ADDIS ABABA UNIVERSITY
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DEPARTMENT OF GEOGRAPHY AND ENVIRONMENTAL STUDIES

Impacts of land use land cover dynamics and climate change and variability on ecosystem services in Maze National Park and its environs, southwestern Ethiopia

A Dissertation Submitted for the Fulfillment of the Requirement for the Degree of Doctor of Philosophy in Geography and Environmental Studies (Environment and Natural Resources Management)

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June, 2025
Addis Ababa, Ethiopia

AUTHOR STATEMENT

I, the undersigned, hereby declare that this dissertation is entirely my own work and it has not been submitted to any other institution elsewhere for the award of any degree. I have dully acknowledged all sources and materials used in this work.

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Acronyms

BAU	Business as Usual
CMIP6	The Coupled Model Intercomparison Project Phase6
CV	Coefficient of Variation
CSA	Central Statistical Agency
DEM	Digital Elevation Model
DOS	Dark Object Subtraction
ED	Edge Density
ESVD	Ecosystem Services Valuation Database
ESVs	Ecosystem Service Values
ETM^+	Enhanced Thematic Mapper Plus
FAO	Food and Agricultural Organization
FGD	Focus Group Discussion
GCMs	General Circulation Models
GOV	Governance
IDW	Inverse Distance Weighting
IPBES	Intergovernmental Science-Policy Platform on Biodiversity
IPCC	Intergovernmental Panel on Climate Change
ITA	Innovative Trend Analysis
KII	Key Informant Interviews
LCM	Land Change Modeler
LPI	Largest Patch Index
LULC	Land Use Land Cover
MEA	Millenium Ecosystem Assessment
MK	Mann-Kendal
MLP	Multi-Layer Perception
MMK	Modified Mann-Kendal
MzNP	Maze National Park

NDVI	Normalized Difference Vegetation Index
NEA	National Ecosystem Assessment of Ethiopia
NMA	National Meteorological Services Agency
OLI	Operational Land Imager
PD	Patch Density
PET	Potential Evapotranspiration
RAI	Rainfall Anomaly Index
RF	Random Forest
SCP	Semi-Automatic Classification Plugin
SENRS	Sothern Ethiopian National Regional State
SHDI	Shannon Diversity Index
SIDI	Simpson Diversity Index
SRTM	Shuttle Radar Topography Mission
SSP	Shared Socioeconomic Pathways
TEEB	The Economics of Ecosystem and Biodiversity
TM	Thematic Mapper
UNCCD	United Nations Convention to Combat Desertification
USD	US Dollar
USGS	U.S. Geological Survey
WBG	World Bank Group
WFP	World Food Program

Acknowledgements

First and foremost, I would like to express my utmost gratitude to the Almighty God for his blessings, guidance, and strength throughout my PhD studies.

I would like to express my deepest gratitude to my supervisor, Dr. Desalegn Wana, for his unwavering support, insightful guidance, and continuous encouragement throughout my PhD journey. His prompt and thoughtful responses to my queries, coupled with his understanding during challenging times, have been a constant source of motivation. This dissertation has reached its current form largely due to his invaluable assistance and friendly demeanor.

I would like to thank Addis Ababa University and Hawassa University for their financial support during this study. I am also deeply appreciating the Southern Ethiopia Region Culture, Tourism, and Sports Office, as well as the Maze National Park Office, for granting me the necessary permissions to conduct research within the park. My sincere thanks extend to the local communities surrounding the park for their cooperation and willingness to share their invaluable experiences; their contributions were essential to this research. Additionally, I am grateful to the National Meteorological Services Agency, southern district office, for providing me with the necessary data required for this study.

I am also profoundly grateful to my family for their unwavering support throughout this journey. My parents, Simeon Tsalke and Workinesh Leye, and my beloved sisters and brothers, thank you for your unwavering love, sacrifices, prayers, and encouragement throughout this journey. Special thanks to my husband, Mesfin Yope, and my son, Nathan Mesfin, for their patience and understanding during my prolonged absences and moments of inattention while I dedicated myself to this study.

I extend my appreciation to my colleagues and friends for their encouragement, support, and thoughtful discussions, which enriched my research experience. I am especially grateful to Tsedey Tesfahun and Sileshi Tadesse, for their invaluable companionship and for covering my responsibilities at Addis Ababa University during my absence.

To everyone who prayed for me during my study and contributed to this dissertation, directly or indirectly, I am truly grateful.

General Abstract

This study was aimed at exploring the impacts of land use land cover (LULC) and climate changes on ecosystem services in Maze national park and its environs in southwestern Ethiopia. The study employed Landsat imageries for LULC change analysis from which landscape structural attributes were computed and the values of ecosystem services were calculated. Climate data were collected from the Ethiopian meteorological services agency, southern district office, and the WorldClim database. In addition, socioeconomic data were collected to assess local community perceptions of LULC change, ecosystem service dynamics, and their interactions. LULC classification was performed using the Random Forest classifier, and ecosystem service values (ESVs) were estimated through the benefit transfer method whereas, climate trend analysis was computed using the Mann-Kendall and innovative trend analysis. The Multi-Layer Perceptron neural network method was applied for LULC change prediction, while climate change projections were based on Shared Socioeconomic Pathways (SSP2-4.5 and SSP5-8.5). Pearson and Spearman correlations were used to analyze ecosystem services-climate relationships, trade-offs, synergies, and predicted climate change impacts on ecosystem services. Spatial trade-offs and synergies were analyzed using the Local Moran's I model. The results indicate significant expansion of croplands and built-up areas, while wooded grasslands, riverine forests, water bodies declined. From 1985 to 2020, overall ESVs declined from 2038.42 million USD to 1628.72 million USD. As for the individual ESVs, only food production increased, while all other services declined. The climate trend analysis revealed a decreasing trend in mean annual and main rainy season rainfall, while temperatures (mean annual, maximum and minimum) exhibited an increasing trend. Spatial and temporal correlations showed that ecosystem services were positively correlated to mean annual and main rainy season rainfall, but negatively associated with mean annual, maximum, and minimum temperatures. The landscape metrics indicated an increase in the number of patches, patch density and edge density, suggesting landscape fragmentation. Spatial and temporal analyses showed a strong trade-off between food production and water supply, raw materials, and climate regulation services, while other services demonstrated strong synergies. Under the business-as-usual scenario, water supply, raw materials, and climate regulation are expected to decline. In contrast, under the governance scenario, all key ecosystem services are anticipated to increase significantly by 2050. Temperature negatively correlated with key ecosystem services under SSP2-4.5 and SSP5-8.5 scenarios, while precipitation positively correlated with these services. These findings support the development of strategies for land use management, ecosystem conservation and restoration, and climate change mitigation and adaptation to minimize the impacts of LULC and climate changes on ecosystem services.

Key words: climate variability, landscape metrics, local *Moran's I model, synergies and trade-offs*

1. General Introduction

1.1. Background and justification of the study

The Economics of Ecosystem and Biodiversity (TEEB) defined ecosystem services as the direct and indirect contributions of ecosystem functions essential to human well-being and survival (TEEB, 2012). Ecosystems provide a wide array of services, including provisioning services (food, fiber, fresh water, and fuelwood), regulating services (climate regulation, flood control, and disease regulation), cultural services (spiritual, recreational, and cultural benefits), and supporting services like nutrient cycling, which are crucial for supporting life (Millennium Ecosystem Assessment (MEA), 2005). These services are vital for sustaining life on earth and maintaining the integrity of the ecosystem (Tolessa et al., 2017). Nonetheless, the Earth's ecosystem services have shown a declining trend in recent years due to increasing anthropogenic pressures (Sannigrahi et al., 2020). Over the last 50 years, environmental changes around the world have been unprecedent, largely due to land use and climate changes, pollution, and biotic exchange (Intergovernmental Science-Policy Platform on Biodiversity (IPBES), 2019). The MEA synthesis report also indicates that about 60% of the ecosystem services which were evaluated in the assessment were either declining or being unsustainably exploited (MEA, 2005). This can mainly be attributed to the drastic rise of human needs on Earth's resources, which was caused by the population and economic growth in the past 50 to 100 years (Haberl et al., 2014). The reduction of these services has economic, social, and political effects and particularly poorer communities that rely on natural resources for their livelihoods are at risk (Brown, 2014).

Land use land cover (LULC) change is modification of the Earth's terrestrial surface, mostly due to human activities (Xu et al., 2023) for livelihoods or other life necessities (Hassan et al., 2016). The conversion of grasslands, forests, wetlands, and other natural ecosystems into croplands and settlements has exerted great pressure on biodiversity and ecosystem services (Polasky et al., 2011). The ecosystem services that are provided by water bodies (Shukla et al., 2018), forests (Baidoo & Obeng, 2023; Solomon et al., 2019), and grasslands (Kalema et al., 2015) in particular are negatively impacted by LULC changes, which are mainly socio-demographically driven besides climate change. The modifications are changing the structure as well as the functionality of an ecosystem and therefore impacting their capacity to provide goods and services to the local communities (Marino et al., 2023). Thus, LULC change is recognized globally as one of the primary causes of loss in biodiversity and degradation of ecosystem services (Foley et al., 2005; Sala et al., 2000). According to the 2019 Global IPBES report, LULC changes account for more than 50% of the human impacts on freshwater and terrestrial ecosystems (IPBES, 2019). Previous studies also indicate that LULC changes are responsible for considerable decline of overall and individual ecosystem service values in different parts of the world (Achmad et al., 2020; Kindu et al., 2016; Sharma et al., 2019; Wayesa et al., 2025).

Even though Africa has different ecosystems that provide crucial goods and services to support water, food, health, energy, and other livelihoods, these ecosystems are impacted by LULC changes due to the conversion of natural habitats into agricultural lands and urban settlements, and climatic changes (IPBES, 2018; Sintayehu, 2018). Uncontrolled conversion of forests, rangelands, and other semi-natural areas to croplands and urban areas (IPBES, 2018) degrades ecosystem functioning and services along with climate change impacts (Sintayehu, 2018). Ethiopia experiences widespread LULC changes characterized by settlements and agricultural activities dominating rural landscapes (Tolessa et al., 2017). Extensive land use pressures, rising natural resource demand (National Ecosystem Assessment of Ethiopia (NEA), 2022), population growth, agricultural land expansion, fuel wood and construction material demand, and poverty, coupled with institutional and policy changes, drive LULC changes in the country (Mathewos, 2019; Ogato et al., 2021; Wubie et al., 2016). Studies in Ethiopia have demonstrated a significant loss of ecosystem service values as a result of unregulated LULC changes (Kindu et al., 2016; Mekuria et al., 2021; Negussie, 2019).

In addition to LULC changes, precipitation and temperature pattern shifts together with climate-induced risks like drought, flooding, and wildfires, dramatically impacted ecosystem quality, quantity, and services they provide (Bakure et al., 2022; Locatelli, 2016). Climate change and variability worsen these effects by increasing the intensity and frequency of floods, wildfires, crop failures, and outbreaks of diseases and insect infestations (MEA, 2005; Scholes, 2016; U.S. Geological Survey (USGS), 2007). Climate change and variability have negative impacts on ecosystem goods and services (van der Geest et al., 2019), causing reduction in food production, drinking water availability, fuel wood, fodder, climate regulation, and carbon sequestration (Bakure et al., 2022). These effects are particularly evident in arid and semi-arid areas, which suffer from recurrent temperature fluctuations, frequent droughts, shortened growing seasons (Intergovernmental Panel on Climate Change (IPCC), 2007), and changes in mean temperature and rainfall (Babu, 2015; Muluneh, 2021). Therefore, provisioning and regulating services such as food production (van der Geest et al., 2019), water supply, pasture availability, and forest based services (Ben Salem et al., 2019) are significantly affected by these factors in semi-arid regions.

Like in many other African countries, Ethiopia faces great challenges with climate change and variability, largely because of its limited ability to adapt (NEA, 2022). Ethiopia is experiencing temperature increases, irregular rainfall patterns, and in some years total failures of seasonal rains (McSweeney et al., 2006). In the period between 1960 and 2006, average temperature of the country has increased by 1.3 °C, at a rate of 0.28 °C per decade (McSweeney et al., 2006). Similarly, Fazzini et al. (2015) reported a rise of 1.1 °C per decade (0.04 °C annually) between the years 1981 and 2010. In addition to that, climate projections have also reported that Ethiopia's mean annual temperature will increase by 1.1-3.1 °C by the 2060s and 1.5-5.1 °C by the 2090s (WBG, 2011). In Ethiopia, climate variability marked by rising temperatures and declining and unreliable rainfall, has negatively impacted ecosystem services, including food production, water availability, and soil organic matter dynamics (Gezie, 2019). The NEA also reported that the multifaceted effects of climate change and variability have caused the loss of biodiversity and the degradation of ecosystem services (NEA, 2022). Understanding the relationships between climate change and ecosystem services is thus important for coming up with effective adaptation and mitigation plans (Schirpke & Tasser, 2024).

Ecosystems offer multiple services interacting each other in nonlinear and intricate ways. Changes in the provision of one service have significant influence on other services (Bennett et al., 2009). For instance, changing natural land cover to farming or built-up areas alters landscape structure and patterns that might result in fragmentation and habitat loss, thereby limits the delivery of such services (Mitchell et al., 2015a). Changes in land use impact the number, size, form, and spatial distribution of landscape patches, which then influences ecosystem function and service provision (Mitchell et al., 2015b). Moreover, the strength and direction of the interaction between ecosystem services are affected by the arrangement of the landscape and the spatial organization of patches, therefore resulting in tradeoffs and synergies (Rieb & Bennett, 2020). A trade-off is a win-lose or lose-win scenario when an increment of one service causes a decrease of another. Synergy, on the other hand, is the unidirectional change of two ecosystem services and indicates a win-win or lose-lose scenario when both services increase or decrease together (Bennett et al., 2009). Synergies and trade-offs between ecosystem services have recently got greater attention among researchers (Li et al., 2022; Tan et al., 2024; Wang et al., 2023; Zeng et al., 2022). Understanding these relationships can help to provide a scientific basis for improving ecosystem protection and management strategies to support human welfare (Wang et al., 2024; Yuan et al., 2024). Furthermore, assessment of temporal and spatial scale trade-offs and synergies aids management and policy making to minimize ecosystem disservices and promote winning more and losing less solutions (Sil et al., 2016).

Predicting LULC change is important to understand future land development patterns based on past and present LULC changes (Chisanga et al., 2024). Understanding future LULC patterns and changes are essential for science based sustainable resource management (Kindu et al., 2018). It also aids decision makers in analyzing changes in LULC intensity and the effects of socioeconomic factors, as well as promoting environmental conservation and sustainable development plans (Baig et al., 2022). Researchers around the world have employed various methodologies to predict future LULC changes within their study areas (Abbas et al., 2023). The Multilayer Perceptron- Markov Chain (MLP-MC) based hybrid approach in the Land Change Modeler (LCM) module of IDRISI SELVA, combines the MLP model with the MC model. Use of MLP-MC hybrid model has received much attention due to its capability to improve prediction accuracy and enhance the performance of overall model (Fortin et al., 2003). The LCM is a powerful tool that captures spatial heterogeneity, analyzes LULC change dynamics, and forecasts land use changes, especially relating to impacts on biodiversity (Roy et al., 2014; Mathewos et al., 2024). The LCM was utilized in this study to identify explanatory variables, generate transition probability maps, and forecast future land cover scenarios.

Climate change has already altered, and will continue to change, the timing, provision, and location of ecosystem functions and services through ongoing increases in temperature and an increase in the frequency of extreme weather events (Nelson et al., 2013). Future climate changes are expected to have substantial effects on ecological systems that will affect their functions and alter the ability of natural and managed systems to provide important ecosystem services (Lawler et al., 2011). Global Climate Models (GCMs) serve as essential tools for projecting future climate patterns and trends (Enyew et al., 2024). The recently developed Coupled Model Intercomparison Project Phase Six (CMIP6) provides advancements over previous phases and introduces five

Shared Socioeconomic Pathways (SSPs) based on future greenhouse gas concentrations and socio-economic challenges (Abbas et al., 2024). These improvements contribute to more robust and reliable climate predictions (Eyring et al., 2016). Climate and land use dynamics are the two main drivers of changes in ecosystem services (Carpenter et al., 2009). Therefore, understanding the future impacts of LULC and climate change on ecosystem services is essential to provide important information for governments to develop land use and ecological management policies to address future environmental changes (Wang et al., 2022).

Although ecosystems benefit human well-being in multiple ways (ecological, socio-cultural, and economic), quantifying the value of ecosystem services in monetary terms is a crucial tool for raising awareness among users and providing evidence for decision/policy makers (de Groot et al., 2012). Conducting original ecosystem services valuation research is expensive, time-consuming, and feasible only for a limited study site (Wilson & Hoehn, 2006). Thus, valuation of environmental goods and services using the benefit transfer method offers a practical alternative for estimating the economic values of ecosystem services when site-specific valuation information is lacking. This approach adapts existing valuation information to new policy contexts, making it particularly useful when financial, time, and data constraints limit primary data collection (Temesgen et al., 2018; Wilson & Hoehn, 2006). The benefit transfer method has been widely applied in national and global ecosystem assessments, value mapping applications, and policy appraisals (Brander et al., 2024). In Ethiopia, where historical land use data are scarce, land degradation is widespread, and ground data collection is expensive, benefit transfer serves as a vital tool for informing land-use decisions (Tolessa et al., 2017).

National parks are vital for biodiversity conservation and for local people who rely on natural resources for their survival (Haq, 2016; Zhao et al., 2019). They offer good pasture, ambient weather, thatching grass, charcoal, construction wood, fuel wood, and cultural services (Kumssa & Bekele, 2014; Zhao et al., 2019). Initially, Maze National Park (MzNP) was designated as a controlled hunting area before being officially established as a national park in 2005 by the regional government (Henok et al., 2017; Tekalign, 2011). The park is mainly covered by savanna grasslands with scattered trees as well as riverine forests (Henok et al., 2017). The varied landscapes of the study area provide several provisioning, regulating, and cultural services. These include water, food, grazing, firewood, thatching grass, construction materials, climate regulation, wild honey, and recreational and aesthetic benefits. These services are essential for the life of local communities, especially in times of drought and famine (Zewude et al., 2022). Despite having many benefits, the park is threatened by human activities such as land cover changes, overgrazing, firewood and construction materials harvesting, and recurrent bushfires. The core conservation area of the park is particularly subjected to fires that set by people during the dry season in search of grass for their livestock (Zewude et al., 2022). As a result, the study area is experiencing LULC changes, vegetation degradation, and a decline in wildlife populations (Andabo & Gamo, 2015; Zewude et al., 2022). The aforementioned pressures lead to environmental degradation and a decline in the ecosystem's numerous benefits. In addition, climate variability caused changes, including recurring droughts, crop pests and disease, and increased frequency of forest and bushfires, reducing the availability of essential ecosystem goods and services (Tekalign & Bekele, 2011). Given the increasing pressure on ecosystem goods and services due to climate variability and LULC changes, there is an urgent need for research to assess the impact of these changes on key ecosystem services.

1.2. Statement of the problem

LULC and climate changes are significant global environmental problems (He et al., 2019) that affect ecosystems and the benefits that people derive from the environment (Tang et al., 2018). Changes in LULC impact ecosystem services by altering ecological processes (disturbing energy exchange, water cycle, increasing soil erosion and accumulation) and causing landscape fragmentation (Tang et al., 2018). Widespread LULC changes exist in Ethiopia, with rural areas being dominated by farmlands and settlements (Tolessa et al., 2017). Similarly, MzNP and its surrounding areas are affected by intense LULC changes from expanding farmlands and settlements into naturally vegetated areas, excessive grazing and grass cutting, and frequent forest fires (Zewude et al., 2022). The conversions of land cover to settlements and farmlands have increased landscape fragmentation by altering the shape, size, number, and spatial arrangement of patches. These alterations affect the strength and direction of ecosystem services, resulting in trade-offs and synergies (Mitchell et al., 2015a; Mitchell et al., 2015b).

Climate change is a global problem of this century but its impact is higher in countries like Ethiopia, which has limited capacity to cope with the effects (Bezu, 2020). It leads to more frequent and sever of extreme events, such as high-winds and extreme temperature fluctuations that can alter ecosystem's biophysical processes, and therefore ecosystem services (Wang et al., 2022). Ethiopia is among the most climate-vulnerable countries, experiencing climate change and variability through rising temperatures, reduced rainfall, and increased rainfall variability (Gezie, 2019). Reports confirm that Ethiopia's annual temperature is rising, while rainfall patterns show no clear trend, exhibiting high variability along with an increasing frequency of floods and droughts (Bezu, 2020; McSweeney et al., 2006). These changes have led to climate-related disturbances such as flooding, drought, and wildfires, which negatively impact ecosystem goods and services. Due to its semi-arid climate, the study area is highly vulnerable to the impacts of climate change and variability, including frequent droughts (Andabo, 2017), which pose a threat to the provision of ecosystem services. In addition to historical climate change reports in Ethiopia, climate change projections indicate a continued increase in temperature, while future rainfall trends remain uncertain (Bezu, 2020; WBG, 2011). These changes are expected to significantly impact ecological systems, disrupting their functionality and altering the ability of natural and managed systems to provide essential ecosystem services (Lawler et al., 2011).

Despite the wide spread impacts of land use changes, few studies have quantified the impacts of LULC dynamics on ecosystem services (Belay et al., 2022; Kindu et al., 2016; Mekuria et al., 2021; Negussie, 2019; Solomon et al., 2019; Temesgen et al., 2018; Tolessa et al., 2017). Nevertheless, most of these studies focused on specific ecosystems such as forest ecosystems in the Ethiopian highlands (Belay et al., 2022; Kindu et al., 2016; Solomon et al., 2019; Tolessa et al., 2017), watersheds and basins (Aneseyee et al., 2020; Markos et al., 2018; Woldeyohannes et al., 2020), and agroforestry dominated landscapes (Temesgen et al., 2018). Conversely, ecosystem services derived from protected areas in semi-arid regions, have received little attention in previous research. Although assessing the trade-offs and synergies among ecosystem services offers a scientific basis for enhancing ecosystem protection and management to improve human well-being (Wang et al., 2024; Yuan et al., 2024), these aspects have also been not sufficiently investigated, especially within the protected areas. Furthermore, to the best of my knowledge, researches linking landscape structures to key ecosystem services and analyzing their synergies and trade-offs remain limited.

Similarly, evaluating how climate change and variability affect ecosystem services and analyzing these relationships quantitatively provides a scientific basis for protecting and restoring ecosystems at local and regional levels (Ma et al., 2021). However, empirical researches on these effects also remain limited in Ethiopia (NEA, 2022). For instance, a few studies, such as (Aneseyee et al., 2022) have examined the impacts of climate variability, particularly precipitation variability, on water yield without considering other provisioning and regulatory services. Additionally, in Ethiopia existing studies focus on historical trends and dynamics of LULC changes and ecosystem services (Muleta et al., 2021; Negussie, 2019; Shiferaw et al., 2019; Tolessa et al., 2017). There is however a noticeable paucity of researches which integrates and predicts the future impacts of land cover and climate changes on ecosystem services in the country. Only a few studies, conducted in the central and southwestern regions, have examined the predicted impacts of LULC changes on ecosystem services (Biratu et al., 2022; Duguma et al., 2024).

Therefore, this study aims to investigate the temporal and spatial changes in ecosystem services under changing LULC and climate conditions, analyze the synergistic and trade-off relationships between these services, and predicts the future impacts of LULC and climate changes on key ecosystem services in MzNP and its surroundings, southwestern Ethiopia.

1.3. Study area description

1.3.1. Location

The study area is situated in the Gofa and Gamo zones of Southern Ethiopia Regional State, about 468 km southwest of Addis Ababa (Fig. 1.1). Geographically, it is located between 06°11′35″N to 06°37′49″N latitudes and 37°03′42″E to 37°24′55″E longitudes (Fig. 1.1). The study area comprises MzNP and the surrounding seventeen *kebeles* (the smallest administrative units in Ethiopia).

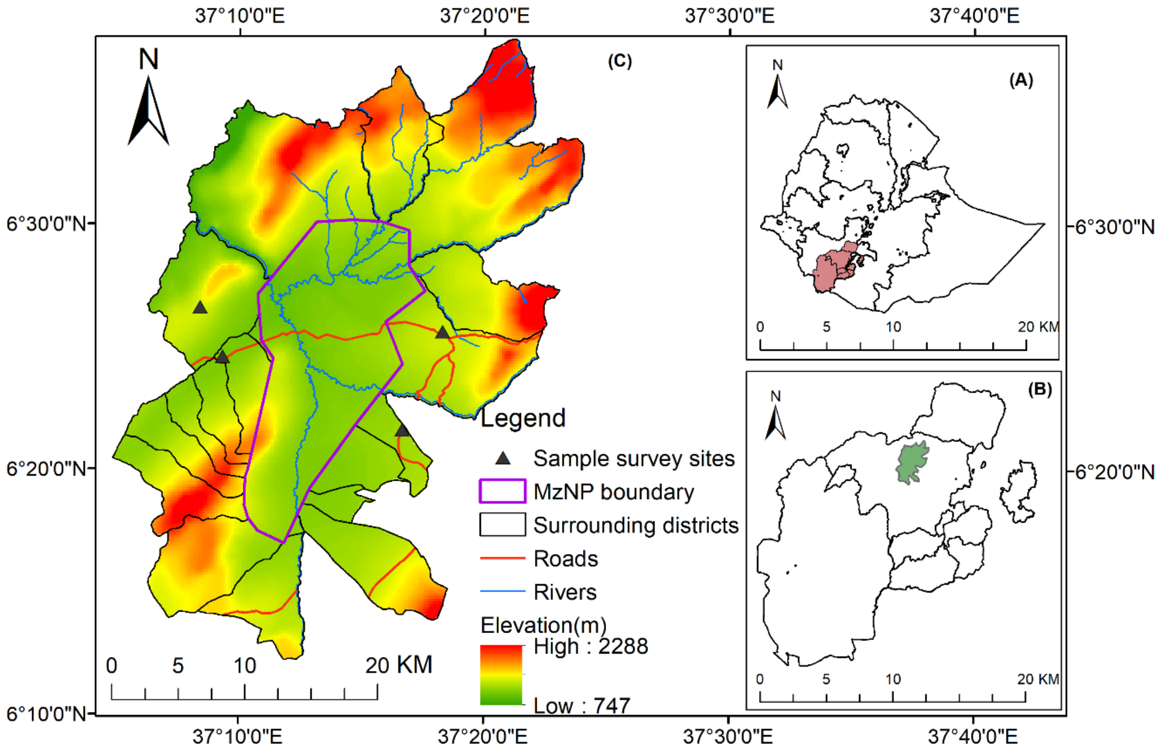

Figure 1.1: Map of the study area

Note: (A) location of SENRS in Ethiopia (B) location of the study area in SENRS, and (C) MzNP and the surrounding districts

1.3.2. Climate

According to Ethiopia's traditional agro-ecological classification, the study area lies within two zones, such as the *Kolla* zone (lowlands, 500 - 1500 meters above sea level) and the *Woinadega* zone (midlands, 1500 - 2300 meters above sea level (Hurni, 2016). Based on meteorological data from 1985 to 2020, the study area's average annual temperature is 23.96°C. Rainfall has two distinct rainy seasons following a bimodal pattern. Spring (March to May) is the main rainy season, with a peak in April/May. Autumn (September to November) is second rainy season, with a peak in October (Fig. 1.2). The mean annual rainfall in the study area is 975 mm (Fig. 1.2). Southern Ethiopia experiences a long rainy season extending from March to May and a shorter one from October to November (Alhamshry et al., 2019; Habte et al., 2023).

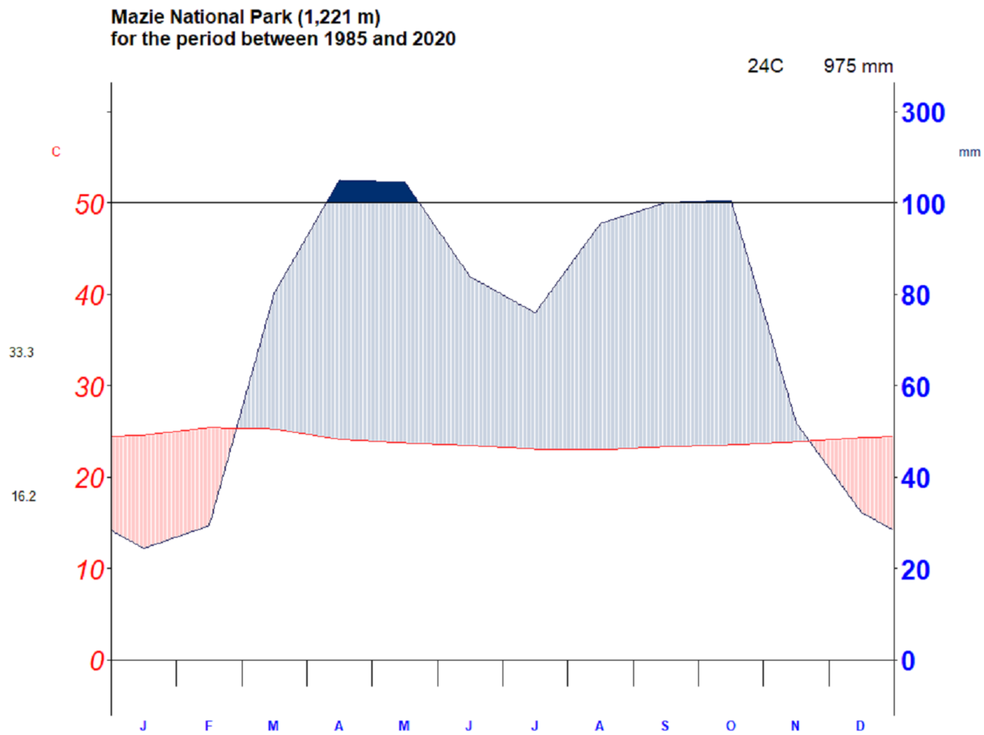

Figure 1. 2:Walter-Lieth climate diagram of the study area between 1985 and 2020 (NMA,2022)

1.3.3. Topography and soils

The study area's elevation extends from 747 to 2288 meters above sea level. The landscape of the study area includes escarpments, a vast plain, small hills, sloppy areas, and rugged mountain ranges. The highest mountain peak in southwest Ethiopia, Mountain Guge, with an altitude of 4200 meters above sea level, is found 40 km away from the national park (Henok et al., 2017). According to the Food and Agriculture Organization (FAO) soil classification system, Nitosols predominate the study area, with additional occurrences of Fluvisols, Cambisols, and Acrisols (in high altitude areas) (FAO, 1984).

1.3.4. Drainage and Vegetation

MzNP is named after the Maze river, which originates from the southern highlands surrounding the park, flows northward, and empties into the Omo river (Siraj, 2017). Other rivers and streams in the study area include Zage, Domba, Lemase, and Daho, which eventually flow into the Omo River (Henok et al., 2017). MzNP and its surrounding areas are home to unique natural, cultural, and historical features and a wide variety of wildlife and vegetation types (Andabo & Gamo, 2015). The Bilbo Hot Spring, which is located in its southern part, is one of the park’s notable features. This natural spring is locally valued for its healing properties (Tolcha et al., 2022). Savannah grasslands with scattered deciduous broadleaved trees and riverine forests along the Maze stream are the primary features of MzNP (Henok et al., 2017). *Senegalia polyacantha Willd, Ficus sycomorus L., Trichilia emetica Vahl, and Lecaniodiscus fraxinifolius Bak* are the dominant tree species in these riverine forests (Zewude et al., 2022). Open Combretum-Terminalia woodland grasslands make up the majority of the park's plains (Siraj, 2017).

1.3.5. Population and economic activities

The major nationality groups close to the park are the Qucha, Gamo, and Gofa (Andabo and Gamo, 2015). According to the Central Statistical Agency’s (CSA) census (2007), the population of the surrounding woredas, such as Zala, Daramalo, Kucha, and Kamba, was 74,369, 81,025, 149,287, and 155,979, respectively. The population of these weredas was projected to be 90,519, 99,451, 182,504, and 190,091 in 2017, respectively (CSA, 2013). Cereal cultivation and livestock rearing are the main sources of livelihood for the local people in the study area. As a supplement to cereals, they cultivate tuber crops such as cassava (*Manihot esculenta*), taro (*Colocasia esculenta*), and sweet potato (*Ipomoea batatas*) (Andabo & Gamo, 2015).

1.4. Objectives of the study

The overall objective of the study is to examine the spatiotemporal impacts of LULC dynamics and climate change and variability on ecosystem services in MzNP and its environs, southwestern Ethiopia.

Specifically, this study aims:

- ➢ To analyze the impacts of LULC changes on key ecosystem services from 1985 to 2020
- ➢ To assess the spatiotemporal dynamics of ecosystem services in response to climate variability
- ➢ To evaluate the spatial and temporal synergies and trade-off between ecosystem services
- ➢ To predict ecosystem services dynamics under different LULC and climate change scenarios

1.5. Research questions

The main focus of this study is the impacts of LULC dynamics and climate change and variability on key ecosystem services. Therefore, in order to meet this objective, this dissertation attempts to address the following specific research questions:

- RQ1: How do changes in LULC types influence the provision of food production, water supply, raw materials, climate regulation, and cultural services?
- RQ2: How do the spatial and temporal patterns of climate variability influence selected provisioning and regulating ecosystem services?
- RQ3: Are there synergistic or trade-off relationships among food production, water supply, raw materials, and climate regulation services?
- RQ4: How will food production, water supply, raw material, and climate regulation services respond to different predicted LULC and climate change scenarios?

1.6. Significance of the study

Ecosystems provide essential services that are crucial for human well-being. Therefore, understanding the impacts of the major driving forces behind changes in these services is important for making informed decisions. Therefore, this study examines the spatiotemporal impacts of LULC dynamics and climate change and variability on the provision of key ecosystem services. The findings of this study provide empirical evidence on the impacts of LULC changes on selected ecosystem services, landscape fragmentation, and the interactions between ecosystem services. This information will assist the government, local communities, and other stakeholders in planning for protected area management, ecosystem conservation, and restoration, helping to reduce uncontrolled land cover changes, landscape fragmentation, and trade-offs. Additionally, this study highlighted the historical and predicted trends of climate change and variability, along with their impacts on key ecosystem services. These insights will aid decision-makers in designing effective climate change adaptation and mitigation measures to minimize the negative impacts on these services. Finally, the findings of this study may be relevant to other semi-arid areas in Ethiopia and around the world that are dealing with comparable challenges from LULC changes and climate variability.

1.7. Scope and limitation of the study

Geographically the study is delimited to the MzNP and the surrounding *Kebeles* (the smallest administrative unit in Ethiopia) in southern Ethiopia regional state. Thematically, it explores LULC dynamics, synergies and trade-offs, landscape fragmentation, historical and predicted climate change trends, and their effects on key ecosystem services across both spatial and temporal scales. Despite the comprehensive approach taken in this study, several limitations were encountered. The study relied on remote sensing data with a spatial resolution of 30 meters, which may have introduced inaccuracies in classifying LULC types. Additionally, due to the scarcity of original valuation data at the local scale, ecosystem services valuation was based on benefit transfer method, where imperfect matches of LULC classes may affect value estimations. However, in the absence of original valuation data, the benefit transfer method is vital offering, a viable alternative and reliable information for decision-making processes (Tolessa et al., 2017). This approach has been widely utilized in previous ecosystem services valuation studies globally (Costanza et al.,1997; de Groot et al.,2012; Li et al., 2007; Wilson & Hoehn,2006). Another problem faced in this study was the limited density of meteorological stations and missing data. In order to overcome these issues, grid-based climate data were used for climate variability analysis, and LULC classification was conducted at an acceptable level of accuracy that exceeded an overall accuracy of 85% (Anderson, 1976) and a kappa coefficient of 0.75 (Monserud & Leemans, 1992). Additionally, a sensitivity analysis confirmed that the value coefficients were robust and reliable.

1.8. Organization of the dissertation

This thesis is structured into seven chapters. **Chapter one** provides an introduction, covering the background, problem statement, study area description, objectives, research questions, significance, and scope and limitations of the study. **Chapter two** presents a concise literature review and theoretical and conceptual frameworks of the study. **Chapter three** examines the impacts of LULC changes on key ecosystem services in Maze National Park and its surroundings. **Chapter four** explores the spatiotemporal dynamics of ecosystem services in response to climate variability. **Chapter five** analyzes the synergies and trade-offs between key ecosystem services. **Chapter six** focuses on modeling and predicting ecosystem services under different LULC and climate change scenarios. Finally, **Chapter seven** presents a synthesis of findings, conclusions, and recommendations.

2. Literature review

2.1. Concepts of ecosystem services

Ecosystem services are generally defined as the direct and indirect benefits ecosystems provide to people (MEA, 2003). The benefits can be tangible products such wood, food, fiber and fresh water production, and intangible products such as habitat for biodiversity conservation, erosion control, air quality, recreation, and aesthetics (TEEB, 2010). The MEA classified ecosystem services into four groups such as provisioning (food, fuel, fiber, fresh water, and genetic resources), regulating (air quality maintenance, climate regulation, erosion control, regulation of human diseases, and water purification), cultural (spiritual, recreational, aesthetic, educational, and cultural benefits), and supporting services (nutrient cycling, soil formation, primary production) (MEA, 2003). These benefits are offered by a variety of ecosystems, such as grasslands, forests, farmlands, and wetlands, at varying extents and levels (Baskent,2020).

Even though, ecosystems provide a wide range of services that contribute to ecological, social, and economic developments, including human development and existence (Baskent,2020), humans have altered them more rapidly and extensively over the past 50 years to meet their growing demands for food, timber, fiber, fresh water, and fuel (MEA, 2005). This has led to a substantial and irreversible loss of biodiversity. These problems are particularly significant in developing countries as the people there are more reliant on ecosystem services for their livelihoods and are more vulnerable to natural hazards (Brown et al.,2014). The most important direct drivers of change in ecosystem services are LULC change, climate change, overexploitation, invasive alien species, and pollution (MEA, 2005).

2.2. Impacts of land use land cover changes on ecosystem services

LULC change is defined as modification of the Earth's terrestrial surface by human activities (Hassan et al., 2016). It involves the conversion of a land from one land use to the other and causes reductions in the land's biological or economic productivity and complexity due to land use or human activity related processes (Reyers et al.,2009). According to Foley et al. (2005) and Sala et al. (2000), LULC change is considered as a primary cause of global environmental change, leading to the loss of biodiversity and the decline of ecosystem services. About 62% of land area worldwide has experienced transformation from naturally vegetated areas to urban and built-up areas and croplands (Afuye et al., 2022; Mpanyaro et al., 2024). These conversions may lead to a decline in ecosystem functioning and provision of ecosystem services (IPBES, 2018). LULC dynamics cause changes in the number, size, shape, and spatial arrangement of landscape patches, which in turn has an effect on ecosystem function and service delivery (Mitchell et al., 2015b). Studies around the world show reduction of different ecosystem services obtained from various ecosystems, primarily due to LULC transformations, particularly expansion of croplands and built-up areas at the expense of vegetated lands, including forests, grasslands, and wetlands (Ma et al., 2024; Marino et al., 2023; Muche et al., 2023; Negussie, 2019). Consequently, in African countries whose livelihood is dependent on natural resources, the impact of these changes is significant (Arfasa et al.,2023; Rotich et al.,2022). In Ethiopia studies revealed that LULC change brought reductions of numerous individual and overall ecosystem services in different ecological settings (Biedemariam et al., 2022; Mekuria et al., 2021; Muche et al., 2023).

2.3. Impacts of climate change on ecosystem services

Climate change exerts a substantial impact on the quantity and quality of ecosystem services directly or indirectly (Bakure et al. 2022) by rising the intensity and frequency of floods, crop failures, disease outbreaks, wildfires, and insect damage (MEA, 2005; Scholes, 2016; USGS, 2007). It causes decline of crop production, shortage of fresh water, and change in forest coverage of a given area. Thus, it affects the well-being of people through its impacts on water availability, food, spirituality and cultural identity, natural hazards regulation, aesthetics, and recreation (Palomo, 2017). The IPCC report shows irreversible losses and substantial damages of global terrestrial and fresh water ecosystems due to increasing climate change (IPCC, 2023). Temperature increases up to 3°C cause significant changes on ecosystem structure process, and functions spatially and temporally (Bakure et al.,2021). Climate change, manifested through climate variability such as increasing temperature, unreliable rainfall, and extreme weather events, affects ecosystem services provision and the well-being of people who depend on these services (IPBES, 2019). Due to their high dependence on ecosystems and their limited capacity to adapt to a changing climate, developing countries are the most vulnerable to climate change impacts (IPCC, 2007). African countries are highly vulnerable to the impacts of climate change because of their high reliance on agriculture which is highly sensitive to weather and climate variables (temperature and precipitation), natural resources, and low capacity for climate change adaptation (Boon &

Ahenkan,2011). Van der Geest et al. (2019) also reported that climate variability, intensified by climate change, is a major factor in semi-arid drylands of East Africa causing crop and livestock losses, food insecurity, and losses of traditional livelihood systems.

2.4. Synergies and tradeoffs among ecosystem services

Ecosystems offer a variety of services to people that interact in nonlinear and dependent way with one another. When one ecosystem service is utilized, it has an impact on the type and extent of other services the ecosystem offers. Cultivating a crop on an area of land, for instance, may increase the production services of food, but it reduces the regulatory services like water quality regulation and soil retention (Reyers et al.,2009). Converting natural land cover to agriculture or built-up areas alter landscape structures and patterns that can lead to fragmentation and habitat loss, which limits the provision of these services (Mitchell et al., 2015a). Furthermore, the spatial arrangement of patches and the landscape's configuration affect the direction and strength of ecosystem services' interactions, leading to trade-offs and synergies (Rieb & Bennett, 2020).

The interactions between ecosystem services can be classified as positive (synergy) relationships and negative (trade-off) relationships (Sannigrahi et al.,2019). The term "trade-off" describes a situation when using one ecosystem service reduces the value of another service (Reyers et al., 2009). It is a win-lose or lose-win situation when one ecosystem service is increased at the expense of another. The majority of tradeoffs occur between the provisioning and regulating services (Bennett et al., 2009; Sannigrahi et al., 2020). According to Sanigrahi et al. (2020), synergy is the simultaneous change of two ecosystem services in a win-win or lose-lose scenario where two ecosystem services increase or decrease together. Knowing the trade-offs and synergies between different ecosystem services is essential for making informed resource management decisions (Bennett et al., 2009). It helps policymakers to promote win-more and lose-less solutions to avoid ecosystem disservices (Sil et al., 2016).

