

**Assessing the Impact of Land Use Land Cover Change on Soil Erosion Using RUSLE
and GIS: A Case Study of Adama Woreda, Ethiopia**



Fekadu Hordofa Dubre

A thesis submitted to the department of Architecture

College of Civil Engineering and Architecture

**Presented in Partial Fulfillment of the Requirement for the Degree of Master's in
Geoinformatics Engineering**

Office of graduate studies

Adama Science and Technology University

**June, 2025
Adama, Ethiopia**

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Advisor: Temesgen Abraham (PhD)

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Declaration and Recommendation

Declaration

I hereby declare that this Master Thesis entitled “**Assessing the Impact of Land Use Land Cover Change on Soil Erosion Using RUSLE and GIS: A Case Study of Adama Woreda, Ethiopia**” is my original work. That is, it has not been submitted for the award of any academic degree, diploma or certificate in any other university. All sources of materials that are used for this thesis have been duly acknowledged through citation

Fekadu Hordofa Dubre

Name of the student

Signature

Date

Recommendation

I/we, the advisor(s) of this thesis, hereby certify that I/we have read the revised version of the thesis entitled “**Assessing the Impact of Land Use Land Cover Change on Soil Erosion Using RUSLE and GIS: A Case Study of Adama Woreda, Ethiopia**” prepared under my/our guidance by **Fekadu Hordofa Dubre**. Submitted in partial fulfillment of the requirements for the degree of Master’s of Science in **Geoinformatics Engineering**. Therefore, I/we recommend the submission of revised version of the thesis to the college following the applicable procedures.

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I/we, the advisors of the thesis entitled “**Assessing the Impact of Land Use Land Cover Change on Soil Erosion Using RUSLE and GIS: A Case Study of Adama Woreda, Ethiopia**” by **Fekadu Hordofa Dubre** hereby certify that the recommendation and suggestions made by the board of examiners are appropriately incorporated into the final version of the thesis.

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We, the undersigned, members of the Board of Examiners of the thesis by **Fekadu Hordofa Dubre** have read and evaluated the thesis entitled “**Assessing the Impact of Land Use Land Cover Change on Soil Erosion Using RUSLE and GIS: A Case Study of Adama Woreda, Ethiopia**” and examined the candidate during open defense. This is, therefore, to certify that the thesis is accepted for partial fulfillment of the requirement of the degree of Master of Science in **Geoinformatics Engineering**.

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List of Acronyms

DEM: Digital Elevation Model

FAO: Food and Agriculture Organization

GCP: Ground Control point

GIS: Geographic information system

GPS: Geographical Positioning System

LULC: Land use Land cover change

NGO: Non-Governmental Organization

RS: Remote Sensing

RUSLE: Revised Universal Soil Loss Equation

STRM: Shuttle Radar Topographic Mission

TRMM: Tropical Rainfall Measuring Mission

USDA: United States Department of Agriculture

USGS: United States Geological Survey

Abstract

Land Use and Land Cover Change (LULCC) is one of the main sources of land degradation, with soil erosion representing one of its most critical consequences. This study assessed the impact of LULCC on soil erosion in Adama Woreda over a 20 year period (2004–2024) using the Revised Universal Soil Loss Equation (RUSLE), integrated with Geographic Information Systems (GIS) and Remote Sensing (RS). Landsat imagery for 2004, 2014, and 2024 was classified into major land use types, and the five RUSLE parameters (R, K, LS, C, and P) were derived from meteorological data, soil maps, DEM, and land cover layers. The results showed an increase in cultivated land and settlements, while forest, shrubland, grassland, and bare land decreased. The estimated mean annual soil loss for the Woreda was 31.59 tons/ha/year in 2004, 24.5 tons/ha/year in 2014, and 22.30 tons/ha/year in 2024, indicating a declining trend. The observed decline in soil loss is likely due to improved land management practices and the reduction of bare land coverage. Despite this reduction, soil erosion remains a significant challenge, with approximately 24.91% of the study area classified under moderate to very severe erosion risk in 2024. Cultivated lands were the largest contributors to soil loss, exhibiting mean erosion rates of 17.97, 17.10, and 16.04 tons/ha/year for 2004, 2014, and 2024, respectively, whereas forested areas and water bodies showed the lowest erosion rates. However, the continued presence of moderate to severe erosion risk in almost a quarter of the area highlights the importance of focused conservation efforts. The study recommends that the Adama Woreda Office of Agriculture, NGOs, and local farmers prioritize soil conservation interventions in erosion prone areas to promote land rehabilitation and sustainable land use planning.

Keywords: *LULC, RUSLE, Soil erosion, remote sensing, and GIS*

CHAPTER ONE

1. INTRODUCTION

1.1 Background

Land use and land cover (LULC) changes are now recognized as one of the most fundamental environmental challenges worldwide. These changes influence ecosystems, hydrology, and soil stability across spatial and temporal scales (Guder & Kabeta, 2025). LULCC alters the Earth's surface due to both natural and human activities, especially agricultural expansion, deforestation and settlement growth (Zhao et al., 2017; Guzha et al., 2018; Guder & Kabeta, 2025). In Ethiopia, where land degradation is already a major concern, LULCC is intensifying soil erosion, leading to diminished agricultural productivity, reduced biodiversity, and siltation of water bodies (Masha et al., 2023; Negese, 2021).

Soil erosion, particularly by water, remains one of the most pressing environmental challenges associated with LULCC. It leads to the loss of fertile topsoil, reduces agricultural productivity, and causes sedimentation in water bodies, affecting reservoir storage capacity and water quality (Thapa et al., 2020; Rupesh, 2017). Ethiopia overall soil loss is estimated to be approximately 1.5 billion tons per year and largely contribute to LULCC and poor land management practices (Negese, 2021).

Soil erosion can be affected by different factors such as climate (Li and Haiyan, 2016), soil properties (Ouyang et al, 2018), topography (Ochoa et al, 2016), vegetation cover (Lieskovsky & Kenderessy, 2014), land management practices (Kairis et al, 2013 & Gashaw et al, 2020). According to Tukura and Akalu, (2019) stated the Soil erosion is a natural process that contributes to the development of the Earth's surface and is governed by the underlying soil characteristics, rainfall, topography, vegetation, land use and management practices.

Adama Woreda, located in East Shewa Zone of the Oromia Region, is among the areas most affected by rainfall induced soil erosion (Masha et al., 2023). The region's steep slopes, intensive cultivation, and poor conservation efforts make it prone to both sheet and rill erosion. Factors such as deforestation, encroachment on upland areas, and the absence

of physical soil and water conservation structures have led to the formation of large and expanding gullies (Negese, 2021).

Accurate estimation of soil erosion is complex and depends on both the process dynamics and the availability of reliable data. While various models exist, factor-based models such as the Revised Universal Soil Loss Equation (RUSLE) are commonly used in Ethiopia due to their relative simplicity and data accessibility (Terefe et al., 2025). RUSLE estimates long-term average annual soil loss based on five factors: rainfall erosivity (R), soil erodibility (K), topography (LS), land cover management (C), and conservation practices (P) (Renard et al., 1997; Wischmeier & Smith, 1978;).

A Geographic Information System (GIS) has become an increasingly important means for understanding and dealing with the pressing problems of water and related resources management like spatiotemporal analysis of LULC and soil loss rate estimation in large areas in world (Wang et al., 2014). GIS technique is an effective tool for assessing soil erosion risk by integrating different soil erosion assessment model. Based on the availability of and simplicity Revised Universal Soil Loss Equation (RUSLE) (Renard et al., 1997) model is used to predict soil loss and planning practice for future with best integration of GIS procedure. Based on the RUSLE model, the amount of soil loss can be determined by the multiplication of five factors including climate, soil property, topography, land cover and conservation practice (Wischmeier and Smith, 1978).

Accordingly, by using this model the present study estimates the long term annual soil loss of the study area and assess the impacts of land use land cover change on soil erosion with the integration of Geographic Information System (GIS) and Remote Sensing (RS) techniques.

1.2 Statement of the problem

The high erosion rates are mainly affecting developing countries due to intensive cultivation, deforestation, plowing of marginal lands and extreme climate hazards (Tegegne and Biniam, 2016). According to UNDRR (2024) an estimated 75 billion tons of soil were lost globally each year. The problem was especially severe in developing nations, where population pressure, deforestation, cultivation on marginal lands, and climate hazards intensified the degradation (Borrelli et al., 2020). Ethiopia loses an estimated 1.5 billion tons of soil annually due to land use land cover changes (LULCC) and poor land management practices (Negese, 2021). Currently, there is no stable mechanism to mitigate soil erosion especially in erosion prone areas.

Adama Woreda, located in Ethiopia's Rift Valley, shows unique geographical and climatic features that increase its vulnerability to soil erosion. The area is affected by common land use problems such as deforestation, overgrazing, and farming on unsuitable lands. Also there is a notable land use and land cover changes (LULCC). As a farmer's child, I have personally seen how land use and cover changes negatively impact the production and health of the soil in my community. These realities motivated me to conduct this study. While studies have highlighted these challenges in the northern highlands (Moges et al., 2020; Tamirat, 2019; Tessema et al., 2020) erosion prone areas like Adama Woreda remain understudied. All those studies identify the strong impacts of land use land cover changes on soil erosion potential by focusing on watershed. Therefore, it is important to understand, analyze, and categorize soil erosion severity based directly on different land use and land cover types. This lack of local-scale analysis limits the capacity of Woreda land administrators and agriculture experts to respond with informed and context-specific strategies.

This study aims to fill this gap using Revised Universal Soil Loss Equation (RUSLE) model, integrated with GIS, to quantify soil loss, analyze LULC dynamics, and develop actionable risk map for sustainable land management in Adama Woreda that can serve as decision-support tools for local stakeholders.

1.3 Objectives

1.3.1 General objective of the study

The general objective of the study was assessing the impact of Land Use Land Cover Change on soil erosion of Adama Woreda using GIS, RS and RUSLE model from 2004 to 2024.

1.3.2 Specific objectives

The specific objectives of the thesis are:-

- To assess LULC change of the study area over 20 years.
- To calculate the annual average soil loss in the study area using RUSLE parameters (R, K, LS, C and P).
- To develop soil erosion risk map based on soil loss rates.
- To compare the impact of LULC types on soil erosion.
- To provide insights for sustainable land management policies based on the study findings.

1.4 Research Questions

- What were the trends of LULC over 20 years in the study area?
- What was the average soil loss of the study area in terms of RUSLE equation?
- How to develop soil erosion risk map of the study area based on severity classes?
- Which LULC types had the greatest impacts on soil erosion of the study area?
- What recommendation could be made for sustainable land management policies based on the findings?

1.5 Significance of the study

This study examines LULC dynamics and their impact on soil erosion, estimating annual soil loss using the RUSLE model integrated with Geoinformatics applications. This is partly due to the fact that there is an increasing of soil erosion due to different factors. To identify the factors causes the problem of soil erosion remote sensing data will use. Generally, this study will be helpful for detecting land use/land cover change for estimating the annual average soil loss of the study area. This study is very important for decision makers, NGOs, and experts who are working on soil and water conservation, land management and environmental protection. It helps them plan and implement their projects in the right locations, in a cost effective way and at the right time. Policymakers can also use the findings to guide their actions. The results can support the implementation of regulations against harmful practices like deforestation and overgrazing, while improving land use methods that help keep the soil stable.

This research has the potential to guide future studies in regions facing similar challenges. By providing a replicable methodology and highlighting the relationship between LULC and soil erosion, it can serve as a reference for researchers in other parts of Ethiopia.

1.6 Scope of the study

This study is geographically limited to Adama Woreda covering an area of approximately 90084 hectare. Temporally, the study covers the period from 2004 to 2024, capturing significant LULCC dynamics over two decades. The year 2004 was chosen as the baseline because of the availability of reliable, cloud free satellite imagery, such as Landsat 7 ETM. By using 2004 as a starting point, the study aligns with key policy milestones, such as Ethiopia's Sustainable Development and Poverty Reduction Program, which commenced in 2002 (Wikipedia, 2024). Importantly, Adama served as the capital city of the Oromia Region from 2000 to 2005 (Wikipedia, 2024). Making 2004 a particularly significant year for assessing land administration, urban development, and planning related land use changes during its time as a regional administrative center. Using decadal intervals (2004, 2014 and 2024) is a common practice in LULCC studies, facilitating consistent comparison of trends.

The study is focused on assessing land use land cover changes on soil erosion using the RUSLE model integrated with GIS and Remote. The studies were bound on impacts of LULC on soil erosion by water.

1.7 Limitations of the study

This study has provided important findings on land use/land cover changes and soil erosion in Adama Woreda using the RUSLE model. However, there are some limitations that need to be considered. One key limitation is that the P-factor values were taken from earlier studies instead of being measured directly in the field. Although this was necessary due to time limitations, it may not accurately reflect the specific soil conservation practices used in the area. In addition, there were no field measurements such as data from sediment traps or river sediment loads to check or confirm the model results. This means the RUSLE estimates should be viewed carefully, as they are based on assumptions rather than direct observations. Another limitation is that the study focused only on natural (biophysical) factors affecting land cover and soil erosion. It did not include human (socioeconomic) influences such as population growth, land use policies, or farming practices, which also play a big role in land changes. Future studies that combine both environmental and human factors would provide a more complete picture of the causes and impacts of land degradation in the area.

CHAPTER TWO

2. LITERATURE REVIEW OF THE STUDY

2.1.Land use land covers change

Land use/land cover (LULC) defined as the manmade and natural cover over the land surface, such as water, vegetation, bare land, and artificial structures (buildings, roads, etc.), as well as the human modification of earth's global surface. Land is the serious resource of the earth on the world. LULC is the consequence of the long era practice of natural events like weather, overflowing, climate variation, and fire and ecosystem dynamics and anthropogenic (human) activities like population growth, land demand for settlement, commercial and industrial expansion that has been practiced on the land. It is fact as many people use the meaning of land use and land cover interchangeably (Wubie et al., 2016). To clarify this confusion it is important to define them as they have different issues and different meanings. Land cover refers to the observed biophysical cover on the earth's surface, including water bodies, vegetation, soil and hard surfaces. Land use is the exploitation/utilization of the land by human activities for the purpose of settlements, agriculture, forestry, and by pasture altering land surface processes including biogeochemistry, hydrology and biodiversity (Belete, 2017).

Historically Ethiopia passed significant dynamics in land use/land cover over long year to date. Land use and land cover changes and degradation are increasing at alarming rate generally throughout the country and specifically in the highlands of Ethiopia that led to the transformation of natural habitats to other land use types (Tsegaye, 2019). Land use land cover (LULC) dynamics are a widespread, accelerating, and significant process driven by human actions. LULC changes analysis is one of the most precise techniques to understand how land was used in the past, what types of changes are to be expected in the future, as well as the forces and processes behind the changes (Alemayehu et al., 2019). Land use and land cover change studies try to clarify where change is happening, what land cover types are changing, the types of change happening, the extents of land change and the driving forces and proximate causes of change (Alam et al., 2019).⁷

Changes in land use and land cover are among the most important processes for the understanding of the pace, magnitude and spatial reach of changes of the earth's surface and immediate sub-surface as a result of human impact (Nigatu, 2014). The changes in

land use and land cover are determined by change detection process. Change detection involves the application of multi-temporal data set to quantitatively the temporal effects of the phenomena of interest based on per-pixel techniques which is the most common method for LULC change detection. The change detection is takes place after post classification techniques applied. Post classification is among the most widely applied techniques for change detection purpose. According to Lu et al. (2011) change detection process categorized into two which are: change between classes and change within classes. A change between classes is the conversion of LULC from one class to completely different classes, whereas a change within classes is a modification of the condition of LULC type within the same category.

2.2.Causes of land use land cover change

Globally, land use land cover today is transformed principally by direct human use, such as: agriculture and livestock raising, forest harvesting and management, and urban and suburban construction and development (Meyer, 1995). The author also stated as natural events such as weather, flooding, fire, climate variations, and ecosystem dynamics may also initiate changes upon land cover. The nature of LULC dynamics importantly varies from country to country as the drivers of LULC change and land management activities vary from place to place. The causes of LULC are agricultural expansion, wood extraction, infrastructure expansion and others that changes the physical state of land cover (Aklile, 2014). According to Miheretu and Yimer (2018), the drivers of LULC are commonly segmented into proximity and underlying drivers. Proximity drivers are the activities and actions that directly affect land use (wood extraction or road building) and Underlying drivers are major forces that support the immediate causes including demographic, economic, technological, institutional, and cultural factors.

2.3.Impacts of land use land cover change on soil erosion.

Changes in land use and land cover are important drivers of soil Erosion at global, regional and local scales. The degree of soil erosion has been hurrying in Ethiopia due to land use and land cover (LULC) change and substandard land use and management practices (Moges et al, 2020, Weldemariam and Harka, 2020). The impact of land cover change on soil erosion is depends on the type of changes happened to the land use. According to Tamirat (2019), land use and land cover changes affect many natural processes such as soil erosion, sediment production, flood, and physical and chemical properties of the soil. The impact of LULC on soil often occurs that land managers hardly expect initiating

counterbalance measures. According to Negese (2021), the variation in land use and land cover due to natural and human activities significantly affects the rate of soil erosion.

2.4. Soil Erosion

Soil erosion is the problem happens all over the world. Soil erosion is one of the significant environmental practices that cannot be replaced within short periods of time. Soil erosion specifically is one form of soil degradation, which is the wearing away of the land surface by physical forces such as rainfall, flowing water, wind, ice, temperature change, gravity or other natural or anthropogenic agents that abrade, detach and remove soil or geological material from one point on the earth's surface to be deposited away. The term erosion was first used in geology to describe the forming of depressions by water, the wearing a way of solid material by the action of water flow (Penck 1894). Soil erosion is the physical movement of soil particles from one location to another, mainly due to forces of water or wind. Soil erosion is a gradual process of movement and transportation of the upper layer of soil (topsoil) by different agents such as water, wind, and mass movement causing its decline in the long term. Erosion removes topsoil's, reduces levels of soil organic matter, and leads to breakdown of soil structure. Soil erosion is a multipart process that depends on soil properties, ground slope, vegetation, precipitation amount and strength and variation in land use (Zhao et al 2013). The severity of erosion depends on the quantity of soil being removed and the capacity of the eroding agents to transport it. According to (Nega, 2019 and Mestawot, 2015) soil erosion has either onsite effect (soil loss, formation of sheet, rill and gullies, soil moisture reduction, organic matter reduction and decrease soil depth surface) or offsite effect (sedimentation, water pollution, block up irrigation canal, increase flooding risk and etc.). Soil erosion has been estimated using various spatial analysis units, typically based on raster grids, including watersheds, river basins, and administrative levels such as national, regional, and global scales (Senanayake et al., 2020).

2.5. Causes of soil erosion

Erosion occurs when soil is unprotected to water or wind energy. The agents of soil erosion are the same as the agents of all types of erosion: water, wind, ice, or gravity. Soil erosion is a complex process that depends on soil properties, ground slope, vegetation, and rainfall amount and intensity. Running water is the primary cause of soil erosion, because water is powerful. Wind is also a leading cause of soil erosion because wind can pick up soil and blow it far away. As well as human activities have great role to accelerate soil erosion. The

major causes for soil erosion in Adama Woreda are deforestation, heavy rainfall, and soil characteristics (Gemechu & Hunde, 2015).

2.5.1. Soil erosion by water

Water erosion can be observed all over the world as one of the most significant factors that can create unpackaged soil movement. Water erosion results from the removal of soil material by flowing water. A part of the process is the detachment of soil material by the impact of raindrops. According to Osman (2014), the detachment of soil particles from masses mainly by raindrops and flowing water and their transport by runoff water are elaborate in soil erosion by water. Water erosion on agricultural land occurs mainly when overland flow entrains soil particles detached by drop impact or runoff, often leading to clearly defined channels such as rills or gullies (FAO, 2015). The soil material is suspended in runoff water and carried away. In Ethiopia, soil erosion by water is the principal degradation practice and occurs mainly on cropland, with annual soil loss rates on average of 42 ton/ha up to 300 ton/ha for croplands in dangerous cases (Tsegaye, 2019). Four kinds of accelerated water erosion are commonly recognized: Splash, sheet, rill, and gully.

2.5.1.1. Rain Splash Erosion

At the start of a rain event, falling raindrops beat the soil aggregates, break them, and detach soil particles. Soil particles are transported to some distance by the splashing. Splash erosion is the beginning of other types of water erosion, since it is the first erosion to occur when an erosive rainfall event takes place (Angulo et al, 2012). It naturally occurs evenly over a uniform slope and goes overlooked until most of the productive topsoil has been lost. Deposition of the eroded soil occurs at the bottom of the slope or in low areas.

2.5.1.2. Sheet Erosion

Sheet erosion refers to the even removal of soil from a broad area, typically without forming noticeable water channels. Initially, small and irregular channels may appear, which become wider and straighter as runoff increases (USDA-NRCS, 2000). This type of erosion happens when a thin layer of topsoil is detached by the impact of raindrops and shallow surface flow across a slope. It gradually strips away the most fertile part of the soil, rich in nutrients and organic matter. The process is slow and uniform, often going unnoticed as the land surface becomes smoother. The buildup of runoff water is influenced

by factors like stream height, surface roughness, vegetation cover, and the pattern of crop distribution.

2.5.1.3.Rill Erosion

Rill erosion is the removal of soil through the cutting of many small, but visible channels where runoff concentrates. Rill erosion is intermediate between sheet and gully erosion. Rill erosion occurs when runoff water forms small channels as it concentrates down a slope and that can be destroyed by farming system and other factors (Sun et al 2013). According to Osman (2014), rill erosion is mainly caused as a result of large amounts of material that are released and transported for variable distances in focused areas.

2.5.1.4.Gully Erosion

Gully erosion is the consequence of water that cuts down into the soil along the line of flow. Gullies form in visible natural drainage-ways, in plow channels, in animal trails, in vehicle ruts, between rows of crop plants, and below broken man-made terraces. Gully erosion happens when runoff concentrates and flow strongly enough to detach and move soil particles. Gullies develop when large quantities of water accumulate and run through a single channel with high speed in relatively steep slopes (Zabihi, et al, 2018). Gullies may be ‘V shaped or ‘U’ shaped.

2.6.Factors affecting soil erosion

The weakness of a soil to water erosion is primarily determined by the erosive potential of the rainfall, the slope of the land surface and position of the soil in the catchment, and the vegetative cover on the soil surface (Montanarella et al, 2015). Erodibility varies with soil texture,

aggregate stability, shear strength, infiltration capacity and organic and chemical content (Morgan, 1995). We can divide factors affecting soil erosion into active (human activity) and passive (climate, topography, soil characteristics, vegetation coverage etc.). The main factors affecting the rates of soil erosion by water are rainfall, soil type, topography, land use and land management (panagos et al 2015). Water erosion is the main cause of soil degradation and is influenced by rainfall, soil, topography, land use, soil cover and management, and conservation practices (Souza et al 2017). The common factors are discussed below.

2.6.1. Climate factors

Climate change in temperatures and the precipitation can directly and indirectly influence soil erosion. Perovic et al. 2019 stated that the production of biomass, the loss of organic matter, the infiltration rate, soil moisture, and land use and crop management will be affected by climate change. Soils are affected by climate change which includes rainfall characteristics, atmospheric temperature and wind velocity. The occurrence, strength and duration of rainfall are fundamental factors in determining the amount of runoff produced in a given area. Rainfall is the most powerful factor that causes erosion through all types of water erosion depending on intensity, duration, amount and frequency of rainfall. Rainfall erosivity is the most significant climatic variable in soil erosion processes, which is related to rainfall amount and rainfall intensity (Bahrawi et al. 2016).

2.6.2. Soil factors

The proportion of clay, silt, and sand particles in soil affects soil erosion by influencing soil infiltration. Soil characteristics affect infiltration rate of soil which depends upon permeability of soil, surface condition and presence of moisture in it. Soil characteristics influencing erosion by rainfall and runoff are those properties which affect the infiltration capacity of soil and those which affect the resistance of the soil to detachment and transport by falling or flowing water. There are different types of soil properties on our earth. Some of them are easily eroded by water and other factors, when others not eroded under the same conditions of climate, vegetation, topography, and land management practice based on the intensity of characteristics. Silt particles are the most easily eroded than clay and sand because they have poor infiltration. Soil organic matter also influences soil erodibility. Wischmeier & Smith, 1978 suggested that increasing soil organic matter decreases soil erodibility as soil organic matter influences soil loss by improving soil structure, root diffusion, water capacity and infiltration.

2.6.3. Topographic factors

Topography is the feature of the earth with its undulation. The land slope, length of slope and shape of slope are main factors which influences soil erosion. Slope has a powerful influence on soil erosion. Slope is the fall and rise of land surface which is highly affect soil erosion because of it accelerates the speed of flowing water. Erosion would normally be expected to increase with increase in slope steepness and slope length as a result of respective increase in velocity and volume of surface runoff.

2.6.4. Vegetation covers

The plant cover is important in reducing erosion. The effectiveness of a plant cover in reducing erosion depends upon the height and continuity of the cover, the density of the ground cover and the root density. A ground cover not only intercepts the rain but also dissipates the energy of running water and wind, imparts roughness to the flow and thereby reduces its velocity. It creates the obstacle for raindrops as well as slowing runoff. A good vegetative cover totally reduces the effect of rainfall on soil erosion. For example forests and grasses are more effective in providing cover than cultivated crops. Generally, vegetation cover is used to hold soil particles in place, maintains the soil capacity to absorb water, reduce the velocity of runoff and shields the soil surface from the impacts of falling rain (<http://ecoursesonline.iasri.res.in>).

2.6.5. Land management practice

Land use alterations like removal of forest, removal of grassland covers by either natural activity or human activities are factors that accelerate soil erosion degree. Land management practice is the process of managing the land use. The land management practice also called support practice or the support practice factor (P-factor) in the RUSLE model quantifies the effectiveness of specific soil conservation practices in reducing erosion compared to standard practices like straight-row farming along the slope. It is defined as the ratio of soil loss with a given support practice to the soil loss with conventional upslope and downslope tillage under otherwise identical conditions (USDA-NRCS, 2003). Common erosion-reducing practices include contour farming, strip cropping, and the construction of terraces, all of which function by slowing runoff and encouraging water infiltration. The P-factor varies depending on slope, land use, and the specific conservation measure applied.

