MODELING FOREST FIRE RISK AND ITS EFFECTS ON LIVELIHOODS OF LOCAL COMMUNITY USING GEOSPATIAL TECHNOLOGY: THE CASE OF ARBA GUGU FOREST IN GUNA WOREDA, OROMIA, ETHIOPIA

Mekdes Teshome

Thesis Submitted to the Department of Architecture

College of Civil Engineering and Architecture (CoCEA)

Office of Graduate Studies

Adama Science and Technology University

June, 2025

Adama, Ethiopia

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Under the Supervision of

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Adama, Ethiopia

DECLARATION

I hereby declare that this research thesis entitled "**Modeling Forest Fire Risk and Its Effects on Livelihoods of Local Community Using Geospatial Technology: The Case of Arba Gugu Forest in Guna Woreda, Oromia, Ethiopia.**" is my original work. It has not been submitted to any other university for a similar purpose. All materials used for this thesis have been duly acknowledged through citation.

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RECOMMENDATION

I, the advisor of this thesis, hereby certify that I have read this thesis entitled "**Modeling Forest Fire Risk and Its Effects on Livelihoods of Local Community Using Geospatial Technology: The Case of Arba Gugu Forest in Guna Woreda, Oromia, Ethiopia.**" prepared under my guidance by Mekdes Teshome. Therefore, I recommend the submission to the department following the applicable procedures.

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APPROVAL PAGE OF THE THESIS

I, the advisor of the thesis entitled "**Modeling Forest Fire Risk and Its Effects on Livelihoods of Local Community Using Geospatial Technology: The Case of Arba Gugu Forest in Guna Woreda, Oromia, Ethiopia.**" developed by Mekdes Teshome hereby certify that the recommendation and suggestions made by the board of reviewers are appropriately incorporated into the final version of the thesis.

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We, the undersigned, members of the Board of Reviewers of the thesis by Mekdes Teshome have read and evaluated the thesis entitled "**Modeling Forest Fire Risk and Its Effects on Livelihoods of Local Community Using Geospatial Technology: The Case of Arba Gugu Forest in Guna Woreda, Oromia, Ethiopia.**" and reviewed the candidate during open defense. This is, therefore, to certify that the thesis is accepted.

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ACRONYMS AND ABBREVIATIONS

Acronym/Abbreviation	Full Form
AHP	Analytic Hierarchy Process
CR	Consistency Ratio
CI	Consistency Index
DEM	Digital Elevation Model
EMA	Ethiopian Meteorological Authority
FAO	Food and Agriculture Organization
GIS	Geographic Information System
IDW	Inverse Distance Weighting
MCE	Multi-Criteria Evaluation
MODIS	Moderate Resolution Imaging Spectroradiometer
NIR	Near-Infrared
RI	Random Index
RS	Remote Sensing
SAR	Synthetic Aperture Radar
SRTM	Shuttle Radar Topography Mission
USGS	United States Geological Survey

Abstract

Forests are highly significant ecosystems that provide important environmental, economic, and social benefits. Forest fires, which are caused by natural and human-induced factors, however, are increasingly threatening these resources both at the global and local levels. The aim of the current study was to assess the effects of forest fires on the environment through the geospatial technology based on LULC changes, forest fire hazard modeling, and the socio-economic impacts on the livelihood of the people. Multi-temporal Landsat satellite imagery for the years 1994, 2004, 2014, and 2024, Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM) data, NASA POWER climate data, and national infrastructure data were utilized in the study. Supervised classification was applied for classifying Landsat imagery, and post-classification comparison (image differencing) method was applied for change detection analysis. The correctness of the classification results was verified using accuracy measures like overall accuracy, producer's accuracy, user's accuracy, and the Kappa coefficient. In addition to this, Analytic Hierarchy Process (AHP) was employed in the modeling of forest fire hazard zones in the research area. The results showed that the forest cover reduced by a whopping 58.92% from 1994 to 2024, while agricultural lands increased by 39.52%, and settlement lands increased by more than 4100%. Fire hazard modeling demonstrated that slope areas, high temperature, low humidity, and road and settlement proximity were most prone to forest fires. Socio-economic analysis also revealed significant adverse impacts of the fires on farm productivity, household income, and livelihood. Overall, the study reveals that LULC transitions are rising and forest cover is experiencing widespread degradation owing to agricultural expansion predominantly. The findings of the AHP justify that ignition of forest fire in the research area is the cumulative result of LULC change, climate, and socio-economic activities. To mitigate these effects, the study recommends increased protection of forests and capacity and sensitization development in forest fire prevention in communities.

Keywords: Forest fire, Land use land cover change, Fire Risk Modelling, Analytic Hierarchy Process

CHAPTER ONE

1. INTRODUCTION

1.1.Back ground of the study

Forests provide natural resources, which are instrumental in the conservation of environmental balance. Forests contribute numerous benefits to humankind throughout human history, making humans' lives healthier in numerous ways (Pawar & Rothkar, 2015). Forests intrinsically have ethical, cultural, economic, and environmental value. The benefits of forests can be categorized into three broad categories. First, forests provide direct products like firewood, fodder, food, and other eatables (Fritz-Vietta, 2016). Second, they are of commercial value in terms of such commodities as timber and medicinal substances. Third, forests play a critical role in regulating ecosystems and holding them in position they act as carbon sinks, moderate the climate, preserve soil fertility, avoid soil erosion, and serve as habitations for different species (Gezahegn et al., 2024).

Fire has been a common feature in most ecosystems in the world, from the boreal forests to tropical savannas, and has played a crucial role in maintaining ecosystem health and regeneration (Bowman et al., 2017). Fire is an essential disturbance in most ecosystems that promotes ecological balance and renewal (Bond et al., 2005; Mu et al., 2011; Pausas & Keeley, 2021; Thonicke et al., 2001). A recent worldwide assessment, using both national observations and satellite-based estimates of area burned, documented a overall reduction in the area burned worldwide, falling by some 2% annually between 2003 and 2012 (Chuvieco et al., 2019). It remains challenging to generalize for patterns of forest-fire occurrence due to heterogeneity of spatial and temporal distribution. For example, in certain areas, like Europe and Australia/New Zealand, forest fire statistics between 1996 and 2012 reveal a considerable reduction in area burned, at an annual rate of around 5% (Doerr & Santín, 2016).

Most inhabitants of sub-Saharan Africa depend on agriculture for livelihood, with smallholder farmers producing 75% of the continent's agricultural production, of which the greater part is rain-fed (Gebeyehu et al., 2023). The most frequent natural disaster in Africa is drought, severely affecting rain-fed agriculture. Rural population expansion is forcing communities into unsustainable agriculture, such as deforestation and burning of tropical forests for crop cultivation, agriculture on landslides, expanding into fragile ecosystems, over-cropping, over-grazing, and over-extraction of groundwater resources. These processes led to degradation of nearly two billion hectares, that is, one-sixth of the surface of the earth, by overgrazing and un-sustainable farm cultivation (Habtamu et al., 2017). The major drivers of deforestation are bad forest management, bad land policies, weak forest laws, and the transfer of agriculture to marginal lands (Kouassi et al., 2021).

Ethiopia has high levels of natural resources, water, and biodiversity.

However, the country faces a genuine deforestation issue (Omisore, 2018). The FAO (2010) reported that forest cover in Ethiopia had been 15.11 million hectares in 1990 but fell to 12.2 million hectares in 2010, which corresponds to a 2.65% loss of forest cover between these two years. Ethiopia had lost 140,900 hectares of land annually, or 0.93% of forest cover annually, between 1990 and 2010. Generally, the country lost an estimated 8.6%, or about 2.8 million hectares, of its forest cover during this period (Keenan et al., 2015), although forest cover has been rising moderately in recent years. Forest fires have been causing a lot of damage to wide areas of forests across numerous parts of Ethiopia annually.

Notwithstanding the regularity of destructive forest fires, there is no overall data on the causes, risk, and nature of the damage resulting from forest fires (Gemechu et al., 2016). During the last two decades, a single significant fire took place in the Bale Mountain National Park (BMNP) in the year 2000, burning 90,000 hectares of the forest. This was one among a history of devastating forest fires in the nation. The Arba Gugu region has also endured constant forest fires for decades, leading to extensive destruction of the forest cover.

1.2.Statement of the problem

Wildfires are a catastrophic environmental risk worldwide, as they impact biodiversity, soil, water resources, and human health. Wildfires are among the primary drivers of deforestation worldwide, resulting in habitat loss, species displacement, and additional emissions of carbon (IPCC, 2021). Wildfires burn out entire ecosystems, alter the soil type, and pollute water, impacting terrestrial and aquatic life (Bowman et al., 2017). Besides ecological loss, forest fires also bring about socioeconomic impacts by influencing agriculture, forestry, and local economies based on the forest.

The African forest fires are particularly worrying since the continent relies on the forests to induce biodiversity, climate, and livelihood for human species (FAO, 2015; Köhl et al., 2015). The African tropical forest ecosystems, such as in the Congo Basin, are experiencing acute fire risks originating from natural sources as well as anthropogenic sources such as deforestation for agriculture. These fires burn productive plants and animals, additional soil erosion, and interference with the water cycle, thus impacting agricultural production and food security within the area (Omuto et al., 2020). Forest fires are always on the increase as an issue in Ethiopia, particularly where forest cover is concentrated like in the parts of Oromia and Southern Nations, Nationalities, and Peoples'. Ethiopian forest fires cause loss of nutrients in soils, reduction in water holding capacity, and erosion and impact adjacent agricultural land and bodies of water (Gebrehiwot et al., 2019; Tesfaye & Melese, 2018).

Successful management of forest fire relies on robust modeling techniques to assess risk, spread, and impact. Statistically, across the world, statistical models, machine learning, and remote sensing are conducted on a large scale. Statistical models rely on historical data for prediction of fire occurrence, while machine learning algorithms, like decision trees and neural networks, analyze environmental and climatic factors in order to identify fire-zones (Jain et al., 2020). Remote sensing sensors like MODIS and Landsat enable instantaneous tracking of fires and burn severity mapping (Roy et al., 2019). GIS and remote sensing are being used more and more to assess fire hazard in Ethiopia, but data and methodology limitations restrict successful forecasting and management (Gebrehiwot et al., 2019).

Though the Arba Gugu forest is of ecological and social importance, no localized fire impacts have been comprehensively studied there. Most studies in Ethiopia assess large-scale patterns, ignoring localized environmental conditions (Tesfaye & Melese, 2018). It constrains the ability of the authorities to formulate fire risk management in Guna Woreda because biodiversity, soil, and water impacts are not adequately understood. This study seeks to bridge these gaps by investigating the impacts of forest fires in Arba Gugu and developing specific predictive models to inform conservation and management responses.

1.3. Objectives of the study

1.3.1. General objectives of the study

The main objective of this study is to assess and model forest fire risk and analyze its effects on the livelihoods of local communities using geospatial techniques the case of Arba Gugu forest in Guna Woreda, Oromia, Ethiopia.

1.3.2. Specific objectives

The specific objectives of the study are:

- To assess land cover and land use changes over the past three decades (1994-2024) in the Arba Gugu forest caused by forest fires
- To develop a spatial model for fire occurrence using Analytic Hierarchy Process (AHP) and spatial overlay analysis in the Arba Gugu Forest.
- To investigate the impacts of forest fires on local communities' livelihood in the study area.

1.4. Research Questions

- What are the land cover and land use changes that have occurred in the Arba Gugu Forest between 1994 and 2024 due to forest fires?
- How can a spatial model for forest fire occurrence be developed for the Arba Gugu Forest using the Analytic Hierarchy Process (AHP) and spatial overlay analysis?
- What are the impacts of forest fires on the livelihoods of local communities in the Arba Gugu Forest area?

1.5. Significance of the study

The significance of this study lies in the fact that it has the potential to improve forest fire management and prevention measures within the Arba Gugu forest. With the remote sensing tools, the study develops a spatial model for fire detection and mapping, which gives vital information regarding the locations and patterns of fires. This information is valuable for governments, as well as fire management agencies, so that they can implement more effective prevention policies and targeted responses to mitigate the impacts of future fires.

In addition, the examination of land cover and land use changes as a result of forest fires within the research provides a better understanding of the manner in which forest fires alter land use trends in the area. This knowledge is essential in informed land use planning as well as developing sustainable land management with a view to ensuring that the impacts of forest fires are incorporated in policy and planning approaches in the future. Another key aspect of the research is evaluating the effects of forest fires on vegetation health and recovery. By analyzing vegetation change and observing recovery patterns, the research aids in the formulation of effective rehabilitation and restoration schemes. This not only helps in the recovery of the forest ecosystem but also ensures that biodiversity and overall environmental health are maintained.

The study also investigates the impact of environmental factors, such as elevation, slope, and proximity to human settlements, on fire occurrence. An understanding of such relationships guides the identification of dominant variables that contribute to fire vulnerability, making it possible to develop measures aimed at mitigating the effects of these variables and enhancing the resilience of the forest against future occurrence of fires. Besides, empirical findings of this research are applicable to guide regional and national forest management, fire prevention, as well as climate change adaptation policy-making. By providing empirical evidence and insights, the study improves evidence-based policy-making as well as enriches the environmental protection and sustainable development paradigm.

1.6.Scope and delimitation of the study

Its emphasis is on analyzing forest fire occurrences and their environmental impacts in the particular case of Arba Gugu forest in Guna Woreda, Oromia Regional State, Ethiopia. It involves the use of remote sensing data and spatial modeling techniques in fire occurrence mapping, land cover and land use change detection, and vegetation health and regeneration analysis over a given time period. The study is confined within this geographical area and relies upon available satellite imagery and environmental data to identify spatial relationships. The constraints include the aspects of specific fire impacts and the limitations imposed by data quality and methodological tools available, which may influence the comprehensiveness of the investigation.

1.7.Organization of the thesis

This thesis is organized into five main chapters, each addressing key aspects of the study on the effects of forest fires on the surrounding environment in the case of Arba Gugu Forest, Oromia Regional State, Ethiopia, using geospatial technology. Chapter 1 introduces the research problem by providing background information on forest fires and their environmental impacts. The chapter highlights the importance of geospatial technology in assessing and monitoring the effects of forest fires. It presents the specific objectives of the study, the research questions, and the scope of the research.

Chapter 2 reviews the existing literature on forest fires and their environmental consequences, with a focus on the use of geospatial technologies (such as remote sensing, GIS, and spatial analysis) in monitoring and assessing these effects. The review covers global, regional, and local perspectives on forest fires, their impact on vegetation, soil, water resources, and biodiversity. It also discusses the role of technology in fire management and disaster response, highlighting relevant studies from Ethiopia and similar ecosystems.

Chapter 3 describes the research design and methodology used in the study. It outlines the geospatial technology tools and techniques, such as remote sensing (satellite imagery) and GIS, used to assess the environmental effects of forest fires. The data collection methods and sources are detailed, including satellite data, aerial photographs, and other geospatial datasets.

Chapter 4 presents the results of the study, based on the analysis of geospatial data. The findings are discussed in detail, with visual representations such as maps, graphs, and tables to illustrate the effects of the forest fires on the environment of Arba Gugu Forest. The analysis covers the impact on vegetation cover, soil quality, water resources, and biodiversity. The results are compared with previous studies and are discussed in the context of the broader environmental and ecological implications.

Chapter 5 summarizes the key findings of the study, providing an overview of the main environmental effects of forest fires on Arba Gugu Forest. It presents conclusions drawn from the research, reflecting on the significance of the findings for forest management and environmental conservation in the region. Recommendations for mitigating fire impacts, improving forest management strategies, and utilizing geospatial technology for ongoing monitoring are provided.

CHAPTER TWO

2. REVIEW OF THE RELATED LITERATURE

2.1.Trends of forest cover change and definition and concepts of forest fire.

2.1.1. Definition and concepts of forest fire.

Various authors have proposed varying definitions for forest fires. Forest fire is a complex phenomenon emerging out of a mixture of regimes of land management, human activities, cultural traditions, along with climatic and meteorological circumstances, according to a report published by the Joint Research Centre in collaboration with other Directorate Generals of the European Commission (WWF, 2017). Climate change influences forest fires both directly, by altering weather conditions that cause and spread fires, and indirectly, through the changing vegetation cover and fuel loads. As mentioned in this report and other studies, weather-driven forest fires have been widespread in most European countries, the USA, Canada, and other North American nations.

Research on forest fire causes and effects indicates that while forest fires are a natural part of many ecosystems, that is not so for all forests. For cold or dry habitats, where duff decomposition is slow and humus accumulates with the help of microorganisms in the soil, forest fires are essential to provide nutrients for future tree generations. Certain species of trees, such as the North American lodgepole pine or California sequoia trees, require fire heat for activating the opening of cones and seed dispersal for young tree generations (Karavani et al., 2018; Wang et al., 2022). Forest fires refer to unwanted and/or unpredictable fires in vegetation, according to the definition provided by FAO (2010). The report then adds that forest fires can also include management-started fires beyond the planned limits in the fire plan, which require enormous response efforts.

2.1.2. Trends of forest cover change: Global and Ethiopia perspectives.

In 2015, the worldwide forest cover was close to 4 billion hectares (Kassie et al., 2010; Kohler, 2013; Kohlin, 2007). While forest cover has declined in the last 25 years, the net rate of forest loss reduced by 50% between the 1990–2000 and 2010–2015 periods. Forest cover transformed from 15.11 million hectares in 1990 to 12.5 million hectares in 2015. Natural forests make up 93% of the total forest area, or about 3.7 billion hectares. Even though over 105 million hectares of forest have been gained through afforestation since 1990, the rate of planting has decelerated since 2010, mainly due to reduced afforestation in regions such as Eastern Asia, Europe, North America, and South and Southeast Asia (Karjalainen et al., 2003).

Ethiopian forest cover has been experiencing severe changes due to the effects of agricultural expansion, settlement growth, forest fire, fuelwood and charcoal needs, logging, poor governance, and policy and land tenure system issues. These have resulted in the serious decline of forest cover, particularly in tropical regions such as Ethiopia, although other factors may also play a role (Bewket, 2012). A century ago, roughly 40% of Ethiopia's land surface was covered in forest. Today, however, forests cover fewer than 3% of the country's land surface (Siraj et al., 2018; Tadesse et al., 2018). The management of forests in Ethiopia over the past 50 years has been a key driver of alteration of the country's forest status, broadly affecting forest resources in a negative manner through restricting local communities' access and use rights (Hailu et al., 2020; Siraj et al., 2018).