2.5. Valuation of ecosystem services

Numerous methods have been used by researchers to estimate the values of ecosystem services. Among these, monetary valuation methods are the most widely applied methods (Selivanov & Hlaváčková, 2021), developed to estimate both the market and non-market values of ecosystem services (Costanza et al., 1997). In market-based valuation methods, economic values of ecosystem services are derived from the existing market prices. The market-based valuation method (the market price method, the replacement cost method, and others) directly or indirectly depends on the existing market price for the valuation of the services. Whereas, the non-market valuation methods, including choice experiment and contingent valuation methods, are based on people's stated preference, which indicates their willingness to pay for the services (Bouma & van Beukering, 2015). Though conducting original ecosystem services valuation research is expensive and time-consuming (Wilson & Hoehn, 2006), estimating ecosystem service values using the benefit transfer method offers a practical alternative when site-specific valuation information is lacking. Benefit transfer approach adapts the monetary value determined in one place and time to make inferences about the monetary value of ecosystem services at another place and time. This method is principally useful when time, information accessibility, and budgets hinder collection of primary data (Temesgen et al.,2018; Wilson & Hoehn, 2006). Despite criticisms over uncertainty in the accuracy of the ESV coefficients, the benefit transfer method has been widely used in global and national ecosystem assessments, value mapping applications, and policy appraisals (Brander et al., 2024; Costanza et al., 1997). Therefore, expressing ESVs in monetary terms is helpful to raise awareness and provide evidence for policy makers (de Groot et al., 2012).

2.6. Theoretical and Conceptual frameworks

2.6.1. Theoretical framework

Reviewing the theoretical underpinnings about the problem under study is of great worth as it is valuable for identifying the view by which the study is governed. Theoretical frameworks serve as a lens through which research questions are conceptualized, the type of research approaches to follow are defined, and the specific methods of data collection and analyses to be applied are identified (Kivunja, 2018).

This study is grounded on socio-ecological systems theory. This theory was developed in the 1980s to explore the dynamics and possible evolutions of socio-ecological systems (Zurlini et al., 2008). The socio-ecological systems theory integrates theories and principles from both social and natural sciences and emphasize the interconnected relationship between people and nature (Berkes & Folke, 1998; Ostrom, 2009). This theory considers human beings as an integral part of natural systems, continuously influencing and being influenced by ecological processes across spatial and temporal scales (Petrosillo et al., 2015). The theory uses an integrated approach to understand the social and ecological processes that affect ecosystem services, non-linear feedback mechanisms, trade-offs, and complex interconnections involved in service delivery (Reyers et al., 2013). By considering insights from environmental and social sciences, the framework enables a more comprehensive analysis of these interdependencies (Petrosillo et al., 2015), facilitating assessments of ecosystem service generation, delivery, management, and human well-being in a linked iterative cycle. The interconnectedness of social and ecological systems suggests the need to consider ecological processes, benefit distribution, and governance in ecosystem service assessments (Rüdisser et al., 2020). Employing a socio-ecological system is useful for examining the dynamic nature of ecosystem services in the context of setting policy targets and indicators (Reyers et al., 2013).

Several established frameworks, including the Driver-Pressure-State-Impact-Response (DPSIR), IPBES, and the MEA frameworks, support the socio-ecological systems theory. The DPSIR framework shows the cause and effect relationships between human activities (drivers) and changes to environmental components helping to analyze environmental problems and identifying options to mitigate them through the categorization of drivers, pressures, states, impacts, and responses (Burkhard & Muller, 2007). Highlighting major social and ecological elements and relationships, the IPBES framework provides a simplified approach to understand the complex interactions between nature and human society, and offers structure for decisions relating to biodiversity and ecosystem services (Díaz et al., 2015). In the same vein, the MEA framework addresses socio-ecological systems by linking direct and indirect drivers to ecosystem services and human well-being (MEA, 2003). This approach considers ecosystems in the context of the services they provide to society, how these services in turn benefit humanity, and how human actions alter ecosystems and the services they provide. The framework categorizes ecosystem benefits into four groups, including provisioning, regulating, supporting and cultural services and emphasizes the links between the spatial and temporal provision of ecosystem services and their beneficiaries (MEA,2003). This allows for a greater understanding of ecological functioning, trade-offs, and synergies between services and their impacts on human well-being. The MEA framework also highlights how these elements feed back into governance and policy-making processes. As a result, it has significantly influenced both scientific research and policy development by supporting problem-solving and encouraging proactive environmental management (Petrosillo et al., 2015). Each framework presents a unique viewpoint and has both advantages and disadvantages, including oversimplifying system dynamics or being complex, and data intensive when assessing the interdependencies between social and ecological systems. This study combined socio-ecological systems theory with the MEA framework to empirically analyze the dynamic interaction between climate change and variability, LULC changes and ecosystem services, including synergies and trade-offs, across a variety of spatial and temporal scales to provide useful insights for sustainable management and policy development.

2.6.2. Conceptual framework

This study adapted a conceptual model from the MEA framework to show the links between drivers of change, ecosystem services, and human interactions (Fig.2.1). The MEA framework was intended to illustrate the interdependencies of ecosystem services, human wellbeing, direct and indirect factors affecting ecosystem services at local, regional, and global scales over time (MEA, 2005). According to this framework, indirect factors such as population growth, economic conditions, sociopolitical dynamics, cultural influences, and religious beliefs do not directly affect ecosystem services. Instead, they shape direct drivers of change, including LULC changes and climate change. These direct drivers, in turn, impact ecosystem services through land cover conversion and variations in temperature, rainfall duration, and intensity. Ultimately, changes in ecosystem services influence human well-being, creating feedback effects that further impact the environment. These complex interactions occur across different spatial and temporal scales (MEA,2003).

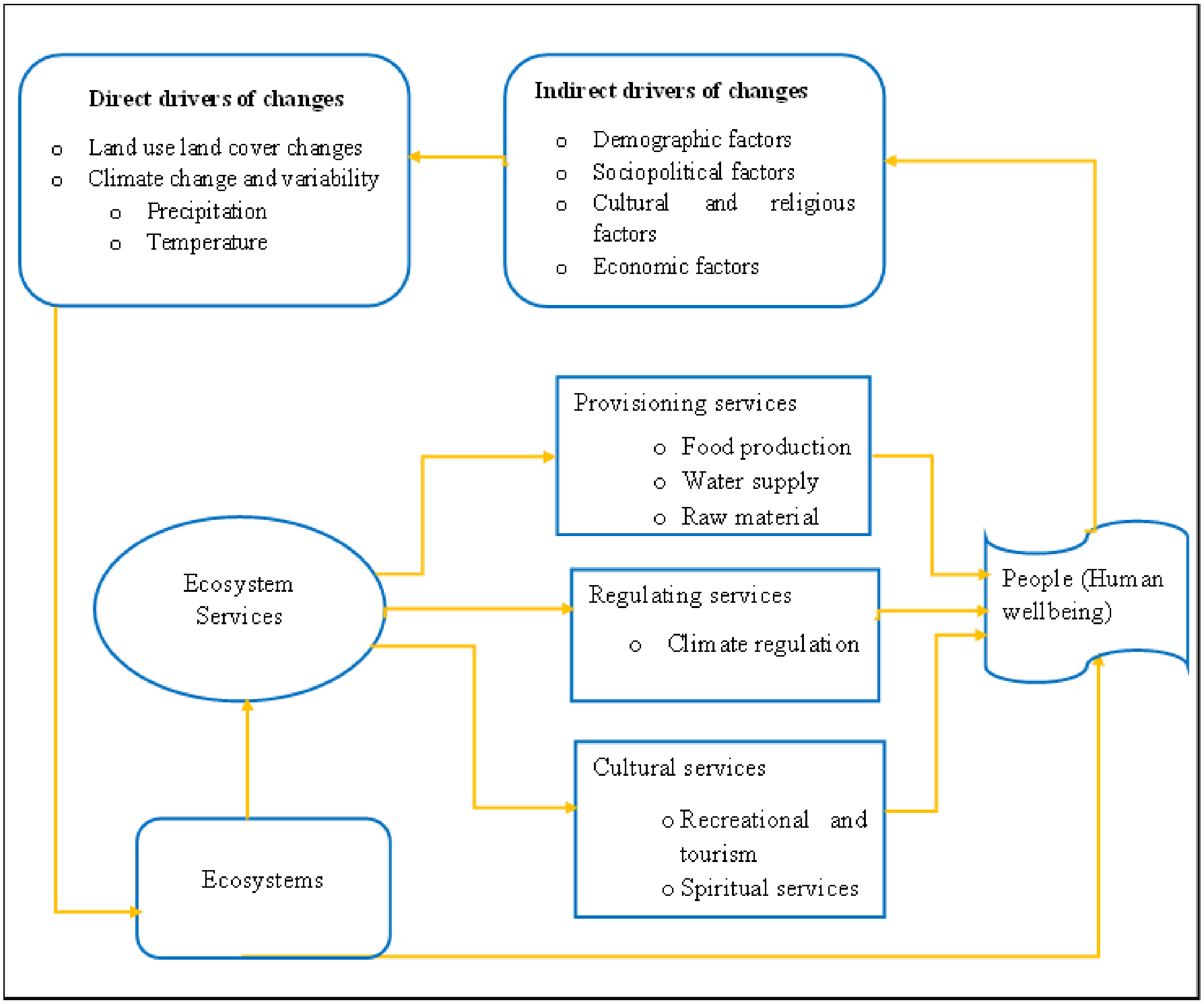

Figure 2.1:Conceptual Framework of the study (Adapted from MEA, 2003)

3. Impacts of land use land cover dynamics on ecosystem services in Maze national park and its environs, southwestern Ethiopia

Abstract

This study investigated the impacts of land use land cover (LULC) changes on selected ecosystem services in Maze National Park (MzNP) and its environs in southwestern Ethiopia. Landsat images from 1985, 2005, and 2020 were used to examine LULC changes. Images were classified using the Random Forest (RF) classifier, and their accuracy was computed in QGIS. Ecosystem service values (ESVs) were then estimated using the benefit transfer method employing Ecosystem Service Valuation Database (ESVD) coefficients. Additionally, socioeconomic survey was conducted to understand the local community's perceptions regarding the dynamics of ecosystem services. The findings revealed a significant increase in croplands (103.7%) and built-up areas (31.32%), while riverine forests, water bodies, and wooded grasslands declined. The overall ESVs decreased by 20%, from 2038.42 million USD in 1985 to 1628.72 million USD in 2020, mainly driven by reductions in riverine forests and wooded grasslands. As for the individual ESVs for the period 1985 to 2020, only food production increased by 0.7 million USD, while water supply, climate regulation, raw materials, and recreation and tourism declined by 180.35, 2.67, 45.72, and 481.62 million USD, respectively. The coefficient of sensitivity ranged from 0.01 to 0.94, <1, revealed that our estimates are relatively robust. Ecosystem services such as grazing, recreation, wild food, and firewood are highly valued by local residents, but they are declining over time due to environmental degradation and restrictions on access to the park. Thus, understanding LULC changes and their impacts on ESVs can help decision-makers design effective protected area management plans and reduce potential conflicts over resource uses. Further investigations are suggested to more accurately quantify ESVs using high resolution satellite imageries and different valuation methods.

Key Words: Benefit Transfer, Ecosystem Services, Land Use Land Cover, Maze National Park, Random Forest

Mestewat Simeon[1,2*], and Desalegn Wana[1] .(2024). Impacts of land use land cover dynamics on ecosystem services in Maze national Park and its environs, Southwestern Ethiopia Heliyon 10 (2024) e30704. https://doi.org/10.1016/j.heliyon.2024.e307

3.1. Introduction

Ecosystems provide a variety of services including food, water, timber, fuel wood, climate regulation, habitat conservation, spiritual and recreational services that are essential for human wellbeing (Millennium Ecosystem Assessment (MEA), 2005). However, an increasing conversion of forests, grasslands, wetlands and other natural ecosystems to croplands and settlements has exerted a great pressure on biodiversity and ecosystem services (Polasky et al., 2011). Particularly, land use land cover (LULC) changes which are driven by socio-demographic dynamics and climate change can have profound impacts on ecosystem services provided by water bodies (Shukla et al., 2018), forests (Baidoo & Obeng, 2023; Solomon et al., 2019), grasslands (Kalema et al., 2015), and urban areas (Nayak et al., 2024). These changes can in turn alter the structure and functionality of ecosystems, affecting their ability to provide goods and services to communities (Marino et al., 2023). As a result, LULC change is recognized globally as a major driver of biodiversity loss and the decline of ecosystem services (Sala et al., 2000). Understanding the relationship between LULC and ecosystem service values (ESVs) is essential for planning resource management (Basu et al., 2023).

Africa's ecosystems, which hold significant ecological, social, economic and cultural importance at the national, regional and global levels, have been affected by LULC changes, especially conversion of natural habitats into agricultural lands and urban settlements (Intergovernmental Science-Policy Platform on Biodiversity (IPBES), 2018). Ethiopia exhibits a typical example, where LULC changes are widespread, with agricultural activities and settlements dominating rural landscapes (Tolessa et al., 2017). Maze National Park (MzNP) and its environs are dominantly covered by savanna grasslands and scattered trees, and riverine forests (Henok et al., 2017). These landscapes offer a diverse range of provisioning, regulating, supporting and cultural services. The benefits derived from the area include food, water, grazing, thatching grass, firewood, construction materials, wild honey, regulation of the local climate, and recreation and aesthetic values. These benefits play a vital role in sustaining the livelihoods of the local people in the study area, especially during times of drought and famine (Zewude et al., 2022). However, extensive land use pressures, increased demand for natural resources (National Ecosystem Assessment of Ethiopia (NEA), 2022), population growth, expansion of agricultural lands, demand for fuel wood and construction materials, poverty, as well as policy and institutional changes, are among the major causes of LULC dynamics in the country (Mathewos, 2019; Ogato et al., 2021; Wubie et al., 2016). Previous studies in Ethiopia have demonstrated a loss of both individual and overall ecosystem services as a result of LULC changes (Kindu et al., 2016; Mekuria et al., 2021; Negussie, 2019; Tolessa et al., 2017).

The quantity and quality of services offered by ecosystems depend on the type and status of ecosystems (MEA, 2005). Each ecosystem provides unique services that cannot be replaced by others (Tolessa et al., 2017). Therefore, assessing the services provided by different ecosystems and quantifying their spatial and temporal changes is crucial for the efficient management of social-ecological systems (Deeksha & Shukla, 2022). In Ethiopia, only few studies have been carried out by quantifying the impacts of LULC dynamics on ecosystem services (Aneseyee et al., 2020; Belay et al., 2022; Kindu et al., 2016; Markos et al., 2018; Mekuria et al., 2021; Negussie, 2019; Solomon et al., 2019; Temesgen et al., 2018; Woldeyohannes et al., 2020). These studies were mainly confined to forest ecosystems of Ethiopian highlands (Belay et al., 2022; Kindu et al., 2016; Solomon et al., 2019), watersheds and basins (Aneseyee et al., 2020; Markos et al., 2018; Woldeyohannes et al., 2020), and agroforestry dominated landscapes (Temesgen et al., 2018). Moreover, semi-arid regions, where grasses and shrubs predominate the landscapes, provide crucial ecosystem services such as food production, water supply, climate regulation, fuel wood, grazing, thatching grasses, construction wood, and other benefits have received little attention in previous studies. Furthermore, to the best of our knowledge, the local community's perceptions regarding the benefits obtained from the MzNP and its surroundings have not been studied.

National Parks play a crucial role in biodiversity conservation and in supporting the livelihoods of local residents who rely on natural resources for their survival (Haq, 2016; Kumssa & Bekele, A., 2014; Zhao et al., 2019). Despite such roles, MzNP is under intense pressure due to human activities such as overgrazing, collection of firewood and construction materials, and frequent bush fires. The core conservation area of the park, in particular, is prone to fires caused by individuals seeking grass for livestock feed in drought affected areas (Zewude et al., 2022). Consequently, the park and its surrounding area are experiencing changes in LULC, degradation of vegetation resources, and a decline in wild life populations (Andabo & Gamo, 2015; Zewude et al., 2022). These factors have led to environmental deterioration, undermining the ecosystem’s many benefits.

The objective of this study is to investigate the impacts of LULC dynamics on key ecosystem services in MzNP and its environs in southwestern Ethiopia. We employed the benefit transfer method to quantify these services and analyzed the local community's perception of ecosystem services dynamics to assess awareness and improve decision-making for the effective management and conservation of the park and its environs.

3.2. Materials and Methods

3.2.1. Data sources and methods

Land use land cover data and classification

The data set for LULC change analysis was derived from time series Landsat images of three different periods (1985, 2005, and 2020), obtained from the United State Geological Survey (USGS) website (https://earthexplorer.usgs.gov). Landsat 4–5 Thematic Mapper (TM) was used for 1985, Landsat 7 Enhanced Thematic Mapper Plus (ETM+) for 2005, and Landsat 8 Operational Land Imager (OLI) for 2020, at 30m spatial resolution (Table 3.1). The satellite images were sourced for path/row 169/56, fully covering the study area. To avoid cloud cover, all three images were acquired during dry seasons (December to January). Image preprocessing including layer stacking, and the Dark Object Subtraction (DOS) method, image-based atmospheric correction (Congedo, 2016), was employed to remove haze, shadow, and dark pixel values caused by atmospheric scattering (Chavez, 1988), using the Semi-Automatic Classification Plugin (SCP) in QGIS. The Landsat 7 ETM+ image has a scan-line error due to sensor failure on May 31, 2003 (Chen et al., 2012), which caused gaps in the Landsat 7 images. These gaps were filled using the mask layer provided with the image (Storey, 2005) in QGIS with the 'fill no data' tool.

Table 3.1: Description of imagery data used for LULC change analysis

Imagery Type	Path/Row	Pixel Size(m)	Bands Used	Acquisition Date	Source
Landsat TM	169/56	30*30	1-5 and 7	01/09/1985	USGS
Landsat ETM^{+}	169/56	30*30	1-5 and 7	01/24/2005	USGS
Landsat OLI	169/56	30*30	2-7	12/11/2020	USGS

Training and test data for LULC classification were collected through stratified random sampling techniques from satellite images with high spatial resolution, including Google Earth, SPOT5, and Sentinel. The LULC classifications were carried out using a Random Forest (RF) supervised classification method in R statistical software (R4.1.3) (R Core Team, 2022). RF is a powerful classifier known for its ability to predict well even in the presence of missing data. It also helps to avoid over-fitting problems, produces more stable results, and is less sensitive to multi-collinearity compared to other machine learning algorithms (Breiman, 2001). The classification identified bare land, built-up area, cropland, riverine forest, and wooded grassland as major LULC classes, with burned area as an additional class in 2020.

To assess the accuracy of LULC classification, 692 verification points were generated from Google Earth, SPOT5, and Sentinel images for the 1985, 2005, and 2020 LULC maps. Reference points were stratified into LULC classes to reduce the standard error of class-specific estimates, based on (Eq.1) (Olofsson et al., 2014).

$$N = \sum_{i=1}(wi * si)/so)2 \qquad (1)$$

Where, Wi = mapped area proportion of class i

Si = standard deviation of stratum i

So = expected standard deviation of overall accuracy

C = total number of classes

The accuracy of the classified image needs to be assessed before it is used as input for any applications (Rwanga & Ndambuki, 2017). Therefore, we assessed the accuracy of images using measures such as Kappa coefficient (Eq.2), overall accuracy (Eq.3), user's accuracy (Eq.4), and producer accuracy (Eq.5). The LULC categories used in this study were identified based on Ethiopian LULC classification and coding Standard (Ethiopian Mapping Agency (EMA), 2018) (Table 3.2).

Table 3.2: Descriptions of LULC types in the study area

Land use land cover Types	Description
Bare land	Non vegetated area dominated by rock outcrops, eroded and degraded lands
Built-up Area	Land dominated with houses, huts and roads
Cropland	Land used primarily for production of food and fiber. This category includes both cultivated and non-cultivated lands
Riverine Forest	Forest along the water way or the rivers
Water Body	Rivers in the study area
Wooded Grassland	Grasslands with scattered trees, herbs and shrubs
Burned Area	Land surface sufficiently affected by fire and display significant changes in vegetation cover and in the ground surface.

$$K = \frac{M\sum_{i=j=1}^{r} nij - \sum_{i=j=1}^{r} ninj}{M^2 - \sum_{i=j=1}^{r} ninj} \tag{2}$$

Where, K = kappa statistics, M = total number of observations in the matrix, r = number of rows in the confusion matrix, nij = number of observations in row i, column j, ni = total number of observations in row I, nj = total number of observations in column j

$$\text{Overall Accuracy} = \frac{\text{Total number of correctly classified pixels(Diagonal)}}{\text{Totan number of reference pixels}} * 100 \tag{3}$$

$$\text{User's Accuracy} = \frac{\text{Number of correctly classified pixels in each category}}{\text{Totan number of reference pixels in that category(the Raw Total}} * 100 \tag{4}$$

$$\text{Producer Accuracy} = \frac{\text{Total number of correctly classified pixels in each category}}{\text{Totan number of reference pixels(the Column Total)}} * 100 \tag{5}$$

Post-classification comparison approach involved calculating percentage changes for each LULC classes over three intervals: 1985-2005, 2005-2020, and 1985-2020, to assess changes in LULC classes. Additionally, changes “from-to” and the areas that remained unchanged for each LULC class from 1985 to 2020 were determined. The percentage change of LULC classes was computed as follows (Eq.6):

$$\Delta L = \frac{A2 - A1}{A1} * 100 \tag{6}$$

Where; ΔL is the LULCC proportion, A2 and A1 are final and initial area coverage of the LULC classes respectively.

Ecosystem services valuation methods

Based on discussions with local residents, agricultural extension agents, and park staff, six ecosystem services that the local community perceives as major benefits, such as food production, water supply, raw material provision, climate regulation, recreation and tourism, and spiritual experiences, were identified.

To quantify the values of the identified ecosystem services, we employed value coefficients from Ecosystem Service Valuation Database (ESVD) (Table 3.3), which was updated in 2020 with support from the UK Department for Environment, Food, and Rural Affairs (Defra). The ESVD is a follow-up to the Economics of Ecosystems and Biodiversity (TEEB), containing 4,042 values based on 693 studies. These values were obtained from six continents, including Africa (de Groot, 2020). We used the benefit transfer method to quantify changes in ESVs of the LULC classes for the identified study periods (Costanza et al., 1997; Kindu et al., 2016; Li et al., 2007). Benefit transfer is employed as an alternative method to estimate the economic values of ecosystem services when site-specific value information is lacking. It adapts existing valuation information to new policy contexts and is particularly useful when budgets, time, and information accessibility constrain primary data collection (Temesgen et al., 2018; Wilson & Hoehn, 2006). The benefit transfer method has been extensively used to value environmental resources in numerous studies (Costanza et al., 1997; Temesgen et al., 2018; Woldeyohannes et al., 2020).

Table 3.3:LULC classes, corresponding biomes and mean standardized values per ecosystem service biome

LULC Categories	**Equivalent Biome**	**Mean Standardized Values per Ecosystem Service Biome (Int$/Hectare/Year; 2020 Price Levels)**
Bare land	Desert	0
Built-up Area	Built-up Area	0
Cropland	Cultivated Areas	4231
Riverine Forest	Tropical Forest	113657
Water Body	Rivers and Lakes	25538
Wooded Grassland	Grassland	1115
Burned Area	Desert	0

Following the approach proposed by Costanza et al. (Costanza et al., 1997), ESVs were calculated per unit area for each LULC class based on ESVD value coefficients (Table 3.3; Table 3.4). Some land use classes, such as bare land and built-up areas, did not have value coefficients in previous studies (Aneseyee et al., 2020; Belay et al., 2022; Kindu et al., 2016; Markos et al., 2018; Mekuria et al., 2021; Negussie, 2019; Solomon et al., 2019; Temesgen et al., 2018; Woldeyohannes et al., 2020). Likewise, in our study, no value coefficients were assigned to bare land, built-up, and burned areas. Using the following equations, ESVs of each LULC class (Eq. 7) and the total values of key ecosystem services (Eq. 8) of reference years were computed.

Table 3.4:Presentation of mean standardized values of selected ecosystem services per LULC classes

Biome	**Mean Standardized Values per Ecosystem Service Biome (Int$/Hectare/Year; 2020 Price Levels)**						
	Food production	Water supply	Raw Material	Climate regulation	Spiritual experiences	Recreation and Tourism	Total ESV Coefficients
Bare land	-	-	-	-	-	-	-
Built-up Area	-	-	-	-	-	-	-
Cropland	510	604	6	10	-	3101	4231
Riverine Forest	602	47869	11739	658	-	52789	113657
Water Body	2288	9198	92	251	76	13633	25538
Wooded Grassland	-	313	637	73	-	92	1115

$$ESV_{kt} = (A_{kt} \times VC_k) \quad (7)$$

$$ESV_{Tt} = \sum(ESV_{kt}) \quad (8)$$

Where, ESV_{kt} and ESV_{Tt} is ecosystem service value of LULC class "k" at reference year "t" and total value of key ecosystem services for a reference year "t", respectively. A_k is area in ha of LULC class "k" and VC_k is value coefficient of LULC class "k"

The changes in ESVs were determined by calculating the difference between the estimated values in each reference year (Eq.9). Additionally, we calculated individual ESVs obtained from each LULC class and quantified the gains and losses of the identified ecosystem services over the study periods.

$$\text{Percentage ESV Change} = \frac{ESV_{t2} - ESV_{t1}}{ESV_{t1}} * 100 \quad (9)$$

Where, ESV is ecosystem service value, t_1 is initial year and t_2 is final year

Analysis of coefficient of sensitivity

Given the uncertainties in the value coefficients and the imperfect matches between the biomes used as proxies for LULC types, sensitivity analysis was conducted to reduce these uncertainties (Kreuter, 2001). The coefficient of sensitivity was calculated for each LULC and year using the standard economics concept of elasticity (Kreuter, 2001), adjusting the value coefficients of each LULC type by 50% with (Eq.10) for the study periods.

$$CS = \frac{\frac{(ESVj - ESVi)}{ESVi}}{\frac{VCjk - VCik}{VCik}} \quad (10)$$

Where; CS is coefficient of sensitivity, ESV is the estimated ecosystem service value, VC is the value coefficient, i and j represent the initial and adjusted values, respectively, and k represents the land use category. If CS > 1, then the estimated ecosystem value is elastic with respect to that coefficient and it is important to accurately define VC, but if CS < 1, then the estimated ecosystem value is considered to be inelastic and robust (Kreuter, 2001; Li et al., 2007).

Socio-economic data collection

MzNP is surrounded by five *woredas:* such as Kucha, Kucha Alpha, Daramalo, Kamba, and Zala. From these *woredas,* four *kebeles* were purposively selected based on their strong interaction with the park (Andabo, 2017) and sharing long boundary with the park. The selected sample *kebeles* were Morka, Domea, Wagesho, and Mela Gayile Tossa. According to the *kebele* administration offices, the total number of households in sample *kebeles* were 2,203. The total sample size of households for the survey was determined using the sample size determination formula developed by Cochran (Cochran, 1977) (Eqs.11; 12).

$$n_0 = \frac{z^2pq}{e^2} \quad (11)$$

Where, n_0 *is* the sample size, z is the selected critical value of desired confidence level, p is the estimated proportion of an attribute that is present in the population, $q = 1 - p$ and e is the desired level of precision.

Therefore, with a total number of 2,203 households, the calculated sample size was 246. However, since this sample size exceeds 5% of the total households (110), Cochran's correction formula was used to calculate the final sample size (Cochran, 1977).

$$n_0 = \frac{n_0}{1 + \frac{(n_0 - 1)}{N}} \tag{12}$$

Where, n_0 is the sample size derived above and N is the population size. Hence, the final sample size determined for this study was 221.

Study participants for the questionnaire, focus group discussions (FGDs) and key informants' interviews (KIIs) were selected purposively based on their length of time living in the study area and their knowledge about the park and the benefits they obtain from it. The selection of the respondents was conducted in consultation with *kebele* administrators and agricultural extension agents of each *kebeles*. A total of 221 study participants were selected from the four *kebeles*. Concerning FGDs and KIIs, six FGDs were conducted including two women-only groups and four groups with both women and men, each containing five to seven members in the selected four *kebeles*. In addition, eight KIIs were conducted with *kebele* administrators, residents, and park staff.

For the quantitative data gathered through questionnaires, descriptive statistics such as frequency and percentage were used for analysis. Qualitative information obtained from FGDs and KIIs was thematically classified into two predefined categories: LULC changes and major benefits obtained from the park. And the findings were presented in a narrative manner. Socio-economic data were used to triangulate how the LULC based analysis correspond to local communities' perceptions regarding ecosystem services dynamics. The overall methodological framework of the study is presented in Fig.3.1.

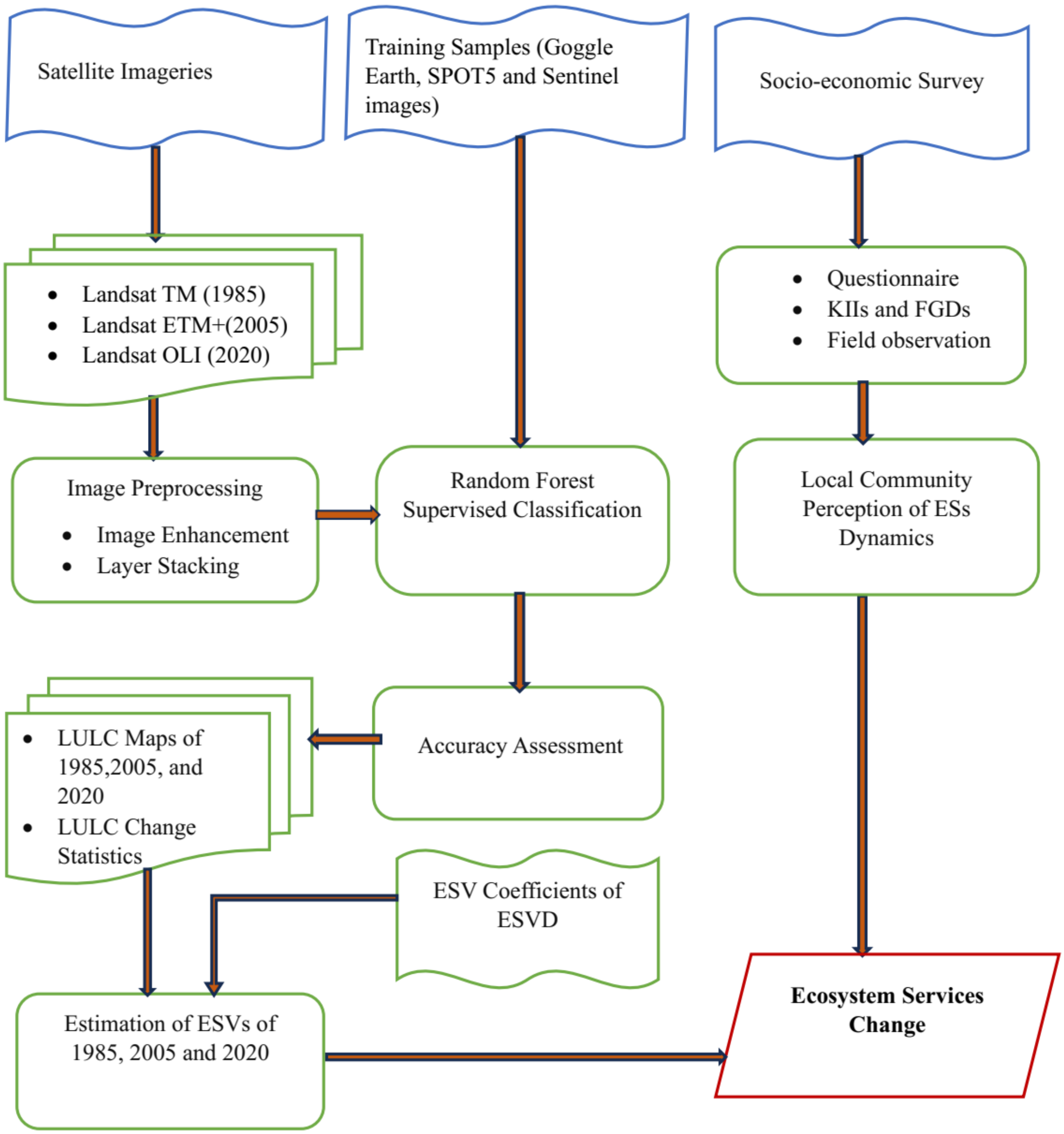

Figure 3.1:Methodological framework of the study

3.3. Results

3.3.1. Land use land cover change analysis

Image classification processes enabled to identify six LULC classes for 1985 and 2005, and seven classes for 2020. Table 3.5 shows the overall accuracy and kappa coefficient values for the years 1985, 2005, and 2020. The overall accuracy was 88.93%, 93.03%, and 91.57%, with kappa coefficient of 0.81, 0.88, and 0.86 respectively. These values indicate very good to excellent agreement with the validation dataset, meeting the required standards (overall accuracy >85% (Anderson, 1976) and kappa coefficient >0.75 (Monserud & Leemans, 1992).

Table 3.5:Accuracy assessment of the classified images

LULC Classes	**Accuracy (%)**								
	1985			2005			2020		
	PA	UA	Kappa hat	PA	UA	Kappa hat	PA	UA	Kappa hat
Bare Land	88.65	84.82	0.83	92.47	98.23	0.98	94.82	94.69	0.94
Built-up Area	55.50	93.22	0.93	73.67	96.61	0.97	77.59	91.53	0.91
Cropland	70.50	97.33	0.97	98.52	89.33	0.88	86.81	84.00	0.81
Riverine Forest	84.40	88.98	0.86	84.47	80.51	0.77	87.63	98.81	0.99
Water Body	42.49	86.54	0.86	24.09	76.92	0.76	65.63	76.92	0.77
Wooded Grassland	97.16	88.36	0.73	97.96	95.99	0.90	95.57	91.63	0.80
Burned Area	-	-	-	-	-	-	63.58	94.20	0.94
Overall Accuracy	88.93			93.03			91.57		
Kappa Coefficient	0.81			0.88			0.86		

As specified in Table 3.6, wooded grassland was the most dominant LULC type in the study area covering 62.43%, 62.26%, and 60.06% of the total area in 1985, 2005, and 2020, respectively. Riverine forest was the second most dominant LULC class in 1985 and 2005, making up 18.68% and 15.4% of the total area, respectively. However, in 2020, cropland significantly increased and replaced riverine forest as the second most dominant LULC type, accounting for 15.92% of the total area (Table 3.6). LULC classes that exhibited positive change progressively over the entire 35 years of the study period were cropland and built-up areas, while riverine forest, water body, and wooded grassland showed a negative change. Due to the park's frequent exposure to illegal fires (Fig.3.2B), a new category, burned area (Fig.3.2A), was included in the 2020 image, covering 1,285 hectares or 1.42% of the total area (Table 3.6).

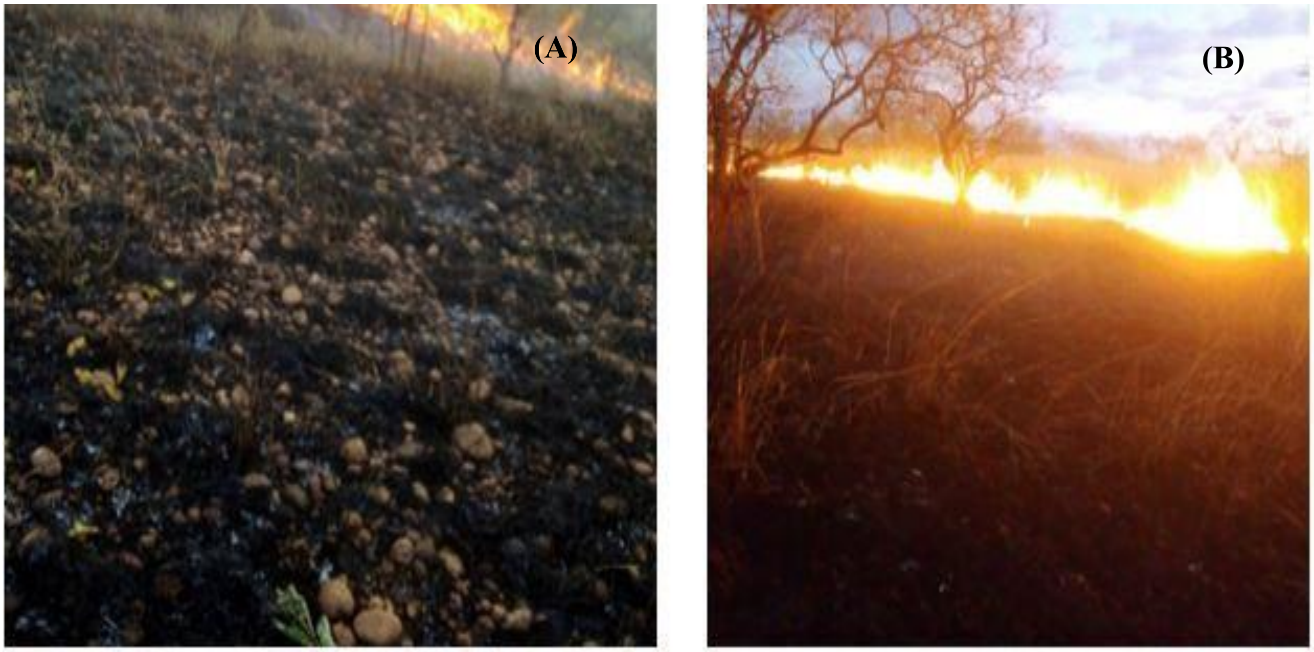

Figure 3.2:Fire in Maze National Park (A: Land destructed by illegal fire, B: Illegal fire incidence)

Photo Courtesy of Aregahegn, Park officer,2021

Table 3.6:Areal coverage of LULC classes and changes in the study periods

LULC Classes	1985		2005		2020		Area Change (ha)		
	Area(ha)	%	Area(ha)	%	Area(ha)	%	1985-2005	2005-2020	1985-2020
Bare land	7774	8.58	9189	10.15	4945	5.46	1415 (18.2)	-4244 (-46.2)	-2829 (-36.4)
Built-up Area	1360	1.5	1427	1.58	1827	2.02	67 (4.93)	359 (25.16)	426 (31.32)
Cropland	7079	7.82	8881	9.8	14420	15.92	1802 (25.45)	5539 (62.37)	7341 (103.7)
Riverine Forest	16914	18.68	13948	15.4	13133	14.5	-2966 (-17.53)	-815 (-5.84)	-3781 (-22.35)
Water Body	902	0.99	731	0.81	558	0.62	-171 (-18.96)	-173 (-23.66)	-344 (-38.14)
Wooded Grassland	56537	62.43	56390	62.26	54398	60.06	-147 (-0.26)	-1992 (-3.53)	-2139 (-3.78)
Burned Area	-	-	-	-	1285	1.42	-	-	-
Total	90566	100	90566	100	90566	100	-	-	-

Figures in the parenthesis refer to the percentage of change

The study area experienced a notable expansion of croplands and built-up areas from 1985 to 2020. Croplands experienced the highest increment rate (103.7%) among the LULC classes, while built-up area also increased by 31.32% over the study periods. On the other hand, Water bodies and riverine forests were the two LULC types that showed the largest continuous spatial reduction in the study area, at 37.47% and 22.35%, respectively. Despite wooded grassland being the largest LULC type in terms of area coverage in the study area, its rate of change (reduction rate) was the smallest compared to other LULC classes decreasing by 3.78% from 1985 to 2020. Bare land exhibited an increment of 18.2%, from 1985 to 2005 but decreased by 45.5% from 2005 to 2020, with an overall decline of 36% over the period of 1985 to 2020 (Table 3.6; Fig.3.3).

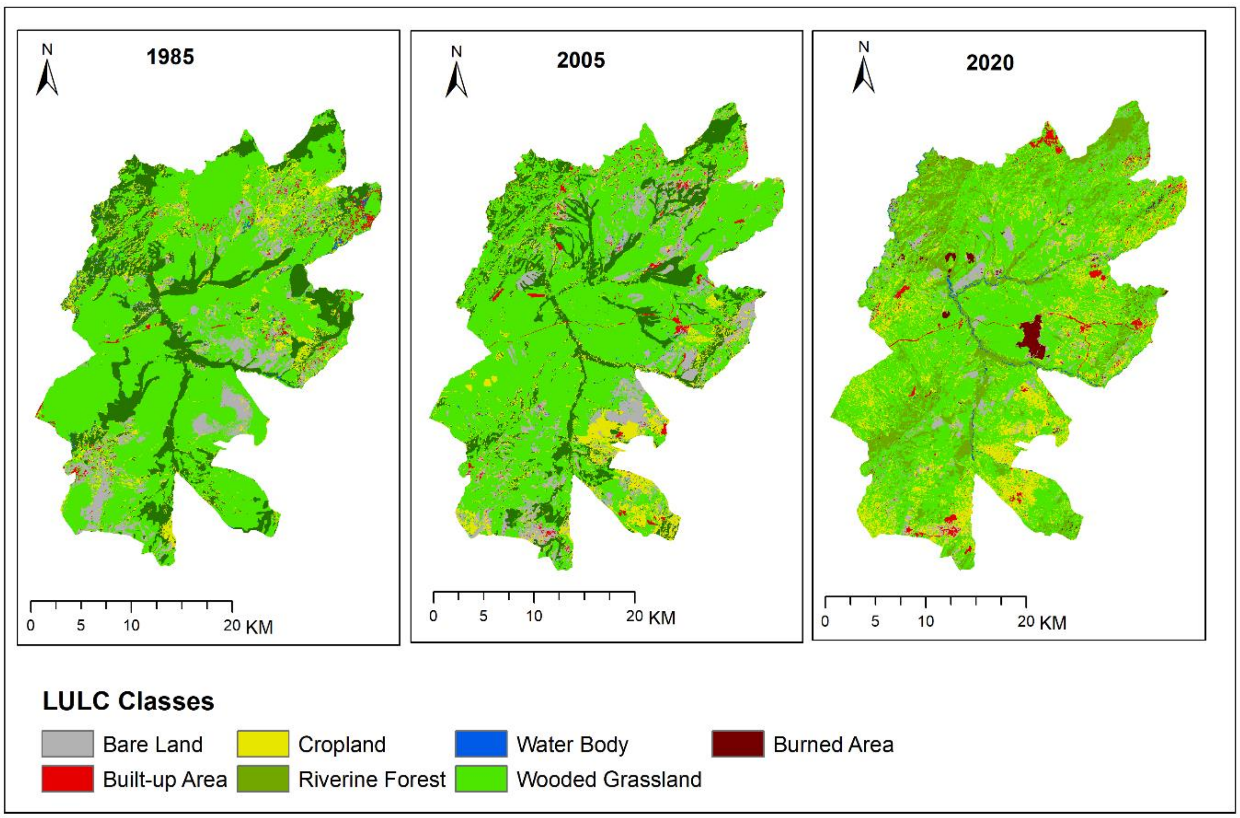

Figure 3.3:LULC map of maze national park and its environs in 1985, 2005 and 2020

The LULC change matrix indicates that the expansion of croplands over the last 35 years period has mainly occurred at the expense of wooded grassland, with 10.89% (9866 hectares) of wooded grassland was converted to farmland. Meanwhile, 46185.6 hectares (51%) of the total area remained unchanged during the study period (Table 3.7). In general, from 1985 to 2020, cropland and built-up areas displayed a net gain of 7340 and 466 hectares respectively, while bare land, riverine forest, water body, and wooded grassland showed net losses (Table 3.7).

