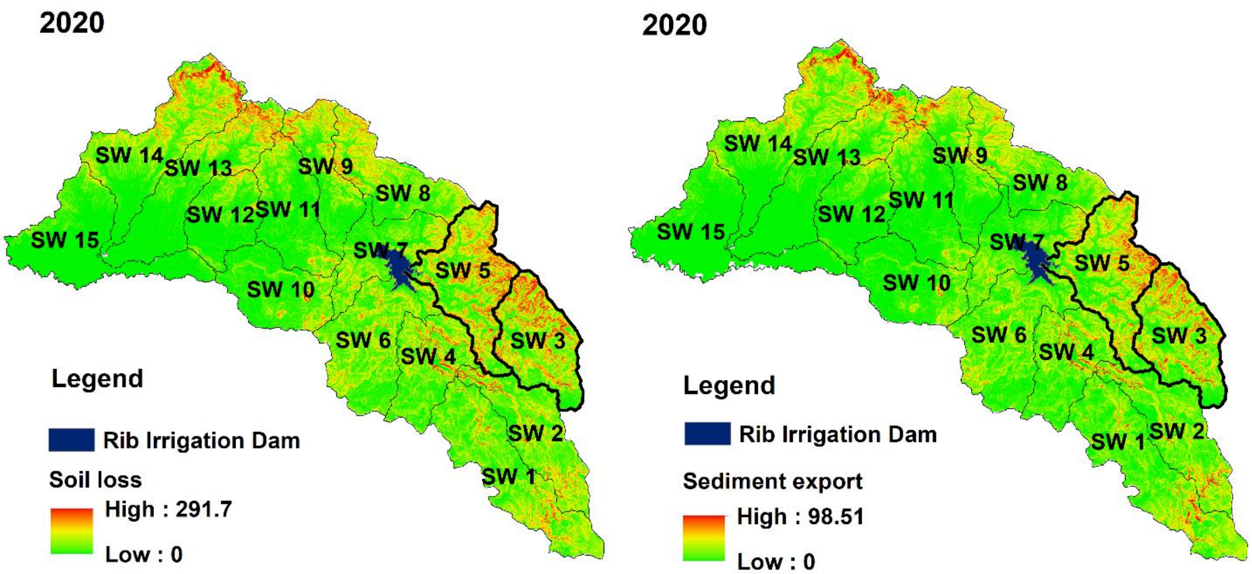


Figure 4.9 The soil loss and sediment export (t/ha/year), Severity level map of each sub-watershed in the year 2020.

4.3.4 InVEST Model Validation

When compared to the comparable estimations derived from the observed data between 2000 and 2020, the estimated sediment export was reliable. This shows the appropriateness of InVEST model for estimating sediment export of the Rib watershed. The observed mean annual sediment loss was found at the river gauging station near Addis Zemen town indicated in Table 6. These results were similar to the results estimated using the Invest model.

The mean value of observed and simulated sediment export, with the difference of 0.49 t/ha/year, was 11.54 t/ha/year and 11.05 t/ha/year respectively. The low difference in sediment loss indicates that LULC impact has been appropriately calculated by the model. Therefore, the maximum of ±10% difference accuracy of the model can be assumed to be a very good rating for the sensitivity analysis of the study. To evaluate the effectiveness of the model for the study area during the preceding two decades, the R^2, RRMSE, and PBIAS values were determined. The average R^2, RRMSE, and PBIAS values were 0.83, 0.82, and − 8.15%, respectively. The observed sediment export statistics from the watershed gaging station are in good agreement with the InVEST model according to the goodness-of-fit test. As a result, the outcome suggests that the InVEST model is suitable for simulating sediment export in the Upper Blue Nile Basin's Rib watershed (Table 4.12).

Table 4.12 Observed and Estimated value of sediment export (t/ha/year).

Years	Station		Observed	Estimated	PBIAS	R^2	RRSME
2000	Near zemen	Addis	7.41	6.54	-8.02	0.84	0.86
2010	Near zemen	Addis	8.24	7.49	-9.27	0.83	0.82
2020	Near zemen	Addis	11.54	11.05	-7.03	0.81	0.84

4.4. Discussion

4.4.1 Land Use and Land Cover Dynamics (2000–2020)

LULC change is unavoidable as it is derived from social and economic development (Wu et al., 2008). In this regards, recent LULC change studies conducted in Ethiopia reported substantial and rapid LULC changes (Miheretu and Yimer, 2017; Tadesse et al., 2017; Gashaw et al., 2018). The results of this study also revealed that in the past two decades, remarkable LULC changes, particularly forest land, shrub land, grassland land and settlement areas were observed. Similar results were reported by prior LULC change studies in the highlands of Ethiopia. For instance, (Birhanu et al. 2019) in the Ethiopia highland; (Abebe et al. 2021) in the Gubalafito district, Northeastern Ethiopia; (Abebe et al. 2021) in Gelda catchment, Lake Tana watershed, Ethiopia; (Tadesse et al. 2017) in the Yezat Watershed, North Western Ethiopia; and (Mariye et al. 2022) in the Ojoje watershed, Southern Ethiopia; reported a considerable expansion of cultivated land at the cost of forest, grassland and shrubland, reported the expansion cultivated land at the expense of forest land, shrubland and grassland. Expansion of cultivated land often comes with many environmental costs as it is being practiced without proper land management.

Likewise, (Belay and Mengistu 2019) explained in his study rapid expansion of agricultural land into steeper slope has aggravated for erosion and degradation in Ethiopia. Similarly, (Tadesse et al. 2017) illustrated destruction of forest cover because of expansion of farming practice into steeper slopes particularly in the highland of Ethiopia in which intensive farming practice undertaken without appropriate conservation practice is resulted for depletion of fertile soil. Expansions of cultivated land at the expense of grazing land resulted for insufficient availability of fodder for livestock and adversely affect the productivity livestock similarly, absence of animals for land preparation and transportation service. Likewise, due to the reduction of gazing land, farmers are forced to reducing livestock number consequently reduced availability of manure for soil fertility amendment. According to (Bantider et al. 2011), the change of land use land cover class significantly aggravated the surface runoff, soil erosion, land degradation, sedimentation, siltation, drought, migration, desertification loss, of biodiversity, and decrease in productivity.

4.4.2 Soil Loss and Sediment Export

4.4.2.1 Soil Loss

Scientific investigations showed that evaluating the severity of SLSE are significant for the viable management of natural resources in a given watershed. The findings of the study demonstrate the increased trend in SLSE in the watershed over the past 20 years, which has been exacerbated by LULC changes. This is in agreement with the findings of Getnet & Mulu (2021), who showed that changes in LULC have an impact on sediment export and soil erosion rates. Further research was carried out around the study area. For instance, the Megech watershed showed that the mean soil loss was 32.84 t/ha/year (Getu et al., 2022), Upper Blue Nile Basin was 30.20 t/ha/year (Yeneneh et al., 2022), the Gumara watershed was 24. 2 t/ha/year (Bekele et al., 2022), Koga watershed with 30.20, (Molla & Sisheber, 2017), Beshlo watershed was 37.00 (Yesuph & Dagnew, 2019)(Table 4.13). This is consistent with the ongoing watershed study, which found a mean soil loss rate of 33.38 t/ha/year.

Table 4.13 Soil loss and Sediment export values (t/ha/year) of selected studies in Ethiopia.

Study area	Study site area	Years	Soil loss (t/ha/yr)	Sediment yield (t/ ha/yr)	Selected studies
Gumara watershed	1591.56 km^2	2019	24.2		Bekele,Gella,andEjigu (2022)
Guang watershed	2500 ha	2012	24.95		Ayalew and selassie(2015b)
Koga watershed	266 km^2	2015	30.20		Molla& Sisheber(2017)
Suha watershed	80,342 ha	1985	15.2	3.95	Yeneneh et al., (2022)
		1999	21.8	5.66	
		2009	30.2	8.02	
		2019	31.4	8.16	
Megech watershed	39,419.2 ha	2016		13.61	Getu et al., (2022)
Beshilo	23,970 ha	2018	37.00		Yesuph and Dagnew (2019)

According to Yesuph & Dagnew (2019), Soil loss tolerance (SLT) is the highest allowable soil loss that will sustain the maximum rate of productivity indefinitely. The SLT rate in the Ethiopian highlands ranged from a minimum of 2 and a maximum of 18 t/ha/year (Hurni, 1983). The mean soil erosion rate was 33.38 t/ha/year in the study Rib watershed in 2020. The value is greater than the Ethiopian condition's soil loss tolerance limit. In this study, the highest soil loss rate for the year 2020 was 291.7 t/ha/year. This is related to the rapid change of different land cover into cultivated land (Aneseyee et al., 2020).

From the study, 13.6% of watersheds had significant soil loss rates, accounting for 25.2% of the estimated soil loss in terms of spatial distribution. The study also showed that a significant portion of the watershed had very slight and slight rates of soil erosion. This suggests that a small area of the watershed that underwent significant rates of erosion was concentrated for the majority of the total soil loss. Consequently, various types of water conservation measures must be used to ensure proper conservation of the watershed resources that are targeted for soil erosion. The soil loss map (Figure 4.7) further demonstrates that the upper portions of the watershed have seen greater soil loss. This is because the agricultural activity has expanded into marginal steep slope areas by clearing vast tracts of grazing, shrub, and forest land, exposing the soil to the direct effects of rainfall.

Massive soil and water conservation measures have been put in place by the Ethiopian government in recent years through community-led watershed management, programs like the Productive Safety Net Programs (PSNP), community mobilization through free labor days, and the Sustainable Land Management Project (SLM) (Ali & Hagos, 2016; Ayalew & Bharti, 2022; Degife et al., 2021). Terracing, soil and stone bunds, and biological conservation measures make up the majority of the implementation. The community involvement and agricultural extension system both support these actions further. These widespread Soil Water Conservation (SWC) movements reveal important developments in land management practices in the studied area. However, ongoing structure maintenance and the persistent use of a scientific methodology are crucial for achieving sustainable ecosystem services protection.

4.4.2.2 Sediment Export

According to the analysis, the watershed's sediment export in 2020 was 11.05 t/ha/year. The result is comparable to earlier estimates of sediment export in the context of Ethiopia. For instance, 8.16 t/ha/year of sediment export from the Suha watershed of Northern West Ethiopia by (Yeneneh et al., 2022). (Getu et al., 2022) also calculated that the Megech Dam Watershed in Ethiopia exported 13.61 t/ha/year of sediment per year (Table 5.13). The estimated sediment export value was compared to the research findings mentioned above. Additionally, field observations revealed that soil removal from the study watershed's steep slopes resulted in the deposit of material in downstream area. Such deposition of sediment leads to lake sedimentation, and sediment accumulation on the agricultural area.

The calculated sediment export of each LULC class was also comparable with the results observed in the spatial distribution of the soil loss. The result showed that cultivated lands contribute the most among other LULCs to the overall export of sediment. The result confirms the findings of (Aneseyee et al., 2020; Gashaw et al., 2021; Moges & Bhat, 2017; Munoth & Goyal, 2020), who found higher sediment export from cultivated lands. This is related to activities such as intense plowing, monoculture farming, agriculture on steep slopes, and inadequate land management. The study indicated that the expansion of cultivation land on higher slopes combined with inadequate land management practices is continuing to erode the top fertile soil and causing sediment deposition in the water bodies. Hence, the result gives cause to suggest the need for effective sustainable land management practices in the vulnerable area in the watershed.