2.7. Modeling soil erosion

Erosion models are used to predict soil erosion. Modeling soil erosion is the process of mathematically describing soil particle detachment, transport and deposition on land surfaces. Various parametric models such as empirical which are simplest and statistical in nature, conceptual which is semi empirical and physical process models are available to compute soil loss (Patil, 2018). Igwe, et al (2017) specified that soil modeling provides a quantitative and consistent approach to estimate soil erosion and sediment yield under a wide range of conditions, and is needed to guide the comprehensive control of soil erosion.

2.7.1. Revised Universal Soil Loss Equation

The Revised Universal Soil Loss Equation (RUSLE) is a widely applied empirical model developed to estimate the long-term average annual rate of soil loss resulting from rainfall and surface runoff. It is an enhancement of the original Universal Soil Loss Equation (USLE), incorporating improved techniques and expanded databases (Renard et al., 1997). RUSLE calculates soil erosion by considering key factors such as rainfall erosivity, soil erodibility, slope length and steepness, land cover management, and conservation practices. The model is particularly favored in data-scarce environments due to its relative simplicity and compatibility with spatial tools such as GIS and Remote Sensing (Renard et al., 1997; USDA-ARS, 2013). Although originally designed for agricultural land, RUSLE has been adapted for use on various land surfaces, including rangelands, forests, and construction sites. RUSLE is used to assess the degree of rill and inter-rill erosion, identify situations where erosion is serious, and guide development of conservation plans to control erosion by numerous government agencies and private organizations and individuals like researchers (<http://www.nrcs.usda.gov/technical/ecs/agronomy>). RUSLE maintains the same empirically based equation as USLE to compute sheet and rill erosion as follows:

$$A=R*K*LS*C*P$$

Where,

A is the average annual soil loss (ton/ha/yr),

R is the rainfall erosivity (MJ·mm/ha·h·yr),

K is the soil erodibility factor (tons·ha·h/ha·MJ·mm),

LS is the topographic factor (dimensionless),

C is the cropping management factors (dimensionless), and

P is the practice support factor (dimensionless).

2.7.2. Use of GIS and RS in soil modeling

Predicting soil erosion in areas prone to water erosion is challenging due to difficulties in collecting reliable data over large regions and converting scientific knowledge into spatially meaningful assessments. However, advancements in Remote Sensing (RS) and Geographic Information Systems (GIS) have made it easier to gather up-to-date and accurate data for erosion modeling (Iacobescu et al., 2012). One of the main challenges in using the RUSLE model is the time-consuming and costly generation of spatial input data.

In this study, distributed data on topography, land use, and soil were obtained through RS and processed in GIS to estimate average and annual soil loss (Patil et al., 2015). RS techniques enable the extraction of land cover and soil characteristics from satellite imagery, while GIS is used to integrate and overlay these factors in raster format for spatial analysis. The combined use of RS and GIS enhances the efficiency and accuracy of large-scale erosion risk assessments and is widely adopted for modeling soil loss (Millward & Mersey, 1999; Patil, 2018).

2.8. Empirical Review

Research in the Ethiopian highlands, such as by Gashaw et al. (2020), has shown that unsustainable land management practices and population pressure are the primary causes of LULCC. These studies quantified soil erosion rates using models like RUSLE integrated with GIS and Remote Sensing (RS). Tamirat (2019) studied sediment yield in northern Ethiopia, noting that changes in land cover, particularly the conversion of forests to agricultural land, significantly increased soil erosion. Bekele et al. (2019) used RUSLE coupled with GIS in the Karesa Watershed, Ethiopia, to quantify soil erosion and evaluate the efficiency of soil conservation measures. Their results indicated that agricultural lands were the most erosion prone areas. Negese (2021) assessed LULCC impacts on soil erosion across Ethiopia's diverse landscapes, identifying agricultural expansion and deforestation as primary drivers.

Previous research predominantly targets the northern highlands, neglecting other regions with unique LULCC dynamics and soil erosion challenges. This gap underlines the need for localized studies utilizing advanced geospatial techniques and long term datasets.

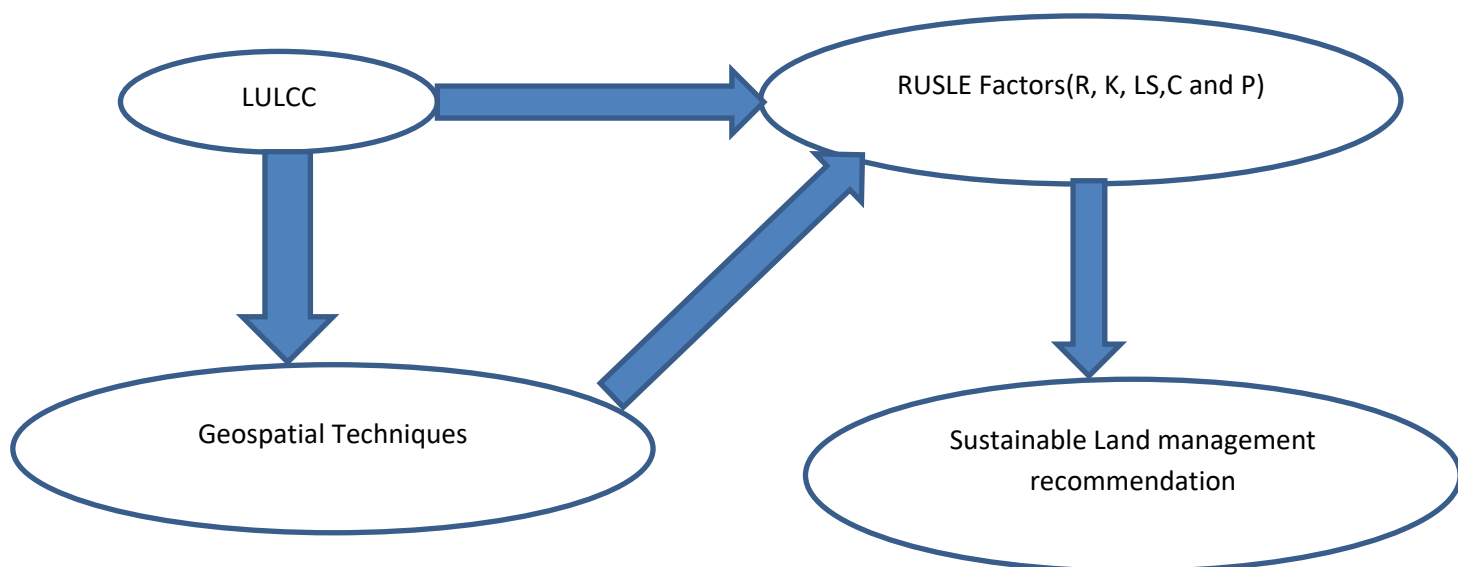
2.9. Literature and Knowledge Gap

Although significant research has been conducted on the relationship between land use/land cover changes (LULCC) and soil erosion, there are notable gaps specific to the Adama District. Previous studies in Ethiopia have primarily focused on the northern highlands, emphasizing broader national-scale analyses or qualitative methods like farmer perceptions. Limited attention has been given to erosion prone areas outside these regions, particularly in the central rift valley area like Adama District.

Additionally, the integration of recent high-resolution spatial data with advanced geospatial techniques, such as GIS and Remote Sensing (RS), remains underutilized in soil erosion studies at a localized scale. This creates a gap in understanding the intricate dynamics of LULCC and its impacts on soil erosion in specific, erosion-vulnerable areas like the Adama District.

2.10. The conceptual framework

This study visualizes the relationship between land use and land cover changes (LULCC) and soil erosion dynamics. LULCC serves as the primary independent variable, influencing soil erosion through changes in vegetation cover, slope stability, and land management practices. These impacts are quantified using the Revised Universal Soil Loss Equation (RUSLE), which integrates five factors: rainfall erosivity (R), soil erodibility (K), topographic factors (LS), cover management (C), and support practices (P). The dependent variable, soil erosion risk, is derived from this model. Geospatial techniques, including Geographic Information Systems (GIS) and Remote Sensing (RS), play a critical role in analyzing LULCC and estimating RUSLE parameters. The framework highlights how these interconnected components provide actionable insights into erosion prone areas, ultimately guiding sustainable land management strategies to mitigate soil erosion and its impacts.



CHAPTER THREE

3. METHODS AND MATERIALS

In this chapter the description of the study area, data source, and material used, over all methods, techniques and other activities were discussed.

3.1. Description of the Study Area

3.1.1. Location and Size

Adama is one of the Woreda, in the Oromia Region of Ethiopia. Adama Woreda is located in the Great Rift Valley. It is bordered by the Arsi Zone to the south, Koka Reservoir to the southwest which separates it from Dugda Bora, Lome to the West, the Amhara region to the north and Boset to the east. It is located at latitude of $8^{\circ} 14' 5''\text{N}$ to $8^{\circ} 43' 32''\text{N}$ and Longitude of $39^{\circ} 6' 26''\text{E}$ to $39^{\circ} 25' 22''\text{E}$ (Fig.3) with altitude of the area range from 1339 to 2445m above sea level.

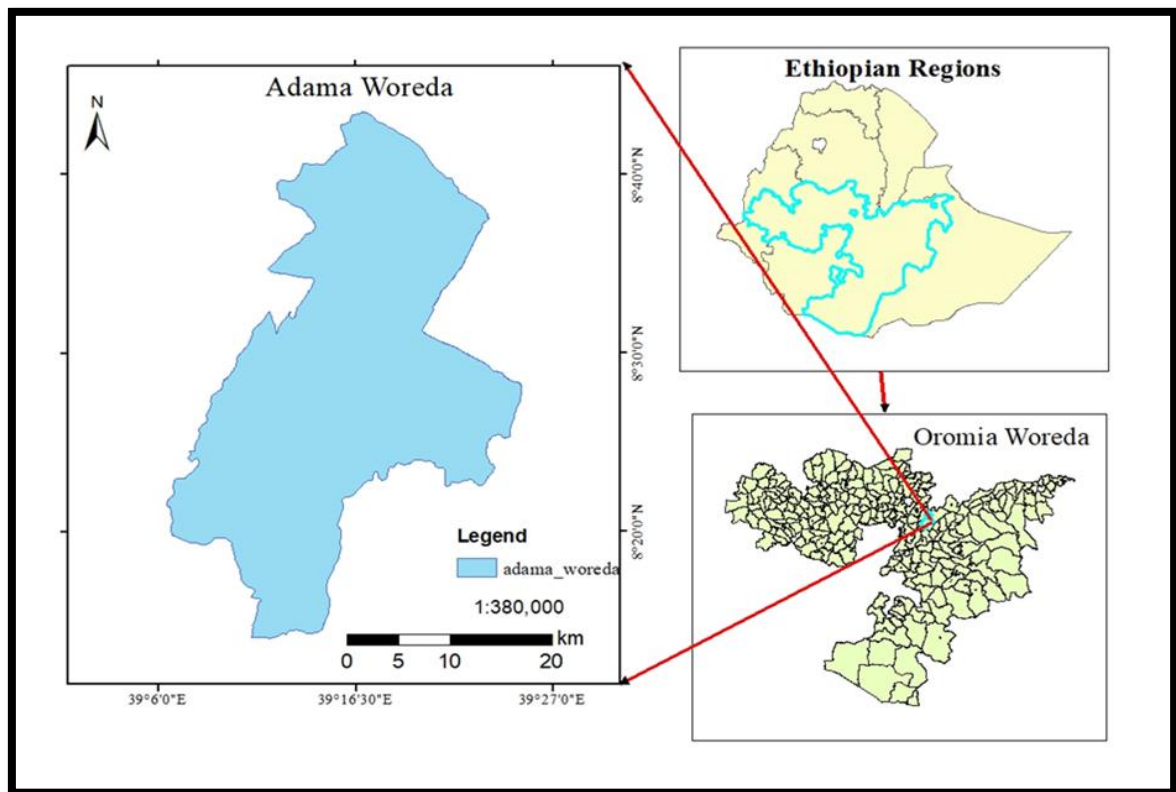


Figure 1 Map of study area

3.1.2. Climate

According to the long term record (1980 to 2024) of Adama meteorological station the mean annual temperature of the Adama Zuria Woreda is 21.6°C and average annual rainfall is 944.11mm. It can be classified as semi humid to semi-arid climate. The months of June, July, August and September have a high chance of precipitation. January, November and December are dry periods, where May is the warmest month with an average maximum temperature of 30°C. The coldest month is December with an average maximum temperature of 20°C. August is the wet month where November is the driest month. December is the sunniest month. (<https://weather-and-climate.com/>)

3.1.3. Population

According to projected population of Ethiopia (2019), the total human population of Adama Woreda including Adama Town is about 393,922 while 192,827 are men and 201,095 are women. The inhabitation of the population of Adama Woreda is both in rural and Urban.

3.1.4. Soil

According to the soil classification data, the study area contains 10 soil types, namely: Calcic Xerosols, Eutric Cambisols, Eutric Fluvisols, Eutric Regosols, Leptosols, Mollic Andosols, Orthic Luvisols, Pellic Vertisols, Phaeozems and Vitric Andosols. Their respective areal coverage is as follows: Mollic Andosols (26,012.23 ha), Eutric Regosols (8,369.84 ha), Eutric Fluvisols (6,408.40 ha), Eutric Regosols (4,617.40 ha), Orthic Luvisols (4,698.71 ha), Phaeozems (4,026.91 ha), Vitric Andosols (3,010.51 ha), Eutric Cambisols (512.67 ha), Pellic Vertisols (504.62 ha), Calcic Xerosols (600 ha) and Leptosols (5.78 ha).

Table 1 Soil type, area and coverage area.

No	Soil Code	Soil type	Area_Hect	Coverage (%)
1	1452	Calcic Xerosols	646.04	0.72%
2	456	Eutric Cambisols	512.67	0.57%
3	556	Eutric Fluvisols	6408.40	7.11%
4	956	Eutric Regosols	12987.24	14.41%
5	700	Leptosols	5.78	0.01%
6	261	Mollic Andosols	26012.23	28.87%
7	864	Orthic Luvisols	4698.71	5.21%
8	1565	Pellic Vertisols	504.62	0.56%
9	1000	Phaeozems	4026.91	4.47%
10	263	Vitric Andosols	3010.51	3.34%

Source: FAO

3.1.5. Land use land cover

For present study different land use and land cover categories of the study area were identified using visual and digital satellite imagery interpretation. The main land use units of the study area are: Settlement, Cultivated Land, Forest Land, Grass Land, Shrubland, Bare land and water Body. Cultivated land and grass land are the most dominant land use in the study area.

3.2 Data Sources

Land use and land cover (LULC) maps for the years 2004, 2014, and 2024 were generated from Landsat satellite imagery, and their classification accuracy was validated using high-resolution images from Google Earth. Rainfall data covering a 40-year period (1984–2023) were obtained from the Ethiopian National Meteorological Institute to compute the rainfall erosivity factor (R-factor) based on mean annual precipitation. The soil erodibility factor (K-factor) was derived from the FAO Digital Soil Map of the World, based on topographic map series produced by the American Geographical Society of New York at a scale of 1:5,000,000. The slope length and steepness (LS-factor) were extracted from a Digital Elevation Model (DEM) downloaded from NASA's Earth Data portal. Additionally, both published and unpublished sources including books, journal articles, and reports were reviewed to support the study's theoretical and methodological framework.

Table 2 Data source and description.

No	Data Source	Description	Uses	Source
1	Rainfall data	Mean Annual Rainfall	For erosivity factor (R) calculation	Ethiopian Meteorological Institute (EMI)
2	Soil Data	Soil Map	For soil erodibility factor (K) factor calculation	Digital Soil Map of the World
3	Satellite Image	Landsat Images	For LULC classification and C-factor and P-factor calculation	USGS
4	DEM	Digital Elevation Model	For slope generation and LS factor calculation	USGS, SRTM
5	Field Survey	Ground Truth Data	For Accuracy assessment	Own

3.2.1. Rainfall data

Rainfall is a most important factor influencing runoff generation and soil erosion, as it determines both the amount and frequency of surface runoff under varying environmental conditions. Accurate precipitation prediction remains a significant challenge in meteorological research (Zhan et al., 2019). For present study, rainfall data were collected from the Ethiopian Meteorological Institute (EMI) for the purpose of calculating the rainfall erosivity factor (R-factor). Data were collected from nine meteorological stations: Adama, Koka Dam, and Sodare, which are located in the study area, and Bofa, Alem Tena, Ejere, Mojo, and Welenchiti, located outside of studies area. Monthly rainfall records covering 40 years (1984–2023) were collected for each station. These rainfall data formed the basis for further analysis of rainfall erosivity in the study area, as described in Section 3.4.5.1.

Table 3 Mean Annual Rainfall for the Years 2004, 2014, and 2024 at nine stations

Station_Name	Elevation	Longitude	Latitude	Mean annual rainfall (mm)		
				2004	2014	2024
Bofa	1425	39.454	8.464	903.64	796.20	1037.94
Alem Tena	1656	38.90783	8.29	775.19	840.33	940.01
Ejere	2254	39.261	8.778	875.33	915.74	991.09
Koka Dam	1625	39.157	8.471	863.52	880.01	907.23
Mojo	1771	39.114	8.609	909.88	1091.22	1201.40
Adama	1622	39.283333	8.55	905.20	911.87	1000.19
Sodere	1347	39.397	8.396	741.85	646.73	812.44
Welenchiti	1457	38.427	8.666	955.73	833.65	984.33
Iteya	2196	39.235	8.136	846.84	826.76	890.60

Source: National Metrological Agency

3.2.2. Soil Data

Soil is a major factor of the environment that determines the modeling capabilities on the global and regional scale, and there is an increasing demand for up-to-date and relevant soil information (Shangguan et al 2014). For this study, Soil data were downloaded from Digital Soil Map of the World (FAO, 1995). The data were provided in polygon format. Soil Map of Ethiopia is extracted by clipping input feature (world soil map) by clip feature (Ethiopia boundary shape file). The study area soil map was clipped from soil map of Ethiopia with extent of study areas boundary using ArcGIS Pro. As shown in Table 1, 10 soil types are found in the study area.

3.2.3. Digital elevation model

A Digital Elevation Model (DEM) is the digital representation of the Earth's surface elevation with respect to any reference datum used to determine terrain attributes such as elevation, slope and landform feature (Balasubramanian, 2017). The DEM used for the present study was downloaded from United States Geological Survey (USGS) via the Earth Explorer platform <https://earthexplorer.usgs.gov/> with a resolution of 30 meter. The DEM was downloaded in raster format and served as a foundational input for deriving topographic parameters required in soil erosion modeling.

3.2.4. Satellite image

For the purpose of image classification of land use land cover the Landsat imagery of three different years 2004 (Landsat 7-ETM), 2014 (Landsat 8-OLI_TIRS) and 2024 (Landsat 8) were used. The Landsat imagery was downloaded from USGS with cloud free and 30m resolution.

Table 4 Description of satellite image used

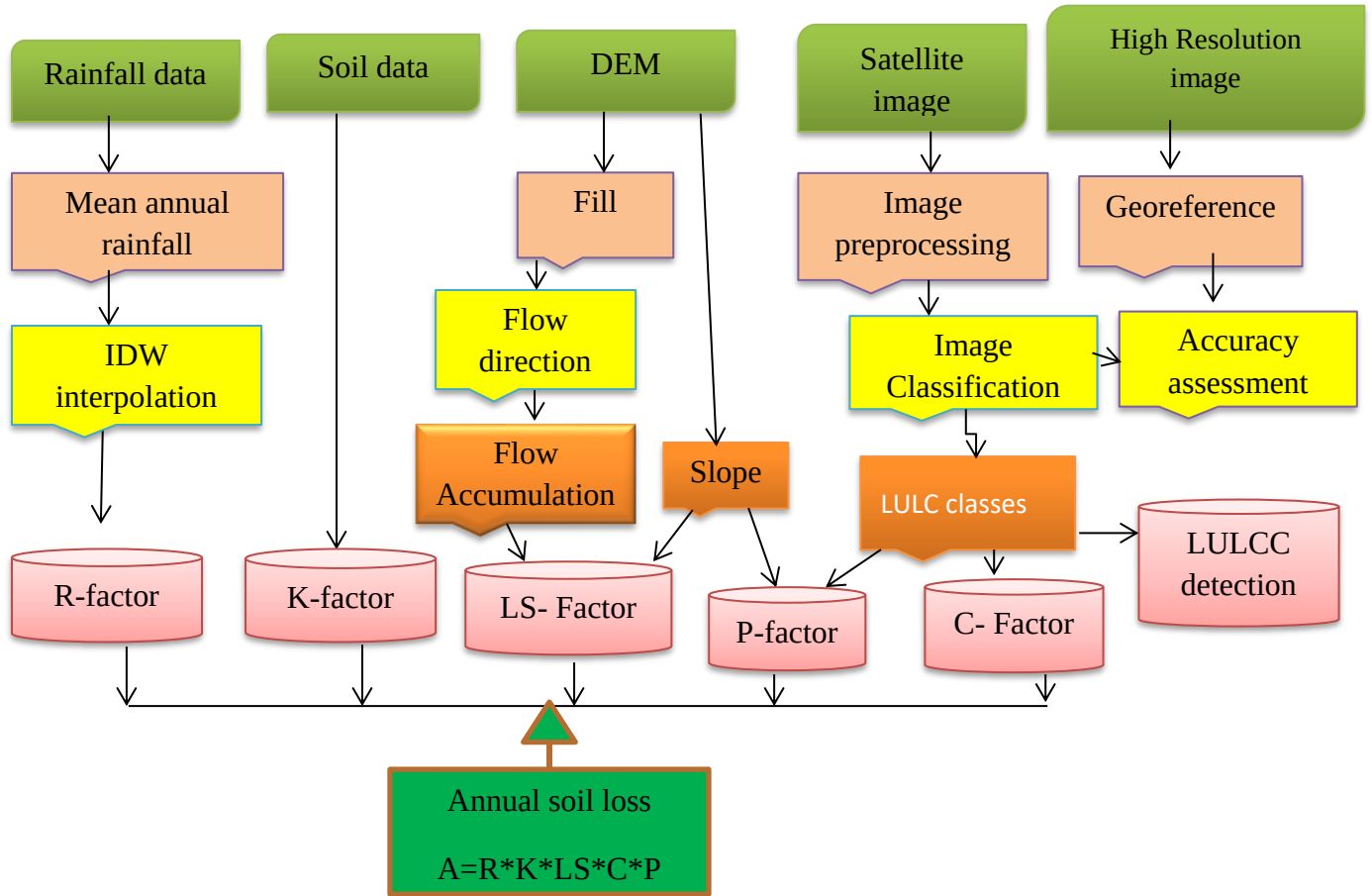
Sensors	Path/Raw	Resolution (m)	Acquisition Date
Landsat 7-ETM (2004)	168/54	30	June 07, 2004
Landsat 8-OLI_TIRS(2014)	168/54	30	Dec 04, 2014
Landsat 8-OLI_TIRS(2024)	168/54	30	Dec 15, 2014

3.3. Software Tools and Data Sources

To conduct this study, different software tools and data sources were used for data collection, processing, analysis, and presentation. ArcGIS Pro 3.1.0 was used for satellite image pre-processing, land use/land cover (LULC) classification, accuracy assessment, post-classification change detection, raster calculations, spatial analysis, and map layout preparation. ENVI software was specifically used to correct scan line errors in Landsat 7 ETM+ imagery using the Scan Line Corrector (SLC) gap-filling method. This step was essential for improving image quality and ensuring accurate classification results. Google Earth Pro was utilized to download high-resolution imagery for the purpose of collecting ground truth reference points used in the accuracy assessment of LULC classification. Microsoft Office applications (Excel, Word, and PowerPoint) supported documentation, data organization, statistical analysis, and the preparation of tables, charts, and reports. The study incorporated both spatial datasets including Digital Elevation Model (DEM), satellite imagery (Landsat), and soil maps and non-spatial datasets, such as long-term rainfall records, as inputs for generating thematic layers and conducting soil erosion modeling using the RUSLE framework.

3.4. Methods of Data Analysis

For this study the steps of method of data analysis to calculate factors used for RUSLE are summarized as follow.



Source: Developed by Author 2025

Figure 2 Methodological Flowchart for Assessing Soil Erosion Risk and Prioritizing Management Options in the Study Area

3.4.1 Image preprocessing

Image preprocessing is a key step in remote sensing analysis to improve the quality and reliability of satellite data for land use/land cover (LULC) classification and change detection. Raw satellite imagery often contains distortions and errors caused by atmospheric interference, sensor limitations, and cloud cover. Therefore, pre-processing techniques such as radiometric correction, atmospheric correction, and geometric alignment are essential to ensure consistency and accuracy (Yohannes et al., 2021; Kassaw & Asfaw, 2022).

In this study, Landsat 7 ETM+ and Landsat 8 OLI/TIRS Level-1 images were downloaded from the USGS Earth Explorer. Image pre-processing was primarily carried out using ArcGIS Pro 3.1.0, including conversion to surface reflectance, radiometric correction and layer stacking. To correct the scan line error affecting the Landsat 7 ETM+ imagery, the ENVI software was used. To identify the land use land cover features the bands 4, 3, 2 were used for Landsat 7, and bands 5, 4, 3 were used for Landsat 8 for visual image. These band combinations are commonly applied in vegetation and land cover studies to enhance interpretability. These pre-processed images were then used in subsequent LULC classification and change detection analysis.

3.4.2 Image classification

Image classification is the process of assigning pixels in a satellite image to specific land use/land cover (LULC) categories based on their spectral signatures. Classification methods are broadly divided into two types: unsupervised and supervised. Unsupervised classification involves grouping pixels based solely on their spectral properties without using any prior ground information. In contrast, supervised classification utilizes training data provided by the user to guide the algorithm in assigning each pixel to a specific land cover class based on its spectral signature.

In the present study, the supervised classification method was employed using the Support Vector Machine (SVM) classifier. SVM has gained significant popularity in recent years due to its high classification accuracy, ability to handle high-dimensional datasets, and reduced sensitivity to noise and small training samples (Kolecka et al., 2022; Hossain et al., 2023). This method works by identifying the optimal hyperplane that separates classes in the feature space, allowing for more accurate classification, especially in heterogeneous landscapes like Adama Woreda. Training samples were selected through high-resolution imagery obtained from Google Earth Pro, ensuring that each class was well-represented by its unique spectral properties.