Table 3.7:LULC transition matrix from 1985-2020

	LULC Classes	Bare land	Built-up Area	Cropland	Riverine Forest	Water Body	Wooded Grassland	Burned Area	Total 1985(ha)	Loss(ha)
		Change to LULC 2020(%)								
From LULC 1985(%)	Bare Land	**0.98**	0.18	1.83	0.08	0.01	5.24	0.26	7774	6888
	Built-up Area	0.14	**0.18**	0.35	0.05	0.00	0.76	0.02	1361	1195
	Cropland	0.35	0.05	**0.73**	1.86	0.05	4.75	0.04	7079	6423
	Riverine Forest	0.82	0.51	1.88	**7.51**	0.42	7.17	0.37	16915	10113
	Water Body	0.06	0.03	0.25	0.05	**0.02**	0.58	0.01	903	882
	Wooded Grassland	3.11	1.07	10.89	4.94	0.11	**41.58**	0.72	56537	18883
	Total 2020(ha)	4946	1827	14420	13134	559	54398	1285	**46185.66[a]**	
	Gain(ha)	4060	1661	13763	6332	538	16744	1285		
	Net change(ha) [b]	-2828	466	7340	-3781	-344	-2139			

Diagonal figures in bold represent percentage of unchanged lands in the study periods

[a] indicates the total area in hectare remained unchanged from 1985 to 2020

[b] Net change = gain – loss

3.3.2. Ecosystem services valuation

The total values of the identified key ecosystem services of the study area in 1985, 2005, and 2020 were 2038.42, 1704.4, and 1628.72million USD, respectively. The total ESVs of the study area declined by over 20% between 1985 and 2020 (Table 3.8). Among the LULC classes, riverine forest constituted the highest ESV, accounting for 94.31%, 93.01%, and 91.65% of the total values in 1985, 2005, and 2020, respectively (Table 3.8). Regarding the overall ESV changes across the different intervals, there was a 16.39%, 4.44%, and 20.1% decline from 1985 - 2005, 2005 - 2020, and 1985 - 2020, respectively. ESVs from croplands showed considerable positive change across the study years with increment of 25.44%, 62.39%, and 103.71% from 1985 - 2005, 2005 - 2020, and from 1985 - 2020, respectively. Whereas, ESVs of the remaining LULC classes showed a negative change during the study periods (Table 3.8).

Table 3.8:Ecosystem service values and changes from 1985-2020

LULC Classes	ESV (US$ million)						ESV (US$ million) Change		
	1985		**2005**		**2020**		**1985–2005**	**2005 -2020**	**1985 -2020**
	Value	%	Value	%	Value	%			
Bare Land	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Built-up Area	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Cropland	29.95	1.47	37.57	2.2	61.01	3.75	7.62 (25.44)	23.44 (62.39)	31.06 (103.71)
Riverine Forest	1922.39	94.31	1585.29	93.01	1492.66	91.65	-337.1 (-17.53)	-92.63 (-5.84)	-429.73 (-22.35)
Water Body	23.04	1.13	18.67	1.1	14.4	0.88	-4.37 (-18.97)	-4.27 (-22.87)	-8.64 (-37.5)
Wooded Grassland	63.04	3.09	62.87	3.69	60.65	3.72	-0.17 (-0.27)	-2.22 (-3.53)	-2.39 (-3.79)
Burned Area	0.00	0.00	0.00	0.00	0.00	0.0	0.00	0.00	0.00
Total	2038.42	100	1704.4	100	1628.72	100	-334.02 (-16.39)	-75.68 (-4.44)	-409.7 (-20.1)

Figures in the parenthesis refer to the percentage of change

With regard to the values of individual ecosystem services such as food production, water supply, raw materials, climate regulation, and recreation and tourism, the major contributor was riverine forest constituting the highest ESVs in the study periods. However, despite having the highest ESVs, the values from riverine forests decreased overtime. ESVs only from croplands showed an increment, whereas values from other LULC classes decreased at varying rates. Only food production service showed a positive change (0.7 million USD increase) from 1985 to 2020. The values of the remaining ecosystem services, e.g., recreation and tourism, water supply, and raw material provision, experienced declines of 481.62 million USD, 180.35 million USD, and 45.72 million USD, respectively (Table 3.9). Compared to other LULC classes, the value coefficient and the resulting ESVs of the riverine forest were the largest in all study periods (Table 3.3, Table 3.8) making it the prime contributor for the values of all ecosystem services in the study area.

Table 3.9:Individual ecosystem service values of LULC classes from 1985-2020

Land use land cover classes and ESVs of individual Ecosystem service in million USD

Ecosystem Services	Cropland			Riverine Forest			Water Body			Wooded Grassland			Total ESV			Overall Change
	1985	2005	2020	1985	2005	2020	1985	2005	2020	1985	2005	2020	1985	2005	2020	1985 - 2020
FP	3.61	4.53	7.35	10.18	8.4	7.91	2.06	1.67	1.29	-	-	-	15.85	14.6	16.55	0.7
WS	4.28	5.36	8.71	809.66	667.68	628.66	8.3	6.72	5.19	17.7	17.65	17.03	839.94	697.41	659.59	-180.35
RM	0.04	0.05	0.09	198.55	163.74	154.17	0.08	0.07	0.05	36.01	35.92	34.65	234.68	199.78	188.96	-45.72
CR	0.07	0.09	0.14	11.13	9.18	8.64	0.23	0.18	0.14	4.13	4.12	3.97	15.56	13.57	12.89	-2.67
SS	-		-	-	-	-	0.07	0.06	0.04	-	-	-	0.07	0.06	0.04	-0.03
RT	21.95	27.54	44.72	892.87	736.3	693.28	12.3	9.97	7.69	5.2	5.19	5.01	932.32	779	750.7	-481.62
Total	29.95	37.57	61.01	1922.39	1585.3	1492.66	23.04	18.67	9.21	63.04	62.88	60.66	2038.42	1704.42	1628.73	-409.69

Where, FP =Food production, WS = Water supply, RM = Raw material, CR = Climate regulation, SS = Spiritual service, RT Recreation and tourism

The sensitivity analysis result revealed that the coefficients of sensitivity for ESVs derived from LULC classes in all study periods were less than 1. The coefficient of sensitivity was highest for values from riverine forest (0.94, 0.93, and 0.92 in 1985, 2005, and 2020, respectively) due to their high value coefficient and large area coverage (Aschonitis et al., 2016). The estimated coefficient of sensitivity values ranged from a minimum of 0.01 for water bodies to a maximum of 0.94 for riverine forests when the value coefficients for these land cover types were adjusted by 50% (Table 3.10). Overall, the sensitivity analysis indicated that the estimates for the study area were robust, despite uncertainties in the value coefficients.

Table 3.10:Percentage change in the estimated total ecosystem service values and coefficients of sensitivity resulting from a 50% adjustment in the ecosystem valuation coefficients

LULC Classes	**1985**		**2005**		**2020**	
	CS	%	CS	%	CS	%
Bare Land VC±50%	-		-	-	-	-
Built-up Area VC±50%	-	-	-	-	-	-
Cropland VC±50%	0.01	0.73	0.02	1.10	0.04	1.87
Riverine Forest VC±50%	0.94	47.15	0.93	46.51	0.92	45.82
Water Body VC±50%	0.01	0.57	0.01	0.55	0.01	0.44
Wooded Grassland VC±50%	0.03	1.55	0.04	1.84	0.04	1.86

3.3.3. Local community perception on the dynamics of ecosystem services

Approximately 83.7% of the study participants had resided in the study area for more than 30 years (Appendix C), providing them with a deep understanding of the major ecosystem services they receive and how these services have changed over time. The vast majority of survey respondents confirmed that the park and its surrounding environment offer benefits to the local community. Cutting grasses and grazing, collecting firewood and charcoal, recreation, gathering wild food, and harvesting wild honey were among the main benefits mentioned by survey respondents. A significant proportion of respondents (88%), stated that they have utilized grasses from MzNP for their livestock and for sale to meet household expenses. Additionally, nearly 74 % of the participants indicated that they have enjoyed the natural beauty of an area, including wild animals and forests, for recreation and relaxation. However, water for irrigation, and hunting were reported as the least utilized services, mentioned by less than 16% of the respondents (Fig. 3.4).

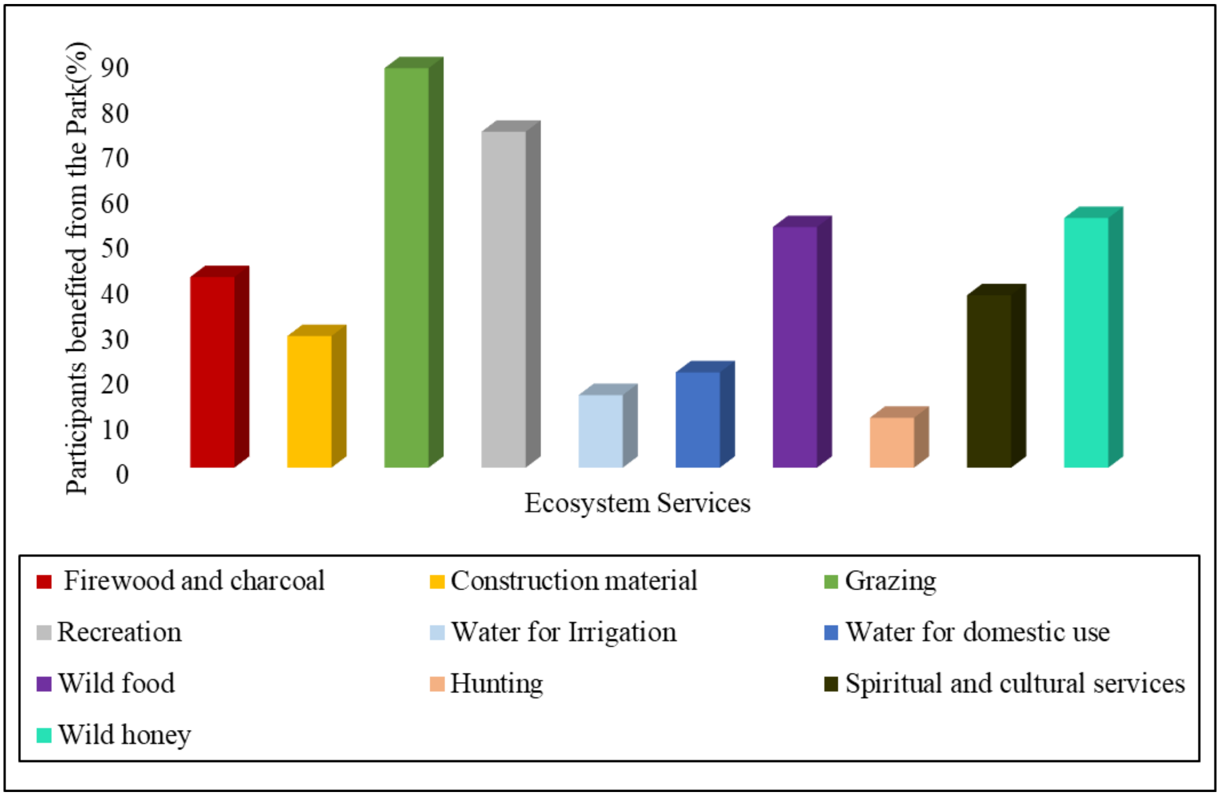

Figure 3.4:Ecosystem services from maze national park

3.4. Discussion

3.4.1. Land use land cover changes

The findings of this study revealed a significant expansion of croplands and built-up areas over the last 35 years (Table 3.6). Given that agriculture serves as the main means of subsistence for smallholder farmers in the study area (Andabo and Gamo, 2015), population increase and the growing demand for new farmlands and settlements are responsible for the expansion of croplands and built-up areas. Similar findings of increasing expansion of croplands and built-up areas were reported in different regions of the country (Markos et al., 2018; Negussie, 2019; Shiferaw et al., 2019). On the other hand, riverine forest, water body, and wooded grassland showed a declining trend, albeit in varying proportions. The considerable decline of riverine forest and wooded grassland was primarily attributed to the expansion of croplands and built-up areas (Table 3.7) in the buffer zone and outside of the park. Several studies in Ethiopia e.g. (Aneseyee et al., 2020; Markos et al., 2018; Mekuria et al., 2021; Woldeyohannes et al., 2020) show a decreasing trend in woodland, grassland, and forest land due to the encroachment of croplands and settlements over vegetated areas.

In contrast, the findings of Zewde et al. (2022) are partially inconsistent with our findings showing, a rapid increase in scattered trees and grassland cover in MzNP. The discrepancy can be attributed to the difference in the scope of the study area; our study included the park's neighboring *kebeles*, which are more severely impacted by anthropogenic activities than the protected area. This result reveals that naturally vegetated lands outside the park territory are more adversely affected by anthropogenic activities than the core protected area. In addition, the FGDs and KIIs confirmed the encroachment of protected areas through illegal farming converting into buffer zones of the protected area, as well as the expansion of built-up areas in some adjacent *kebeles* through deforestation and the subsequent burning of grasses and shrubs. Similarly, Yadeta et al. (2022) revealed an increase in agricultural land in Chebera Churchura National Park's buffer zone, while grassland and wooded grassland showed a decline. The quality of services that communities derive from the ecosystems across the country has been altered as a result of the conversion of natural forests and grasslands to agricultural lands, affecting ecosystem structure and function (Woldeyohannes et al., 2020). Therefore, designing and implementing better ecosystem protection and restoration mechanisms inside and outside of protected areas is needed at both the local and national levels.

The establishment of national parks can significantly impact LULC changes by limiting human and domestic animals' access to the park region (Yadeta et al., 2022). Prior to the establishment of MzNP (1985–2005), there was a notable increase in bare lands, primarily at the expense of wooded grassland (Table 3.6). This trend was driven by unrestricted access to resources, including overgrazing, thatching roofs, and cutting trees for firewood and building material. However, after the establishment of the park in 2005, this trend reversed, and from 2005 to 2020, the percentage of bare lands decreased (Table 3.6). This change can be attributed to the park's designation as a protected area, which restricted access to resources and allowed degraded fields to regenerate grasses and trees. Similarly, Mingarro and Lobo (2023) revealed that the designation of protected areas increases the naturalization of an area, thus providing beneficial effects on the surrounding environment. However, (Al Mamun et al., 2022) and (Belay et al., 2014) reported an expansion of bare lands in Baroiyadhala National Park, Bangladesh, and Awash National Park, Ethiopia, respectively, due to pronounced deforestation and degradation. The KIIs and FGDs noted the rehabilitation of the environment due to restricted access to the park. However, participants expressed concerns that their livelihoods have been negatively affected by these restrictions.

Fire is a natural and important disturbance in grasslands, but it can initiate changes in ecosystems that affect vegetation composition, structure, and patterns, as well as soil and water resources, which are critical to overall ecosystem functions and processes (Neary & Leonard, 2020). Fig.3.2 and Table 3.6 show that the burned land in 2020 constituted 1.42% of the entire study area. This indicates that, in addition to other factors, frequent fire contributed to reduction of wooded grasslands and riverine forests, resulting in the loss of ESVs. In line with this finding, Zewude et al. (2022) identified two types of fires practiced in MzNP: controlled fire set by the park staff and illegal fire conducted twice a year by locals to induce the sprouting of new grass for grazing.

3.4.2. Ecosystem services value changes

In contrast to the improvement of ecosystem services in developed countries where cropland is converted in to forests (Li et al., 2018), the majority of developing countries, including

Ethiopia, are experiencing significant loss of ecosystem services (Baidoo & Obeng, 2023; Rotich et al., 2022; Tolessa et al., 2017). In MzNP and its surrounding districts, a considerable loss of ESVs was observed in response to LULC changes over the last 35 years, mostly due to reduction of riverine forests. The overall ESVs of the study area was found to be highly reduced (-409.7 million USD) from 1985 to 2020 (Table 3.8). This finding is consistent with other studies in Ethiopia, where dynamics of LULC over time have led to the loss of total as well as specific ESVs (Kindu et al., 2016; Negussie, 2019; Tolessa et al., 2017). The primary cause for the loss of the overall ESVs was the reduction of ecosystem services obtained from the riverine forest, which constituted the largest share, more than 90%, in all study periods (337.1 million USD from 1985 to 2005, 92.63 million USD from 2005 to 2020, and 429.73 million USD from 1985 to 2020 (Table 3.8). Additionally, the ESVs from wooded grassland decreased by 0.17, 2.22, and 2.39 million USD from 1985 to 2005, 2005 to 2020, and 1985 to 2020, respectively. Previous studies (Markos et al., 2018; Mekuria et al., 2021; Shiferaw et al., 2019) have reported similar findings, where the decline of forests, woodlands, and grasslands contributed to the reduction of ESVs.

On the other hand, ESVs from croplands showed an increase of 7.62, 23.44, and 31.06 million USD from 1985 to 2005, 2005 to 2020, and 1985 to 2020, respectively (Table 3.8). This increase was mostly associated with the expansion of agricultural lands in the study area. The result is supported by previous studies in the central rift valley of Ethiopia (Mekuria et al., 2021) and the Bilate Alaba sub-watershed (Markos et al., 2018), which reported an increase in ESVs from farmlands, likely related to the expansion of agricultural lands.

The analysis of individual ESVs showed that the total value of food production increased between 1985 and 2020 by 0.7 million USD (Table 3.9), largely due to the expansion of croplands (Belay et al., 2022; Kindu et al., 2016; Solomon et al., 2019). The values of the remaining ecosystem services, such as water supply, provision of raw materials, climate regulation, spiritual services, and recreation and tourism, consistently declined from 1985 to 2020, with an overall change of -180.35, -45.72, -2.67, -0.03, and -481.62 million USD, respectively (Table 3.9). The reduction of these individual ecosystem services was a consequence of LULC changes, particularly reduction of riverine forests and wooded grasslands. This trend is supported by previous studies conducted in different parts of the country (Aneseyee et al., 2020; Belay et al., 2022; Mekuria et al., 2021). Although agriculture is the mainstay of Ethiopian economy (Welteji, 2018), expanding agricultural lands at the expense of natural vegetation leads to degradation of the ecosystem as a whole and loss of ESVs.

3.4.3. Sensitivity analysis

Previous studies have identified limitations in using LULC classes as proxies for estimating ESVs due to imperfect matches of LULC classes and the accuracy of the ecosystem value coefficients (Costanza et al., 1997; Kreuter et al., 2001). Despite these limitations, sensitivity analysis in several previous studies indicated that the estimation of ESVs was robust and reliable (Fang et al., 2014; Li et al., 2010; Solomon et al., 2019; Tianhong et al., 2010). Furthermore, it has been demonstrated that this method is more reliable for the temporal assessment of ESV changes in response to LULC dynamics (Tianhong et al., 2010). In Ethiopia, where ground data collection is expensive and there is a scarcity of historical data on land uses of rural areas, estimating ESVs using LULC classes and established value coefficient is very important. It provides alternatives and robust information for decision making processes at the landscape level, and similar works can be conducted in other parts of the country (Tolessa et al., 2017). Therefore, despite uncertainties, the sensitivity analysis results of this study indicate that the estimated ESVs for the study area using LULC information and value coefficients were robust and reliable.

3.4.4. Local community perception on ecosystem services dynamics

The local community surrounding the park obtains a variety of ecosystem services, including food, water, grazing, grass cutting, firewood, charcoal, wild food, and wild honey (Fig. 3.4). Among these services, livestock grazing and grass cutting are the most important benefits for the local community. Therefore, the community in the vicinity refers to the park as *"ፓርኩ ካዝናችን ወይም ጎተራችን ነዉ"* meaning "The Park is Our Treasury or Granary" in time of drought and famine. The harvesting of grass is mainly permitted by the park administrators to support the poor during hard times. Thus, ecosystem services provided by riverine forests and wooded grasslands are the most important benefits in the study area that sustain the livelihood of the local population. The KIIs and FGDs also revealed that grasses in the park were not only used for the community's livestock but also sold in nearby regions to help people survive during times of drought. Despite the fact that grazing and grass cutting help the local poor in the vicinity, higher grazing intensity reduced vegetation cover (Wachiye et al., 2022), contributing to the loss of ecosystem services provided by the park's environment.

Other ecosystem services, such as hunting, access to water, and cutting trees for the building were the least used services (Fig. 3.4). This is attributed to limited access to the park and legal and cultural sanctions against illegal hunting and tree harvesting. Previous studies also confirmed that delineating a protected area was perceived by the local communities as a reason for losing access to resources (Hussein, 2021; Kumssa & Bekele,2014). Along with access restrictions, vegetation degradation (Zewude et al., 2022) has contributed to the reduction of ecosystem services obtained by people from the park.

According to KIIs and FGDs, the establishment of the park benefitted the vicinity by moderating the local climate, regulating strong winds, and provision of grasses for their livestock. On the other hand, it was a major cause for losing access to resources such as firewood, charcoal, wild food, wild honey, construction material, and hunting of wild animals. Additionally, due to access restrictions to a river that crosses the park, some study *kebeles* are experiencing critical water scarcity for their cattle. In line with this, (Abachebsa, 2017; Hussein, 2021) stated that rural poor people's livelihoods and well-being are more vulnerable with the establishment of protected areas, especially in developing nations, because their livelihoods are primarily dependent on agriculture and natural resources. As a result, MzNP is perceived by the local community as a reason for losing access to some resources that were previously available to them and as a means of obtaining benefits, either directly or indirectly, from the conservation efforts in the park. These indicate that although the establishment of protected areas has a positive effect on regulation, cultural, and some provisioning services (Abachebsa, 2017), human and livestock activities contribute significantly to LULC changes (Yadeta et al., 2022) and the subsequent loss of ESVs.

3.5. Conclusion

This study assessed the impacts of LULC change on selected ecosystem services in MzNP and its surrounding districts from 1985 to 2020. The results indicate a loss of overall as well as individual ESVs in the study area in response to LULC changes. Among the LULC classes, croplands and built-up areas showed a rapid expansion by 103.7% and 31.32%, respectively, largely at the expense of riverine forests and wooded grasslands, while the remaining LULC classes exhibited a negative change. As a result, the overall value of selected ecosystem services declined by 20% (409.7 million USD) from 1985 to 2020. Among individual ecosystem services, only food production service demonstrated an increase of 0.7 million USD, whereas the remaining ecosystem services, such as water supply (-180.35 million USD), climate regulation (-2.67 million USD), provision of raw materials (-45.72 million USD), and tourism and recreation (-481.62 million USD), decreased throughout the study period. Despite agriculture being the back bone of the country's economy and the wellbeing of its people, illegal encroachment of farmlands onto the natural vegetation and the resulting negative impacts on the ecosystem require proper attention.

Understanding the spatial and temporal patterns of LULC changes and the resulting impacts on ecosystem services can help decision-makers to design effective controlling mechanisms. The findings of this study can be applied to the conservation and sustainable management of natural resources, as well as to the management of protected areas in MzNP and its surrounding districts. The following recommendations are made for decision-makers and stakeholders for application in ecosystem protection and restoration to ensure the long-term sustainability of the region's natural resources.: (1) control illegal farmland and built-up areas expansion in the buffer zone (2) implement measures to control illegal fires, (3) reduce the heavy dependency of the local community on the park for grazing and grass cutting, (4) implement effective protected area management strategies, such as negotiating access route to water points for the community's cattle to minimize conflicts over water use. Finally, further studies are suggested to quantify the values of ecosystem services using satellite imageries with higher spatial resolution and employing different ecosystem services valuation methods (e.g., market price-based methods). This is because the benefit transfer method has limitations, including imperfect matches of LULC classes as proxies and uncertainty in the accuracy of the ESV coefficients.

4. Spatiotemporal dynamics of ecosystem services in response to climate variability in Maze National Park and its environs, southwestern Ethiopia

Abstract

Climate variability is one of the major factors affecting the supply of ecosystem services and the well-being of people who rely on them. Despite the substantial effects of climate variability on ecosystem goods and services, empirical researches on these effects are generally lacking. Thus, this study examines the spatiotemporal impacts of climate variability on selected ecosystem services in Maze National Park and its surroundings, in southwestern Ethiopia. We conducted climate trend and variability analysis by using the Mann-Kendall (MK) trend test, Sen's slope estimator, and innovative trend analysis (ITA). Relationships among ecosystem services and climate variables were evaluated using Pearson's correlation coefficient (r), while partial correlation was used to evaluate the relationship among key ecosystem services and potential evapotranspiration (PET). The MK tests show a decreasing trend for both mean annual and main rainy season rainfall, with Sen's slope (β) = -0.721 and β = -0.1.23, respectively. Whereas, the ITA method depicted a significant increase in the second rainy season rainfall (Slope(s) = 1.487), and the mean annual (s = 0.042), maximum (s = 0.024), and minimum (s = 0.060) temperature. Spatial correlations revealed significant positive relationships between ecosystem services and the mean annual rainfall and Normalized Difference Vegetation Index (NDVI), while negative correlations with the mean annual temperature. Additionally, temporal correlations highlighted positive relationships among key ecosystem services and the main rainy season rainfall. The maximum and minimum temperatures and ecosystem services were negatively correlated; whereas, there was strong negative correlations between annual (r = -0.929), main rainy season (r = -0.990), and second rainy season (r = -0.814) PET and food production. Thus, understanding the spatiotemporal variability of climate and the resulting impacts on ecosystem services helps decision-makers design ecosystem conservation and restoration strategies to increase the potential of the ecosystems to adapt to and mitigate the impacts of climate variability.

Key words: Climate Variability trend, Partial Correlation, Ecosystem Services, Innovative Trend Analysis, Mann-Kendall test, NDVI

Simeon, M., Wana, D., & Woldu, Z. (2024). Spatiotemporal dynamics of ecosystem services in response to climate variability in Maze National Park and its environs, southwestern Ethiopia. *PLOS ONE*, *19*(7), e0307931. https://doi.org/10.1371/journal.pone.0307931

4.1. Introduction

Climate change significantly affects both the quality and quantity of ecosystem services (Bakure et al., 2022) by increasing the frequency and intensity of wildfires, floods, crop failures, and outbreaks of disease and insect damages (Millennium Ecosystem Assessment (MEA), 2005; Scholes, 2016; U.S. Geological Survey (USGS), 2007). Ecosystem services are defined as the benefits society obtains from ecosystems, and are categorized as provisioning, regulating, supporting, and cultural services (MEA, 2005). Nonetheless, climate variability is often negatively affecting these ecosystem goods and services (van der Geest et al., 2019), such as food production, drinking water, wood fuel, fodder, climate regulation, and carbon sequestration (Bakure et al., 2022).This is particularly evident through frequent temperature variability, recurrent droughts, shortened growing seasons(Intergovernmental Panel on Climate Change (IPCC), 2007), and changes in mean temperature and rainfall (Babu, 2015; Muluneh, 2021) in arid and semi-arid areas (IPCC, 2007). Climate variability is primarily distinguished by trends and fluctuations in the climate's state on spatial and temporal scales at a relatively shorter period of time, while climate change refers to the changes in climate elements over the longer period of time (Gashure et al., 2022). The extent to which climate change and variability affect ecosystem goods and services are highly localized and varies spatially. Hence, provisioning services such as food production in semi-arid areas are significantly impacted by these factors (van der Geest et al., 2019). Overall, climate change and variability have numerous potentially serious negative impacts on key provisioning and regulatory services obtained from ecosystems (Scholes, 2016; Sintayehu, 2018; Tang et al., 2018).

The changing climate, evidenced by climate variability, affects the provision of ecosystem services and the well-being of people who rely on these services (Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES), 2019). Ethiopia, like many other African countries, is very susceptible to the negative impacts of climate change and variability due to its low adaptive capacity (National Ecosystem Assessment (NEA), 2022). In Ethiopia, climate variability due to increasing temperature, and declining and unreliable rainfall have negatively affected ecosystem services such as food production, groundwater availability, and soil organic matter dynamics (Gezie, 2019). In addition, the National Ecosystem Assessment report of Ethiopia indicated that the multidimensional impacts of climate change and variability caused the loss of biodiversity and ecosystem services in the country, which are vital for human well-being (NEA, 2022).

With this regard, national parks are crucial for biodiversity conservation and for local residents who depend on natural resources for their survival (Haq, 2016; Zhao et al., 2019). They provide ambient weather, good pasture, construction wood, charcoal, fuel wood, thatching grass, and cultural services (Kumssa & Bekele, 2014; Zhao et al., 2019). The study area, MzNP and its surroundings, provide the local communities with ecosystem goods such as food, water, pasture, thatching grass, fuel wood, and construction materials and a host of other ecosystem services such as clean water, climate regulations, and cultural and environmental amenities. However, the supply of these vital ecosystem goods and services is dwindling due to climate variability-induced changes, such as recurrent droughts, crop pests, and frequent forest/bush fires (Tekalign & Bekele, 2011).

Previous ecosystem goods and services related studies in Ethiopia have primarily focused on evaluating the impacts of LULC changes on ecosystem services in different parts of the country (Aneseyee et al., 2020; Belay et al., 2022; Mekuria et al., 2021). Despite the substantial negative effects of climate variability, including changes in temperature and precipitation, as well as climate variability related disturbances such as flooding, drought, and wildfires on ecosystem goods and services (Arenas-Wong et al., 2023; Bakure et al., 2022), empirical research on these effects remains lacking in the country (NEA, 2022). Few studies for instance, (Aneseyee et al., 2022) have focused on the impacts of climate variability, particularly the variability of precipitation, only on water yield, without considering other provisioning and regulatory services. In a broader context, previous reviews, for example (Sintayehu, 2018), has addressed the observed and anticipated impacts of climate change on biodiversity and ecosystem services in Africa, but did not include any quantitative analysis of the relationship between these variables. Therefore, assessing the impacts of climate change and variability on ecosystem services and quantitatively analyzing their associations can provide scientific basis for the protection and restoration of local and regional ecosystems (Ma et al., 2021). Therefore, this study aims at investigating the spatio-temporal impacts of climate variability on the provisioning of key ecosystem services in MzNP and its environs, in southwestern Ethiopia. In this study, the temporal and spatial variability of temperature and rainfall and their correlation with selected key ecosystem services, including food production, water supply, raw materials, and climate regulation services were assessed.

Additionally, the relationship between potential evapotranspiration and ecosystem services, as well as between Normalized Difference Vegetation Index (NDVI) and ecosystem services were evaluated.

4.2. Materials and methods

4.2.1. Data sources and methods

Sources of data

Temperature and rainfall data were used to analyze climate variability in the study area because these variables have received great attention worldwide to deal with climate variability (Panda & Sahu, 2019). The climatic data used in this study was obtained from the Meteorological Services Agency of Ethiopia, southern district office. The study used gridded monthly data of rainfall, maximum temperature, and minimum temperature of seven grid points from varying agro-ecological settings (*Kola and Woinadega*) covering the period of 36 years (1985 –2020). The dataset has a spatial resolution of 4km x 4 km, and the data were reconstructed into series based on records of weather stations and meteorological satellite observations. Grid data was preferred due to the absence of sufficient meteorological stations in the study area due to its remoteness and the critical problem of missing data. The averaged values of these grid points were used to analyze rainfall and temperature variability in the study area.

We conducted FGDs and KII with the local community, agricultural extension agents, and park staff to identify four ecosystem goods and services such as food production, water supply, raw material provision, and climate regulatory services (Table 4.1). These services were considered as major benefits (Simeon & Wana, 2024) they obtain from the park and were also highly affected by climate variability in the last three decades.

Table 4.1: Description of key ecosystem services

Ecosystem Services	Description	Sources
Food production	Production of crops, nuts, fruits by hunting, gathering, subsistence farming or fishing.	(Costanza et al., 1997; MEA, 2005)
Water supply	Provisioning of water by watersheds for drinking, irrigation and other domestic uses	(Costanza et al., 1997; de Groot R., 2020)
Raw materials	The production of lumber, fuel wood, fodder/pasture, charcoal, and thatching grass	(Costanza et al., 1997; de Groot R., 2020)
Climate regulation	Regulation of local temperature and precipitation	(Costanza et al., 1997; MEA, 2005)

The values of the above selected key ecosystem goods and services were estimated from the LULC maps of 1985, 2005, and 2020 (Simeon & Wana, 2024) using the benefit transfer method (Costanza et al., 1997; Kindu et al., 2016; Li et al., 2007). In addition to the ESVs for 1985, 2005, and 2020 from the previous study (Simeon & Wana, 2024), we also estimated the values of the selected services for 1995 and 2015 using a similar method. The benefit transfer method was utilized to estimate the economic value of ecosystem goods and services when specific valuation data were lacking. This approach adapts existing valuation information to suite new policy contexts, especially valuable when limitations such as budget, time, and data availability restrict the collection of primary data (Temesgen et al., 2018; Wilson & Hoehn, 2006). This method has extensively been used to value environmental resources in numerous studies (Costanza et al., 1997; Kindu et al., 2016; Li et al., 2007). The LULC classifications were carried out using a Random Forest (RF) supervised classification method in R statistical software (R4.1.3) (R Core Team, 2022). Accuracy assessment of the classified images was done via the Semi-Automatic Classification Plugin (SCP) in QGIS using high spatial resolution satellite images and Google Earth images as a reference (Simeon & Wana, 2024).

We used value coefficients from the ecosystem service valuation database (ESVD) to quantify the values of the identified ecosystem goods and services. The ESVD was updated in 2020 with the support from the UK Department for Environment, Food, and Rural Affairs (Defra) (de Groot R., 2020). Estimated values of key ecosystem services are presented in Table 4.2.

Table 4.2:Values of selected key ecosystem services of the study area (US$ million)

Year	Ecosystem Services				
	Food production	Water supply	Raw material provision	Climate regulation	Total
1985	15.85	839.94	234.68	15.56	1106.03
1995	15.30	779.00	218.04	14.56	1026.9
2005	14.60	697.41	199.78	13.57	925.36
2015	16.26	671.81	188.57	12.67	889.31
2020	16.55	659.59	188.96	12.89	877.99

Measurement of variability

This study used the coefficient of variation (CV) and rainfall anomaly index (RAI) to analyze temperature and rainfall variability. CV examines the year-to-year variation in the data series. The higher the value of CV, the higher the variability of rainfall in the study area, and vice versa. The value of CV can be computed as follows:

$$CV = \frac{\sigma}{\mu} \times 100 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(1)}$$

Where CV is the coefficient of variation, σ is the standard deviation and μ is the mean. According to Hare, (2003) the degree of rainfall variability is classified as low variability (CV < 20), moderate variability (20 < CV < 30), and high variability (CV > 30). Therefore, the coefficient of variation was calculated to detect the variation of monthly, seasonal, and annual rainfall and temperature records during the study period.

RAI is used to examine the frequency and intensity of prior dry and wet years (Teshome et al., 2021). In this study, RAI was employed to identify years of positive and negative anomalies of rainfall fluctuations. Positive rainfall anomalies indicate wet years, while negative rainfall anomalies indicate dry years (Teshome et al., 2021). RAI was calculated using the following equation:

$$RAI = 3 * \left[\frac{N-\overline{N}}{\overline{M}-\overline{N}}\right] = \text{for positive anomalies} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(2)}$$

$$RAI = -3 * \left[\frac{N-\overline{N}}{\overline{X}-\overline{N}}\right] = \text{for negative anomalies} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(3)}$$

Where N is monthly/yearly/seasonal rainfall (mm), $\overline{N}$ is average monthly/yearly/seasonal rainfall of the historical series (mm), $\overline{M}$ is average of the ten highest monthly/yearly/seasonal rainfall of the historic series (mm) and $\overline{X}$ is average of the ten lowest monthly/yearly/seasonal rainfall of the historic series (mm)

Trend analysis

Mann-Kendall (MK) trend test

To understand the long-term trends of rainfall and temperature, we applied the non-parametric Mann-Kendall (MK) test for monthly, seasonal, and annual time series data of temperature and rainfall from 1985 to 2020 in R statistical software (R4.1.3). The MK test is used to detect monotonically increasing or decreasing trends of annual and seasonal climate data (Belay et al., 2021). The MK test is commonly used to identify trends in time series analysis due to its insensitivity to outliers and does not consider any distribution assumptions (Irwandi et al., 2023; Yue et al., 2002). However, the result of the MK test may contain some error if autocorrelation exists in the time series data (Liu et al., 2022). Therefore, in this study, autocorrelation is tested by calculating the autocorrelation coefficient at lag-1, and significant serial autocorrelation was found in the monthly rainfall records for December and June. Except for January, March and October monthly temperature data, significant serial autocorrelation was found in all months as well as average annual, average maximum and minimum temperature. Thus, to overcome this problem, the modified Mann-Kendall (MMK) method was used for serially autocorrelated data with a significant lag-1 autocorrelation coefficient using the variance correction method in R statistical software (Hamed, 1998). Based on (Mann, 1945) and (Kendall, 1975) the MK statistics S is computed using the following formula:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} sign(x_j - x_i) \ldots\ldots (4)$$

Where n is the number of data and xi and x_j are sequential data values sign (.) is the sign function which can be calculated by the following equation.

$$sign(x_j - x_i) = \begin{cases} 1\ if\ (x_j - x_i) > 0 \\ 0\ if\ (x_j - x_i) = 0 \\ -1\ if\ (x_j - x_i) < 0 \end{cases} \ldots\ldots (5)$$

If the dataset is identically and independently distributed, then the mean of S is zero and the variance of S is given as:

$$var(s) = \frac{n(n-1)(2n+5) - \sum_{i=1}^{m} t_i (t_i - 1)(2t_i + 5)}{18} \ldots\ldots (6)$$

Where m is the number of tied groups and t_i is the number of data points in group t. When the number of sample size n>10, the standardized test statistic (Z_{mk}) is calculated as(Kendall, 1975; Mann, 1945) :

$$Z_{mk}= \begin{cases} \frac{s-1}{\sqrt{var(s)}}, s > 0 \\ 0, \quad s = 0 \\ \frac{s-1}{\sqrt{var(s)}}, s < 0 \end{cases} \qquad (7)$$

Sen's slope estimator test

The MK test does not provide an estimate of the magnitude of the trends (Diress, 2021). Thus, in this study, we applied Theil-Sen approach, another nonparametric method, which is very popular among other techniques to quantify the slope of the trend or magnitude (Sen, 1968). Sen's method has been widely used for determining trend magnitude in hydro-meteorological time series (Wang et al., 2020). In this method, the slopes (β) of all data pairs are first calculated by using the following equation:

$$\beta = median\left({(x_j - x_k)}/{(j - k)} \right) \qquad (8)$$

for i = 1, 2, . . ., N, where x_j *and* x_k are data values at times j and k (j > k) respectively, and N is the number of all pairs x_j *and* x_k . A positive value of β indicates an upward (increasing) trend and a negative value indicates a downward (decreasing) trend in the time series.

Innovative trend analysis method (ITA)

The ITA method, proposed by (Şen, 2012) has been used by several studies in combination with other trend analysis approaches to find differences in climatological, meteorological, and hydrological data time series due to its advantages over other non-parametric approaches (Gujree et al., 2022). ITA is valid regardless of the sample size, serial correlation structure of the time series, and non-normal probability distribution of the data (Şen, 2012). In ITA, the hydro-meteorological time series were divided into two equal halves and then sorted both sub-series in ascending order. The first half of the series is placed on the X-axis, and the second half is placed on the Y-axis of the Cartesian coordinate system. If the data points on a scattered plot are collected on the 1:1 (45°) straight line, it indicates there is no trend in the data. However, the trend is increasing when the data points fall above the 1:1 straight line and decreasing if the data points accumulate below the 1:1 straight line (Şen, 2012). The indicator of trend is derived by dividing the mean difference between the linear line and the first half of the series. The trend indicator of ITA is multiplied by 10 to make the scale similar to the other two tests (the Sen's slope estimator and MK tests). The trend indicator is calculated as:

$$D = \frac{1}{n}\sum_{i=1}^{n}\frac{10(x_j - x_i)}{\mu} \quad \text{(9)}$$

where D is trend indicator, n is number of observations in the subseries, Xi is data series in the first half subseries class, Xj is data series in the second half subseries class and μ is mean of data series in the first half subseries class. A positive and negative values of D indicate an increasing and decreasing trend, respectively. The ITA plots of annual and seasonal rainfall and temperature were generated using RStudio (package '*trendchange::innovetrend (X)')* (Şen, 2012).

Pearson and partial correlation analysis

In this study, temporal and spatial correlation between climate variables and key ecosystem goods and services such as food production, water supply, raw material provision, and climate regulation were examined. Since the distribution of the data affects parametric tests, histograms and normality tests were used to determine whether the distribution of the data was normal. Then, using the statistical package for the social sciences (SPSS) version 24, non-normally distributed data were transformed using Log10 data transformation techniques. The association between meteorological variables and key ecosystem services in 1985, 1995, 2005, 2015, and 2020 was evaluated using Pearson's correlation coefficient (r) with a two-tailed, 95% significance level. Ecosystem service values estimated from the LULC maps (Appendix D, E, Fig 1 in Appendix G) were used to conduct the correlation analysis. Meteorological variables such as mean annual rainfall, main rainy season's rainfall, the second rainy season's rainfall, mean annual temperature, mean maximum temperature, mean minimum temperature, annual and seasonal potential evapotranspiration were included as climate variables in the correlation analysis. The correlation between key ecosystem services and mean annual rainfall, main rainy season's rainfall, the second rainy season's rainfall, mean annual temperature, mean maximum temperature, and mean minimum temperature was computed using Pearson's correlation coefficient. Pearson's correlation coefficient (r) is given by:

$$r = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \bar{X})\sum(Y_i - \bar{Y})^2}}, \quad \text{(10)}$$

where n is the number of observations, x and y are the variables, and $\bar{X}$ and $\bar{Y}$ are the means respectively. The correlation coefficient (r) takes a value that ranges between +1 and −1, where a value of +1 represents a perfect positive correlation, −1 represents a perfect negative correlation, and a value of 0 indicates no correlation. The results of the Pearson correlation coefficient are categorized into several grading scales: very weak positive/negative correlation ($0 < |r| < \pm0.2$); weak positive/negative correlation ($\pm0.20 \leq |r| < \pm0.4$), moderate positive/negative correlation ($\pm 0.40 \leq |r| < \pm0.6$); strong positive/negative correlation ($\pm0.60 \leq |r| < \pm 0.8$), and very strong positive/negative correlation ($\geq\pm.8$) following (Worku et al., 2023) and (Xu et al., 2023).