4.4.3 Limitations and Strengths of the Study

InVEST model is a recently announced model used for natural resource conservation in a data-scare area. Additionally, the InVEST model was chosen for this study over other complex (data-intensive) models due to its restriction of fewer input parameters, accessibility of input geographical data, and compatibility with different GIS data. The distinctive characteristic of InVEST model is its capability to examine soil loss and sediment export from individual land use types and to quantify the extent of sediment export reached the water bodies. No one was doing research in the Rib watershed. Hence this is the positive side of the study.

In this study, LULC datasets were used to model the impact of LULC change on soil loss and sediment export. However, there are some limitations concerning the LULC datasets that were used. For instance, we were unable to use land sat 7 images from USGS for image classification between 2000 to 2010, because the data set is not free from the strip as a result land sat 5 images were employed for image classification. The other limitation of the model was the inability to account for types of soil erosion and sediment export other than rill or inter-rill erosion (unable to measure gulley erosion like RUSLE model).

4.5 Conclusion

According to the InVEST model's estimation, the study Rib watershed has experienced significant LULC change as well as historical variations in SLSE. The findings illustrated that the decline of the grazing, forest, and shrubland areas was mainly the effect of the conversion of cultivated lands for the past two decades (2000 to 2020). This caused a decrease in the regulatory capability of the land, which in turn, exacerbates SLSE. Over the past 20 years, the total SLSE in the watershed grew by 4. 51 t/ha/year from 2000 to 2010 and, 11. 01 t/ha/year from 2000 to 2020.

Soil loss and sediment export have highly increased in the cultivated land, forest land, shrub land, grassland, and settlement while none in the waterbody. This implies that the change in SLSE is directly proportional to LULC, except in the case of the waterbody.

In comparison to the rest of the study watershed, soil loss and sediment export are more severe in the eastern and northern parts. Sub-watersheds (SW-3 and SW-5) were extremely susceptible to SLSE. To address the issues of Rib dam siltation and loss of ecosystem services in the study watershed, the findings suggest the need for more conservation measures in the extremely vulnerable sub-watershed and a decrease in continuous farming in the higher altitude sections of mountainous parts of the watershed. The results of the study also imply that to prevent SLSE to the Rib dams, policy instruments need to be enforced by carrying out urgent conservation efforts in the study area in above mentioned sub-watershed. One of the suggested future research areas in the Rib watershed is the study of how soil fertility changes over time concerning LULC and soil erosion.

CHAPTER FIVE

5. Synthesis, Conclusion and Recommendation

5.1 Synthesis

The LDN status in the study Rib Watershed was examined using the Scientific Conceptual Framework (SCF) developed by (Cowie et al. 2018). Accordingly, the LUC, NPP, and SOC were used as indicators to check the LDN in the study area. Similarly, the study which was done by (Kiani-Harchegani and Sadeghi 2020) used the above three indicator for the assessment of LDN in shazad watershed of Iran. In this study, the years 2000, 2010, and 2020 were used to examine the LDN status of the study watershed. The existing approach for evaluating and assessing LDN consists of the use of site-based data to measure the quantitative value of the sub-indicators resulting from Earth observation and geospatial information. For those indicators, the baseline data was prepared. After the baseline data was prepared, change detection for each sub-indicator was done to identify the area subject to change and mostly where the change in two or three indicators overlap spatially. Lastly, the methodological and conceptual scientific framework conducted by (Cowie et al. 2018) was applied to evaluate the status of LDN in the study Rib watershed.

In this framework, the evaluation of LD uses the "one out all out (1OAO)" approach to integrating the three indicators, where the degradation of any indicator shows in the degradation of the status of LDN. According to this framework, if any of the three indicators displays considerable negative change, it is considered as degradation. Conversely, it is deemed an improvement of the land condition if at least one indicator shows a significant positive change and none shows a significant negative change. The combined findings of the study measurements showed that there was a net loss in cultivated land (123,977 ha), forest land (5623 ha), shrub lands (13984 ha), grassland (11,999 ha), water body (1056 ha) and settlement (1993 ha) for the past two decades (2000 to 2020). For the past two decades LDN status of the Rib Watershed was generally in a net loss condition. The information delivered by the three sub-indicators is important for experts for the good recognition of their spatial distribution and types of land degradation to attain the LDN targets.

The ESVs between 2000, 2010, and 2020 years with concern to LULC were estimated. The LULC map was classified and the areal extent of each type was calculated. Hence using the modified ecosystem value coefficient, the total ESV and their changes to each LULC type were calculated between 2000, 2010, and 2020. In this study, the ESV of six LULC categories was calculated using a modified ecosystem service value coefficient developed by (Kindu et al. 2016, 2018) for 11 biomes for Ethiopia conditions. The value coefficients were given to each LULC type during the ecosystem service value calculation procedure. After that, by multiplying the hectare area of each LULC type by the value coefficients for each LULC type, the total ESV for each LULC type was computed. The value of LULC type was summed to estimate the total ESV of the landscape for each year (2000, 2010, and 2020). The total ESVs of the watershed were estimated to be US$ 68.6 million in 2000, US$ 59.4 million in 2010, and US$ 59.3 million in 2020. The ESVs lost between 2000 and 2020 periods in the study watershed was about US$ 9.3 million (13.5%). The reduction of ESVs through 2000 to 2020 periods indicates the effects of LULC changes on ecological degradation. Hence, it is suggested that land managers and policymakers can use LULC change and ESVs together for good decision-making processes.

The Combined study of soil loss with sediment export in a particular watershed is vital because it allows for the identification of sediment transport routes from the watershed to water bodies. This is significant to study possible downstream impacts of sedimentation. The model also offers an important valuation of how landscape scenarios may impact on annual sediment export. Additionally, the InVEST model was chosen for this study over other complex (data-intensive) models due to its restriction of fewer input parameters, accessibility of input geographical data, and compatibility with different GIS data. The RUSLE equation is mostly employed in the model, and some of its input factors have been calibrated for Ethiopian conditions (Hurni 1985), making them enthusiastically usable in the model.

Most importantly, the InVEST model has only been used in a very small number of studies in Ethiopia and most likely none at all in the Rib watershed. The distinctive characteristic of the InVEST model is its capability to examine soil loss and sediment export from individually land use type and quantify the extent of sediment export reached to the waterbodies. The results reveal that while the equivalent sediment export grew from 6.54 t/ha/year to 11.05 t/ha/year in 2000 and 2020, respectively, the average soil loss increased from 22.37 t/ha/year in 2000 to 33.38 t/ha/year in 2020. The largest rate of soil erosion was seen on cultivated land, which increased from 40.86 t/ha/year in 2000 to 53.90 t/ha/year in 2020. This relates to the expansion of the agricultural land. The result concluded that prioritizing those sub-watersheds is important for informed decision-making processes.

5.2 Conclusion

One of the goals of the current study was to evaluate the current LDN status by using the LDN approach in the Rib Watershed of the Upper Blue Nile Basin. To plan and manage the many compartments in a watershed ecosystem adequately, managers and planners require information on the LDN status for at least 20 years. To assess the LDN status in the Rib Watershed, the metrics provided by UNCCD, including changes in land cover, NPP, and SOC, were employed. Different land uses were classified as being in a state of degradation (sign - ve change), improvement (sign +ve change), or stability (no change) based on the analysis of the trend in each metric. To prevent, decrease, and stop degradation appropriate managerial actions such as land use planning for LULC, afforestation for NPP, and actions to improve soil organic carbon for SOC might be planned using the research findings.

Therefore, managers and planners must take into account the capability and potential of the lands in diverse ecosystems given the LDN status in various types of land use in the Rib Watershed. Meanwhile, it is essential to put suitable managerial and developmental plans into place to prevent interventions or changes in land use that would worsen land degradation in the research area. In conclusion, experts are suggested to take managerial actions to avoid the degradation of different types of land cover.

Land use and land cover change is a single parameter used to analyze ecosystem service value estimation. The importance of such estimations at the local, regional, and global levels influencing decision-making processes through the modification of national accounting systems to reflect the true worth of ecosystem services. This estimation also ultimately be used for the sustainable development of ecosystem service. Besides, land-use planners, experts, and communities will be aware on the impact of each land cover conversion on the total ecosystem value.

The study illustrates that the expansion of cultivated land, waterbody, and settlement by 22.70%, 80.06%, and 136.54% respectively. The remaining land cover shows a significant reduction for the past two decades from 2000 to 2020. As a result, the overall ESV decreased by 13.50%. Among the specific ecosystem services identified Water supply (0.87 US$ in million), Food Production (2.80 US$ in million), and Biological control (0.35 US$ in millions) had increased the ecosystem service value which is very small as compared to other ESVs, while the remaining services had negative values indicating a decrease in those ecosystem service values. This result shows that the total ESV was lost in the study area. Finally, it is concluded that the reduction in ESVs reflected the effects of ecological degradation at the Rib watershed and also suggested that land managers and policymakers can use LULC change and ecosystem service value together during their decision-making processes.

In this study, CS shows the estimation of ESVs was robust regarding all the values for each LULC less than one. For the study periods, the CS for cultivated land use is the greatest of all land uses, indicating the greatest size and greater ESV for cultivated land use. The finding of this study will be an important milestone for future research related to the change of ESV in response to LULC.

According to the InVEST model's estimation, the study Rib watershed has experienced significant LULC change as well as historical change in SLSE. The findings illustrated that the decline of the grazing, forest, and shrubland areas was mainly the effect of the conversion of cultivated lands for the past two decades (2000 to 2020). This caused a decrease in the regulatory capability of the land, which in turn, exacerbated SLSE. Over the past 20 years, the total SLSE in the watershed grew by 4. 41 t/h from 2000 to 2010 and, 11. 00 t/h from 2000 to 2020. Soil loss and sediment export have highly grown in cultivated land, forest land, shrub land, grassland, and settlement. This implies that the change in SLSE is directly proportional to LULC, except in the case of the waterbody.

In comparison to the rest of the study watershed, soil loss and sediment export are more severe in the eastern and northern parts. Sub-watersheds (SW-3 and SW-5) were extremely susceptible to SLSE. To address the issues of Rib dam siltation and loss of ecosystem services in the study watershed, the findings suggest the need for more conservation measures in the extremely vulnerable sub-watershed and a decrease in continuous farming in the higher altitude sections of mountainous parts of the watershed. The results of the study also imply that in order to prevent SLSE to the Rib dams, policy instruments need to be enforced by carrying out urgent conservation efforts in the study area of above mentioned sub-watershed.

5.3 Recommendation

Based on the results of this study, the following recommendations are given:

- Systematic techniques to improve NPP and soil organic carbon are important to achieve LDN in the study watershed.
- Further research is needed to enrich additional indicators of LDN from the local degradation situation and the principle of One out all-out rule.
- The government should facilitate Payment for Ecosystem Services value at the sub-watershed level as a conservation strategy.
- Successive efforts towards increasing vegetation covers are very important in vulnerable areas to reduce soil erosion, sediment yield, and the loss of ecosystem services. Therefore, the establishment of seedling centers at the two sub-watersheds (SW 3 and SW 5) is important to reduce soil loss and sediment export.
- Considerable attention to improving the livelihoods of the watershed community will restrain further expansions of cultivation and thereby will reduce its subsequent effects on, ecosystem services, soil erosion, and sediment export.
- Implementing proper soil and water conservation measures is highly necessary in vulnerable areas to arrest the expected increase of soil erosion and sediment yield to save the Rib dam from siltation.
- Experts in resource management, and sustainability, ecology, and ecosystem are required to develop a plan for sustainable use of the site to ensure its functions for the next generations.