Seven major LULC classes were identified: Forest, Cultivated Land, Grassland, Settlement, Shrubland, Bare Land, and Water Body (Table 5). Each class was defined based on spectral reflectance and supported by references and ground validation.

Table 5 Description and land use land cover of the study area

Land category	Description	Reference
Forest	Land covered with relatively tall trees, at least have 20% canopy coverage including integral open space and felled areas that mainly eucalyptus trees	Mathewos, 2019 & Ayele et al., 2019
Cultivated land	This land-use encompasses areas that allocated for production of perennial and seasonal crops	Mathewos, 2019 & Ayele et al., 2019
Grass land	Lands that are used for livestock grazing. It includes land covered with mixture of small grasses, grass like plants and shrubs less than 2m and it is used for grazing.	Adane, 2016
Settlement	Land feature such as towns and small rural villages that roofed with corrugated iron sheets, scarp land and sandy areas	Ayele et al., 2019
Shrub land	Areas covered with shrubs, bushes and small trees, with little useful wood, mixed with some grasses and less dense than forests.	Belete, 2017
Bare land	Salt flats, beaches, sand dunes, exposed rocks, stripe mines, queries and gravel pits/non-vegetated area dominated by rock ou, roads, eroded and degraded lands.	Belete, 2017
Water body	Areas covered by natural and manmade small dams, like pond, lake and river.	Mathewos, 2019

3.4.3 Accuracy assessment

Accuracy assessment is a critical step in the evaluation of land use/land cover (LULC) classification results derived from remote sensing imagery. It involves comparing the classified image with reference data that are assumed to represent the true land cover on the ground. The main objective of this process is to evaluate how well the classification matches real-world conditions, and to quantify the reliability of the generated thematic maps. This final verification stage is essential for assessing the reliability of classified outputs before they are used for further environmental modeling or decision-making (Li et al., 2021).

In this study, accuracy assessment was conducted after supervised classification was completed for the years 2004, 2014, and 2024 independently. For the purpose of accuracy assessments, points were generated using stratified random sampling in ArcGIS Pro to ensure that every land cover class was represented, including the smaller and less-frequent ones. This method served to increase classification accuracy while simultaneously avoiding bias towards class size. In this process, a total of 390 points for the years 2004 & 2014 year, and 402 for 2024 were collected and used to verify the classification outcomes.

To obtain reference data, Google Earth Pro was used to extract high-resolution imagery through the time slider function. This enabled the visual inspection of historical land cover conditions for each year, which is especially valuable in assessing changes that may no longer be observable on the ground today. The accuracy of classification results was evaluated using error matrices (also known as confusion matrices), which compare classified pixel values against the ground truth data. Key metrics derived from this matrix include overall accuracy, producer's accuracy, and user's accuracy. Producer's accuracy indicates the probability that a given land cover type on the ground is correctly classified, while user's accuracy refers to the likelihood that a pixel classified into a certain category actually represents that category on the ground (Ghosh et al., 2022). In addition to these metrics, the Kappa coefficient was also calculated to measure the degree of agreement between the classified image and the reference data beyond chance agreement. The Kappa statistic is a robust indicator that accounts for potential random agreement between the classification and reference data, offering a more rigorous evaluation of classification accuracy (Niu et al., 2020). This metric is particularly valuable in studies involving multiple land cover classes where chance agreement could inflate traditional accuracy scores.

Overall, this approach ensured that the classified maps for the three time periods were evaluated using both statistical validation techniques and high-resolution temporal imagery. This step enhances the scientific credibility of the findings and supports the subsequent analysis of land cover change and its environmental implications.

3.4.4 Land Use/Land Cover Change detection

Land use/land cover (LULC) change detection was carried out using the post-classification comparison technique. This method is widely used for comparing maps from different dates and allows for detailed analysis of "from-to" change classes (Teferi et al., 2013).

High classification accuracy was considered a prerequisite for effective change detection; therefore, images from each reference year were independently classified and subjected to accuracy assessment to ensure that the assigned LULC classes accurately represented the actual land use on the ground. Only the classified images with the highest accuracy were selected for the change detection analysis. The analysis was conducted for three time periods: 2004–2014, 2014–2024, and 2004–2024. Change statistics were computed by comparing the pixel values between image pairs for each period. The magnitude of change between datasets indicated whether specific LULC classes experienced an increase or a decrease in area. The results were summarized in tabular form, showing overall changes in hectares for each LULC class. Positive values indicated an increase in area, while negative values signified a decrease over the study period.

The change statistics were derived using two approaches. The first method calculated the total change in area for each LULC class by subtracting the initial year's area from that of the final year (area of final year – area of initial year). This provided an overview of trends over time but did not reveal which land cover types transitioned into others. To gain a deeper understanding of the spatial dynamics and transition patterns, a second method was employed: the change comparison matrix. This matrix captured the "from-to" relationships among LULC classes. To generate it, classified images from the initial and final years were converted from raster to polygon format using the Raster to Polygon conversion tool. The resulting features were dissolved and then intersected to identify overlapping areas representing LULC transitions. Following the intersection, changes were quantified in the attribute table by calculating the area (in hectares) for each land cover transition. The resulting change matrix, created in ArcGIS Pro, was exported to Excel in text file format. The matrix was organized into rows and columns, representing LULC classes in the initial and final years, respectively, and illustrated the extent and direction of changes over time. The calculated change detection in matrix was prepared in row and column table based on the initial and final year.

3.4.5 Soil loss estimation

Because of erosion is gradual process, there are complications in distinguishing between the natural and accelerated rate of erosion (Habtamu, et al, 2020). To address this challenge different models are developed by different authors. The best model used for soil loss estimation over the world is RUSLE model. This model, coupled with GIS and RS, has also been widely applied and tested by many researchers to estimate soil erosion

(Demeke & Andualem, 2025). Revised universal soil loss equation is an empirically based model that has the ability to predict the long-term average annual rate of soil erosion in a field slope as a result of rainfall pattern, soil type, topography, crop coverage and management practices (Renard et al. 1997). The model estimates soil loss based on five parameters: rainfall erosivity factor (R), soil erodibility factor (K), slope length and steepness factor (LS), cover management factor (C) and conservation practice factor (P) were used in the RUSLE model. The relationship is expressed as:

$$A = R \times K \times LS \times C \times P \quad (1)$$

3.4.5.1 Rainfall erosivity factor (R)

Rainfall erosivity refers to the potential of rainfall to cause soil erosion, primarily through its amount and intensity. In the RUSLE model, this is quantified as the R-factor, which integrates rainfall energy and intensity over time (Panagos et al., 2015). Due to the lack of high-resolution rainfall intensity data in the study area, the R-factor was estimated using mean annual precipitation values, consistent with the approach recommended by Hurni (1985) for Ethiopian conditions.

Using Microsoft Excel, annual mean precipitation was computed for three representative years: 2004, 2014, and 2024 based on the long-term monthly rainfall data described in Section 3.2.1. These years represent three time periods (1984–2005, 2005–2015, and 2015–2024, respectively). The RUSLE model recommends using long-term rainfall data of 10–30 years to estimate annual soil loss, accounting for interannual variations, seasonal patterns, and extreme events, and establishing a more robust estimate of rainfall erosivity (Renard et al., 1997). The calculated annual mean rainfall values were then georeferenced using the latitude and longitude of each station in ArcGIS Pro. To generate continuous spatial surfaces of rainfall for each time period, Inverse Distance Weighting (IDW) interpolation was applied in ArcGIS Pro. The resulting rainfall maps were then used to calculate the rainfall erosivity factor using the empirical equation developed by Hurni (1985) for Ethiopian conditions:

$$R = -8.12 + 0.562P \quad (2)$$

Where R is the rainfall erosivity factor in MJ mm/ha/h/year and P is the mean annual rainfall in millimeters.

This method has been widely adopted in previous Ethiopian studies due to the unavailability of direct rainfall intensity data (Yesuph & Dagnew, 2019; Habtamu et al., 2020; Girmay et al., 2020; Balyneh et al., 2019; Esa et al., 2018). By applying this equation, spatially distributed R-factor maps were generated for the years 2004, 2014, and 2024, representing different periods of land cover and climate conditions in the study area.

3.4.5.2 Soil erodibility factor (K)

The soil erodibility factor (K) represents the susceptibility of soil to erosion, accounting for both detachment and transport processes. It is influenced by several intrinsic soil properties, including texture, organic matter content, structure, and permeability (Tesfaye et al., 2015). In this study, K-factor values were assigned to each soil type based on its characteristics, particularly type and color. The values were derived from previous empirical studies conducted in Ethiopia. Table 6 below summarizes the soil types, corresponding colors, assigned K-factors, and relevant references used in the analysis.

Table 6 Soil Erodibility K- factor Values

No	Soil Type	Soil Color	K-Factor	Reference
1	No soil	Water	0	Common value for bare/rocky land in Ethiopia (e.g., Hurni, 1985)
2	Calcic Xerosols	Light brown to yellowish	0.2	Gebreselassie et al. (2020)
3	Eutric Cambisols	Very dark gray	0.3	Tessema et al. (2020)
4	Eutric Fluvisols	Black	0.15	Hurni (1985)
5	Eutric Regosols	Very dark brown	0.15	Hurni (1985)
6	Leptosols	Brown to yellowish	0.3	Hurni (1985); FAO (2001)
7	Mollic Andosols	Very dark brown to black	0.25	Dagnachew et al. (2023)
8	No soil	Gray or rocky brown	0.05	Common value for bare/rocky land in Ethiopia (e.g., Hurni, 1985)
9	Orthic Luvisols	Brown to dark brown	0.2	Hurni (1985)
10	Pellic Vertisols	Very dark grayish brown	0.22	Dagnachew et al. (2023)
11	Phaeozems	Dark brown to black	0.2	Haregeweyn et al. (2023)
12	Vitric Andosols	Very dark gray (volcanic)	0.14	FAO (2001); Gashaw et al. (2020)

The data were processed in ArcGIS Pro, where each soil unit was attributed with a corresponding K-value from published sources. The resulting K-factor map served as a key input for the RUSLE model, representing spatial variability in soil erosion susceptibility.

3.4.5.3 Topographic factors (L and S)

The topographic factor, often referred to as the LS-factor in the RUSLE model, is one of the most critical parameters for assessing soil erosion, as it represents the combined effect of slope length (L) and slope steepness (S). These components affect the velocity and volume of surface runoff, which are driven by gravitational force and are key contributors to soil detachment and transport (Kidane et al., 2019).

In this study, a Digital Elevation Model (DEM) was used as the primary input for deriving topographic variables. Using ArcGIS Pro 3.1.0, both slope and flow accumulation layers were generated from the DEM. The calculation of LS-factor was based on the widely applied equation developed by Wischmeier and Smith (1978):

$$LS = (FA * (\frac{cell\ size}{22.21}))^{0.4} * (\frac{Sin(Slope)}{0.0896})^{1.3} \quad (3)$$

Where FA is the flow accumulation and LS is the slope length and steepness factor. Cell Size is the raster resolution (30 meters). This LS-factor layer serves as an essential input for the RUSLE model, enabling the spatial estimation of topographically induced soil erosion risks across the study area.

3.4.5.4 Land-cover factor (C)

The land cover management factor (C-factor) is a key component of the RUSLE model, reflecting the impact of land use and vegetation cover on soil erosion rates. It is defined as the ratio of soil loss from land under a particular cover condition to the corresponding loss from continuously fallow and tilled land (Habtamu et al., 2020). The C-factor varies depending on land use type, crop cover, agricultural practices, and seasonal variations, particularly those related to rainfall patterns and vegetation growth.

In this study, C-factor values were assigned to land use/land cover (LULC) classes derived from supervised classification of satellite imagery. Each LULC type was linked to C-values based on published literature relevant to Ethiopian conditions. The C-factors for various land use types used in this study are summarized in the table below (Table 7).

Table 7 Land Use/Land Cover C-factor Values

No	Land Use	C-factor	References
1	Water body	0	Kebede & Fufa (2023); Gashaw et al. (2020)
2	Forest	0.001	Gashaw et al. (2020) ; Mengie et al. (2023)
3	Cultivated land	0.18	Moisa, Dejene, Merga, and Gemed (2022)
4	Grassland	0.01	Gashaw et al. (2020) ; Mengie et al. (2023)
5	Shrubland	0.014	Gashaw et al. (2020) ; Mengie et al. (2023)
6	Settlement	0.09	Gashaw et al. (2020) ; Hagos (2020)
7	Bare land	1	Gashaw et al. (2020) ; Hagos (2020)

3.4.5.5 The support practice factor (P)

The support practice factor (P) in the RUSLE model quantifies the effectiveness of conservation measures in reducing soil erosion, expressed as the ratio of soil loss with a specific practice (e.g., contouring, terracing) to that with conventional up-and-down slope farming (Wischmeier & Smith, 1978). P-values range from 0 (high protection) to 1 (no protection), with recent Ethiopian studies adopting similar methods (Yohannes et al., 2020; Tebebu et al., 2024). In this study, P-factor values were assigned based on land use/land cover (LULC) and slope. A slope map was derived from the DEM, reclassified into six slope classes, and intersected with agricultural land from the LULC map. P-values were then allocated by slope class, allowing for a realistic estimation of erosion reduction due to conservation practices.

Table 8 Land use Land Cover P- factor values based on slope.

Land use type	Slope (%)	P-factor
Agricultural land	0-5	0.1
	5-10	0.12
	10-20	0.14
	20-30	0.19
	30-50	0.25
	50-100	0.33
Other Land	All	1.00

CHAPTER FOUR

4. RESULTS AND DISCUSSIONS

4.1 Land Use Land Cover Analysis

Satellite images from 2004, 2014, and 2024 were classified into seven land cover types: Forest, Cultivated Land, Grassland, Settlement, Shrubland, Bare Land, and Water Body (Figure 5). Cultivated land was the most widespread in all directions throughout the study period. Settlements were mainly concentrated in central (Adama), southeastern (Awash), and southwestern (Wonji) areas. A clear expansion of builtup areas was observed over the 20 years, indicating rapid urban growth.

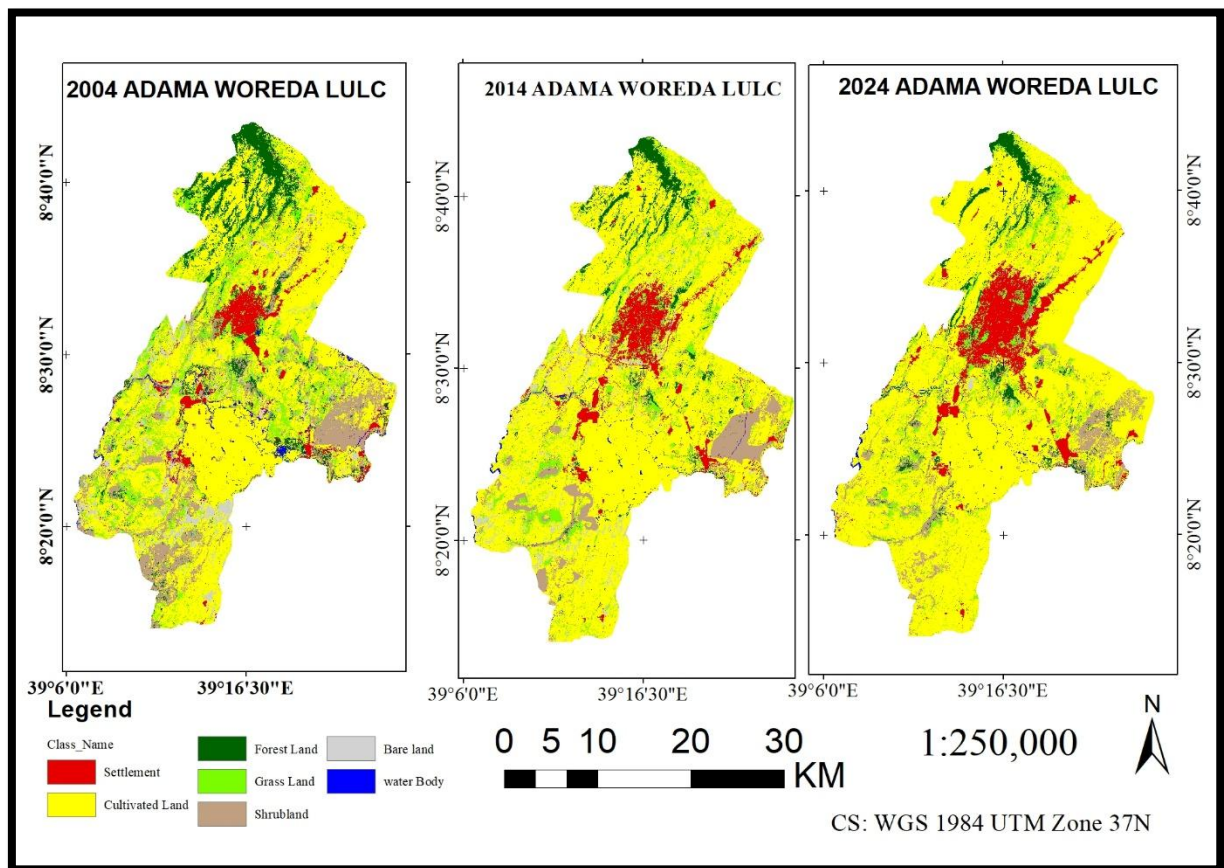


Figure 3 LULC Classification maps for 2004, 2014 and 2024

Based on the land use/land cover (LULC) data presented in the table 9 for the years 2004, 2014, and 2024, significant changes have occurred over the past two decades. Cultivated land has consistently dominated the landscape, increasing from 56.87% in 2004 to 71.93% in 2024, indicating agricultural expansion likely driven by population growth and food

demand. In contrast, forest land, grassland, and shrubland all show a declining trend, reflecting ongoing vegetation degradation and land conversion. Settlement areas have also notably expanded from 4.79% to 8.81%, particularly around urban centers like Adama and Awash, highlighting urban sprawl. Meanwhile, bare land and water bodies have sharply declined, especially bare land, which dropped from 4.37% to just 0.36%, possibly due to land rehabilitation or encroachment by other uses. These changes, also reflected in the pie charts and bar graphs, suggest a strong shift from natural cover types to human-dominated land uses, raising concerns for sustainability and ecosystem health. These findings are consistent with studies such as Hailemariam et al. (2020) and Girma et al. (2021), which noted similar LULC transitions in response to anthropogenic activities in Ethiopia.

Table 9 Land use land cover dynamics of the study periods 2004, 2014, and 2024.

S.N	LULC Types	Area2004 Hec	% Coverage	Area2014 hec	% Coverage	Area2024 hec	% Coverage
1	Settlement	4,318.54	4.79	5,714.99	6.34	7,936.66	8.81
2	Cultivated Land	51,231.53	56.87	62,885.54	69.81	64,793.86	71.93
3	Forest Land	7,396.10	8.21	4,025.51	4.47	3,985.89	4.42
4	Grass Land	11,211.56	12.45	7,784.15	8.64	6,561.78	7.28
5	Shrubland	11,074.06	12.29	6,535.45	7.25	6,168.88	6.85
6	Bare land	3,933.78	4.37	2,703.62	3.00	322.16	0.36
7	water Body	918.46	1.02	436.28	0.48	314.80	0.35
	Total	90084.03	100.00	90084.03	100.00	90,084.02	100.00

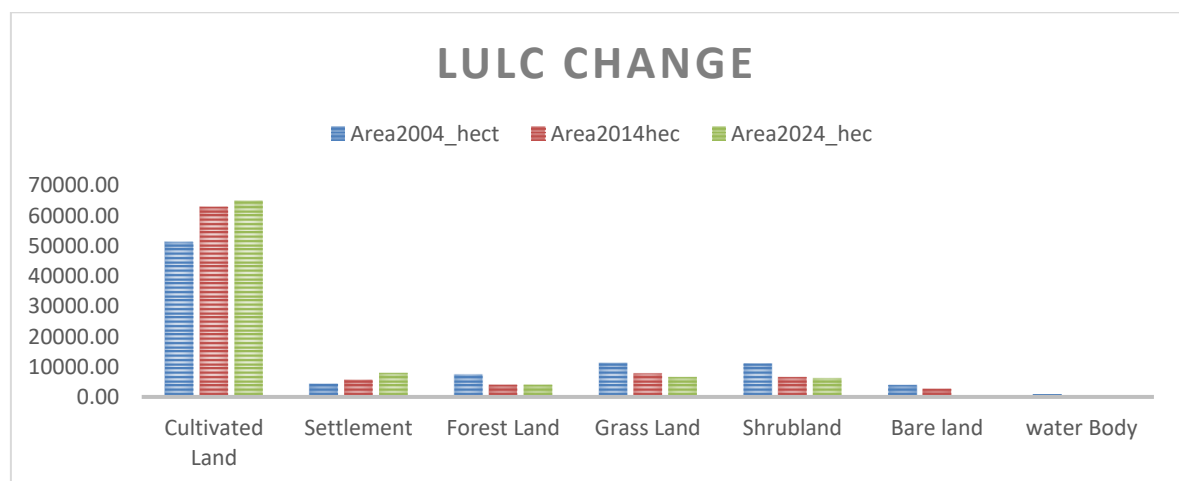


Figure 4 LULC area coverage's of 2004, 2014, and 2024

In the year 2004, the land use/land cover (LULC) distribution in the Adama Woreda was dominated by cultivated land, which covered approximately 51,231.53 hectares. This was followed by grassland and shrubland, covering about 11,211.56 hectares and 11,074.06 hectares respectively. Forest land occupied around 7,396.10 hectares, while settlement areas accounted for 4,318.54 hectares. Bare land comprised 3,933.78 hectares, and water bodies covered approximately 918.46 hectares. The total land area assessed in the Woreda amounted to 90,084.03 hectares. In 2014, land use in the Adama Woreda was predominantly composed of cultivated land, which accounted for approximately 70% of the total area. This was followed by grassland (9%), shrubland (7%), and settlement areas (6%). Forest land made up around 4%, while bare land and water bodies occupied smaller portions, comprising 3% and 1%, respectively. By 2024, a noticeable shift in land use patterns had occurred. Cultivated land expanded further to 72%, reinforcing its dominance in the region. Settlement areas also increased significantly to 9%, indicating urban growth and possibly population pressure. Grassland and shrubland remained relatively stable, each representing about 7% of the land area. Forest land experienced a slight decrease.

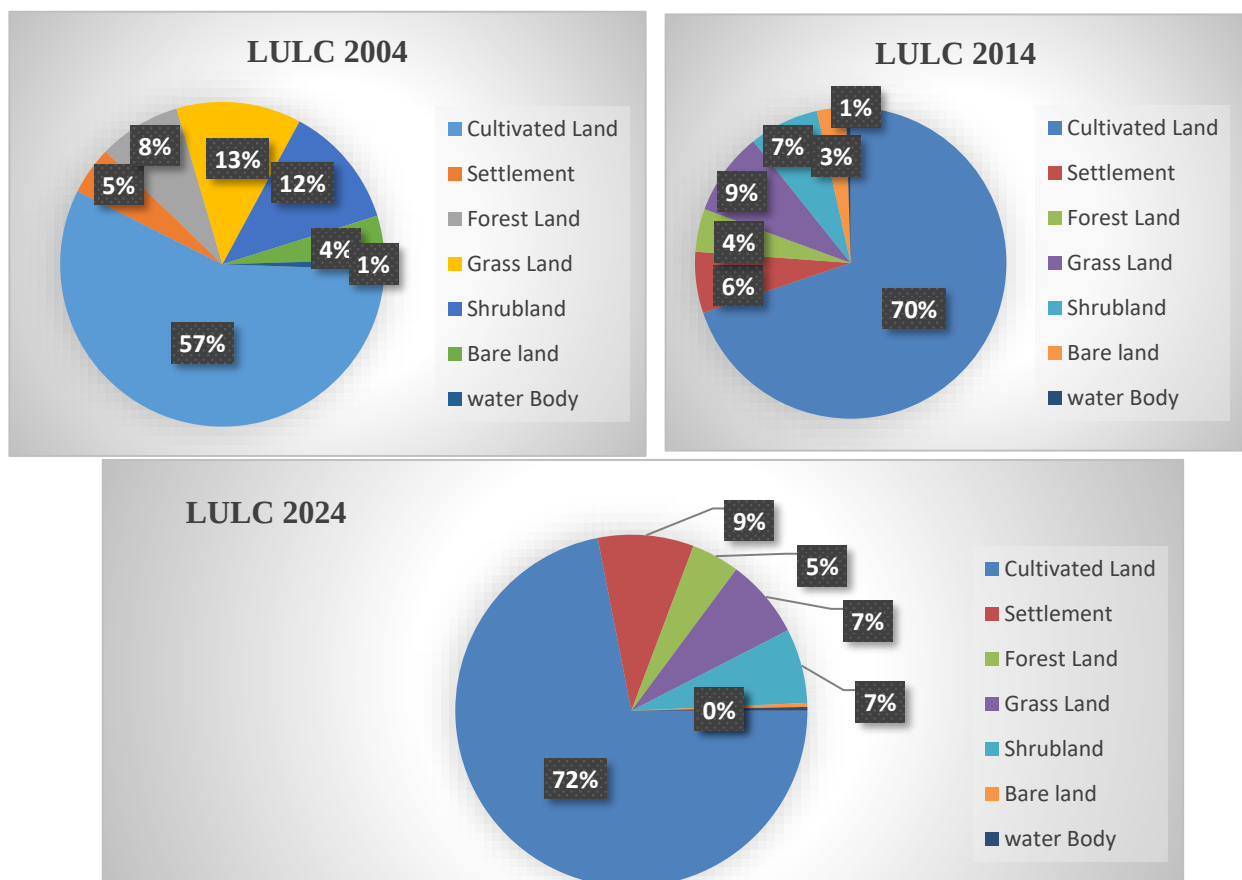


Figure 5 LULC percentage coverage's of 2004, 2014, 2024

4.1.1 Accuracy assessment analysis

The classified land use/land cover (LULC) maps for the years 2004, 2014, and 2024 were validated using ground truth points generated through stratified random sampling. A total of 390 reference points were used for both 2004 and 2014, and 402 for 2024, ensuring balanced representation across all land cover types.