Potential evapotranspiration was computed using the Thornthwaite method (Thornthwaite, 1948) from monthly mean annual temperature data via the following equation:

$$PE = 16\left(\frac{10T}{I}\right)^{a} \quad (11)$$

where PE: monthly potential evapotranspiration, T: monthly mean air temperature (℃), *I*: heat index, a: $6.75\ 10^{-7}I^3 - 7.71\ 10^{-5}\ I^2\ + -1.7921\ 10^{-2}\ I + 0.49239$

The correlation between annual and seasonal evapotranspiration and key ecosystem services was calculated using the partial correlation analysis method in SPSS. The main rainy season's rainfall, one of the main climatic determinants of food production in Ethiopia (WFP, 2014) was used as a control variable. Partial correlation coefficient is a more intrinsic correlation of the two variables which eliminates the influence of other variables on the correlation of these two variables (Lipsitz et al., 2001) when the relationship between the variables was complex and influenced by multiple factors (Hussien et al., 2023). Partial correlation coefficient is calculated as:

$$r_{xy,z} = \frac{r_{xy} - r_{xz} * r_{yz}}{\sqrt{(1 - r^2_{xz}) * (1 - r^2_{yz})}} \quad (12)$$

where $r_{xy,z}$ is the partial correlation between variable x and variable y after independent variable z is fixed, r_{xy} is correlation between variable x and y, r_{xz}, is correlation of the third variable z with the variable x and r_{yz} is correlation of the third variable z with the variable y.

The spatial dynamics of temperature, rainfall, and key ecosystem goods and services in the study area were analyzed by interpolating the annual average values of rainfall and temperature using the Inverse Distance Weighted (IDW) interpolation technique. In order to develop maps of key ecosystem goods and services, random points were generated for the study area and ecosystem service values of LULC classes were extracted using the ‘extract point values’ tool for each key ecosystem service included in this study. Then, using the IDW interpolation technique, a continuous surface was created for each ecosystem good and service, and their spatial association with meteorological variables was examined via the Pearson correlation coefficient. In addition, the average NDVI, which has a strong relationship with Net Primary Productivity (NPP), vegetation cover, and ecosystem productivity (Das et al., 2023) for 1985, 1995, 2005, 2015, and 2020 were derived from the Landsat images (Appendix D). The spatial distribution and variation of NDVI in the study periods was analyzed using the NDVI maps made in ArcGIS and a Boxplot. The correlation between the NDVI and key ecosystem goods and services was examined using the Pearson correlation coefficient. NDVI, a measure of greenness is a reflectance recorded in the red and near-infrared band of the remote sensing imagery is calculated as:

$$NDVI = \frac{NIR-R}{NIR+R} \quad (13)$$

Where, R represents red and NIR represents near-infrared. Red = visible red Landsat band 3; NIR = near-infrared Landsat band 4 for Landsat TM, ETM+ and bands 4 and 5, respectively for OLI/TIRS. The NDVI value ranges from −1 to 1, where higher values indicate healthier and denser vegetation. Values lower than 0.1 represent bare areas of soil, rock, water (in the case of Maze) or snow elsewhere in other parts of the world snow occurs temporarily or permanently (Gross, 2005). The overall methodological flow of the study is shown in Fig. 4.1.

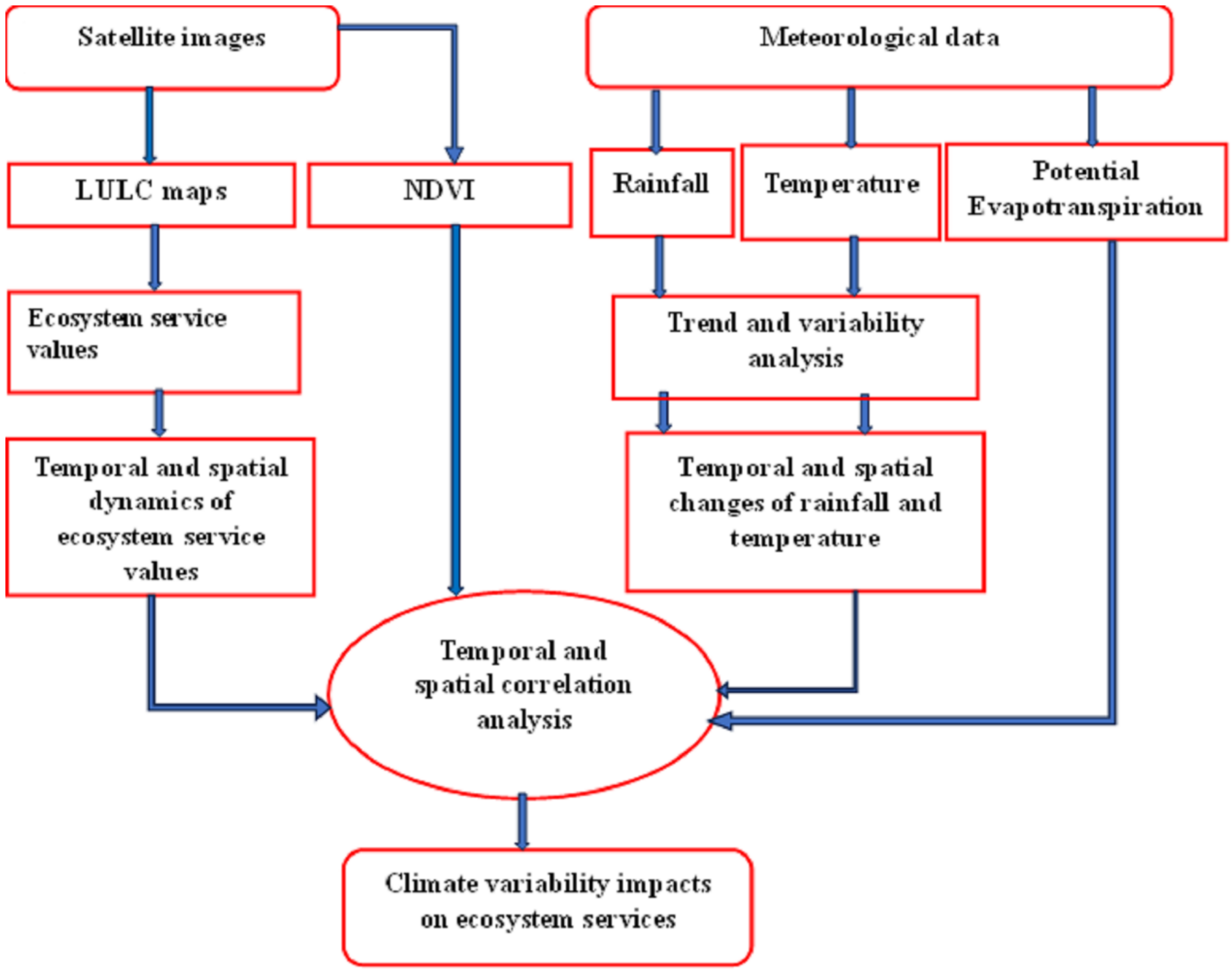

Figure 4.1:Methodological framework of the study

4.3. Results and discussion

4.3.1. Variability and trends of rainfall

The computed CV values of rainfall for all months were greater than 30%, ranging between 34.1% and 122.3% (Table 4.3). Therefore, there is high monthly rainfall variability in the study area, which is above 100% in December and January (Hare, 2003). Whereas, rainfall exhibited moderate variability in the main (24.3%) and second (25.5%) rainy seasons and variability is low for annual rainfall (13.9%). Our findings indicate that monthly rainfall exhibits higher inter-annual variability than the mean annual and seasonal rainfall in the study area. This is consistent with other studies (Worku et al., 2022a) which reported high monthly and moderate (spring) March-April-May rainfall variability in southern Ethiopia. However, CV value lower than 10% was reported in East Africa especially in western Uganda, Rwanda, Burundi, Tanzania and northwest Zambia with moist climatic conditions (Achite et al., 2021).

Table 4.3: Variability and MK trend test of monthly rainfall (1985 – 2020)

Months	Mean	Std. Deviation	CV (%)	MK Test (P-value)	Sen's slope
January	24.371	26.332	108.0	0.131	-0.364
February	29.312	22.636	77.2	0.487	-0.301
March	80.2578	44.852	55.9	0.270	-0.890
April	149.682	51.040	34.1	0.838	-0.152
May	145.768	53.779	36.9	0.902	0.130
June	83.851	31.476	37.5	0.755	-0.144
July	75.897	29.181	38.4	0.634	-0.148
August	95.481	34.365	36.0	0.258	0.579
September	100.494	44.352	44.1	0.713	0.333
October	105.771	56.349	53.3	0.406	0.745
November	51.887	48.582	93.6	0.011**	0.868
December	32.238	39.432	122.3	0.038	-0.913
Annual Rainfall	975.009	135.394	13.9	0.649	-0.721
Main Rainy Season	375.708	91.240	24.3	0.577	-1.231
Second Rainy Season	301.748	76.833	25.5	0.186	1.901

** significant at 0.01 level

Similarly, the RAI of the annual and seasonal rainfall shows high inter-annual variability (Fig. 4.2). Previous studies have shown that the country's rainfall variability is primarily driven by the seasonal shift of the Intertropical Convergence Zone (ITCZ), the influence of topography, and various interactions within the regional hydro-climate system (Alhamshry et al., 2019; Dejene et al., 2023). The proportion of negative RAI values is 52.8%, 47.2%, and 52.8% in the mean annual, main rainy season, and second rainy season, respectively. This result implies that the study area experienced more dry periods than wet periods from 1985 to 2020. Negative annual and seasonal rainfall anomalies were also noted in the upper Genale river basin (Shigute et al., 2023). According to Nafchi (2018) RAI classification, 36.1% (annual), 38.9% (main rainy season), and 30.6% (second rainy season) of years were categorized as dry periods ranging from moderately dry to extremely dry conditions. Extremely dry conditions in the main rainy season and the mean annual rainfall were recorded in 1985, 1988, 1992, 1999, 2009, 2016, and 2017 (Fig. 4.2). These periods were identified as drought periods in previous studies in Ethiopia (Asfaw et al., 2018), which coinciding with El Niño events (Belay et al., 2021).

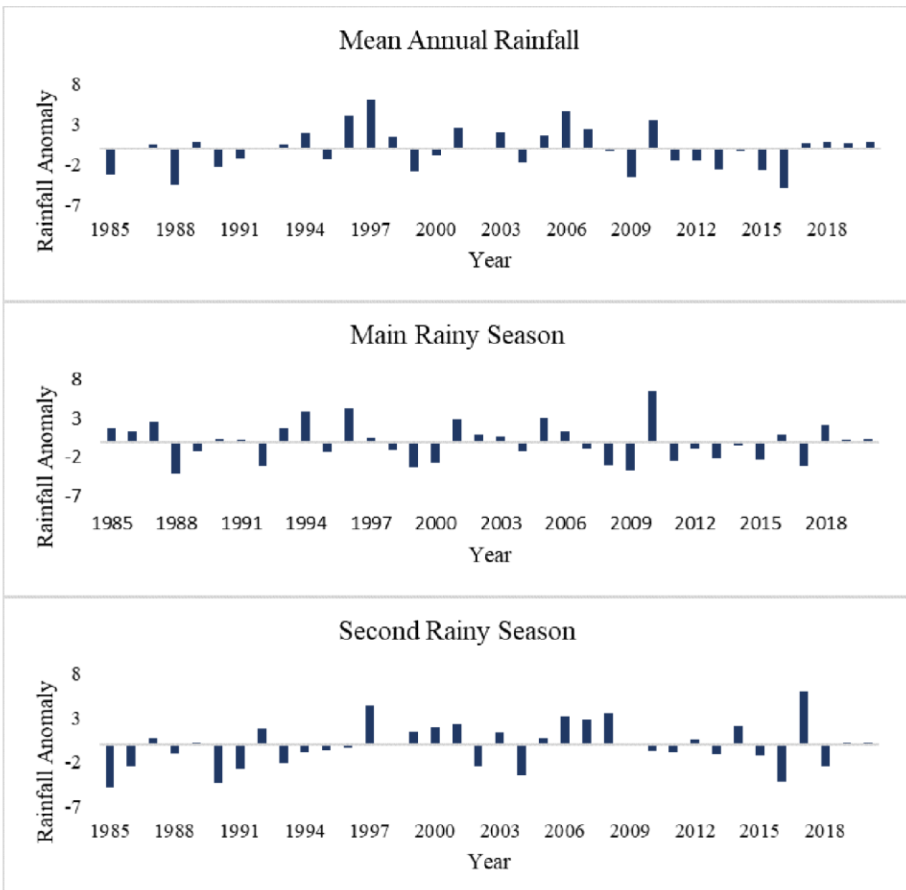

Figure 4.2:Temporal variations in rainfall anomalies

Mann Kendal's trend test of rainfall

The MK test results (Table 4.3) indicated a decreasing trend of rainfall in December, January, February, March, April, June, and July. In addition, the mean annual, and the main rainy season rainfall also showed a decreasing trend. Unexpectedly, November rainfall alone showed a statistically significant increase at 99% confidence interval. The change point detection analysis conducted using the Pettitt's test (Pettitt, 1997) for November rainfall revealed that the year 2003 (p value 0.03) was a shift period for the month's rainfall. This might be explained by changes in the timing of the rainy seasons over the years, particularly since 2003, due to the impacts of climate change and variability. However, this requires further investigation. Even though the MK trend test results are statistically insignificant, the values of Sen's slope test and the slope value of the trend line equation (Table 4.3; Fig 2 in Appendix G) show a high variability of rainfall in the study periods. This result implies that the monthly, annual, and seasonal rainfall in the study area does not have a monotonic increasing or decreasing trend, but it shows variability by fluctuating from its long-term mean (Table 4.3). Statistically non-significant increasing or decreasing trend of rainfall was reported by (Ayalew et al., 2012; Esayas et al., 2019) in different agroecological zones of Ethiopia. The non-significant decreasing trend of the main rainy season (spring) rainfall in the study area is consistent with the findings at Negelle station (Urgessa, 2014) and across most parts of the country (WFP, 2014). The decreasing trend of rainfall during the main rainy season affects crop production and food security (Bayable et al., 2021). Comparable to this finding, statistically non-significant changes in rainfall were observed in countries of the southern and eastern African regions, while statistically significant increases were recorded in the countries of the northern and central African regions (Alahacoon et al., 2021).

Innovative trend analysis of rainfall

The ITA statistical test result indicates a statistically insignificant decreasing trend in the main rainy season and mean annual rainfall. The ITA method is more sensitive in detecting hidden trends missed by the traditional MK tests (Singh et al., 2021) and hence showed a statistically significant ($P<0.01$) increasing trend for the second rainy season (autumn) rainfall (Table 4.4).

Table 4.4: Innovative trend analysis of rainfall

Seasonal and Annual RF	Trend Slope(s)	Trend Indicator(D)	UCL/LCL 95%	UCL/LCL 99%
Mean Annual RF	-0.492	-0.090	±0.450	±0.591
Main Rainy Season	-0.993	-0.465	±0.580	±0.762
Second rainy season	1.487	0.928**	±0.188	±0.247

** significant at the 0.01 level and UCL/LCL represent upper and lower confidence limits

Except for the second rainy season, it’s all data points lie above the 1:1 line, the decreasing trend of the main rainy season and the mean annual rainfall can be seen from most of the scattered points that lie below the 1:1 line in the Cartesian coordinate system (Fig. 4.3). From the ITA result of the mean annual rainfall, where the scatter points are closest around the 1:1 straight line, one can see that there is no significant trend.

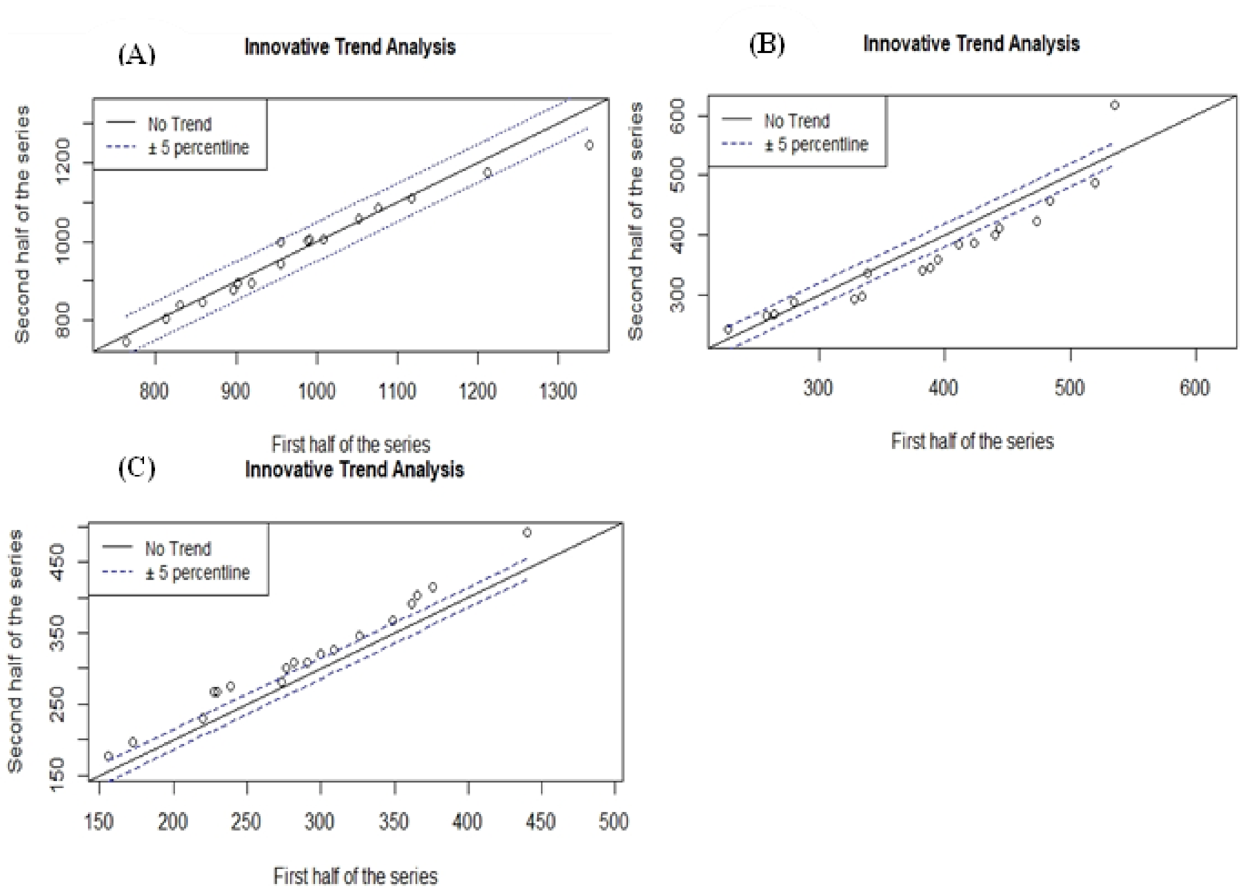

Figure 4.3:ITA of (A) mean annual rainfall, (B) main rainy season and (C) second rainy season

4.3.2. Variability and trends of temperature

The mean annual temperature of the study area from 1985 to 2020 was 23.96°C, and the mean maximum and mean minimum temperature were 31.18°C and 16.75 °C, respectively, with the coefficients of variation 4.7%, 2.2%, and 12.6%, respectively (Table 4.5). The computed CV values showed low variability of temperature for all months and 4.7%, 2.2%, and 12.6% for mean annual, maximum, and minimum temperature, respectively. This result shows that variability of the minimum temperature is the highest compared to the mean annual and maximum temperature. In general, variability of the mean annual, minimum, and maximum temperature was low, and the minimum temperature was more variable than the maximum temperature in the study area as well as in the country (Fenta et al., 2023; Tirfi & Oyekale, 2022).

Table 4.5: Variability and MK trend test of monthly temperature (1985 – 2020)

Months	Mean	Std. Deviation	CV (%)	MK Test (P-value)	Sen’s slope
Jan	24.578	1.528	6.2	0.191	0.031
Feb	25.397	1.670	6.6	0.233	0.046
Mar	25.249	1.716	6.8	0.141	0.044
Apr	24.117	1.478	6.1	0.140	0.030
May	23.732	1.310	5.5	0.712	0.008
Jun	23.457	1.494	6.4	0.820	0.002
Jul	23.063	1.384	6.0	0.798	0.006
Aug	22.974	1.325	5.8	0.865	-0.005
Sep	23.32	1.331	5.7	0.733	-0.011
Oct	23.521	1.111	4.7	0.978	0.002
Nov	23.859	1.130	4.7	0.733	-0.013
Dec	24.295	1.361	5.6	1.000	0.003
Mean Annual	23.964	1.136	4.7	0.887	0.001
Maximum Temp	31.178	.672	2.2	0.394	0.010
Minimum Temp	16.748	2.110	12.6	0.532	0.007

The inter-annual variability of the mean annual, maximum, and minimum temperature (Fig. 4.4) indicates that the study area has experienced both warm and cool years from 1985 to 2020. The anomaly index exhibited a prolonged increase in the mean annual temperature from 2000 to 2014, and 1989 was the coolest year with -6.67 anomaly index value. The positive anomalies were indications of higher mean annual, maximum, and minimum temperatures than a long-term average, while the negative anomaly values indicate a lower temperature than the long-term mean. The higher proportion of positive anomaly values in the study area (55.6%, 63.9%, and 55.6% of the mean annual, minimum temperature and maximum temperature, respectively; Fig. 4.4) implies that most of the study years were hotter than the long-term mean. This is most likely because of the changing climate, which leads to a rise in the country’s temperature (Berihun et al., 2023) in general and in southern Ethiopia (Esayas et al., 2019) in particular.

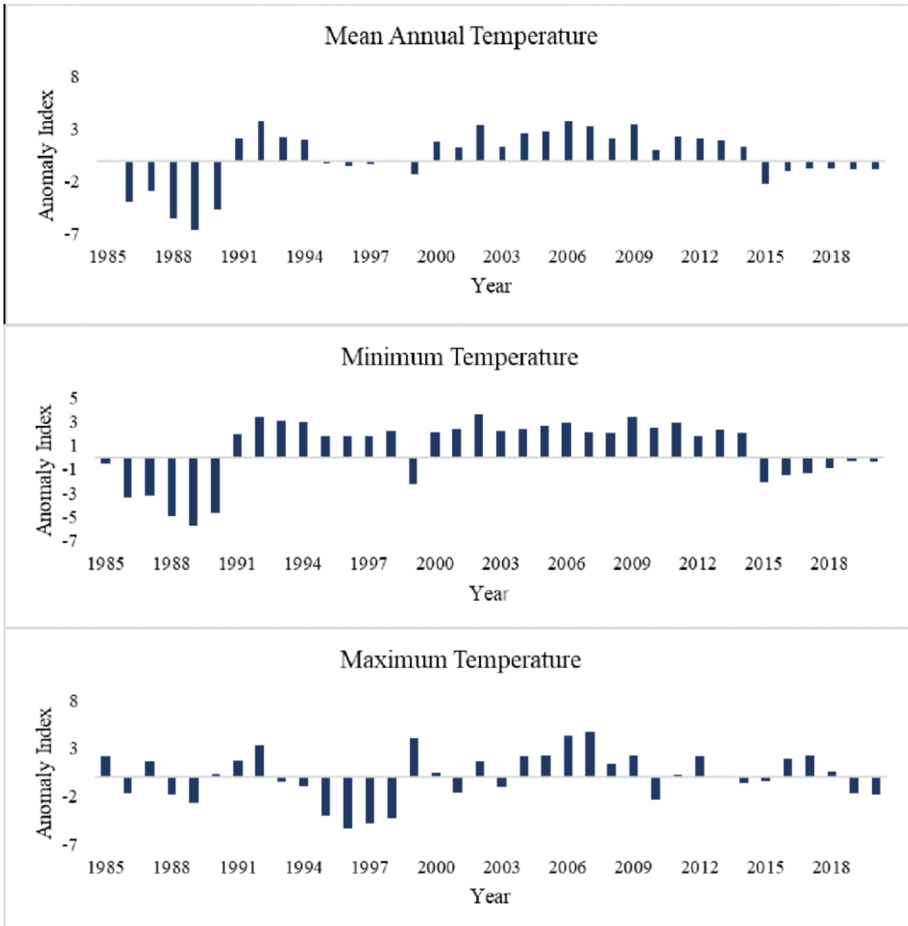

Figure 4.4:Temporal variations in mean annual temperature anomalies

Mann Kendal trend test of temperature

The MK test of monthly, mean annual, maximum, and minimum temperature showed no significant trend, where the computed p value was greater than the significance level. Even though the p value is greater than the significance level, the positive Sen's slope values of all months except for August, September, and November, exhibited the presence of an increasing trend in temperature (Table 4.5). In addition, the trend line equation (Fig 3 in Appendix G) also reveals that the slope of the trend line has a positive value, which implies an increasing trend of the mean annual, minimum, and maximum temperature. Similar results have been reported from eastern Kenya (Muia et al., 2024) and India (Panda & Sahu, 2019) where the annual minimum and maximum temperatures show an increasing trend, whereas with variations in the monthly and seasonal minimum and maximum temperatures.

Innovative trend analysis of temperature

The statistical result of ITA (Table 4.6) shows significantly increasing trend in the mean annual, maximum, and minimum temperature at 0.01 significance level. A significantly increasing trend in the mean annual, maximum, and minimum temperature in Ethiopia was also reported by (Lebeza et al., 2023) at Lemi and Wereilu stations. In addition, from the graphical ITA result (Fig. 4.5), one can notice that most of the scattered points fall above the 1:1 straight line, indicating an increasing trend in the mean annual, maximum, and minimum temperature in the study area.

Table 4.6:Innovative trend analysis of temperature

Temperature	Trend Slope(s)	Trend Indicator(D)	UCL/LCL 95%	UCL/LCL 99%
Mean Annual Temp	0.042	0.319**	±0.006	±0.007
Max. Temp	0.024	0.139**	±0.002	±0.003
Min. Temp	0.060	0.662**	±0.005	±0.007

** significant at the 0.01 level and UCL/LCL represent upper and lower confidence limits

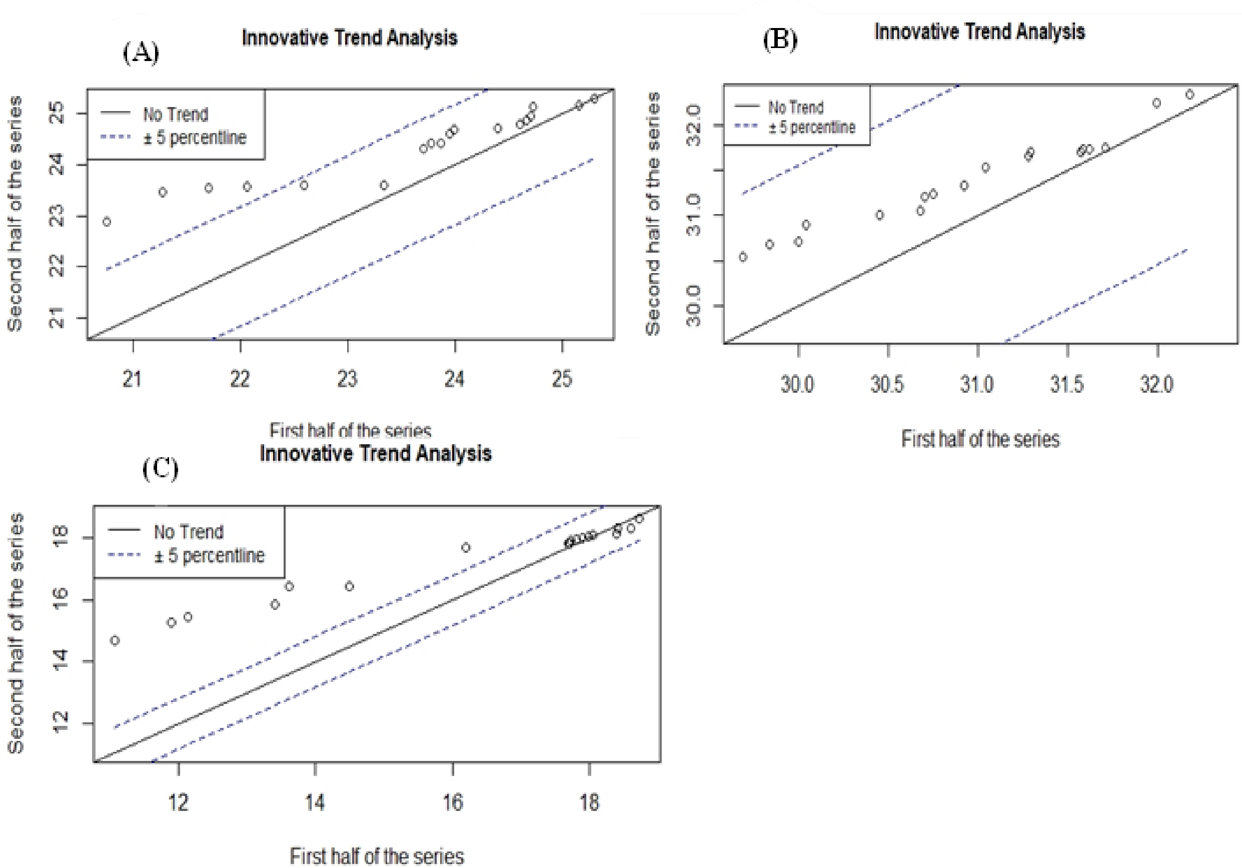

Figure 4.5:ITA of (A) mean annual temperature, (B) maximum temperature and (C) minimum temperature

4.3.3. Correlation between ecosystem services and climate variables

Spatial dynamics of ecosystem services in relation to climate variables and NDVI

We tested spatial correlation between the values of key ecosystem services (food production, water supply, raw material provision, and climate regulation) and mean annual rainfall, and mean annual temperature. The mean annual rainfall from 1985–2020 shows high spatial variability in the study area, ranging from 830.79 mm to 1044.01 mm (Fig. 4.6). A large proportion of the study area experiences lower rainfall except in the northeastern part, with the highest mean annual rainfall value of about 1044.01 mm. The spatial distribution of the mean annual rainfall increases from the southeastern to northeastern parts of the study area. Whereas, almost all parts of the study area receive higher temperature except the northeastern part, which has the lowest temperature, about 22.07ºC. The spatial distribution of the mean annual temperature increases from the northeastern part to the central and southeastern parts. The highest mean annual rainfall values were observed in the highest elevation areas, and the lowest mean annual rainfall values were observed in the lowest elevation areas. Conversely, the lowest mean annual temperature values were observed in the highest elevation areas (Fig.4.6). This indicates that the spatial distribution of the mean annual rainfall and temperature was related to the topography of the study area. Studies also reported that rainfall distribution is highly correlated with topography in Eastern Ethiopian highlands (Bayable et al., 2021) and Meki watershed in the rift valley region (Terefe, 2022).

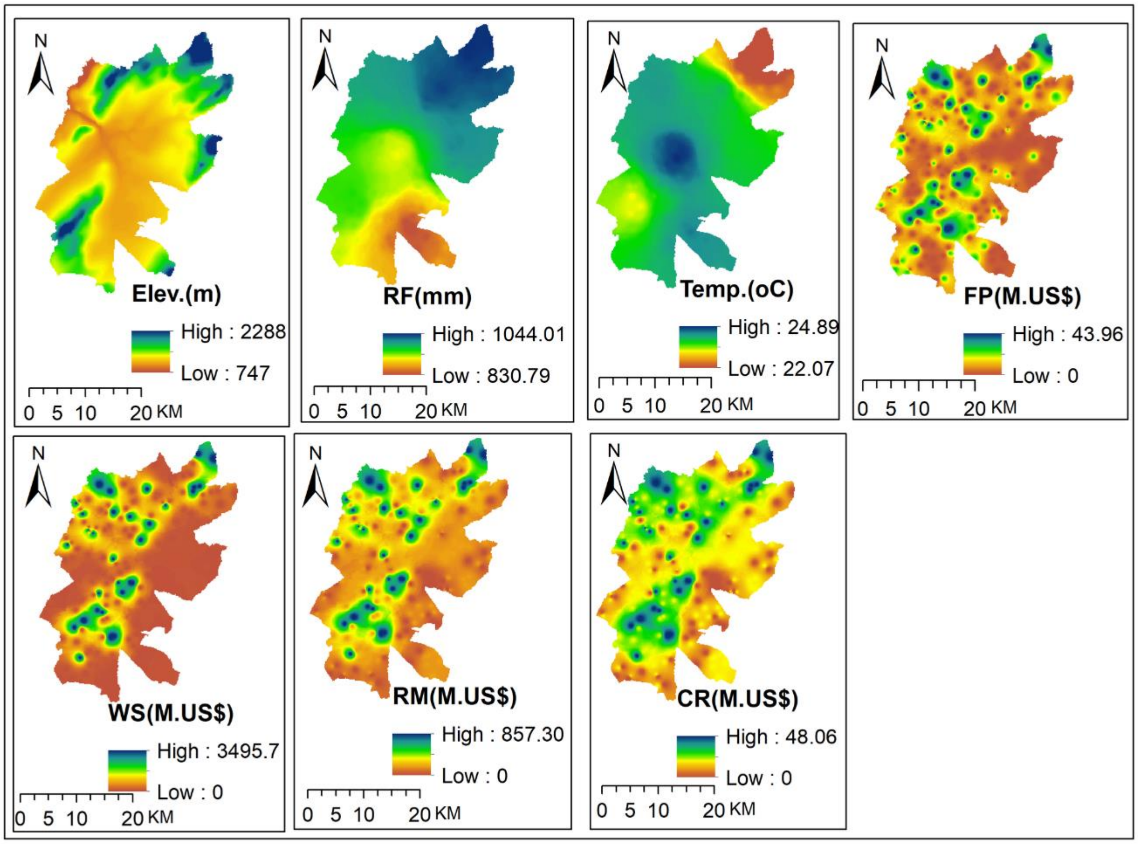

Figure 4.6:Spatial distribution of ecosystem services and climate variables

Note: Elev. = Elevation, RF = Rainfall, Temp. = Temperature, FP = Food Production, WS = Water Supply, RM = Raw Material, and CR = Climate Regulation

The spatial correlation analysis result (Table 4.7) indicates that water supply, raw material provision, and climate regulation services have a significant positive correlation with the mean annual rainfall. In agreement with this finding, positive spatial correlation between precipitation and regulatory services was found in northern China (Fang et al., 2018). Whereas, all ecosystem services included in this study showed a negative correlation with the mean annual temperature. These indicate that areas with higher rainfall have better food production, water supply, raw material, and climate regulation service provision than areas receiving lower rainfall. On the other hand, areas with high mean annual temperature have a lower provision of ecosystem services and need management measures to reduce the negative impacts of temperature increase on ecosystem services. Therefore, the correlation result (Table 4.7) implies that the spatial variability of rainfall affects the provision of key ecosystem services essential for human wellbeing. Because changes in rainfall patterns increase the frequency of climate extreme events and have an effect on ecosystem services (Berihun et al., 2023).

Table 4.7:Spatial correlation among ecosystem services, climate variables and NDVI

Ecosystem Services	Pearson Correlation	Mean Annual Rainfall	Mean Annual Temperature	NDVI
Food production	r	.176	-.206	.051**
	Sig.	.136	.081	.000
Water Supply	r	.268*	-.168	.111**
	Sig.	.022	.156	.000
Raw material provision	r	.268*	-.168	.126**
	Sig.	.022	.156	.000
Climate Regulation	r	.269*	-.167	.166**
	Sig.	.021	.158	.000

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed)

The spatial distribution of NDVI, a measure of greenness that is highly correlated with NPP, plant cover, and ecosystem productivity (Das et al., 2023), in 1985, 1995, 2005, 2015, and 2020 and the mean NDVI were calculated and mapped for the study area (Fig. 4.7). The spatial distribution of the annual and mean NDVI in the study area varies widely, ranging from -0.14 to 0.68, -0.11 to 0.74, -0.37 to 0.50, -0.01 to 0.53, 0.00 to 0.57, and -0.22 to 0.63 in 1985, 1995, 2005, 2015, 2020, and average NDVI, respectively (Fig. 4.7). The highest NDVI for all study periods was primarily observed in the northern and southwestern parts of the study area, with varying amounts. As elevation is found to be the most important topographic factor that determines the spatial distribution of NDVI (Fang et al., 2018), the northern and southwestern parts of the study area have high elevation and thus high NDVI values. Additionally, the Maze stream course, which includes riverine forests, also has a higher NDVI. The spatial distribution of the NDVI was linked to land cover types (Hussien et al., 2023) with higher NDVI values found in riverine forests, wooded grasslands, and cropped farmlands. The lowest NDVI values were observed primarily in bare lands, fallowed farmlands, and built-up areas (Fig. 4.7; Fig 1 in Appendix G).

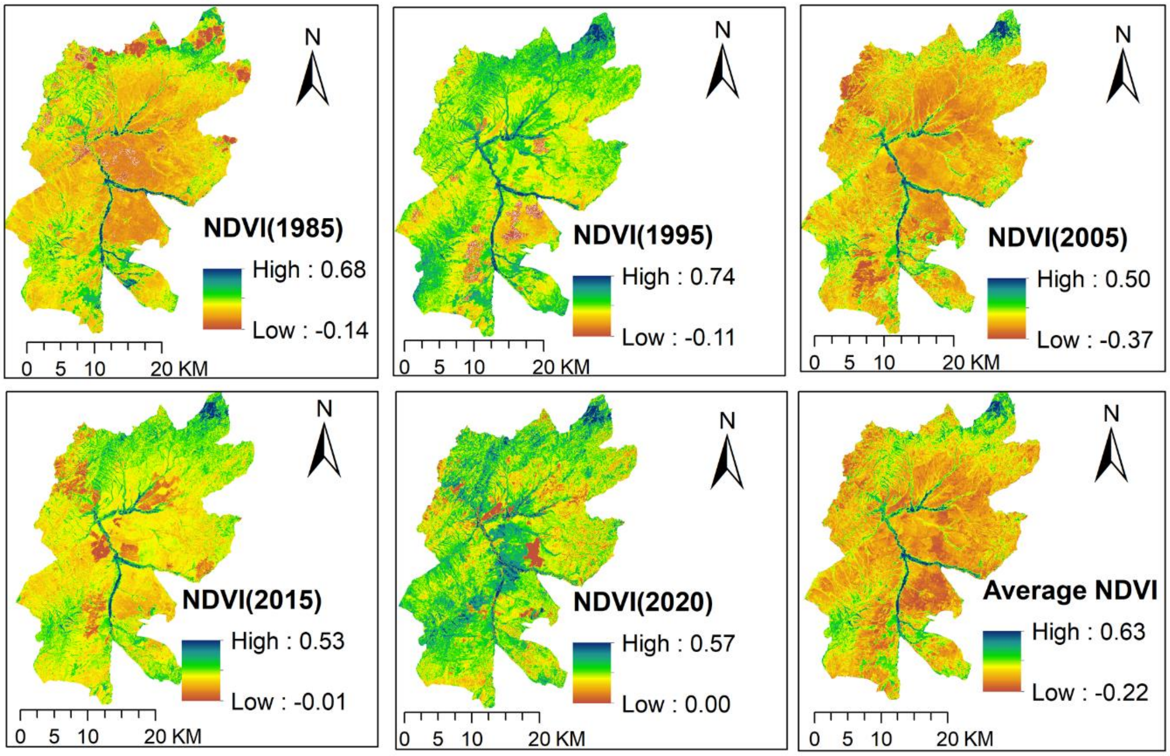

Figure 4.7:Spatial distribution of NDVI from 1985 to 2020

Fig. 4.8 shows the inter-annual variability of NDVI from 1985 –2020 in boxplots. The boxplot, which shows a significant variation among the study periods, is developed from the NDVI data of 1985, 1995, 2005, 2015, and 2020. The minimum value of NDVI is -0.37, which was in 2005, and the maximum one is 0.74, which was in 1995. In addition, the 25th percentile of the NDVI ranges from ~ - 0.1 to ~ 0.2 while the 75th percentile of the NDVI ranges from ~ 0.1 to ~ 0.5 across the study periods. Based on the boxplots (Fig. 4.8), NDVI increased from 1985 to 1995 and from 2005 to 2015 and 2020. From 1995 to 2005, a significant decrease in NDVI was observed. A decrease in NDVI from 1995 to 2005 was mostly due to people and domestic animals unrestricted access and effect on vegetation coverage of the study area by cutting grass for their cattle and for thatching roofs, and cutting trees for construction material and firewood. The establishment of national parks contributes to maintaining the ecosystem and biodiversity conservation (Haq, 2016). Maze national park was established in 2005, and since then, unrestricted access to park resources has been prohibited, allowing degraded fields to regenerate grasses and trees. This led to gradual increase in NDVI after 2005, especially inside the park boundary (Fig.4.8).