References

Abbato, S. (2009). Book Review: Foundations of Mixed Methods Research: Integrating Quantitative and Qualitative Approaches in the Social and Behavioral Sciences. *Evaluation Journal of Australasia*, *9*(2), 60–63. https://doi.org/10.1177/1035719x0900900213

Abebe, G., Getachew, D., & Ewunetu, A. (2021). Analyzing land use/land cover changes and its dynamics using remote sensing and GIS in Gubalafito district, Northeastern Ethiopia. *SN Applied Sciences*, *August*. https://doi.org/10.1007/s42452-021-04915-8

Abegaz, A., Winowiecki, L. A., Vågen, T. G., Langan, S., & Smith, J. U. (2016). Spatial and temporal dynamics of soil organic carbon in landscapes of the upper Blue Nile Basin of the Ethiopian Highlands. *Agriculture, Ecosystems and Environment*, *218*, 190–208. https://doi.org/10.1016/j.agee.2015.11.019

Ackerson, A. J. P. (2018). Soil Sampling Guidelines. In *Agronomy* (pp. 1–6).

Adem, A. A., Dile, Y. T., Worqlul, A. W., Ayana, E. K., Tilahun, S. A., & Steenhuis, T. S. (2020). Assessing digital soil inventories for predicting streamflow in the headwaters of the Blue Nile. *Hydrology*, *7*(1), 1–19. https://doi.org/10.3390/hydrology7010008

Adnan, M. (2020). Land Degradation and its Management: A Review. *International Journal of Environmental Sciences & Natural Resources*, *25*(1), 63–66. https://doi.org/10.19080/ijesnr.2020.25.556157

Akale, A. T., Dagnew, D. C., Belete, M. A., Tilahun, S. A., Mekuria, W., & Steenhuis, T. S. (2017). Impact of soil depth and topography on the effectiveness of conservation practices on discharge and soil loss in the Ethiopian highlands. *Land*, *6*(4). https://doi.org/10.3390/land6040078

Akhtar-Schuster, M., Stringer, L. C., Erlewein, A., Metternicht, G., Minelli, S., Safriel, U., & Sommer, S. (2017). Unpacking the concept of land degradation neutrality and addressing its operation through the Rio Conventions. *Journal of Environmental Management*, *195*, 4–15. https://doi.org/10.1016/j.jenvman.2016.09.044

Ali, S. A., & Hagos, H. (2016). Estimation of soil erosion using USLE and GIS in Awassa Catchment, Rift Valley, Central Ethiopia. *Geoderma Regional*, *7*(2), 159–166. https://doi.org/10.1016/j.geodrs.2016.03.005

Amanuel, W., Yimer, F., & Karltun, E. (2018). Soil organic carbon variation in relation to land use changes: The case of Birr watershed, upper Blue Nile River Basin, Ethiopia. *Journal of*

Ecology and Environment, *42*(1), 1–11. https://doi.org/10.1186/s41610-018-0076-1

Amsalu, T., & Mengaw, A. (2014a). GIS-Based Soil Loss Estimation Using RUSLE Model : The Case of Jabi Tehinan Woreda ,. 616–626.

Aneseyee, A. B., Elias, E., Soromessa, T., & Feyisa, G. L. (2020). Land use/land cover change effect on soil erosion and sediment delivery in the Winike watershed, Omo Gibe Basin, Ethiopia. *Science of the Total Environment*, *728*, 138776. https://doi.org/10.1016/j.scitotenv.2020.138776

Anley, M. A., Minale, A. S., Ayehu, N. H., & Gashaw, T. (2022). Assessing the impacts of land use/cover changes on ecosystem service values in Rib watershed, Upper Blue Nile Basin, Ethiopia. *Trees, Forests and People*, *7*(3), 100212. https://doi.org/10.1016/j.tfp.2022.100212

Annys, S., Van Passel, S., Dessein, J., Adgo, E., & Nyssen, J. (2020). From fast-track implementation to livelihood deterioration: The dam-based Ribb Irrigation and Drainage Project in Northwest Ethiopia. *Agricultural Systems*, *184*(July), 102909. https://doi.org/10.1016/j.agsy.2020.102909

Arsea, K. C. (2014). *Accuracy Assessment of Pixel-Based Image Classification Of*. *4*(22), 133–140.

Arunyawat, S., & Shrestha, R. P. (2016). Assessing land use change and its impact on ecosystem services in northern Thailand. *Sustainability (Switzerland)*, *8*(8). https://doi.org/10.3390/su8080768

Assfaw, A. T. (2020). *Modeling Impact of Land Use Dynamics on Hydrology and Sedimentation of Megech Dam Watershed, Ethiopia*. *2020*.

Ayalew, G. (2015). *Soil Loss Estimation for Soil Conservation Planning using Geographic Information System in Guang Watershed, Blue Nile Basin*. *5*(1), 126–135.

Ayele, G. T., Kuriqi, A., Jemberrie, M. A., Saia, S. M., Seka, A. M., Teshale, E. Z., Daba, M. H., Ahmad Bhat, S., Demissie, S. S., Jeong, J., & Melesse, A. M. (2021). Sediment yield and reservoir sedimentation in highly dynamic watersheds: The case of Koga reservoir, Ethiopia. *Water (Switzerland)*, *13*(23), 1–20. https://doi.org/10.3390/w13233374

Bantider, A., Hurni, H., & Zeleke, G. (2011). Responses of rural households to the impacts of population and land-use changes along the Eastern Escarpment of Wello, Ethiopia. *Norsk Geografisk Tidsskrift*, *65*(1), 42–53. https://doi.org/10.1080/00291951.2010.549954

Beatriz, S., Manuela, M., Raposo, M., & Cortez, N. (2020). Geoderma Water erosion aspects of land degradation neutrality to landscape planning tools at the national scale. *Geoderma*, *363*(May 2019), 114093. https://doi.org/10.1016/j.geoderma.2019.114093

Bekele, D. A., Gella, G. W., & Ejigu, M. A. (2022). Erosion risk assessment: A contribution for conservation priority area identification in the sub-basin of Lake Tana, north-western

Ethiopia. *International Soil and Water Conservation Research*, *10*(1), 46–61. https://doi.org/10.1016/j.iswcr.2021.04.010

Belay, T., & Mengistu, D. A. (2019a). Land use and land cover dynamics and drivers in the Muga watershed, Upper Blue Nile basin, Ethiopia. *Remote Sensing Applications: Society and Environment*, *15*(February), 100249. https://doi.org/10.1016/j.rsase.2019.100249

Belay Tegene. (2002). Land-Cover/Land-Use Changes in the Derekolli Catchment of the South Welo Zone of Amhara Region, Ethiopia. *Eastern Africa Social Science Research Review*, *18*(1), 1–20. https://doi.org/10.1353/eas.2002.0005

Bewket, Woldeamlak. (2002). Land cover dynamics since the 1950s in Chemoga watershed, Blue Nile basin, Ethiopia. *Mountain Research and Development*, *22*(3), 263–269. https://doi.org/10.1659/0276-4741(2002)022[0263:LCDSTI]2.0.CO;2

Birhanu, L., Hailu, B. T., Bekele, T., & Demissew, S. (2019). Land use/land cover change along elevation and slope gradient in highlands of Ethiopia. *Remote Sensing Applications: Society and Environment*, *16*(March), 100260. https://doi.org/10.1016/j.rsase.2019.100260

Bobushev, T. S., & Sultanaliev, K. E. (2020). Evaluation and Adaptation of the Land Degradation Neutrality Approach to Land Classification Resources in the Kyrgyz Republic. *Arid Ecosystems*, *10*(2), 123–126. https://doi.org/10.1134/S2079096120020031

Borrelli, P., Robinson, D. A., Fleischer, L. R., Lugato, E., Ballabio, C., Alewell, C., Meusburger, K., Modugno, S., Schütt, B., Ferro, V., Bagarello, V., Oost, K. Van, Montanarella, L., & Panagos, P. (2012). land use change on soil erosion. *Nature Communications*, *8*, 1–13. https://doi.org/10.1038/s41467-017-02142-7

Boskidis, I., Gikas, G. D., Pisinaras, V., & Tsihrintzis, V. A. (2010). Spatial and temporal changes of water quality, and SWAT modeling of Vosvozis river basin, North Greece. *Journal of Environmental Science and Health - Part A Toxic/Hazardous Substances and Environmental Engineering*, *45*(11), 1421–1440. https://doi.org/10.1080/10934529.2010.500936

Bouguerra, S., & Jebari, S. (2017). *Identification and prioritization of sub-watersheds for land and water management using InVEST SDR model : Rmel river basin, Tunisia*. 1–9. https://doi.org/10.1007/s12517-017-3104-z

Braat, L. C., & Groot, R. De. (2012). The ecosystem services agenda : bridging the worlds of natural science and economics, conservation and development, and public and private policy. *Ecosystem Services*, *1*(1), 4–15. https://doi.org/10.1016/j.ecoser.2012.07.011

Buruso, F. H. (2020). Influences of Land Use / Cover Changes on Soil Properties in Rib Watershed, *Materials And Methods*. 1–12.

Central Statistical Agency. (2014). Federal Democratic Republic of Ethiopia Central Statistical

Agency Population Projection of Ethiopia for All Regions At Wereda Level from 2014 – 2017 (Issue August 2013).

Chen, J., Yu, L., Yan, F., & Zhang, S. (2020). Ecosystem Service Loss in Response to Agricultural Expansion in the Small Sanjiang Plain, Northeast China : *Process, Driver and Management*.

Chmiel, J., & Fijałkowska, A. (2002). Thematic accuracy assessment for object-based classification in agriculture areas : comparative analysis of selected approaches.

Collins, A. L., Blackwell, M., Boeckx, P., Chivers, C. A., Emelko, M., Evrard, O., Foster, I., Gellis, A., Gholami, H., Granger, S., Harris, P., Horowitz, A. J., Laceby, J. P., Martinez-Carreras, N., Minella, J., Mol, L., Nosrati, K., Pulley, S., Silins, U., … Zhang, Y. (2020). Sediment source fingerprinting: benchmarking recent outputs, remaining challenges, and emerging themes. In *Journal of Soils and Sediments* (Vol. 20, Issue 12). Journal of Soils and Sediments. https://doi.org/10.1007/s11368-020-02755-4

Congalton, R. G. (1991). *A Review of Assessing the Accuracy of Classifications of Remotely Sensed Data*. *46*(October 1990), 35–46.

Costanza, R., Groot, R. De, Sutton, P., Ploeg, S. Van Der, Anderson, S. J., Kubiszewski, I., Farber, S., & Turner, R. K. (2014). Changes in the global value of ecosystem services. *Global Environmental Change*, *26*, 152–158. https://doi.org/10.1016/j.gloenvcha.2014.04.002

Costanza, R., J, R. A., Groot, R. De, Farberll, S., Grassot, M., Hannon, B., Limburg, K., Naeem, S., Neilltt, R. V. O., J, J. P. J., Raskin, R. G., Suttonllll, P., & Belt, M. Van Den. (1997). value of the world's ecosystem services and natural capital. *387*(May), 253–260.

Cover, L. (2020). *Assessing Changes in Ecosystem Service Values over*.