During the imperial era (1941–1974), the forest land was regarded as wasteland and was allocated for commercial and small-scale farming to build the economy. During this period, 100,000 hectares of forestland were given to royal elites, military officers, and other dignitaries for conversion into cropland (Ayana et al., 2013). The Socialist-Derg regime (1975–1991) initiated a new land reform policy with the motto of "land to the tillers," which increased the migration and resettlement of landless people, creating further pressure on virgin forests. Under the current federal government (1995–present), forest management has been transferred to federal and regional administrative bodies (Gedefaw & Soromessa, 2015; Mohammed & Inoue, 2013). It was also in this period that participatory forest management, through which the local community is encouraged to get involved, was initiated. However, especially with the change of government from the Socialist-Derg to the current government, large areas of forestland were devastated due to frustration with earlier forest policies, confusion over ownership rights, and misconceptions among the local communities.

2.1.3. Causes of forest fire: Global and Ethiopian perspectives

Forest fires can be categorized based on their cause into two broad categories: natural and manmade (Wang et al., 2022). Manmade forest fires are again divided into intentional and accidental causes. Natural forest fires are most likely caused by lightning, heat generated by dry forest material due to strong winds, stone impacts during earthquakes, volcanic activity, and other geological processes (Xue et al., 2022). Out of the earth's surface, naturally occurring forest fires affect only about 4%, such as by lightning. While naturally occurring forest fires exist, the majority are triggered by a combination of human activity, fuel, weather, and climate. Natural forest fires are mainly found in temperate forests and are dominated by some weather patterns, climate, and vegetation cover (Bradstock et al., 2014).

Natural wildfires in tropical and sub-tropical forests are mostly triggered by hot weather and extreme climatic weather, often where there are extensive savanna regions with the inclusion of wind throughout summer months (Köhl et al., 2015). Natural wildfires, however, are found to be relatively small compared to man-induced natural wildfires (Gezahegn et al., 2024). As the above comments have noted, human activity causes the majority of forest fires. FAO (2010) statistics on forest fire show that human activity accounts for the majority of fire incidents. The report establishes that at least 80% of the forest fires in the world are as a result of human activities, with other regions being 99% of human-made fires.

Incendiarism or intentional fires in the forest are often started to promote the growth of fodder or edible grasses (Megersa, 2017). Some of the other motives for which fires are deliberately started are their use for hunting, improvement of pastures, early or back burning to reduce fuel and the risk of wildfires, firebreaks, arson, and even smoking out bees during wild honey harvesting, among others, together with usage for cooking, disposal of rubbish, and carelessness, for example, discarding lighted cigarettes (Ager et al., 2015; Pausas & Keeley, 2021). Uncontrolled forest fires typically occur when Africa, Asia, and other smallholder farmers lacking machinery land preparation resources and equipment use fire to clear land.

These land-clearing fires can grow rapidly beyond the cleared land and become wildfires and be a significant contributor to forest fire in recent times. Further, whenever the pastoralists use fire to clear ranchland by killing unwanted species and nasty pasture grasses for animals, the fire might spread to adjacent forests, causing much damage. Pastureland burning is a common method used in the majority of African countries (Bernués et al., 2011). Similar to global trends, the majority of forest fires in Ethiopia are caused by human activities.

Human actions contribute to almost 100% of the country's forest fires, as suggested by other scholars. Forest fires are sometimes set deliberately in some regions for different reasons, including clearing land to get rid of wild animals' habitat, causing the germination of new grasses for grazing, cutting disease vectors for humans and animals, honey harvesting, charcoal production for money, or generating money for the poor rural communities. In addition, fires are sometimes lit for the purpose of cooking, especially in regions where herders, farmers, and hunters cook outside during dry weather (Peacock & Sherman, 2010).

2.1.4. Consequences of forest fire: Global and Ethiopian perspectives.

Comprehensive, consistent, and reliable data on the worldwide distribution and expansion of forest fires do not exist, and it is hard to determine whether the burned area or the number of fire events is increasing (Chuvieco et al., 2019; Giglio et al., 2006). While the intensity of wildfires is region- and year-specific, statistical estimates suggest that some 350 million hectares of forest worldwide are affected by wildfires every year (Shvidenko et al., 2011). In the USA, for instance, almost 4 million hectares of forest were burned in 2006, marking one of the worst fire seasons in decades. An identical catastrophe happened in Australia in 2003, at the time of an acute and extended drought (Grégoire et al., 2013).

In Africa, research indicated that the continent accounted for 64% of the global area burned by wildfires during the year 2000, when 230 million hectares were burnt, equivalent to 7.7% of the entire land surface of the continent (FAO, 2005). Some of the countries frequently affected by forest fires are northern Angola, the southern Democratic Republic of Congo, southern Sudan, and the Central African Republic (FAO, 2006). Although there is no authentic information on the total extent and type of damage caused by forest fires in Ethiopia, the country has lost significant economic and biological resources. For example, a fire in early 1984 destroyed an estimated 308,198 hectares of forest. The worst wildfire event in Ethiopia's 21st century occurred in March 2000, when Afromontane forests were ravaged by fires, particularly in the Oromia Regional State, with damage to 95,000 hectares of forest land. The 2008 fire also threatened the Afromontane forests, consuming approximately 11,947 hectares, which was the second worst forest fire in the Bale Mountain National Park (BMNP) (Megersa, 2017).

2.1.5. Impacts of forest fire on major biophysical environment functioning and services.

Forest fires penetrate and extend deeply into the biophysical environment, having impacts on land use, land cover, biodiversity, weather (short term), climate, and forest ecosystems (Emiru et al., 2018). Their impacts are not only environmental but also have serious impacts on human health, particularly where the fires are extensive and intensive, and have different impacts on ecosystems and biodiversity (Ryan, 2018). For example, Southeast Asian Forest fires have caused economic losses worth $4 billion, and 20 million inhabitants in the region experience respiratory disorders due to smoke and contaminants (Nghiem et al., 2013).

Biomass combustion, the most significant part of wildfires, emits greenhouse gases (GHG), leading to climate change. Biomass combustion contributes 32% of global carbon monoxide, 10% of methane, and more than 86% of soot. Wildfires make a significant contribution to the world's carbon dioxide emissions, with savannah and forest fires emitting between 1.7 billion and 4.1 billion tons of CO_2 yearly. Apart from that, about 39 million tons of methane (CH_4), 20.7 million tons of nitrogen oxides (NO_x), and 3.5 million tons of sulfur dioxide (SO_2) are released each year. Forest fires contribute to 15% of global GHG emissions, much of which comes from fire-induced land conversion of rainforests in the tropics. The fires also disrupt the hydrological cycle (WWF, 2017).

In addition to the climate and environmental impacts, forest fires have long-term influences on wildlife in forests, vertebrates, and invertebrates (Gowlett, 2016). Some of these species are involved in ecological processes such as litter decomposition and soil formation. Habitat loss, home area loss, shelter, and food loss are some indirect consequences of forest fires that may lead to wildlife displacement. This consequently results in species extinction, particularly territorial birds and mammals (Bonada & Resh, 2013).

2.2.Empirical Literature

Forest fires penetrate and spread far into an environment biophysically, impacting land cover, land use, biodiversity, weather (short term), climate, and forest ecosystems (Emiru et al., 2018). These impacts not only exert a physical effect on the environment but also impact human health considerably, particularly where the fires are intensive and extensive in size, and influence ecosystems and biodiversity differently (Ryan, 2018). For example, Southeast Asian wildfires have caused economic losses worth $4 billion, and 20 million residents of the region are afflicted by respiratory diseases due to smoke and pollutants (Nghiem et al., 2013).

Biomass burning, the most significant aspect of wildfires, emits greenhouse gases (GHG) leading to global warming. Biomass burning supplies 32% of the world's carbon monoxide, 10% of methane, and more than 86% of soot. Wildfires significantly contribute to global carbon dioxide emissions since savannah and forest fires emit between 1.7 and 4.1 billion tons of CO_2 every year. Besides that, 39 million tons of methane (CH_4), 20.7 million tons of nitrogen oxides (NO_x), and 3.5 million tons of sulfur dioxide (SO_2) are released each year. Forest fires contribute 15% of GHG emissions globally, predominantly due to fire-induced land conversion of rainforests. The fires also disrupt the hydrological cycle (WWF, 2017).

Beyond the climate and environmental impacts, long-term forest fire effects on forest wildlife, vertebrates, and invertebrates have been established (Gowlett, 2016). Some of these affected species are involved in ecological processes such as litter decomposition and soil formation. Habitat loss, home range loss, shelter, and food loss are some of the indirect consequences of forest fire that can lead to wildlife displacement. This eventually leads to species extinction, particularly territorial birds and mammals (Bonada & Resh, 2013).

2.3.Conceptual Framework

Forest fires are the results of several interdependent factors. Depending on its causative factor, forest fires have been classified as natural and manmade based on its cause. Though nature initiates forest fire in some countries, human-induced causes form the major causes mainly in Ethiopian context. The anthropogenic causes of forest fire have been further divided into proximate and root/underlying causes. The direct causes are a rise from human direct action on behalf of something willingly, and the second is unwilling for nothing, e.g., irresponsible smoker. While the root/cutting causes/motivations are indirect causes of forest fire. For example, farmer's will to extinguish fire on behalf of more land to cultivate and to harvest honey. It is that choice that gets included in different factors such as economic/livelihood status, government policy/management strategy, settlement and road proximity to forest cover, weather condition, socio-cultural setting where a community is based. Thus, human immediate action because of economic causes, negligence, myths prevailing in the society, forest policy which is incompatible to the real scenario might cause forest fire. This flame subsequently, negatively affect forest resource, wildlife, shift in biodiversity, decrease in availability of water, soil erosion/flooding, siltation in the downstream areas etc.

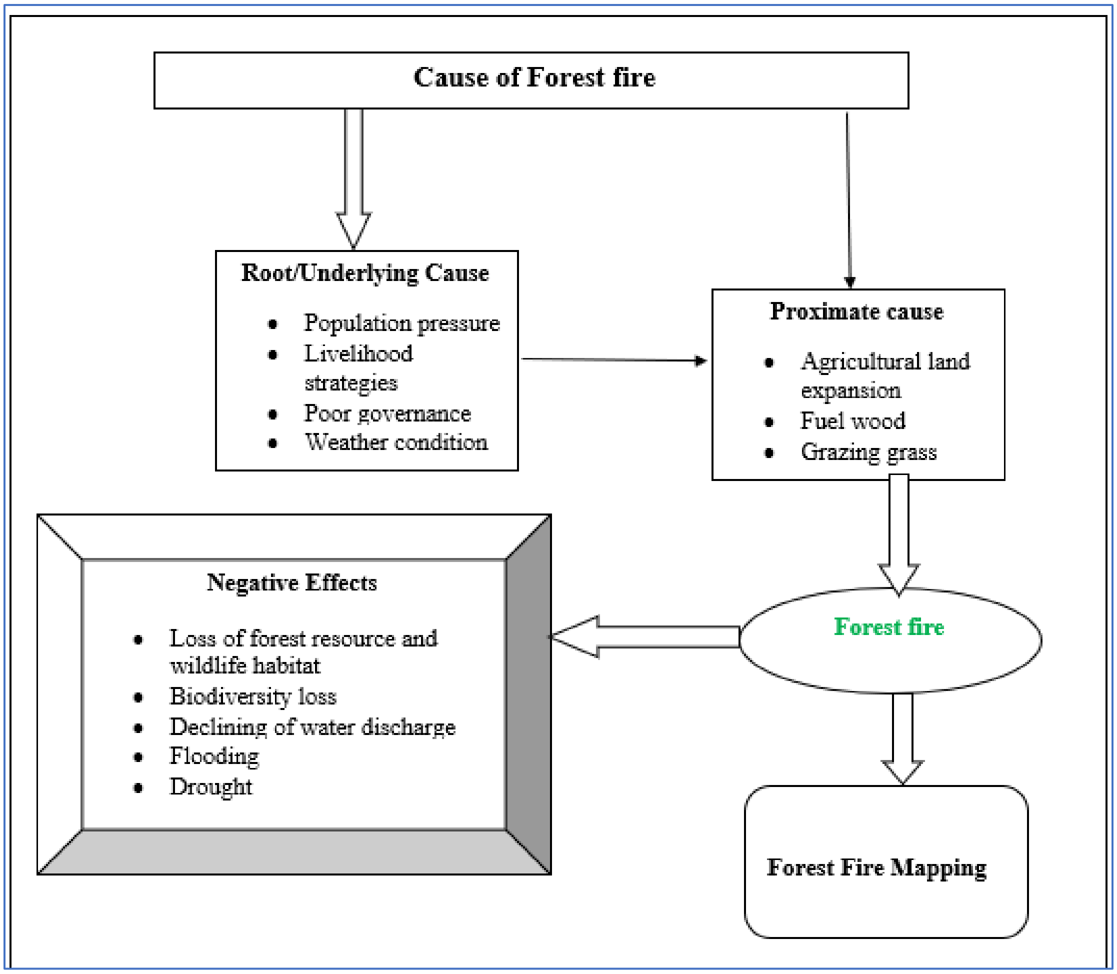

Figure 2-1: Conceptual framework

CHAPTER THREE

3. RESEARCH METHODOLOGY

3.1.Study area description

This study was conducted in Guna Woreda in the Arsi Zone of the Oromia National Regional State of Ethiopia. The woreda geographically falls under latitudes 8°10′42″N and 8°27′10″N, and longitudes 39°45′36″E and 40°06′34″E. In the north, it is bordered by North Merti Woreda, to the south-by-South Chole Woreda, in the east by Aseko Woreda, and to the west by Jeju Woreda. Guna Woreda is located in the highlands of southeastern Ethiopia, approximately 224 kilometers from the capital city of Addis Ababa and 133 kilometers east of Asalla, which is the capital of the Arsi Zone. Figure 3-1 below illustrates the study area indicating its significant geography and location.

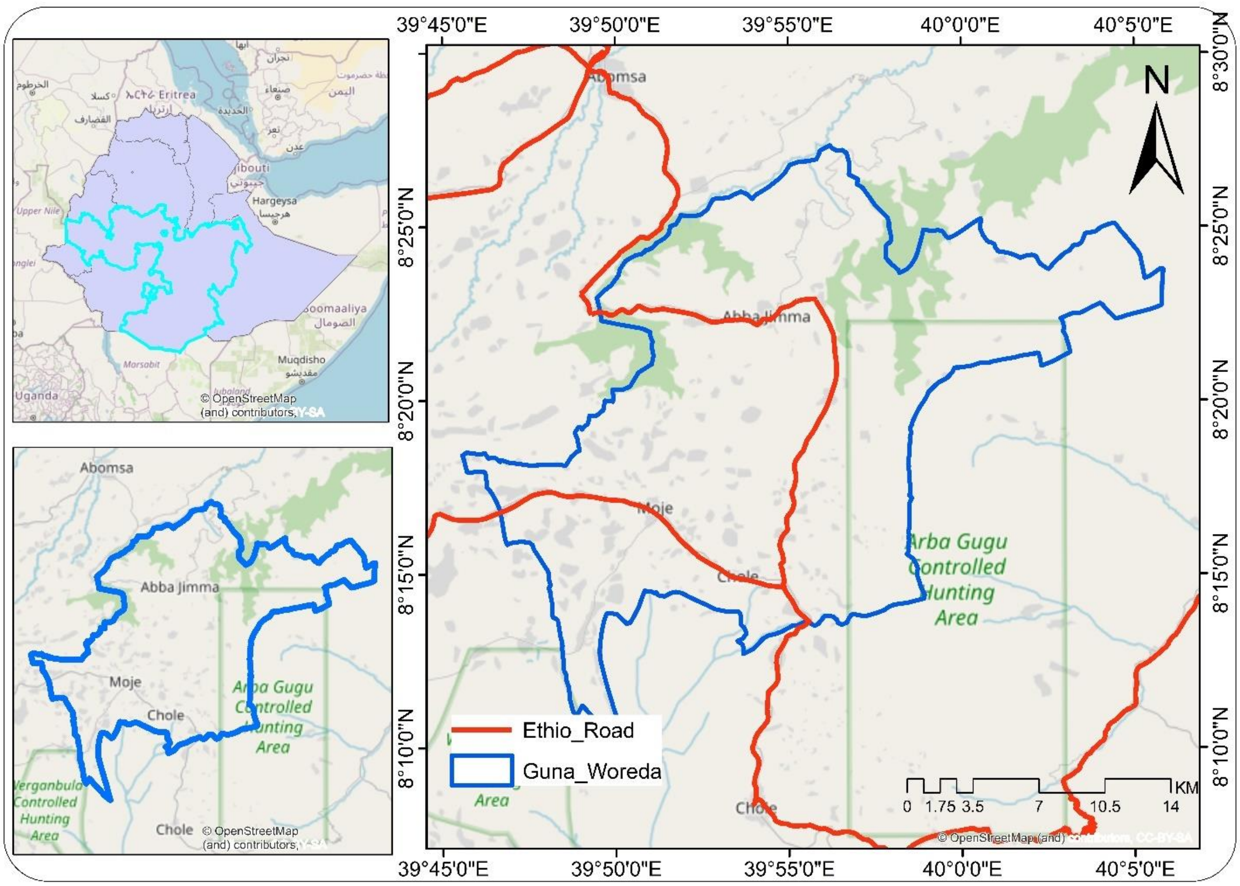

Figure 3-1: Location map of the study area

3.2. Research approach

A mixed-methods design was used in the study, integrating both quantitative and qualitative approaches in investigating the spatial and socio-economic impacts of forest fires in the Arba Gugu forest. The quantitative component involved the use of remote sensing and GIS techniques to map the extent and severity of forest fires based on satellite imagery such as Landsat and Sentinel data. Fire indices, such as the Normalized Burn Ratio (NBR), were used to identify fire severity. Past climate data, including temperature, humidity, and precipitation, were collected to analyze the effects of climate variability on forest fires. Land cover and vegetation study were also conducted by comparing pre-fire and post-fire land cover maps. The qualitative component involved interviews and focus group discussions with environmental experts, forest management authorities, and local communities to gather data on the socio-economic impacts of forest fires and local adaptation strategies.