As shown in Tables 10, 11, and 12, the overall classification accuracies were 90.51% for 2004, 92.11% for 2014, and 96.02% for 2024, with corresponding kappa coefficient of 0.85, 0.85, and 0.92, respectively. All classified images achieved an overall accuracy greater than 85%, which is considered excellent and indicates a strong agreement with the corresponding thematic maps. According to Salghuna et al. (2018), classification accuracies above 85% are acceptable for digital image classification and support reliable interpretation of derived thematic maps. Producer's accuracy was defined as the number of correctly classified pixels in a category divided by the total number of reference pixels for that category.

Table 10 Error matrix accuracy totals for the classified image of 2004

Class types from classified map	Class types from reference data							Row Total
	Settlement	Cultivated Land	Forest Land	Grass Land	Shrubland	Bare land	water Body	
Settlement	16	2	0	1	0	0	0	19
Cultivated Land	0	200	5	5	5	1	0	216
Forest Land	0	2	26	1	3	0	0	32
Grass Land	0	6	0	44	0	0	0	50
Shrubland	0	3	0	0	44	0	0	47
Bare land	0	0	0	1	0	15	0	16
water Body	0	1	0	1	0	0	8	10
column Total	16	214	31	53	52	16	8	390
Overall Classification Accuracy = 90.51%								
Overall Kappa Statistics = 0.85								

Table 11 Error matrix accuracy totals for the classified image of 2014

Class types from classified map	Class types from reference data							Row Total
	Settlement	Cultivated Land	Forest Land	Grass Land	Shrubland	Bare land	water Body	
Settlement	20	2	0	0	0	5	0	27
Cultivated Land	0	247	1	8	5	2	0	263
Forest Land	0	1	16	1	0	0	0	18
Grass Land	0	2	0	33	0	0	0	35
Shrubland	0	1	0	0	29	0	0	30
Bare land	1	1	0	0	0	8	0	10
water Body	0	1	0	0	0	0	9	10
column Total	21	255	17	42	34	15	9	393
Overall Classification Accuracy = 92.11%								
Overall Kappa Statistics = 0.85								

Table 12 Error matrix accuracy totals for the classified image of 2024

Class types from classified map	Class types from reference data							Row Total
	Settlement	Cultivated Land	Forest Land	Grass Land	Shrubland	Bare land	water Body	
Settlement	34	0	0	0	0	1	0	35
Cultivated Land	1	264	0	6	2	0	0	273
Forest Land	0	0	17	0	0	0	0	17
Grass Land	0	3	0	28	0	0	0	31
Shrubland	0	1	0	0	26	0	0	27
Bare land	1	1	0	0	0	8	0	10
water Body	0	0	0	0	0	0	9	9
column Total	36	269	17	34	28	9	9	402
Overall Classification Accuracy = 96.02%								
Overall Kappa Statistics = 0.924								

The overall classification accuracy and kappa values obtained in the present study are consistent with findings from recent research conducted in Ethiopia. For instance, Yimer et al. (2020) evaluated the seasonal effects on classification accuracy in the Bilate Sub-basin, reporting overall accuracies of 80% for the wet season and 90% for the dry season, with kappa coefficients of 0.8 and 0.9, respectively. Seifu et al. (2023) conducted a study in Western Ethiopia using MODIS satellite data and found an overall classification accuracy of 85.4% with a kappa statistic of 0.812, indicating substantial agreement between classified maps and ground truth data. Additionally, Abdeta et al. (2024) analyzed land use and land cover changes in Southwestern Ethiopia, reporting overall accuracies ranging from 85.33% to 89.13% between 1994 and 2021, with kappa values improving from 0.78 to 0.84 over the same period. These studies support the reliability of the classification accuracy achieved in the current research, demonstrating consistency with recent findings in various Ethiopian regions.

4.1.2 Land Use Land covers change detection.

The change detection of the classified images was conducted by comparing land cover values across three periods: 2004–2014, 2014–2024, and the overall period of 2004–2024, as outlined in the methodology. This analysis is summarized in Table 13.

Cultivated land consistently increased during all periods. It expanded from 51,231.53 ha in 2004 to 62,885.54 ha in 2014, and further to 64,793.86 ha in 2024. The most rapid increase occurred in the first decade (2004–2014), while the rate slowed down in the second decade. Similarly, Settlement land also showed continuous growth. It increased from 4,318.54 ha in 2004 to 5,714.99 ha in 2014, and to 7,936.66 ha in 2024. This indicates a faster urban expansion rate in the last decade. Forest land, on the other hand, decreased significantly from 7,396.10 ha in 2004 to 4,025.51 ha in 2014. A smaller reduction was observed from 2014 to 2024, indicating slight recovery or stabilization.

Grassland declined throughout the study period. The decline was more severe between 2004 and 2014, reducing from 11,211.56 ha to 7,784.15 ha. A further decrease occurred between 2014 and 2024, bringing it down to 6,561.78 ha. Shrubland followed a similar trend. It declined sharply from 11,074.06 ha in 2004 to 6,535.45 ha in 2014, and then slightly to 6,168.88 ha in 2024.

Bare land decline from 3,933.78 ha in 2004 to 2,703.62 ha in 2014, and then to 322.16 ha in 2024. This sharp reduction indicating rapid land conversion, potentially due to recovery or development. Water bodies also showed a downward trend, declining from 918.46 ha in 2004 to 436.28 ha in 2014, and then to 314.80 ha in 2024.

These findings align with recent studies in Ethiopia. For example, Masha et al. (2023) reported significant land use change in Adama Woreda, with a trend of agricultural expansion and urban growth. Similarly, Yimer et al. (2020) and Seifu et al. (2023) highlighted notable reductions in forest and water bodies linked to anthropogenic pressures and climate variability.

Table 13 Land Use Land Cover Area and Rate of Change (2004–2024)

SN	LULC				Rate of Change hectare/Year		
		Area2004 _hect	Area2014 hec	Area2024 _hec	Δ 2004– 2014	Δ 2014– 2024	Δ 2004– 2024
1	Cultivated Land	51231.53	62885.54	64793.86	1,165.40	191.13	678.26
2	Settlement	4318.54	5714.99	7936.66	139.64	222.17	180.91
3	Forest Land	7396.10	4025.51	3985.89	- 337.06	- 3.96	-170.51
4	Grass Land	11211.56	7784.15	6561.78	- 342.74	- 122.24	-232.49
5	Shrubland	11074.06	6535.45	6168.88	- 453.86	- 36.66	-245.26
6	Bare land	3933.78	2703.62	322.16	- 123.02	-238.15	-180.58
7	water Body	918.46	436.28	314.80	- 48.22	- 12.15	-30.18

4.1.3. Land use land cover matrix

The land use/land cover (LULC) change matrix for Adama Woreda over the 20 year period from 2004 to 2024 tells significant transformations across the landscape. The matrix compares the initial (2004) and final (2024) land cover categories, where the rows represent the 2004 LULC classes and the columns show the 2024 classes. Diagonal values in the matrix indicate areas that remained unchanged, while off-diagonal values reflect transitions between lands cover types. Cultivated land showed the greatest degree of stability and expansion, with 43,816.32 hectares remaining under cultivation and substantial land gained from grassland (7,330.90 ha), shrubland (5,443.26 ha), forest land (3,454.84 ha), and bare land (3,079.86 ha). This strong increase in agricultural land suggests a growing demand for farmland, likely driven by population growth and food security concerns.

Grassland and shrubland were the most affected by conversion to other land uses. Grassland lost a notable portion of its area to cultivated land and settlements, with 7,330.90 ha and 1,151.84 ha converted, respectively. Similarly, shrubland saw 5,443.26 ha converted to cropland and 835.22 ha to grassland, highlighting the high vulnerability of natural vegetative covers. Settlement areas also expanded markedly, gaining 2,953.06 ha from cultivated land, 1,151.84 ha from grassland, and 300.86 ha from shrubland, indicating rapid urbanization and infrastructure development. Forest land experienced a major reduction, with only 2,361.03 ha remaining unchanged and large portions converted to cropland, shrubland, and grassland. This decline reflects significant deforestation, particularly during the first decade of the study. Bare land decreased drastically, with 3,079.86 ha converted to cultivated land and only 66.67 ha remaining as bare land by 2024. Water bodies also decreased, from 915.55 ha in 2004 to 310.97 ha in 2024, with reductions likely due to climatic variability, water abstraction, and land encroachment. Overall, the analysis shows that cultivated land and settlements were the only classes with net gains, while forest, shrubland, grassland, bare land, and water bodies declined. These results are consistent with recent studies in Ethiopia, such as Yohannes et al. (2022), who identified agricultural expansion as the main driver of LULC changes in the Central Rift Valley. Tadesse and Tulu (2021) similarly found that grasslands and shrublands in Oromia were heavily converted to cropland, while Girma et al. (2023) highlighted rapid urban growth and vegetation loss in central Ethiopia due to socio economic pressure and population growth.

Table 14 Land use land cover change matrix in hectare from 2004 to 2024

LULC Classes		2024							
		Column Labels							
	Row Labels	BL	CL	FL	GL	S	ShL	WB	Grand Total
2004	BL	66.67	3079.86	21.23	377.21	306.87	69.63	9.59	3931.06
	CL	141.97	43816.32	551.84	2556.45	2953.06	1117.91	78.09	51215.63
	FL	7.27	3454.84	2361.03	636.86	354.58	567.12	9.55	7391.25
	GL	39.14	7330.90	223.88	1823.12	1151.84	633.59	3.72	11206.18
	S	27.57	1027.21	46.72	296.80	2829.95	71.69	16.08	4316.02
	ShL	38.00	5443.26	750.78	835.22	300.86	3669.84	30.08	11068.04
	WB	1.48	611.99	27.93	34.67	38.64	36.98	163.86	915.55
	Grand Total	322.10	64764.37	3983.42	6560.33	7935.79	6166.76	310.97	90043.74

BL=Bare land; S=Settlement; CL=Cultivated land; FL=Forest land; GL=Grass land;
ShL=Shrub land; WB=Water body

4.2 RUSLE factors analysis

The Revised Universal Soil Loss Equation (RUSLE) model estimates soil erosion by integrating five key factors: rainfall erosivity (R), soil erodibility (K), slope length and steepness (LS), cover management (C), and support or conservation practices (P). Each of these factors was calculated independently as outlined in the methodology section. The resulting raster layers were generated and overlaid using ArcGIS Pro to compute the spatial distribution of soil loss across the study area, by using the formula in equation 1.

4.2.1 R-Factor

The R-factor was computed for 2004, 2014, and 2024 using interpolated mean annual rainfall data from nine stations listed in Section 3.2.1. The result indicate that overall rainfall increased over time, particularly in Mojo, Alem Tena, and Adama, suggesting a rising trend in rainfall erosivity. For example the mean annual rainfall in Mojo increased from 909.88mm in 2004 to 1201.40mm in 2024. Sodere remained the lowest mean rainfall across all years. In 2004, Bofa had the highest rainfall (903.64 mm), while Sodere had the lowest (741.85 mm).

The spatial variability in rainfall across the study period highlights the dynamic nature of the R-factor, which can influence soil erosion potential and land management practices over time. The R-factor maps generated for each year are shown in Figure 9.

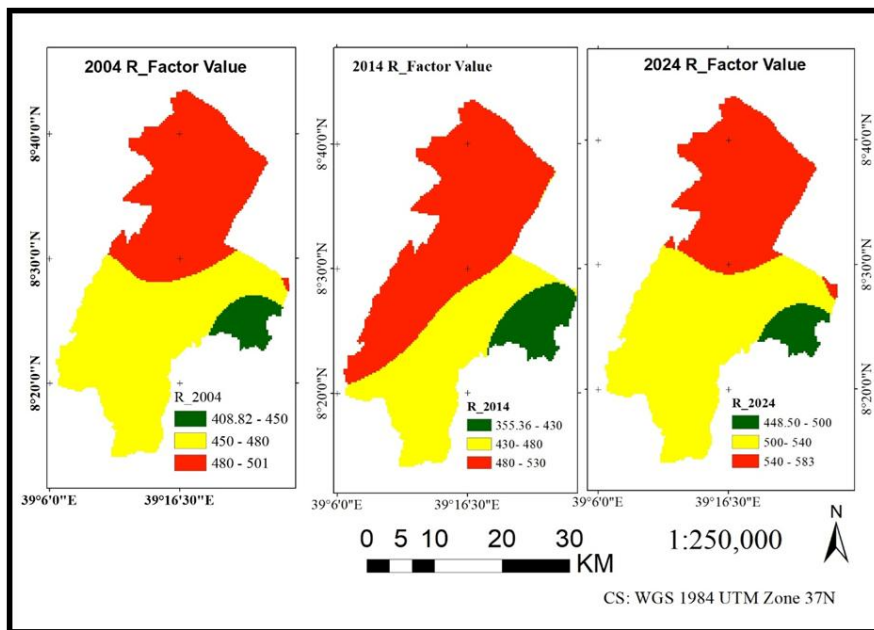


Figure 6 Spatial distribution of R-factor

4.2.2 K-Factor

The spatial distribution of the soil erodibility factor (K) in the study area is presented in Figure 10. As previously described in Section 3.4.5.2, K-values were assigned to different soil types based on established empirical studies conducted in Ethiopia. K-values varied spatially in relation to dominant soil classes. Higher K-values (0.3) were recorded in areas with Leptosols and Eutric Cambisols, indicating greater vulnerability to soil detachment and transport. Mollic Andosols, covering the largest area (26,012.23 ha), were assigned a K-value of 0.25, representing high erodibility. In contrast, lower K-values (0.15) were attributed to Eutric Regosols (12,987.24 ha) and Eutric Fluvisols (6,408.40 ha), which are relatively more resistant to erosion. Moderately erodible soils such as Calcic Xerosols (600 ha) and Orthic Luvisols (4698.7 ha) were given a K-value of 0.2. Water bodies, covering a small portion (46.04 ha), were assigned a K-value of 0, as they do not contribute to soil erosion (Erdogan, Erpul & Bayramin, 2006). This variability is a crucial input for the RUSLE model, enabling accurate estimation of spatial patterns of soil loss. The specific K-values assigned to each soil type are summarized in Table 14.

Table 15 Soil type, texture and organic percentage of topsoil and K-value

SOILTYPE	Soil Color	K_Factor	Area
Mollic Andosols	Very dark brown to black	0.25	26012.23
Eutric Regosols	Very dark brown	0.15	8369.84
Eutric Fluvisols	Black	0.15	6408.40
Eutric Regosols	Very dark brown	0.15	4617.40
Calcic Xerosols	Light brown to yellowish	0.2	600.00
Eutric Cambisols	Very dark gray	0.3	512.67
	Water	0	46.04
Orthic Luvisols	Brown to dark brown	0.2	4698.7
Leptosols	Brown to yellowish	0.3	5.78

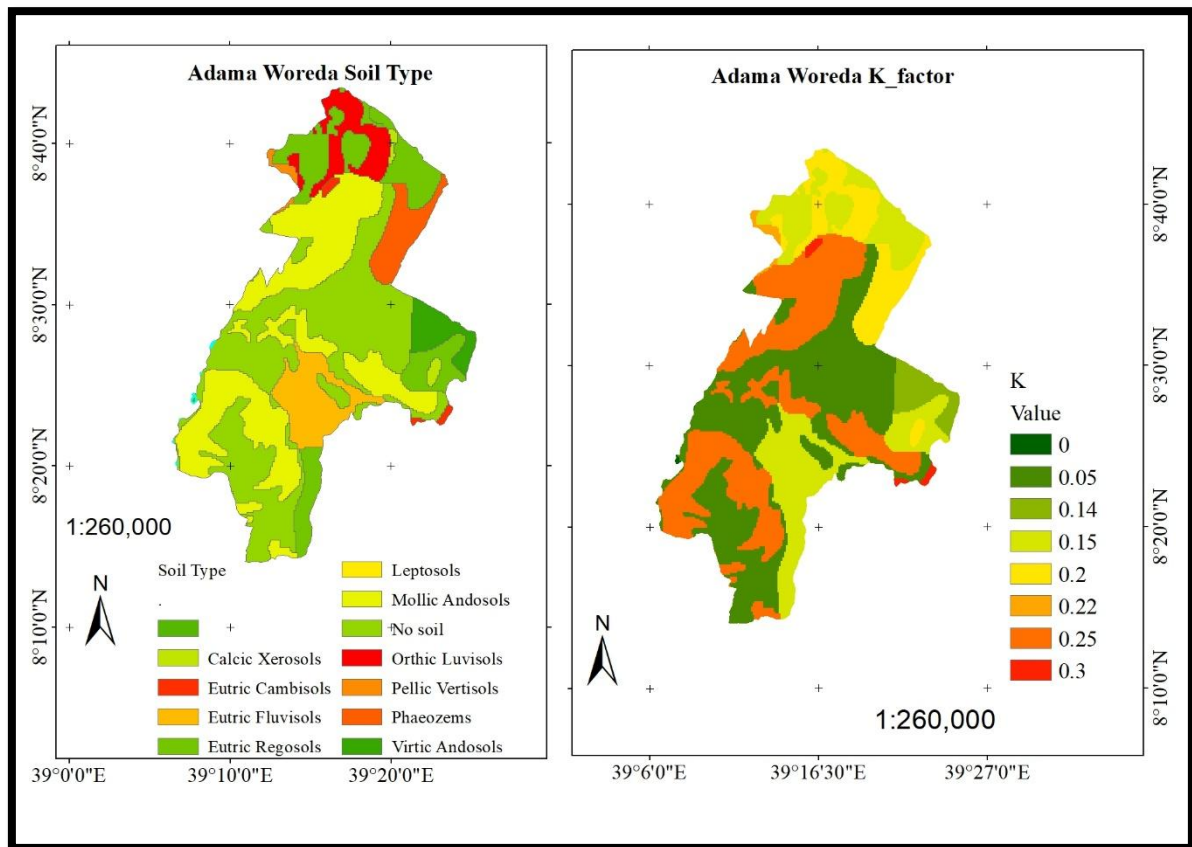


Figure 7 Spatial distribution of K- factor

4.2.3 LS-Factor

The raster layers of flow accumulation and slope, derived from the study area's DEM, were used to calculate the LS-factor in ArcGIS Pro. The formula in equation (8) defined by Wischmeier and Smith (1978) was used to calculate LS factor using the raster calculator tool of ArcGIS Pro. As shown in Fig. 12 the raster output of LS-Factor is range from 0 to 6.18. The low values of the LS were distributed at low land of the study site, whereas the medium and high values distributed at steep slope of the study areas. The area with low LS was less vulnerable to soil erosion, while area with high LS was vulnerable to soil erosion.

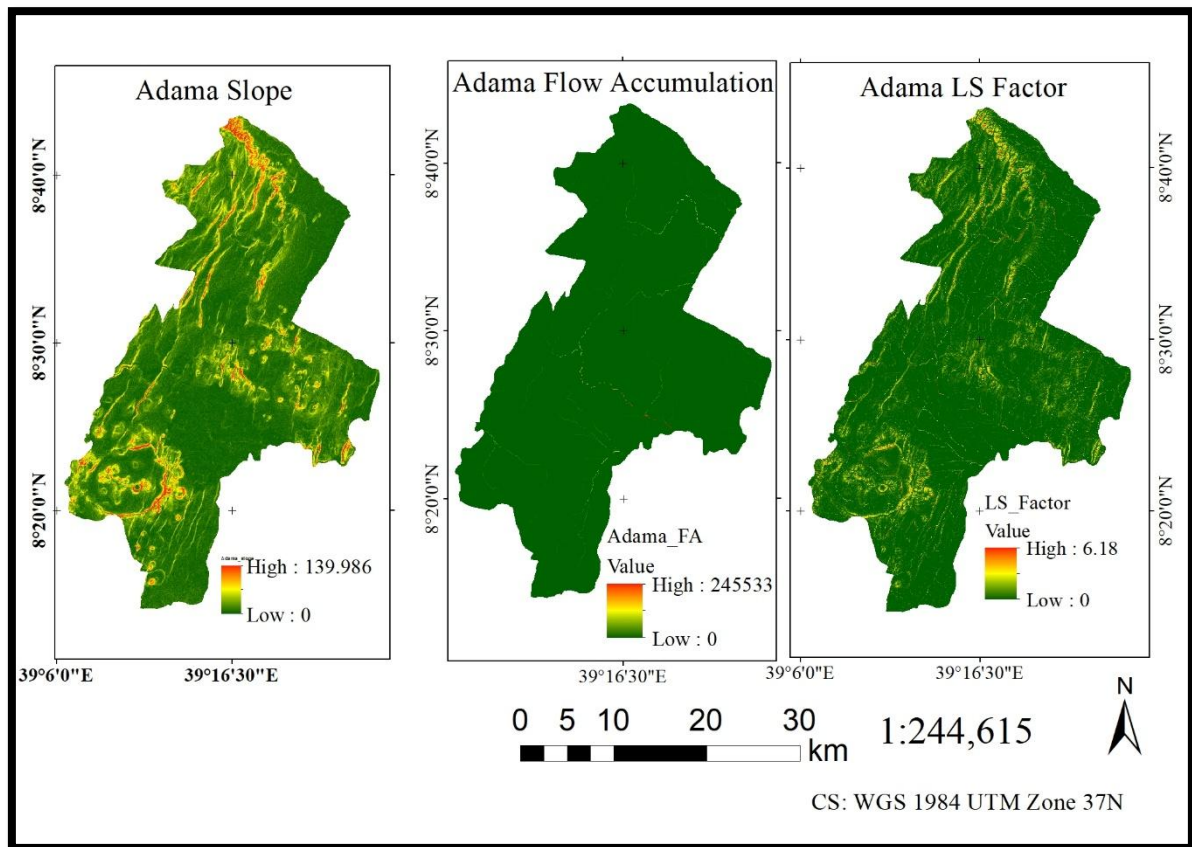


Figure 8 Spatial distribution of LS- factor

4.2.4 C-Factor

The classified images for all study periods were converted from raster to vector format to assign a unique identity to each land cover class. After the values had been assigned, feature classes were converted to raster format to have the spatial distribution of C-factor in the study area. The C-factor of the study area ranged from 0 to 1 during all study periods (2004, 2014, and 2024).

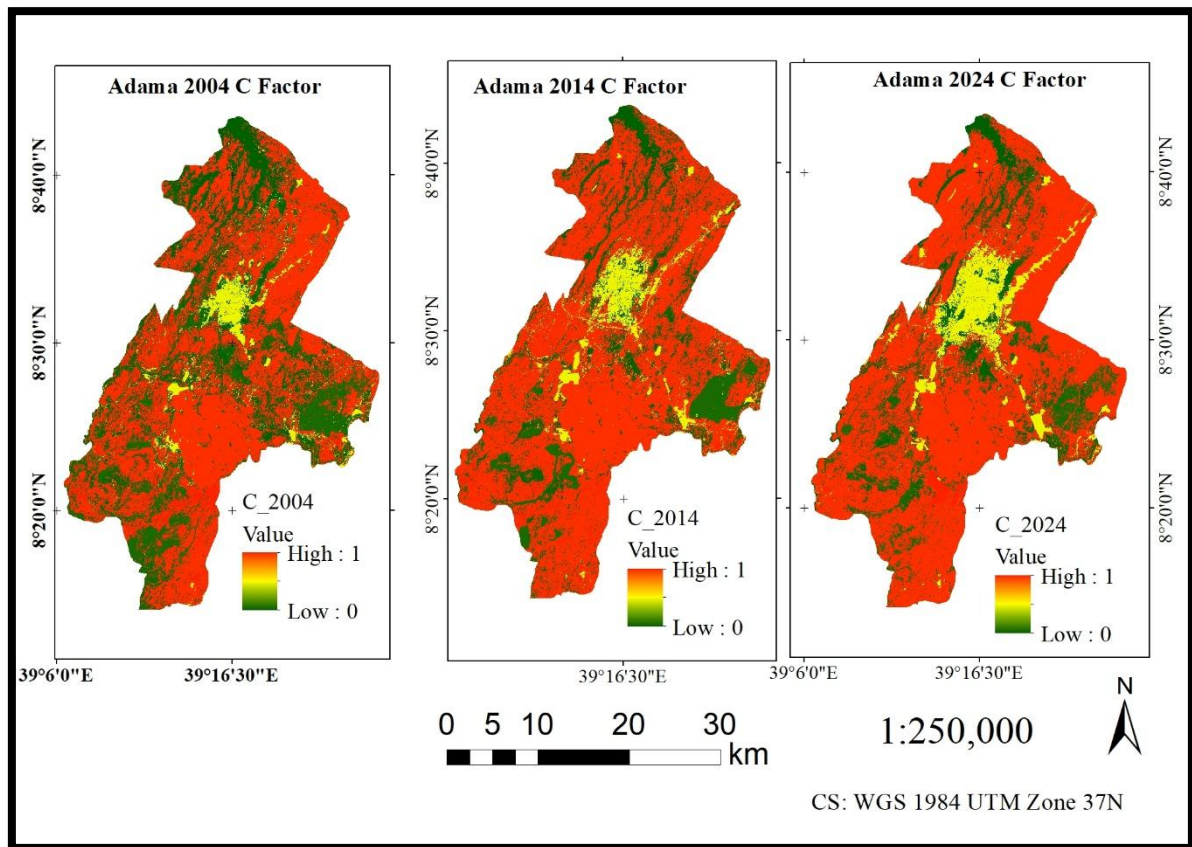


Figure 9 C-factor spatial distribution of 2004, 2014 and 2024

From Fig. 11 the map indicates that the high value of C-factor shows the most erodible areas which are covered by bare land and cultivated land. The low C-factor values correspond to less erodible areas, including forest land, water body and shrub land. The red area on the map indicates the high of C-factor values, while green areas indicates low values.

4.2.5 P-Factor

P-factor is a parameter that allows consideration of existing anti-erosion practices in the estimation of soil losses. As discussed in the methodology section, the P-factor was calculated based on agricultural land, since there were no permanent conservation measures in the area. The LULC was grouped into agricultural land use and non-agricultural land use. Non-agricultural land use was given a P value of 1, regardless of slope class, whereas the agricultural land use was classified into six slope classes and assigned their respective P-values. The P-factor ranged from 0.1 to 1 (Table 8).