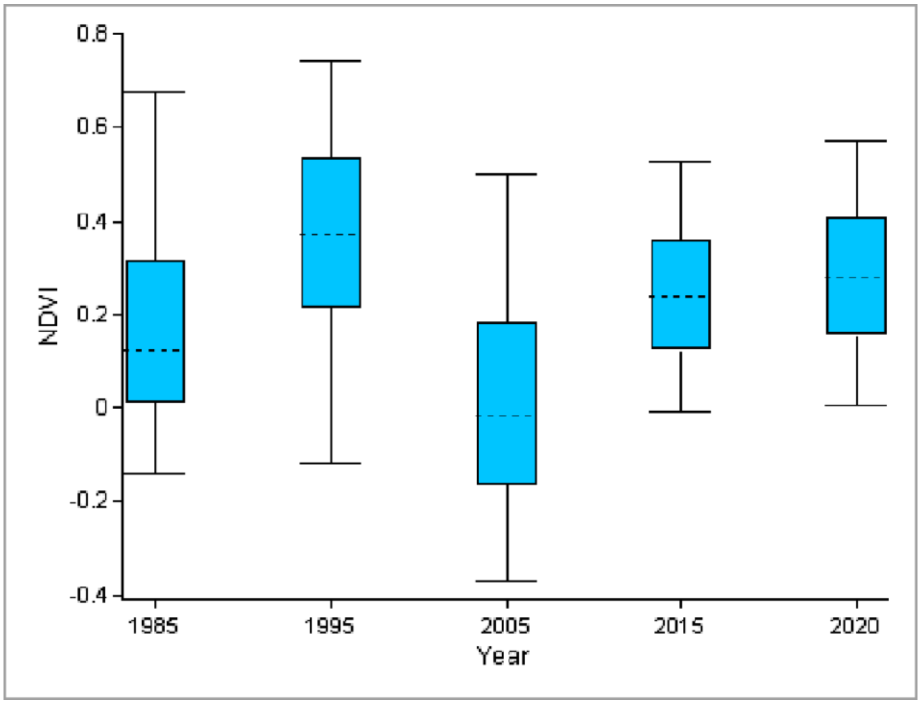

Figure 4.8:NDVI's inter-annual fluctuation from 1985–2020

We carried out a correlation analysis between the mean NDVI (the average of 1985, 1995, 2005, 2015, and 2020) and key ecosystem services. The Pearson correlation analysis result showed a significant positive correlation between NDVI and all key ecosystem services (Table 4.7). This implies that areas with high elevation, high rainfall and relatively dense vegetation coverage or NDVI (Fig 4.6) provide better food production, water supply, raw material, and climate regulation services. Positive correlations between NDVI and ecosystem services, for instance, water yield, soil conservation, and carbon storage services, have also been reported in southern China (Zhu et al., 2021). In the same vein, NDVI showed positive correlation with NPP and overall ecosystem productivity in India (Das et al., 2023).

Temporal correlation between climate variables and ecosystem services

Temporal correlation between the values of key ecosystem services and rainfall (mean annual, main rainy season, and secondary rainy season), temperature (mean annual, maximum, and minimum temperature), and potential evapotranspiration (the annual, main rainy season and second rainy season) was analyzed using the Pearson’s correlation coefficient at 95% confidence level.

Food production had a positive (r = 0.475) correlation with the main rainy season's rainfall than the mean annual rainfall and the second rainy season's rainfall (Table 4.8). This positive statistical correlation coefficient suggests that higher precipitation is linked to higher food production services. Since rainfall is one of the main climatic determinants of food production in Ethiopia (WFP, 2014), wetter years are generally associated with higher food production, while dry years are linked to lower production. Therefore, despite the fact that the correlation is not statistically significant, rainfall variability has an impact on food production in the study area. The second rainy season (autumn) rainfall showed an increasing trend in the study area (Table 4.3) and exhibited moderate negative correlation (r = -.496; Table 4.8) with food production service. This result reveals that an increase in rainfall might not be an indication of improved agricultural practices and food production since an increasing trend of rainfall would not necessarily mean good distribution of rainfall, especially during the crop-growing season (Habte et al., 2021). Whereas, the correlation analysis showed a strong negative correlation (r = -.837; Table 4.8), with minimum temperature and moderate negative correlation with maximum temperature. This is due to decreasing crop productivity for even small local temperature increases in arid and semi-arid areas (IPCC, 2007).

Table 4.8:Temporal correlation between ecosystem services and climate variables (1985 – 2020)

Ecosystem Services	Pearson Correlation	Mean Annual RF	MRS RF	SRS RF	Annual Temp.	T_{max}	T_{min}
Food production	r	.247	.475	-.496	.800	-.349	-.837
	Sig.	.689	.419	.396	.104	.565	.077
Water supply	r	-.568	.207	.512	.248	-.196	-.115
	Sig.	.318	.738	.377	.688	.752	.854
Raw material provision	r	-.494	.291	.448	.326	-.234	-.178
	Sig.	.398	.635	.450	.592	.704	.775
Climate regulation	r	-.428	.350	.394	.385	-.252	-.231
	Sig.	.472	.563	.512	.522	.683	.709

Note: MRS, Main rainy season; SRS, second rainy season; RF, Rainfall; T_{max}, Maximum Temperature; T_{min}, Minimum Temperature

The quantity or availability of water for various purposes is very much dependent on the amount of rain, and annual and seasonal rainfall variability significantly affects rural water supply services (Twisa & Buchroithner, 2019). Likewise, water supply service in the study area had a positive correlation with the main and second rainy season's rainfall (Table 4.8). This result implies that, since precipitation affects the availability of water, the main and second rain seasons positively contribute to water availability and supply in the study area. On the other hand, the water supply service showed a negative relationship with maximum and minimum temperature, with a correlation coefficient (r = -.196 and -.115, respectively; Table 4.8). This result indicates that an increase in minimum and maximum temperature exerts a negative impact and reduces the supply of water in the study area, though the correlation is not significant. Similarly, previous studies reported climate variability and increasing temperature reduced the availability of water in the semi-arid lowlands (IPCC, 2007) and in sub–Saharan Africa (Vanacker et al., 2005).

Raw material provisioning services include the production of lumber, fuelwood, or fodder that are extracted as raw materials (Costanza et al., 1997). In the local context, raw materials also encompass the production of charcoal, thatching grass, pasture, and cutting trees for building houses and fences. As indicated in Table 4.8, raw material provisioning service exhibited a positive correlation with the main and second rainy season's rainfall (Table 4.8). But a negative correlation was observed with the maximum and minimum temperature (r = -.234 and -.178, respectively; Table 4.8). This result suggests that the reduction of raw material provisioning services in the study area is attributed to the rising impact of temperature along other determining factors. Rising temperature and altered precipitation patterns would increase aridity, worsen water stress, alter the distribution pattern of grassland in the tropical grassland ecosystem, and consequently reduce raw material provisioning services (Babu, 2015). In line with this finding, a study in Kenya noted that climate change and variability, such as recurrent drought and rainfall variability, along with other anthropogenic factors, are reported as determining factors of provision of pasture, thatching grass, and fuel wood for household energy needs including other ecosystem services (Muhati, 2022).

The climate regulation service and the main and second rainy seasons' rainfall showed a positive correlation, though the correlation coefficient is low (Table 4.8). This positive correlation resulted from the increased precipitation, which promotes an increase in vegetation density (Fang et al., 2018) and hence contributes positively to climate regulation. A similar positive correlation between precipitation and regulatory services was reported (Fang et al., 2018; Liu et al., 2023). On the other hand, the climate regulation service in the study area exhibited a negative correlation with the minimum and maximum temperature (Table 4.8). A rise in both minimum and maximum temperatures exerts pressure on vegetation coverage and climate regulation services. A previous study in the Sudan identified an increase in minimum and maximum temperature and decreasing precipitation as a threat to vegetation coverage of the country (Loh et al., 2020). In addition to climate change and variability, human activities such as LULC changes have also contributed to the decline in vegetation cover and the reduction of climate regulation services in the study area. This is due to the encroachment of farmlands and built-up areas over naturally vegetated lands (Simeon & Wana, 2024; Zewude et al., 2022).

The trend analysis results (Tables 4.3, 4.4, 4.5, and 4.6) illustrated increasing trends in the mean annual, maximum, and minimum temperature, whereas the mean annual and main rainy season's rainfall showed decreasing trends from 1985 to 2020 in the study area. Increasing temperature resulted in water loss due to evaporation, and this affected agriculture and livestock production, domestic water supply, and municipal services in southern Ethiopia (Belay et al., 2021) and in the tropics (Habte et al., 2021). Similarly, the correlation analysis result exhibited a negative relationship between maximum and minimum temperature and key ecosystem services, though the correlation was not statistically significant. A positive trend of temperature (Table 4.5; Table 4.6) shows that there has been a rising sign of climate change in the study area and closely similar results have been reported in Kenya (Maina, 2019) that negatively affects the provisioning as well as regulation services of ecosystems at local and regional scales in varying degrees. The main rainy season is the major contributor to the annual rainfall in the study area, and during this season, food production, water supply, and vegetation growth are expected to be better once the season turns out. As indicated in Table 4.8, main rain season's rainfall exhibited a positive relationship with all ecosystem services included in this study. Previous studies in China and the 2014 World Food Program (WFP) report shows a positive correlation between precipitation and different provisioning and regulatory ecosystem services, for instance, Water yield, NPP, and soil conservation services (Fang et al., 2018; Liu et al., 2023; WFP, 2014).

The relationship between annual and seasonal evapotranspiration and key ecosystem services was explored using the partial correlation analysis. Main rainy season rainfall was used as a control variable since rainfall is one of the main climatic determinants of food production in Ethiopia (WFP, 2014) and greatly affects provisioning of ecosystem services. The annual and seasonal potential evapotranspiration exhibited a strong negative correlation with food production service ($r = -.929$, $-.990$, and $-.814$ for the annual, main rainy season, and second rainy season, respectively; Table 4.9). Water supply, raw material provisioning, and climate regulation services also showed a similar negative correlation with annual and seasonal potential evapotranspiration

(Table 4.9). Evapotranspiration greatly contributes to the water loss (Wanniarachchi & Sarukkalige, 2022), which has a negative impact on the water resources and water supply (Yu et al., 2021). Therefore, insufficient water supply affects the growth of crops and harvests, and reduces food supply (Yu et al., 2021). Particularly, the impact is strong in arid and semi-arid regions where a small amount of precipitation is available for plant growth (Lu et al., 2011). Comparing the relationship between key ecosystem services and climate variables, the negative impact of both annual and seasonal evapotranspiration on food production was the strongest. In arid regions, a large proportion of precipitation is returned to the atmosphere through evapotranspiration (Lu et al., 2011) due to increased temperature (Belay et al., 2021), affecting soil moisture availability and, consequently, the provision of key ecosystem services.

Table 4.9:Partial correlation between potential evapotranspiration and ecosystem services

Ecosystem Services	Partial Correlation	Annual PET	MRS PET	SRS PET
Food production	r	-.929	-.990	-.814
	Sig.	.071	.010	.186
Water supply	r	-.017	.135	-.145
	Sig.	.983	.865	.855
Raw material provision	r	-.005	.140	-.162
	Sig.	.995	.860	.838
Climate regulation	r	-.012	.122	-.210
	Sig.	.988	.878	.790

Note: MRS, Main rainy season; SRS, second rainy season; PET, potential evapotranspiration

4.4. Conclusion

Our study demonstrated statistically significant positive spatial correlation among key ecosystem services and the mean annual rainfall and NDVI, whereas, negative correlations were observed among key ecosystem services and mean annual temperature. Temporally, key ecosystem services and main rainy season rainfall were positively correlated. However, negative correlations were observed among ecosystem services and maximum and minimum temperatures. In addition, a strong negative correlation was observed between food production service and potential evapotranspiration. Therefore, the spatiotemporal variability of rainfall and temperature has largely negative effect on the capacity of the ecosystem to provide services that are essential for human well-being. Employing various statistical methods and extensive data, the patterns observed in our study are not confined to MzNP and its surroundings but are indicative of broader trends in similar ecosystems globally. Thus, our findings could be applicable to other semi-arid regions experiencing similar pressures from LULC changes and climate variability.

Understanding the levels of severity of climate variability is the first and fundamental step in planning and implementing appropriate measures. Hence, designing ecosystem conservation and restoration strategies such as implementing reforestation and afforestation, and balancing conservation and agriculture through integrated land management are crucial. Such strategies require involving the local communities in conservation planning and decision-making process, and raising awareness of the local community about the importance of ecosystem conservation. Thus, ecosystem conservation and restoration are crucial steps to increase the potential of ecosystems to adapt and mitigate the impacts of climate change and variability. We considered only four ecosystem services, which may have limitations to fully representing the status of the study region's ecosystem services. Additionally, because there was a dearth of documented historical and field data in the research area, the quantification of ecosystem service values was based solely on the dynamics of LULC classes across space and time. Therefore, we recommend future research in this and other similar settings, such as national parks under pressure from human activities and climate variability, to take into account other important ecosystem services. Additionally, it is important to estimate the values of these services using more precise models (such as the INVEST model), market price-based valuation methods, and extensive field data.

5. Trade-offs and synergies among key ecosystem services in Maze National Park and its environs, southwestern Ethiopia

Abstract

The aim of this study is to assess synergies and trade-offs between ecosystem services in Maze National Park and its environs in southwestern Ethiopia. We employed land use and land cover data along with ecosystem services values from previous studies and performed a landscape diversity analysis to examine correlations with ecosystem services dynamics. The spatiotemporal trade-offs/synergy relationships were analyzed using ecosystem service values from the years 1985, 1995, 2005, 2015, and 2020, employing the Spearman correlation coefficient and the Local Moran's I autocorrelation model. Additionally, we collected socioeconomic data to get insight into the local people's perceptions of the interactions between ecosystem services. The landscape metrics results revealed a rise in the number of patches, patch density, and edge density, indicating landscape fragmentation. From 1985 to 2020, food production service exhibited a moderate negative correlation with water supply (rs = -0.6), raw material (rs = -0.5), and climate regulation (rs = -0.5), indicating a moderate trade-off relationship. Conversely, a very strong and significant positive correlation (rs = 1), indicating a strong synergistic relationship, was observed between raw material and climate regulation, water supply and climate regulation (rs = 0.9), and raw material and water supply services (rs = 0.9). Spatially, the relationships among ecosystem services were predominantly synergistic, though a higher proportion of trade-offs was observed between food production and other services. The Chi-Square test results indicated that local community perceptions of the interactions between ecosystem services vary depending on their distance from the park. Therefore, understanding the relationships between ecosystem services is crucial for developing effective ecosystem protection strategies and addressing the effects of anthropogenic disturbances in protected areas and beyond. Finally, we recommend future studies to incorporate additional provisioning, regulating, and cultural services to fully represent the region's ecosystem services status in trade-offs and synergy analyses.

Key Words: Ecosystem services, Anthropogenic disturbance, Landscape diversity, Landscape fragmentation, Spearman correlation

Mestewat Simeon[1,2*], and Desalegn Wana[1] (2025). Synergies and trade-offs among key ecosystem services in Maze National Park and its environs, southwestern Ethiopia. Global Ecology and Conservation 57 (2025) e03398. https://doi.org/10.1016/j.gecco.2024.e03398

5.1. Introduction

Ecosystem services are the direct and indirect contributions/benefits of ecosystem functions essential for human well-being and survival (Costanza et al., 1997; The Economics of Ecosystems and Biodiversity (TEEB), 2012). Ecosystems offer a wide range of benefits such as water, food, fuel wood, timber, habitat conservation, climate regulation, and spiritual and recreational services that are crucial for human survival (Millennium Ecosystem Assessment (MEA), 2005). However, the majority of the Earth's ecosystem services have shown a declining trend in recent decades, largely due to increasing anthropogenic disturbances (Sannigrahi et al., 2020). The rate of global changes in nature over the past 50 years has been unprecedented, driven primarily by changes in land use, climate change, pollution, and biotic exchange (Intergovernmental Science-Policy Platform on Biodiversity (IPBES), 2019). Therefore, the relationships between various ecosystem services are shaped by both human activities and natural factors, often resulting in patterns such as synergies and trade-offs (Yuan et al., 2024). Trade-offs happen when the enhancement of one service leads to the reduction of another, whereas synergistic relationships occur when both services either rise or decline together (Bennett et al., 2009).

Africa is endowed with a wealth of diverse ecosystems that produce vital goods and services, supporting the continent's needs for food, water, energy, health, and secure livelihoods (IPBES, 2018). However, the unregulated transformation of rangelands, forests, and other semi-natural areas to food production and urban areas (IPBES,2018), along with the impacts of climate change, has led to a decline in ecosystem functioning and service provision (Sintayehu, 2018). As a result, both synergistic and tradeoff interactions have been observed among provisioning, regulating, supporting, and cultural services in different regions of Africa (Ogbodo et al., 2023).

Human activities, such as converting natural land cover into agricultural or built-up areas, lead to fragmentation and loss of natural habitats, significantly impacting the provision of ecosystem services (Mitchell et al., 2015a). Alterations in landscape pattern and structure significantly influence ESs by changing the size, shape, number, and spatial arrangement of patches (Mitchell et al., 2015b). Additionally, the dynamics of landscape configuration and the spatial arrangement of patches influence the strength and direction of interactions among ecosystem services, leading to both trade-offs and synergies (Rieb & Bennett, 2020). Therefore, investigating the role of landscape patterns in the synergies and trade-offs among ecosystem services is crucial for managing multiple ecosystem services (Shi et al., 2023) and promoting positive interactions while avoiding negative ones among ecosystem services (Rieb & Bennett, 2020).

Recently, the relationships between various ecosystem services, including synergies and trade-offs, have become a significant focus in ecosystem services research (Li et al., 2022; Tan et al., 2024; Wang et al., 2023; Zeng et al., 2022). Assessing synergistic and trade-off interactions among ecosystem services provides a scientific foundation for optimizing ecosystem protection and management to enhance human well-being (Wang et al., 2024; Yuan et al., 2024). The study area, Maze National Park (MzNP) and its environs, provides a wide range of provisioning, regulating, cultural, and supporting services for residents (Simeon & Wana, 2024). However, anthropogenic activities such as land use and land cover (LULC) changes and illegal fires (Zewude et al., 2022) have led to the loss of individual and total ecosystem services provided by the environment (Simeon & Wana, 2024). Despite these challenges, several previous studies in Ethiopia (Mekuria et al., 2021; Negussie, 2019; Solomon et al., 2019; Temesgen et al., 2018) have primarily focused on the effects of LULC changes on ecosystem services. Although exploring the synergy/trade-off relationships among ecosystem services provides valuable insights for ecological protection policy development and future intervention options (Geng et al., 2022; Jia et al., 2022; MEA, 2005), little attention has been given to these matters in the protected area systems in Ethiopia. In addition, relating landscape structures to key ecosystem services and their synergy and trade-offs analysis are largely lacking. Our study, therefore, aims at investigating the synergies and trade-offs between key ecosystem services in MzNP and its environs, as well as the correlations between landscape metrics and these key ecosystem services. Furthermore, we conducted a socioeconomic survey to assess local people's perceptions of the interactions between ecosystem services, an aspect that has received little attention in previous studies (Admasu et al.,2023; Mekuria et al., 2021; Shifaw et al.,2024).

5.2. Materials and methods

5.2.1. Sources of data

Land use land cover data and ecosystem service values

The LULC data and ecosystem service values (ESVs) used for landscape diversity, tradeoffs, and synergy analysis were obtained from (Simeon & Wana, 2024; Simeon et al., 2024) (Fig. 1 in Appendix G; Table 4.2). The quantification of ESVs was based on value coefficients from the ecosystem service valuation database (ESVD), which was updated in 2020 (de Groot et al., 2020). Details of LULC classifications and ESVs estimation are presented in (Simeon & Wana, 2024). We selected four ecosystem services such as food production (FP), water supply (WS), raw material provision (RM), and climate regulation (CR), based on their value to local community through focus group discussion (FGD) and key informant's interview (KII) (Simeon & Wana, 2024).

Socio-economic data collection

MzNP is bordered by five *woredas*: Zala, Kamba, Kucha, Kucha Alpha, and Daramalo. Among these, four *kebeles* were purposively selected due to their significant interaction with the park (Andabo, 2017) and their extensive boundary with the park. The selected *kebeles* were Mela Gayile Tossa, Morka, Domea, and Wagesho. According to the *kebele* administration offices, the total number of households in these *kebeles* was 2,203. The overall sample size for the survey was calculated using the sample size determination formula established by Cochran (Cochran, 1977) (Eqs.1;2).

$$n_0 = \frac{z^2 pq}{e^2} \tag{1}$$

Where, n_0 is the sample size, z is the selected critical value of desired confidence level, p is the estimated proportion of an attribute that is present in the population, $q = 1 - p$ and e is the desired level of precision.

Thus, for a total household of 2,203, the calculated sample size was 246. However, since this sample size exceeds 5% of the total households (110), Cochran's correction formula was used to calculate the final sample size (Cochran, 1977).

$$n_o = \frac{n_0}{1 + \frac{(n_0 - 1)}{N}} \tag{2}$$

Where, n_0 is the sample size derived above and N is the population size. As a result, the final sample size set for this study was 221.

Survey participants were selected purposively, considering their duration of residence in the study area and their knowledge of LULC dynamics as well as the benefits they have derived from the park over the past decades. Respondents were selected in consultation with *kebele* administrators and agricultural extension agents from each *kebele*. A total of 221 participants were chosen from the four selected *kebeles*. For the FGDs and KIIs, six FGDs were held, two consisting of women only and four mixed-gender groups, each with five to seven participants. Additionally, eight KIIs were conducted with *kebele* administrators, residents, and park staff.

5.2.2. Methods

Land use land cover change and landscape diversity analysis

Based on LULC data obtained from Simeon et al. (2024) and Simeon & Wana (2024), the relative changes in LULC classes from 1985 to 2020 were displayed using a bar chart. The change of natural land cover into agricultural or built-up areas leads to fragmentation and loss of natural habitats, significantly impacting the provision of ecosystem services (Mitchell et al., 2015a). Therefore, in addition to examining spatial and temporal changes in LULC types in the study area, landscape diversity indices were employed to illustrate the overall spatial and temporal variations in the landscape. Landscape diversity encompasses the complex variety and richness of landscape elements, including their composition, structure, and function, as well as the spatial arrangement and connectivity of different patch types within the landscape (Doğan, 2022). Changes in landscape patterns lead to alterations in the components, structure, and function of ecosystems, which in turn affect ecosystem services provision (Liu et al., 2020; Mitchell et al., 2013). We employed landscape and class-level diversity metrics to identify areas with the greatest landscape fragmentation, which undergo significant land cover changes over time (Chmielewski et al., 2014). Considering the strong spatial dependence between ecosystem services and the landscape pattern index (Liu et al., 2020), we calculated the landscape diversity indices in the study area. Thus, landscape diversity indices such as Shannon's and Simpson's diversity indices were employed to analyze the spatial and temporal diversity of the landscape. Shannon's diversity index (SHDI) highlights the presence of rare land cover types and the richness aspects of diversity, while Simpson's diversity index (SIDI) emphasizes on dominant land cover types and the evenness component of diversity (Nagendra, 2002). Although using both indices may lead to ambiguous results (Nagendra, 2002), they allow for the exploration of different facets of diversity.

Additionally, we employed class-level landscape metrics including, the number of patches (NP), patch density (PD), largest patch index (LPI), and edge density (ED) to assess the fragmentation of the landscape due to the conversion of naturally vegetated lands to farmland and built-up areas using the FRAGSTATS 4.2 software (Table 5.1). These metrics were selected due to their applicability in numerous previous landscape diversity and fragmentation studies, as well as their capacity to demonstrate significant variations in the landscape in response to changes in landscape patterns (Kefalas et al., 2023; Liu et al., 2020; Midha & Mathur, 2010; Mulatu et al., 2024; Nagendra, 2002). FRAGSTATS software is employed to quantify landscape structure and patterns, and to analyze changes in landscape ecology over time (McGarigal &Marks, 1995). The SHDI and SIDI were applied using the following equations (Eqs. 3 and 4).

$$SHDI = 1 - \sum_{i=1}^{N} p_i \times Inp_{i,} \tag{3}$$

$$SIDI = 1 - \sum_{i=1}^{N} p_i \times p_{i,} \tag{4}$$

Where N is the number of land cover types, pi is the proportional abundance of the ith type andln is the natural logarithm of the proportion Pi. SHDI values theoretically range from 0 to infinity (Nagendra, 2002), with higher values signifying greater diversity (Doğan, 2022). The SIDI ranges from 0 to 1, where values close to 1 indicate high diversity and values near 0 reflect low diversity (Kudas et al., 2024).

Table 5.1:Metrics employed in landscape diversity/fragmentation analysis

Class level metrics	Description	Sources
NP	The number of individual patches of each land-cover class. A change in the number of patches indicates fragmentation or loss of habitat.	(Daye & Healey, 2015)
PD	Number of patches in the landscape per unit area. A class that has more patch density shows that it is divided into numerous patches and thus considered more fragmented.	(Chen et al., 2023; Midha & Mathur, 2010)
LPI	The relative size of the largest cluster, calculated for a specific cover type, reflects the degree of fragmentation of that cover type. When the cover type is divided into very small patches, the index approaches zero.	(Turner & Gardner, 2015)
ED	The ratio of the total edge length of all patches in each land-cover class to the overall landscape area. A high edge density value indicates significant human disturbance and fragmentation within the class.	(Daye & Healey, 2015)

NP = number of patches, PD = patch density, LPI = largest patch index, ED = edge density

The relationships between landscape diversity metrics such as NP, PD, LPI, ED, SHDI, and SIDI and key ecosystem services (FP, WS, RM, and CR) were evaluated using the non-parametric Spearman rank correlation in Statistical Package for the Social Sciences (SPSS). Spearman rank correlation was chosen because of its robustness to non-normality and its less sensitivity to outliers (Zar, 2005). The correlations between landscape diversity metrics and ecosystem services are visually displayed in graphs. Spearman rank correlation was calculated using the following equation (Eq.5).

$$r_{s} = 1 - \frac{6(\sum d^2)}{n-(n^2-1)} \tag{5}$$

where d or $x_{i-} y_i$ is the difference between ranks, n is the number of ranked pairs. The correlation coefficient value ranges between +1 and −1, where a value of +1 represents a perfect positive correlation, −1 represents a perfect negative correlation, and a value of 0 indicates no correlation. The strength of the Spearman correlation values is considered strong if the coefficient ranges from 0.7 to 1, moderate from 0.4 to 0.6, and weak when less than 0.4 (Akoglu, 2018).

Spatial and temporal distribution of ecosystem services

Maps showing the spatial and temporal distribution of key ecosystem services were developed by generating random points within the study area and extracting the ESVs of LULC classes using the 'extract point values' tool of Arc GIS for each ecosystem service included in this study. Subsequently, a continuous surface for each ecosystem service was created using the Inverse Distance Weighting (IDW) interpolation method. Additionally, the temporal dynamics of key ecosystem services from 1985 to 2020 were presented using a line graph.

Temporal analysis of synergies and tradeoffs

The Spearman rank correlation coefficient was employed to evaluate the temporal trade-offs and synergies between ecosystem services from 1985 to 2020 using SPSS and R studio (R4.1.3)(R Core Team, 2022).This method was chosen for its low sensitivity to data distribution and outliers(Zar, 2005),working with less raw data, and wide applicability in ecosystem services trade-off and synergy studies (Li & Luo, 2023; Wang et al., 2021; Zeng et al., 2022; Zhang et al., 2023).The coefficients show the direction and strength of the relationships between each ecosystem service (Sylla et al., 2020). A positive correlation coefficient indicates that the synergies between two services were mutually promoted, whereas a negative correlation coefficient indicates a trade-off between the two services (Wu et al.,2022). If the correlation coefficient was neither positive nor negative, it suggested that the two functions were independent of each other.

Spatial analysis of synergies and tradeoffs

Spatial autocorrelation is a crucial metric for determining whether the attribute value of a given location is significantly related to the attribute values of its neighboring locations (Bing et al., 2019). Therefore, global and local spatial autocorrelation analyses were employed to characterize the spatial relationships among key ecosystem services. The global Moran's I statistic was calculated in ArcGIS via the spatial autocorrelation tool to show the spatial autocorrelation/aggregation of ESs in the study area. The values of global Moran's I statistic range from −1 to 1: a value of 1 indicates perfect positive spatial autocorrelation, 0signifies spatial randomness, and −1 shows perfect negative spatial autocorrelation (Tian et al., 2024). It was calculated using the following equation (Eq. 6).

$$I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{ij(x_i-\bar{x})}(x_j-\bar{x})}{s^2\ (\sum_i\sum_j\omega_{ij})} \tag{6}$$

Where n is the total number of grid cells in the study area; xi, xj are the measurement values of an attribute feature in regions i and j, respectively; x is the average value of all observations of a certain attribute feature x in the study area; wij is the standardized space–weight matrix; and s^2 is the variance.

Moran’s I statistics can effectively measure the spatial association and interactions between two geographical elements (Chi & Zhu, 2008). Furthermore, this model is widely applicable in ecosystem services synergy and trade-off analysis at regional and local scales (Deng & Cao, 2023; Guoping et al., 2021; Ji et al., 2021). Thus, in order to analyze the spatial synergy and trade-off relationships among key ecosystem services in the study area, we applied the Local Moran’s I spatial autocorrelation model, also referred to as the local indicators of spatial association (LISA) developed by (Anselin, 1995) in GeoDA software. LISA identifies four types of spatial clusters for bivariate Local Moran's I analysis: high-high (HH) and low-low (LL) clusters, which indicate positive associations and are described as synergy relationships, and high-low (HL) and low-high (LH) clusters, which indicate negative associations and are described as trade-off relationships (Ji et al., 2021; Li et al., 2022).

Local community perception of LULC dynamics and interactions among ecosystem services

Descriptive statistics, including frequencies and percentages, were used to illustrate the local community's views of ecosystem services dynamics over the last three decades. A stacked bar chart was employed to display these perceptions visually. We also examined the community's perception of ecosystem services changes and interactions based on their distance from MzNP. The data were collected using a five-point Likert scale, which was subsequently regrouped into three categories: synergy (strongly disagree and disagree), not sure, and tradeoff (agree and strongly agree). Distance from the park was categorized into three groups: close (< 2 km), medium (2-5 km), and far (>5 km). We tested the relationship between these categorical variables using a Chi-Square test of independence. Additionally, the qualitative information gathered from survey participants was thematically grouped into two predefined categories: perceived changes of LULC classes and interactions among key ecosystem services obtained from the park. This information was presented narratively. Socio-economic data were employed to triangulate the alignment between the empirical analysis of synergies and trade-offs among ecosystem services and the local communities' perceptions of these interactions.

5.3. Results and Discussions

5.3.1. Spatiotemporal variation of LULC types, landscape diversity and ecosystem services

Land use land cover changes and landscape diversity

The LULC maps of the study area from 1985 to 2020 showed a substantial increase in croplands and built-up areas, while riverine forests, wooded grasslands, and water bodies showed a decreasing trend (Simeon & Wana, 2024). From 1985 to 2020, farmlands and built-up areas increased by 103.7% and 31.32%, respectively. In contrast, the remaining LULC classes, such as wooded grasslands, water bodies, riverine forests, and bare land, decreased by 3.78%, 38.14%, 22.35%, and 36.4%, respectively (Simeon & Wana, 2024) (Fig. 5.1).

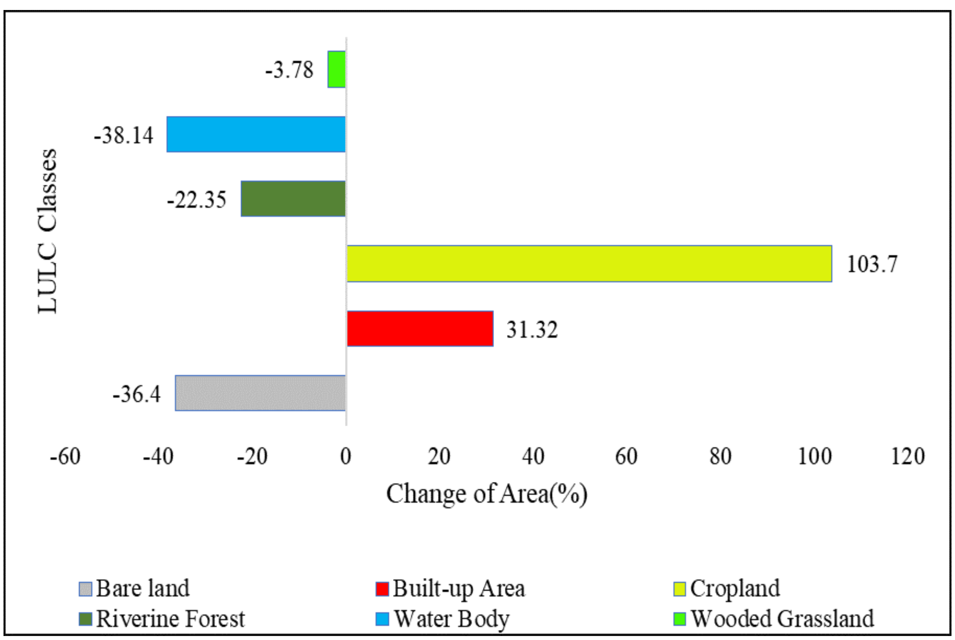

Figure 5.1:Relative change of land use land cover classes from 1985 to 2020

In order to quantify the landscape diversity, we applied Shannon's and Simpson's diversity indices, which are among the most popular and frequently used diversity metrics (Nagendra, 2002). Results indicate spatially varying (Fig. 5.2) and temporally increasing (Fig. 5.3) diversity of the landscape. High SHDI values, which indicate high landscape diversity (Doğan, 2022), were associated with built-up areas and farmlands, varying temporally since large forests and vast agricultural lands have low SHDI values (Chmielewski et al., 2014). The spatial and temporal dynamics of LULC changes due to land cover transformation have resulted in landscape fragmentation and ecosystem deterioration (Mulatu et al., 2024).

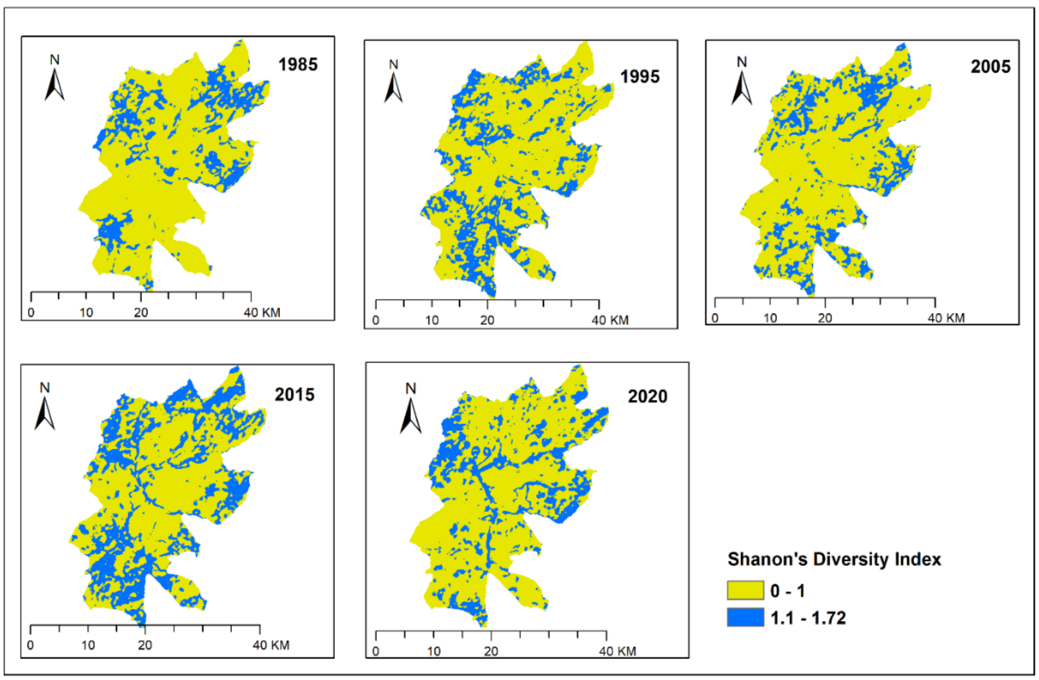

Figure 5.2:Spatial distribution of Shannon Diversity Index Values

The SHDI showed a general increase from 1985 (1.13) to 2020 (1.21). Similarly, the SIDI value also exhibited a slight increase from 0.56 in 1985 to 0.59 in 2020 (Fig. 5.3). These results indicate an overall increase in both SHDI and SIDI, reflecting a shift towards greater diversity and increased fragmentation of land cover categories (Fig. 5.3). Unlike the findings of (Daye & Healey, 2015), where fragmentation decreased from 1995 to 2010, leading to a reduction in SHDI and SIDI values in Gamo highlands, the study area exhibited increased SHDI and SIDI values from 1985 to 2020 due to the alteration of natural and semi-natural forests and wooded grasslands to croplands and settlements, resulting in greater fragmentation (Mulatu et al., 2024). An increased heterogeneity and diversity of the landscape indicated by SHDI from 1985 to 2020 was explained by the breakdown of existing large patches of land covers into smaller, more numerous patches, increasing the number of land cover types. Particularly, conversion of large wooded grasslands to smaller farmlands and settlement areas causes an increase in the diversity of the landscape. Similarly, (Kudas et al., 2024) reported an increase in artificial surfaces in commuting zones around urban areas led to increased LULC class diversity. Furthermore, (Su et al., 2012) also noted that landscape diversity increases as built-up areas develop, resulting in fragmented landscapes and decreased dominance of natural areas. This fragmentation accounts for higher SHDI values, indicating a shift from a single dominant LULC type to a more mixed landscape pattern.

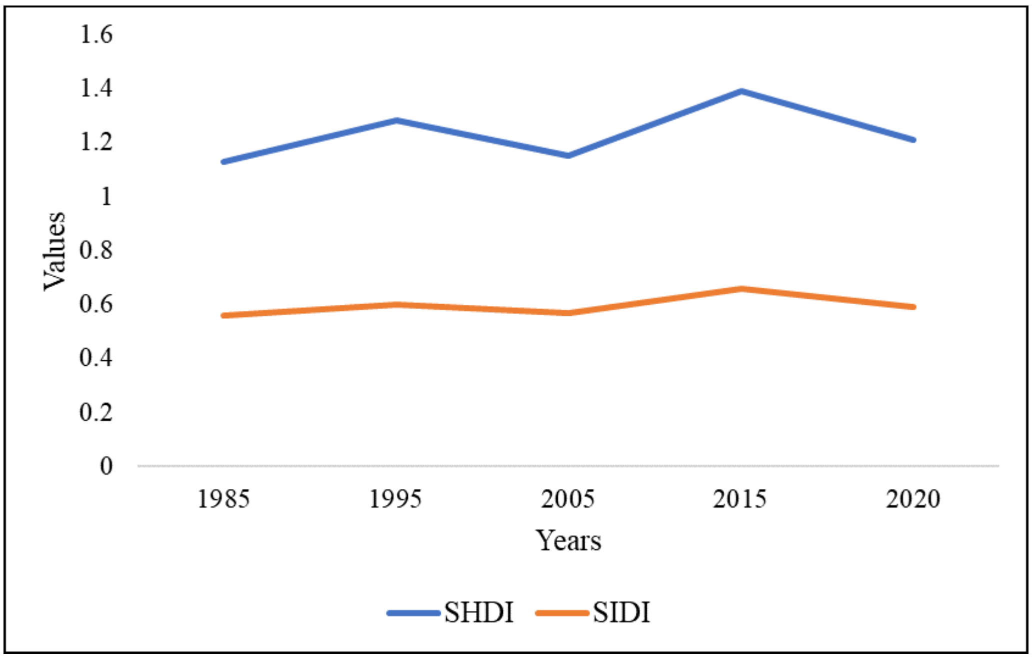

Figure 5.3: Shannon and Simpson Diversity Indices from 1985 to 2020

Shannon's Diversity Index (SHDI); Simpson's Diversity Index (SIDI)

Landscape fragmentation is manifested by a rise in the number of patches, decrease in the mean patch size, and increase in the total amount of edge (Rutledge, 2003).In this study evidence for an increase in landscape fragmentation was obtained from the landscape level analysis, which showed increases in the NP, PD, and ED by 81.24%, 81.19%, and 83%, respectively, from 1985 to 2020 (Table 5.2).Previous studies have also shown an increase in landscape fragmentation, indicated by increased NP, PD, and ED in various regions around the world (Hu et al., 2021; Mulatu et al., 2024; Muleta and Biru, 2019; Su et al., 2012; Tolessa et al., 2016).

Table 5.2:Landscape diversity metrics

Year	NP	PD	LPI	ED
1985	19976	22.06	26.89	84.62
1995	42295	46.70	45.70	140.19
2005	22934	25.32	53.20	87.67
2015	40653	44.89	29.28	148.39
2020	36204	39.97	46.03	154.84
Change 1985-2020(%)	81.24	81.19	71.18	83.00

NP = number of patches, PD = patch density, LPI = largest patch index, ED = edge density

Moreover, at the class level, increases in NP, PD, and ED for all LULC classes indicate fragmentation of the landscape over time (Hu et al., 2021). Among the LULC classes, croplands exhibited the most significant increase in the NP (Appendix F), highlighting greater fragmentation of the landscape due to the conversion of naturally vegetated areas into farmlands. The increase in LPI for built-up areas and croplands suggests that the proportion of the study area covered by large patches of these land use classes has grown (Mulatu et al., 2024). An increase in the LPI for farmlands could be attributed to the establishment of Zage Agroindustry in one of the districts of the study area, which covers significantly larger agricultural land compared to smaller individual farms. Conversely, the decrease in LPI for bare land and riverine forests is attributed to the reduction of these land cover types over the study period (Simeon & Wana, 2024). The increase in LPI at both the landscape level and the class level (wooded grassland) is due to the establishment of the park, which has allowed for the regeneration of grasslands and woodlands within the core protected area. However, in the park's buffer zone and areas outside the park, wooded grasslands are increasingly fragmented due to their conversion into farmlands and settlement areas.

The fragmentation of landscapes has a profound effect on ESs provision, particularly as natural land cover is lost and the ability of smaller fragments to support these services reduced (Mitchell et al., 2015a). Fig. 5.4 illustrates the relationship between key ecosystem services (FP, WS, RM, and CR) and landscape metrics using Spearman correlation coefficients. The results indicate that NP and PD had a weak positive correlation ($r_s = 0.1$) with food production services. SHDI and SIDI also exhibited a weak positive correlation ($r_s = 0.3$), while ED showed a strong positive correlation ($r_s = 0.7$) with food production services. The positive relationship between food production and NP, PD, and ED is due to landscape fragmentation caused by the transformation of natural land covers into farmlands and the subsequent expansion of agricultural areas. Conversely, LPI demonstrated a weak negative correlation ($r_s = -0.3$) with food production service (Fig.5.4). The negative correlation between food production and LPI can be explained by the estimation of food production values from not only farmlands but also other LULC classes, including riverine forests, using the benefit transfer method (Costanza et al., 1997; Simeon & Wana, 2024). The land cover has reduced over time, as indicated by the decreased LPI (Appendix F). For WS, RM, and CR services, NP, PD, and LPI displayed weak to moderate negative correlations (Fig.5.4). This aligns with findings by (Mirghaed & Souri, 2022), who reported an inverse relationship between PD and both habitat quality and carbon storage. Additionally, ED, SHDI, and SIDI exhibited moderate to strong negative correlations with WS, RM, and CR services (Fig.5.4). The degradation of wooded grasslands and riverine forests has reduced the ecosystem services obtained from these land covers in the study area (Simeon & Wana, 2024), as also evidenced by the increased values of NP, PD, ED, SHDI, and SIDI. Further landscape fragmentation significantly reduces ESs (Mirghaed & Souri, 2022). Therefore, controlling landscape fragmentation of different land cover type is important to simultaneously conserve biodiversity and sustain ecosystem services (Mitchell et al., 2015a).