3.3. Research design

An explanatory research design was employed in the study to investigate the relationships between certain environmental and socio-economic factors and the occurrence of forest fires. The approach was founded upon an investigation of the underlying causes of forest fires by examining the interlinkages among parameters such as climate change, land use change, and vegetation cover. Through this approach, the study aimed to explain how these parameters resulted in forest fire occurrence, spread, and intensity in the Arba Gugu forest. Moreover, the research simulated these relationships in order to explain the impacts of forest fires on the environment and the surrounding communities.

3.4. Software

In this research, various software packages were utilized to achieve collective analysis and results. Spatial analysis, mapping, and visualization of land cover change in the Arba Gugu Forest were performed using ArcGIS. Satellite image processing to analyze land use and land cover change over time was performed by Google Earth Engine (GEE). Microsoft Excel sorted out data, performed initial calculations, and conducted simple Analytic Hierarchy Process (AHP) pairwise comparisons to support fire risk modeling.

Table 3-1: Software to be used in this research

Software	Purpose
ArcGIS	For spatial analysis, mapping, and visualization of land cover changes.
Google Earth Engine (GEE)	To process satellite imagery for analyzing land use and land cover changes over time.
Microsoft Excel	For organizing data, preliminary calculations, and performing simple AHP pairwise comparisons.

3.5.Data source and types

3.5.1. Topography

Topographic data was downloaded from the USGS SRTM (Shuttle Radar Topography Mission) site, where it was provided as Digital Elevation Model (DEM) data at a spatial resolution of 30 meters. The DEM data at high resolution were employed to generate high-detail models of the study area terrain. It was specifically utilized to derive important topographic features, including elevation, slope, and aspect, that played a crucial role in fire dynamics.

3.5.2. Land Use and Land Cover

Land use and land cover (LULC) mapping was done using Landsat data to study the status and change in land use of the study area. The analysis was intended to understand how the land use changes and land cover changes influenced forest fire incidence in the region. To enable this analysis, the Landsat data were downloaded from the USGS website—from the Landsat 5 MSS, Landsat 7 ETM+, and Landsat 8 OLI sensors for the years 1994, 2004, 2014, and 2024, respectively. Each dataset provided valuable information about the land cover characteristics of the area at these times. LULC map generated was essential in identifying land conversion trends such as deforestation, urbanization, and agricultural expansion and assessing their possible impact on fire risk.

Table 3-2: Satellite data types, sources and date of acquisitions for land use land cover mapping and analysis

Sensor	Path/Row	Spatial Resolution	Spectral resolution	Year	Source	Acquisition date
Landsat 5 MSS	168/054	30m	7 bands	1994	www.glovis.gov	30-Jan-94
Landsat 7 ETM+	168/054	30m	7 bands	2004	www.glovis.gov	10-Feb-04
Landsat ETM+	168/054	30m	7 bands	2014	www.glovis.gov	15-Jan-14
Landsat OLI	168/054	30m	11 bands	2024	www.glovis.gov	8-Feb-24

3.5.3. Climate data

Climate data, including precipitation, temperature, wind speed, wind direction, and humidity, were obtained from the NASA Prediction of Worldwide Energy Resources (POWER) data archive. These parameters were integral in the interpretation of environmental conditions that dictated the occurrence, behavior, and risk of forest fires in the study area. Climatic information was critical in identifying trends and correlations between atmospheric conditions and fire incidence, providing a foundation for modeling fire risk. The precipitation data were utilized to establish vegetation and soil moisture levels, which directly influenced susceptibility to fires. Temperature readings played a critical role in determining how heat and aridity affected fire ignition and spread. Wind speed and direction were the most important parameters in modeling fire behavior because they determined how quickly and in which direction a fire would spread. Humidity, as a measure of airborne moisture, affected fire spread by influencing the flammability of fuels and vegetation. Table 3-3 specifies the climate data types, spatial resolution, temporal resolution, and their sources. Infrastructure data

Table 3-3: Climate data types and sources to be used for this research work

Climate data type	Spatial Resolution	Temporal Resolution	File format	Source
Precipitation	5km	Monthly and Annual	CSV	POWER | DAV (nasa.gov)
Temperature	5km	Monthly and Annual	CSV	POWER | DAV (nasa.gov)
Wind Direction	5km	Monthly and Annual	CSV	POWER | DAV (nasa.gov)
Wind Speed	5km	Monthly and Annual	CSV	POWER | DAV (nasa.gov)
Humidity	5km	Monthly and Annual	CSV	POWER | DAV (nasa.gov)

3.5.4. Infrastructure data

Infrastructure played a crucial role in the determination of the probability and distribution of forest fires as human activity was often the cause of ignition or had developed the conditions enhancing fire risk. Roads, power lines, settlements, and agriculture were the most significant infrastructure components in this research. They had the role of leading to the occurrence of fire outbreaks either through direct ignition or by rendering the areas prone to easy fire spread. The infrastructure data were included in the fire risk modeling in order to analyze the effect of the proximity of the features on the likelihood of fire occurrences in the study area. Road networks were significant in fire risk because they opened the forest areas to human activities that had the potential to accidentally or deliberately result in land clearing using fire, for instance, vehicle exhaust, discarded cigarettes, or even arson.

In this study, the closeness of the forest areas to major roads was analyzed in order to determine how human access impacted fire risk. Power lines posed another key threat since they could cause fires due to electrical faults or when lines were damaged, particularly under windy conditions. Cartography of power line positions and analysis of their proximity to woodland regions helped assess how much they contributed to the outbreak of fires. Human settlements near woodlands increased the risk of fire through household activities, construction of buildings, and land clearing activities.

These settlements introduced additional sources of ignition, either from within the community itself or from contact with the adjacent agricultural lands. The proximity of the settlements to woodland zones was plotted to examine the relationship between human activity and fire occurrence. Farm infrastructure, such as farms and related facilities, also helped increase fire hazard, especially when farmers used practices like slash-and-burn agriculture or burned crop residues. These activities would readily extend to the surrounding forests if not properly managed, and therefore it is essential to access their contribution to fire hazard.

Table 3-4: Infrastructure data type and source

Infrastructure data type	Data type	Data format	Data source
Road	Line	Shapefile	Ethiopian Geospatial Institute
Settlement	Polygon	Shapefile	Extracted from Land Use Land Cover Maps
Agricultural activities	Polygon	Shapefile	Extracted from Land Use Land Cover Maps

3.6.Data pre-processing

Preprocessing was a very critical step in preparing the datasets for successful fire risk modeling. It ensured that all of the data, both topography, land use/land cover (LULC), climate, and infrastructure data, were cleaned, normalized, and formatted for usage in a geographic information system (GIS) environment.

The topographical data, derived from the USGS Shuttle Radar Topography Mission (SRTM) with a 30-meter spatial resolution, were acquired by a process of extracting necessary terrain attributes.

The Digital Elevation Model (DEM) was first clipped to the study area boundary to eliminate redundant data. Elevation, slope, and aspect, as influential factors, were extracted from the DEM. Slope and aspect play a significant role in fire dynamics when modeling the spread of fires across the landscape. These were derived through the use of spatial functions in GIS software like ArcGIS or QGIS. The DEM was also resampled to the same spatial resolution as the other datasets so that they would integrate well during the analysis.

LULC data were obtained from Landsat imagery for the years 1994, 2004, 2014, and 2024. Images were first taken through atmospheric correction to remove distortions caused by atmospheric conditions, with the help of tools such as the Fast Line-of-sight Atmospheric Analysis of Hypercubes (FLAASH). Atmospherically corrected images were then clipped to the study area. Supervised classification was conducted in order to classify different land cover types into forest, agriculture, and settlements. This was done by training the classifiers using reference samples to identify each land use type accurately. Change detection analysis was conducted between different years after classification to determine how land cover change, i.e., agricultural expansion or deforestation, influenced fire risks. The LULC maps thus acquired were rasterized and resampled to the DEM and infrastructure data resolution. For climate data, precipitation, temperature, wind speed, wind direction, and humidity variables were acquired from NASA POWER with a 5-kilometer spatial resolution.

Since the resolution of the above was coarser compared to the other data, spatial interpolation techniques like Kriging or Inverse Distance Weighting (IDW) were applied to generate finer-resolution surfaces. This put the climate data in spatial harmony with the other layers, particularly the DEM and LULC data. The climate data, which were given in monthly and yearly time scales, were also aggregated temporally as needed for seasonal fire danger modeling. The data were clipped to the study area, converted to raster layers, and prepared to import into the GIS environment. Infrastructural information, including roads, power lines, settlements, and farming activities, was obtained in vector format as shapefiles.

Roads and power lines were provided as line shapefiles, while settlements and fields were polygon shapefiles. The datasets were clipped to the study area and rasterized for conformity with the other layers. Distance maps of roads and power lines were generated using the spatial analysis functions to ascertain proximity to woodland areas, an important factor in fire risk mapping. Similarly, the closeness of agricultural activities and settlements to areas of fire hazard was established because such human activities either served as ignition sources or created conditions that heightened fire risks. After preprocessing all of the datasets, they were all resampled to the same spatial resolution and coordinate reference system (CRS) for compatibility.

This allowed stacking of the different data layers in the GIS environment for analysis. All of the datasets were also verified to be complete and accurate, with no gaps or inconsistencies in the data that would affect the final modeling results. This comprehensive preprocessing approach constituted the basis of a precise and dependable fire risk model, embedding the various spatial and environmental drivers of fire occurrence and spread in the study area.

3.7.Data processing

Following the preprocessing of the datasets, the data processing stage with the objective of integrating, analyzing, and extracting meaningful information to model fire risks in the study region. The stage comprised some critical steps: reclassification, spatial analysis, and statistical modeling, which all worked together to develop an elaborate fire risk map.

The first step in the data processing stage was the reclassification of the various data layers. For the topography data, both aspect and slope were reclassed into classes of varying fire hazard levels. For example, steeper slopes would accelerate fire spread rate, so the slope classes were reclassed into low, moderate, and high fire hazard zones. Aspect (slope facing direction) was reclassed as well since sun-facing slopes (i.e., slopes that face south in the Northern Hemisphere) dried faster, which increased fire hazard. Elevation was reclassed based on vegetation types and their flammability at different elevations. The reclassed layers were used as the basis for creating how terrain influences fire hazard.

Second, the LULC data were recoded to rank land cover categories according to their different susceptibilities to fires. Forest cover, for example, was assigned greater values of fire-risk due to their high fuel content, whereas urban land and waterbodies were assigned lower risk values. The year-specific LULC data after reclassification (1994, 2004, 2014, and 2024) were then analyzed to detect land cover changes over time; e.g., deforestation or cultivation expansion—that could have exacerbated fire threats. Change detection analysis was employed to detect land conversion patterns related to an increase in fire frequency or severity.

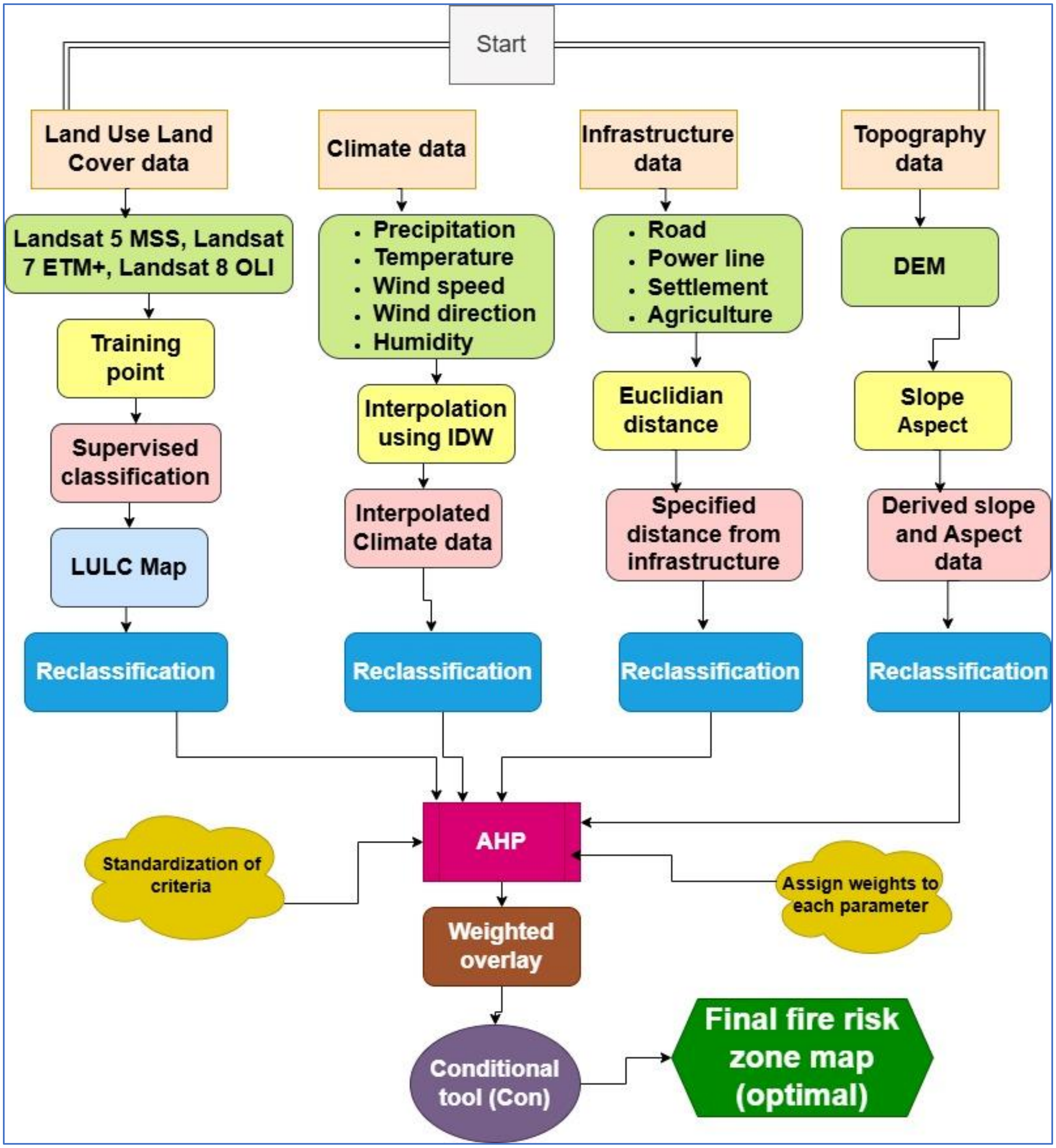

Figure 3-2: Methodological flowchart

Climate variables including precipitation, temperature, wind speed, wind direction, and humidity were interpolated using Inverse Distance Weighting (IDW) for spatial analysis and Euclidean distance to measure proximity to the significant fire-prone areas. IDW generated continuous surfaces for all climate variables, which allowed for the identification of spatial patterns such as dry spots, hot spots, and areas with strong wind speeds across the study area. These climatic factors were subsequently analyzed for Euclidean distance so as to establish their closeness to critical infrastructure, roadways, power lines, and settlements; so that it would be possible to study how climatic factors influenced the incidence and spread of fire against human activities and land use changes.

The infrastructure information was analyzed spatially to establish nearness to roadways, power lines, habitations, and agriculture land since these influence ignitions. Distances between every element of the infrastructure and forest areas were calculated using buffer analysis, and fire-risk values based on proximity were determined. Roadside or power line proximity was scored high in risk due to the potential for accidental ignition, whereas along agricultural fields, where slash-and-burning might occur, were also given high risk values.

Once all individual data layers (topography, LULC, climate, and infrastructure) were reclassified and processed, they were subsequently merged using a multi-criteria decision analysis (MCDA) protocol. The method assigned weightings to each factor (e.g., slope, land cover, wind speed) based on their relative influence on fire risk, as derived from expert opinion and statistical modeling. For example, wind speed and temperature as climatic parameters were given higher weights when it was fire season, and slope was focused on when it came to steep slopes. Finally, the weighted layers were overlayed to produce a composite fire danger map.

3.7.1. Selection of criteria for each parameter

Criteria selection for fire risk modeling in this study is supported by a broad set of environmental and infrastructural parameters with a direct relation to forest fire occurrence and spread. The criteria are carefully selected from established studies to make the model complete and representative of real fire risks in Arba Gugu forest.

Land Cover and Land Use (LULC) is also a critical parameter to describe fire risk since different covers have differential fuel potential for fire. Closed broad-leaved forests that are heavily vegetated qualify as very high risk due to their broad fuel load and sensitivity to being burned, followed by open forest and grasslands. Parajuli et al. (2020) take this categorization on loan and demonstrate the influence of vegetation types on fire dynamics.

Fire behavior is also affected by elevation since cooler temperatures and higher humidity are likely to dominate at higher elevations, thus being less hazardous for fires. 1800m to 3000m is a medium to high-risk zone due to certain ecological conditions that are still likely to promote the spread of fire. This, as Gai et al. (2011) explained, demonstrated the role of elevation in contributing to fire hazard.

Slope is another important parameter of fire risk modeling. Steeper slopes enable fires to move faster upwards due to the larger angle of slope. Slopes greater than 35% are considered highly risky areas as increased slope steepness promotes fire movement. This criterion bases its findings on Abedi Gheshlaghi (2019), whose study highlighted the relationship between slope and fire spreading.