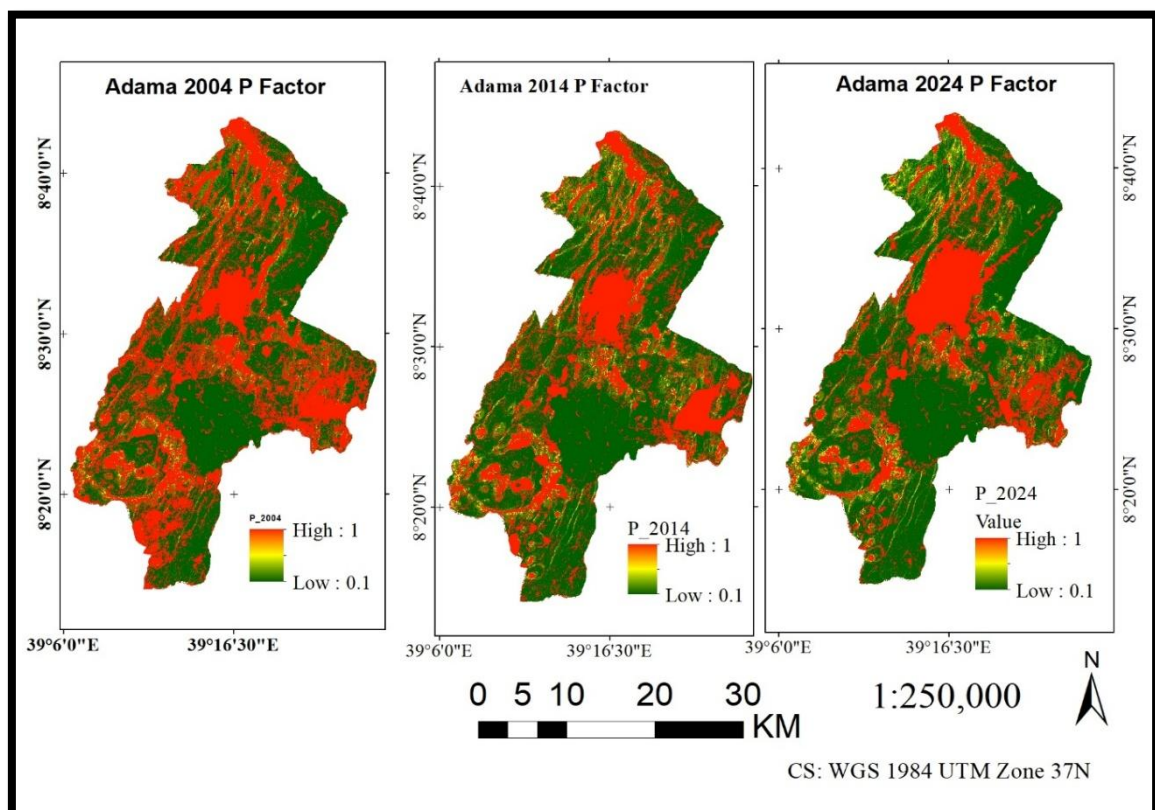
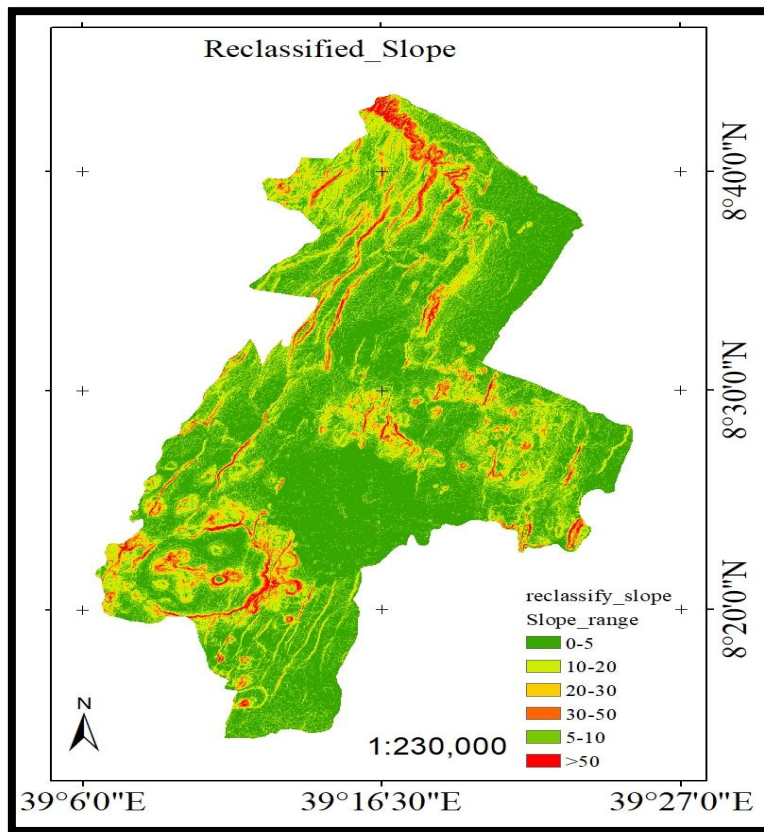


Figure 10 Spatial distribution of P-factor for 2004, 2014 and 2024

4.3 Soil loss estimation

The long term annual soil loss in the study area was estimated using the Revised Universal Soil Loss Equation (RUSLE) model. The required input factors (R, K, LS, C, and P) were prepared in raster format and multiplied using the Raster Calculator in ArcGIS Pro with the support of the Spatial Analyst tool.

According to the results, the annual soil loss ranged from 0 to 565.61 ton/ha/year in 2004, from 0 to 570.17 ton/ha/year in 2014, and from 0 to 357.76 ton/ha/year in 2024 (Figure 13). The corresponding mean annual soil loss was 31.59 ton/ha/year, 24.50 ton/ha/year, and 22.30 ton/ha/year for the years 2004, 2014, and 2024, respectively. The total annual soil loss was estimated to be 2,846,283.49 tons/year in 2004, 2,207,262.68 tons/year in 2014, and 2,009,318.09 tons/year in 2024 (Table 16).

The results show a consistent reduction in both mean and total annual soil loss across the three time periods. Although the maximum soil loss increased slightly from 565.61 ton/ha/year in 2004 to 570.17 ton/ha/year in 2014, it significantly decreased to 357.76 ton/ha/year by 2024. Similarly, the mean soil loss decreased gradually from 31.59 ton/ha/year in 2004 to 22.30 ton/ha/year in 2024. This decline is likely the result of improved land use practices and the expansion of vegetation cover. Another aspect that brings positive implications in the Woreda is its active participation in Ethiopia's Green Legacy initiative. Over last year's more than 50 hectares of hillsides around the Adama city have been planted with trees and fruit plants. <https://cities4forests.com/city/adama/>. The sharp conversion of bare land to other LULC types during 2004-2024 is another very vital factor. Bare land has changed from 3,933.78 hectares in 2004 to 322.16 hectares by 2024. Out of this 21.23 hectares have been changed to forest areas, which provide soil stabilization and help in erosion control.

Despite this reduction, the 20 year average soil loss rate remains beyond the tolerable threshold proposed by Hurni (1986) for agro-ecological zones in Ethiopia, which is 18 ton/ha/year. It also exceeds the global tolerable soil loss limits proposed by Wischmeier and Smith (1978) and Renard et al. (1996), which range between 5–11 ton/ha/year, and as adopted by Weledemariam and Harka (2020).

Table 16 Annual soil loss and total soil loss of 2004, 2014, and 2024.

year	soil loss (ton/ha/yr.			Total soil loss (ton/yr.)
	min	Max	mean	
2004	0	565.61	31.59	2846283.49
2014	0	570.17	24.5	2207262.68
2024	0	357.76	22.3	2009318.09

The current estimated mean soil loss of 22.3 ton/ha/year therefore indicates that the study area remains vulnerable to severe soil erosion, with potential long term impacts on soil fertility, agricultural productivity, and sustainability. If the current trend continues, sheet and rill erosion may progress into gully erosion, causing even more detrimental effects on land and livelihoods.

The present findings are consistent with previous studies. For example, Gashaw et al. (2020) reported a mean annual soil erosion of 32.8 ton/ha/year in the Gilgel Abay watershed, and Tadesse and Abebe (2014) found 30.4 ton/ha/year in Jabi Tehinan watershed. Similarly, Estifanos (2014) and Wijesundara et al. (2018) recorded 39.8 ton/ha/year and 33 ton/ha/year in Ribb watershed (Ethiopia) and Kirindi Oya basin (Sri Lanka), respectively. In some cases, even higher rates were reported: 47.4 ton/ha/year in Koga watershed (Gelagay & Minale, 2016), 45 ton/ha/year in Chaleleka wetland (Kebede et al., 2015), and 78 ton/ha/year in Chitral, Pakistan (Maqsoon et al., 2020).

Conversely, studies such as Tilahun et al. (2018) and Tesfaye et al. (2018) reported lower soil loss rates of 8.25 ton/ha/year in Ajema watershed and 18.69 ton/ha/year in Somodo watershed, respectively. These results, especially Tilahun et al.'s, fall within the tolerable limits, potentially due to local differences in topography, rainfall erosivity, soil types, and conservation measures.

In general, the variation in soil loss across different places is largely influenced by spatial differences in rainfall erosivity (R), soil erodibility (K), and slope length and steepness (LS), while changes in soil loss from one time period to another are mainly driven by temporal changes in rainfall erosivity (R), Cover management (C), and conservation practices (P) factors.

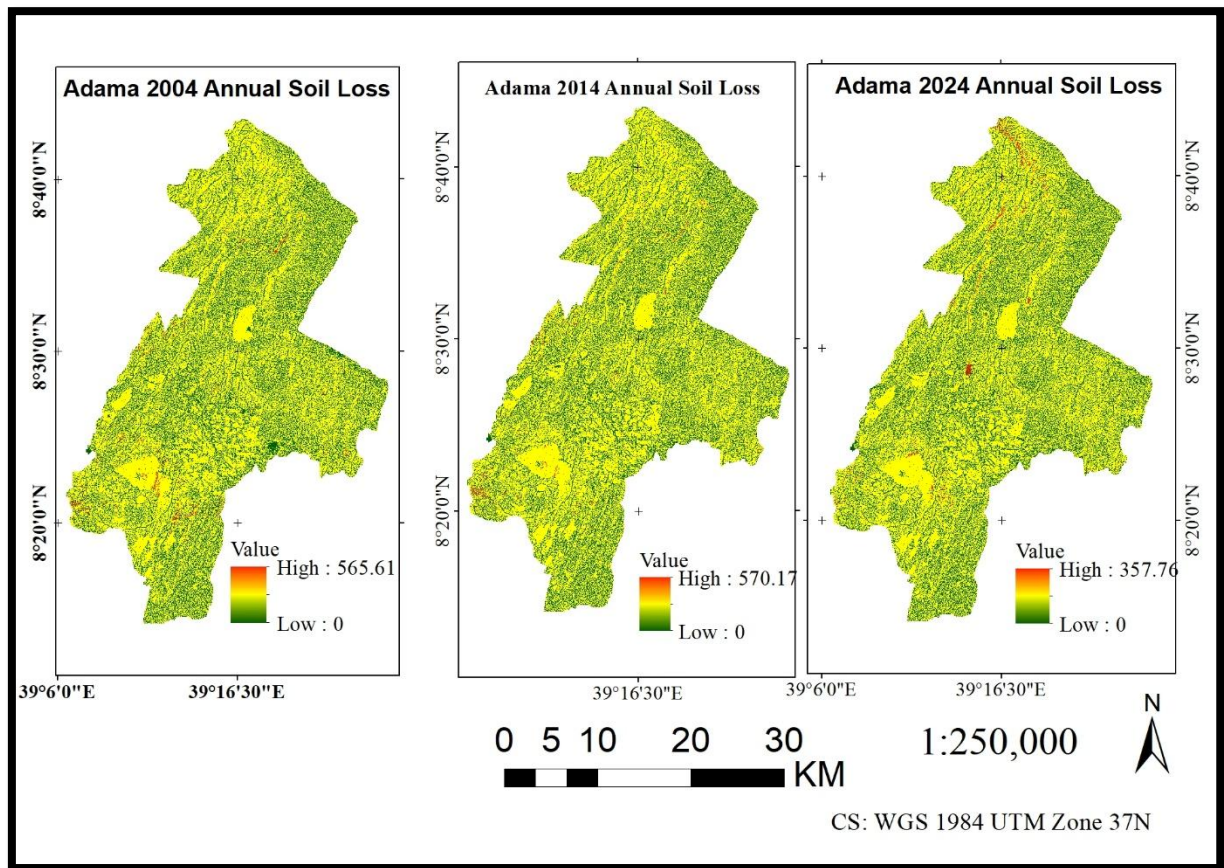


Figure 11 the spatial distribution of annual soil loss of 2004, 2014, and 2024

4.4 Soil loss rates

To better understand soil erosion, it was categorized into five severity classes, adopted from previous researchers such as Gashaw et al. (2020) and Negese (2021): very slight (0–5 ton/ha/yr), slight (5–10 ton/ha/yr), moderate (11–30 ton/ha/yr), severe (30–50 ton/ha/yr) and very severe (>50 ton/ha/yr). This classification allows for the prioritization of erosion control interventions by identifying areas most affected by soil loss.

The results (Table 17) indicate that the Very Slight risk class (0–5 ton/ha/yr) covered the majority of the study area across all three years: 63.92% in 2004, 65.95% in 2014 and 64.92% in 2024. This class represents land with erosion below the tolerable limits, suggesting relatively stable land use or effective conservation in those zones. The Slight risk category (5–10 ton/ha/yr) showed a gradual increase from 9.17% in 2004 to 10.16% in 2024, possibly reflecting expanding areas under initial stage degradation. Similarly, moderate risk areas (10–30 ton/ha/yr) also increased slightly from 12.46% in 2004 to 13.37% in 2024, which may indicate areas of increasing erosion risk.

On the other hand, severe risk (30–50 ton/ha/yr) and very severe risk (>50 ton/ha/yr) zones declined in percentage coverage. Severe risk areas decreased from 4.18% in 2004 to 3.99% in 2024, while very severe risk zones reduced from 10.27% to 7.55% over the same period. These reductions are likely associated with improved land cover conditions and the implementation of targeted soil conservation practices in the most erosion prone areas. Specifically, the decline could be linked to reduced cultivation on steep slopes, afforestation activities, and the application of soil and water conservation measures.

Table 17 Soil loss severity class and percentage coverage

Severity class	Annual soil loss(t/h/yr)	Area (ha)			Coverage %		
		2004	2014	2024	2004	2014	2024
Very Slight	0 – 5	56638.17	58442.31	57607.92	63.92	65.95	64.92
Slight	5 10	8125.74	8581.05	9013.95	9.17	9.68	10.16
Moderate	10 30	11044.44	10870.47	11866.77	12.46	12.27	13.37
Severe	30 50	3705.66	3298.77	3544.74	4.18	3.72	3.99
Very Severe	>50	9097.65	7421.85	6701.58	10.27	8.38	7.55
Total		88,611.66	88,614.45	88,734.96	100.00	100.00	100.00

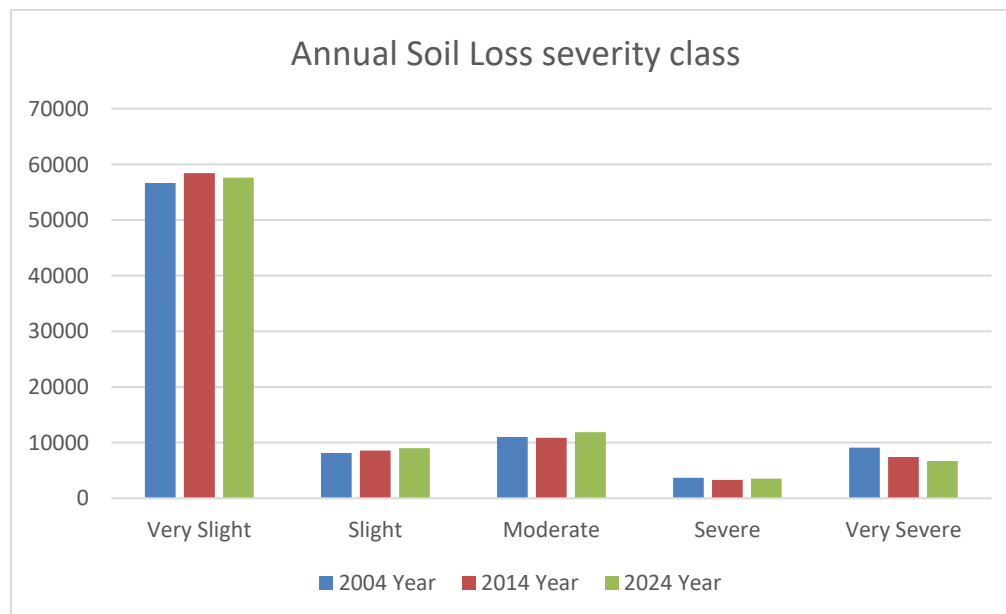


Figure 12 Annual soil loss severity classes of 2004, 2014, 2024.

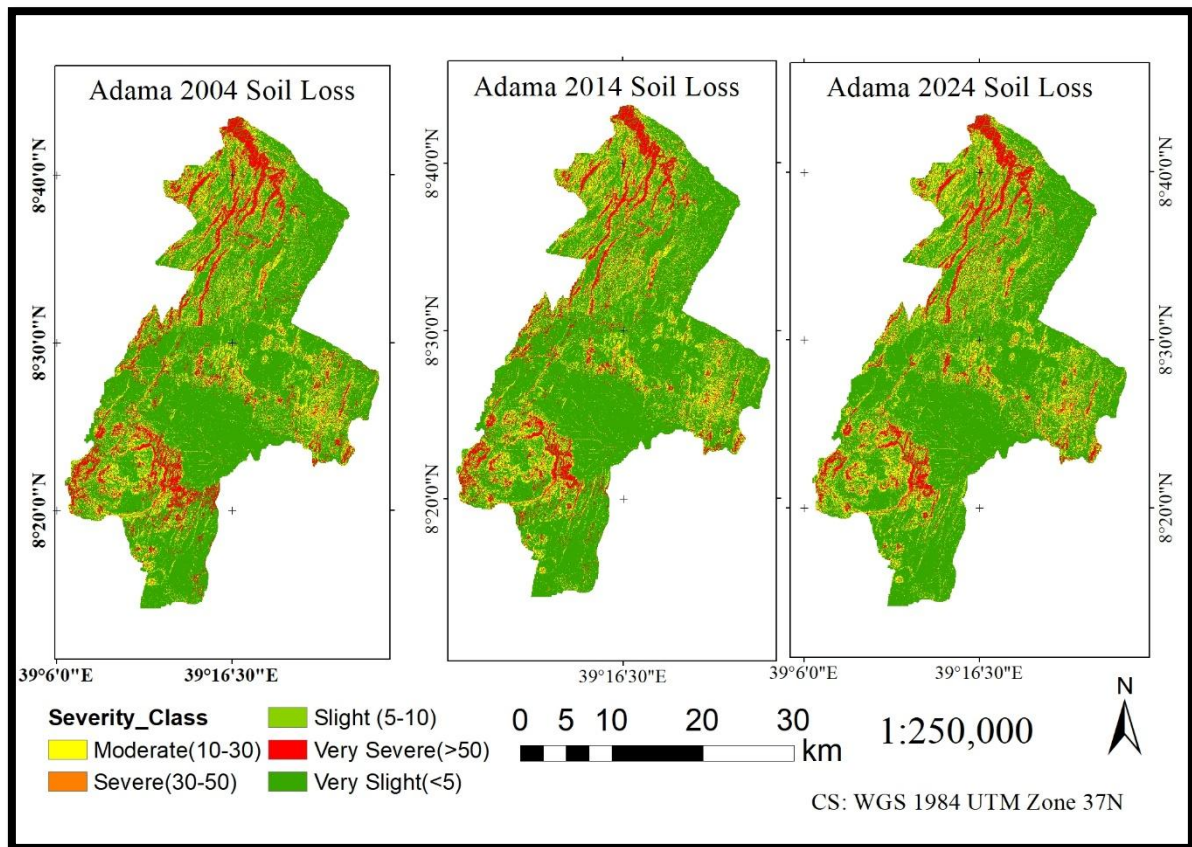


Figure 13 Soil erosion severity rates of 2004, 2014 and 2024

In line with the findings of this study, Gashaw et al. (2020) found that 59% of the land area falls into low soil erosion hazard category while 3.6%, 8.9%, 7.6% and 20.9% of the areas falls into slight, Moderate, Severe and very severe soil erosion hazard categories in Gilgel Abay watershed, Upper Blue Nile basin. Negese (2021) in the Chereti Watershed of Northeastern Ethiopia, found that 56.3%, 12.9%, 26.9%, 3.9% and 0.1% of the area falls into Very slight, slight, Moderate, Severe and very severe soil erosion categories, respectively. Similarly, Girmay et al. (2020) reported that 67.18% of the Agewmariam Watershed was under slight erosion, while 5.43%, 5.78%, 3.25% and 18.36% of the area fall into slight, moderate, severe, and very severe soil erosion classes respectively.

Habtamu (2018), in the Huluka Watershed, Central Ethiopia, found that 73% of the watershed area was under low to moderate erosion risk, while 6% underwent severe erosion. This aligns closely with the findings of the present study, where approximately 75% of the area fell under very slight to slight erosion risk in 2024.

In contrast, Gurebiyaw et al. (2018) reported a much higher proportion of high erosion risk (75.45%) in the Gumara Maksegnit watershed, suggesting more severe erosion conditions

compared to the study area. This indicates that the erosion status in the present study area is less critical when compared to other northern Ethiopian watersheds.

4.5 Impacts of Land Use Land Cover on soil erosion

To assess the impacts of land use/land cover change (LULCC) on soil erosion, the mean soil loss for each land use type was evaluated based on the relationship between LULC and soil erosion processes. This was done by integrating the soil erosion severity map with LULC maps for 2004, 2014, and 2024. Zonal Statistics (Spatial Analyst tool) was used to extract the mean soil loss values by overlaying the soil loss raster with each LULC class. The calculation of the mean soil loss for each LULC class was carried out by multiplying the area of each LULC class by the mean soil loss of the study area and then dividing by the total area of the study area:

The mean soil loss estimated from each land use varies from one land use to other land use based on the area coverage of LULC classes. As detected from the result the mean soil loss of the study area was different through all study period (Table 18). The mean soil loss of the study area decreased over time, with values of 31.59 ton/ha/yr in 2004, 24.5 ton/ha/yr in 2014, and 22.3 ton/ha/yr in 2024. This decline reflects land cover improvements or conservation interventions.

Among all land use types, cultivated land contributed the highest mean soil loss: 17.97 ton/ha/yr in 2004, 17.10 ton/ha/yr in 2014, and 16.04 ton/ha/yr in 2024. The dominance of cultivated land covering over half of the total area in all study years explains its major role in erosion. Grassland and shrubland also showed notable contributions to soil erosion, though their impacts declined over time. Grassland's mean soil loss dropped from 3.93 ton/ha/yr in 2004 to 1.62 ton/ha/yr in 2024, while shrubland declined from 3.88 to 1.53 ton/ha/yr. This decline may be attributed to the reduction in area coverage or changes in vegetation density.

Forest land, bare land, and water bodies had the lowest mean soil loss. Forest cover, which declined significantly across the study period, showed a reduction in erosion contribution from 2.59 ton/ha/yr in 2004 to 0.99 ton/ha/yr in 2024, consistent with its protective vegetation role. Bare land's erosion impact also decreased sharply from 1.38 to 0.08 ton/ha/yr mainly due to shrinking coverage. Water bodies contributed the least erosion, with values consistently below 0.5 ton/ha/yr.

Table 18 Mean soil loss of the study area with regard to LULC classes

S.N	Class_name	Area2004 Hectar	Area2014 Hectar	Area2024 Hectar	MEAN 2004	MEAN 2014	MEAN 2024
1	Settlement	4,318.54	5,714.99	7,936.66	1.51	1.55	1.96
2	Cultivated Land	51,231.53	62,885.54	64,793.86	17.97	17.10	16.04
3	Forest Land	7,396.10	4,025.51	3,985.89	2.59	1.09	0.99
4	Grass Land	11,211.56	7,784.15	6,561.78	3.93	2.12	1.62
5	Shrubland	11,074.06	6,535.45	6,168.88	3.88	1.78	1.53
6	Bare land	3,933.78	2,703.62	322.16	1.38	0.74	0.08
7	water Body	918.46	436.28	314.80	0.32	0.12	0.08
	Total	90,085.54	90,085.54	90,085.53	31.59	24.5	22.3

Settlements, though contributing minimal erosion initially (1.51 ton/ha/yr in 2004), showed an increase to 1.96 ton/ha/yr by 2024. This reflects the growing built up area and the associated land surface alterations that can enhance surface runoff.

Overall, cultivated land remained the main driver of soil loss in the study area throughout the study period, with increasing settlement areas and decreasing forest and grassland areas contributing to the dynamic erosion patterns observed.