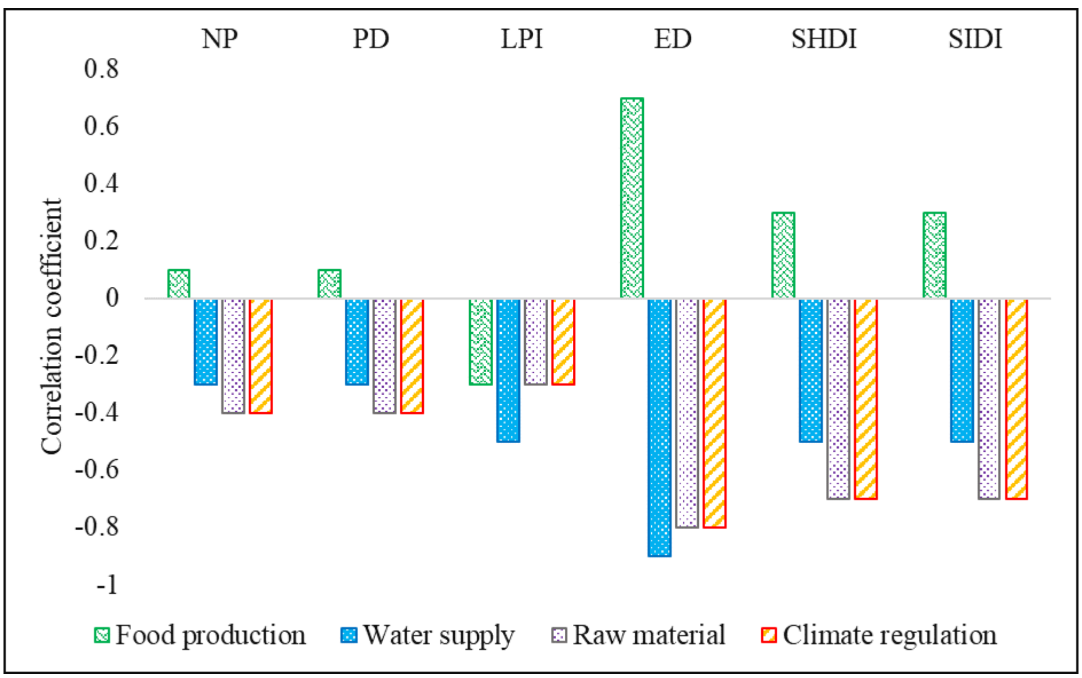

Figure 5.3:Relationship between key ESs and landscape metrics

NP = Number of patches, PD = Patch density, LPI = Largest patch index, ED = Edge density

Spatial and temporal patterns and dynamics of ecosystem services

The results show that the spatial distribution of ecosystem services in the study area is influenced by changes in altitude (Gao et al., 2021) and LULC types, with forested areas showing higher ESVs than settlements and farmlands (Li et al., 2022). Lower values for FP, WS, CR, and RM provisioning services are observed in the low-lying areas and southeastern part of the study area (Fig. 5.5). In contrast, high ESVs are found in high-altitude areas and along the Maze River course in riverine forests. This pattern aligns with the findings of (Gao et al., 2021), who reported that high-altitude areas provide more substantial supporting and regulating services compared to lowlands. Generally, the spatial distribution of ESVs decreases from the north and northwest towards the south and southeastern parts of the study area. This trend is attributed to the relatively higher-altitude areas of semi-arid regions receiving greater rainfall and experiencing lower temperatures (Worku et al., 2022b), along with having better forest coverage (Zeng et al., 2022) than lowlands, thereby offering higher provisioning and regulating services.

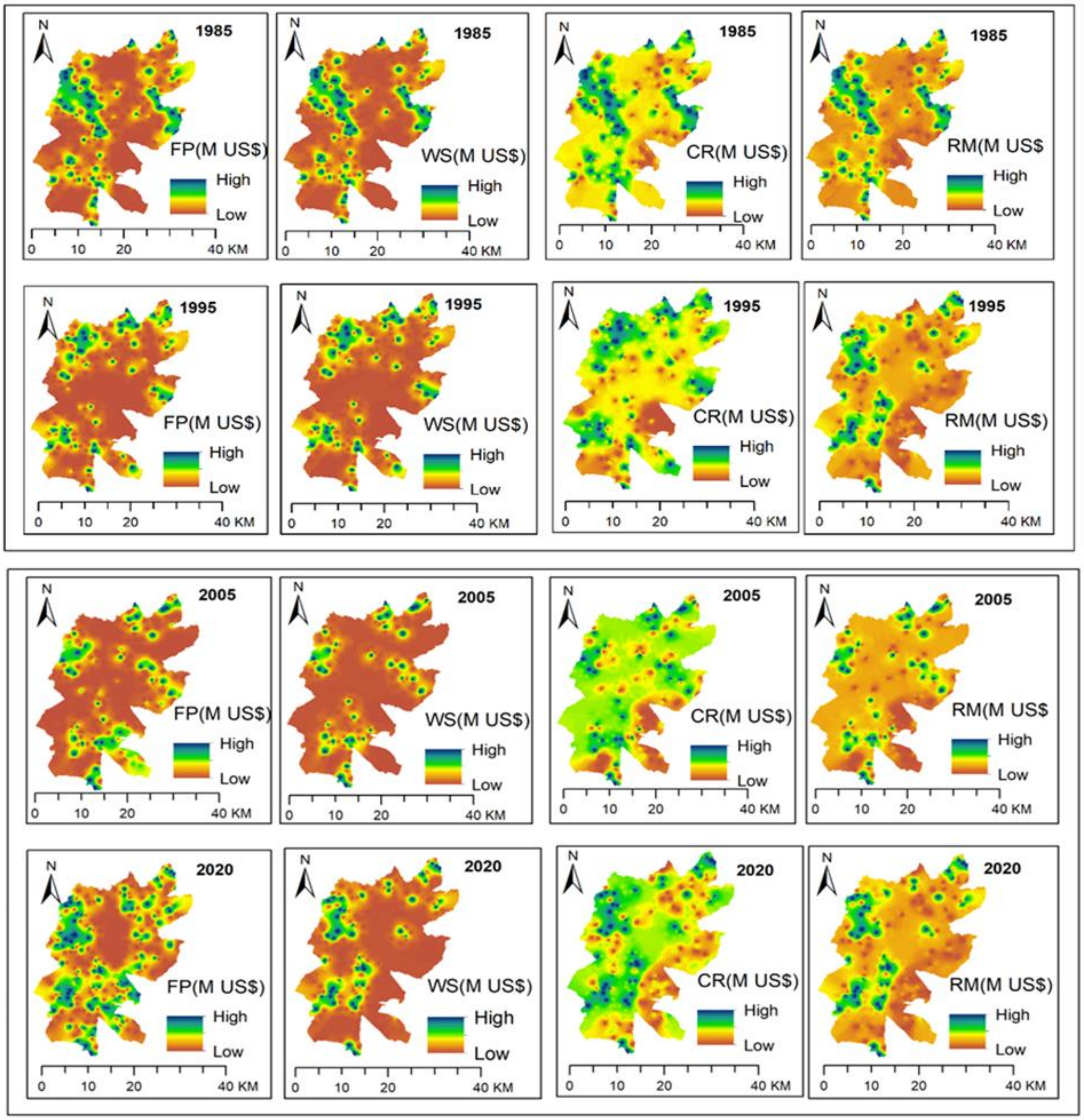

Figure 5.5: Spatial and temporal distribution of ecosystem services in 1985, 1995, 2005 and 2020

FP = Food production, WS= Water supply, CR= Climate regulation, RM= Raw material provision services

Except for FP service, the values of WS, CR, and RM provisioning services have shown a continuous decrease from 1985 to 2020 in the study area (Simeon & Wana, 2024), while FP service has shown an increase, particularly since 2005 (Fig. 5.6). Similarly, a decline in the values of WS, CR, and RM provision, along with an increase in FP, was also reported in the northeastern highlands of Ethiopia (Muche et al., 2023), the central highlands of Ethiopia (Admasu et al., 2023), and the Jibat forest landscape (Muleta et al., 2021). The values of FP exhibited a decreasing trend from 1985 to 2005 due to a reduction in food provisioning from the natural ecosystem, primarily from riverine forests, which contribute the most to ecosystem service values. According to Simeon and Wana (2024), the establishment of the park in 2005 had conservation effects, leading to a decrease in the reduction rate of riverine forests from 17.53% between 1985 and 2005 to 5.84% between 2005 and 2020. In contrast, the expansion rate of croplands increased from 25.45% between 1985 and 2005 to 62.37% between 2005 and 2020, resulting in an overall increase in food production since 2005 by compensating for the decline in food production from other LULC classes. This indicates that the reduction rate of food production services from riverine forests exceeded the increase in food production from croplands from 1985 to 2005, whereas the reverse was true from 2005 to 2020 (Fig. 5.6).

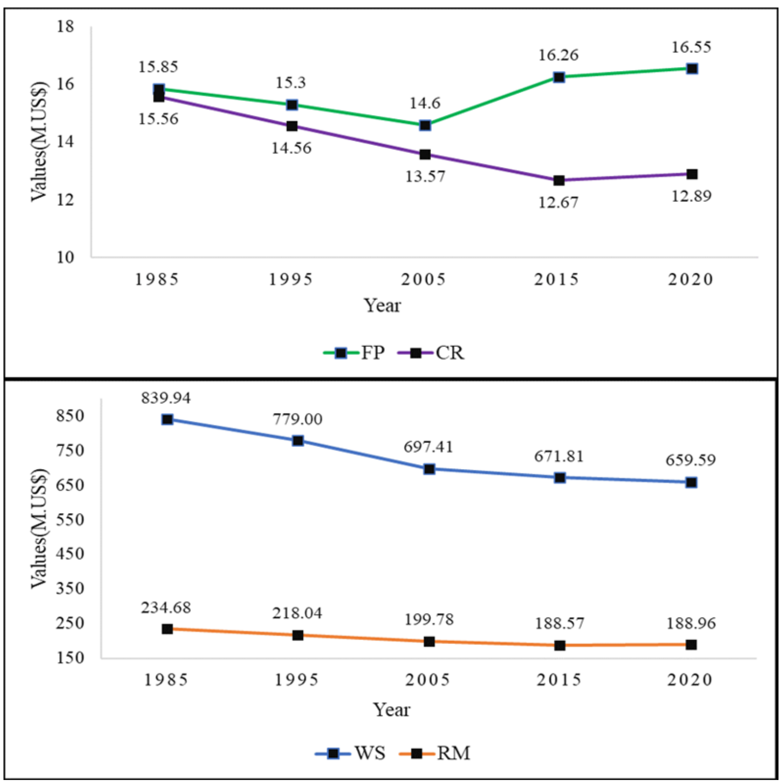

Figure 5.4:Temporal changes in ecosystem services from 1985 to 2020

FP = Food production, WS = Water supply, CR = Climate regulation, RM = Raw material

5.3.2. Synergy and Trade-offs among ecosystem services

Temporal analysis of synergy and trade-offs

The temporal characteristics and changes in the relationships among key ecosystem services were analyzed by applying the Spearman correlation coefficient. Out of six pairs of ecosystem services, statistically significant ($p < 0.05$) positive or synergetic relationships were observed between WS and CR, WS and RM, and CR and RM services. Conversely, the correlation between food production and the remaining services was found to be a statistically non-significant negative or tradeoff relationship. Food production service exhibited a negative moderate correlation (r_s= -.600, -.500, and -.500; Table 5.3; Fig.5.7) with WS, RM, and CR services, respectively, indicating a trade-off relationship. Similar results have been reported a negative or trade-off relationship between FP and other ecosystem services such as water supply, soil conservation, gas regulation, recreation, carbon storage, and habitat quality services (Biratu et al., 2022; Wei et al., 2022). The negative correlation or trade-off relationship between food production and the remaining ecosystem services was primarily attributed to the significant increase in agricultural lands at the expense of other LULC classes (Biratu et al., 2022).

Table 5.3:Temporal tradeoffs and synergies among ecosystem services

		FP	WS	RM	CR
FP	r				
	Sig.				
WS	r	-.600			
	Sig.	.285			
RM	r	-.500	.900*		
	Sig.	.391	.037		
CR	r	-.500	.900*	1.000**	
	Sig.	.391	.037	0.00	

*. Correlation is significant at the 0.05 level (2-tailed).
**. Correlation is significant at the 0.01 level (2-tailed).

FP = Food production, WS = Water supply, CR = Climate regulation, RM = Raw material

A statistically significant (p-value < 0.05) strong positive correlation, indicating a synergetic relationship, was observed between WS and CR, and RM provision and WS services, with similar correlation coefficient value of (r_s = 0.9, Table 5.3; Fig.5.7).Perfect positive relationship was observed between CR and RM provisioning services (Table 5.3; Fig.5.7).Similar findings were reported by (Tan et al., 2024) in southern China, where a statistically significant positive correlation between water yield and carbon storage services was noted. The significant role of naturally vegetated lands in providing climate regulation, water supply, and raw materials is the primary cause of the strong synergy among these services. Therefore, integrating ecosystem restoration with a sustainable agricultural intensification approach can help maintain the balance between agricultural productivity and ecosystem service synergies, while avoiding adverse effects on the natural environment (Biratu et al., 2022).

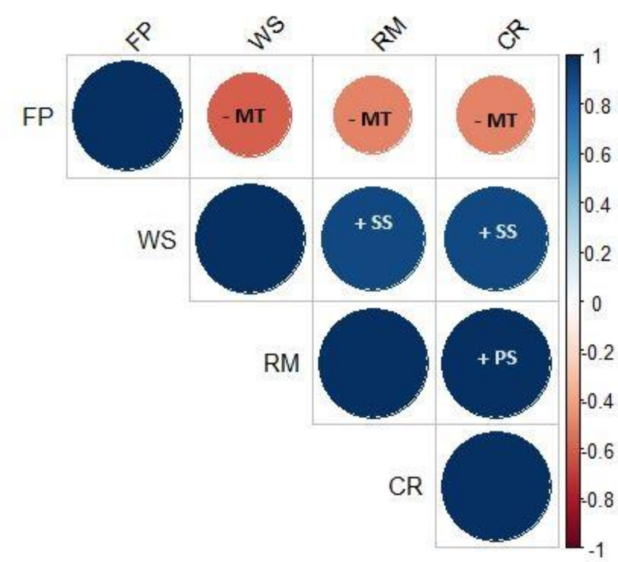

Figure 5.5: Synergy and tradeoff between ecosystem services

FP = Food production, WS = Water supply, RM = Raw material, CR = Climate regulation, -MT = negative moderate tradeoff, +SS = positive strong synergy, +PS = positive perfect synergy

Spatial analysis of synergy and trade-offs

We conducted the global Moran's I statistics (Table 5.4) to test the spatial autocorrelation or aggregation of ecosystem service values. The results indicate that the spatial distribution of key ecosystem services in the study area exhibited strong interactions with neighboring cells, demonstrating characteristics of aggregated distribution (Wang et al., 2023). All global Moran's I values were positive and greater than 0, with p-values less than 0.01, indicating a significant clustering pattern rather than a random or uniform distribution (Tian et al., 2024).

Table 5.4:Global Moran's I statistics of ecosystem services

Ecosystem services	Moran's I	Z- score	P- value
FP	0.991	408.493	0.00
WS	0.956	394.095	0.00
RM	0.952	392.378	0.00
CR	0.962	396.562	0.00

FP = Food production, WS = Water supply, RM = Raw material, CR = Climate regulation

LISA cluster maps of key ecosystem services from 1985 to 2020 indicate that the percentage of synergy relationships of all key ecosystem services is greater than that of the trade-off (Fig. 5.8). For food production and climate regulation 22.59% synergetic and 14.4% tradeoff, food production and water supply 30.8% synergy and 10.09% tradeoff, food production and raw material 23.06% synergy and 15.54% tradeoff, water supply and climate regulation 23.72% synergy and 13.23% tradeoff, water supply and raw material 36.12% synergy and 2.49% tradeoff, and climate regulation and raw material 25.08% synergy and 13.58% tradeoff relationships were observed in the study area (Fig.5.8).This result indicates that the relationships among ecosystem services were dominated by synergies, but trade-offs were also observed among these services. Yuan et al. (2024) also reported that synergies dominate relationships among ecosystem services in the Tibetan Plateau. The relationship between FP and other ecosystem services showed a higher trade-off proportion (Fig.5.8) compared to other ecosystem services, primarily due to the encroachment of agricultural lands over natural ecosystems (Biratu et al., 2022). Generally, high-high clusters, indicating positive synergies (Ji et al., 2021; Li et al., 2022), are mostly observed in the northern and northeastern parts in high-altitude areas. Conversely, the distribution of negative synergies, such as low-low clusters (Ji et al., 2021), increases towards the eastern and southeastern parts of the study area. This is because low-elevation areas are characterized by drought, water shortage, and sparse vegetation, exhibiting low-low agglomeration of synergistic relationships among ecosystem services (Li et al., 2022).

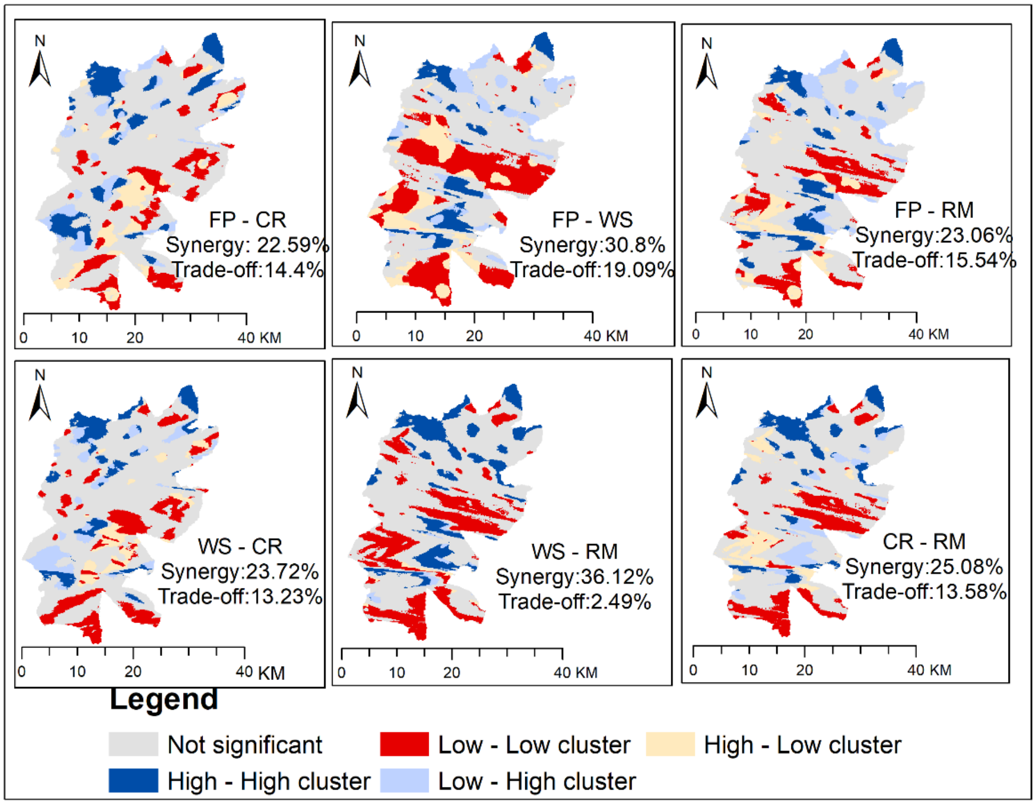

Figure 5.6:LISA cluster map of the ecosystem services from 1985 to 2020

FP: Food Production; WS: Water Supply; CR: Climate Regulation; RM: Raw Material Provision. High–high clusters and low–low clusters indicate synergy relationships, and high–low clusters and low–high clusters indicate trade-off relationships. The numbers indicate synergy and trade-offs as a percentage of the overall study area.

5.3.3. Local community's perceptions of LULC changes and interactions among ecosystem services

Survey results indicated that 63.8% and 65.6% of respondents observed an increase in built-up areas and agricultural lands, respectively (Fig. 5.9). This observation was corroborated by FGDs and interviews, which noted the encroachment of farmlands and built-up areas over naturally vegetated regions. Conversely, 57.5% of respondents reported a decline in wooded grasslands over the past decades. Although 48% of survey participants indicated an increase in riverine forests over time, FGDs and KIIs revealed that the riverine forest coverage has actually been decreasing due to increased sediment deposition and changing climate. An interview with the park staff noted that illegal expansion of built-up areas and farmlands included the park buffer zone in some adjoining districts. Farmers' perceptions of LULC changes align with the remote sensing data and LULC classification results (Fig. 5.1) (Ariti et al., 2015; Kudas et al., 2024), which shows an expansion of built-up areas and agricultural lands while other land uses are declining. This result indicates that a decrease in naturally vegetated lands over time can be explained as a major cause of reduction of ecosystem services obtained from these ecosystems. Consequently, synergetic and tradeoff interactions were observed among the major ecosystem services.

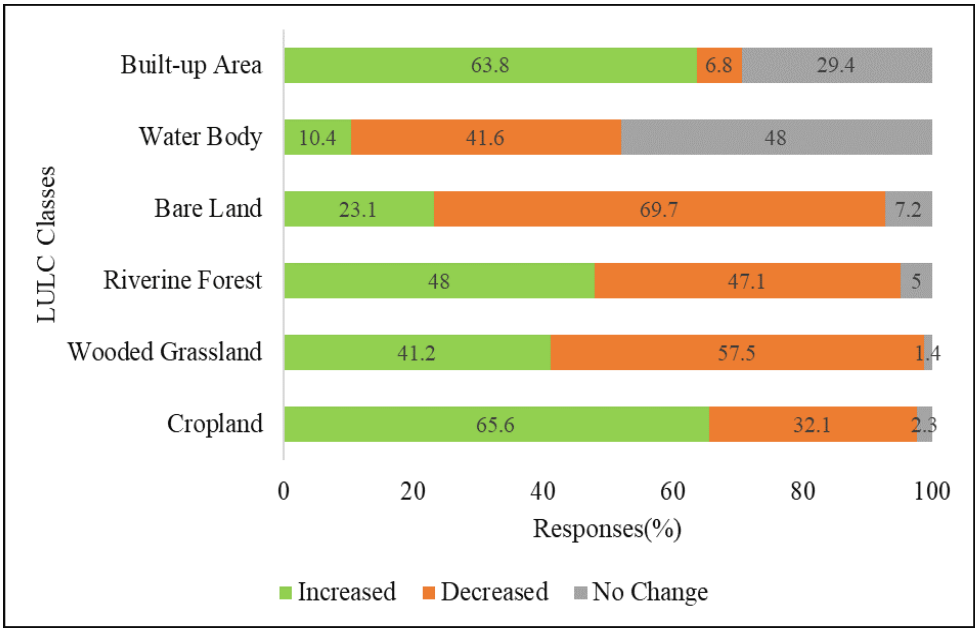

Figure 5.7:Local community perception of LULC changes

A Chi-Square test of independence was performed to examine the association between the distance from the park and the local community's perception of interactions between ecosystem services. The Chi-Square test result ($\chi 2 = 12.029$, $p = 0.020$) shows a statistically significant association between the distance from the park and the local community's perception of the relationship between farmland expansion, and ecosystem services obtained from vegetated areas (Table 5.5). Respondents closer to and farther from the park tended to perceive more tradeoffs, while those at a medium distance from the park were more likely to perceive synergies. The synergistic response to the expansion of agricultural lands at the cost of other natural land cover classes can be explained by a fear of accountability due to restrictions on illegal farmland expansion, vegetation clearance for firewood, construction, and grass collection in the park region and its buffer zone. However, both the local community's perception (Fig. 5.9) and the LULC classification (Fig. 5.1) demonstrate an increase in agricultural land and built-up areas at the expense of the other LULC classes (Simeon & Wana, 2024; Zewude et al., 2022).On the other hand, no statistically significant association was observed between the distance from the park and the local community's perception of raw material services (intensive grazing and grass cutting for fodder and thatching roofs) and vegetation coverage and the ecosystem services they provide ($\chi2$= 5.628, p = 0.216). The results indicate that most of the respondents (58.8%) living close to, at a medium distance from, and far from the park were more likely to perceive a trade-off relationship between intensive grazing, grass cutting, and vegetation coverage. This is due to the local community's heavy dependence on the park for grazing, grass cutting, and firewood collection (Zewude et al., 2022), which exerts on vegetation coverage.

With the Chi-Square test result ($\chi2$= 12.911, p = 0.013), there is a statistically significant association between the distance from the park and the local community's perception of interactions between firewood and charcoal collection and vegetation coverage, as well as the benefits obtained from vegetated areas. Respondents living close to and at a medium distance from the park are more likely to perceive a synergistic relationship between tree cutting for firewood and charcoal and vegetation coverage, compared to those living farther away. This synergistic response among people living close to and at a medium distance from the park is likely influenced by a fear of accountability due to restrictions on the illegal clearance of vegetation for firewood, charcoal, and construction. Additionally, the Chi-Square test result ($\chi2$= 10.301, p = 0.037) indicates a statistically significant association between the distance from the park and the local community's perception of the relationship between water supply and vegetation coverage in the study area. However, despite this statistical significance, the analysis (Table 5.5) does not reveal a meaningful variation in the community's perceptions with distance from the park. This suggests that while the association is statistically significant, the practical implications or the nature of the variation with distance are not substantial. Given the crucial role of terrestrial vegetation in controlling the water balance (Sun et al., 2017), most respondents (59.7%) living at various distances from the park perceive a synergistic relationship between water supply for domestic use and vegetation coverage (Table 5.5). This finding aligns with the LULC change matrix (Fig. 5.1), which shows declines in water bodies, riverine forests, and wooded grasslands from 1985 to 2020. Consequently, a negative synergistic relationship is observed between vegetation coverage and water supply in the study area. Land degradation, including vegetation degradation, leads to increased frequency and severity of droughts and scarcity of water for domestic use and small-scale irrigation (UNCCD & FAO,2020). Therefore, implementing catchment and ecosystem restoration practices is essential for enhancing freshwater availability (Meaza et al., 2022).

Table 5.5:Contingency table of perception of ecosystem services by distance from the park

Ecosystem services	**Relationships**	**Distance from the park**			**X^2 test**	**P-value**
		Close	Medium	Far		
Farmland expansion Vs vegetation cover	Synergy	55(24.9)	53(24)	1(0.5)	12.029	.020
	Not sure	7(3.2)	4(1.8)	0(0.0)		
	Tradeoff	59(26.7)	33(14.9)	9(4.1)		
Grazing and grass cutting Vs vegetation cover	Synergy	41(18.6)	42(19)	2(0.9)	5.628	.216
	Not sure	4(1.8)	2(0.9)	0(0.0)		
	Tradeoff	76(34.4)	46(20.8)	8(3.6)		
Firewood and charcoal collection Vs vegetation cover	Synergy	67(30.3)	59(26.7)	2(0.9)	12.911	.013
	Not sure	1(0.5)	1(0.5)	1(0.5)		
	Tradeoff	53(24)	30(13.6)	7(3.2)		
Vegetation cover Vs water supply	Synergy	77(34.8)	48(21.7)	7(3.2)	10.301	.037
	Not sure	17(7.7)	6(2.7)	0(0.0)		
	Tradeoff	27(12.2)	36(16.3)	3(1.4)		

Figures in the parenthesis indicate percentages

5.4. Conclusion

In this study we aim at investigating the synergies and trade-offs between key ecosystem services in the study area, as well as the correlations between landscape metrics and these key ecosystem services. In addition, we explore the local people's perceptions on the interaction of the key ESs. Our study indicates the following 4 patterns: 1) Spatially, the relationships among ecosystem services were predominantly synergistic, although a higher proportion of trade-offs were observed between FP and other ecosystem services. Positive synergies are generally observed in higher elevation areas as compared to the low-lying areas. 2) Temporally, both synergies and trade-offs were observed between key ecosystem services during the study period (1985-2020). In this regard, FP has shown trade-off relationship with WS, RM, and CR services, while others have shown a strong synergetic relationship. 3) The landscape structural attributes (SHDI, SIDI, NP, PD, and ED) have shown spatial variability and an increase in diversity over time. The landscape structural variability and diversity are the results of human disturbances such as agriculture and built-up areas expansion with a consequent decline in ecosystem services. Finally, (4) The proximity of local communities to the park influences their perceptions of whether a given ecosystem service is synergistically related to or in trade-off with other ecosystem services.

Understanding the landscape structural changes and trade-offs among ecosystem services are essential for managing multiple ecosystem services and promoting positive interactions while avoiding negative ones among ecosystem services. The findings of this study underscore the need for integrated landscape and ecosystem management strategies that reduce landscape fragmentation, promote synergy among ecosystem services, and consider local community participation to guide sustainable protected area management and ecosystem conservation efforts. Proactive measures, such as ecosystem protection and restoration, are essential to balance trade-offs and ensure the continued provision of vital ecosystem services in the study area. Nevertheless, in this study, we applied only four ecosystem services for analysis of temporal and spatial interactions. Hence, future studies should consider additional provisioning, regulating, and cultural services for full representation of the region's ecosystem services status in the synergy and trade-off analysis.

6. Prediction of ecosystem service values based on land use land cover and climate change scenarios in Maze national park and its environs, southwestern Ethiopia

Abstract

This study aims to predict ecosystem service values under land use land cover (LULC) and climate change scenarios in Maze National Park and its environs, southwestern Ethiopia. The multi-layer perceptron neural network method incorporated under IDRISI Selva's Land change modeler was employed for LULC change prediction, forming the basis for ecosystem services prediction in 2050 under the business-as-usual (BAU) and governance (GOV) scenarios. Climate change predictions were based on General Circulation Models from the Coupled Model Inter-comparison Project Phase Six under Shared Socioeconomic Pathways (SSP2-4.5 and SSP5-8.5) and the Spearman correlation was employed to analyze predicted climate change impacts on ecosystem services. The results indicate that, under the BAU scenario, food production is projected to increase slightly by 2.3%, while water supply (-7.61%), raw material (-6.72%), and climate regulation (-5.57%) are expected to decline due to expansion of built-up areas and croplands. Conversely, under the GOV scenario, food production (10.94%), water supply (22.26%), raw material (19.93%), and climate regulation (17.07%) services are projected to increase substantially by 2050, driven largely by an expected expansion in vegetated areas. Additionally, the spatial distribution of predicted ecosystem services reveals both changes in values and spatial shifts compared to 2020.The Spearman correlation analysis revealed a statistically significant negative relationship between maximum and minimum temperatures and key ecosystem services under SSP2-4.5 and SSP5-8.5 scenarios. In contrast, precipitation showed a significant positive correlation with key ecosystem services. Therefore, the predicted decline of ecosystem services under the BAU scenario along with the significant negative correlation with temperatures provide key insights for decision-makers. These findings can guide development of effective land use management and climate change mitigation and adaptation strategies to reduce the anticipated impacts of LULC and climate changes on ecosystem services.

Key words: *Global climate circulation models, IDRISI SELVA, Land change modeler, land cover change scenarios, Spearman correlation*

6.1. Introduction

Land use and land cover (LULC) and climate changes are the two biggest environmental problems the world is facing today (He et al., 2019). These changes impact the ecosystems and degrade the benefits people derive from the environment (Tang et al., 2018). Converting grasslands, wetlands, forests, and natural ecosystems to croplands and settlement areas greatly affects biodiversity and ecosystem services (Polasky et al., 2011). These changes disrupt the hydrological cycle and lead to biodiversity loss, soil degradation, and reduction of ecosystem services. Ultimately these problems affect environmental sustainability and human well-being (Arfasa et al., 2023). Climate change and variability also affect the quality and quantity of ecosystem services directly and indirectly (Bakure et al., 2022) by increasing the intensity and frequency of floods, wildfires, crop failures, disease, and insect outbreaks (Millennium Ecosystem Assessment (MEA), 2005; Scholes, 2016; U.S. Geological Survey (USGS), 2007). Climate change and variability are changing the timing, provision, and spatial configuration of ecosystem functions and services, which are being altered through ongoing warming and an increase in extreme weather events (Nelson et al., 2013).

LULC prediction based on historical and current trends is essential for understanding future land use development patterns and the dynamics of associated ecosystem services (Chisanga et al., 2024). The IDRISI Selva software (version 17.0)'s Land Change Modeler (LCM) can depict the dynamics of LULC change and spatial heterogeneity. It also allows exploration of future scenarios based on varying input parameters and assumptions (Mathewos et al., 2024). According to Abbas et al. (2023), the LCM module's multi-layer perceptron (MLP) neural network has the capability to generalize transition potentials in LULC change simulations. The MLP-MC model has superior predictive performance for scenario-based LULC change predictions compared to that of the CA-Markov Chain model (Hamad et al., 2018), and it is also important for understanding spatiotemporal dynamics and predicting future landscape scenarios (Mishra et al., 2018).

Future climate changes will impact ecological systems, changing their function and the ability of managed and natural systems to deliver ecosystem services (Lawler et al., 2011). Five Shared Socioeconomic Pathways (SSPs) based on future greenhouse gas concentrations and socioeconomic challenges are presented by the latest climate model, CMIP6 (Abbas et al., 2024). Many recent climate change studies around the world have used Global Circulation Models (GCM) derived from CMIP6 (Abbas et al., 2024; Anil et al., 2024; Semenov et al., 2024).

In Ethiopia there is pervasive LULC change, where rural lands are dominated by agriculture and settlements (Tolessa et al., 2017). Similar to other African nations, Ethiopia is extremely susceptible to climate change and variability impacts due to its limited capacity to adapt (National Ecosystem Assessment (NEA), 2022). Maze National Park (MzNP) and the surrounding areas provide ecosystem goods like water, food, pasture, fuelwood, thatching grass, and building materials, as well as ecosystem services, including climate regulation, clean water, and cultural and environmental benefits (Simeon et al., 2024). But these important ecosystem goods and services of the study area are declining due to LULC changes (Simeon & Wana, 2024) and climate variability induced challenges, including crop pests, recurring droughts, and frequent forest and bush fires (Tekalign & Bekele, 2011).

Several studies in Ethiopia examined on how LULC change affects ecosystem services; however, most of these studies focused on historical LULC changes (Kindu et al., 2016; Muleta et al., 2021; Negussie, 2019; Shiferaw et al., 2019). Recently, a few studies have evaluated both short and long-term scenarios of future land cover changes in different regions of the country (Belay et al., 2024; Gashaw et al., 2017; Kindu et al., 2018; Leta et al., 2021). However, there are still dearth of studies that evaluate the predicted effect of LULC change on ecosystem services in Ethiopia, with only a few examples from the central and southern regions (Biratu et al., 2022; Duguma et al., 2024). There are also some studies in Ethiopia which examined how climate change has affected ecosystem services in the past and at present (Simeon et al., 2024; Bakure et al., 2022), but little is known about its future impact on these services. Therefore, understanding the impacts of future LULC and climatic changes on ecosystem services is very important to provide scientific insights to policy makers on land use and ecosystem management strategies to cope with the future environmental changes (Wang et al., 2022). Besides, it also facilitates the development of climate change adaptation and mitigation measures that help sustainability of ecosystem services. This research is, thus, aimed at predicting the future effects of LULC and climate changes on ecosystem services in MzNP and the adjacent areas in the southwestern part of Ethiopia.

6.2. Materials and methods

6.2.1. Data sources and methods

Land use land cover and ecosystem service values

The LULC data of 1985, 1995, and 2020 was taken from previous studies (Simeon et al., 2024; Simeon & Wana, 2024). These studies offer detailed discussion of the data types used, classification methods, and accuracy assessment and ensure that datasets could be used to compare changes in land cover over time. Additionally, these datasets help to create simulated maps used in model validation as well as to predict future land cover changes. In this study the 1995 and 2020 LULC maps were reclassified into six categories for predicting future land cover changes. Burned areas in these maps were reclassified as wooded grasslands, as these areas are temporary and tend to be quickly replaced by newly regenerated grasses and woody vegetation within a few weeks or months.

Table 6.1:Description of data types

Dataset	Description	Sources
LULC maps	LULC map of 1985, 1995 and 2020	(Simeon et al., 2024; Simeon & Wana, 2024)
Road shp.	Main roads in the study area	Ethio-GIS
Rivers shp.	Rivers in the study area	Ethio-GIS
Elevation	Derived from DEM data with a 30-meter resolution from the Shuttle Radar Topography Mission (SRTM)	https://earthexplorer.usgs.gov/
Slope	Derived from DEM data with a 30-meter resolution from the Shuttle Radar Topography Mission (SRTM)	https://earthexplorer.usgs.gov/
Historical and Predicted climate data	CMIP6 GCM climate models	https://www.worldclim.org/

LULC change prediction

To evaluate the possible impacts of future LULC changes on ecosystem services, two scenarios, the BAU (business-as-usual) and the GOV (governance) scenarios, were developed. The BAU as a reference scenario assumes a continuation of the historical socioeconomic development trends. According to the GOV scenario, environmentally friendly and regulated LULC change is planned in the study area (Ruben et al., 2020), considering the Green Legacy Initiative (GLI) program of Ethiopia launched in 2019 by the government (Belay et al., 2024) with the goal of conserving soil and water resources and planting seedlings to increase forest cover (Kassa et al., 2022). Five LULC change drivers such as elevation, slope, distance to roads, distance to rivers, and distance to settlements were selected based on data availability for scenario-based analysis. Elevation and slope maps were derived from 30meter resolution DEM data from the Shuttle Radar Topography Mission (SRTM). Proximity related variables (distance to rivers, to roads and to settlements) were computed in ArcGIS using the Euclidean distance method. In the BAU scenario, distance to rivers, roads, and settlement areas were considered as dynamic variables, whereas elevation and slope as static variables. Proximity related variables were excluded in the GOV scenario because of their low contribution for encroachment of croplands and built-up areas due to controlled land cover change and tree planting (Biratu et al., 2022). Topographic factors, including elevation and slope were added as static variables.

The LULC change prediction was conducted using the LCM in IDRISI Selva software, version 17.0. The tool captures the complex and varied nature of landscape changes over time and allows future scenario exploration under various assumptions and input parameters, as well as providing tools for calibration and validation (Mathewos et al., 2024). The LCM module increases its predicting power by integrating advanced techniques such as logistic regression, the MLP neural network and Similarity-Weighted Instance-based Machine Learning (SimWeight). The MLP is a useful approach for generalizing transition potentials in LULC change simulations (Abbas et al., 2023). The MLP-MC model has shown better results in scenario-based projections than the CA-Markov Chain model (Hamad et al., 2018), and is crucial for better understanding of spatiotemporal dynamics as well as prediction of future landscape scenario (Mishra et al., 2018).

The projected and actual LULC maps of 2020 were compared to assess how well the model predicts future LULC changes. The actual map of 2020 was used as a reference map while a simulated map of 2020 was used as a comparison. Accuracy was measured using commonly used kappa coefficients reported in previous studies (Ait El Haj et al., 2023; Belay et al., 2024; Hamad et al., 2018) such as kappa for no information (K_{no}), kappa for location ($K_{location}$), and kappa for standard ($K_{standard}$), were calculated using the “VALIDATE” module in IDRISI Selva. There is no agreement if a kappa coefficient is less than 0, slight agreement if it is between 0 and 0.2, fair agreement between 0.2 and 0.41, moderate agreement between 0.41 and 0.60, substantial agreement between 0.60 and 0.80, and perfect agreement between 0.81 and 1.0 (Belay et al., 2024; Congalton, 2001; Viera & Garrett,2005).

Predicting ecosystem services based on LULC changes

The key ecosystem services assessed in this study (food production, water supply, raw material provision, and climate regulating services) were chosen in consultation with agricultural extension agents, local people, and park staff. Land cover change and climatic variability have greatly affected these services over the past thirty years in the study area (Simeon et al., 2024; Simeon & Wana, 2024).

The benefit transfer approach, which has been widely employed to value environmental resources in several research (Costanza et al., 1997; Kindu et al., 2016; Li et al., 2007), was used to estimate the predicted values of ecosystem services. Value coefficients from the Ecosystem Service Valuation Database (ESVD) were utilized to estimate changes in ecosystem service values under the BAU and GOV scenarios (de Groot et al., 2020). To analyze spatial distribution and variation of future ecosystem services, prediction maps of food production, water supply, raw materials, and climate regulation services were developed by generating random points from the 2050's BAU land cover map and extracting key ecosystem service values from each land cover class, employing the Inverse Distance Weighted (IDW) interpolation technique to create a continuous surface in ArcGIS software.

Future climate change impacts on key ecosystem services

Two GCMs from CMIP6 (MPI-ESM1-2-LR for maximum temperature and INM-CM5-0 for minimum temperature and precipitation) were used to obtain future climate data. These models were chosen based on their relatively better performance in previous climate modeling studies within the country and the study region (Enyew et al., 2024; Feyissa et al., 2023; Gashaw et al., 2024; Gebisa et al., 2023). Future temperature and precipitation data under SSP245 and SSP585 scenarios were obtained from the WorldClim dataset (https://www.worldclim.org/), where the data had been downscaled and bias-corrected using WorldClim v2.1 as the baseline climate. The spatial resolution of the data is 30 seconds (approximately 1 km by 1 km), and no further downscaling was applied due to its fine resolution.

The study analyzed maximum temperature, minimum temperature, and precipitation data from 2041 to 2060 under SSP2-4.5 and SSP5-8.5 scenarios. SSP2-4.5 represents a moderate emission scenario with a radiative forcing of 4.5 W/m², while SSP5-8.5 represents the highest emission scenario with a radiative forcing of 8.5 W/m² (Chen et al., 2024). To compare the temporal changes in predicted temperature and precipitation with historical data, historical climate data from 1970 to 2000 were obtained from the same source, WorldClim (https://www.worldclim.org/). The data included downscaled maximum temperature, minimum temperature, and precipitation at a 30-seconds spatial resolution.

The Spearman rank correlation was employed to examine the relationship between future (2041 to 2060) maximum temperature, minimum temperature, and precipitation and predicted food production, water supply, raw material, and climate regulation services under the SSP2-4.5 and SSP5-8.5 scenarios. This method was chosen for its low sensitivity to outliers and data distribution (Zar, 2005). The overall workflow of the study is presented in Fig.6.1.