Table 3-5: Criteria for fire risk modeling

Parameter	Very high	High	Medium	Low	Very low	Reference
Land use	Broad-leaved closed forest	Broad-leaved open forest	Grassland	open forest	Grassland, Shrubland,	(Parajuli et al., 2020)
Elevation (m)	>3000m	2500-3000m	1800-2500m	1000-1500m	<1000m	(Gai et al., 2011)
Slope (%)	>35	25-35	15-25	5-15%	<5	(Abedi Gheshlaghi, 2019)
Aspect (direction)	S	SE and E	NE	N	W, NW, SW, and Flat	(Parajuli et al., 2020)
Humidity (g/kg)	15-20	10-15	8-10	5-8	<5	(Tien Bui et al., 2017)
Temperature (Celsius)	>31	28-31	27-29	25-27	<25	(Eugenio et al., 2016)
Wind speed (m/s)	10-15	8-10	5-8	3-5	<3	(Zhao et al., 2021)
Wind direction (degree)	110-120	100-110	95-100	90-95	<90	(Tien Bui et al., 2017)
Proximity to road	0-300m	300-500m	5000-1km	1km-1.5km	>2km	(Solomon, 2019
Distance from settlement	0-500m	500-1km	1km-2km	2km-3km	>5km	(Abebe, 2010)

Aspect (direction) defines the direction of land in relation to the sun and wind, which defines how much the area can dry out or stay wet. Slopes south-facing, experiencing greater sunlight and hence drier, are said to be more at risk to fire, and slopes north-facing and plains areas are given lower risk classes. The aspect ranking, as per Parajuli et al. (2020), considers the effect of sun exposure on the likelihood of fire to occur.

Humidity is a key climatic parameter as lower humidity increases the susceptibility of igniting and spreading fires. Humidity values between 15-20 g/kg are classified under very high risk since dry air favors the flammability of fuel. The terminology has been borrowed from Tien Bui et al. (2017), which also reflects the role of moisture content in fire hazard.

Temperature is also crucial in determining fire risk, and areas with temperatures of over 31°C are extremely high risk. High heat dries out vegetation, and the heat can easily trigger ignition. Temperature risk levels are classified based on Eugenio et al. (2016), which underscores how heat increases the risk of fire.

Wind direction is also a significant climatic parameter in fire modeling since it defines the fire front's speed and direction of propagation. Higher wind speeds, especially 10-15 m/s, are in very high risk since they can easily spread flames and spread the fire front. The parameter borrows from Zhao et al. (2021), which analyzed how wind speed affects fire behavior.

Wind direction is also vital in determining fire danger. There are certain wind directions, say 110-120 degrees, that have high potentials of escalating fire danger by driving the fire into open spaces. The classification of wind direction is borrowed from Tien Bui et al. (2017), who studied how wind directions influence fire behavior.

Proximity to roads is a key infrastructural factor, considering that roads introduce human access to potential causes of accidental fires, such as those from the exhaust of cars or discarded cigarette ends. Road proximity zones of 300m are viewed as being very high risk because these are more vulnerable to human-initiated fires. This is based on Solomon (2019), illustrating the impact of human access on fire hazard.

Closeness to settlements also influences fire danger since settlements are usually sources of ignition depending on local activities, urbanization, and deforestation activities. Forest regions within 500m from settlements are ranked as very high risk due to proximity to human activities increasing the likelihood of starting fires and fire spread. This is as argued by Abebe (2010), which emphasizes the influence of humans on fire danger.

3.7.2. Standardization of criteria

Standardization of criteria within fire risk modeling is a process of ensuring that different input data that may be in different units and scales are transformed to a common measurement scale. Standardization allows for the integration of different data sources and types into a comparable format for conducting meaningful analysis and assessment. In this research, the various input datasets like land use, elevation, slope, aspect, humidity, temperature, wind speed, and wind direction were normalized to allow their comparison and incorporation in the fire risk modeling process.

To start the standardization process, each of the input datasets was converted into a raster form. Raster data is a grid-based representation commonly used in Geographic Information Systems (GIS) and remote sensing applications and thus is susceptible to spatial analysis. The pixels of every parameter dataset were then classified into distinct fire risk zone classes after being in raster form. These classes typically ranged from Very high to Very low, indicating different levels of fire risk. After classification, a common range of values was assigned to each class to represent the degree of fire risk. For instance, Very high risk may be equal to 5 and High risk to 4, and so on. The standardized values provide a common scale for all the criteria, and hence, the various datasets become integrable and comparable in the process of fire risk modeling.

Standardization of the parameters is required since it unites the multiple forms and units of data to enable the creation of composite fire risk maps or models that are capable of considering more than a single factor simultaneously. The standardized system enables one to easily identify areas bearing the maximum and minimum risk of catching fire, which helps decision-makers and stakeholders in implementing targeted measures for fire prevention and management. It also enhances the reproducibility and transparency of the modeling process, as others can easily understand and replicate the standardized approach and scale.

3.7.3. Weighing of criteria

Weighing of criteria in overlay analysis is a procedure in which relative importance is assigned to each criterion to enable stronger and better-informed decision-making in complex issues like fire risk modeling. In this study, the Analytic Hierarchy Process (AHP) method, founded by Saaty in 1977, was applied to calculate the significance of each criterion. This method relies on a pair-wise comparison matrix, where each criterion is systematically compared with all other criteria in the study. What is particularly useful in AHP is that it manages to measure the relative significance of one criterion over another on a well-established scale.

The importance values of pair-wise comparison matrix are computed according to a nine-point scale ranging from 1 (equal importance) to 9 (extreme importance). The other values on the scale, viz., 3, 5, 7, and 9, represent various degrees of importance, where 9 indicates that one criterion is much more important than the other. The scale also includes intermediate numbers like 2, 4, 6, and 8 to capture nuances of importance. Apart from this, the reciprocal property ensures balanced and consistent comparisons. Consistency Ratio (CR)

Table 3-6:Analyticalal hierarchical process (AHP) criteria importance

Importance score	Definition
1	Equal importance of i and j
3	Weak importance of i over j
5	Strong importance of i over j
7	Very strong importance of i over j
9	Extreme importance of i over j
2,4,6,8	Intermediate values between i and j
Reciprocal of the above	If criterion i has one of the above non-zero numbers assigned to it when compared with criterion j, then j has the reciprocal value when compared with i

Source: Saaty, (1977)

3.7.4. Consistency Ratio (CR)

In order to prevent bias in criteria weighting, consistency ratio was used as a tool for ensuring coherent comparisons. Consistency ratio is a general measure of goodness of the comparative judgments in making decision matrices in the AHP. It was estimated as the ratio of consistency index (CI) and random consistency index (RI). The RI is random index of consistency of a randomly generated pair-wise comparison matrix. Consistency ratio is a decision aid to consider whether an AHP is acceptable for decision making or not (Saaty 1999). Analytic Hierarchy Process (AHP)

$$CI = \frac{(\lambda max - n)}{(n-1)}$$

$$CR = \frac{CI}{RI}$$

Where; n=number of items being compared

λmax = the largest eigen value

CI = consistency index

CR = consistency ratio

3.7.5. Analytic Hierarchy Process (AHP)

Spatial model used for suitability analysis was developed in ArcGIS (version 10.8). In spatial model; format conversion, reclassification and final weighted overlay analysis were performed. Various factors (elevation, slope, aspect, wind speed, land use, wind direction, temperature and humidity) were combined to demarcate forest fire risk zone. In the final weighted overlay analysis, each criterion was weighted by importance value of it, which shows influence of the criteria in the overall fire risk zone modelling.

$$S = \sum_{i=1}^{n} (Wi \ x \ CI)$$

Where; S = over all suitability, Wi= weight of each criterion, CI = consistency index.

3.8.Methods for Qualitative Data Collection

3.8.1. Sampling Technique

For the qualitative aspect of the research, purposive sampling was employed in selecting participants for both Key Informant Interviews (KIIs) and Focus Group Discussions (FGDs). Participants were selected based on their knowledgeability, experience, and direct exposure to the consequences of forest fires in order to get rich and relevant information.

3.8.2. Sample Size

A single Focus Group Discussions (FGDs) session was conducted with 6–10 members of elders, farmers, women, and youth representatives of vulnerable kebeles. Ten Key Informant Interviews (KIIs) were also held with individuals such as local leaders, development agents, forestry experts, kebele administrators, and disaster management office representatives.

3.8.3. Themes for Discussion

The discussions and interviews were guided by a set of thematic areas intended to explore the complex impacts of forest fires on local livelihoods. These themes are shown in the table below:

Table 3-7: Themes for discussion

No.	Themes for Discussion	Description
1	Livelihood activities	Main sources of income and how forest fires have affected them
2	Forest resource dependence	Role of forest products (fuelwood, grazing, etc.) in daily life
3	Perceived causes of forest fires	Community beliefs on what causes forest fires
4	Coping and adaptation strategies	How households and communities respond and adapt to forest fire impacts
5	Institutional support and interventions	Availability and effectiveness of government or NGO support
6	Community participation in fire prevention	Local roles in managing and preventing forest fires
7	Environmental and social consequences	Perceived long-term effects on natural resources and community well-being

3.9.Ethical consideration

Ethical considerations were closely followed throughout the study in order to safeguard the rights, dignity, and safety of all the respondents. Informed verbal consent was obtained prior to data collection after providing a clear description of the purpose, benefits, and voluntary participation. Confidentiality and anonymity were assured to participants, and no personal identifiers were revealed or documented. Local norms, values, and culture were honored in discussions and interviews, and care was taken to avoid psychological, social, or physical harm.

CHAPTER FOUR

4. RESULT AND DESCUSSION

4.1.Introduction

This chapter explains and presents the results of the study in relation to all the research objectives. Three specific objectives were addressed in order to achieve the general research objective. The first was the analysis of the Land Use and Land Cover (LULC) dynamics for thirty years (1994–2024) change in the Arba Gugu region. Second, the forest fire risk zones in the study site were simulated using the Analytic Hierarchy Process (AHP) relative to various factors of influence. Third, the socio-economic impacts of forest fires on the communities living around the Arba Gugu forest particularly on agricultural production and livelihood were assessed. Assessment of land use land cover (LULC) changes within the Arba Gugu forest

4.2.Assessment of land use land cover (LULC) changes in the Arba Gugu forest

4.2.1.1.LULC in 1994

There were five dominant land use land cover (LULC) classes which were described in this study: Forest, Agriculture, Settlement, Shrubland, and Grassland (Figure 4-1). The greatest land cover in 1994 was Agriculture, measuring 25,875.09 hectares or 55.08% of the entire area. Forest cover came next as it occupied 12,528.81 hectares or 26.67% of the study area (Table 4-1). Agricultural land was dense in the south and the central part of the region, where agricultural land use was most intensive. The north part and the eastern edge of the study region were dominated by forestland. The north part with mountainous topography was dominated by forestland with high ecological and environmental values. Settlement areas were extremely rare in 1994, and only 8.46 hectares (0.02%) were recorded as settlement land.

4.2.2. LULC in 2004

Agriculture had increased significantly and become the dominant land cover in the study area by the year 2004. Agricultural land cover increased from 25,875.09 hectares (55.08%) in 1994 to 32,752.08 hectares (69.72%), showing large-scale agricultural intensification (Table 4-1).

It was observed particularly in the northern region, formerly occupied by shrubland and forest, and along the eastern edge of the study area where degraded land was evident (Figure 4-2). The cover of the forest lost a great deal of ground during this period, dropping from 12,528.81 hectares

(26.67%) to 11,161.89 hectares (23.76%) from 1994 to 2004. This amounts to a loss of 1,366.92 hectares, a net drop of approximately 2.91% of the area it stood for. The same goes for shrubland as it was hit by a spectacular drop, from 6,844.23 hectares (14.57%) to 715.95 hectares (1.52%). Grassland, on the other hand, saw a modest increase from 1,717.38 hectares (3.66%) to 2,308.77 hectares (4.91%). Settled areas also increased progressively, from 8.46 hectares in 1994 to 35.28 hectares in 2004.

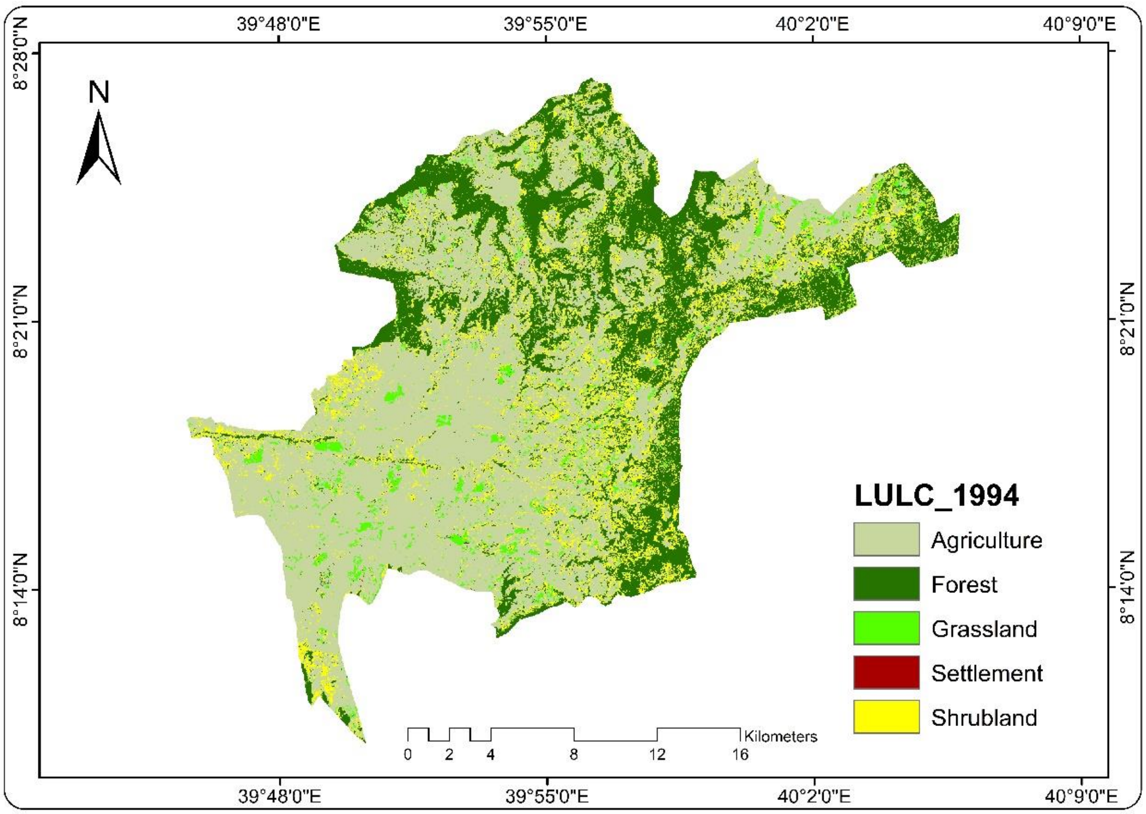

Figure 4-1: LULC map of the study area for the year 1994

4.2.1. LULC in 2014

Even in 2014, agricultural spread continued to rise, with agricultural land further increasing to 35,400.33 hectares (75.36%).

This is an additional addition of 2,648.25 hectares in 2004. Agricultural expansion was still enabling significant land cover change, mainly the further loss of forest cover.

As forest cover declined significantly to 8,294.4 hectares (17.66%), losing 2,867.49 hectares (a reduction of 6.10% from 2004) (Table 4-1). Forest degradation was particularly evident around the mountainous regions, where the trees had retreated towards the summit and upper slopes. Areas at the base of the mountains, which were forested in 1994 as well as 2004, had largely been cleared and converted into cultivated land in 2014. The eastern part of the study region also experienced tremendous change (Figure 4-3). Areas initially covered by forest and shrubland were mostly converted to grassland, representing further land cover transition. Shrubland remained fairly stable compared to 2004, going up slightly from 715.95 hectares to 731.25 hectares (1.56%). Grassland also went up slightly, representing 2,507.78 hectares (5.34%). Settlement areas went up moderately to 40.21 hectares (0.09%), which showed gradual urban expansion. By 2014, towns such as Moye, Efo, and Aseko had emerged as growing settlement centers, contributing to the growth of built-up areas.

Table 4-1: LULC area coverage and percentage share for the years 1994, 2004, 2014 and 2024

		1994		2004		2014		2024	
S/N	Class	Area	%	Area	%	Area	%	Area	%
1	Forest	12528.81	26.67	11161.89	23.76	8294.4	17.66	5147.37	10.96
2	Agriculture	25875.09	55.08	32752.08	69.72	35400.33	75.36	36102.06	76.86
3	Settlement	8.46	0.02	35.28	0.08	40.21	0.09	356.94	0.76
4	Shrubland	6844.23	14.57	715.95	1.52	731.25	1.56	2177.01	4.63
5	Grassland	1717.38	3.66	2308.77	4.91	2507.78	5.34	3190.59	6.79
	Total	46973.97	100	46973.97	100	46973.97	100	46973.97	100

4.2.2. LULC in 2024

By 2024, arable land was the biggest land use category in the research area, covering 36,102.06 hectares (76.86%).

Though agriculture continued to increase, the rate of growth decelerated compared to previous decades by an increase of 701.73 hectares since 2014 (Table 4-1).

Forest cover continued further critical decline, going down to 5,147.37 hectares (10.96%). This represents an area loss of 3,147.03 ha, or approximately 6.7% loss from 2014. The north mountainous areas, which heretofore had been under the cover of dense forests, were still on the decline due to continued agricultural encroachment since 1994 (Figure 4-4). As of 2024, almost all of the forest cover in the east half of the study area had disappeared, with only scattered remnants along the northeastern boundary. These formerly forested areas are now significantly converted to agricultural land, with patches of limited grassland here and there. Shrubland remarkably noted a considerable recovery in 2024 to 2,177.01 hectares (4.63%), a turn around from the continuous decline which had been constantly observed from 1994 to 2014. Grassland also grew continuously, to 3,190.59 hectares (6.79%), the maximum coverage observed during the research period. Settlement areas recorded a major increase, from 40.21 hectares in 2014 to 356.94 hectares (0.76%) in 2024. The good growth is a sign of the quick growth of Abajema Town, and the growth and development of other future towns such as Moye, Efo, and Aseko. The increment in settlement area between 2024 is much greater compared to the past, reflecting increased urbanization and infrastructure development in the region.