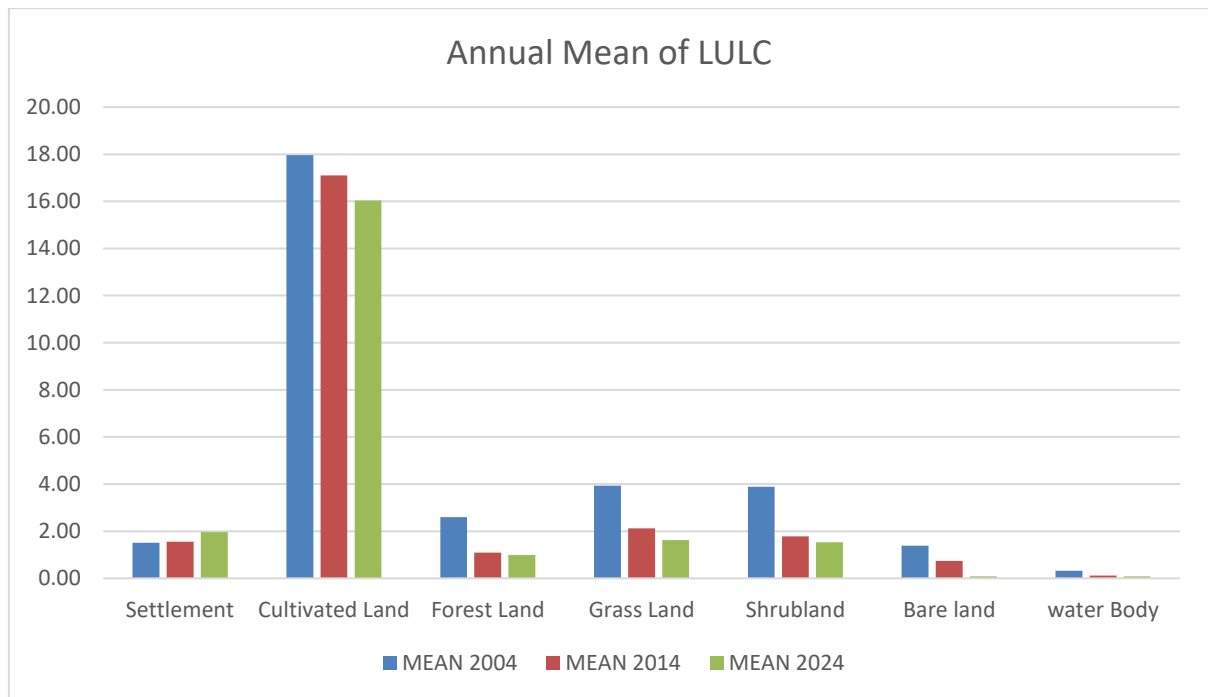


Figure 14 Mean soil loss of each LULC in 2004, 2014 and 2024

Several studies have demonstrated the significant impact of land use and land cover changes (LULCC) on soil erosion in Ethiopia. For instance, Kidane et al. (2019) reported that the expansion of cultivated land at the expense of forest and shrubland led to an increase in mean annual soil loss from 25.8 ton/ha/yr in 1973 to 30.3 ton/ha/yr in 2015 in the Guder Sub-watershed, part of the Blue Nile Basin. Similarly, Gashaw et al. (2019) found that over three decades (1985–2015), the rapid expansion of cultivated and builtup areas, replacing forest, shrubland, and grassland, increased the average soil erosion rate from 35.5 ton/ha/yr in 1985 to 55 ton/ha/yr in 2015 in the Andassa Watershed, Upper Blue Nile Basin. Furthermore, studies emphasized that land use changes especially deforestation and agricultural expansion have played a major role in accelerating soil erosion across various regions of Ethiopia.

CHAPTER FIVE

5. CONCLUSION AND RECOMMENDATION

5.1 conclusion

This study evaluated the impact of land use and land cover change (LULCC) on soil erosion in the Adama Woreda over a 20 year period (2004–2024) using the Revised Universal Soil Loss Equation (RUSLE) integrated with GIS and remote sensing. The analysis demonstrated that land cover dynamics significantly influenced soil erosion rates across the study area. Between 2004 and 2024, significant changes were observed in LULC distribution. Cultivated land increased markedly from 51,231.53 ha in 2004 to 64,793.86 ha in 2024, and settlement areas expanded from 4,318.54 ha to 7,936.66 ha. These increases occurred mainly at the expense of forest land, which decreased from 7,396.10 ha to 3,985.89 ha, and grassland, which declined from 11,211.56 ha to 6,561.78 ha. Shrubland and bare land also decreased significantly, with bare land shrinking from 3,933.78 ha in 2004 to just 322.16 ha in 2024. These LULC shifts are largely due to human driven expansion.

The soil erosion model incorporated five RUSLE factors: rainfall erosivity (R), soil erodibility (K), slope length and steepness (LS), cover management (C), and conservation practice (P). The R-factor was derived from long-term rainfall data, the K-factor from soil property maps, the LS-factor from DEM analysis, and C and P-factors were assigned based on land cover types and conservation assumptions. These factors were multiplied in a GIS environment to estimate annual soil loss spatially across the Woreda. The model results indicated that both mean annual soil loss and total soil loss in the study area decreased consistently over the 20 year period. In 2004, the mean annual soil loss was estimated at 31.59 ton/ha/yr, resulting in a total soil loss of approximately 2,846,283.49 tons/year. By 2014, this declined to a mean of 24.5 ton/ha/yr with a total of 2,207,262.68 tons/year, and further dropped in 2024 to 22.3 ton/ha/yr, with a total soil loss of 2,009,318.09 tons/year.

The steady decline in soil loss may reflect the combined effects of decreasing bare land, changes in land management practices, and shifts in LULC composition, particularly the reduction of erosion prone areas such as forest, grassland, and shrubland, and possible conservation efforts in cultivated lands. Nevertheless, cultivated land remained the dominant contributor to erosion throughout the study period. Despite improvements, a

substantial portion of the study area continued to face erosion risks, highlighting the need for sustained and area specific soil conservation strategies to further reduce erosion and maintain soil productivity.

5.2 Recommendations

This study shown that land use and land cover changes significantly affect soil erosion in Adama Woreda. While total and average soil loss decreased from 2004 to 2024, erosion on cultivated lands and settlement expansion into sensitive areas remain key concerns. To address these issues and promote sustainable land management, the following recommendations are made:

➤ **Use of Erosion Risk Maps:**

The erosion risk maps developed in this study should be used by the Woreda Office of Agriculture and planners to guide conservation efforts, helping prioritize highrisk areas and allocate resources effectively.

➤ **Target Priority Areas:**

Around 24.91% of the Woreda is under moderate to very severe erosion risk. Cultivated lands on steep slopes should be targeted first for conservation interventions.

➤ **Awareness and Capacity Building for Land Users:**

The Woreda Office of Agriculture should provide ongoing training and awareness campaigns for farmers, focusing on soil erosion causes and

➤ **Conservation and Land Restoration in High Risk Areas:**

The Woreda Office of Agriculture, with support from NGOs and local communities, should implement practices such as watershed management, construction of stone bunds, and contour plowing on slopes exceeding 15%. In addition, afforestation and tree planting initiatives such as the Green Legacy program should be expanded, particularly in steep and severely degraded areas, to stabilize soil, prevent further erosion, and restore ecosystem functions.

➤ **Encourage Further Research:**

Future studies should incorporate field based soil loss measurements to validate RUSLE estimates and integrate socioeconomic data to better understand the underlying drivers of land cover change.

Reference

- Aklile, N. (2014). Impact of Land Use Land Cover Change on Soil Erosion Risk: The Case Of Denki River Catchment Of Ankober Woreda
- Alam, A., Bhat, M. S., & Maheen, M. (2020). Using Landsat satellite data for assessing the land use and land cover change in Kashmir valley. *GeoJournal*, 85(6), 1529-1543.
- Alemayehu, B. (2015). GIS and Remote Sensing Based Land Use/Land Cover Change Detection and Prediction in Fagita Lekoma Woreda, Awi Zone, North Western Ethiopia.
- Alemayehu, F., Tolera, M., & Tesfaye, G. (2019). Land use land cover change trend and its drivers in Somodo watershed South Western, Ethiopia. *African Journal of Agricultural Research*, 14(2), 102-117.
- Ameztegui, A., Coll, L., Brotons, L., & Ninot, J. M. (2016). Land-use legacies rather than climate change are driving the recent upward shift of the mountain tree line in the P yrenees. *Global Ecology and Biogeography*, 25(3), 263-273.
- Angulo-Martinez, M., Beguería, S., Navas, A., & Machin, J. (2012). Splash erosion under natural rainfall on three soil types in NE Spain. *Geomorphology*, 175, 38-44.
- Anissa, G., Shinji, S., Fumio, W., Sawahiko, S. & Hiromichi, T. (2011). Soil Erosion Assessment Using USLE in East Shewa, Ethiopia.
- Annisa, B., Heluf, G., Yimer, F., & Mahmoud, M. (2011). Effects of land use change on soil erosion and conservation practices in East Shewa. *Journal of Environmental Management*, 92(4), 982–989.
- Arowolo, A. O., & Deng, X. (2018). Land use/land cover change and statistical modelling of cultivated land change drivers in Nigeria. *Regional environmental change*, 18(1), 247-259.
- Ayele, G., Hayicho, H., and Alemu, M. (2019). Land Use Land Cover Change Detection and Deforestation Modeling: In Delomena District of Bale Zone, Ethiopia. *Journal of Environmental Protection*, 10(4), 532-561

- Bahrawi, J. A., Elhag, M., Aldhebiani, A. Y., Galal, H. K., and Hegazy, E. (2016). Soil erosion estimation using remote sensing techniques in Wadi Yalamlam Basin, Saudi Arabia. *Advances in Materials Science and Engineering*, 2016.
- Balasubramanian, A. (2017). Digital elevation model (DEM) in GIS. *University of Mysore*, https://www.researchgate.net/publication/319454004_Digital_Elevation_Model_Dem_in_GIS.
- Baqa, M. F., Chen, F., Lu, L., Qureshi, S., Tariq, A., Wang, S., & Li, Q. (2021). Monitoring and modeling the pattern and trends of Urban growth using Urban Sprawl matrix and CA markov model: A case study of Karachi, Pakistan. *Land*, 10(7), 700.
- Bekele, B., Muluneh, A., & Wondrade, N. (2019). Geographic Information System (GIS) based soil loss estimation using Universal Soil Loss Equation Model (USLE) for soil conservation planning in Karesa Watershed, Dawuro Zone, South West Ethiopia. *International Journal of Water Resources and Environmental Engineering*, 11(8), 143-158.
- Bekele, M. (2021). Geographic information system (GIS) based soil loss estimation using RUSLE model for soil and water conservation planning in Anka Shashara watershed, southern Ethiopia. *International Journal of Hydrology*, 5(1), 9–21. <https://doi.org/10.15406/ijh.2021.05.00260>
- Belay, T. T., (2014). Perception of farmers on soil erosion and conservation practices in Dejen District, Ethiopia. *International Journal of Environmental Protection and Policy*.
- Belayneh, M., Yirgu, T., & Tsegaye, D. (2019). Potential soil erosion estimation and area prioritization for better conservation planning in Gumara watershed using RUSLE and GIS techniques'. *Environmental Systems Research*, 8(1), 1-17.
- Belete, T. (2017). Impact of Land-Use/Land-Cover Changes on Land Surface Temperature in Adama Zuria Woreda, Ethiopia, Using Geospatial Tools.
- Cresswell, J. W. (2021). A consise introduction to mixed methods research. *SAGE publications*, 2021.

- Cresswell, J. W. and Creswell, J. D. (2017). Research design: Qualitative, quantitative, and mixed methods approaches. *Sage publications*, 2017.
- Dagnachew, M., Moges, M. A., & Tamene, L. (2023). Soil erosion hotspots and conservation prioritization using RUSLE and geospatial techniques in Ethiopia. *Heliyon*, 9(6), e17123. <https://doi.org/10.1016/j.heliyon.2023.e17123>
- Demeke, G. G., & Andualem, T. G. (2025). Soil loss estimation in Ethiopia: A comprehensive review of the RUSLE model integrated with geospatial technologies. *Discover Sustainability*, 6, 334. <https://doi.org/10.1007/s43621-025-01037-8>
- Desalew, M. & H. Gangadhara, B. (2017). Integration of geospatial technologies with RUSLE for analysis of land use/cover change impact on soil erosion: case study in Rib watershed, north-western highland Ethiopia
- Dregne, H. E. (1990). Erosion and soil productivity in Africa. *Journal of Soil and Water Conservation*, 45(4), 431-436.
- Esa, E., Assen, M., & Legass, A. (2018). Implications of land use/cover dynamics on soil erosion potential of agricultural watershed, northwestern highlands of Ethiopia. *Environmental Systems Research*, 7(1), 21.
- Estifanos, A. (2014). Assessment of Micro-Watershed Vulnerability for Soil Erosion in Ribb Watershed using GIS and Remote Sensing. MSc Thesis. Mekelle University, Ethiopia.
- FAO, (2003). The Digital Soil Map of the World. *World Soil Resources Report*
- FAO, (2015). Status of the World's Soil Resources. Intergovernmental Technical Panel on Soils.
- FAO. (2001). Lecture notes on the major soils of the world. *World Soil Resources Report* 94. Rome: FAO.
- Gashaw, T., Tulu, T., Argaw, M. & W. Worqlul, A. (2017). Evaluation and prediction of land use/land cover changes in the Andassa watershed, Blue Nile Basin, Ethiopia. *Environmental systems research*, 6(1), 1-15.

- Gashaw, T., Tulu, T., Argaw, M. & Worqlul, A. W. (2019). Modeling the impacts of land use–land cover changes on soil erosion and sediment yield in the Andassa watershed, upper Blue Nile basin, Ethiopia. *Environmental Earth Sciences*, 78(24), 1-22.
- Gashaw, T., Tulu, T., Argaw, M., & Worqlul, A. (2020). Modeling the impacts of land use/land cover change on ecosystem services in Ethiopia. *Environmental Systems Research*, 9(1), 1-17.
- Gashaw, T., Worqlul, A. W., Dile, Y. T., Addisu, S., Bantider, A., & Zeleke, G. (2020). Evaluating potential impacts of land management practices on soil erosion in the Gilgel Abay watershed, upper Blue Nile basin. *Heliyon*, 6(8), e04777.
- Gebreselassie, S., Molla, M. B., & Gashaw, T. (2020). Soil erosion modeling using RUSLE and GIS in Ethiopia. *Environmental Systems Research*, 9, 27. <https://doi.org/10.1186/s40068-020-00180-x>
- 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.
- Gemechu, T. and Hunde, K. K. (2015). Assessment on Farmers' Practices on Soil Erosion Control and Soil Fertility Improvement in Rift Valley Areas of East Shoa and West Arsi Zones of Oromia, Ethiopia. *EC Agriculture*, 2, 391-400.
- Girma, T., Alemayehu, G., & Teka, D. (2023). Land use and land cover change detection and its impact on ecosystem service values in Central Ethiopia. *Environmental Challenges*, 10, 100669. <https://doi.org/10.1016/j.envc.2022.100669>
- Girmay, G., Moges, A., & Muluneh, A. (2020). Estimation of soil loss rate using the USLE model for Agewmariyam Watershed, northern Ethiopia. *Agriculture & Food Security*, 9(1), 1-12.
- Guder, A. C., & Kabeta, W. F. (2025). Evaluation of future land use change impacts on soil erosion for Holota watershed, Ethiopia. *Scientific Reports*, 15, 6782. <https://doi.org/10.1038/s41598-025-91381-6>

- Gurebiyaw, K., Addis, K. H., Teklay, A. (2018). Assessment of Spatial Soil Erosion Susceptibility Based on the CORINE Model in the Gumara-Maksegnit Watershed Ethiopia
- 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, 49-67.
- Guzha, A. C., Rufino, M. C., Okoth, S., Jacobs, S., & Nóbrega, R. L. B. (2018). Impacts of land use and land cover change on hydrological and soil erosion processes in the Upper Blue Nile Basin, Ethiopia. *Science of the Total Environment*, 622–623, 701–714.
- Habtam, A. F., (2018). Assessment of Soil Erosion by RUSLE Model Using Remote sensing and GIS Techniques: A Case Study of Huluka Watershed, Central Ethiopia.
- Hailemariam, S. N, Soromessa, T. & Teketay, D. (2016). Land use and land cover change in the Bale Mountain Eco-Regional of Ethiopia during 1985 to 2015. *Land*, 5(4), 41.
- Hurni H. 1985. Soil Conservation Manual for Ethiopia. Ministry of Agriculture, Addis Ababa.
- Hurni, H. (1985). Erosion–productivity–conservation systems in Ethiopia. Proceedings of the 4th International Conference on Soil Conservation, Maracay, Venezuela.
- Hurni, H. (1988). Degradation and conservation of the resources in the Ethiopian highlands. *Mountain research and development*, 123-130.
- Iacobescu, O., Barnoaiea, I., & Bofu, C. (2012). An up-to-date land degradation inventory in Suceava Plateau using digital orthophotographs. *Environmental Engineering & Management Journal (EEMJ)*, 11(9).
- Igwe, P. U., Onuigbo, A. A., Chinedu, O. C., Ezeaku, I. I., & Muoneke, M. M. (2017). Soil erosion: a review of models and applications. *International Journal of Advanced Engineering Research and Science*, 4(12), 237341.
- Islam, K., Jashimuddin, M., Nath, B., and Nath, T. K. (2018). Land use classification and change detection by using multi-temporal remotely sensed imagery: The case of

- Chunati wildlife sanctuary, Bangladesh. *The Egyptian Journal of Remote Sensing and Space Science*, 21(1), 37-47.
- Kairis, O., Karavitis, C., Kounalaki, A., Salvati, L., & Kosmas, C. (2013). The effect of land management practices on soil erosion and land desertification in an olive grove. *Soil Use and Management*, 29(4), 597-606.
- Kairis, O., Karavitis, C., Salvati, L., Kounalaki, A., Fasouliotis, D., & Kosmas, C. (2013). Exploring the impact of overgrazing on soil erosion and land degradation in a semi-arid Mediterranean environment. *Land Degradation & Development*, 26(1), 77–85.
- Kassaw, M., & Asfaw, Z. (2022). GIS and Remote Sensing-Based Analysis of Land Use/Land Cover Dynamics and Its Implication on Soil Loss in Upper Awash Watershed, Ethiopia. *Applied Geomatics*, 14(4), 777–791. <https://doi.org/10.1007/s12518-022-00461-3>
- Kebede, W., Habitamu, T., Efrem, G. and Fantaw, Y. 2015. Soil erosion risk assessment in the Chaleleka wetland watershed, Central rift valley of Ethiopia. *Environmental System Research* 4(5):1–12.
- Keesstra, S., Pereira, P., Novara, A., Brevik, E. C., Azorin-Molina, C., Parras-Alcántara, L., ... & Cerdà, A. (2016). Effects of soil management techniques on soil water erosion in apricot orchards. *Science of the Total Environment*, 551, 357-366.
- Kim, Y. (2014). Soil erosion assessment using GIS and revised universal soil loss equation (RUSLE). *CE 394K GIS in Water Resources*, David R. Maidment, 5.
- Koch, A., McBratney, A., Adams, M., Field, D., Hill, R., Crawford, J., ... & Angers, D. (2013). Soil security: solving the global soil crisis. *Global Policy*, 4(4), 434-441.
- Kolecka, N., Kozak, J., & Dobosz, M. (2022). Support Vector Machine classification of Landsat imagery for land cover mapping: A case study from Central Europe. *Remote Sensing*, 14(9), 2131. <https://doi.org/10.3390/rs14092131>
- Li, R., & Haiyan, T. (2016). Effects of rainfall characteristics on soil erosion in Ethiopia: A meta-analysis. *Catena*, 145, 31–38.
- Li, Z., and Fang, H. (2016). Impacts of climate change on water erosion: a review

- Li, Z., Cheng, X., and Han, H. (2020). Future impacts of land use change on ecosystem service under different scenarios in the ecological areas, Beijing China. *Forest*, 11(5), 584.
- Lieskovský, J., & Kenderessy, P. (2014). Modelling the effect of vegetation cover and different tillage practices on soil erosion in vineyards: a case study in Vráble (Slovakia) using WATEM/SEDEM. *Land Degradation & Development*, 25(3), 288-296.
- Lieskovsky, J., & Kenderessy, P. (2014). Modelling the effects of vegetation cover and terrain on soil erosion. *Land Degradation & Development*, 25(4), 358–367.
- Lu, D., Morgan, E., Hetrick, S., and Li, G. (2011). Land use land cover change detection. *Advances in Environmental Remote sensing sensors*. CRC press Taylor and Francis Group, New York (2011): 273-290.
- Masha, M., Belayneh, M., & Tedila, G. (2023). Assessment of land use land cover dynamics and its contributing factors in Adama District, central Ethiopia. *International Journal of Environmental Quality*, 55, 16917. <https://doi.org/10.6092/issn.2281-4485/16917>
- Masha, M., Belayneh, M., & Tedila, G. (2023). Assessment of land use land cover dynamics and its contributing factors in Adama district, central Ethiopia. *EQA - International Journal of Environmental Quality*, 55(1), 42–54
- Masqoom, A., Aslam, B., Hassan, U., Kazmi, Z. A., Sodangi, M., Tufail, R. F., & Farooq, D. (2020). Geospatial Assessment of Soil Erosion Intensity and Sediment Yield Using the Revised Universal Soil Loss Equation (RUSLE) Model. *ISPRS International Journal of Geo-Information*, 9(6), 356.
- Mathewos, M. (2023). Soil erosion variations along land use and land cover dynamics in Matenchose watershed, Rift Valley Basin, Southern Ethiopia. *Natural Resource Modeling*, 36(1), e12379.
- Mestawot, A. (2015). Soil Erosion Risk Assessment Using Rusle, Mce And Gis In Gerbi River Watershed, Ethiopia.

- Meyer, W.B. 1995. Past and Present Land-Use and Land-Cover in the U.S.A. *Consequences: The nature and implications of environmental change*, 1(1).
- Millward AA, Mersey JE. 1999. Adapting the RUSLE to Model Soil Erosion Potential in a Mountainous Tropical Watershed. *Catena* 38: 109–129.
- Moges, D. M. and Bhat, H. G. (2017). Integration of geospatial technologies with RUSLE for analysis of land use/cover change impact on soil erosion: case study in Rib watershed, north-western highland Ethiopia. *Environmental Earth Sciences*, vol. 76, no. 22.
- Moges, D. M., Kmoch, A., Bhat, G. H., and Uuema, E. (2020). Future soil loss in highland Ethiopia under changing climate and land use. *Regional Environmental Change*, 20(1), 1-14.
- Moisa MB, Dejene IN, Merga BB, Gameda DO. Soil loss estimation and prioritization using geographic information systems and the RUSLE model : a case study of the Anger River sub-basin, Western Ethiopia. *J Water Climate Change*. 2022;13(3):1170–84. <https://doi.org/10.2166/wcc.2022.433>.
- Molla, T. and Sisheber, B. 2017. Estimating soil erosion risk and evaluating erosion control
- Montanarella, L., Badraoui, M., Chude, V., Costa, I. D. S. B., Mamo, T., Yemefack, M., ... & Zhang, G. L. (2015). Status of the world's soil resources: main report. *Embrapa Solos-Livro científico (ALICE)*.
- Montgomery, D. R. (2007). Soil erosion and agricultural sustainability. *Proceedings of the National Academy of Sciences*, 104(33), 13268-13272.
- Morgan, R. P. C. (1995). Soil erosion and soil conservation. *Essex: Longman*
- Naschen, K., Diekkrüger, B. Evers, M., Hollermann, B. Steinbach, S. and Thonfeld, F. (2019). The impact of land use/land cover change (LULCC) on water resources in a tropical catchment in Tanzania under different climate change scenarios. *Sustainability*, 11(24), 7083.
- Negese, G. (2021). Soil erosion in Ethiopia: Extent, causes and management strategies. *Ethiopian Journal of Environmental Studies*, 13(1), 34–44.

- Negese,(2021). Impacts of Land Use and Land Cover Change on Soil Erosion and Hydrological Responses Ethiopia. *Applied and Environmental science*, 2021.
- Ochoa, P. A. A., Fries, A., Mejia, D., Burneo, J. I., Ruíz-Sinoga, J. D., & Cerdà, A. (2016). Effects of climate, land cover and topography on soil erosion risk in a semiarid basin of the Andes. *Catena*, 140, 31-42.
- Ochoa, P. A., Fries, A., Mejia, D., Burneo, J. I., Ruíz-Sinoga, J. D., & Cerdà, A. (2016). Effects of climate, land cover and topography on soil erosion risk in the Andes. *Catena*, 140, 31–42.
- Osman, K. T. (2014). *Soil degradation, conservation and remediation*. Springer Netherlands.
- Ouyang, W., Hao, F., Skidmore, A. K., Toxopeus, A. G., & Wang, X. (2018). Soil and water conservation effects of land use change in a catchment of the Loess Plateau, China. *International Journal of Sediment Research*, 33(4), 391–402.
- Ouyang, W., Wu, Y., Hao, Z., Zhang, Q., Bu, Q., & Gao, X. (2018). Combined impacts of land use and soil property changes on soil erosion in a mollisol area under long-term agricultural development. *Science of the total environment*, 613, 798-809.
- Panagos, P., Ballabio, C., Borrelli, P., Meusburger, K., Klik, A., Rousseva, S., ... & Aalto, J. (2015). Rainfall erosivity in Europe. *Science of the Total Environment*, 511, 801-814.
- Panagos, P., Borrelli, P., Poesen, J., Ballabio, C., Lugato, E., Meusburger, K., ... & Alewell, C. (2015). The new assessment of soil loss by water erosion in Europe. *Environmental science & policy*, 54, 438-447
- Patil, J. R., (2018). Spatial Techniques for Soil Erosion Estimation: Remote Sensing and GIS Approach. *Department of Soil and Water Engineering*.
- Patil, R. J., Sharma, S. K., & Tignath, S. (2015). Remote Sensing and GIS based soil erosion assessment from an agricultural watershed. *Arabian Journal of Geosciences*, 8(9), 6967-6984.
- Perivic, V., Kadovic, R., Djurdjevic, V., Braunovic, S., Cakmak, D., Mitrovic, M., & Pavlovic, P. (2019). Effects of changes in climate and land use on soil erosion: a

- case study of the Vranjska velly, Serbia. *Regional Environmental Change*, 19(4), 1035-1046.
- Piyathilake, I. D. U. H., Sumudumali, R. G. I., Udayakumara, E. P. N., Ranaweera, L. V., Jayawardana J. M. C. K., & Gunatilake, S. K. (2021). Modeling predictive assessment of soil erosion related hazards at the Uva province in Sri Lanka. *Modeling Earth Systems and Environment*, 7(3), 1947-1962.
- Renard, K. G., Foster, G. R. (1983). Soil conservation: principles of erosion by water. Dry land agriculture/editors, HE Dregne and WO Willis.
- Renard, K. G., Foster, G. R., Weesies, G. A., McCool, D. K., & Yoder, D. C. (1997). Predicting soil erosion by water. *Agriculture handbook*, 703.
- Renard, K. G., Foster, G. R., Weesies, G. A., McCool, D. K., & Yoder, D. C. (1997). Predicting soil erosion by water: A guide to conservation planning with the Revised Universal Soil Loss Equation (RUSLE). USDA Agriculture Handbook No. 703.
- Rupesh, K. (2017). Soil erosion and conservation: A global review. *Environmental Management Reports*, 12(2), 56–65.
- Ruth, D. (2018). Assessment of Soil Erosion Risk Using Gis And Rusle In Meja Watershed, West Shewa, Ethiopia
- Salghuna, N. N., Prasad, P. R. C. & Kumari, J. A. (2018). Asssessin the impact of land use and land cover changes on the remnant patches of kondapalli reserve forest of the Eastern Ghats, Andhra Pradesh, Idia. *The Egyptian Journa of Remote Sensing and Space Science*, 21(3), 419-429.
- Seifu, T. K., Woldesenbet, T. A., Alemayehu, T., & Ayenew, T. (2023). Spatio-Temporal Change of Land Use/Land Cover and Vegetation Using Multi-MODIS Satellite Data, Western Ethiopia. *The Scientific World Journal*, 2023, Article ID 7454137.
- Senanayake, S., Pradhan, B., Huete, A. and Brennan, J. (2020). A Review on Assessing and Mapping Soil Erosion Hazard Using Geo-Informatics Technology for Farming System Management.