Cowie, A. L., Orr, B. J., Castillo Sanchez, V. M., Chasek, P., Crossman, N. D., Erlewein, A., Louwagie, G., Maron, M., Metternicht, G. I., Minelli, S., Tengberg, A. E., Walter, S., & Welton, S. (2018). Land in balance: The scientific conceptual framework for Land Degradation Neutrality. *Environmental Science and Policy*, *79*(October 2017), 25–35. https://doi.org/10.1016/j.envsci.2017.10.011

Crespin, S. J., & Simonetti, J. A. (2016). Loss of ecosystem services and the decapitalization of nature in El Salvador. *Ecosystem Services*, *17*, 5–13. https://doi.org/10.1016/j.ecoser.2015.10.020

Cui, Y., & Li, X. (2022). A new global land productivity dynamic product based on the consistency of various vegetation biophysical indicators. *Big Earth Data*, *6*(1), 36–53. https://doi.org/10.1080/20964471.2021.2018789

De La Fuente, B., Weynants, M., Bertzky, B., Delli, G., Mandrici, A., Bendito, E. G., & Dubois, G. (2020). Land productivity dynamics in and around protected areas globally from 1999 to

2013. *PLoS ONE*, *15*(8 August 2020), 1–13. https://doi.org/10.1371/journal.pone.0224958

Degife, A., Worku, H., & Gizaw, S. (2021a). Environmental implications of soil erosion and sediment yield in Lake Hawassa watershed, south-central Ethiopia. *Environmental Systems Research*, *10*(1), 3–24. https://doi.org/10.1186/s40068-021-00232-6

Degife, A., Worku, H., Gizaw, S., & Legesse, A. (2019). Land use land cover dynamics, its drivers and environmental implications in Lake Hawassa Watershed of Ethiopia. *Remote Sensing Applications: Society and Environment*, *14*(April), 178–190. https://doi.org/10.1016/j.rsase.2019.03.005

del Barrio, G., Sanjuán, M. E., Martínez-Valderrama, J., Ruiz, A., & Puigdefábregas, J. (2021). Land degradation means a loss of management options. *Journal of Arid Environments*, *189*(2021). https://doi.org/10.1016/j.jaridenv.2021.104502

Deng, J., Lin, Y., Zhou, M., Wu, C., Chen, B., Xiao, G., & Cai, J. (2019). Ecosystem services dynamics response to tremendous reclamation in a coastal island city. *Ecosystem Health and Sustainability*, *5*(1), 155–168. https://doi.org/10.1080/20964129.2019.1646103

Dengiz, O. (2018a). Potential impact of land use change on land productivity dynamics with a focus on land degradation in a sub-humid terrestrial ecosystem. *Theoretical and Applied Climatology*, *133*(1–2), 73–88. https://doi.org/10.1007/s00704-017-2162-1

Dessie, G., & Kleman, J. (2007). Pattern and magnitude of deforestation in the south-central Rift Valley region of Ethiopia. *Mountain Research and Development*, *27*(2), 162–168. https://doi.org/10.1659/mrd.0730

Dube, A. K., Fawole, W. O., Govindasamy, R., & Ozkan, B. (2019). Agricultural Development Led Industrialization in Ethiopia: Structural Break Analysis. *International Journal of Agriculture, Forestry and Life Sciences*, *3*(1), 193–201.

Durigon, V. L., Carvalho, D. F., Antunes, M. A. H., Oliveira, P. T. S., & Fernandes, M. M. (2014). International Journal of Remote NDVI time series for monitoring RUSLE cover management factor in a tropical watershed. *International Journal of Remote Sensing*, *00*(00), 441–453. https://doi.org/10.1080/01431161.2013.871081

Egarter Vigl, L., Tasser, E., Schirpke, U., & Tappeiner, U. (2017). Using land use/land cover trajectories to uncover ecosystem service patterns across the Alps. *Regional Environmental Change*, *17*(8), 2237–2250. https://doi.org/10.1007/s10113-017-1132-6

Emde, D., Hannam, K. D., Most, I., Nelson, L. M., & Jones, M. D. (2021). Soil organic carbon in irrigated agricultural systems *: A meta-analysis*. *October 2020*, 3898–3910. https://doi.org/10.1111/gcb.15680

EPRDF. (2003). Government of the Federal Democratic Republic of Rural Development Policy and Government of the Federal Democratic Republic *of*. 1–74.

ERDAS Inc. (2008). ERDAS Field Guide (Fifth). ERDAS, Inc.

Erşahin, S. (2020). A method for calculating land degradation neutrality. *MethodsX*, *7*(April), 100969. https://doi.org/10.1016/j.mex.2020.100969

Ethiopia Central Statistical Agency. (2013). *Federal Demographic Republic of Population Projection of Ethiopia from 2014 – 2017*. *August 2013*, 1–118.

Fedele, G., Locatelli, B., & Djoudi, H. (2017). Mechanisms mediating the contribution of ecosystem services to human well-being and resilience. *Ecosystem Services*, *28*, 43–54. https://doi.org/10.1016/j.ecoser.2017.09.011

Feng, S., Zhao, W., Zhan, T., Yan, Y., & Pereira, P. (2022). Land degradation neutrality : A review of progress and perspectives. *Ecological Indicators*, *144*(August), 109530. https://doi.org/10.1016/j.ecolind.2022.109530

Foley, J. A., Foley, J. A., Defries, R., Asner, G. P., Barford, C., Bonan, G., Carpenter, S. R., Chapin, F. S., Coe, M. T., Daily, G. C., Gibbs, H. K., Helkowski, J. H., Holloway, T., Howard, E. A., Kucharik, C. J., Monfreda, C., Patz, J. A., Prentice, I. C., Ramankutty, N., & Snyder, P. K. (2010). *Global Consequences of Land Use*. *570*(2005). https://doi.org/10.1126/science.1111772

Foody, G. M. (2002). Status of land cover classification accuracy assessment. *80*, 185–201.

Formulas, E. (2018). Assessment of Siltation Processes of the Koronowski Reservoir in the Northern Polish Lowland Based on Bathymetry and Empirical Formulas. https://doi.org/10.3390/w10111681

Freimund, J. R., & Renard, K. G. (1994). Using monthly precipitation data to estimate the R-factor in the revised USLE. *Journal of Hydrology*, *157*(December 1992), 287–306. https://www.sciencedirect.com/science/article/pii/0022169494901104

Fu, B., Xu, P., Wang, Y., & Guo, Y. (2020). Integrating Ecosystem Services and Human Demand for a New Ecosystem Management Approach : A Case Study from the Giant Panda World Heritage Site.

Gandhi, G. M., Parthiban, S., Thummalu, N., & Christy, A. (2015). Ndvi: Vegetation Change Detection Using Remote Sensing and Gis - A Case Study of Vellore District. *Procedia Computer Science*, *57*, 1199–1210. https://doi.org/10.1016/j.procs.2015.07.415

Gashaw, T., Bantider, A., Zeleke, G., Alamirew, T., Jemberu, W., Adem, A. A., & Addisu, S. (2021). Evaluating InVEST model for estimating soil loss and sediment export in data-scarce regions of the Abbay (Upper Blue Nile) Basin : Implications for land managers. *Environmental Challenges*, *5*(July), 100381. https://doi.org/10.1016/j.envc.2021.100381

Gashu, K., & Muchie, Y. (2018). Rethink the interlink between land degradation and livelihood of rural communities in Chilga district, Northwest Ethiopia. *Journal of Ecology and Environment*, *42*(1), 1–11. https://doi.org/10.1186/s41610-018-0077-0

Gebremicael, T. G., Mohamed, Y. A., Betrie, G. D., Zaag, P. Van Der, & Teferi, E. (2013). Trend analysis of runoff and sediment fluxes in the Upper Blue Nile basin : A combined analysis of statistical tests, physically-based models and land use maps. *Journal of Hydrology*, *482*, 57–68. https://doi.org/10.1016/j.jhydrol.2012.12.023

Gelagay, H. S., & Minale, A. S. (2016). Soil loss estimation using GIS and Remote sensing techniques: A case of Koga watershed, Northwestern Ethiopia. *International Soil and Water Conservation Research*, *4*(2), 126–136. https://doi.org/10.1016/j.iswcr.2016.01.002

Getnet, T., & Mulu, A. (2021). Assessment of soil erosion rate and hotspot areas using RUSLE and multi-criteria evaluation technique at Jedeb watershed, Upper Blue Nile, Amhara Region, Ethiopia. *Environmental Challenges*, *4*(February), 100174. https://doi.org/10.1016/j.envc.2021.100174

Getu, L. A., Nagy, A., & Addis, H. K. (2022). Soil loss estimation and severity mapping using the RUSLE model and GIS in the Megech watershed, Ethiopia. *Environmental Challenges*, *8*(May), 100560. https://doi.org/10.1016/j.envc.2022.100560

Ghosh, A., Rakshit, S., Tikle, S., Das, S., Chatterjee, U., Pande, C. B., Alataway, A., Al-Othman, A. A., Dewidar, A. Z., & Mattar, M. A. (2023). Integration of GIS and Remote Sensing with RUSLE Model for Estimation of Soil Erosion. *Land*, *12*(1). https://doi.org/10.3390/land12010116

Gichenje, H., & Godinho, S. (2019). A Climate-smart Approach to the Implementation of Land Degradation Neutrality Within a water catchment area in Kenya. *Climate*, *7*(12). https://doi.org/10.3390/cli7120136

Gómez, D., & Montero, J. (2011). Determining the accuracy in image-supervised classification problems. July.

Gondwe, J. F., Lin, S., & Munthali, R. M. (2021). Analysis of Land Use and Land Cover Changes in Urban Areas Using Remote Sensing : Case of Blantyre City. 2021.

Gonzalez-Roglich, M., Zvoleff, A., Noon, M., Liniger, H., Fleiner, R., Harari, N., & Garcia, C. (2019). Synergizing global tools to monitor progress towards land degradation neutrality: Trends.Earth and the World Overview of Conservation Approaches and Technologies sustainable land management database. *Environmental Science and Policy*, *93*(December 2018), 34–42. https://doi.org/10.1016/j.envsci.2018.12.019

Grainger, A. (2015). Is Land Degradation Neutrality feasible in dry areas? *Journal of Arid*

Environments, *112*(PA), 14–24. https://doi.org/10.1016/j.jaridenv.2014.05.014

Groot, R. De, Brander, L., Ploeg, S. Van Der, Costanza, R., Bernard, F., Braat, L., Christie, M., Crossman, N., Ghermandi, A., Hein, L., Hussain, S., Kumar, P., Mcvittie, A., Portela, R., Rodriguez, L. C., & Beukering, P. Van. (2012). Global estimates of the value of ecosystems and their services in monetary units. *Ecosystem Services*, *1*(1), 50–61. https://doi.org/10.1016/j.ecoser.2012.07.005

Guzha, A. C., Rufino, M. C., Okoth, S., Jacobs, S., & Nóbrega, R. L. B. (2018). Impacts of land use and land cover change on surface runoff, discharge and low flows: Evidence from East Africa. *Journal of Hydrology: Regional Studies*, *15*(December 2017), 49–67. https://doi.org/10.1016/j.ejrh.2017.11.005

Haeni, M., Id, S. Q., Id, T. R., & Baumga, S. (2018). Private-sector investor's intention and motivation to invest in Land Degradation Neutrality. 1–18. https://doi.org/10.1371/journal.pone.0208813

Hall, L. J. S., & Foster, G. R. (2000). *from both crop and rangeland areas. The revision includes data not available at the time*.