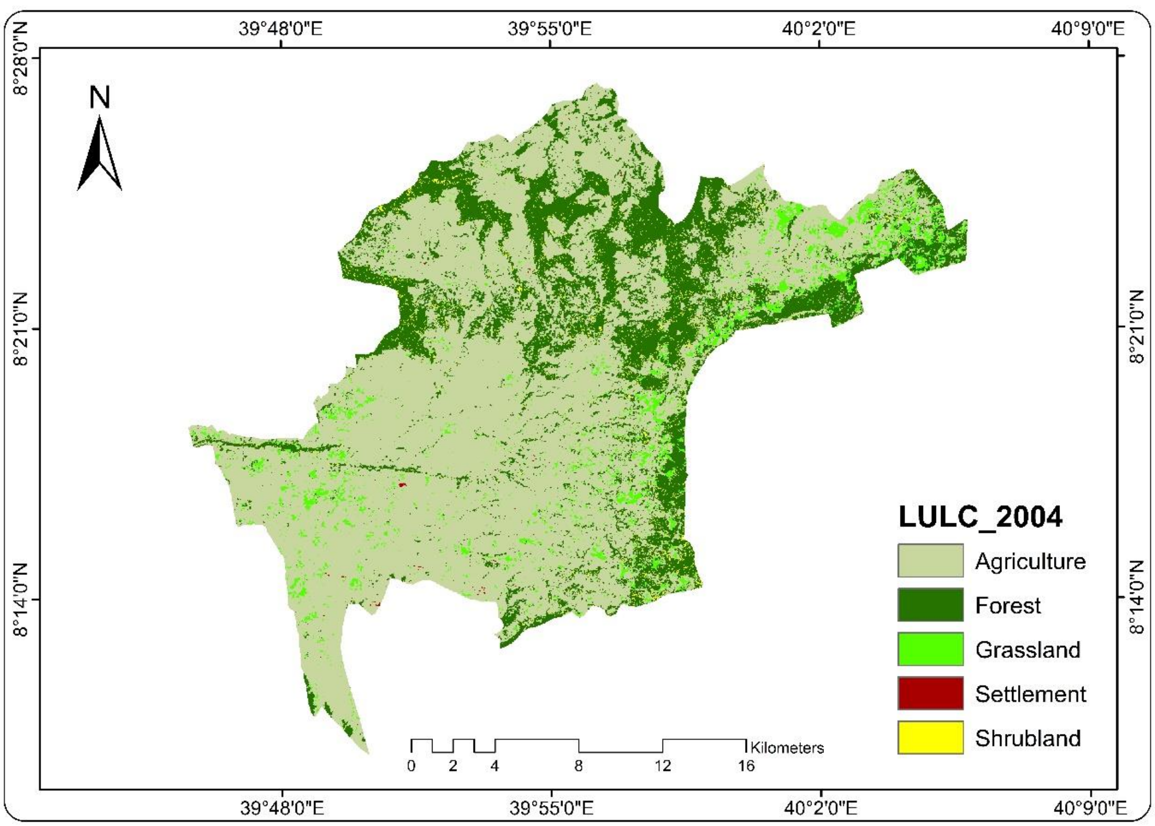

Figure 4-2: LULC map of the study area for the year 2004

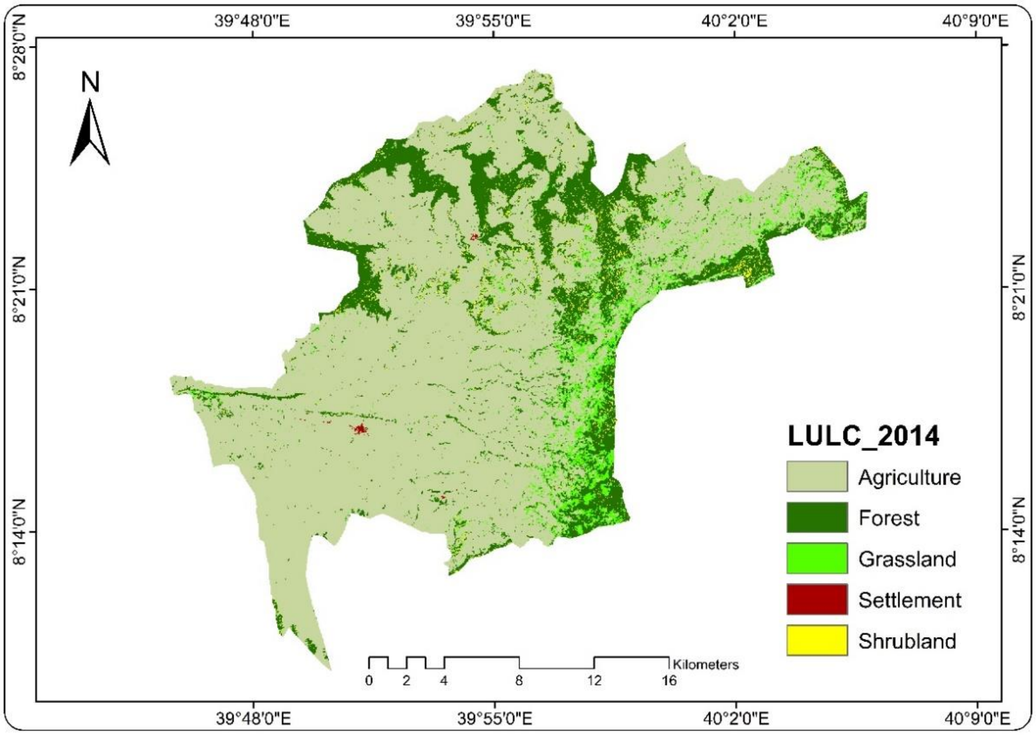

Figure 4-3: LULC map of the study area for the year 2014

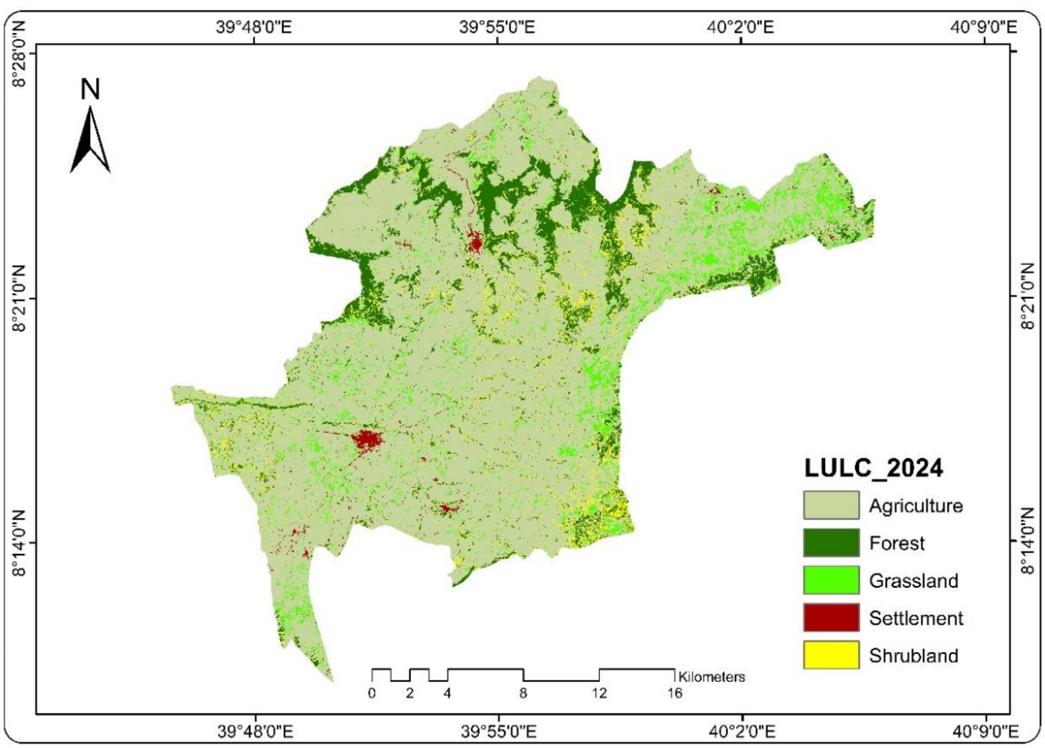

Figure 4-4: LULC map of the study area for the year 2024

4.3.Rate of Change of Land Use Land Cover (LULC)

The change analysis for the past three decades (1994–2024) shows an impressive fluctuation in land use and land cover (LULC) trends in the study area, characterized by agricultural expansion, forest degradation, and urbanization. Forest cover, in the study duration, has been experiencing a consistent and dramatic decline. Between 1994 and 2004, forest cover decreased by 10.91%, followed by a steeper fall by 25.69% from 2004 to 2014 (Table 4-2). The loss from 2014 to 2024 was the greatest at 37.94%. Forest cover decreased by 58.92% during the entire period of 1994 to 2024, indicating extensive deforestation. This long-term loss is due primarily to agricultural encroachment and forest harvesting for agricultural purposes and settlement.

Agricultural land has continued to expand over the three decades. The largest growth occurred between 1994 and 2004 with 26.58% growth, corresponding to large-scale conversion of forest and shrubland into agricultural land. Agricultural expansion slowed down to 8.09% from 2004 to 2014, and then dropped further to 1.98% from 2014 to 2024, which meant that much of the potential land was already converted by then. During the period (1994–2024), agricultural land increased by 39.52% and continued to be the leading land use in the region.

Settlement areas experienced the most dramatic proportional growth of all LULC categories. Between 1994-2004, settlement areas increased by 317.02%, albeit from a low base. Growth continued between 2004-2014 with a further increase of 13.97%. But the most phenomenal growth was from 2014 to 2024, when settlement areas increased by 787.69%, recording phenomenal growth in urbanization, particularly in Abajema and other emerging towns such as Moye, Efo, and Aseko. For the entire study period, settlement areas increased by a phenomenal 4119.15%, recording tremendous urban growth and infrastructure development.

Shrubland cover decreased significantly by 89.54% from the time period 1994 to 2004 principally because of its use as farm land. However, for the time period from 2004 to 2014, shrubland recovered slightly by 2.14%, only to rise significantly by 197.71% for the time period from 2014 to 2024. Even though there was this recent recovery, shrubland still has a net loss of 68.19% for the overall period. The recent increase can imply land abandonment places or natural regrowth on already degraded or unused lands.

Grassland recorded a consistent positive trend throughout all decades. Grassland cover increased by 34.44% during the period 1994–2004, and thereafter by 8.62% during 2004–2014, and 27.23%

during 2014–2024. For the total period (1994–2024), the increase in grassland growth was 85.78%. The persistent growth may be a result of the recovery of degraded shrublands and forests, as well as because of changes in land use management practices to support grassland cover.

Table 4-2: Rate of change of LULC area over the past three decades

S/N	Class	1994-2004 (%)	2004-2014 (%)	2014-2024 (%)	1994-2024 (%)
1	Forest	-10.91	-25.69	-37.94	-58.92
2	Agriculture	26.58	8.09	1.98	39.52
3	Settlement	317.02	13.97	787.69	4119.15
4	Shrubland	-89.54	2.14	197.71	-68.19
5	Grassland	34.44	8.62	27.23	85.78

4.4.LULC Change detection analysis

4.4.1. LULC Change Detection between 1994 and 2004

Land use and land cover (LULC) change detection between the periods 1994-2004 indicates severe changes in the landscape, which were primarily due to the intensification of agriculture by encroaching forests, shrubland, and grassland. The figures indicate widespread land conversion, which has altered the spatial pattern of land cover classes in the study area. Severe conversion of a huge area of forest land into other uses occurred in this period. Of 12,670.27 hectares of forest in 1994, only 8,659.38 hectares remained as forest in 2004. Agricultural land was the greatest conversion that involved 3,205.68 hectares of forest cut and converted into farm land. 440.97 hectares were also converted into shrubland, and 361.54 hectares became grassland. Some small area of 2.69 hectares was converted into settlement land (Table 4-3). A rise in agricultural land was most significant during this period.

24,236.35 hectares out of the agricultural area in 1994 remained agricultural by 2004. Agriculture further extended itself by encroaching into other land cover classes, providing 3,205.68 hectares of forest, 4,401.51 hectares of shrubland, and 1,174.29 hectares of grassland. There are slight losses in that 902.72 hectares went back to forest, 43.60 hectares to shrubland, 1,065.82 hectares to grassland, and 20.76 hectares to settlements. This confirms that agriculture remained the dominant force reshaping land in this decade. Settlement sites tended to be small but recorded localized expansion. 6.61 hectares of settlements were recorded in 1994, and 29.03 hectares was classified as settlement in 2004. Some of the settlement sites (around 5.23 hectares) were reclassified to agriculture, maybe due to population migration or abandonment of smaller sites of settlement.

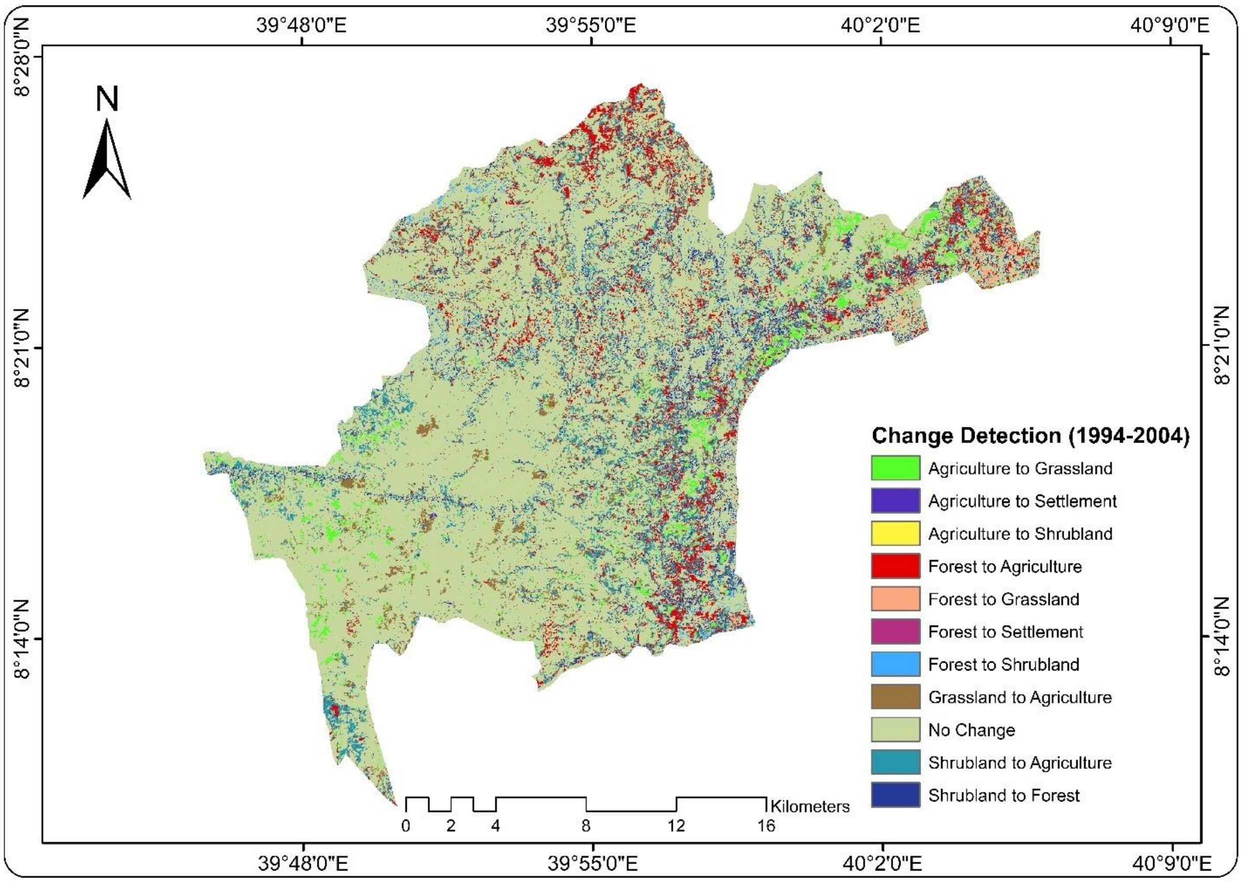

Figure 4-5: LULC change detection between 1994-2004

Shrubland reduced drastically. Out of 6,378.18 hectares of shrubland in 1994, a mere 82.22 hectares remained shrubland by the year 2004. It changed most into agriculture, a maximum of 4,401.51 hectares. It also got changed to forest, with an area of 1,533.78 hectares, perhaps due to natural regeneration or remapping. Grassland (359.19 hectares) and settlement (1.47 hectares) lands reduced to a smaller degree. Grassland lands reduced in the same span of time too. Of the 1,614.77 hectares of grassland that existed in 1994, only 397.16 hectares remained by 2004. Most of the grassland (1,174.29 hectares) was converted to agriculture, and 39 hectares was reforested. Minor conversions to shrubland (1.17 hectares) and settlements (3.16 hectares) occurred.

Table 4-3: LULC change detection between 1994-2004

		2004					
		Forest	Agriculture	Settlement	Shrubland	Grassland	Grand Total
1994	Forest	8659.38	3205.68	2.69	440.97	361.54	12670.27
	Agriculture	902.72	24236.35	20.76	43.60	1065.82	26269.24
	Settlement	0.00	5.23	0.95	0.00	0.43	6.61
	Shrubland	1533.78	4401.51	1.47	82.22	359.19	6378.18
	Grassland	39.00	1174.29	3.16	1.17	397.16	1614.77
	Grand Total	11134.87	33023.06	29.03	567.97	2184.14	46939.07

4.4.2. LULC Change Detection between 2004 and 2014

The change in land use and land cover (LULC) from 2004 to 2014 is indicative of the continuation of trends over past decades, with agricultural land expansion remaining the dominant force of change. Forest and shrubland cover continued to decline from 2004 to 2014, while grassland and settlement area expanded but at a slower pace. Forest land continued to decline from 2004 to 2014. Of the 11,133.56 hectares of forest land listed in 2004, only 6,931.63 hectares were still forest in 2014. Much of the forest is changed to agricultural land, approximately 2,863.37 hectares. Additionally, 535.84 hectares of forest became shrubland and. 802.73 hectares became grassland (Table 4-4). It indicates very much a trend towards forest degradation and conversion, to agricultural land and secondary vegetation such as shrubland and grassland. There had not been extensive conversion of forest to settlement areas during this decade.

The most extensive land cover category during this period was agriculture. Of the agricultural area of 33,027.53 hectares in 2004, 30,908.88 hectares remained under agriculture in 2014. Agriculture expanded into other classes: 897.48 hectares from forest, 122.93 hectares from shrubland, and 1,726.87 hectares from grassland. Additionally, 21.23 hectares of urban settlement were reassigned to farming use, suggesting potential return of sparsely inhabited areas to cultivation. Areas of urban settlements witnessed moderate growth from 2004 to 2014. Settlements increased from 28.99 hectares in 2004 to 31.05 hectares in 2014.