- Shangguan, W., Dai, Y., Duan, Q., Liu, B., & Yuan, H. (2014). A global soil data set for earth system modeling. *Journal of Advances in Modeling Earth Systems*, 6(1), 249-263.
- Shiferaw, A. 2011. Evaluating the Land Use and Land Cover Dynamics in Borena Woreda of South Wollo Highlands, Ethiopia. *Journal of Sustainable Development in Africa*, 13 (1): 87-107.
- Singh, A. (1989). Review article digital change detection techniques using remotely-sensed data. *International journal of remote sensing*, 10(6), 989-1003.
- Solid Earth*, 8, 13-25.
- Souza, V. F. C. D., Bertol, I., & Wolschick, N. H. (2017). Effects of soil management practices on water erosion under natural rainfall conditions on a Humic Dystrudept. *Revista Brasileira de Ciência do Solo*, 41.
- Sun, L., Fang, H., Qi, D., Li, J., & Cai, Q. (2013). A Review on Rill Erosion Process and Its Influencing Factors. *Chinese Geographical Science*, (4).
- Tadesse, T., & Tulu, T. (2021). Analysis of land use/land cover changes and their driving forces: The case of Sebeta Hawas district, Central Ethiopia. *Environmental Systems Research*, 10(1), 1–16. <https://doi.org/10.1186/s40068-021-00232-3>
- Tamene, N. (2019). Potential Soil Loss Estimation Using RUSLE and MCDE Model for conservation planning at the watershed level: In Gilegel Beles watershed, Abbay Basin, Ethiopia (Doctoral dissertation).
- Tamirat, S. (2019). Gis And Remote Sensing Based Assessment of Land Use Land Cover Change And Its Impact on Soil Erosion In Chercher Watershed: West Harerge, Ethiopia.
- Teferi E, Bewket W, Uhlenbrook S, Wenninger J (2013) Understanding recent land use and land cover dynamics in the source region of the Upper Blue Nile, Ethiopia:Spatially explicit statistical modeling of systematic transitions. *Agriculture, Ecosystems and Environment* ,165: 98– 117.

- Tegegne, M. & Biniam, S. (2016). Estimating soil erosion risk and evaluating erosion control measures for soil conservation planning at Koga watershed in the highlands of Ethiopia.
- Terefe, B., Melese, T., Tsegaye, A., Afework, A., Yibeltal, T., Anagaw, A., Temesgen, F., Belay, T., Assefa, G., & Mencho, B. B. (2025). Soil loss estimation in Ethiopia: A comprehensive review of the RUSLE model integrated with geospatial technologies. *Discover Sustainability*, 6, 334. <https://doi.org/10.1007/s43621-025-01037-8>
- Tesfaye, A. (2015). GIS-Based Time Series Assessment of Soil Erosion Risk using RUSLE Model.
- Tesfaye, G., Debebe, Y., and Fikirte, K. (2018). Soil Erosion Risk Assessment Using GIS Based USLE Model for Soil and Water Conservation Planning in Somodo Watershed, South West Ethiopia. *International Journal of Environmental & Agriculture Research*, 4(5), 35-43.
- Tesfaye, S. (2015). Estimating soil loss using RUSLE and GIS in Ethiopia: A case of Koga watershed. *Ethiopian Journal of Natural Resources*, 17(1), 35–49.
- Teshome, A., Halefom, A. and Gadissa, E. (2019). An Analysis On Land Use/Land Cover Change Using Remote Sensing And GIS - A Case Study In Amjaye District, South Gondar, Ethiopia
- Tessema, W., Tulu, T., & Belayneh, M. (2020). Estimating soil erosion using RUSLE and GIS in Ethiopia's highlands. *International Journal of Environmental Studies*, 77(4), 620–635. <https://doi.org/10.1080/00207233.2019.1688477>
- Thapa, P. (2020). Spatial Estimation of Soil Erosion Using RUSLE Modeling: A case study of Dolakha District, Nepal.
- Thapa, R. B., Murayama, Y., & Alehegn, E. (2020). Soil erosion modeling and mitigation planning in the Upper Blue Nile basin, Ethiopia. *Sustainability*, 12(9), 3873.
- Tilahun, H., Taddese, G., Melese, A., and Mebrate, T. (2018). Assessment of spatial soil erosion hazard in Ajema Watershed, North Shewa Zone, Ethiopia. *Advances plants and Agricultural Research*, 8, 552-558.

- Tiruneh, G., and Ayalew, M. (2015). Soil loss estimation using geographic information system in Enfraz watershed for soil conservation planning in highlands of Ethiopia. *International Journal of Agricultural Research, Innovation and Technology*, 5(2), 21-30
- Tsegay , A.G. (2015). Assessing Runoff and Soil Erosion by Water Using GIS and RS Techniques at Midmar Catchment, Northern Ethiopia. *Institute of Geo-information and Earth Observation Sciences (I-GEOS)*
- Tsegaye, B. (2019). Effect of Land Use and Land Cover Changes on Soil Erosion in Ethiopia. *International Journal of Agricultural Science and Food Technology*.
- Tukura, K. A., & Akalu, T. Y. (2019). Soil erosion: Mechanisms, assessment and control in Ethiopia. *African Journal of Agricultural Research*, 14(32), 1532–1542.
- Tukura, N. G., & Akalu, M. M. (2019). Soil Erosion Risk Assessment Due to Land Use. *Journal of Sedimentary Environments*, 4(4), 379-386.
- Tumebo, A. A. (2017). Land Use and Land Cover Change Detection Analysis using Remote Sensing Techniques: The Case of Hawassa Town, Southern Ethiopia (Doctoral dissertation, M. Sc. thesis).
- Twisa, S., and Buchroithner, M. F. (2019). Land-Use and Land-Cover (LULC) Change Detection in Wami River Basin, Tanzania. *Land*, 8(9), 136.
- Wang, G., Gertner, G. Z., Fang, S., & Anderson, A. B. (2014). Mapping soil erosion and sediment yield using RUSLE, GIS and remote sensing for a large-scale basin. *Water*, 6(12), 3515–3535.
- Wang, S., Zhang, Z., & Wang, X. (2014). Land use change and prediction in the Baimahe Basin using GIS and CA-Markov model. In IOP conference series: *earth and environmental science* (Vol. 17, No. 1, p. 012074).
- Wijesundara, N. C., Abeysingha, N. S. & Dissanayake, D. M. S. L. B. (2018) GIS-based soil loss estimation using RUSLE model: a case of Kirindi Oya river basin, Sri Lanka. *Modeling Earth Systems and Environment*, 4(1), 251-262.
- Williams, J.R. 1995. The EPIC Model. In Computer Models of Watershed Hydrology. *Water Resources Publications, Highlands Ranch, Colorado (1995): 909-1000.*

- Wischmeier, W. H., & Smith, D. D. (1978). Predicting rainfall erosion losses: A guide to conservation planning. USDA Agriculture Handbook No. 537.
- Wischmeier, W.H. and Smith, D.D. (1978). Predicting rainfall erosion losses, a guide to conservation planning (No. 537). *Department of Agriculture, Science and Education Administration*.
- Woldemariam, G. and Harka, A. (2020). Effect of land use and land cover change on soil erosion in erer sub-basin, northeast Wabi Shebelle Basin, Ethiopia.
- Woldemariam, G. W., Iguala, A. D., Tekalign, S., & Reddy, R. U. (2018). Spatial modeling of soil erosion risk and its implication for conservation planning: the case of the Gobeles watershed, east Hararghe zone, Ethiopia. *Land*, 7(1), 25.
- Yesuph, A. Y., and Dagnew, A. B. (2020). Soil erosion mapping and severity analysis based on RUSLE model and local perception in the Beshilo Catchment of the Blue Nile Basin, Ethiopia. *Environmental Research System*, 8(1), 1-21.
- Yimer, A. K., Haile, A. T., Hatiye, S. D., & Azeref, A. G. (2020). Seasonal effect on the accuracy of Land use/Land cover classification in the Bilate Sub-basin, Abaya-Chamo Basin, Rift valley Lakes Basin of Ethiopia. *Ethiopian Journal of Water Science and Technology*, 3, 23-50.
- Yohannes, H., Elias, E., & Karlun, E. (2021). Land use and land cover changes and their effects on the landscape of Abaya-Chamo Basin, Southern Ethiopia. *Heliyon*, 7(3), e06405. <https://doi.org/10.1016/j.heliyon.2021.e06405>
- Yohannes, H., Soromessa, T., & Argaw, M. (2022). Monitoring land use and land cover changes using remote sensing and GIS: A case study of Central Rift Valley Region of Ethiopia. *The Egyptian Journal of Remote Sensing and Space Science*, 25(2), 289–299. <https://doi.org/10.1016/j.ejrs.2021.08.003>
- Zabihi, M., Mircholi, F., Motevalli, A., Darvishan, A. K., Pourghasemi, H. R., Zakeri, M. A., & Sadighi, F. (2018). Spatial modelling of gully erosion in Mazandaran Province, northern Iran. *Catena*, 161, 1-13.
- Zachar, D. (2011). Soil erosion. *Elsevier*.

- Zerihun, N., Atsushi, T., Nigussie, H., Enyew, A., Makoto, N., Mitsuru, T., Dagnachew, A., Derege, T. & Steffen, A. (2016). Farmers' Perception about Soil Erosion in Ethiopia.
- Zhan, C., Wu, F., Wu, Z., & Chi, K. T. (2019, May). Daily Rainfall Data Construction and Application to Weather Prediction. In *2019 IEEE International Symposium on Circuits and Systems (ISCAS)* (pp. 1-5). IEEE.
- Zhao, B., Zhang, L., Xia, Z., Xu, W., Xia, L., Liang, Y., & Xia, D. (2019). Effects of Rainfall Intensity and Vegetation Cover on Erosion Characteristics of a Soil Containing Rock Fragments Slope. *Advances in Civil Engineering*, 2019.
- Zhao, G., Mu, X., Wen, Z., Wang, F., & Gao, P. (2013). Soil erosion, conservation, and eco-environment changes in the Loess Plateau of China. *Land Degradation & Development*, 24(5), 499-510.
- Zhao, W., Liu, Z., Zhang, Y., Zhang, Z., & Wang, T. (2017). Effects of land use change on soil erosion in China. *Science of the Total Environment*, 599–600, 1139–1145.

APPENDICES

Rainfall Data from Ethiopia Metrology Agency

Name	Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Total Annual
Bofa	2006	5.45	29.15	59.15	110.3	15.9	56.5	226.3	182	92.6	13.7	0	36.4	827.45
Bofa	2007	2.7	58.3	118.3	195.4	41.2	21.8	145.3	248.5	56.5	0	7.8	18.2	914.00
Bofa	2008	8.2	0	0	50.7	22.8	35.7	293.7	225.9	71.7	93.7	71.2	0	873.60
Bofa	2009	64	0	42.7	5.5	19.5	146.7	80.9	170.8	40.9	67.7	0	17.6	656.30
Bofa	2010	0	229.4	149.5	94.9	18	132.8	99.5	96.6	55.6	0	0	0	876.30
Bofa	2011	0	5.5	5.6	9.8	27.5	73.6	92.2	146.8	189.8	0	46	1.9	598.70
Bofa	2012	0	0	0	25.05	20.4	41.5	402.8	228.9	123.8	2.5	2	0	846.95
Bofa	2013	5.2	0	99	40.3	23.5	58.1	396.7	179.4	121.6	18.7	11.3	0	953.80
Bofa	2014	0	4.6	117.8	4.8	36.2	4.9	132	196.5	142.5	92.8	20.4	0	752.50
Bofa	2015	0	0	1.2	1.7	117.2	182.6	78.3	155.1	83.1	6.5	26.8	9.9	662.40
Bofa	2016	0	14.3	20.2	112.3	70.5	180.3	287.7	108.4	62.9	0	4.3	0	860.90
Bofa	2017	0	14.8	59.4	87.4	67.6	19.9	319.9	193.1	109.7	2	4.3	0	878.10
Bofa	2018	0	14.7	11.3	243.2	26.3	78.4	136.6	241.5	48.7	2.4	40.2	0	843.30
Bofa	2019	0	0	44.8	112	58.3	90.3	246	138.3	217.8	48	112.3	19.1	1086.90

Bofa	2020	0	2.5	60.7	233.6	60.6	95.2	341.3	212.3	113	0	76.25	0	1195.45
Bofa	2021	0	4.7	0	172.8	59.45	92.75	293.65	175.3	165.4	24	94.275	9.55	1091.88
Bofa	2022	39.5	0	127.35	203.2	60.025	93.975	317.475	193.8	139.2	12	85.2625	4.775	1276.56
Bofa	2023	0	0	194	127.8	120.9	48.05	230.3	192.6	118	0.65	38.125	0	1070.43
											1425	39.454	8.464	903.64
Alem Tena	1987	5.75	0	118.75	87.4	181.2	0.9	119.3	172.9	123	1.3	0	0	810.50
Alem Tena	1988	11.5	0	43.5	47	5.7	85.7	161.8	200.1	172	19.4	0	1.7	748.40
Alem Tena	1989	0.9	52.6	32.3	92.6	0	123.1	105.6	198.3	136.8	11.6	0	2.5	756.30
Alem Tena	1990	0	166.9	21.1	132.4	11.9	26.3	206.7	191.75	107.85	17.6	0	1.45	883.95
Alem Tena	1991	0	32.3	11.2	29.5	16	44.4	208.95	191.75	107.85	17.6	0	1.45	661.00
Alem Tena	1993	26.9	66.8	0	158.9	39.3	59.8	312.3	185.2	78.9	23.6	0	0.4	952.10
Alem Tena	1994	0	0	8.6	25.3	17.2	117.1	206.1	126.5	188	1	16	13.2	719.00
Alem Tena	1995	0	44.8	95.2	47.5	31.5	29.9	159.8	135.6	89	5.2	0	0	638.50
Alem Tena	1996	65.4	0	100	31.1	63	113.4	197.6	153.5	92.5	0.8	0	0	817.30
Alem Tena	1997	10.4	0	32.3	85.6	9.3	39.85	194.6	151.2	70.7	48	6	0	647.95
Alem Tena	1998	7.1	21.8	36.3	102.6	33.1	49.8	216.4	190.7	52	93.4	0	0	803.20
Alem Tena	1999	2.4	0	19.7	6.8	19.2	80.8	227.5	165.6	71.8	73.05	0	0	666.85
Alem Tena	2000	0	0	0	127.1	89	51.7	207.8	144	155.8	52.7	54.2	0	882.30
Alem Tena	2001	0	24.6	158.2	15.7	113.8	113.9	212.2	155.3	72.8	0	0	0	866.50
Alem Tena	2002	1.5	35.4	24.3	82.9	15.5	45	181.1	150.7	33.1	0.5	0	19	589.00

Alem Tena	2003	19	16.7	116.3	54	29.4	84.6	392.5	105.4	96.5	0	0	21.7	936.10
Alem Tena	2004	89.4	0	58.4	174.3	0	78.8	122.9	145	110.6	40.5	0	2.5	822.40
Alem Tena	2005	32.7	1.2	100.9	130.7	39.15	55.1	103.6	134.75	136	12.5	5.5	0	752.10
Alem Tena	2006	1.2	64.9	147.9	46.4	48.9	55.3	130.1	124.5	69.4	27.7	0	15.4	731.70
Alem Tena	2007	10.1	32.45	73.95	47.8	101.5	109.05	156.6	172.2	125.5	36.8	5.2	0	871.15
Alem Tena	2008	0	0	0	36	90.1	162.8	244.8	226.8	121	31.5	44.6	0	957.60
Alem Tena	2009	120.9	0	19.6	28.8	92.95	61.3	147.6	185.75	57.5	80.4	0	0.75	795.55
Alem Tena	2010	0	55.4	134.9	58.7	95.8	81.6	185.5	144.7	64	0	16.2	1.5	838.30
Alem Tena	2011	0	0.8	45.7	0	64	85.475	157.1	235.2	216	0	16.2	0	820.48
Alem Tena	2012	0	0	0	50.7	32.2	89.35	235.35	192	247.7	0	0	0.5	847.80
Alem Tena	2013	4.2	0	129.8	4	77.2	97.1	285.2	152.3	157.7	36	1.5	0	945.00
Alem Tena	2014	0	19	46.3	4	158.1	15.5	258.9	228.3	112	90.3	1.5	0	933.90
Alem Tena	2015	0	0	15.3	0	161.7	103	146.2	178.3	51.4	1.5	3.7	0.7	661.80
Alem Tena	2016	9.8	0	9.4	8.9	179.8	137.2	360.6	104.8	88.5	30.7	15.4	0	945.10
Alem Tena	2017	0	37.4	67.3	17.8	178	39.9	240	86.2	163.3	0	0	0	829.90
Alem Tena	2018	0	5.6	96	179.6	30.1	90	161.8	173.2	22.2	0	16.7	0	775.20
Alem Tena	2019	0	0	9.7	63.9	92.2	81.6	397.1	117.6	168.4	61.8	42.6	0	1034.90
Alem Tena	2020	0	0.5	69	112	55	156.8	384	232.2	73.8	5.2	0	0	1088.50
Alem Tena	2021	1.6	8.5	0	51.2	58.4	66	268	161.8	168.9	100.5	5.4	0	890.30
Alem Tena	2022	0	0	21	71.7	53.1	99.2	152	191.1	126	50.25	0	0	764.35

Alem Tena	2023	4.4	0	211.9	92.2	47.8	163.6	299.5	126.45	96.15	0	171.8	0	1213.80
Alem Tena	2024	0	33.1	156.1	77.85	42.6	144.1	207.5	61.8	66.3	15.25	87.65	25.75	918.00
											1656	38.90783	8.29	832.89
Ejere	1980	0	25.05	44.1	63.5	23.05	83.8	224.15	255.5	113.5	30.5	3.5	51.5	918.15
Ejere	1981	0	17	227.2	57.8	3.5	23.5	240.8	212.8	230	18.6	0	0	1031.20
Ejere	1982	15.5	71.2	24.3	52.1	103.9	39.2	183.2	412.7	29.6	72.3	58	6.6	1068.60
Ejere	1983	0	37.9	96.5	85	138.5	67.4	173.4	248.8	90.1	13.4	0	10.05	961.05
Ejere	1984	0	0	7.7	5	88	97	269.1	198.2	39.3	0	0	13.5	717.80
Ejere	1985	0.5	0	17.4	61.5	91.2	8.5	394.5	210.6	93.5	15.4	0	0	893.10
Ejere	1986	0	67.8	59.5	102.7	22.9	160.7	98.3	134.4	62.5	13.1	0	0.4	722.30
Ejere	1987	0	47.7	82.9	75.3	234.3	17.8	65	214.7	31.5	10.8	0	0	780.00
Ejere	1988	3.3	20.8	12.5	16.7	117.15	46.45	166.3	245	119.7	22.1	0	0	770.00
Ejere	1989	0	45.8	50.8	139.7	0	75.1	175.4	220.95	78.5	3.9	0	0	790.15
Ejere	1990	2	145.3	41.3	67.7	8	18.3	195.55	196.9	152	1.95	0	0	829.00
Ejere	1991	0	36	87.6	17	21.5	27.7	215.7	192	131.9	0	0	0	729.40
Ejere	1992	5.1	30.3	43.8	2	0	32.5	230.3	187.85	134.8	5.95	0	3.7	676.30
Ejere	1993	10.2	24.6	0	79.4	40.4	62.05	244.9	183.7	137.7	11.9	0	4.5	799.35
Ejere	1994	0	0	5.4	79.05	43.8	91.6	210.4	109.7	134.3	0.9	27.1	4.1	706.35
Ejere	1995	0	44.5	64.7	78.7	16.6	52.5	134.9	276.7	88.2	1.5	0	1.4	759.70
Ejere	1996	104.7	0	94.6	30.2	151.7	170.7	191.6	151.1	121.4	0	17.5	0	1033.50

Ejere	1997	23.4	0	29	39.9	99.65	117.15	221.7	210.75	26.3	132.8	62.4	0	963.05
Ejere	1998	2.2	128.3	4.1	32.8	47.6	63.6	251.8	270.4	107.3	153.2	0	0	1061.30
Ejere	1999	1.1	64.15	56	0	25.6	57.5	319	305.2	60.8	95.6	0	0	984.95
Ejere	2000	0	0	10	20.9	16	97	259.2	162.6	143	21.4	32.6	10.2	772.90
Ejere	2001	0	12.8	99.3	14.7	75.3	131.3	306.5	224.4	42.3	0	0	14.5	921.10
Ejere	2002	2.2	9.5	49.3	4.3	39.4	29.2	203.2	254.3	100.4	0	0	49.2	741.00
Ejere	2003	29.4	50.8	5.7	101	0	112.5	318.9	359.5	124.9	0	0	66.4	1169.10
Ejere	2004	47.2	2.9	76.4	64.9	0	74	165.6	392.7	100.1	28	0	0	951.80
Ejere	2005	49.5	0.6	81	71.3	25.7	90.8	227.3	327.9	118.4	6.9	8	0	1007.40
Ejere	2006	29.1	14.8	87.3	173.7	29.4	89.6	259.6	297.15	128.2	20.1	0	46.2	1175.15
Ejere	2007	8.7	21.8	69.1	39.8	80.4	78.9	255.7	266.4	149	34.35	17.6	0	1021.75
Ejere	2008	9.3	1	0	71	60.8	119	263.9	254.1	76.4	48.6	58	0	962.10
Ejere	2009	0	0	7.1	53	57.1	33.7	169.9	306.3	78.1	60.4	8.7	17	791.30
Ejere	2010	0	46	89.3	100.7	53.4	163.1	197.6	128.5	149.6	0	0	5.5	933.70
Ejere	2011	0	0	48.7	21.5	95	54.1	236.5	279.8	160	0	21.6	0	917.20
Ejere	2012	0	0	14.3	56.2	34.4	95.8	232.1	361.3	91.7	0	43.2	0	929.00
Ejere	2013	0	0	109.2	74.9	21.5	54.4	375.3	208.1	88.7	33.4	3.1	0	968.60
Ejere	2014	0	27	49.6	10.5	24.8	30.7	176.2	219.6	114.8	27.1	6.6	0	686.90
Ejere	2015	0	0	14.4	0	84.2	69.1	119.9	279.7	200.1	0	4.3	0	771.70
Ejere	2016	73.6	18.4	20.2	382.5	51.5	77.1	502.4	79	76.4	0	81.1	0	1362.20

Ejere	2017	0	36.8	29.2	55.2	34.55	60.4	219.1	283.9	127.7	22.2	0	0	869.05
Ejere	2018	0	0	0	30.8	17.6	43.7	0	233.6	13	11.8	24	0	374.50
Ejere	2019	0	0	127.8	100.9	58.1	109.7	299.6	157.2	195.1	32.7	13.55	0	1094.65
Ejere	2020	1.5	3.35	118.65	219.8	36.1	90.7	250.9	220.025	138.45	19.3	27.35	0	1126.13
Ejere	2023	3	6.7	109.5	122.9	57.2	83.8	202.2	282.85	81.8	5.9	41.15	0	997.00
Ejere	2024	3	34.3	79.3	25.3	123.3	210.2	345.8	140.3	95.9	53.6	3.1	0	1114.10
											2254	39.261	8.778	903.57
Koka Dam	1981	7.8	11.05	16.35	91.8	84.75	113.35	363.9	50.5	81.1	2.9	0	0	823.50
Koka Dam	1982	15.6	9.9	14.7	17.2	72.4	11.7	204.8	356.2	33.7	46	12.6	44	838.80
Koka Dam	1983	0	29.6	2.2	53	31.9	7.6	20.5	138	84.3	14.5	0	4.4	386.00
Koka Dam	1984	0	0	2	0	43	21.2	53.9	34.4	13.5	0	0	4.2	172.20
Koka Dam	1985	0	0	0	19.1	89.5	0	127	129.2	26	0	0	0	390.80
Koka Dam	1986	0	10.8	11.7	3.2	6.5	26.8	72.8	24.6	12.9	0	0	0	169.30
Koka Dam	1987	0	0	17.9	16.6	103.8	14.3	70.7	134.7	12.8	0	0	0	370.80
Koka Dam	1988	16.4	21.2	15	64	8.5	48.7	237	244.8	132.4	29.9	0	1	818.90
Koka Dam	1989	0.5	22.8	64.9	185.9	2.7	55.2	107.1	283.7	95.7	14	0	0.5	833.00
Koka Dam	1990	0	152.8	292	151.2	0.5	5	225.1	213.4	168.4	0	0	0	1208.40
Koka Dam	1991	0	8.8	43.7	0	0	0	164.4	220.9	289.5	9.2	1.275	0	737.78
Koka Dam	1992	23.5	142.9	161.675	222.1	90.4	249.1	499.7	666.8	410.6	18.4	2.55	0	2487.73
Koka Dam	1993	47	133	31.35	293	143	75	289.4	698.4	122.4	36.8	5.1	0	1874.45