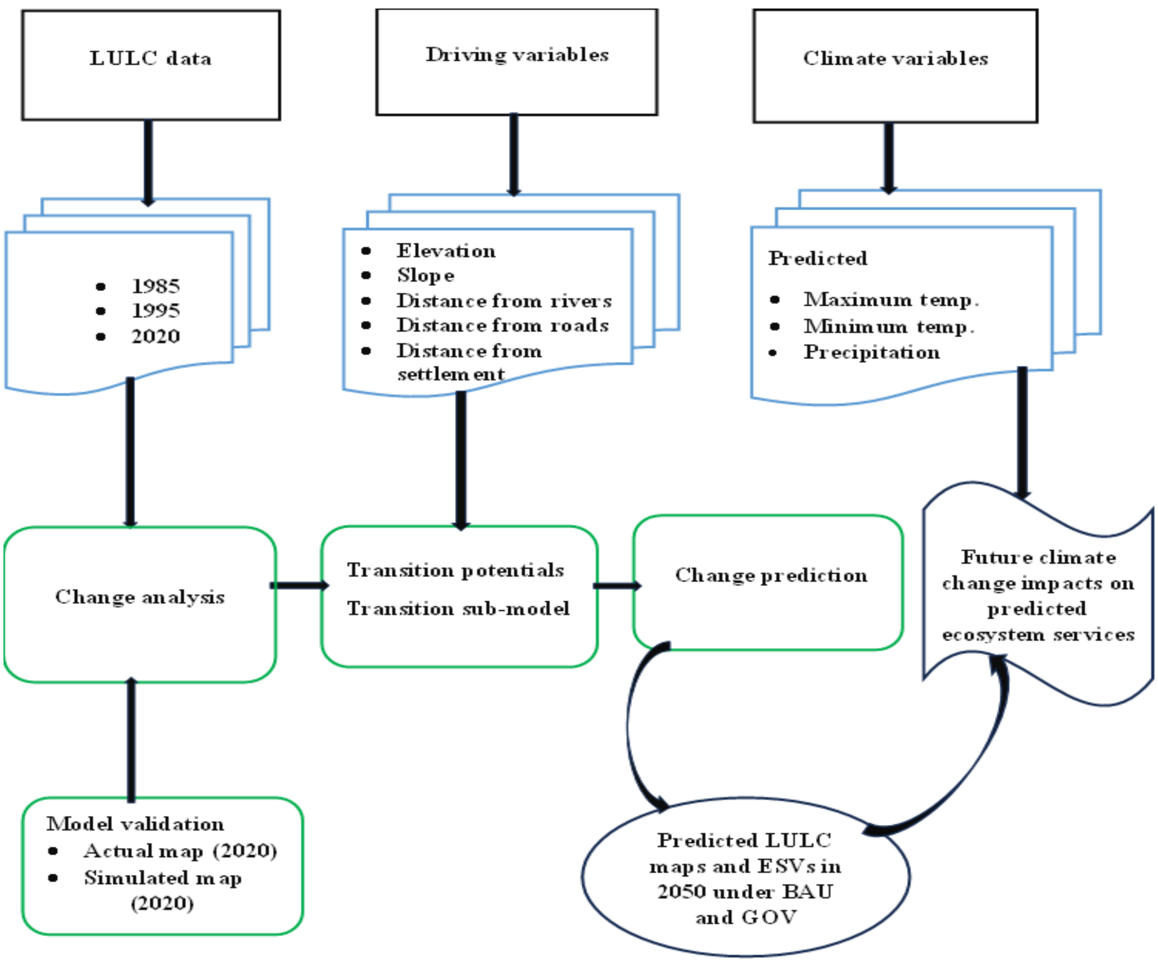

Figure 6.1:Work flow of the study

6.3. Results and discussions

6.3.1. Land cover change

The LULC maps utilized for predicting future land cover changes were derived from previous studies (Simeon et al., 2024; Simeon & Wana, 2024). These studies identified an increase in built-up areas and croplands from 1985 to 2020, accompanied by a declining trend in wooded grasslands, water bodies, and riverine forests (Table 6.2). Simeon and Wana reported that LULC changes primarily attributed to anthropogenic activities, such as the clearance of vegetation for the expansion of built-up areas and croplands. A comprehensive discussion on the conversion of land cover classes and the methodologies employed is provided in (Simeon & Wana, 2024).

Table 6.2: Areas of LULC classes for 1985,1995 and 2020

LULC Classes	**Area(ha)**		
	1985	**1995**	**2020**
Bare Land	7774	6915.96	4945
Built-up Area	1360	1728.36	1827
Cropland	7079	6890.22	14420
Riverine Forest	16914	15634.17	13133
Water Body	902	1038.6	558
Wooded Grassland	56537	53956.89	54398
Burned Area	-	4405.41	1285

The reclassified LULC map (Fig.6.2) reflects similar patterns of LULC changes as summarized in Table 6. 2. These changes include the expansion of built-up areas and croplands, alongside the reduction of riverine forests, water bodies, and wooded grasslands between 1985 and 2020. Notably, the reduction in wooded grasslands appears as a slight area change in the reclassified map during this period.

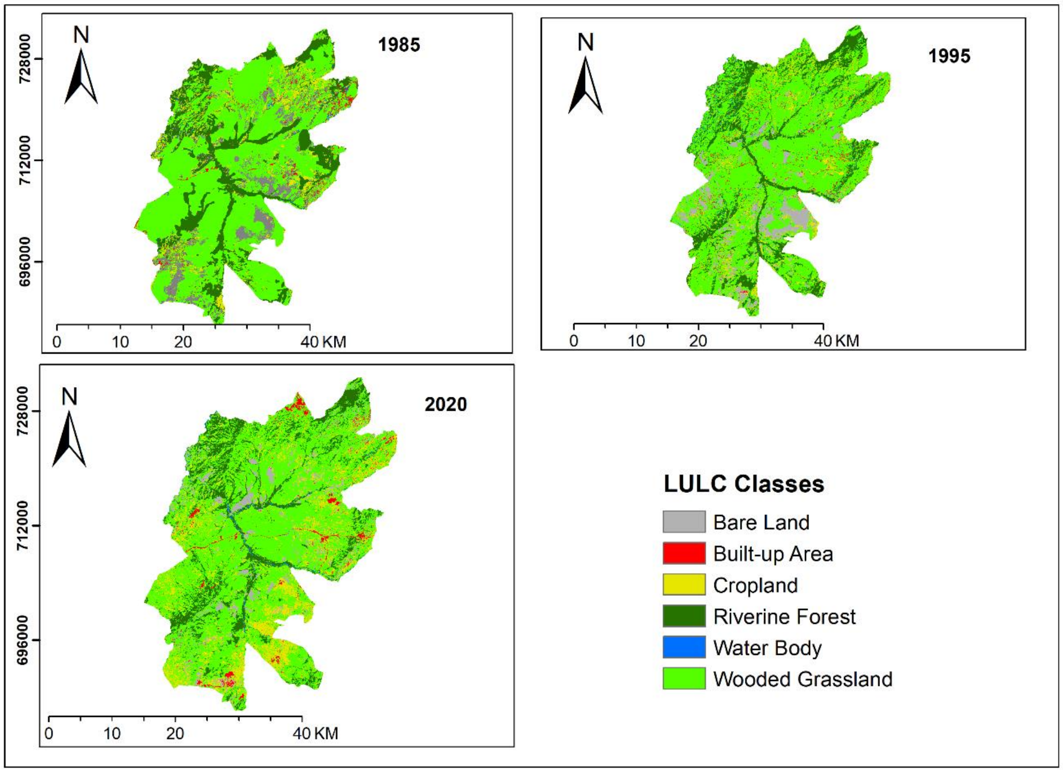

Figure 6.2:Land use land cover maps of the study area (1985,1995,2020)

The net change between 1985 and 2020 land cover classes (Fig. 6.3) indicates that cropland and built-up areas increased by 7,349 ha and 473 ha, respectively, showing a positive change in the study periods. In contrast, other land cover classes such as water bodies, riverine forests, and wooded grasslands experienced a negative change, -332 ha, -3,806 ha, and -861 ha, respectively. Bare lands also showed a decreasing trend, with a reduction (-2,823 ha) during this period (Fig.6.3). As noted by Simeon & Wana (2024), the establishment of MzNP in 2005 contributed to the decline of bare lands within the park boundaries. This was achieved by restricting human access and cattle grazing, which facilitated the regeneration of grasses and trees.

In addition, the gains and losses graph (Fig. 6.4) demonstrates that gains (green color) exceed losses (purple color) for built-up areas and croplands. In contrast, for riverine forests, water bodies, wooded grasslands, and bare lands, losses outweigh gains during the period from 1985 to 2020. This trend highlights the expansion of built-up areas and croplands at the cost of other land cover classes. Similar results have been reported in the study area (Simeon & Wana, 2024; Zewude et al., 2022) and other regions of the country (Negussie, 2019; Shiferaw et al., 2019).

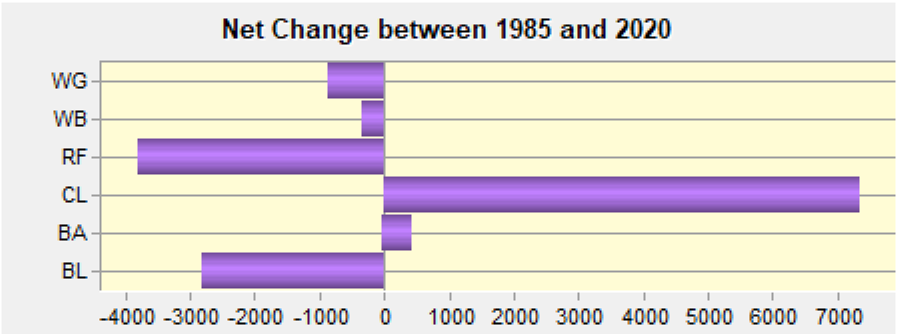

Figure 6.3:Net changes between LULC classes (1985 to 2020)

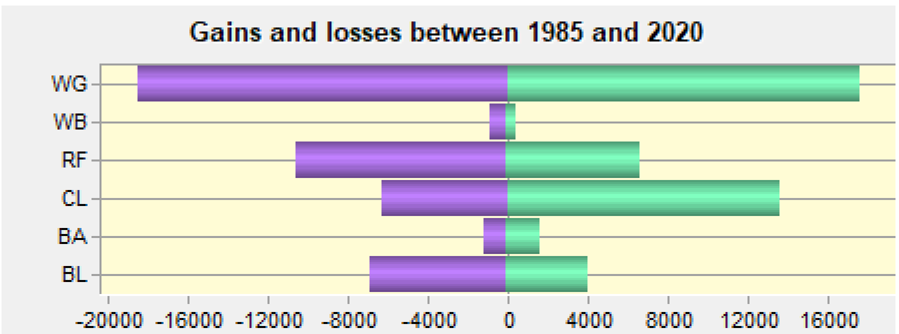

Figure 6.4:Gains and losses between LULC classes (1985 to 2020)

6.3.2. LULC change driving Variables

In this study, topographic factors such as elevation and slope, as well as proximity related factors including distance to roads, distance to rivers, and distance to settlement areas, were employed as driving variables for LULC change modeling (Fig. 6.5). Slope and elevation were included as driving variables in the model because they influence the distribution and conversion of LULC classes, such as settlements, farmlands, forests, and grazing lands (Birhanu et al., 2019). Proximity to rivers, roads, and settlement areas facilitates access to resources (Leta et al., 2021), making areas closer to these features more susceptible to land cover changes compared to those farther away.

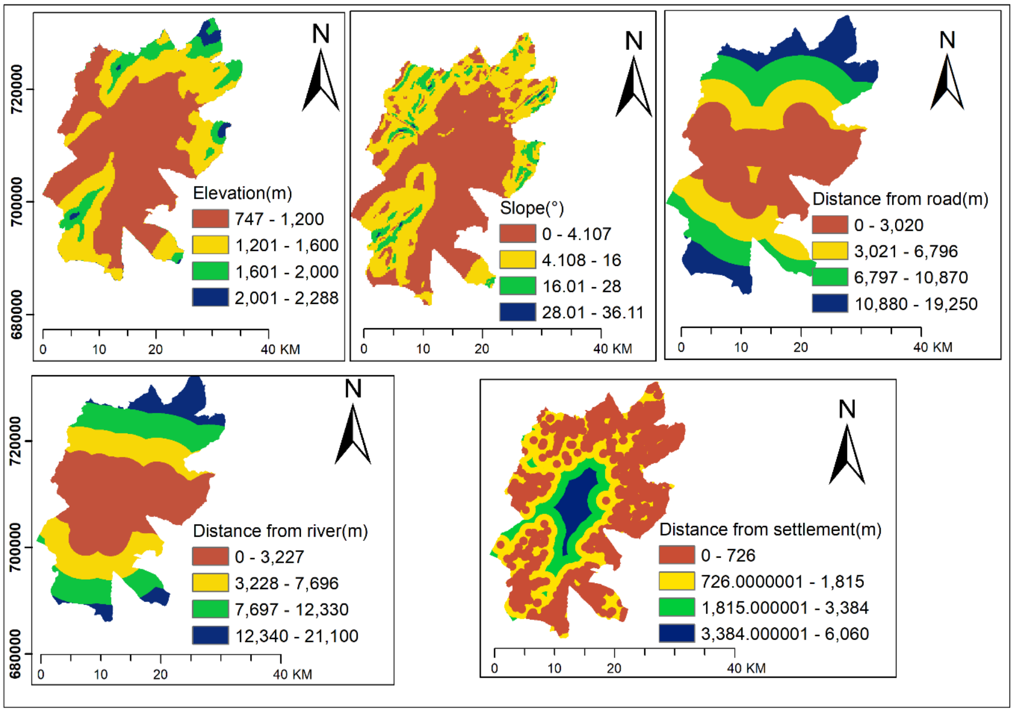

Figure 6.5:LULC change driving variables

The capability of the driving variables to explain LULC changes was assessed using Cramér's V and p-values before incorporating them into the model. Variables with higher Cramér's V values are considered the most explanatory for LULC changes. However, Cramér's V does not provide definitive proof that a specific variable directly explains land use change; rather, it serves as an intuitive tool to assess the relative significance of variables in influencing such changes (Leta et al., 2021). A low p-value indicates that the corresponding Cramér's V value should not be rejected, whereas a high p-value suggests the opposite, confirming that the test is not statistically significant (Belay et al., 2024). In this study, the low p-values confirm that all the variables used are significant in explaining LULC changes in the study area. Among these, based on Cramér's V values, topographic factors have lower impact on LULC change compared to proximity related variables (Table 6.3).

Table 6.3:Cramer's test result of variables

Variables	**Cramer's V**	**P Value**
Elevation	0.1160	0.0000
Slope	0.1094	0.0000
Distance from settlement	0.1198	0.0000
Distance from rivers	0.1250	0.0000
Distance from road	0.1245	0.0000

6.3.3. Model validation

In this study, the actual (reference) and predicted LULC maps of 2020 were compared in order to validate the model. The Kappa indicator values, ranging from 0.6 to 0.8, indicate substantial agreement between the predicted and reference maps (Table 6.4), suggesting that the model performs well in predicting future LULC changes (Leta et al., 2021; Viera & Garrett, 2005). Furthermore, Fig. 6.6 illustrates the high similarity between the simulated and actual LULC maps of 2020, despite a slight overestimation of bare lands.

Table 6.4:Kappa values of model

K Indicators	Values
^{K}no	0.72
^{K}location	0.65
^{K}locationStrata	0.65
^{K}standard	0.64

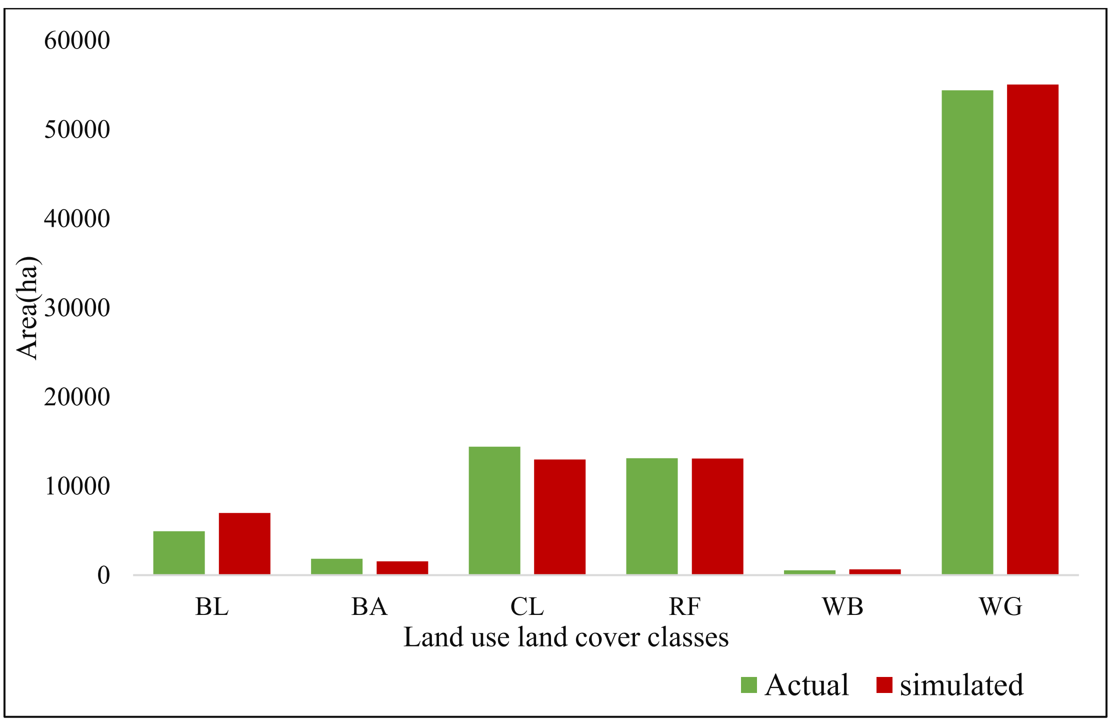

Figure 6.6:The comparison between simulated and actual maps of 2020

6.3.4. Predicted land cover changes under BAU and GOV scenario

LULC change prediction was conducted using the CA–Markov model within the LCM module of IDRISI Selva version 17.0. The predicted LULC maps for the BAU and GOV scenarios include six land cover classes: bare land, built-up area, cropland, riverine forest, and wooded grassland, consistent with the 2020 baseline classification (Fig.6.7; Table 6.5). Both scenarios forecast significant land cover changes by 2050 compared to the baseline year, highlighting substantial shifts in the spatial distribution of land cover classes. These findings align with previous land cover modeling studies in Ethiopia, which also anticipate considerable land cover conversions, particularly cropland expansion and forest loss, if current trends persist (Belay et al., 2024; Gashaw et al., 2017; Girma et al., 2022).

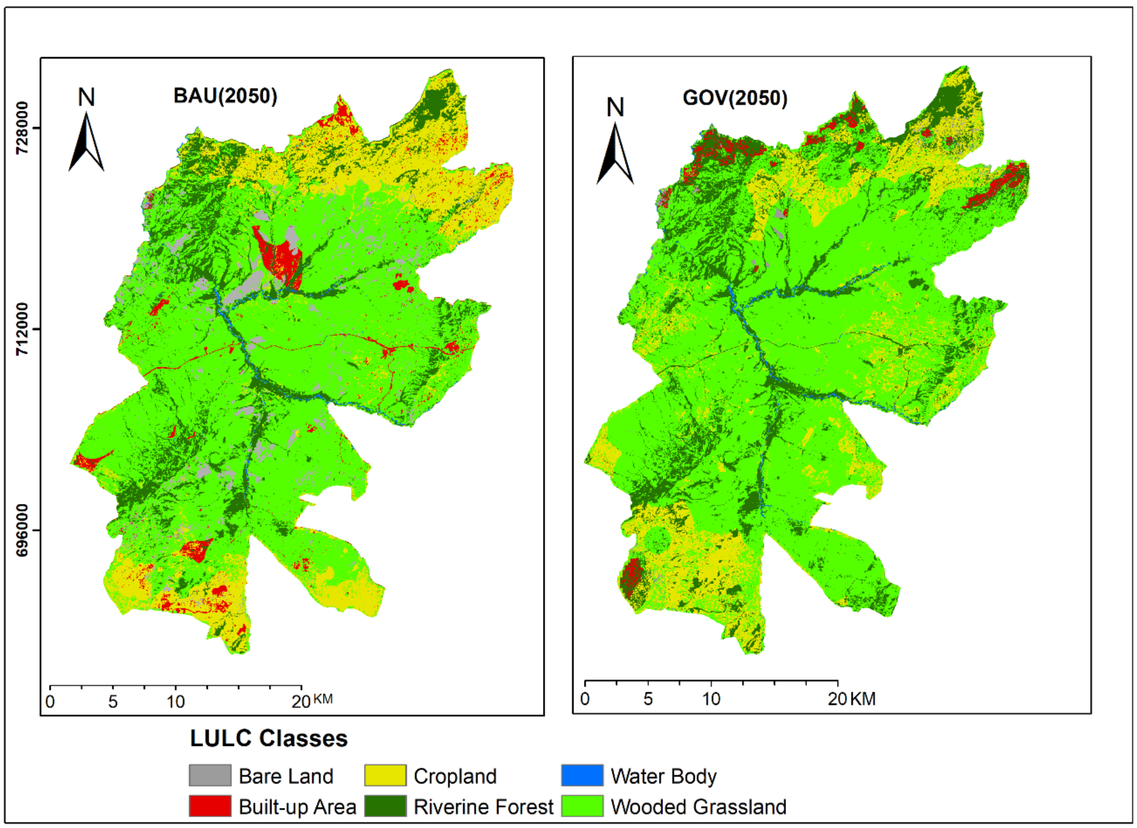

Figure 6.7:Predicted land use land cover map under BAU and GOV scenarios (2050)

Under the BAU scenario, cropland and built-up areas are projected to increase by 2,393.53 ha and 1,297.89 ha, respectively, from the baseline year (2020). In contrast, riverine forests (-1,058.69 ha), water bodies (-81.72 ha), and wooded grasslands (-438.5 ha) are expected to decrease by 2050. Bare lands are also predicted to decline by 1,103.17 ha during the same period. If current land cover conversion trends and socioeconomic developments persist, naturally vegetated areas, such as wooded grasslands and riverine forests, are likely to experience significant reductions by 2050. This underscores the urgent need for governmental and community interventions to promote ecosystem conservation and restoration. The prediction results under the GOV scenario, which focuses on planting seedlings to increase forest cover (Kassa et al., 2022), indicate a decrease in built-up areas by 632.43 ha and bare lands by 4,271.6 ha from the baseline year (2020). Cropland is projected to show a slight increase of 341.8 ha by 2050 under the GOV scenario, although this increase is minimal compared to the BAU scenario (2,393.53 ha; Table 6.5). In contrast to the BAU scenario, riverine forests (3,062.23 ha) and wooded grasslands (2,698.63 ha) are expected to increase by 2050 due to conservation efforts and seedling plantations (Table 6.5). Previous studies in Ethiopia (Belay et al., 2024; Biratu et al., 2022) have also reported similar findings, where under the BAU scenario, encroachment of farmlands and built-up areas over forested lands is projected, while under the GOV and ecosystem protection scenarios, forested/vegetated areas are expected to increase. These findings suggest the importance of implementing environmental or ecosystem conservation strategies, rather than solely relying on socioeconomic development, in both the study area and the country as a whole.

Table 6.5:Predicted land use land cover changes under different scenarios

LULC Classes	**Baseline (2020)**	**BAU (2050)**	**GOV (2050)**	**Change 1985 - 2020**	**Change 2020 – 2050(BAU)**	**Change 2020-2050(GOV)**
BL	4945	3841.83	673.38	-2829(-36.4)	-1103.17(-22.31)	-4271.62(-86.38)
BA	1827	3124.89	1194.57	426(31.32)	1297.89(71.04)	-632.43(-34.62)
CL	14420	16813.53	14761.80	7341(103.7)	2393.53(16.6)	341.8(2.37)
RF	13133	12074.31	16195.23	-3781(-22.35)	-1058.69(-8.06)	3062.23(23.32)
WB	558	476.28	472.86	-344(-38.14)	-81.72(-14.65)	-85.14(-15.26)
WG	54398	53959.50	57096.63	-2139(-3.78)	-438.5(-0.81)	2698.63(4.96)

Note: Figures in the parenthesis indicates percentage changes of land use land cover classes

BL= Bare land, BA= Built-up areas, CL= Croplands, RF= Riverine Forest, WB= Water body, WG= Wooded grasslands

The percentage share of LULC classes in the baseline year (2020), as well as the BAU and GOV scenarios, indicates that wooded grassland constitutes the largest share, accounting for 60.93% in the baseline year, 59.76% in the BAU scenario, and 63.16% in the GOV scenario (Table 6.6). In contrast, water bodies represent the smallest proportion among all land cover classes across the baseline year, BAU and GOV scenarios. These findings align with the previous study (Zewude et al., 2022), which also reported that wooded grasslands (savanna grassland, scattered trees and grasslands, and bushes) accounted for the largest area share in Maze national park. This can be attributed to the dominance of savanna grassland and scattered trees in the study area (Henok et al., 2017).

Table 6.6:Percentage of land use land cover types under different scenarios

	BL	BA	CL	RF	WB	WG
Babseline_2020	5.54	2.05	16.15	14.71	0.62	60.93
BAU_2050	4.25	3.46	18.62	13.37	0.53	59.76
GOV_2050	0.74	1.32	16.33	17.92	0.52	63.16

Note: BL= Bare land, BA= Built-up areas, CL= Croplands, RF= Riverine Forest, WB= Water body, WG= Wooded grasslands

6.3.5. LULC change based prediction of ecosystem services under BAU and GOV scenarios

Predicted ecosystem service values, based on future LULC dynamics, show variations under the BAU and GOV scenarios when compared to historical data. Between 1985 and 2020, food production services increased by 0.7 million USD, while the remaining ecosystem services such as water supply, raw material, and climate regulation exhibited negative changes (Table 6.7) (Simeon & Wana, 2024). Under the BAU scenario, food production services are projected to increase slightly by 2.3% by 2050, whereas other ecosystem services, including water supply (-7.61%), raw material (-6.72%), and climate regulation (-5.57%) services, are expected to decline. Conversely, under the GOV scenario food production (10.94%), water supply (22.26%), raw material (19.93%), and climate regulation (17.07%) services are predicted to increase by 2050 (Table 6.7).

The projected increase in food production under the BAU scenario is primarily driven by the expansion of croplands, whereas under the GOV scenario, it is attributed to the expansion of other land cover classes, such as riverine forests, which also contribute to food production. Since this study uses the benefit transfer method (Costanza et al., 1997), to value ecosystem services based on land cover changes, reductions in riverine forests, wooded grasslands, and water bodies are expected to lead to declines in water supply, raw materials, and climate regulation services. In contrast, conservation initiatives and tree planting efforts are anticipated to offset these losses, enhancing food production, water supply, raw materials, climate regulation services, and the overall ecosystem service values of the region. These findings are consistent with a study in

Afghanistan, which reported a decline in ecosystem service values under the BAU scenario but an increase under an Environmental Protection scenario (ENP) by 2030 (Najmuddin et al., 2022). This underscores that continuing past and current socioeconomic development trends without integrating environmental conservation measures will likely diminish individual and overall ecosystem service values in the region.

Table 6.7:Predicted ecosystem service values under different scenarios (million USD)

Ecosystem services	ESVs (2020)	BAU (2050)	GOV (2050)	Change 1985 -2020	Change 2020-2050(BAU)	Change 2020-2050(GOV)
FP	16.55	16.93	18.36	0.7	0.38(2.30)	1.81(10.94)
WS	659.59	609.41	806.39	-180.35	-50.18(-7.61)	146.80(22.26)
RM	188.96	176.26	226.62	-45.72	-12.70(-6.72)	37.66(19.93)
CR	12.89	12.17	15.09	-2.67	-0.72(-5.57)	2.20(17.07)
Total	877.99	814.38	1066.46	-228.04	-63.61(-7.20)	188.47(21.47)

Note: FP=Food production, WS= Water supply, RM= Raw material, CR=Climate regulation

6.3.6. Spatial distribution of predicted ecosystem services

The spatial distribution of predicted ecosystem service values for the study area was derived from the BAU scenario land cover map for 2050, with values computed for each land cover class individually rather than as a total (Fig. 6.8). The results reveal significant changes in both the values and spatial distribution of ecosystem services compared to 2020.

Specifically, the value of food production services is expected to rise slightly, with the highest value increasing from 7.91 million USD in 2020 to 8.57 million USD in 2050 (Fig. 6.8). In contrast, the values of water supply, raw materials, and climate regulation services are predicted to decline by 2050 compared to the baseline values. The projected increase in food production services is ascribed to the potential increase of agricultural lands under the BAU scenario. Conversely, the decline in other ecosystem services is linked to the anticipated reduction in wooded grasslands, riverine forests, and water bodies under the same scenario. This finding contrasts with a study by (Hou et al., 2021), reported an overall increase in predicted ecosystem service values in the Yiluo River Basin, China, primarily due to the expansion of forestlands and water bodies. On the other hand, consistent with this result, (Duguma et al., 2024) highlighted that the expansion of food or coffee production would lead to future losses in ecosystem services in southwestern Ethiopia.

The 2050 prediction maps also reveal spatial shifts in ecosystem services. For instance, areas with the highest food production values are projected to migrate towards the high-altitude regions in the northern part of the study area, shifting away from the central and southern lowland regions. This shift can be attributed to the relationship between topography and precipitation, which plays a crucial role in influencing food production. Higher altitude areas generally receive more rainfall (Terefe, 2022), and under changing climatic conditions, higher precipitation levels in the study area are projected to be associated with elevated regions (Fig. 6.9; Fig. 6.10). Additionally, the spatial extent of high-value ecosystem service areas is anticipated to decrease across all ecosystem service maps (Fig. 6.8).

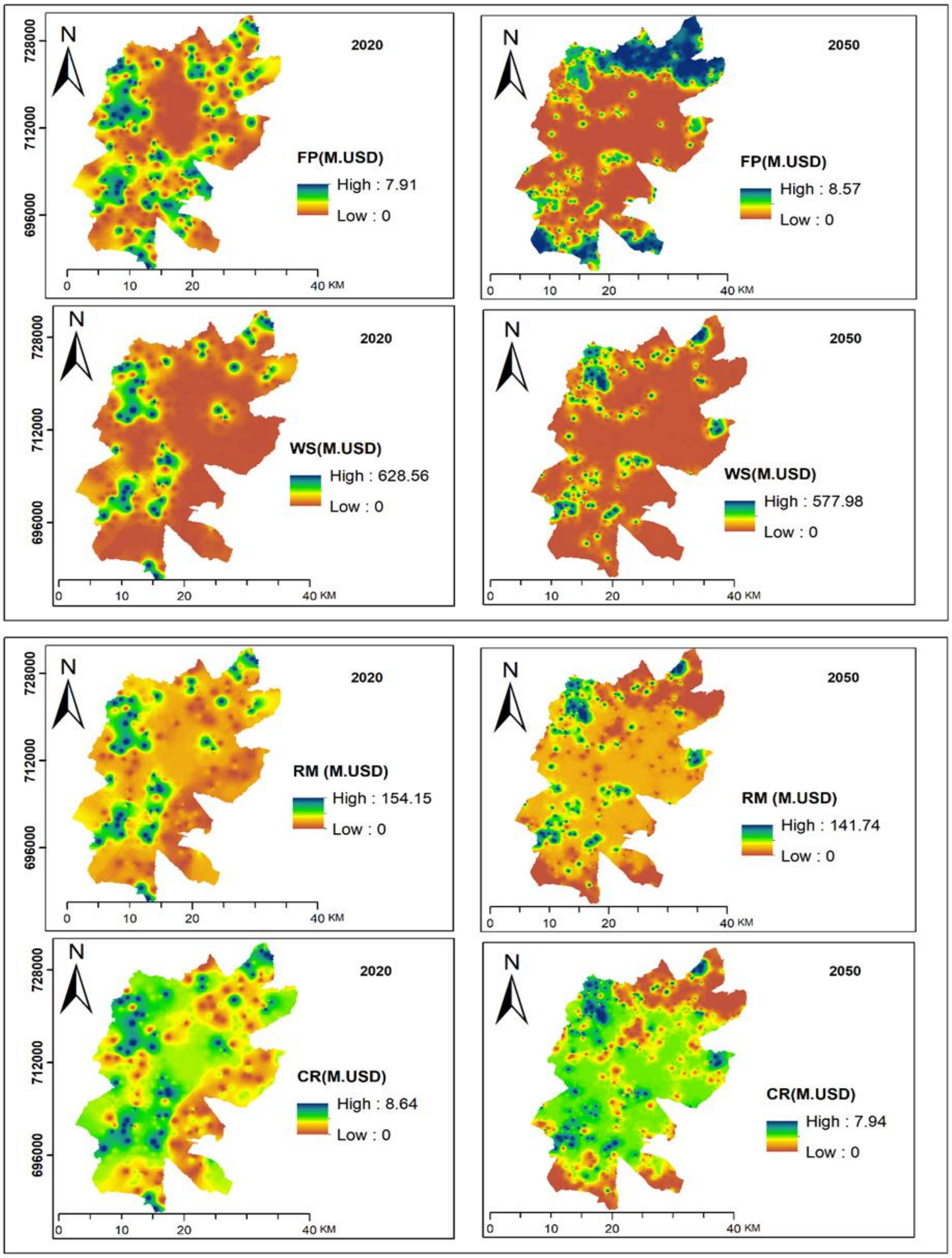

Figure 6.8:Changes in spatial distribution of ecosystem services in 2020 and 2050

6.3.7. Future climate change scenario and ecosystem services

The spatial distribution of precipitation and temperature is affected by the topography of a particular area (Li et al., 2021; Prager et al., 2021; Terefe, 2022). Accordingly, the predicted maximum temperature, minimum temperature, and precipitation show variations with altitude under both SSP2-4.5 and SSP5-8.5 scenarios (Fig. 6.9 and Fig.6.10). High-altitude areas in the northern part of the study area are associated with higher precipitation and lower maximum and minimum temperature values in both scenarios. Comparable to our results, Abate et al. (2024) reported the spatial variation of projected precipitation and temperature following the topographic pattern of an area in the upper Danakil basin. Interestingly, low minimum temperature values are also predicted in the central low-lying areas, in addition to the highlands in the northern parts of the study area. This may be ascribed to the presence of the national park that possess the central position of the region. The national park, dominated by wooded grasslands and riverine forests, likely contributes to local climate regulation by moderating temperatures. In contrast, low precipitation and high maximum temperature are projected in the low-lying areas, where the effects of topography and vegetation cover are less pronounced.

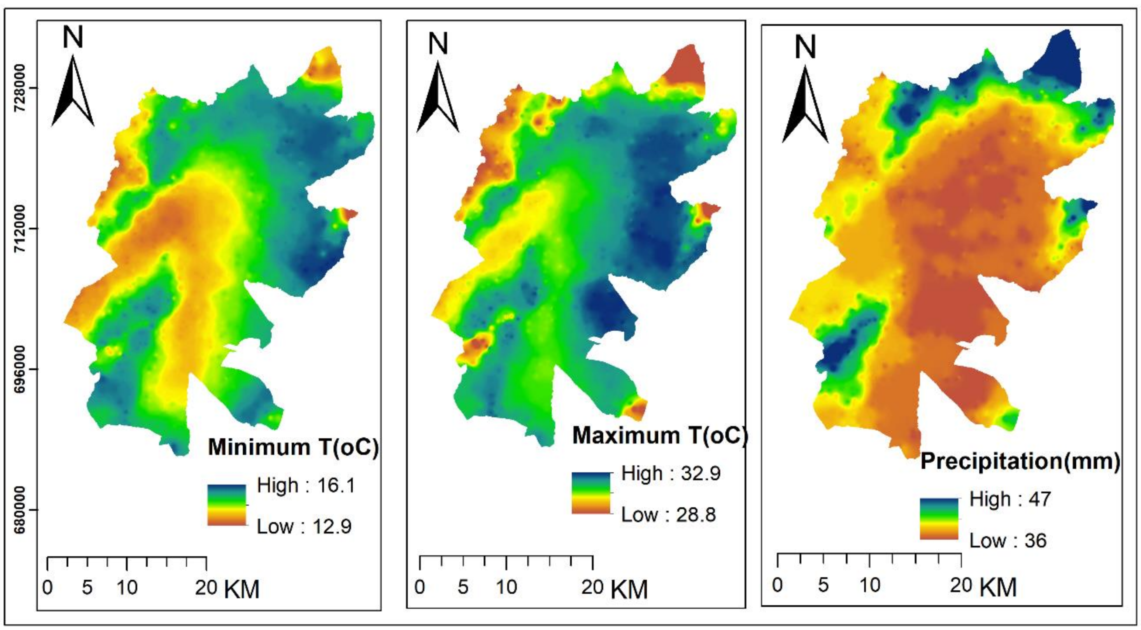

Figure 6.9:Minimum temperature, maximum temperature and precipitation from 2041 – 2060(SSP2-4.5)

The minimum temperature values are projected to increase under SSP2-4.5 (12.9 to 16.1°C) and SSP5-8.5 (13.4 to 16.6°C) scenarios compared to the historical data (12.02 to 15.47°C) (Figs. 6.9, 6.10, and Fig 5 in Appendix G). Similarly, the predicted maximum temperature values show an increase under SSP2-4.5 (28.8 to 32.9°C) and SSP5-8.5 (29.0 to 33.1°C) relative to historical records (25.42 to 29.35°C). In contrast, precipitation is expected to decline under both SSP2-4.5 (36 to 47 mm) and SSP5-8.5 (38 to 51 mm) scenarios, compared to historical data (81 to 128 mm). These findings are well in agreement with previous climate projections in Ethiopia, which indicate rising minimum and maximum temperatures and declining precipitation trends compared to baseline data (Geleta et al., 2022; Toma et al., 2024).

The high emission scenario (SSP5-8.5) predicts slightly higher temperatures and precipitation compared to the moderate emission scenario (SSP2-4.5), highlighting the intensified effects of higher emissions. Similar trends were observed in southern Ethiopia, where mean maximum temperatures were projected to rise significantly under the high emission scenario (RCP 8.5) compared to the medium emission scenario (RCP 4.5) (Aga & Shomre, 2024). Climatic change and variability are expected to have profound effects on semi-arid tropical regions, likely resulting in more frequent, intense, and prolonged droughts in the future (Anil et al., 2024). Projected increases in temperatures and decreases in precipitation could intensify water scarcity, degrade vegetation cover, and diminish the provision of ecosystem services vital to local communities. These challenges underscore the urgency of implementing climate change mitigation and adaptation strategies to alleviate potential impacts on biodiversity and livelihoods.

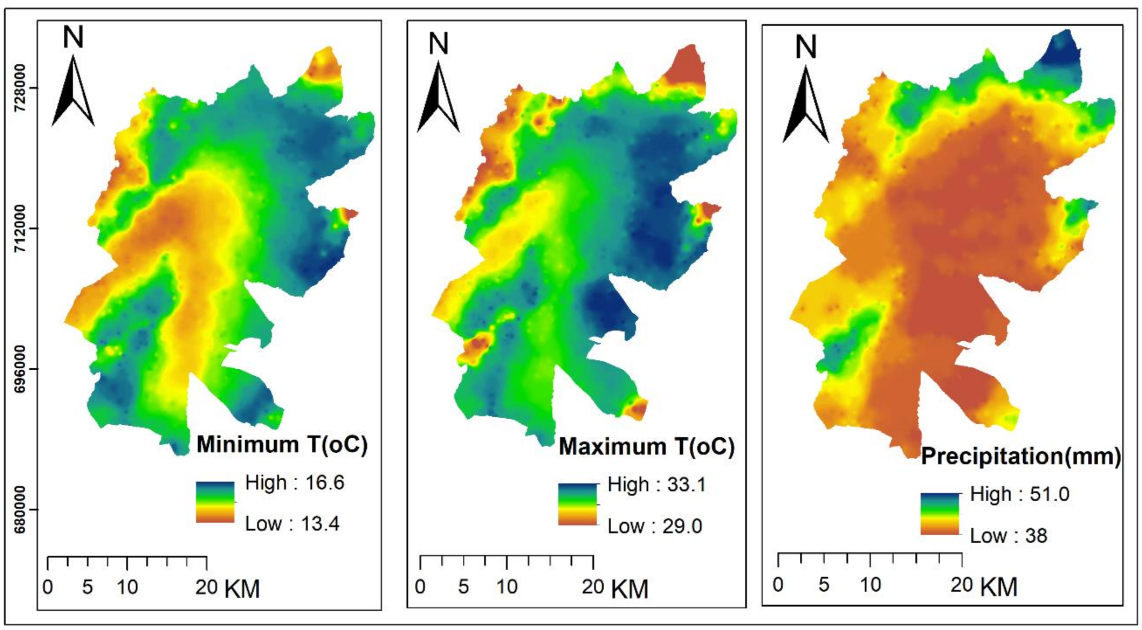

Figure 6.10:Minimum temperature, maximum temperature and precipitation from 2041 – 2060(SSP5-8.5)

6.3.8. Future climate change impacts on key ecosystem services

Maximum and minimum temperatures under both moderate (SSP2-4.5) and high emission (SSP5-8.5) scenarios exhibited a statistically significant but weak negative correlation with food production, water supply, raw materials, and climate regulation services (Table 6.8). This indicates that rising maximum and minimum temperatures negatively impact ecosystem service provision.

However, minimum temperature showed a statistically significant moderate positive correlation with food production services (rs = 0.316 under SSP2-4.5 and rs = 0.321 under SSP5-8.5; Table 6.8). Precipitation demonstrated a statistically significant moderate positive correlation with food production (rs = 0.481 under SSP2-4.5 and rs = 0.489 under SSP5-8.5; Table 6.8). Additionally, precipitation revealed a positive but weak correlation with water supply, raw material, and climate regulation services.

The observed relationships align with the understanding that rising temperatures increase evaporation, leading to drought and reduced water availability for ecosystems, drinking water supplies, and agriculture (Mahadevan et al., 2024). Conversely, rainfall positively influences food availability (Affoh et al., 2022), although changes in precipitation patterns can lead to increased crop failures and production declines (Mahadevan et al., 2024). These findings highlight the vulnerability of ecosystem service provisions to increasing temperatures and changing rainfall patterns. To mitigate these adverse impacts, the implementation of effective climate change mitigation strategies is essential.