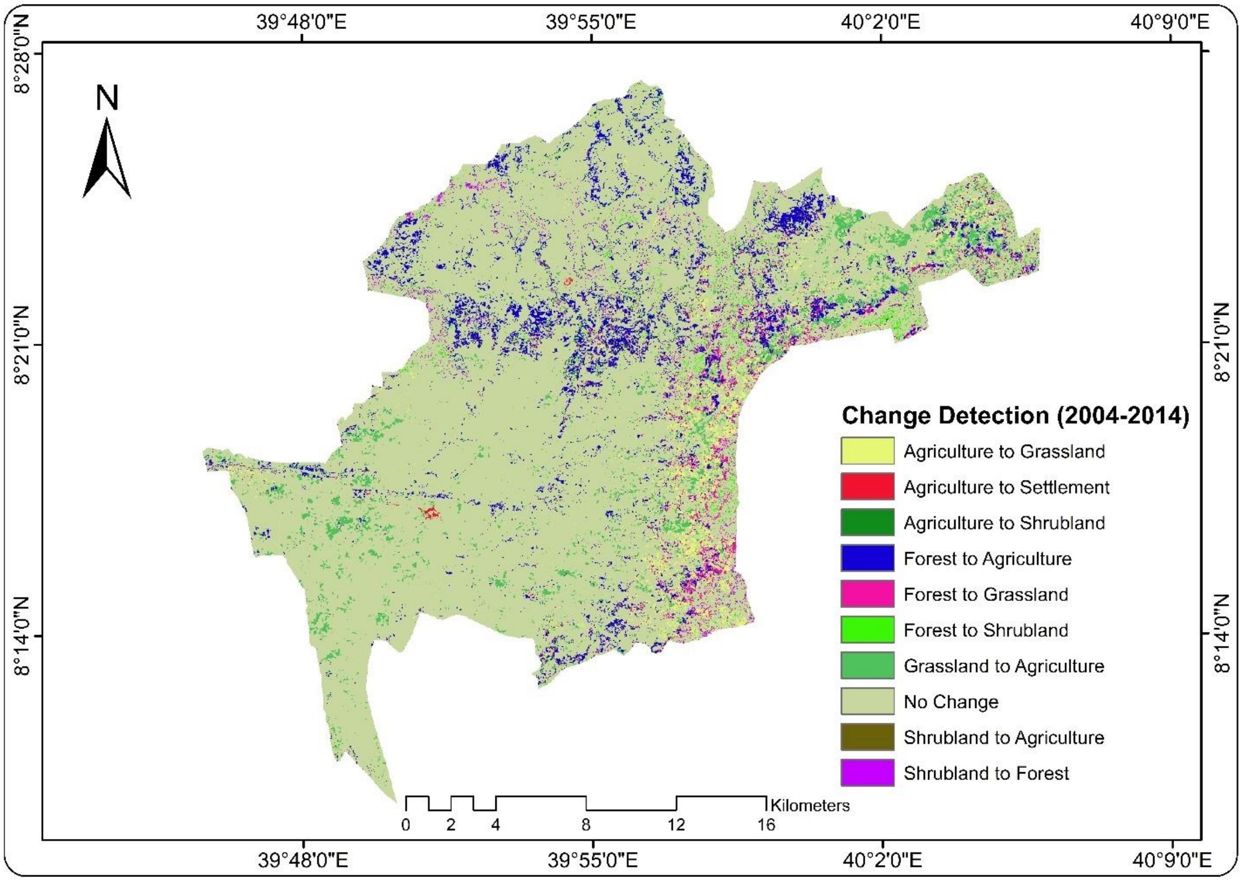

Figure 4-6: LULC change detection between 2004-2014

Shrubland coverage declined somewhat over this period. Of 568.15 hectares of shrubland in 2004, just 28.66 hectares remained by 2014. Much of the shrubland was converted to other uses: 363 hectares were converted to forest, 122.93 hectares to agriculture, and 53.56 hectares to grassland. The figures reflect the unstable nature of shrubland patches, often serving as transition fields in land cover processes. Grassland areas increased slightly from 2004 to 2014. Of the 2,183.89 hectares that existed as grassland in 2004, 346.66 hectares remained grassland by 2014. The major source of grassland expansion was forest (802.73 hectares) and agricultural land (1,148.54 hectares). Shrubs (53.56 hectares) and settlements (1.31 hectares) also made minor contributions.

During the period of 2004-2014, agricultural land expanded vigorously, mostly at the expense of grassland and forest. Forest decline was very high, with a vigorous reduction in the forest cover since large expanses were being brought under agriculture and grassland. Shrubland reduced further, while settlements rose moderately, reflecting the process of rural urbanization. Grasslands recorded a moderate expansion, which is likely to be due to forest and shrubland degradation. The land cover transformation here underscores the pressures exerted by agricultural encroachment and human settlement on the remaining natural land cover categories.

Table 4-4: LULC change detection between 2004-2014

		2014					
		Forest	Agriculture	Settlement	Shrubland	Grassland	Grand Total
2004	Forest	6931.63	2863.37	0.00	535.84	802.73	11133.56
	Agriculture	897.48	30908.88	25.06	47.58	1148.54	33027.53
	Settlement	0.91	21.23	5.55	0.00	1.31	28.99
	Shrubland	363.00	122.93	0.00	28.66	53.56	568.15
	Grassland	107.21	1726.87	0.45	2.70	346.66	2183.89
	Grand Total	8300.24	35643.26	31.05	614.78	2352.79	46942.12

4.4.3. LULC Change Detection Between 2014 and 2024

From 2014 to 2024, land use and land cover change in the Arba Gugu forest area continued to reflect ongoing trends of deforestation and agricultural expansion, while notable changes in settlement expansion and shrubland recovery occurred. Forest cover still decreased remarkably over the entire period. Of the 8,299.06 hectares of forest in 2014, only 4,270.06 hectares remained forest in 2024. A very high proportion of 2,604.52 hectares was converted into agricultural land, allowing cultivation extension into former forest areas. In addition, 1,227.95 hectares of forest were converted into shrubland and 194.47 hectares were converted into grassland. Less than a quarter, 2.05 hectares, was converted for settlements. This trend of conversion recognizes the massive land pressure within forests, particularly that generated by agricultural expansion and secondary regrowth in already depleted areas.

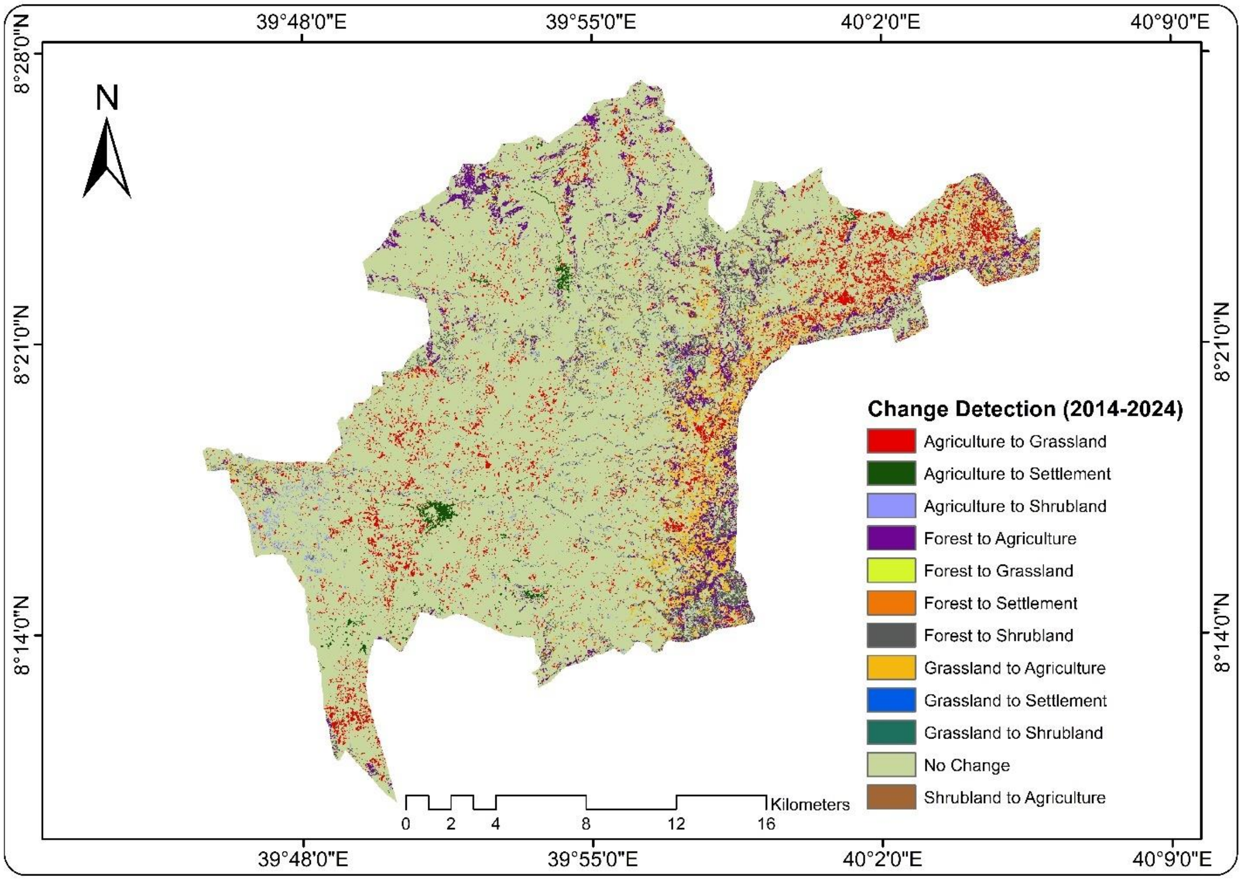

Figure 4-7: LULC change detection between 2014-2024

Agriculture continued to be the biggest cover category even in 2024. Of the 35,642.62 hectares of agricultural land in 2014, 32,123.24 hectares continued to be agricultural land in 2024. Meanwhile, agriculture also gained some of its lands from the other covers: 526.06 hectares from forestland, 204.06 hectares from shrubland, and 1,729.95 hectares from grassland. Another 1.72 hectares of settlements were reclaimed as agricultural land, albeit tiny. Most notably, 295.39 hectares of farming land were converted to settlements, meaning expanding towns and settlements in previous farming lands. Signs of settlement areas indicated a significant rise between 2014 and 2024. Whereas in 2014 coverage of settlement areas was 31.05 hectares, in 2024 it increased to 329.27 hectares. The increase was mainly from conversions of cultivated land (295.39 hectares), with minor increments from forest (2.05 hectares) and grassland lands (2.46 hectares). The widening settlements exhibited urban growth, particularly within already settled towns such as Abajema, Moye, Efo, and Aseko.

Among the notable trends during this period was the expansion of the shrubland cover. Of the 614.98 hectares of shrubland cover in 2014, 158.56 hectares remained as shrubland cover in 2024. Shrubland expanded even with the conversion from forest (1,227.95 hectares), agriculture (429.00 hectares), and grassland (141.44 hectares). While the majority of this bushland is degraded land transition, the expansion shows where forest cover was lost but not yet altered to agriculture or settlements. Grassland covers also expanded slightly during the decade. Grasslands increased from 2,352.84 hectares in 2014 to 2,879.78 hectares in 2024. The expansion was through conversions from agriculture (2,268.94 hectares), forest (194.47 hectares), bushland (1.56 hectares), and settlements (0.06 hectares). As grasslands expanded, much of that was likely from land abandoned or degraded for other uses, perhaps because land productivity was reducing or because land was being abandoned.

Table 4-5: LULC change detection between 2014-2024

		2024					
		Forest	Agriculture	Settlement	Shrubland	Grassland	Grand Total
2014	Forest	4270.06	2604.52	2.05	1227.95	194.47	8299.06
	Agriculture	526.06	32123.24	295.39	429.00	2268.94	35642.62
	Settlement	0.05	1.72	29.17	0.06	0.06	31.05
	Shrubland	250.61	204.06	0.20	158.56	1.56	614.98
	Grassland	64.25	1729.95	2.46	141.44	414.75	2352.84
	Grand Total	5111.02	36663.48	329.27	1957.00	2879.78	46940.55

4.4.4. LULC Change Detection Between 1994 and 2024

Land cover and land use (LULC) change of Arba Gugu forestland between 1994 and 2024, i.e., 30 years, indicates great change predominantly in the form of agricultural encroachment, forest depletion, and settlement growth. The forestland was 12,666.63 hectares in 1994, but for 2024 it had fallen significantly to 5,110.38 hectares. Alteration matrix indicates that huge tracts of forestland were altered into cultivation land as 6,418.56 hectares were altered into cultivation land.

Further 1,395.33 hectares of forestland was altered into shrubland and 624.71 hectares into grassland. A small portion of area of 13.41 hectares was altered into settlement land.

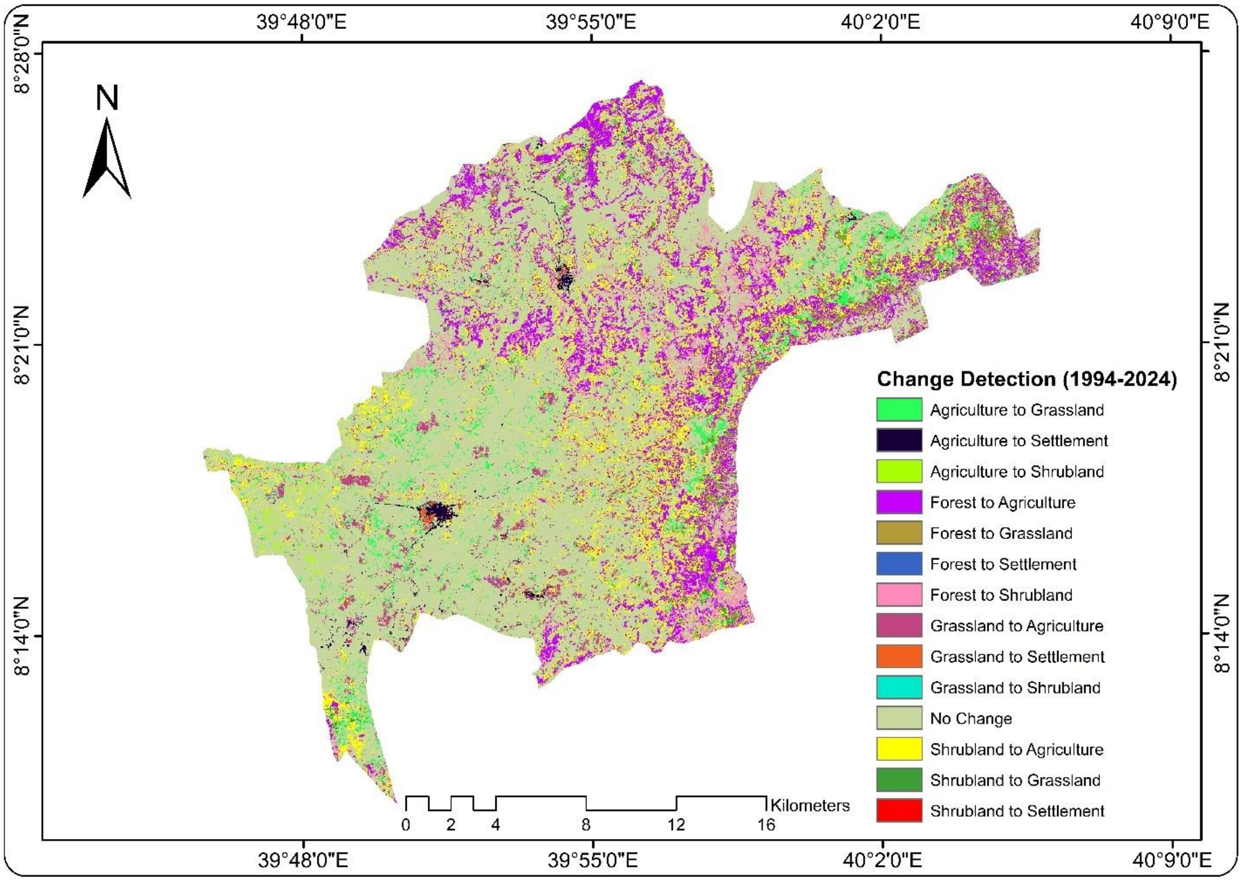

Figure 4-8: LULC change detection between 1994-2024

Agricultural land also grew substantially over the period. Of the 26,268.15 ha of agriculture in 1994, 23,877.15 ha remained agricultural land in 2024. Agriculture, however, gained land from a variety of other LULC classes, including 6,418.56 ha from forest, 5,108.24 ha from shrubland, and 1,249.95 ha from grassland. Settlements also lost a minor conversion of 4.61 ha to agriculture. Moreover, 260.83 hectares of agricultural land were taken over by settlements and 282.97 hectares by shrubland, experiencing some reversals and land-use changes. Settlement zones expanded extensively over the 30 years. Settlements in 1994 covered just 6.61 hectares, but in 2024 settlements expanded over 329.30 hectares. Most of the expansion was due to conversion of agricultural land into settlements, with 260.83 hectares of agriculture lost to settlements. In addition, 14.75 hectares of bushland, 38.47 hectares of grassland, and 13.41 hectares of woodland were all converted into settlements. Increases in the areas of settlement are parallel to urbanization, particularly in and around Abajema town and newly emerging towns such as Moye, Efo, and Aseko.

Shrubland type regions saw a net decline from 6,378.37 hectares in 1994 to 1,956.82 hectares in 2024. While this was a decline, some regions did transition to shrubland over the years. For instance, 1,395.33 hectares of former forest, 282.97 hectares of cropland, and 18.48 hectares of grassland became shrubland. This pattern could be indicative of land degradation in some areas where cropland or forest became shrubland. Grassland cover area increased from 1,614.92 hectares in 1994 to 2,879.67 hectares in 2024. Agricultural land (1,482.07 hectares) and forest (624.71 hectares) were the key drivers of expansion contributing to grassland expansion. Shrubland also contributed 494.03 hectares to grassland expansion.