Hamel, P., Chaplin-Kramer, R., Sim, S., & Mueller, C. (2015). A new approach to modeling the sediment retention service (InVEST 3.0): A case study of the Cape Fear catchment, North Carolina, USA. *Science of the Total Environment*, *524–525*, 166–177. https://doi.org/10.1016/j.scitotenv.2015.04.027

Hao, F., Lai, X., Ouyang, W., Xu, Y., Wei, X., & Song, K. (2012). Effects of Land Use changes on the ecosystem service values of a reclamation farm in northeast China. *Environmental Management*, *50*(5), 888–899. https://doi.org/10.1007/s00267-012-9923-5

Haregeweyn, N, Tsunekawa, A., Tsubo, M., & Meshesha, D. T. (2011). *Derege Meshesha & Bedru Babulo*. *May 2014*. https://doi.org/10.1007/s11368-011-0447-z

Haregeweyn, Nigussie, Berhe, A., Tsunekawa, A., Tsubo, M., & Meshesha, D. T. (2012). Integrated watershed management as an effective approach to curb land degradation: A case study of the enabered watershed in northern Ethiopia. *Environmental Management*, *50*(6), 1219–1233. https://doi.org/10.1007/s00267-012-9952-0

Haregeweyn, Nigussie, Poesen, J., Nyssen, J., Govers, G., Verstraeten, G., Vente, J. De, Deckers, J., Moeyersons, J., & Haile, M. (2008). *Catena Sediment yield variability in Northern Ethiopia : A quantitative analysis of its controlling factors*. *75*, 65–76. https://doi.org/10.1016/j.catena.2008.04.011

Haregeweyn, Nigussie, Tsunekawa, A., Nyssen, J., Poesen, J., Tsubo, M., Tsegaye Meshesha, D., Schütt, B., Adgo, E., & Tegegne, F. (2015). Soil erosion and conservation in Ethiopia: A review. *Progress in Physical Geography*, *39*(6), 750–774. https://doi.org/10.1177/0309133315598725

Haregeweyn, Nigussie, Tsunekawa, A., Poesen, J., Tsubo, M., Meshesha, D. T., Fenta, A. A., Nyssen, J., & Adgo, E. (2017). Comprehensive assessment of soil erosion risk for better land use planning in river basins: Case study of the Upper Blue Nile River. *Science of the Total Environment*, *574*, 95–108. https://doi.org/10.1016/j.scitotenv.2016.09.019

Hassen, E. E., & Assen, M. (2017). Land use/cover dynamics and its drivers in Gelda catchment, Lake Tana watershed ,. *Environmental Systems Research*. https://doi.org/10.1186/s40068-017-0081-x

Hazarika, M., & Honda, K. (2001). Estimation of soil erosion using remote sensing and GIS: Its valuation and economic implications on agricultural production. *Sustaining the Global Farm*, *22*(3), 1090–1093. http://www.tucson.ars.ag.gov/isco/isco10/sustainingtheglobalfarm/p068-hazaika.pdf

Hengl, T., De Jesus, J. M., Heuvelink, G. B. M., Gonzalez, M. R., Kilibarda, M., Blagotić, A., Shangguan, W., Wright, M. N., Geng, X., Bauer-Marschallinger, B., Guevara, M. A., Vargas, R., MacMillan, R. A., Batjes, N. H., Leenaars, J. G. B., Ribeiro, E., Wheeler, I., Mantel, S., & Kempen, B. (2017). SoilGrids250m: Global gridded soil information based on machine learning. In *PLoS ONE* (Vol. 12, Issue 2). https://doi.org/10.1371/journal.pone.0169748

Hu, H., Liu, W., & Cao, M. (2008). Impact of land use and land cover changes on ecosystem services in Menglun, Xishuangbanna, Southwest China. *Environmental Monitoring and Assessment*, *146*(1–3), 147–156. https://doi.org/10.1007/s10661-007-0067-7

Hurni, H. (1983). Soil formation rates in Ethiopia (highlands) - Ethiopian highlands reclamation study. *Fao, December 1983*.

Hurni, H. (1985). Erosion-Productivity-Conservation Systems in Ethiopia. Soil Conservation Research Project (SCRP). *Soil Conservation and Productivity. Proceedings of the 4th International Conference on Soil Conservation, Venezuela*, *July*, 654–674.

Hurni, H. (2020). *Erosion-Productivity-Conservation Systems in Ethiopia. Soil Conservation Research Project (SCRP) Conservation Systems in Ethiopia IV International Conference on*. *January 1985*, 1–21.

Husein, H. H., Mousa, M., Sahwan, W., Bäumler, R., & Lucke, B. (2019). Spatial Distribution of Soil Organic Matter and Soil Organic Carbon Stocks in Semi-Arid Area of Northeastern Syria. *Natural Resources*, *10*(12), 415–432. https://doi.org/10.4236/nr.2019.1012028

Ifejika Speranza, C., Adenle, A., & Boillat, S. (2019). Land Degradation Neutrality - Potentials for its operationalization at multi-levels in Nigeria. *Environmental Science and Policy*, *94*(December 2018), 63–71. https://doi.org/10.1016/j.envsci.2018.12.018

Jacobs, S., Dendoncker, N., Martín-lópez, B., Nicholas, D., Gomez-baggethun, E., Boeraeve, F., Mcgrath, F. L., Vierikko, K., Geneletti, D., Sevecke, K. J., Pipart, N., Primmer, E., Mederly, P., Schmidt, S., Aragão, A., Baral, H., Bark, R. H., Briceno, T., Brogna, D., … Washbourne, C. (2016). A new valuation school : Integrating diverse values of nature in resource and land use decisions. *Ecosystem Services*, *22*(December), 213–220. https://doi.org/10.1016/j.ecoser.2016.11.007

Jiru, E. B. (2019). Review on Contribution of GIS and RS for Soil Degradation Assessment in Ethiopia. *Journal of Environment and Earth Science,* 1–18. https://doi.org/10.7176/jees/9-12-01

Johansen, K., Phinn, S., & Taylor, M. (2015). Mapping woody vegetation clearing in Queensland, Australia from Landsat imagery using the Google Earth Engine. *Remote Sensing Applications: Society and Environment*, *1*(October 2017), 36–49. https://doi.org/10.1016/j.rsase.2015.06.002

Kapovi, M., Barger, N., Cerda, A., & Keesstra, S. (2020). Assessing land condition as a first step to achieving land degradation neutrality : A case study of the Republic of Srpska December *2018*. https://doi.org/10.1016/j.envsci.2018.09.014

Karki, S., Thandar, A. M., Uddin, K., Tun, S., Aye, W. M., Aryal, K., Kandel, P., & Chettri, N. (2018). Impact of land use land cover change on ecosystem services: a comparative analysis on observed data and people's perception in Inle Lake, Myanmar. *Environmental Systems Research*, *7*(1). https://doi.org/10.1186/s40068-018-0128-7

Kebede, Y. S., Endalamaw, N. T., Sinshaw, B. G., & Atinkut, H. B. (2021). Modeling soil erosion using RUSLE and GIS at watershed level in the upper beles, Ethiopia. *Environmental Challenges*, *2*(December 2020), 100009. https://doi.org/10.1016/j.envc.2020.100009

Kiani-Harchegani, M., & Sadeghi, S. H. (2020). Practicing land degradation neutrality (LDN) approach in the Shazand Watershed, Iran. *Science of the Total Environment*, *698*, 134319. https://doi.org/10.1016/j.scitotenv.2019.134319

Kidane, M., Bezie, A., Kesete, N., & Tolessa, T. (2019). Heliyon The impact of land use and land cover (LULC) dynamics on soil erosion and sediment yield in Ethiopia. *Heliyon*, *5*(November), e02981. https://doi.org/10.1016/j.heliyon.2019.e02981

Kindu, M., Schneider, T., Döllerer, M., Teketay, D., & Knoke, T. (2018). Scenario modeling of land use/land cover changes in Munessa-Shashemene landscape of the Ethiopian highlands. *Science of the Total Environment*, *622–623*, 534–546. https://doi.org/10.1016/j.scitotenv.2017.11.338

Kindu, M., Schneider, T., Teketay, D., & Knoke, T. (2016). Changes of ecosystem service values in response to land use/land cover dynamics in Munessa-Shashemene landscape of the Ethiopian highlands. *Science of the Total Environment*, *547*, 137–147. https://doi.org/10.1016/j.scitotenv.2015.12.127

Kreuter, U. P., Harris, H. G., Matlock, M. D., & Lacey, R. E. (2001). Change in ecosystem service values in the san antonio area, Texas. *Ecological Economics*, *39*(3), 333–346. https://doi.org/10.1016/S0921-8009(01)00250-6

Kruczkowska, B., Jonczak, J., Słowińska, S., Bartczak, A., Kramkowski, M., Uzarowicz, Ł., Tyszkowski, S., & Słowiński, M. (2021). Stages of soil development in the coastal zone of a disappearing lake—a case study from central Poland. *Journal of Soils and Sediments*, *21*(3), 1420–1436. https://doi.org/10.1007/s11368-021-02880-8

Kulimushi, L. C., Maniragaba, A., Choudhari, P., Elbeltagi, A., Uwemeye, J., Rushema, E., & Singh, S. K. (2021). Evaluation of soil erosion and sediment yield spatio-temporal pattern during 1990–2019. *Geomatics, Natural Hazards and Risk*, *12*(1), 2676–2707. https://doi.org/10.1080/19475705.2021.1973118

Lambin, E. F., Geist, H. J., & Lepers, E. (2003). Dynamics of l and -use and l and -cover change in tropical regions. https://doi.org/10.1146/annurev.energy.28.050302.105459

Landi, A., Barzegar, A. R., Sayadi, J., & Khademalrasoul, A. (2011). Assessment of soil loss using WEPP model and geographical information system. *Journal of Spatial Hydrology, 11*(1), 40–51.

Leh, M. D. K., Matlock, M. D., Cummings, E. C., & Nalley, L. L. (2013). Agriculture, Ecosystems, and Environment Quantifying and mapping multiple ecosystem services change in West Africa. *"Agriculture, Ecosystems and Environment," 165*, 6–18. https://doi.org/10.1016/j.agee.2012.12.001

Li, J., Wang, W., Hu, G., & Wei, Z. (2010). Changes in ecosystem service values in Zoige Plateau, China. *Agriculture, Ecosystems and Environment*, *139*(4), 766–770. https://doi.org/10.1016/j.agee.2010.10.019

Lindsay-Smith, G., O'Sullivan, G., Eime, R., Harvey, J., & Van Uffelen, J. G. Z. (2018). A mixed methods case study exploring the impact of membership of a multi-activity, multicentre community group on the social well-being of older adults. *BMC Geriatrics*, *18*(1), 1–14. https://doi.org/10.1186/s12877-018-0913-1

Ling-xing, X. U., De-wei, Y., Tong-hua, W. U., Shu-hua, Y. I., & Yi-ping, F. (2019). ScienceDirect An ecosystem services zoning framework for the permafrost regions of China. *Advances in Climate Change Research*, *10*(2), 92–98.

https://doi.org/10.1016/j.accre.2019.06.007

Liniger, H., Harari, N., van Lynden, G., Fleiner, R., de Leeuw, J., Bai, Z., & Critchley, W. (2019). Achieving land degradation neutrality: The role of SLM knowledge in evidence-based decision-making. *Environmental Science and Policy*, *94*(June 2018), 123–134. https://doi.org/10.1016/j.envsci.2019.01.001

Liu, J., Li, S., Ouyang, Z., Tam, C., & Chen, X. (2007). Ecological and socioeconomic effects of China's policies for ecosystem services.

Liu, Y., Wang, X., Xin, L., & Lu, Y. (2022). Impact of Farmland Change on Vegetation NPP in the One River and Two Streams Region of Tibet. *Land*, *11*(12). https://doi.org/10.3390/land11122223

Lu, A., Tian, P., Mu, X., Zhao, G., Feng, Q., Guo, J., & Xu, W. (2022). Fuzzy Logic Modeling of Land Degradation in a Loess Plateau Watershed, China. *Remote Sensing*, *14*(19). https://doi.org/10.3390/rs14194779

Lucas, L., Janssen, F., & Wel, F. J. M. Van Der. (1994). Accuracy Assessment Derived of Satellite Data : A Review.