Table 6.8:Correlation between predicted ESVs and climate variables

		SSP2-4.5			SSP5-8.5		
		T_{mx}	T_{min}	Prec	T_{mx}	T_{min}	Prec
FP	rs	-.124**	.316**	.481**	-.124**	.321**	.489**
	Sig.	.000	.000	.000	.000	.000	.000
WS	rs	-.183**	-.193**	.068*	-.183**	-.191**	.051
	Sig.	.000	.000	.031	.000	.000	.104
RM	rs	-.166**	-.214**	.034	-.166**	-.213**	.016
	Sig.	.000	.000	.283	.000	.000	.605
CR	rs	-.129**	-.179**	.040	-.129**	-.178**	.024
	Sig.	.000	.000	.205	.000	.000	.450

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed)

6.4. Conclusion

The aim of this study was to predict the future LULC and climate change impacts on key ecosystem services in Maze national park and its environs, southwestern Ethiopia. We utilized the MLP neural network method incorporated under the LCM of IDRISI Selva for LULC change prediction. These predictions formed the basis for forecasting ecosystem services in 2050 under the BAU and GOV scenarios. Additionally, spearman correlation was employed to analyze predicted climate change impacts on ecosystem services. The main conclusions of the study are;(i) based on predicted LULC changes, food production will increase slightly (2.3%), while water supply (-7.61%), raw materials (-6.72%), and climate regulation (-5.57%) will decline under the BAU scenario. In contrast, the GOV scenario forecasts substantial increases in food production (10.94%), water supply (22.26%), raw materials (19.93%), and climate regulation (17.07%) services in 2050. (ii) compared to historical data (1970 – 2000), minimum and maximum temperatures are projected to increase, while rainfall is expected to decline in the future under both moderate and high emission scenarios. (iii) predicted increase in minimum and maximum temperatures, coupled with a decline in rainfall under both moderate and high emission scenarios, is expected to have significant negative impacts on the provision of key ecosystem services.

The study highlights the critical need to integrate future climate and LULC change predictions into regional planning and development policies. This integration is essential for designing effective land use management strategies, climate change adaptation and mitigation measures, and ecosystem conservation and protection efforts. Such proactive measures can help mitigate the predicted declines in ecosystem services and safeguard biodiversity and ecosystems. By addressing these areas, effective management strategies will ensure that ecosystems continue to provide vital services despite the challenges posed by climate change and controlled land cover changes. Due to data dearth, prediction of LULC changes in this study was performed using only topography and proximity related variables as LULC change driving factors. Hence, we recommend future studies to include socioeconomic and population related variables in the future change predictions.

7. Synthesis, conclusion and recommendation

7.1. Synthesis

Ecosystems offer a diverse range of direct and indirect benefits which are essential for human wellbeing (MEA, 2005). However, an increase in anthropogenic disturbances resulted in degradation of most ecosystems services on Earth in the recent decades (Sannigrahi et al., 2020). LULC change and climatic change and variability have been identified as the major drivers of change that affect biodiversity and ecosystem functions and services that are fundamental to human well-being (Tang et al., 2018). In Ethiopia extensive LULC changes have been observed, especially expansion of agricultural lands and settlements modify rural landscapes, putting considerable pressure on biodiversity and ecosystem services (Polasky et al., 2011; Tolessa et al., 2017). In addition, Ethiopia is one of the countries most affected by the negative impacts of climate change and variability because of its weak adaptive capacity (NEA, 2022). Climate variability including rising temperatures and unreliable and declining rainfall have led to the degradation of ecosystem services in the country (Gezie, 2019). The conversion of natural land cover into agricultural and built-up areas has changed landscape patterns and structures resulting in fragmentation and habitat loss (Mitchell et al., 2015a). Changes in landscape patterns and structures affect the size, shape, number, and spatial arrangement of landscape patches (Mitchell et al., 2015b), which in turn influence the strength and direction of interactions among ecosystem services, leading to both trade-offs and synergies (Rieb & Bennett, 2020). Thus, this study specifically examined the impacts of LULC dynamics and climate change and variability on selected ecosystem services in MzNP and surrounding area of southwestern Ethiopia. The study addressed the following four research questions by examining the temporal and spatial impacts of LULC dynamics, historical and projected climate change and variability trends, and synergies and trade-offs among key ecosystem services.

7.1.1. How do changes in LULC types influence the provision of food production, water supply, raw materials, climate regulation, and cultural services?

Analyzing how LULC changes affect ecosystem service values is essential for developing land management strategies that support livelihoods and human well-being while shaping development of policies (Biedemariam et al., 2022). Using land cover changes as proxy for estimating ecosystem services is a widely applied method in areas where data is unavailable for direct valuation (Tolessa et al., 2017). Chapter 3 assesses how changes in LULC affected the provision of selected ecosystem services in MzNP and its adjacent areas over the past decades (1985–2020). The results showed an increase in the area of croplands and built-up areas by 103.7% and 31.32%, respectively, across the period of 1985 and 2020, while there was a decrease in wooded grasslands, riverine forests, water bodies, and bare land (Simeon & Wana, 2024). The increase in croplands and built-up areas came at the cost of wooded grassland and riverine forests.

The LULC changes resulted in a loss of total ecosystem service values of 409.7 million USD between 1985 and 2020, with declines in individual ecosystem services such as water supply, climate regulation, raw materials, and tourism and recreation services. With the exception of food production service which grew by 0.7 million USD, all other ecosystem services declined during the study period. Water supply decreased by 180.35 million USD, climate regulation by 2.67 million USD, raw material provision by 45.72 million USD, and tourism and recreation by 481.62 million USD. These results are consistent with previous studies in the country that reported expansion of croplands and built-up areas (Mekuria et al., 2021; Ogato et al., 2021) and reductions of overall as well as individual ecosystem services (Belay et al., 2022; Mekuria et al., 2021). The results suggest that encroachment of croplands and built-up areas into naturally vegetated lands leads to a significant decline in essential ecosystem services that support human well-being. Therefore, addressing this issue requires strong protected area management efforts, including measures to prevent illegal land cover conversions.

7.1.2. How do the spatial and temporal patterns of climate variability influence selected provisioning and regulating ecosystem services?

Chapter 4 focuses on the spatial and temporal responses of key ecosystem services to climate variability, with an emphasis on variabilities in temperature and rainfall. It examines how variations in these climatic factors affect the provision of essential ecosystem services across different areas and time periods. In line with previous studies on climate change and variability in southern Ethiopia (Dejene et al., 2023; Worku et al., 2022a), this chapter highlights high rainfall variability, fluctuating from its long-term mean, particularly on a monthly and seasonal scale, with no monotonic increasing or decreasing trend (Simeon et al., 2024). The findings of this study reveal a decreasing trend in the main rainy season (spring) and mean annual rainfall, while mean annual, maximum, and minimum temperatures have shown an increasing trend. Closely similar results have been reported by (Asfaw et al., 2018) in north central Ethiopia. As shown both locally (Terefe,

2022) and globally (Li et al., 2021), the spatial distribution of rainfall and temperature are governed by topography. In this study, higher mean annual rainfall values were observed in higher elevations, while lower elevations received reduced rainfall. Conversely, the lowest mean annual temperatures were recorded in higher elevation areas. The spatial distribution of key ecosystem services in the study area also varied with rainfall and temperature patterns. Areas with higher rainfall provided better provision of food production, water supply, raw materials, and climate regulation services compared to areas with lower rainfall. In contrast, areas characterized by higher mean annual temperature showed reduced provision of these services. This is evidenced by strong positive correlation observed between key ecosystem services and both mean annual rainfall and NDVI, while negative relationship with mean annual temperature.

Chapter 4 reveals a positive correlation between main rainy season rainfall and key ecosystem services. However, there were negative correlations between ecosystem services and temperatures. This shows that the main rainy season, which contributes the most to annual rainfall, positively influenced food production, water supply, raw materials, and climate regulation services during the study period (1985–2020) (Simeon et al., 2024). In contrast, increasing mean annual, maximum, and minimum temperatures negatively affected these services. These results suggest that variability of rainfall and increasing trends in temperature have a largely negative impact on the ecosystem's ability to provide services that are vital for human well-being. This is in line with findings from previous studies, which highlight the key role of rainfall in determining water availability (Twisa & Buchroithner, 2019), food production (WFP, 2014), and vegetation growth and density (Fang et al., 2018). The study findings emphasize the importance of integrating climate change considerations into regional land use planning, emphasizing protecting natural vegetation and implementing effective climate

7.1.3. Are there trade-offs or synergistic relationships between food production, water supply, raw materials, and climate regulation services?

Spatial and temporal changes in one ecosystem service bring change on the other ecosystem service either positively or negatively, leading to both trade-offs and synergies. Consistent with previous studies (Mulatu et al., 2024; Rieb & Bennett, 2020), Chapter 5 analyzes synergies and trade-offs among food production, water supply, raw materials, and climate regulation services. It also incorporates landscape metrics to assess landscape fragmentation and heterogeneity in the study area. The findings show that LULC changes, along with increasing landscape fragmentation and diversity caused by human disturbances such as farmland and built-up area expansion, have led to a decline in ecosystem services (Simeon & Wana, 2025). In addition, similar to findings in previous research (Doğan, 2022; Hu et al., 2021; Rutledge, 2003), Chapter 5 presents increased landscape fragmentation and diversity as indicated by increasing SHDI, SIDI, NP, PD, and ED at both class and landscape levels. Unlike the findings of (Daye and Healey, 2015), where fragmentation decreased between 1995 to 2010, resulting in reduced SHDI and SIDI values in the Gamo highlands, this study observed an increase in SHDI and SIDI values from 1985 to 2020. This increase is attributed to the alteration of natural and semi-natural forests and wooded grasslands to farmlands and settlements. Chapter 5 also reveals that spatially, the relationships among ecosystem services were predominantly synergistic (Simeon & Wana, 2025). However, a higher proportion of trade-offs was observed between food production and other ecosystem services. Positive synergies were generally more common in higher elevation areas compared to the low-lying areas.

Furthermore, the temporal analysis revealed trade-off between food production and water supply, raw material, and climate regulation services, driven by the expansion of agricultural lands at the expense of naturally vegetated areas. In contrast, water supply, raw material, and climate regulation services exhibited a strong synergistic relationship. This result aligns with the findings of (Biratu et al., 2022; Wei et al., 2022) both of whom reported trade-off between food production and other ecosystem services, such as water supply, soil conservation, gas regulation, recreation, carbon storage, and habitat quality. Understanding the relationships among key ecosystem services is crucial for designing strategies that enhance ecosystem protection and address the impacts of human activities in protected areas. This study also highlights local community perceptions of ecosystem services relationships, which vary based on their distance from the protected area that serves as the main source of these services.

7.1.4. How will food production, water supply, raw material, and climate regulation services respond to different predicted LULC and climate change scenarios?

Future LULC and climate changes are expected to significantly impact ecological systems, affecting their functionality and altering the capacity of natural and managed systems to provide essential ecosystem services (Lawler et al., 2011). Chapter 6 shows significant land cover shifts by 2050 compared to the baseline year (2020) under the BAU and GOV scenarios. Under the BAU scenario, croplands and built-up areas are projected to expand, while wooded grasslands, riverine forests, and water bodies are expected to decline, leading to a reduction in key ecosystem services such as water supply (-7.61%), raw materials (-6.72%), and climate regulation (-5.57%) services. Conversely, under the GOV scenario, where tree planting and environmental conservation measures are implemented, riverine forests and wooded grasslands are projected to increase, resulting in improvements in food production (10.94%), water supply (22.26%), raw materials (19.93%), and climate regulation (17.07%) services. These results are consistent with previous land cover change modeling studies in Ethiopia (Belay et al., 2024; Gashaw et al., 2017; Girma et al., 2022).

Similar to the findings of previous climate change modeling studies conducted in Ethiopia, the projected maximum and minimum temperatures in the study area are expected to increase in the future compared to historical data. In contrast, precipitation is predicted to decline under both medium and high emission scenarios. Projected increase in temperatures and decrease in precipitation could increase water scarcity, degrade vegetation cover, and diminish the provision of ecosystem services vital to local communities (Geleta et al., 2022; Toma et al., 2024). Chapter 6 further indicates that the predicted increase in maximum and minimum temperatures will have negative impacts on the future provision of ecosystem services, while precipitation is positively correlated with key ecosystem services. The study highlights that if current land cover changes and climatic trends continue, vital ecosystem services are expected to decline. This emphasizes the importance of interventions for sustaining ecosystem productivity in the region.

This study was based on the socioecological systems theory, which enables analysis of interconnected relationships/interdependence between people and the natural environment. This framework helped to examine the nonlinear relationships between people and the protected area's environment in semi-arid region in spatial and temporal scale. The findings of this study demonstrated human activities such as expansion of farm lands and built-up areas, frequent forest fire, heavy dependence of local people on the protected area for grazing, grass cutting, and fire wood along with climate change and variability have led to reduction of overall as well as individual ecosystem services. Since the local population in the study area, like many other developing nations, depends heavily on natural resources for survival, the reduction in ecosystem services has a negative impact on people's well-being and ability to survive. Thus, the socioecological systems theory can be used to assess the spatial and temporal implications of LULC and climate change and variability on ecosystem services and on local communities.

7.2. General Conclusion

This study examines the complex interactions of LULC change and climate change and variability with ecosystem services in and around Maze National Park. It examines the connectedness of human activities and natural ecosystems, demonstrating how they influence each other at spatial and temporal scales as socioecological systems. It examined historical and future LULC change as well as climate change and variability, providing a holistic evaluation of their implications for key ecosystem services in the region. The results demonstrated extensive conversions of naturally vegetated lands to farmlands and built-up areas that have led to increased landscape fragmentation, declines in key ecosystem services, and trade-offs among ecosystem services that are necessary for sustainable resource management. The results also illustrated increasing temperature and erratic and declining rainfall in both the historical and future predictions, indicating a need for action to mitigate and adapt to climate change. Through the integration of socioeconomic survey data, the study offers valuable insights into how local residents perceive changes in ecosystem services and LULC and how their proximity to the protected area affects these perceptions. Understanding these dynamics is crucial for informing conservation efforts, sustainable land use planning and policy decisions aimed at balancing ecological integrity with human well-being.

In this thesis, the MEA framework has offered a structured approach for examining how LULC changes, along with climate variability and change, have affected key ecosystem services in Maze national park and the surrounding districts. By clearly categorizing ecosystem services into provisioning, regulating, cultural, and supporting services, the framework makes the assessment of these services at spatial and temporal scale easier. Moreover, the MEA's focus on trade-offs has enabled the evaluation of interactions between key ecosystem services. Although the MEA framework has been criticized for not fully portraying the complexity of interactions between ecosystem services, this study found that the MEA framework remains a valuable approach for evaluating socio-ecological interdependence between people and nature, as well as for informing policy and decision-making.

7.3 Recommendations and the way forward

Based on the above conclusions the following recommendations have been drawn:

- This study underscores the need to regulate unrestricted human access to the protected area to prevent illegal land cover conversions, particularly into built-up areas and croplands.
- The study recommends implementing reforestation and afforestation initiatives, as well as promoting integrated land management approaches that balance ecosystem conservation and agriculture, reduce landscape fragmentation, and minimize trade-offs and promote synergies among ecosystem services.
- Future climate and LULC change predictions should be integrated into regional planning and policy development to ensure that environmental conservation is prioritized alongside socioeconomic development.
- Policymakers, regional authorities and local land managers should work on sustainable land use planning, ecosystem conservation, and climate change adaptation and mitigation strategies to enhance and sustain ecosystem services in the region.
- Future research in the field should incorporate market price, stated preference, or participatory mapping methods to enable the inclusion of additional ecosystem services, such as cultural and more provisioning and regulatory services, providing a more comprehensive representation of the overall ecosystem service status in the study area.

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Appendices

Appendix A: Survey questionnaire

Addis Ababa University College of Social Science Department of Geography and Environmental Studies, PhD Dissertation Survey Questionnaire.

This research aims to gather relevant data about the impacts of climate change and land use and land cover dynamics on ecosystem services in Maze national park and its environs. Therefore, you are kindly requested to provide correct information for questions that you want to answer. The information you provide is strictly confidential and your personal details will remain anonymous and protected.

(Put an "X" mark on the given space and provide written answer where applicable)

I. Background Information of the Respondents

1.Sex ☐ Male ☐ Female

2.Age ☐ 20-40 ☐41-64 ☐Above 65

3.Marital Status ☐ Single ☐ Married ☐ Widowed ☐Divorced

4. Family size ☐ Below 4 ☐ 4-8 ☐8-12 ☐Above 12

5. Educational Status ☐Can't read &write ☐Primary ☐ High school and above

6. For how long have you been living in this kebele?

☐Below 10 years ☐10-20 years

☐20-30 years ☐Above 30 years

7.Family income (mark multiple if you do more than one)

☐Crop production/selling ☐Fire wood, wood for construction or charcoal selling

☐Livestock selling ☐If any specify________________________________

8. Source of water for domestic use

☐Piped tap water at home ☐Flowing stream/ river

☐Bore hole communal water ☐Dam/pool ☐Rainwater tank

9.Land holding size in hectare ________________________________

10. Crop production per year per quintal_________________________

11.Distance from the Park (in Km/meter) ________________________

12.Number of cattle you own___________________________________

II. Land use land cover dynamics and ecosystem services

1. Have you observed changes in land use land cover in the park and the adjoining districts?

   A. Yes B. No C. Don't know

2. If your answer is "Yes", what do you think the driving forces of land use land cover changes? (You can choose one or more answers)

   ☐Population growth ☐Deforestation

   ☐Climate change/variability ☐If any specify_________________________

3. What major shifts of land use land cover occurred in your district and the park in the last decades? (Put an "X" mark under your choice)

Land Use Land Cover Types	**Increased**	**Decreased**	**No Change**
Agricultural lands			
Grazing lands			
Grasslands			
Riverian forests			
Bare lands			
Bush lands			
Water bodies			
Settlement			

4. Do you think that changes in land use land cover negatively or positively influenced food production, water supply and forest coverage in your locality?

   A. Yes B. No C. Don't know

5. If your answer for question number 4 is "yes", mention the positive and negative effects of land use land cover changes on the aforesaid ecosystem services.

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6. Select the factors influencing vegetation coverage in your district. (You can choose one or more)
   - ➢ Cultivation and livestock farming
   - ➢ Timber extraction
   - ➢ Road and infrastructure development
   - ➢ Fire incidence
   - ➢ Unsustainable forest management

Specify if any____

7. Is crop production per quintal shows an increase/decrease (variation) in the past decades?

   A. Yes B. No C. Don’t know

8. If your answer is “Yes”, show the changes in the past decades.

   I. Five years ago____________________quintal/year

   II. Ten years ago____________________quintal/year

   III. Twenty years ago_________________quintal/year

   IV. Thirty years ago__________________quintal/year

9. What do you think the reason behind for the change?

____

____

____

____

10.Farmlands in your district have been expanding over time?

   A. Yes B. No C. Don’t know

11.If your answer is “yes”, do you think that expansion of farm lands contributed to the increase of crop production in your district?

   A. Yes B. No C. Don’t know

12.Do you think that expansion of new agricultural lands caused clearance of vegetation coverage in your kebele and the park?

A. Yes B. No C. Don't know

13.Do you think that Maze national park benefits the surrounding districts and other stakeholders?

A. Yes B. No C. Don't know

14. If your answer is "Yes", what are the benefits do you obtain from the park? (Put an "X" mark for your choices)

No.	Benefits Obtained from the Park	Yes	No
1.	Fire wood and charcoal		
2.	Construction material		
3.	Grazing		
4.	Recreation		
5.	Water for irrigation		
6.	Water for domestic use		
7.	Food gathering		
8.	Hunting		
9.	Spiritual services		

14.What are other benefits you obtain from the park?

____

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15.Are the benefits you get from the park shows variation over time?

A. Yes B. No C. Don't know

16.What major changes occurred in the benefits you get from the park?

Benefits from the park	**Increased**	**Decreased**	**No Change**
Food gathering			
Fire wood and charcoal			
Grazing			
Construction material			
Water for irrigation			
Water for domestic use			
Recreation			
Hunting			
Spiritual experiences			
Apiculture and wild honey collection			

17.What do you think that the major causes of changes in benefits you get from the park?

____

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18.Does the park provide cultural and spiritual services for your community?

A. Yes B. No C. Don't know

19. If your answer is "Yes", what are the cultural and spiritual services you obtain from the park?

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20.Do you think that wild animals in Maze national park are exposed to threat?

A. Yes B. No C. Don't know

21.If your answer is “Yes”, what do you think the problems affecting wild animals in the park?

____

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____

22.Have you been ever engaged in conservation of vegetation and protection of wild animals in Maze national park and your district?

A. Yes B. No

23. If your answer is “Yes”, what activities you made in the park (you can choose more than one)

☐Protecting the park from Livestock interference for grazing

☐Protecting the park from human intervention to have new farmland

☐Protecting cutting and burning of trees in the park

☐Specify if any______________________________

III. Perceptions on synergies and trade-offs between ecosystem services

The following statements are about trade-offs and synergies among the benefits you get in the past decades from your district and Maze national park. Please read each and put an “X” mark to show to what extent you agree or disagree with the statements.

Note: 1= Strongly Disagree, 2=Disagree, 3=Not Sure, 4=Agree and 5=Strongly Agree

No.	Tradeoffs and Synergies of Ecosystem Services Related Statements	1	2	3	4	5
1.	Crop production has increased at the cost of vegetated areas in your locality through the clearing of vegetation cover.					
2.	Firewood and charcoal collection rely on tree cutting in the park and its surroundings.					
3.	Grazing and grass cutting have degraded vegetation cover within the park and its surroundings.					
4.	Vegetation degradation has reduced the water supply for irrigation and domestic use over the past decades.					
5.	Agricultural land has expanded at the expense of vegetated areas.					

Thank You for Your Cooperation

Appendix B: Key informant interview and FGDs guides

1. Do you think the land use and land cover in Maze National Park and the surrounding districts have changed over time? If yes, which land cover types have increased, and which ones have decreased?
2. What do you think the major driving forces of land use land cover changes?
3. Do you think changes in land use land cover have an effect on crop production, forest coverage and water supply?
4. Have you observed changes on the ecosystem services particularly on food production, water supply, raw material, and climate regulation?
5. Have you perceived variation in the amount and duration of rainfall and temperature over time in your locality?
6. Do you think that variability of rainfall and temperature have impact on crop production, vegetation coverage, raw material provision, and water supply?
7. Did the community have any role in conservation activities and decision making in the park?
8. Does the community have access to resources in the park? (Fire wood, charcoal, grazing, grass cutting…)

Appendix C: Socio-economic characteristics of survey participants

Socio-economic characteristics		Frequency	Percentage
Gender	Male	145	65.6
	Female	76	34.4
	Total	221	100
Age	20-40	74	33.48
	41-64	95	42.99
	>64	52	23.53
	Total	221	100
Marital status	Single	8	3.62
	Married	176	79.64
	Widowed	25	11.31
	Divorced	12	5.43
	Total	221	100
Family size	<4	38	17.2
	4-8	114	51.58
	9-12	60	27.15
	>12	9	4.07
	Total	221	100
Educational background	Cannot read and write	107	48.41
	Primary	91	41.18
	Highschool and above	23	10.41
	Total	221	100
Source of income	Crop production	17	7.7
	Livestock rearing	4	1.8
	Firewood and charcoal selling	2	0.9
	Other activities	6	2.7
	Crop production and animal rearing	165	74.7
	Crop production, animal rearing, selling firewood and charcoal, and other activities in combination	27	12.3
	Total	221	100
Duration of the residence(year)	<10	4	1.81
	10-20	5	2.26
	21-30	27	12.22
	>30	185	83.71
	Total	221	100

Appendix D: Satellite images used for LULC and NDVI analysis including 1995 and 2015

Imagery Type	Path/Row	Pixel Size(m)	Bands Used	Acquisition Date	Source
Landsat TM	169/56	30*30	1-5 and 7	01/09/1985	USGS
Landsat TM	169/56	30*30	1-5 and 7	01/20/1995	USGS
Landsat ETM^{+}	169/56	30*30	1-5 and 7	01/24/2005	USGS
Landsat OLI	169/56	30*30	2-7	01/28/2015	USGS
Landsat OLI	169/56	30*30	2-7	12/11/2020	USGS

Appendix E: Accuracy assessment result of the classified images including 1995 and 2015

LULC Classes	Accuracy (%)														
	1985			1995			2005			2015			2020		
	PA	UA	Kappa hat	PA	UA	Kappa hat	PA	UA	Kappa hat	PA	UA	Kappa hat	PA	UA	Kappa hat
Bare Land	88.65	84.82	0.83	96.91	80	0.79	92.47	98.23	0.98	78.74	90	0.90	94.82	94.69	0.94
Built-up Area	55.50	93.22	0.93	100	80	0.8	73.67	96.61	0.97	100	80	0.80	77.59	91.53	0.91
Cropland	70.50	97.33	0.97	100	100	1.00	98.52	89.33	0.88	100	90	0.89	86.81	84.00	0.81
Riverine Forest	84.40	88.98	0.86	100	100	1.00	84.47	80.51	0.77	95.40	100	1.00	87.63	98.81	0.99
Water Body	42.49	86.54	0.86	100	100	1.00	24.09	76.92	0.76	29.98	100	1.00	65.63	76.92	0.77
Wooded Grassland	97.16	88.36	0.73	99.67	96.67	0.92	97.96	95.99	0.90	96.55	93.33	0.86	95.57	91.63	0.80
Burned Area	-	-	-	58.06	100	1.00	-	-	-	100	100	1.00	63.58	94.20	0.94
Overall Accuracy	88.93			96.11			93.03			93.93			91.57		
Kappa Coefficient	0.81			0.94			0.88			0.91			0.86		

Appendix F: Landscape metrics of the land use land cover classes

LULC Classes	Year	NP	PD	LPI	ED
Bare Land	1985	3671	4.0532	0.9517	27.866
	1995	4278	4.7234	2.2768	24.6861
	2005	3155	3.4835	1.1059	29.6146
	2015	4824	5.3263	0.6729	29.2419
	2020	6133	6.7716	0.3601	25.6208
Built-up Area	1985	2434	2.6874	0.0903	9.5655
	1995	8323	9.1896	0.0142	18.9024
	2005	1791	1.9775	0.1245	7.3727
	2015	3655	4.0356	0.0365	11.4634
	2020	2468	2.725	0.1833	9.1607
Cropland	1985	6081	6.7142	1.1077	41.2897
	1995	14193	15.6708	0.1447	55.4888
	2005	8408	9.2835	1.407	46.4007
	2015	18120	20.0067	0.7635	93.9736
	2020	14867	16.415	1.563	85.6917
Riverine forest	1985	1520	1.6783	6.0775	24.2677
	1995	4439	4.9012	3.9808	44.8806
	2005	2115	2.3352	1.3877	29.2741
	2015	5276	5.8254	2.2805	44.4023
	2020	5567	6.1467	1.4265	45.3967
Water Body	1985	3156	3.4846	0.0275	8.5694
	1995	5703	6.2968	0.004	11.9255
	2005	4234	4.6749	0.0039	8.4724
	2015	3091	3.4128	0.0088	7.2256
	2020	1011	1.1163	0.0756	3.9311
Wooded Grassland	1985	3114	3.4382	26.8852	57.6793
	1995	4239	4.6804	45.6993	116.3493
	2005	3231	3.5674	53.2037	54.2
	2015	4311	4.7599	29.2772	97.2876
	2020	4513	4.9829	46.0294	135.1592

Appendix G: Supplementary figures

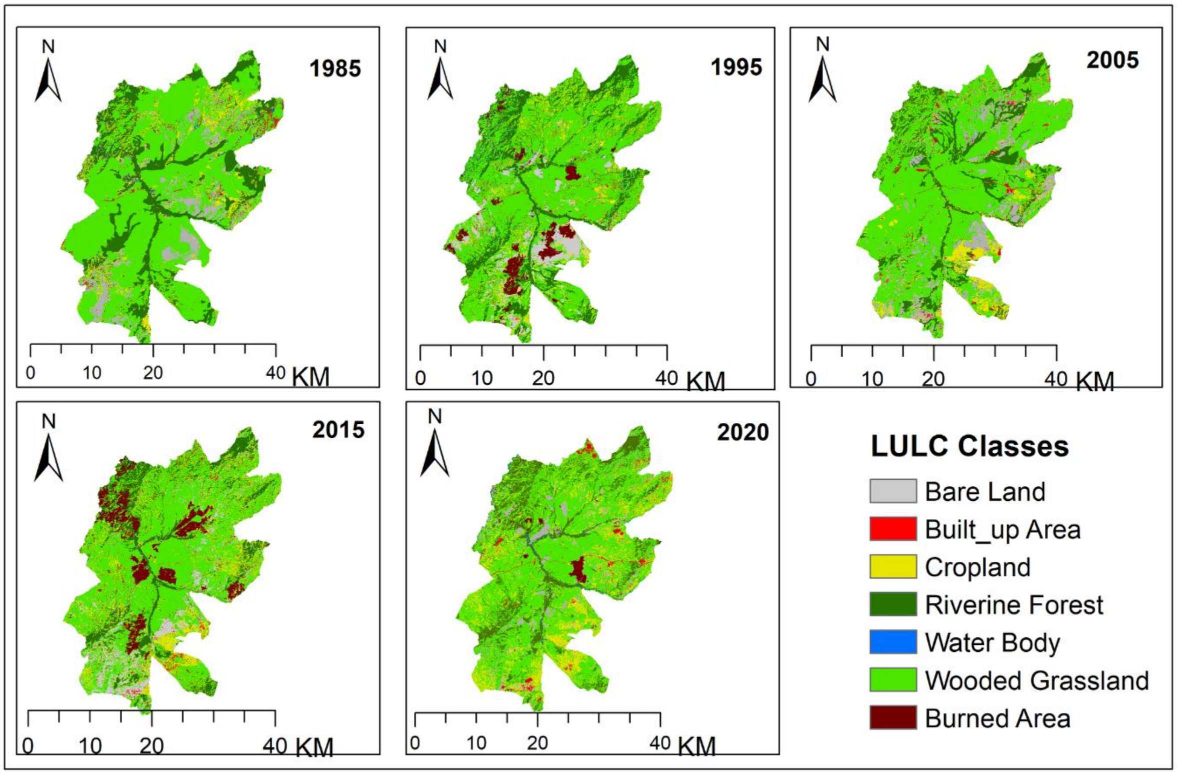

Fig 1: LULC Maps including 1995 and 2015

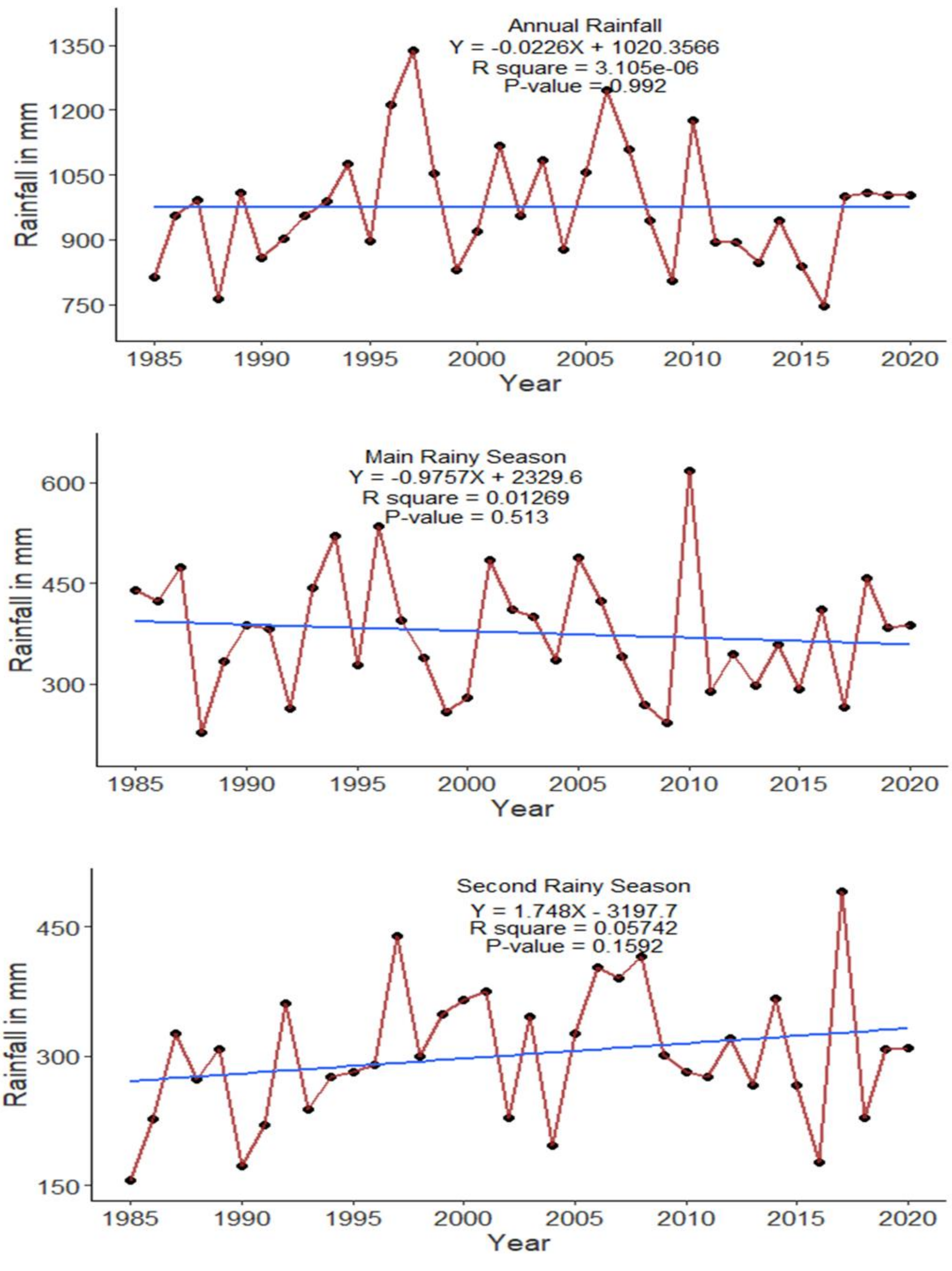

Fig 2: Trends of annual rainfall, main rainy season and second rainy season (1985 – 2020)

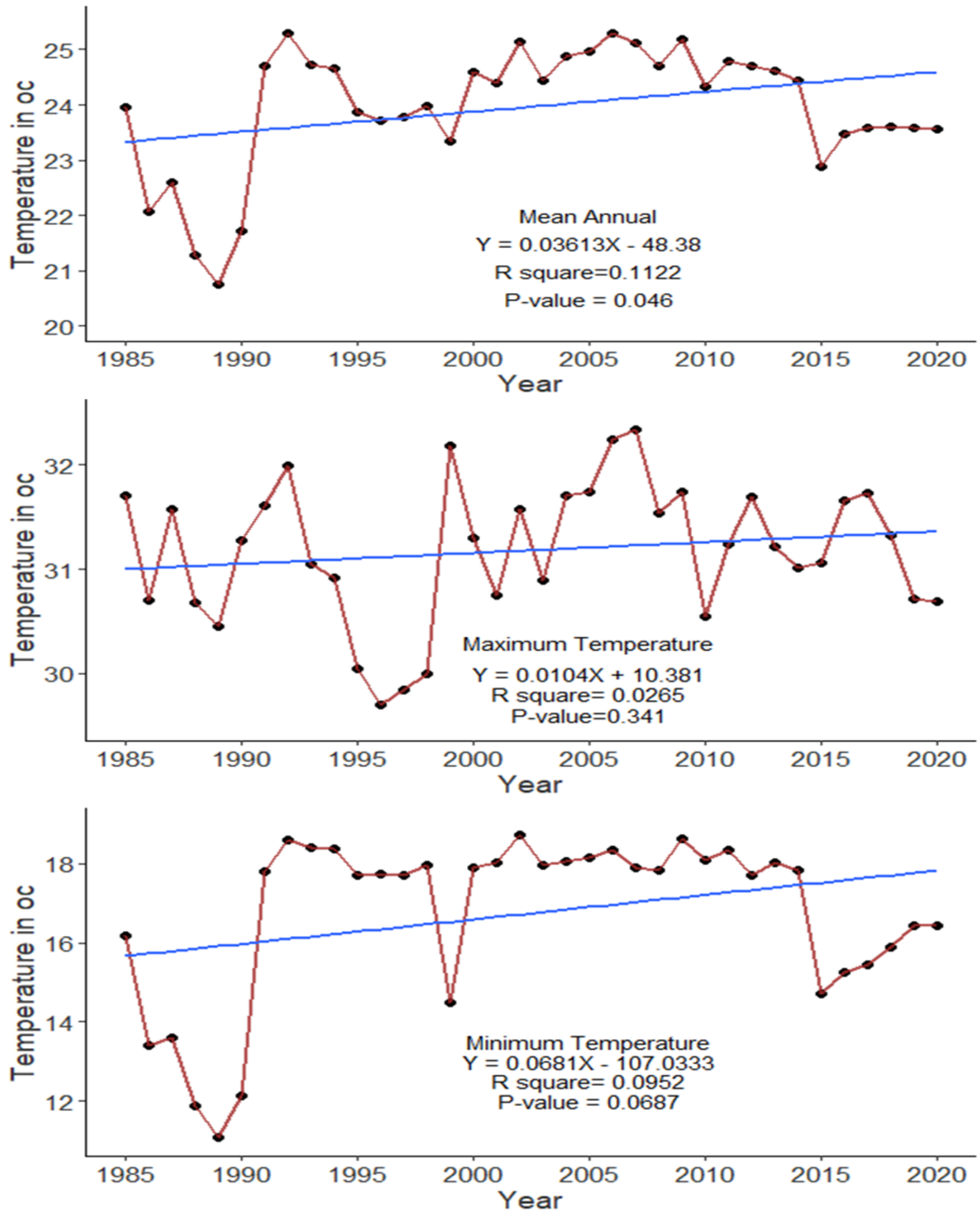

Fig 3: Trends of mean, maximum and minimum temperature (1985- 2020)

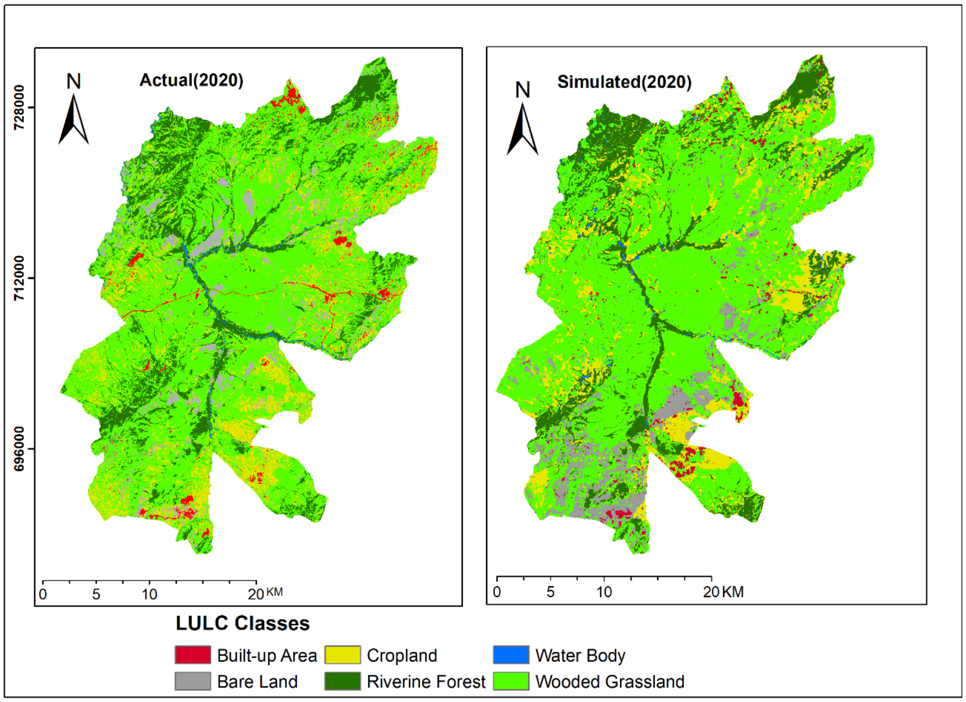

Fig 4: Actual and simulated maps of 2020

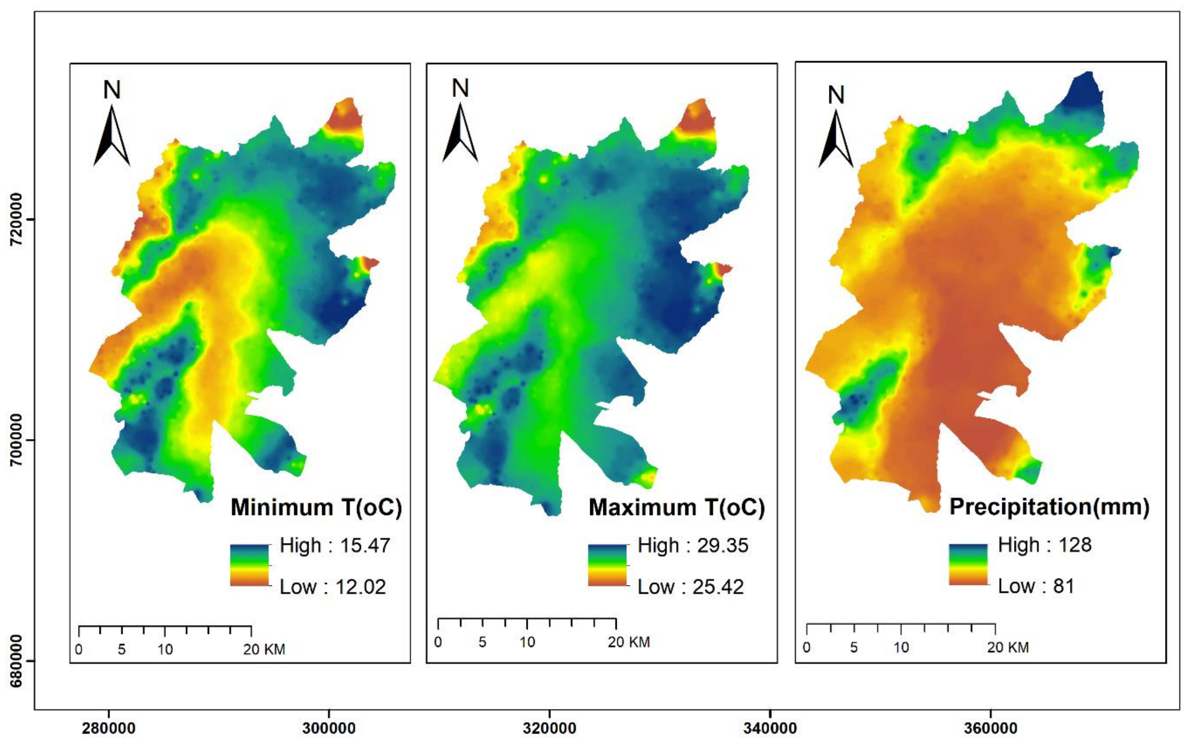

Fig 5: Average monthly maximum, minimum temperature, and precipitation (1970- 2000)