Table 4-6: LULC change detection between 1994-2024

		2024					
		Forest	Agriculture	Settlement	Shrubland	Grassland	Grand Total
1994	Forest	4214.62	6418.56	13.41	1395.33	624.71	12666.63
	Agriculture	365.14	23877.15	260.83	282.97	1482.07	26268.15
	Settlement	0.01	4.61	1.84	0.00	0.15	6.61
	Shrubland	501.31	5108.24	14.75	260.04	494.03	6378.37
	Grassland	29.31	1249.95	38.47	18.48	278.71	1614.92
	Grand Total	5110.38	36658.51	329.30	1956.82	2879.67	46934.69

4.5.Accuracy Assessments

4.5.1.1.Accuracy Assessment of LULC Classification Result for the Year 1994

Producer Accuracy (PA) measures how well real-world reference points were correctly classified on the map. The PA for Forest was 91%, indicating that most of the actual forest areas were correctly mapped. Agriculture had the highest PA at 96%, showing excellent reliability in identifying agricultural land. On the other hand, Settlement had a lower PA of 67%, suggesting that many areas classified as settlements in the reference data were either missed or incorrectly assigned to other categories. Shrubland and Grassland had PA values of 73% and 75%, respectively, indicating moderate omission errors in these classes.

Table 4-7: Accuracy assessment of LULC classification result for the year 1994

	Forest	Agriculture	Settlement	Shrubland	Grassland	Total	PA
Forest	51	3	0	1	1	56	0.91
Agriculture	0	44	0	2	0	46	0.96
Settlement	0	6	12	0	0	18	0.67
Shrubland	3	2	0	22	3	30	0.73
Grassland	4	0	1	0	15	20	0.75
Total	58	55	13	25	19	170	
UA	0.88	0.80	0.92	0.88	0.79		
OA	0.85						
Kappa	0.80						

User Accuracy (UA), the rate at which a pixel identified as a given class on the map actually represents that class on the ground, was best for Settlement at 92%. Although lower in PA, however, this high UA for Settlement is a good sign that although some areas of settlement have been excluded, those that have been classified are mainly correct. Forest and Shrubland both registered UA of 88%, showing high confidence in their classes. Agriculture also registered a UA of 80%, and Grassland had 79%, registering a moderate commission error in which pixels could have been incorrectly classified to them.

The Overall Accuracy (OA) of the classification was 85%, which means that 85% of all the reference points were correctly classified. It is reasonable and good in land cover studies. It reflects that the classification result is reliable and useful for further analysis. The Kappa Coefficient, taking into account the chance agreement potential, was 0.80.

Note: These two sentences appear exactly in both the original and human-annotated versions. This value indicates high agreement of the classified map and reference data. 0.80 Kappa is outstanding classification performance, and it indicates that the classification was correct and consistent.

4.5.2. Accuracy Assessment of LULC Classification Result for the Year 2004

Producer Accuracy reflects the accuracy with which the reference points are rightly classified on the map. Forest in 2004 was at 73% accuracy, which means that 73% of real forest reference points were well marked as forest. Agriculture was 94% accurate with a high accuracy for detecting agricultural land. Settlement was 72%, meaning moderate omission errors in such a way that some settlements could have been mistakenly classified. Both Shrubland and Grassland had PA values of 73% and 86%, respectively, which indicated good reliability in correctly discriminating the two land cover classes.

User Accuracy is the probability that a class on the map actually corresponds to that category on the ground. At 90% UA in 2004, Settlement indicated highest confidence that the places labeled as settlement on the map were indeed settlements on the ground. Grassland indicated highest UA at 86%, then Shrubland at 88%, then Forest at 82%, and Agriculture at 71%. The lower UA for Agriculture means a higher percentage of commission errors, i.e., a portion of the land that was classified as agriculture was likely in some other class.

Table 4-8: Accuracy assessment of LULC classification result for the year 2004

	Forest	Agriculture	Settlement	Shrubland	Grassland	Total	PA
Forest	37	10	1	3	0	51	0.73
Agriculture	1	47	0	0	2	50	0.94
Settlement	0	7	18	0	0	25	0.72
Shrubland	6	2	0	22	0	30	0.73
Grassland	1	0	1	0	12	14	0.86
Total	45	66	20	25	14	170	
UA	0.82	0.71	0.90	0.88	0.86		
OA	0.80						
Kappa	0.74						

The Overall Accuracy of the 2004 classification was 80%, with 80% of all the reference points having been correctly classified. This is an accepted level of accuracy for LULC studies and provides a consistent foundation for change detection and further analysis. The Kappa Coefficient for the 2004 classification was 0.74, indicating a substantial agreement between the classification results and the reference data. Though slightly short of the 1994 classification (Kappa = 0.80), it is still a measure of a robust and consistent process with minimal random agreement.

4.5.3. Accuracy Assessment of LULC Classification Result for the Year 2014

Producer Accuracy measures the probability that reference points from a given class are correctly classified. Forest class was 86% in 2014, which means most of the actual forest cover was accurately classified in the map. Agriculture was also very good with a PA of 92%, which was exemplary in defining agricultural fields. Settlement registered a better PA of 97%, and this demonstrated good accuracy with minimal omission errors. Shrubland and Grassland, however, were both at 81% and 82% in their PA values, with fairly good performance in classifying these land cover types.

User Accuracy is the measure of the user's belief in how accurate the labeled information is. Forest possessed the highest UA of 94% indicating very high user confidence that the places labeled as forest on the map are indeed forest on the ground. Agriculture was in second place with UA = 88%, while Settlement had UA = 91%, which showed relatively low commission errors for both groups. Shrubland and Grassland had results of 79% and 82%, respectively, which indicated moderate reliability in both groups.

Table 4-9: Accuracy assessment of LULC classification result for the year 2014

	Forest	Agriculture	Settlement	Shrubland	Grassland	Total	PA
Forest	48	2	2	4	0	56	0.86
Agriculture	1	36	0	0	2	39	0.92
Settlement	1	0	30	0	0	31	0.97
Shrubland	0	3	1	22	1	27	0.81
Grassland	1	0	0	2	14	17	0.82
Total	51	41	33	28	17	170	
UA	0.94	0.88	0.91	0.79	0.82		
OA	0.88						
Kappa	0.85						

Overall Accuracy of 2014 LULC classification was 88%, or 88% of all reference points were accurately classified. It is an improvement from the 2004 OA of 80%. An OA of 88% is typically considered excellent in land cover classification studies, which provides a solid platform on which to examine LULC changes over time. The Kappa Coefficient of 2014 was 0.85, reflecting extremely high agreement between the classified data and the points of reference, well above chance. This is higher than the Kappa of 2004 at 0.74, and it reflects extremely high reliability in the process of classification.

4.5.4. Accuracy Assessment of LULC Classification Result for the Year 2024

Producer Accuracy reflects how closely reference data for each class has been transferred accurately. Forest class in 2024 exhibited a very accurate PA of 94%, which signifies that nearly all actual forest regions were correctly labeled in the classification. Agriculture class was not far behind with PA 93%, having negligible omission error for this class. The Settlement class achieved a PA of 90%, excellent classification accuracy for urban and built-up land. Shrubland's PA was a moderate 84% but Grassland's PA was quite low at 53%, reflecting that nearly half the grassland patches were poorly classified, which could be because of spectral similarity with other classes or patch fragmentation.

User Accuracy is the proportion of how often a mapped class actually occurred in that class on the ground. Grassland class had the highest UA of 94%, signifying that the majority of land area marked as grassland on the map were grassland on the ground. Shrubland class also achieved a high UA of 93%, signifying high confidence in its mapping. Forest, Agriculture, and Settlement classes were categorized with UA values of 80%, 81%, and 82%, respectively. It indicates a high level of confidence in the classes, but there were some commission errors, especially in the forest and agriculture classes.

The Total Accuracy of the 2024 LULC classification was 84%. It is 84% of all reference points utilized in the accuracy assessment that were correctly classified. Even though it is somewhat poorer compared to the 88% OA achieved in 2014, it remains highly commendable overall classification performance given the complexity and dynamic characteristics of land cover change within the region. The Kappa Classification of 2024 was 0.80, which reflects very high agreement between the classification and reference data beyond that which would be expected by chance. This Kappa value demonstrates a reliable and consistent classification outcome. While a bit lower than that of 2014 Kappa (0.85), it remains at the level of a high-quality classification.

Table 4-10: Accuracy assessment of LULC classification result for the year 2024

	Forest	Agriculture	Settlement	Shrubland	Grassland	Total	PA
Forest	44	2	0	0	1	47	0.94
Agriculture	1	38	2	0	0	41	0.93
Settlement	0	1	18	1	0	20	0.90
Shrubland	0	5	0	27	0	32	0.84
Grassland	10	1	2	1	16	30	0.53
Total	55	47	22	29	17	170	
UA	0.80	0.81	0.82	0.93	0.94		
OA	0.84						
Kappa	0.80						

4.6.Modelling forest fire risk zone using AHP

4.6.1. Parameters that affect the forest fire

Precipitation

Precipitation is also of intrinsic importance in governing the incidence and spread of forest fires. On the whole, areas with lower yearly precipitation are more susceptible to forest fires due to lower fuel moisture content enabling more susceptible ignition and fire spread (Liu et al., 2013). Yearly precipitation was applied within this study as an intrinsic parameter to model forest fire danger zones within the Arba Gugu forest environment. As illustrated by Figure 4-9, the study area annual rainfall ranges from a minimum of approximately 1000 mm to a maximum of 1500 mm. Spatially, the south and northwest borders of the study area experience minimum levels of rainfall, creating favorable conditions for the initiation and spread of wildfires. On the other hand, the central part of the region, particularly in the northwestern core, receives the highest amount of precipitation, suggesting a relatively reduced fire threat in these regions due to higher fuel moistures.

There has been extensive research establishing the inverse relationship of precipitation with the occurrence of fires. For instance, Westerling et al. (2006) demonstrated that low levels of precipitation directly correspond with high fire activity, especially where there are long dry seasons. Flannigan et al. (2009) also established that trends of decreasing precipitation significantly raise fire dangers by both drying out vegetation and contributing to the amount of flammable material. In Arba Gugu, there is observed precipitation spatial variability which shows that forest fire management activities within the southern and northwestern boundaries of the drier conditions should be prioritized (Mitchell et al., 2014).

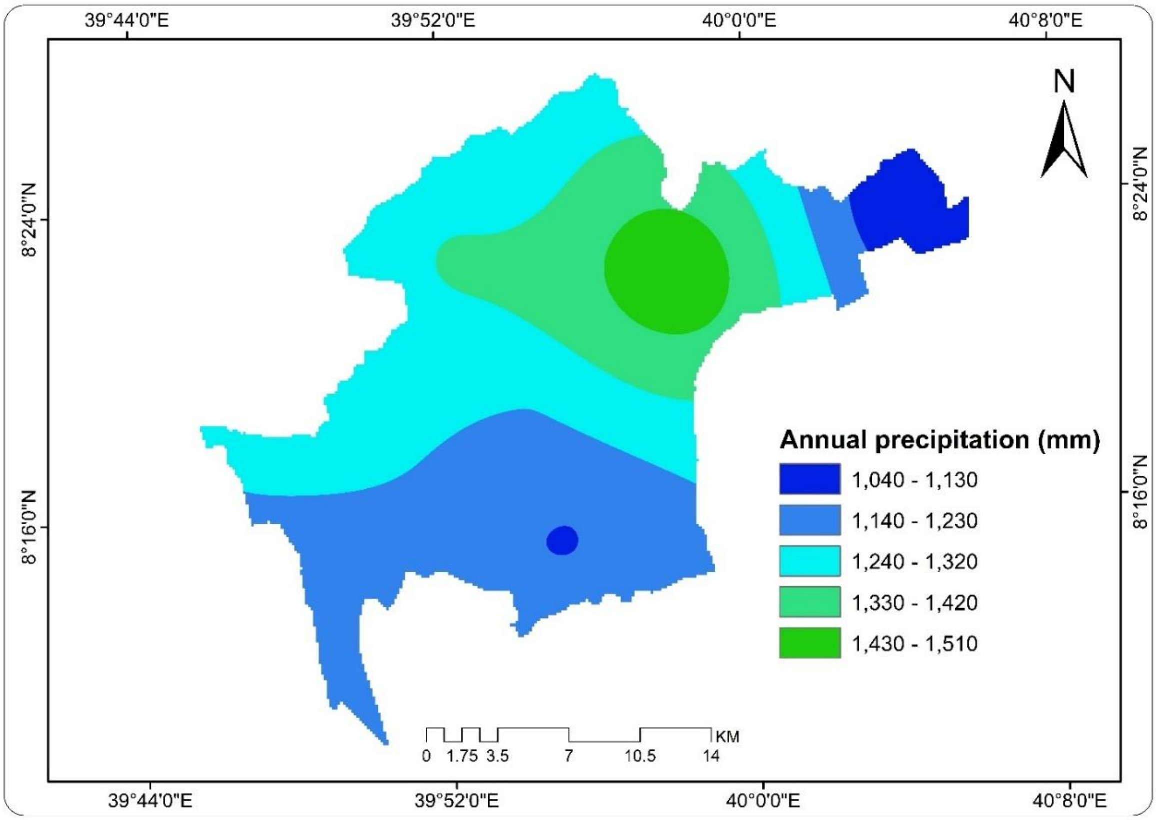

Figure 4-9: Annual precipitation (mm) of the study area

Temperature

Temperature is also an important factor that controls the frequency and intensity of forest fires (Zhu et al., 2022). Temperature reduces fuel moisture content, which makes the forest duff and vegetation more flammable and susceptible to being burned (Flannigan et al., 2000). For this study, annual minimum and maximum temperatures were employed to model risk areas of forest fires in the Arba Gugu forest. As shown in Figure 4-10, the highest annual temperature over the study area varies from 23°C to 28°C. Spatial analysis identifies maximum temperatures as being highly concentrated in the center of the study area. The high temperatures in this area enhance the chances of vegetation drying up and, therefore, increase the potential for ignition and fire spread. Conversely, the south region of the study area has relatively lower maximum temperatures, reflecting a relatively decreased fire risk compared to the middle sections.

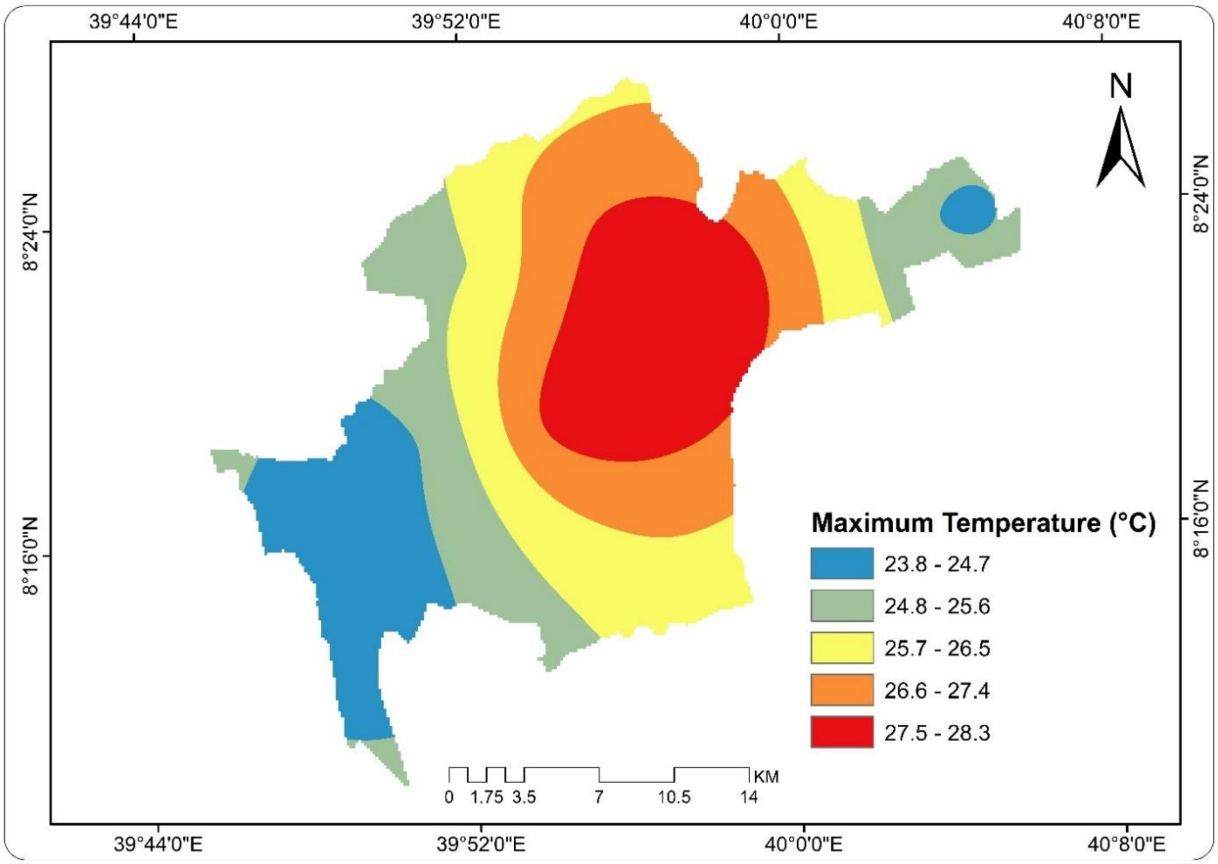

Figure 4-10: Maximum temperature

For minimum temperatures, Figure 4-11 shows that they range from 6°C to 10°C annually. Minimum temperatures are most elevated along the southern and western edges of the study site. The northern part of Arba Gugu has the lowest minimum temperatures. While minimum temperature is less immediately influential on day fire behavior than maximum temperature, above-average nighttime temperatures suppress the cooling and humidification of fuels, thereby perpetuating a heightened fire danger over extended durations (Abatzoglou & Williams, 2016).

Evidence concurs with the strong connection between hot temperatures and increased fire activity. For instance, Westerling et al. (2006) found that hot temperatures are highly correlated with increased wildfire occurrence and longer durations of fire seasons, particularly in those regions with seasonal dryness. Similarly, research by Jolly et al. (2015) shows that increased global temperatures will lengthen and strengthen the duration and intensity of fire seasons.