Malla, R., Neupane, P. R., & Köhl, M. (2022). Modeling Soil Organic Carbon as a Function of Topography and Stand Variables. 1–14.

Mariye, M., Jianhua, L., & Maryo, M. (2022). Heliyon Land use and land cover change, and analysis of its drivers in Ojoje. *Heliyon*, *8*(December 2021), e09267. https://doi.org/10.1016/j.heliyon.2022.e09267

Markos, M. G., Mihret, D. U., Teklu, E. J., & Getachew, M. G. (2018). Influence of land use and land cover changes on ecosystem services in the Bilate Alaba Sub-watershed, Southern Ethiopia. *Journal of Ecology and The Natural Environment*, *10*(9), 228–238. https://doi.org/10.5897/jene2018.0709

Martin, H., Bernhard, K., Jochen, S., Marius, M., Markus, M., Paul, S., & Fliessbach, A. (2022). Biological soil quality and soil organic carbon change in biodynamic, organic, and conventional farming systems after 42 years. *Agronomy for Sustainable Development*, *42*, 1–14. https://doi.org/10.1007/s13593-022-00843-y

Megerssa, G. R., & Bekere, Y. B. (2019). Causes, consequences and coping strategies of land degradation: Evidence from Ethiopia. *Journal of Degraded and Mining Lands Management*, *7*(1), 1953–1957. https://doi.org/10.15243/jdmlm.2019.071.1953

Mekuriaw, A. (2017). Assessing the effectiveness of land resource management practices on erosion and vegetative cover using GIS and remote sensing techniques in Melaka watershed ,. https://doi.org/10.1186/s40068-017-0093-6

Melaku, N. D., Renschler, C. S., Holzmann, H., Strohmeier, S., Bayu, W., Zucca, C., Ziadat, F., & Klik, A. (2018). Prediction of soil and water conservation structure impacts on runoff and erosion processes using SWAT model in the northern Ethiopian highlands. *Journal of Soils and Sediments*, *18*(4), 1743–1755. https://doi.org/10.1007/s11368-017-1901-3

Meseret, D. (2016). Land Degradation in Amhara Region of Ethiopia: Review on Extent, Impacts and Rehabilitation Practices. *Journal of Environment and Earth Science*, *6*(1), 120–130.

Meshesha, D. T., Tsunekawa, A., & Tsubo, M. (2012). Continuing land degradation: Cause-effect in Ethiopia's Central Rift Valley. *Land Degradation and Development*, *23*(2), 130–143. https://doi.org/10.1002/ldr.1061

Meshesha, Derege Tsegaye, Tsunekawa, A., Tsubo, M., Ali, S. A., & Haregeweyn, N. (2014). Land-use change and its socio-environmental impact in Eastern Ethiopia's highland. *Regional Environmental Change*, *14*(2), 757–768. https://doi.org/10.1007/s10113-013-0535-2

Minelli, C., van der Plaat, D. A., Leynaert, B., Granell, R., Amaral, A. F. S., Pereira, M., Mahmoud, O., Potts, J., Sheehan, N. A., Bowden, J., Thompson, J., Jarvis, D., Davey Smith, G., & Henderson, J. (2018). Age at puberty and risk of asthma: A Mendelian randomisation study. *PLoS Medicine*, *15*(8), 1–14. https://doi.org/10.1371/journal.pmed.1002634

Minta, M., Kibret, K., Thorne, P., Nigussie, T., & Nigatu, L. (2018a). Geoderma Land use and land cover dynamics in Dendi-Jeldu hilly-mountainous areas in the central Ethiopian highlands. *Geoderma*, *314*(May 2017), 27–36. https://doi.org/10.1016/j.geoderma.2017.10.035

Minta, M., Kibret, K., Thorne, P., Nigussie, T., & Nigatu, L. (2018b). Land use and land cover dynamics in Dendi-Jeldu hilly-mountainous areas in the central Ethiopian highlands. *Geoderma*, *314*(May 2017), 27–36. https://doi.org/10.1016/j.geoderma.2017.10.035

Moges, D. M., & Bhat, H. G. (2018). An insight into land use and land cover changes and their impacts in Rib watershed, north-western highland Ethiopia. *Land Degradation and Development*, *29*(10), 3317–3330. https://doi.org/10.1002/ldr.3091

Moisa, M. B. (2021). Impact of land-use and land-cover change on soil erosion using the RUSLE model and the geographic information system : a case of Temeji watershed, Western Ethiopia. *00*(0), 1–17. https://doi.org/10.2166/wcc.2021.131

Molla, T., & Sisheber, B. (2017). Estimating soil erosion risk and evaluating erosion control measures for soil conservation planning at Koga watershed in the highlands of Ethiopia. *Solid Earth*, *8*(1), 13–25. https://doi.org/10.5194/se-8-13-2017

Nabila, I. A. (2019). Accuracy Assessment of Satellite Image Classification for Land Cover and Land Use Using MultiSpec as a Tool. *24*(3), 77–84. https://doi.org/10.9790/0837-2403037784

Negese, A. (2021). Impacts of Land Use and Land Cover Change on Soil Erosion and Hydrological Responses in Ethiopia. *Applied and Environmental Soil Science*, *2021*, 15–17. https://doi.org/10.1155/2021/6669438

Nelson, G. C., & Geoghegan, J. (2002). Deforestation and land use change : sparse data environments. *27*, 201–216.

Nunes, M. R., Es, H. M. Van, Veum, K. S., Amsili, J. P., & Karlen, D. L. (n.d.). sustainability Anthropogenic and Inherent E ff ects on Soil Organic Carbon across the U . S. 1–19.

Nut, N., Mihara, M., Jeong, J., Ngo, B., Sigua, G., Prasad, P. V. V., & Reyes, M. R. (2021). Land use and land cover changes and its impact on soil erosion in stung sangkae catchment of cambodia. *Sustainability (Switzerland)*, *13*(16). https://doi.org/10.3390/su13169276

Nyssen, J., Poesen, J., Haile, M., Moeyersons, J., Deckers, J., & Hurni, H. (2009). *Effects of land use and land cover on sheet and rill erosion rates in the Tigray* highland*, Ethiopia by Asmara*. https://doi.org/10.1127/0372-8854/2009/0053-0171

Olofsson, P., Foody, G. M., Herold, M., Stehman, S. V., Woodcock, C. E., & Wulder, M. A. (2014). Good practices for estimating area and assessing the accuracy of land change. *Remote Sensing of Environment*, *148*, 42–57. https://doi.org/10.1016/j.rse.2014.02.015

Orr, B. J. (2020). *Introduction to the Land Degradation Neutrality (LDN) and its indicators, now and the future*. *February 2019*.

Owens, P. N. (2020). Soil erosion and sediment dynamics in the Anthropocene: a review of human impacts during a period of rapid global environmental change. *Journal of Soils and Sediments*, *20*(12), 4115–4143. https://doi.org/10.1007/s11368-020-02815-9

Pan, S., Dangal, S. R. S., Tao, B., Yang, J., & Tian, H. (2014). Recent patterns of terrestrial net primary production in Africa influenced by multiple environmental changes. *Unicef*, 1–15.

Paula, M., María, J., Benayas, R., Meli, P., & Oscar, N. (2015). Agriculture, Ecosystems and Environment Quantifying the impacts of ecological restoration on biodiversity and ecosystem services in agroecosystems : A global meta-analysis. *"Agriculture, Ecosystems and Environment," 202*, 223–231. https://doi.org/10.1016/j.agee.2015.01.009

Peng, D., Zhang, B., Wu, C., Huete, A. R., Gonsamo, A., Lei, L., Ponce-campos, G. E., Liu, X., & Wu, Y. (2017). Science of the Total Environment Country-level net primary production distribution and response to drought and land cover change. *Science of the Total Environment*, *574*, 65–77. https://doi.org/10.1016/j.scitotenv.2016.09.033

Potapov, P., Hansen, M. C., Pickens, A., Hernandez-Serna, A., Tyukavina, A., Turubanova, S., Zalles, V., Li, X., Khan, A., Stolle, F., Harris, N., Song, X.-P., Baggett, A., Kommareddy, I., & Kommareddy, A. (2022). The Global 2000-2020 Land Cover and Land Use Change

Dataset Derived From the Landsat Archive: First Results. *Frontiers in Remote Sensing*, *3*(April), 1–22. https://doi.org/10.3389/frsen.2022.856903

Pritchard, R., Ryan, C. M., Grundy, I., & Horst, D. Van Der. (2018). Human Appropriation of Net Primary Productivity and Rural Livelihoods : Findings From Six Villages in Zimbabwe. *Ecological Economics*, *146*(July 2017), 115–124. https://doi.org/10.1016/j.ecolecon.2017.10.003

Prout, J. M., Shepherd, K. D., Mcgrath, S. P., Kirk, G. J. D., Hassall, K. L., & Haefele, S. M. (2022). Changes in organic carbon to clay ratios in different soils and land uses in England and Wales over time. *Scientific Reports*, 1–13. https://doi.org/10.1038/s41598-022-09101-3

Reith, J., Ghazaryan, G., Muthoni, F., & Dubovyk, O. (2021). Assessment of land degradation in semiarid Tanzania-using multiscale remote sensing datasets to support sustainable development goal 15.3. *Remote Sensing*, *13*(9), 1–21. https://doi.org/10.3390/rs13091754

Renard. (1996). Predicting Soil Erosion. In *ASAE Publ* (Issues 4–77, pp. 31–42).

Renard, K. G., Foster, G. R., Weesies, G. A., & Porter, J. P. (1991). RUSLE: revised universal soil loss equation. *Journal of Soil & Water Conservation*, *46*(1), 30–33.

Rodríguez, J. P., Beard, T. D., Bennett, E. M., Cumming, G. S., & Cork, S. J. (2005). *Trade-offs across Space , Time , and Ecosystem Services*. *June 2014*. https://doi.org/10.5751/ES-01667-110128

Saavedra, C. (2005). Estimating spatial patterns of soil erosion and deposition in the Andean region using geo-information techniques. Wageningen University.

Safriel, U. (2017). Land degradation neutrality (LDN) in drylands and beyond – where has it come from and where does it go. *Silva Fennica*, *51*(1), 1–19. https://doi.org/10.14214/sf.1650

Sanogo, K., Birhanu, B. Z., Sanogo, S., & Ba, A. (2023). Landscape pattern analysis using GIS and remote sensing to diagnose soil erosion and nutrient availability in two agroecological zones of Southern Mali. *Agriculture and Food Security*, *12*(1), 1–11. https://doi.org/10.1186/s40066-023-00408-6

Sathya, P. (2019). Classification process of satellite images. *1*(9), 1–5.

Schirpke, U., Tappeiner, U., & Tasser, E. (2019). A transnational perspective of global and regional ecosystem service flows from and to mountain regions. *Scientific Reports*, *April*, 1–11. https://doi.org/10.1038/s41598-019-43229-z

Scholastica. (2021). The Application of Theoretical and Conceptual Frameworks in Open and Distance Learning. June, 0–2. https://doi.org/10.25159/UnisaRxiv/000023.v1

Sciortino, M., De Felice, M., De Cecco, L., & Borfecchia, F. (2020). Remote sensing for monitoring and mapping Land Productivity in Italy: A rapid assessment methodology.

Catena, *188*(May 2018), 104375. https://doi.org/10.1016/j.catena.2019.104375

Senti, E. T., Tufa, B. W., & Gebrehiwot, K. A. (2014). Soil erosion, sediment yield, and conservation practices assessment on Lake Haramaya Catchment. *World Journal of Agricultural Sciences*, *2*(7), 186–193.