Koka Dam	1994	0	0	19	231.775	83.5	42.1	113.6	109.4	51.7	0	10.2	0	661.28
Koka Dam	1995	6.425	29.2	21.95	170.55	76.6	9.2	225.4	88.2	9.5	0	0	0	637.03
Koka Dam	1996	12.85	0	24.9	48.1	10.2	39	116.2	260.6	49.3	0	0	0	561.15
Koka Dam	1997	25.7	0	30.8	39.3	10.7	145.4	210.9	259.2	51.5	66.6	24.7	0	864.80
Koka Dam	1998	31	37.6	17.9	27.2	130.3	65.8	245.4	399.1	71.5	167.9	0	0	1193.70
Koka Dam	1999	15.6	0	3.5	0	10	110.2	219.3	211.4	67	177.6	0	0	814.60
Koka Dam	2000	0	0	1.6	57.9	122.7	90.6	337	264.9	212.1	0	67.8	10.1	1164.70
Koka Dam	2001	0	16.15	141.2	40.9	154.7	178.3	501	436	119	13.3	5.9	21.7	1628.15
Koka Dam	2002	19.8	32.3	13.1	58.3	8.9	13	217	175.6	63.1	0.6	0	13.9	615.60
Koka Dam	2003	46.1	65.6	104.2	28.2	1.3	121.3	274.7	273.4	33.2	0	3.8	55.7	1007.50
Koka Dam	2004	6.3	0	68.8	84.5	0	103.4	153.9	272.1	47.5	35.7	4.2	0	776.40
Koka Dam	2005	47.9	0	34.8	30.4	10.6	126.3	92.8	141.7	61.2	0	5.8	0	551.50
Koka Dam	2006	0.3	11	38.1	68.3	62	131.3	234.5	171.4	86.6	4.5	0	25	833.00
Koka Dam	2007	44.7	8.5	83.2	37.2	81.15	69.1	151.7	179.6	140.2	23	1.3	0	819.65
Koka Dam	2008	5.1	0	0	26.5	100.3	94.2	302.3	292	165.7	59	77	23.55	1145.65
Koka Dam	2009	2.55	34.85	45.05	53.45	90.25	90.85	269.55	156.9	49.6	87.4	1.5	47.1	929.05
Koka Dam	2010	0	69.7	90.1	80.4	80.2	87.5	236.8	272.3	201.7	0	1.4	0	1120.10
Koka Dam	2011	0	0	72.1	18.2	51.4	100.3	256.8	198.7	214.7	0	38.8	0	951.00
Koka Dam	2012	0	0	0	15.4	42.2	38.4	501	185.7	103.8	0	0	0	886.50
Koka Dam	2013	0	0	36.7	12.6	97.7	55.2	297.9	172.7	115.6	17.5	1.6	0	807.50

Koka Dam	2014	0	3.5	87.3	0.5	54.9	5.3	260.5	195.9	100.85	8.75	6.3	1.7	725.50
Koka Dam	2015	0	0	0	0	205.6	10.7	103.1	162.2	86.1	0	11	3.4	582.10
Koka Dam	2016	0	0	15.3	95.4	153.2	92.3	350.5	77.9	102.8	0	6.5	0	893.90
Koka Dam	2017	0	0	19.125	6.4	147.5	50.9	268	318.4	207.1	6.4	0	0	1023.83
Koka Dam	2018	0	0	22.95	86.95	23.1	115.8	142.7	183	57	57	9.4	0	697.90
Koka Dam	2019	0	0	30.6	78.5	40.2	125.5	318	136.8	284	5.2	29.5	0	1048.30
Koka Dam	2020	0	0	63.6	157.6	41.9	171.1	294.5	288.5	73.3	0	0	8.2	1098.70
Koka Dam	2021	0	0	61.35	114.3	60.7	80.85	232.725	159.8	118.9	52.5	4.8	0	885.93
Koka Dam	2022	3.1	0	77.85	151.85	60.7	60.4	151.9	131	120.9	28	0	4.1	789.80
Koka Dam	2023	6.2	0	92.1	146.1	81.2	36.2	147.45	155.6	80.45	35.5	14	2.05	796.85
Koka Dam	2024	0	65	36.3	52.75	54.1	68.75	230.5	209.4	162	24.1	27	0	929.90
											1625	39.157	8.471	876.21
Mojo	1982	40	130	42	27	68	12	143	282	40	43	28	0	855.00
Mojo	1983	4	31	75.1	95	161.2	96.4	192	253.2	100.6	19	0	0	1027.50
Mojo	1984	0	0	14.2	0	81	64.4	248.6	226	114.8	0	0	7	756.00
Mojo	1985	0	0	6	29.6	83	10	304	287	128	2	0	0	849.60
Mojo	1986	0	56.2	34	59.2	32.7	182.8	66.1	65.1	72.6	3.1	0	0	571.80
Mojo	1987	0	22.8	96.6	75.7	205.3	8.9	154.3	233.6	53.3	14.5	0	0	865.00
Mojo	1988	20.5	6.5	6.8	29.7	10.7	124.8	255.7	300.7	243.3	62.8	0	0	1061.50
Mojo	1989	0	14.9	125.1	84.9	0.2	77	175.5	415.3	116.4	22.5	0	1.8	1033.60

Mojo	1990	0	131.1	48.2	54.6	7	20.6	291.8	228.9	125.4	0.4	0	0	908.00
Mojo	1991	0	31.1	147.1	4.3	13.8	55.2	329.9	205	92.2	0	0	0.95	879.55
Mojo	1992	41.2	5.4	9.9	48.5	14	86.2	182.9	287	82.9	27.4	10.7	1.9	798.00
Mojo	1993	2	19.5	0	83.3	73	86.7	286.5	216.6	82.1	5.4	0	0	855.10
Mojo	1994	0	0	22.6	39.7	52.2	87.2	251	117.5	127.3	0	40.1	2.5	740.10
Mojo	1995	7.6	45.6	37	73.4	31.4	32.7	185.8	143.7	103.4	0	0	0	660.60
Mojo	1996	15.2	22.8	97.5	72.2	127	214.9	221.3	220.9	79.5	0	3	0	1074.30
Mojo	1997	30.4	0	37.6	16.8	16.1	130.6	216.1	158.6	77.8	55.3	21	0	760.30
Mojo	1998	32.3	7.6	28	46	46	112.1	161.3	274.8	149	154.1	0	0	1011.20
Mojo	1999	16.15	0	18.4	0	4.2	90.9	541.5	252.8	67.4	87.4	0	0	1078.75
Mojo	2000	0	0	12	10.1	33.2	128	285.9	230.8	114.1	12.6	25.4	0	852.10
Mojo	2001	0	28.5	79.4	22.5	111	131.5	184.7	175.6	54.9	0	0	0	788.10
Mojo	2002	0	0	8.9	13.7	6.5	62.4	193.5	169.2	95.2	0	0	14.9	564.30
Mojo	2003	40.6	55.9	74.9	84.3	23.2	129	393.2	148.6	96.1	0	0	14.3	1060.10
Mojo	2004	15.5	0	99.3	114.6	9.8	164.75	393.8	201.2	116.9	99.1	32.4	7.15	1254.50
Mojo	2005	8.55	19.25	160.5	149.6	195.4	200.5	320.6	308.7	143.5	14.6	10.9	0	1532.10
Mojo	2006	1.6	38.5	90.5	61.6	19.2	109	344.4	362.7	131.8	24.9	2.6	12.3	1199.10
Mojo	2007	54.1	23.7	83.8	49.6	111	129.7	222.8	227.9	91.4	7.6	0	0	1001.60
Mojo	2008	1.5	0	0	61.9	76.7	137	431	404.4	188.7	89.4	50.8	0	1441.40
Mojo	2009	39.2	6	26.3	62.9	12.7	95.3	213.8	330.3	66.2	214.5	6.5	34.6	1108.30

Mojo	2010	0	85.2	7.7	151.9	119.5	73.4	254.2	170.4	246.7	0	1.4	0	1110.40
Mojo	2011	0	0	47.4	54.9	122	54.6	193	175.6	196.85	0	0	0	844.35
Mojo	2012	0	0	37.8	43	121.65	76.55	524.4	419.7	147	0	0	0	1370.10
Mojo	2013	0	0	85.8	32.9	121.3	98.5	420	232.3	69.2	36.4	0	0	1096.40
Mojo	2014	0	16.8	51.9	2.9	7.6	27.4	260.7	257.2	154.3	96.3	0	0	875.10
Mojo	2015	6.05	0	0	0	186.3	117.6	156.9	275.2	93.9	8.5	21	0	865.45
Mojo	2016	12.1	32.7	18.2	258.7	83.6	117.7	531.6	112.9	76.8	0	31.5	0	1275.80
Mojo	2017	0	19.6	57.4	17.8	155.2	44.1	319.1	211.6	198.3	0	0	0	1023.10
Mojo	2018	31	6.5	61.35	12.95	77.6	133.4	351.4	297.8	43.2	0	17.5	0	1032.70
Mojo	2019	0	0	65.3	8.1	0	134.3	463.8	261	238.6	19.5	84.8	17.1	1292.50
Mojo	2020	0	0	37.5	44.4	50.6	113.3	172.4	471.5	106.4	17.9	0	0	1014.00
Mojo	2021	0	0	0	99.2	66.9	38.4	391.5	313.1	178.9	0	2.15	0	1090.15
Mojo	2022	0	0	74.25	146.9	87.25	125.6	271.9	289.7	129.4	34	0	0	1159.00
Mojo	2023	0	0	148.5	194.6	107.6	190.2	379.6	266.3	79.9	69.25	15.65	5.45	1457.05
Mojo	2024	16	14.8	196.9	93.4	22.3	145	500	281	168.1	28.65	2.15	0	1468.30
											1771	39.114	8.609	1013.07
Adama	1980	8	27.75	181.8	75.45	36.5	73.95	373.15	295.4	153	39.4	4.3	0	1268.70
Adama	1981	0	40.7	166.7	57.5	50.7	2.9	246.3	309.8	137.9	4.7	0	0	1017.20
Adama	1982	8.8	41.6	35.5	29.7	79.1	31.7	230.55	259.8	47.6	104.5	31.3	10.9	911.05
Adama	1983	0	43.4	33.8	79.3	188	24.7	214.8	221.3	72.4	14.3	0	0	892.00

Adama	1984	0	0	4.3	0.4	173.1	84.6	202.7	148.3	66.9	0	0	19.8	700.10
Adama	1985	3	48.25	23.1	183.4	67.3	8	399.4	327.4	174	0	0	0	1233.85
Adama	1986	0	96.5	41	6.2	54.4	152.4	263.3	285.4	20.4	0	0	0	919.60
Adama	1987	0	11.2	80.2	81.1	259.6	0	161.6	243.4	30.8	0	0	0	867.90
Adama	1988	34	31.3	6.8	50.9	9.4	50.3	185.4	171.4	186.9	52.9	0	0	779.30
Adama	1989	0	29.9	21.7	95.4	0	54.7	182.5	281.2	80.3	5.7	0	3.5	754.90
Adama	1990	0.7	183.9	83	114.7	13.3	12	337.8	168.7	153.7	7	0	0	1074.80
Adama	1991	0	105.85	111	13.5	10.95	6	322	232.8	89	10.4	0	1.7	903.20
Adama	1992	41.2	27.8	0	58.05	8.6	38.05	333.6	187.6	84.15	15.2	0	0.85	795.10
Adama	1993	20.6	51.9	0	102.6	17.55	64.1	345.2	142.4	79.3	20	0	0	843.65
Adama	1994	0	0	2.6	49.1	26.5	70.1	229.6	171.5	173.8	13.8	35.6	51	823.60
Adama	1995	0	36.5	46.9	127.2	33	46.5	203.1	251.4	88.2	14.7	0	2.8	850.30
Adama	1996	27.2	0	111.5	65.1	115.2	120.2	220.2	250	93.9	0	7.9	0	1011.20
Adama	1997	14.4	0	75.3	28.5	6.9	94	193.1	240.9	75.5	116.5	31.5	0	876.60
Adama	1998	11.8	25.6	105.2	19.8	49.3	55.3	196.5	220.6	144.7	132.8	0	0	961.60
Adama	1999	9.2	0	34.6	1.2	18.6	74	283.2	194.4	66.3	164.7	3.1	0	849.30
Adama	2000	0	0	20.2	16.1	51.5	60.8	355.1	269	133.6	85.7	57.8	12.9	1062.70
Adama	2001	0	6.2	108.3	28.7	177	51.2	216.8	145.3	107.8	1.7	0	6.6	849.60
Adama	2002	20.9	11.1	129.75	51.3	22.5	50.2	129.9	205.7	65.3	1.1	0	34.5	722.25
Adama	2003	46.5	69.1	151.2	88.9	3.6	75.2	235.6	279.7	122.8	0	5.3	48.8	1126.70

Adama	2004	28.8	3.3	77.4	53.1	1.9	63.3	114.4	227.3	77.1	58.6	12.8	1.6	719.60
Adama	2005	72.5	6.3	90.1	41.3	71.1	50.2	144.3	165	68.4	6	5.3	0	720.50
Adama	2006	17.6	88.4	64.6	88.7	27.8	58.7	173.5	225	128.8	10.1	0.5	28.5	912.20
Adama	2007	23.1	31.6	82.1	101.7	64.7	62.8	225.7	344.4	138	25.6	7.5	0	1107.20
Adama	2008	9.6	0	0	79.9	69.5	71.3	353.1	302.2	100.3	37.5	69.5	0	1092.90
Adama	2009	62.6	0	3.1	2.3	22.1	50	156.1	113.3	34	132.7	0	12.5	588.70
Adama	2010	0	97.3	6.75	27.4	68.1	100.6	227.8	242.9	164.7	0	17.6	0.3	953.45
Adama	2011	0	0	10.4	17.6	68.7	54.8	215.1	155.8	192.1	0	30.2	0	744.70
Adama	2012	56	0	39.8	78.2	48.8	33	508.9	313	130.2	1.4	0.5	0	1209.80
Adama	2013	4.4	0.2	69.2	35.1	36	38.9	443.2	105.2	132.8	34	5.2	0	904.20
Adama	2014	0	4.8	123	7.1	62.3	7.7	211.7	180	150.6	91.7	8.9	0	847.80
Adama	2015	0	0	11	3.6	190.2	74.9	131.3	207.9	78.6	2.7	47	10.5	757.70
Adama	2016	1.3	23	21.7	146	52.5	122.2	345.4	103.9	135	0.9	53.7	0	1005.60
Adama	2017	0	38.9	121.8	36.4	110.6	31.9	250	207.5	224.8	9.1	0.9	0	1031.90
Adama	2018	0	13	0	108.2	42.4	107.6	221.3	179.8	51.2	1.2	18.8	1.5	745.00
Adama	2019	0	0	0	72.9	50.65	112.8	317.6	141.1	283.9	23.4	93.6	16.6	1112.55
Adama	2020	0	0.65	3.85	76.4	52.2	103.3	344	307.5	62.8	8.1	4.5	8.5	971.80
Adama	2021	0.2	9.3	0	37.6	58.9	42.2	325.35	252.9	101.6	45.3	10.875	6.375	890.60
Adama	2022	25.8	1.3	7.7	68.2	79.3	69.75	211	225.6	121	26.8875	0.7	5.3125	842.55
Adama	2023	11.7	0	163.5	98.8	99.7	97.3	306.7	198.3	140.4	8.475	17.25	4.25	1146.38

Adama	2024	0	29.5	81.75	114.5	65.4	63.95	393.85	267.15	142.4	77.3	19.5	0	1255.30
Adama	2011	0	34.25	108.1	34.6	132.1	31.05	243	206.95	218	8.85	30	0	1046.90
Adama	2012	0	0	0	75.4	15.6	30.6	481	336	144.4	2.6	17.5	2.525	1105.63
Adama	2013	0	2.4	62.1	7.6	36.8	34.4	436.6	271.2	122.6	33.8	5	1.6	1014.10
Adama	2014	0	4.8	124.2	1.6	58.8	6	336.3	271.2	166.9	21.2	3.1	0.8	994.90
Adama	2017	0	29.6	94.4	32.8	153.6	30.2	236	206.4	211.2	8.6	1.2	0	1004.00
Adama	2018	0	13.8	11.4	100.8	43.8	105.8	215.8	167	49	1	18.8	1.2	728.40
Adama	2019	0	0	61	113	61.8	103	319.6	133.4	278.4	24.2	90.6	17.8	1202.80
Adama	2020	0.2	1.2	64.4	74.6	49.6	126.6	340.6	306	55	7.4	3.6	8.2	1037.40
Adama	2021	0.2	8.6	0	36.8	53.6	39.2	163.4	198.6	163.6	44.2	1.8	0.4	710.40
Adama	2022	25.6	2	17.2	10.6	0	121.6	204.8	179.2	205	22.2	0.6	5.8	794.60
Adama	2023	13.4	0	141.2	129.2	95.8	111.6	298.8	194.8	215.4	61.2	77.6	0.6	1339.60
Adama	2024	0	30	196.8	114	71.8	121.2	289.8	162.8	87.6	81	24.8	0	1179.80
											1622	39.283333	8.55	944.11
Sodere	1998	11.8	25.6	105.2	19.8	49.3	17.5	172.7	213.2	94.6	101.1	0	0	810.80
Sodere	1999	9.2	0	78.4	2.9	10.4	68.7	181.9	213.9	76.9	109.7	0	0	752.00
Sodere	2000	0	0	7.5	16.9	0	25.1	237.65	179.8	75	82.275	29.5	19	672.73
Sodere	2001	0	5	107.1	10.8	111.6	92	293.4	225.7	73.1	54.85	0	9.2	982.75
Sodere	2002	14.6	7.3	17.8	15.1	63.1	24.8	107	157.5	48	0	0	4.7	459.90
Sodere	2003	13.7	12.6	103.8	81.2	7.3	56.5	156.8	194	85	50.4	3.5	2.35	767.15

Sodere	2004	30.4	0	66	97	0	33	163.2	115.3	71.2	100.8	27.7	0	704.60
Sodere	2005	12.2	0.6	66.5	108.75	72.2	66.5	96.5	203.3	83.9	60.85	13.6	0	784.90
Sodere	2006	18.8	22.8	70.4	120.5	11.1	52.5	193.5	191.3	88.1	20.9	0	29.5	819.40
Sodere	2007	25.4	22.5	38	122	69.5	48.9	130	140.9	86.55	8.7	5.9	0	698.35
Sodere	2008	1.1	0.6	0	61.4	71.8	65.4	199.7	171.9	85	74.2	97.7	0	828.80
Sodere	2009	21.6	3.05	59	29.4	53.25	24.8	73.1	78.1	13.4	25.4	0.4	1.1	382.60
Sodere	2010	0.55	0.3	11.75	42.55	45.75	32.7	147.7	144	119.8	0	4.7	2.2	552.00
Sodere	2011	0	5.5	19.4	10	34.7	84.4	93.2	138.6	129.2	0	52.9	0	567.90
Sodere	2012	0	0	23.5	23.7	19.7	0	317.7	202.1	130.8	2.3	0	0	719.80
Sodere	2013	9.3	0	66.9	13	15.8	56.4	346.3	104.7	82.6	33.3	8.1	0	736.40
Sodere	2014	0	10.5	125.8	8	36.4	7.5	131.8	128.6	38.4	96.8	8.6	0	592.40
Sodere	2015	0	0	3.5	0	102.9	100.2	65.9	140.5	96.6	1.9	58.1	0	569.60
Sodere	2016	0	0	18.5	182.7	121.8	54.4	206.7	59.6	98.8	0	0	0	742.50
Sodere	2017	0	33	44	47.5	78.4	8.6	6.4	129.4	133.7	6.4	0.2	0	487.60
Sodere	2018	0	0	22	45.25	48.45	79.7	192.6	302.1	21.2	3.9	11.1	6.5	732.80
Sodere	2019	0	0	0	43	18.5	40.7	301.6	127	213.6	82	0	8.5	834.90
Sodere	2020	5.9	0	0	26.5	90.5	95.2	287.8	213.3	48.1	0	0	0	767.30
Sodere	2021	0	6.5	0	60.3	58.9	17	291.65	172.2	69.6	0	0	0	676.15
Sodere	2022	0	0	76.65	71	41.3	19.8	295.5	89.9	91.1	6.5	0	0	691.75
Sodere	2023	0	54.7	153.3	115	23.7	32.2	303.2	114.8	104.8	63.8	126.4	0	1091.90

Sodere	2024	0	109.4	234.7	76.8	19.5	32.2	366.7	114.8	104.8	161.5	66.7	0	1287.10
											1347	39.397	8.396	730.15
Welenchiti	2013	0	56	168.05	38.6	46.5	44.6	437.9	139.7	118.5	60.6	16.2	0	1126.65
Welenchiti	2014	0	2.6	101.4	2.2	34.5	7.2	169.9	207.4	152.4	93.6	26.6	0	797.80
Welenchiti	2015	0	0	8.4	6.9	139.2	66.8	157.3	140.7	44.4	0.2	4	8.6	576.50
Welenchiti	2016	29.6	25.5	16.5	236.5	91.4	58.9	309.2	85.3	88.3	1.6	0	0	942.80
Welenchiti	2017	0	99.1	31.8	54.8	111.8	51	233.6	207.8	157.3	3	2.5	0	952.70
Welenchiti	2018	31	2.5	23.75	58.6	86.3	44.55	236.2	201.3	178.35	6.7	28.5	2.6	900.35
Welenchiti	2019	0	1.1	15.7	62.4	60.8	38.1	238.8	182.4	199.4	34.6	135.7	32.8	1001.80
Welenchiti	2020	3.2	2.8	33.6	163.5	54.8	75.2	338.8	282.3	61.2	0	0	17.7	1033.10
Welenchiti	2021	0	2.8	77.15	73	86.8	56.65	189	439.8	76.8	51.5	1.8	25.25	1080.55
Welenchiti	2023	13	4.5	138.6	120	57.8	56.65	288.8	228.8	130.3	17.3	67.85	21.475	1145.08
											1457	38.427	8.666	955.73
Name	Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Total
Iteya	1990	11.8	86.5	64.1	127.4	27.6	61.5	177.7	239.2	112.6	52.1	8.3	10	978.8
Iteya	1991	7.8	20.8	61.9	62.8	117.8	61.3	221.7	206.1	106.9	10.6	17.1	17.5	912.3
Iteya	1992	23	46.5	16.6	77.8	73	89.8	171.5	244.2	74.2	41.7	16.8	11.9	887
Iteya	1993	28	22.4	27.5	99.2	111.7	115.6	211.2	229.1	107.9	78.6	3.5	11.1	1045.8
Iteya	1994	0	0.5	25.4	100.4	71.7	85.4	217.5	218.2	146.9	19.2	33.9	3.6	922.7
Iteya	1995	0.2	34.9	48.6	93.3	51.4	70.6	157.1	234.7	113.8	22.3	10.4	19.3	856.6

Iteya	1996	21.2	5.4	111.1	90.1	124.1	173.6	230.5	253.6	151.7	26.7	24.6	3	1215.6
Iteya	1997	16.7	0.2	39.7	124.5	99.1	111.6	163.7	162.1	59.6	211.4	54.3	9.1	1052
Iteya	1998	40.4	38.7	19.9	41.4	76.9	144.1	282	230.5	158	178.4	18.8	1	1230.1
Iteya	1999	19.9	0.6	90.1	35.8	47.4	109.9	195.2	194.5	85.6	148.8	4	7	938.8
Iteya	2000	0.5	0.1	3.7	55.9	36.6	64.7	129.3	152.7	65.3	50	3.9	9.4	572.1
Iteya	2001	7.9	11.1	104.1	30.9	78.5	61	164.7	116.3	85.5	44.8	9.8	3.1	717.7
Iteya	2002	14.8	0.6	66.6	55.9	32.8	73.6	94.1	103.1	40.9	14.1	8.9	30.4	535.8
Iteya	2003	8.9	22.5	44.8	52.3	8.1	39.2	99.5	146.7	57.5	3.8	26.2	40.6	550.1
Iteya	2004	8.3	7.6	39.1	43.8	6.8	48.7	110.6	92.4	65.3	34.8	24	21.8	503.2
Iteya	2005	19.2	6.6	48.8	103.9	118.2	30.9	134.7	95.2	46.3	20.3	6.7	0.1	630.9
											2196	39.235	8.136	846.84
Iteya	2006	11.7	58.1	75.4	100.9	50.5	70.8	242.2	156.5	80.5	57.6	27.6	30.6	962.4
Iteya	2007	19.2	40.8	56.3	81.3	89.6	68.3	191.9	159.8	100.3	34.1	25.9	0	867.5
Iteya	2008	7.7	1.6	2	45.1	39.5	51.2	216.8	205.2	105.1	57.5	72.4	1.9	806
Iteya	2009	41.9	3.6	29.3	58.7	23.3	50.7	177.8	142.5	99.2	99.3	5.9	58	790.2
Iteya	2010	1.2	76	90	97.2	85.2	107.8	209.1	174.8	140.3	24.1	10.4	9.5	1025.6
Iteya	2011	3.2	4.7	33.1	48.1	78.3	62.2	106	84.2	48.7	16.9	34.5	0.9	520.8
Iteya	2012	0.2	0.5	7.7	97.4	28.1	47.2	215.8	248.4	103.6	14.9	3.3	8	775.1
Iteya	2013	15.2	1.2	54.6	117.5	68	98.4	238.8	188.7	92	58.7	57.8	1	991.9
Iteya	2014	1.4	22.6	41	65.1	73.4	53.6	152.8	146.9	105.3	100.2	25.9	20.5	808.7

Iteya	2015	6	4.5	15.4	19.7	104	128.4	95.3	160.2	66.6	37.3	55.5	26.5	719.4
											2196	39.235	8.136	826.76
Iteya	2016	29.9	24.3	49.8	221.3	133.7	67.9	163.1	181	101.5	48.6	36.1	7.9	1065.1
Iteya	2017	0	38.9	61.8	45.7	153.3	70.5	174.3	188.3	210.7	54.5	31.8	3.2	1033
Iteya	2018	6	14	44	86	81	92	182	202	128	55	25	5	920
Iteya	2019	14.95	31.6	55.8	133.5	143.5	69.2	168.7	184.65	156.1	51.55	33.95	11.1	1054.6
Iteya	2020	7.7	1.6	2	45.1	39.5	51.2	216.8	205.2	105.1	57.5	72.4	1.9	806
Iteya	2021	6.85	7.8	23	65.55	60.25	71.6	199.4	203.6	116.55	56.25	48.7	3.45	863
Iteya	2022	3.2	4.7	33.1	48.1	78.3	62.2	106	84.2	48.7	16.9	34.5	0.9	520.8
Iteya	2023	6	14	44	86	81	92	182	202	128	55	25	5	920
Iteya	2024	7.74	11.94	31.58	75.65	80.51	69.24	174.58	175.93	110.89	47.44	42.91	4.47	832.88
											2196	39.235	8.136	890.60