Seutloali, K. E., Dube, T., & Sibanda, M. (2018). Developments in the remote sensing of soil erosion in the perspective of sub-Saharan Africa. Implications on future food security and biodiversity. *Remote Sensing Applications: Society and Environment*, *9*, 100–106. https://doi.org/10.1016/j.rsase.2017.12.002

Sewnet, H., & Sewnet, A. (2016). International Soil and Water Conservation Research Soil loss estimation using GIS and Remote sensing techniques : A case of Koga watershed, Northwestern Ethiopia. *International Soil and Water Conservation Research*, *4*(2), 126–136. https://doi.org/10.1016/j.iswcr.2016.01.002

Shahin, M. M. A. (1993). An overview of reservoir sedimentation in some African river basins. *Sediment Problems. Proc. International Symposium, Yokohama, 1993*, *217*, 93–100.

Shaikh, S., & Palanisamy, M. (2020). Estimate the annual soil loss in kummattipatti nadi watershed using rusle model through geospatial technology. *46*(2), 75–82.

Shi, Z. H., Ai, L., Fang, N. F., & Zhu, H. D. (2012). Modeling the impacts of integrated small watershed management on soil erosion and sediment delivery : A case study in the Three Gorges Area, China. *439*, 156–167. https://doi.org/10.1016/j.jhydrol.2012.03.016

Shiferaw, H., Alamirew, T., Kassawmar, T., & Zeleke, G. (2021). Evaluating ecosystem services values due to land use transformation in the Gojeb watershed, Southwest Ethiopia. *Environmental Systems Research*, *10*(1). https://doi.org/10.1186/s40068-021-00227-3

Sims, N. C., Barger, N. N., Metternicht, G. I., & England, J. R. (2020). A land degradation interpretation matrix for reporting on UN SDG indicator 15.3.1 and land degradation neutrality. *Environmental Science and Policy*, *114*(July), 1–6. https://doi.org/10.1016/j.envsci.2020.07.015

Sinshaw, B. G., Belete, A. M., Mekonen, B. M., & Wubetu, T. G. (2021). Watershed-based soil erosion and sediment yield modeling in the Rib watershed of the Upper Blue Nile Basin, Ethiopia Watershed-based soil erosion and sediment yield modeling in the Rib watershed of the Upper Blue Nile Basin, Ethiopia. *Energy Nexus*, *3*(November), 100023. https://doi.org/10.1016/j.nexus.2021.100023

Solomon, N., Segnon, A. C., & Birhane, E. (2019). Ecosystem service values changes in response to land-use/land-cover dynamics in dry afromontane forest in northern ethiopia. *International Journal of Environmental Research and Public Health*, *16*(23), 7–11.

https://doi.org/10.3390/ijerph16234653

Srichaichana, J., Trisurat, Y., & Ongsomwang, S. (2019). *Land Use and Land Cover Scenarios for Optimum Water Yield and Sediment Retention Ecosystem Services in Klong U-Tapao Watershed ,. i*.

Sutton, P. C., Anderson, S. J., Costanza, R., & Kubiszewski, I. (2016). The ecological economics of land degradation : Impacts on ecosystem service values. *Ecological Economics*, *129*, 182–192. https://doi.org/10.1016/j.ecolecon.2016.06.016

Tadesse, L., Suryabhagavan, K. V., Sridhar, G., & Legesse, G. (2017). Land use and land cover changes and Soil erosion in Yezat Watershed, North Western Ethiopia. *International Soil and Water Conservation Research*, *5*(2), 85–94. https://doi.org/10.1016/j.iswcr.2017.05.004

Tekle, K., & Hedlund, L. (2000). Land cover changes between 1958 and 1986 in Kalu District, Southern Wello, Ethiopia. *Mountain Research and Development*, *20*(1), 42–51. https://doi.org/10.1659/0276-4741(2000)020[0042:LCCBAI]2.0.CO;2

Temesgen, H., Wu, W., Shi, X., Yirsaw, E., Bekele, B., & Kindu, M. (2018). Variation in ecosystem service values in an agroforestry dominated landscape in Ethiopia: Implications for land use and conservation policy. *Sustainability (Switzerland)*, *10*(4), 1–20. https://doi.org/10.3390/su10041126

Tesema, T. A., & Leta, O. T. (2020). Sediment Yield Estimation and Effect of Management Options on Sediment Yield of Kesem Dam Watershed, Awash Basin, Ethiopia. *Scientific African*, *9*, e00425. https://doi.org/10.1016/j.sciaf.2020.e00425

Thakuriah, G. (2023). GIS-based revised universal soil loss equation for estimating annual soil erosion: a case of lower Kulsi basin, India. *SN Applied Sciences*, *5*(3). https://doi.org/10.1007/s42452-023-05303-0

Thapa, P. (2020). Spatial estimation of soil erosion using RUSLE modeling : a case study of Dolakha district, Nepal. *Environmental Systems Research*, *15*(9), 1–10. https://doi.org/10.1186/s40068-020-00177-2

Tolessa, T., Senbeta, F., & Abebe, T. (2017). Land use/land cover analysis and ecosystem services valuation in the central highlands of Ethiopia. *Forests Trees and Livelihoods*, *26*(2), 111–123. https://doi.org/10.1080/14728028.2016.1221780

Tripathi, R., & Panda, B. B. (2010). Soil organic carbon sequestration in agriculture : *Issues and priorities*. 17–32.

Tsegaye, D., Moe, S. R., Vedeld, P., & Aynekulu, E. (2010). Agriculture, Ecosystems, and Environment Land-use / cover dynamics in Northern Afar rangelands, Ethiopia. *“Agriculture, Ecosystems and Environment,” 139*(1–2), 174–180.

https://doi.org/10.1016/j.agee.2010.07.017

Tully, K., Sullivan, C., Weil, R., & Sanchez, P. (2015). The State of soil degradation in sub-Saharan Africa: Baselines, trajectories, and solutions. *Sustainability (Switzerland)*, *7*(6), 6523–6552. https://doi.org/10.3390/su7066523

Twisa, S., & Buchroithner, M. F. (2019). Land-Use and Land-Cover (LULC) Change Detection in Wami River Basin, Tanzania.

Uddin, K., Matin, M. A., & Maharjan, S. (2018). Assessment of Land Cover Change and Its Impact on Changes in Soil Erosion Risk in Nepal. https://doi.org/10.3390/su10124715

Venter, Z. S., Barton, D. N., Chakraborty, T., & Simensen, T. (2022). Global 10 m Land Use Land Cover Datasets : A Comparison of Dynamic World, World Cover and Esri Land Cover.

Vigiak, O., Borselli, L., Newham, L. T. H., McInnes, J., & Roberts, A. M. (2012). Comparison of conceptual landscape metrics to define hillslope-scale sediment delivery ratio. *Geomorphology*, *138*(1), 74–88. https://doi.org/10.1016/j.geomorph.2011.08.026

Walter V Reid. (2005). Millennium Ecosystem Assessment: *Objectives, Focus, and Approach* (S. Chopra, Leemans, Kumar (ed.); 3rd ed.).

Wenng, H., Barneveld, R., Bechmann, M., Marttila, H., Krogstad, T., & Skarbøvik, E. (2021). Sediment transport dynamics in small agricultural catchments in a cold climate: A case study from Norway. *Agriculture, Ecosystems and Environment*, *317*(December 2020). https://doi.org/10.1016/j.agee.2021.107484

Winkler, K., Fuchs, R., Rounsevell, M., & Herold, M. (2019). previously estimated. *Nature Communications*, *2021*, 1–10. https://doi.org/10.1038/s41467-021-22702-2

Wischmeier. (1978). Predicting Rainfall Erosion Loss. In *U.S Department of Agriculture*.

Witchmeier w m and Smith. (1978). Predicting Rainfall Erosion Losses. *Fresenius Environmental Bulletin*, *26*(12), 7034–7044.

Worku, T., Tripathi, M. S. K., & Khare, D. (2016). Analyses of land use and land cover change dynamics using GIS and remote sensing during 1984 and 2015 in the Beressa Watershed Northern Central Highland of Ethiopia. *168*(2), 1–12. https://doi.org/10.1007/s40808-016-0233-4

Yesuph, A. Y., & Dagnew, A. B. (2019). Soil erosion mapping and severity analysis based on RUSLE model and local perception in the Beshillo Catchment of the Blue Nile Basin, Ethiopia. *Environmental Systems Research*, *8*(1), 1–21. https://doi.org/10.1186/s40068-019-0145-1

Yu, H., & Song, W. (2023). Research Progress on the Impact of Land Use Change on Soil Carbon Sequestration. *Land*, *12*(1), 213. https://doi.org/10.3390/land12010213

Zeghmar, A., Marouf, N., & Mokhtari, E. (2022). Assessment of soil erosion using the GIS-based erosion potential method in the Kebir Rhumel Watershed, Northeast Algeria. *Journal of Water and Land Development*, *52*, 133–144. https://doi.org/10.24425/jwld.2022.140383

Zeleke, G., & Hurni, H. (2001). Implications of land use and land cover dynamics for mountain resource degradation in the Northwestern Ethiopian highlands. *Mountain Research and Development*, *21*(2), 184–191. https://doi.org/10.1659/0276-4741(2001)021[0184:IOLUAL]2.0.CO;2

Zeraatpishe, M., & Khormali, F. (2012). Carbon stock and mineral factors controlling soil organic carbon in a climatic gradient, *Golestan province*. *12*(4), 637–654.

Zinabu Tebeje Zewdu. (2012). Determination of groundwater quality of former Lake Haramaya, Oromia Regional State, Ethiopia. *Journal of Ecology and the Natural Environment*, *4*(7). https://doi.org/10.5897/jene12.009

Zolotov, D. V., Chernykh, D. V., Biryukov, R. Y., Pershin, D. K., Malygina, N. S., & Gribkov, A. V. (2020). Change of Land Use in Altai Krai: Problems and Prospects for the Achievement of Land Degradation Neutrality. *Arid Ecosystems*, *10*(2), 106–113. https://doi.org/10.1134/S2079096120020134

Appendix A. Temperature and rainfall data.

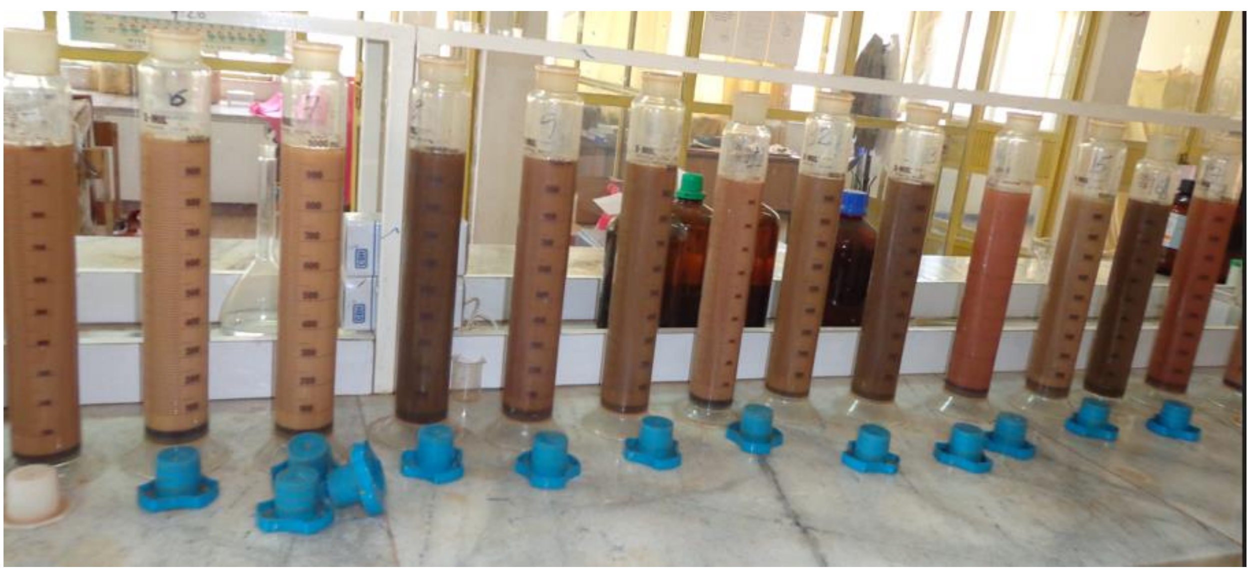
Year	Mean annual Rain fall	Maximum Temperature	Minimum Temperature	Mean annual Temperature
2000	1426	25.70	15.84	21.77
2001	1620	25.64	15.92	20.78
2002	1439	26.65	16.46	21.55
2003	1592	26.52	16.29	21.40
2004	788.15	26.57	16.18	21.37
2005	875.87	26.28	16.04	21.16
2006	1774.29	25.34	15.87	20.60
2007	1334.8	25.41	15.60	20.50
2008	1286.57	25.53	15.64	20.58
2009	1175.12	26.11	16.30	21.20
2010	1363.92	25.37	16.19	20.78
2011	1489	25.79	15.84	20.81
2012	1065.37	25.98	15.94	20.96
2013	1519.7	25.4	16.04	20.72
2014	1749.73	24.9	15.83	20.36
2015	1212.92	26.21	16.34	21.27
2016	1637.12	25.47	15.98	20.72
2017	1213.73	25.71	15.87	20.79
2018	1560	25.6	15.88	20.74
2019	1340	26.06	16.4	21.23
2020	1350	24.2	15.3	19.75

Appendix B. Soil sample from the field.

Soil sample from stable land cover **Soil sample from changed land cover**

Appendix C. laboratory analysis of soil sample



Appendix D. The first published article from the thesis

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Assessing the impacts of land use/cover changes on ecosystem service values in Rib watershed, Upper Blue Nile Basin, Ethiopia

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Modified ecosystem value coefficient

ABSTRACT

This study aims to assess the impacts of land use/land cover (LULC) changes on ecosystem service values (ESVs) in the Rib watershed of the Upper Blue Nile Basin between 2000 and 2020 periods. Image classifications were carried out using Landsat 5 TM for 2000 and 2010, and Landsat 8 OLI_TIRS for 2020 periods following the supervised classification technique with a Maximum Likelihood Algorithm (MLA) in ERDAS Imagine 2014. The study estimated the effects of LULC changes on ESVs using the modified ecosystem service value coefficients. The result indicated that a reduction of forest (46%), shrubland (44%), grassland (42%), and an increase of cultivated land (23%), settlement (137%), and waterbody (80%) during 2000 and 2020 periods. The total ESVs of the watershed were estimated about US$ 68.6 million in 2000, US$ 59.4 million in 2010, and US$ 59.3 million in 2020. The ESVs lost between 2000 and 2020 periods was about US$ 9.3 million (13.5%). The observed LULC changes during this period have also affected the individual ecosystem services. The reduction of ESVs through 2000 to 2020 periods indicates the effects of LULC changes on ecological degradation. Hence, the authors suggested the use of LULC change and ESVs together during land management decision-making processes.

1. Introduction

Scientific investigations indicated that land use land cover (LULC) changes can alter provision of ecosystem services. Our earth provides a vast range of ecosystem services that vary in quality and quantity depending on the type and status of ecosystem (Fetene Admasu et al., 2020; Marzec, 2018; Mooney, 2005). For instance, tropical forest is different in service provision compared to grassland (Costanza et al., 1997, 2014; de Groot et al., 2012) and hence, it is clear that ecosystem provide different services that could not be substituted by another (Gashaw et al., 2018; Kindu et al., 2018). Ecosystem services are essential for human well-being and survival (Schägner et al., 2013; Costanza et al., 2014; Marzec, 2018). However, when an ecosystem is managed for providing a single service others ecosystem services are negatively affected (Braat and de Groot, 2012). As a result, analysis of ecosystem service values (ESVs) is important for decision-makers to allocate resources (Barral et al., 2015; Guo et al., 2010), and design a policy related to ecosystem services (Schägner et al., 2013).

Throughout the world, the total net reduction of ecosystem services as a result of the LULC changes from 1997 to 2011 periods is estimated at US$ 20.20 trillion per year (Costanza et al., 2014). Many regions of Africa especially, eastern part are facing rapid and profound economic, social, and environmental transformations (Babalola and Borokini, 1988). As a result, the greatest areas of the continent are experiencing persistent ecosystem degradation at the expense of future generations' well-being (de Groot et al., 2012; Kubiszewski et al., 2017), which is especially true for Ethiopia, which lost roughly 17.7% of ESVs owing to LULC changes (Sutton et al., 2016).

LULC changes mainly expansions of cultivated lands and reductions of forestlands are a common phenomenon in Ethiopia, which are affecting ecosystem services. Combining LULC and ESVs data helps to identify the most vulnerable ecosystems and, hence provide an entry point for land management (Tolessa et al., 2017). Therefore, recognizing and estimating the effects of LULC changes on global, regional, and local ESVs is a practical approach for evaluating the costs and benefits of sustainable land management decisions (Deng et al., 2013; Liu et al.,

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Appendix E. The second published article from the thesis

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Examining the Land Degradation Neutrality (LDN) status of Rib watershed, Upper Blue Nile Basin, Ethiopia

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ABSTRACT
Land degradation because of the overutilization of natural resources is a suitable strategy for many countries of the world. This crucial strategy hasn't been introduced or implemented widely enough. The present study intended to examine the status of Land Degradation Neutrality (LDN) for the study Rib Watershed, which covers an area of 1585 km^2 and is situated in the Upper Blue Nile Basin, Ethiopia. For the past two periods between 2000 and 2020, three indicators, such as Land Cover/Use Changes (LUC), Soil Organic Carbon (SOC), and Net Primary Productivity (NPP) metrics were primarily used to assess the LDN status of the study site. A total of 80 soil samples were then collected from the top 15 cm for six different types of LULC, including cultivated land, forest land, shrub lands, grassland, settlement, and water body. Consequently, land uses land cover matrices, NPP metric, and SOC metrics were also obtained using Land sat images, soil samples, and MODIS satellite images, respectively, for three periods of 2000, 2010, and 2020. Lastly, by integrating the three indicators and using one out all out framework, the status of LDN in the study area was evaluated. The combined findings of the study measurements showed that there was a net loss in cultivated land (123,977 ha), forest land (5623 ha), shrub lands (13984 ha), grassland (11,999 ha), water body (1056 ha) and settlement (1993 ha) for the past two decades (2000 to 2020). For the past two decades, LDN status of the Rib Watershed was generally in a net loss condition. The information delivered by the three sub-indicators is important for experts for the good recognition of their spatial distribution and types of land degradation to attain the LDN targets.

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Land Degradation Neutrality; Land use/cover; Net primary product; Soil organic carbon

1. Introduction

Land degradation (LD) is a serious environmental problematic issue that harmfully affects ecosystem services, biodiversity, and the lives of millions of people in the world by promoting poverty and migration (Gashu & Muchie, 2018; Meseret, 2016; Susilowati & Syekhfani, 2015). LD can indicate the decline of biological or economic productivity in rain-fed farmland (Reith et al., 2021; Susilowati & Syekhfani, 2015). However, due to the complexity and variety of the biophysical and socio-economic factors that affect land resources, it is challenging to identify this phenomenon (Lu et al., 2022; Meseret, 2016). By integrating information about ecosystems and the mechanisms that produce degradation, numerous research has evaluated the phenomenon of LD at the international as well as national levels. Due to the complexity, variety, and quantity of indicators employed in the research carried out during the past 30 years, the evidence is not similar throughout regions (Gashu & Muchie, 2018; Lu et al., 2022). However, data was scarce, and the cost of repeatability and implementation of techniques makes them rarely practical at more local and regional scales (Adnan, 2020; Del Barrio et al., 2021; Malav et al., 2022).

The notion of 'Land Degradation Neutrality' (LDN), which is a component of one of the Sustainable Development Goals (SDG), target 15 articles 3 (15.3), was recently introduced by the United Nations General Assembly as a novel approach to tackling land degradation (LD). A state in which the quantity and quality of land resources required to maintain ecosystem functions and services and enhance food security within particular temporal and spatial scales and ecosystems is referred to as LDN". and is served as a measurement of SDG 15.3 (Cowie et al., 2018). To reach a healthy, productive state for land resources with no net loss, land degradation must therefore be avoided, reduced, and reversed.

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Appendix F. The third published article from the thesis

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Modeling the impact of land use land cover change on the estimation of soil loss and sediment export using InVEST model at the Rib watershed of Upper Blue Nile Basin, Ethiopia

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ABSTRACT

Information on soil loss and sediment export is essential to identify vulnerable area of soil erosion and to inform conservation interventions in a given watershed. The goal of this study was to analyze the changes in soil loss and sediment exports in the Rib watershed of Ethiopia's Upper Blue Nile Basin. The study used spatial data by using a variety of data sources, including topographic maps, soil maps, meteorological data, and satellite images. Cultivated land, forests, grazing areas, shrubs, water bodies, and settlements were all identified in the study watershed. Soil loss and sediment export were calculated using the Integrated Valuation of Ecosystem Services and Tradeoff (In-VEST) model. The model was calibrated using the sediment yield data gathered in the sample watersheds. The results reveal that while the equivalent sediment export grew from 6.54 t/ha/year to 11.05 t/ha/year in 2000 and 2020, respectively, the average soil loss increased from 22.37 t/ha/year in 2000 to 33.38 t/ha/year in 2020. The largest rate of soil erosion was seen on cultivated land, which increased from 40.86 t/ha/year in 2000 to 53.9 t/ha/year in 2020. This relates to the expansion of the agricultural land. The soil loss and sediment export rates in sub-watersheds three (SW-3) and five (SW-5) were the highest, at 61.80 and 63.48 t/ha/year and 18.75 and 19.35 t/ha/year, respectively. The least amount of soil loss occurs in sub-watershed twelve (SW-12) (2.56 t/ha/year). This is because SW-12 is situated in the watershed's lower reaches fogera plain parts of the watershed experiencing less erosion. The result concluded that prioritizing those sub-watersheds is important for informed decision-making processes.

1. Introduction

Land degradation (LD) is a serious environmental problematic issue that harmfully affects ecosystem services, biodiversity, and the lives of millions of people in the world by promoting poverty and migration (Gashu and Muchie, 2018; Meseret, 2016; Susilowati and Syekhfani, 2015). However, due to the complexity and variety of the biophysical and socioeconomic factors that affect land resources, it is challenging to identify this phenomenon (Lu et al., 2022; Meseret, 2016). It can also be used to describe how sophisticated rain-fed farmland, irrigated cropland, or rangelands, grasslands, forests, and woodlands have become and how their biological or economic productivity has declined (Reith et al., 2021; Susilowati and Syekhfani, 2015). Therefore Land uses and land cover change is one of the indicators of land degradation (LULC). By integrating information about LULC and the mechanisms that produce degradation, numerous research has evaluated the phenomenon of LD at the international as well as national levels.

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