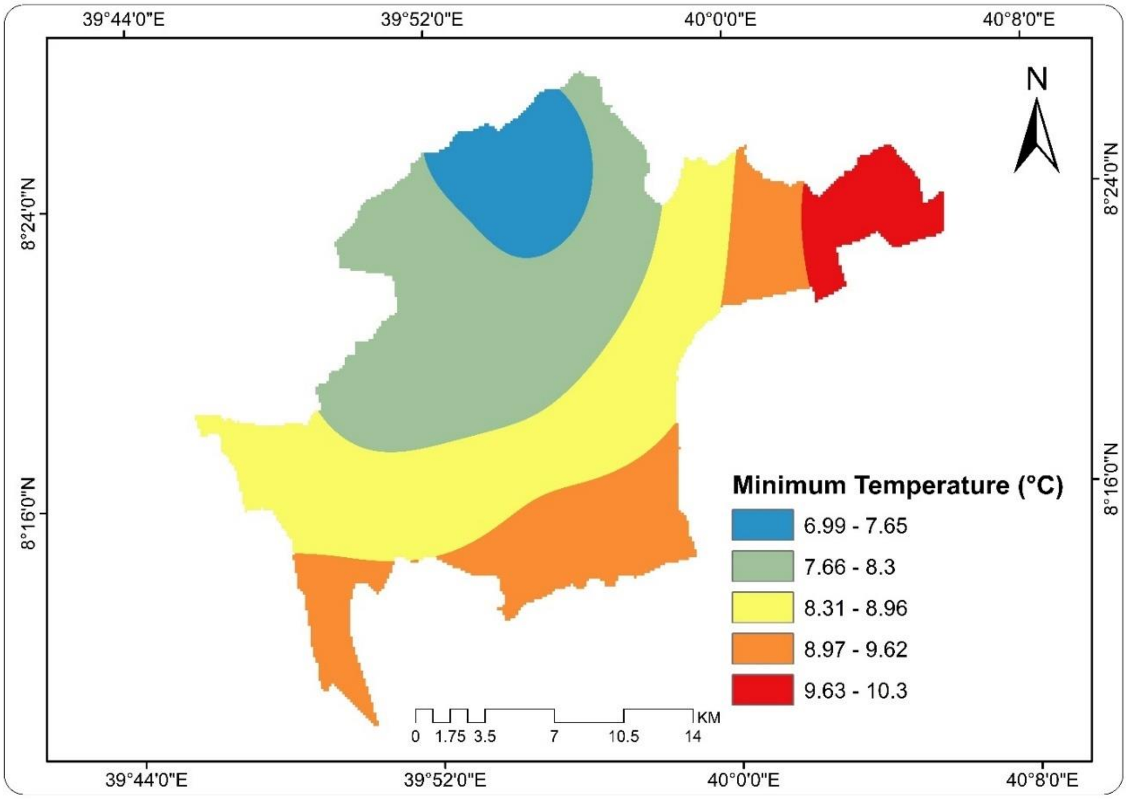

Figure 4-11: Minimum temperature

Humidity

Humidity is a climatic element essential with a significant effect on forest fire behavior and occurrence (Daşdemir et al., 2021). Low humidity leads to drier atmospheric conditions, which reduce the moisture of fuel of vegetation and surface fuels, making them more ignitable and susceptible to fire spread (Viegas, 2006). In turn, drier humid conditions can be able to inhibit fire behavior due to the maintenance of increased fuel moisture (Li et al., 2021). On this basis, the spatial pattern of humidity within the Arba Gugu forest was assessed on the annual average basis. As can be seen from Figure 4-12, humidity in the study area ranges from 10 to 11 grams per cubic meter (g/m³). Spatially, the highest humidity occurs on the southern and northwestern edges of the study area. These areas, with relatively higher atmospheric humidity, will likely face a reduced risk of forest fires compared to dry areas (Flannigan et al., 2016). On the contrary, the worst humidity levels occur in the north of the research area. Areas with lower humidity, such as in this northern part, are more prone to forest fires due to increased vegetation and ground cover dryness. Extended periods of low humidity will also lead to dry biomass accumulation, enhancing the likelihood of intense fires (Keywood et al., 2013). Empirical observations provide solid proof of the influence of humidity on wildfire behavior. Sharples et al. (2016), for example, observed that low humidity itself is positively associated with intense fire behavior, including increased fire spread rates and flame lengths. Likewise, research by Andrews (2012) has highlighted that relative humidity is a major input within fire danger rating systems employed globally.

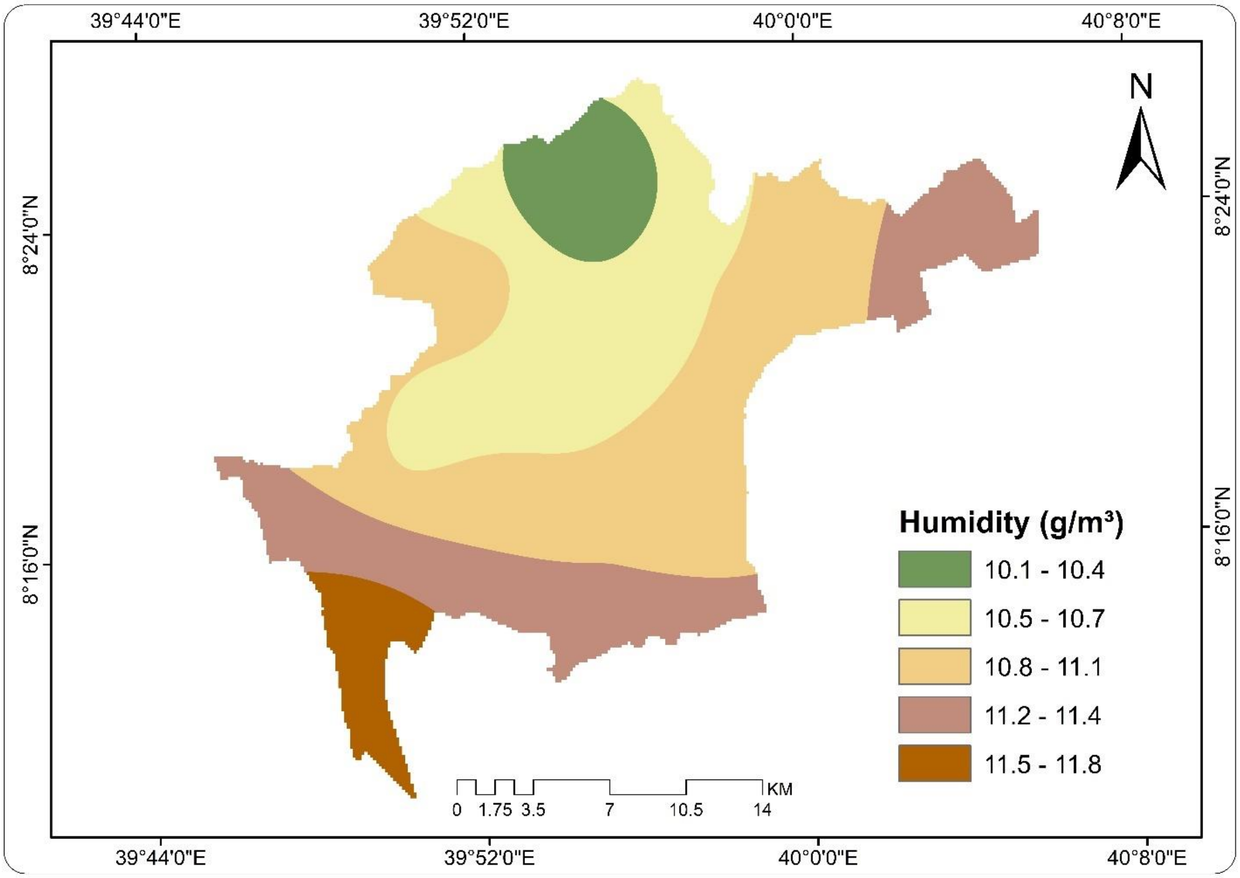

Figure 4-12: Humidity

Wind Speed

Wind speed is a significant parameter controlling both the ignition and spread of forest fires (Ganteaume et al., 2013). High wind speeds can efficiently spread the fire in the transportation of burning embers over distances, enhancing the rate of expansion of the fire, and rendering its nature more vigorous (Sharples et al., 2010). Wind further dries up the vegetation and surface fuels, rendering them extremely flammable under relatively damp conditions (Keeley, 2019). In this current study, wind speeds in the Arba Gugu forest were studied to model forest fire danger zones. Wind speed ranges from 7 to 11 meters per second (m/s) in the study area (Figure 4-13). Spatially, the northern study area contains the highest wind speed with a higher potential for fire spread in such regions. On the other hand, there are regions in the central area with low wind speed, with values in most of this area being between 8 and 9 m/s.

Although the core zone is indicated as comparatively moderate in wind velocity, it remains within a bracket that can hold and spread fires during times of dryness. The regions subject to the most rapid wind velocities, particularly the northern ones, are more worrisome because greater winds tend to generate quicker-moving and uncontrollable fires.

past work supports the central influence of wind speed on the behavior of fires. Viegas (2005) proposes that wind is often the most influential environmental component, especially during dry conditions, to impact the fire behavior of wildfires. Findings in research by Cruz et al. (2012) support that an increase in wind speed can double the rate of fire spread exponentially, considerably making wildfires more dangerous and difficult to put out.

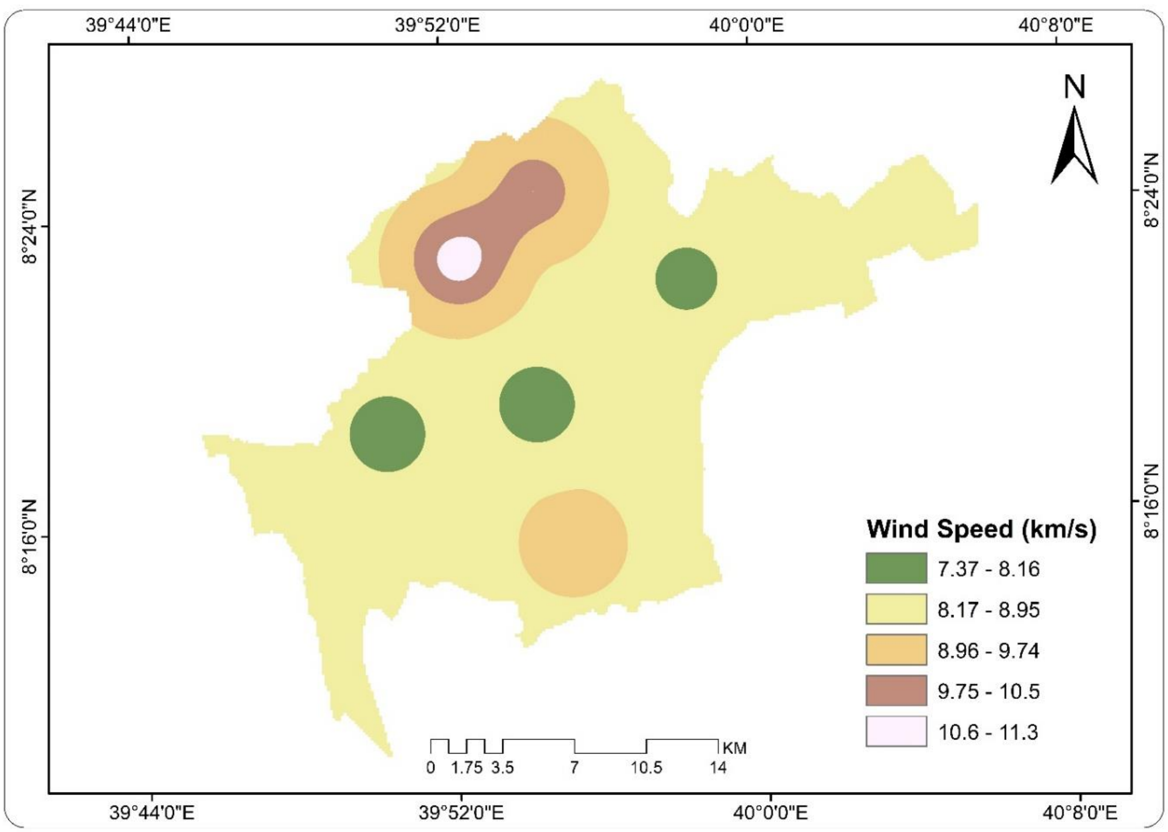

Figure 4-13: Wind speed

Wind direction

Direction of the wind is also an important factor that influences the occurrence and spread of forest fires (Daşdemir et al., 2021). Wind direction determines where a wildfire is most likely to spread, thereby influencing behavior, its potential spread, and the most vulnerable areas (Finney, 2005). The Arba Gugu forest wind direction data were analyzed in this research, as illustrated in Figure 4-14. Wind direction, in terms of degrees, ranges from 79° to 122°. These values of degrees are roughly equivalent to winds from the east and southeast directions blowing more or less towards the west and northwest. Based on ordinary meteorological categorization, wind direction in the research area is divided into two. Winds ranging from 79°–101° are easterly winds (eastward) and Winds ranging from 102°–122° tend more towards southeasterly winds. The influence of wind direction on fire spread has been well established. To Rothermel (1972), wind direction not only determines the general direction of a fire but also has a large impact on the intensity of the fire, the flame height, and the spotting distance (how far embers travel to start new fires).

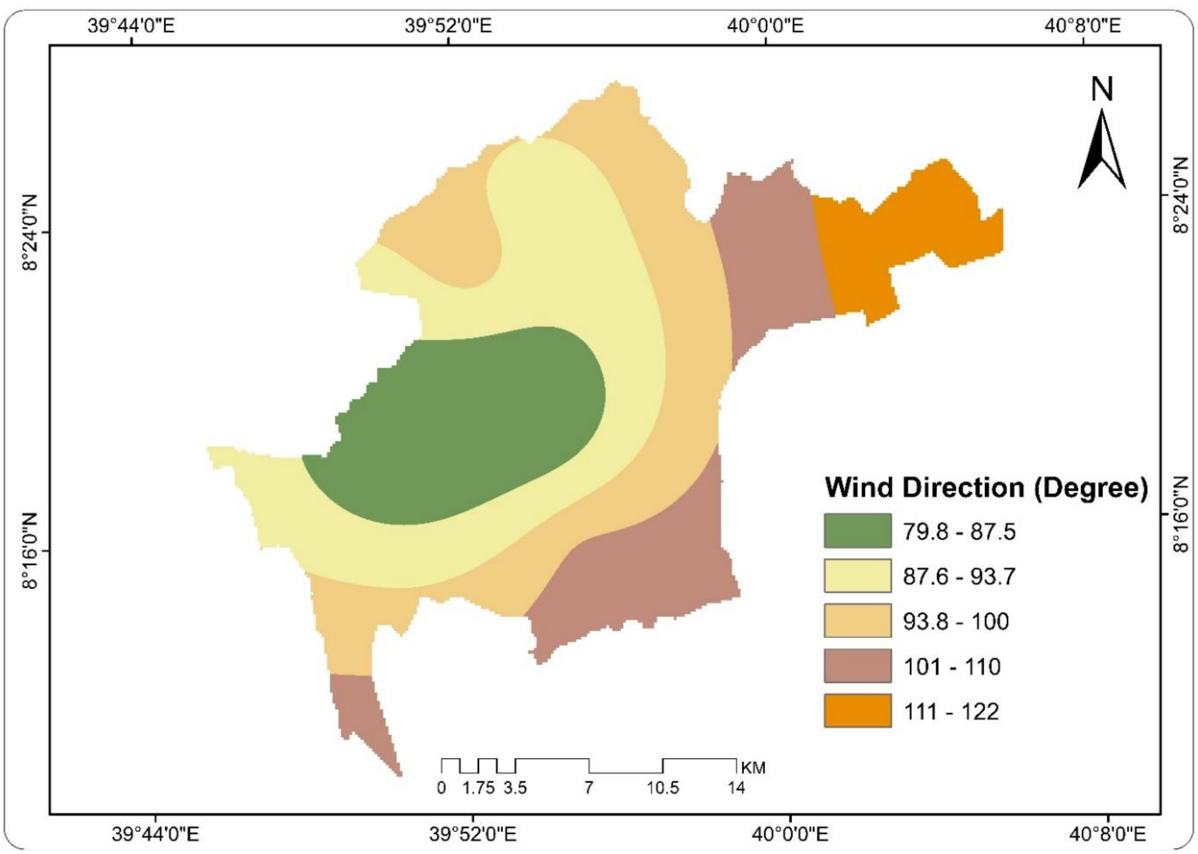

Figure 4-14: Wind direction

Distance from river

Proximity to rivers is another significant environmental factor influencing forest fire incidence and activity (Zhu et al., 2022). Proximity to rivers will more frequently have higher humidity in the overlying soils and vegetation, which can act as natural firebreaks (Moody, 2009). Areas distant from water bodies will be drier and more likely to afford ignition sources and fuel accumulation for wildland fires (Dwire & Kauffman, 2003).

For this study, Euclidean Distance tool was used to measure distance from rivers within the Arba Gugu woodland, as shown in Figure 4-15. Buffer zones were created based on distance from rivers with particular focus on thresholds with importance in fire hazard. Rivers are largely located in the northern and southeastern segments of the study area, and the areas were buffered to a distance of approximately 1.5 kilometers. The lower proximity zones reflect relatively less fire danger owing to the moderating influence of water bodies around them. Contrary to this, the western part of the study area reflects the lack or insignificant presence of rivers. The highest fire distance buffers here are 6 to 8 kilometers from the nearest water body. These areas being far from water sources are usually drier and therefore offer conducive environments for the occurrence and propagation of fires.

It has been established through research that riparian corridors (river and stream border areas) can significantly slow or even prevent fire spread under certain conditions. For instance, Pettit and Naiman (2007) emphasized that riparian corridors are more vegetatively dense and moist, hence natural firebreaks. Similarly, Dwire and Kauffman (2003) illustrated that dry streamside cover will most likely provide critical resistance to wildfire spread. Therefore, for Arba Gugu, areas away from rivers especially in the west region have to be considered as high-risk areas.

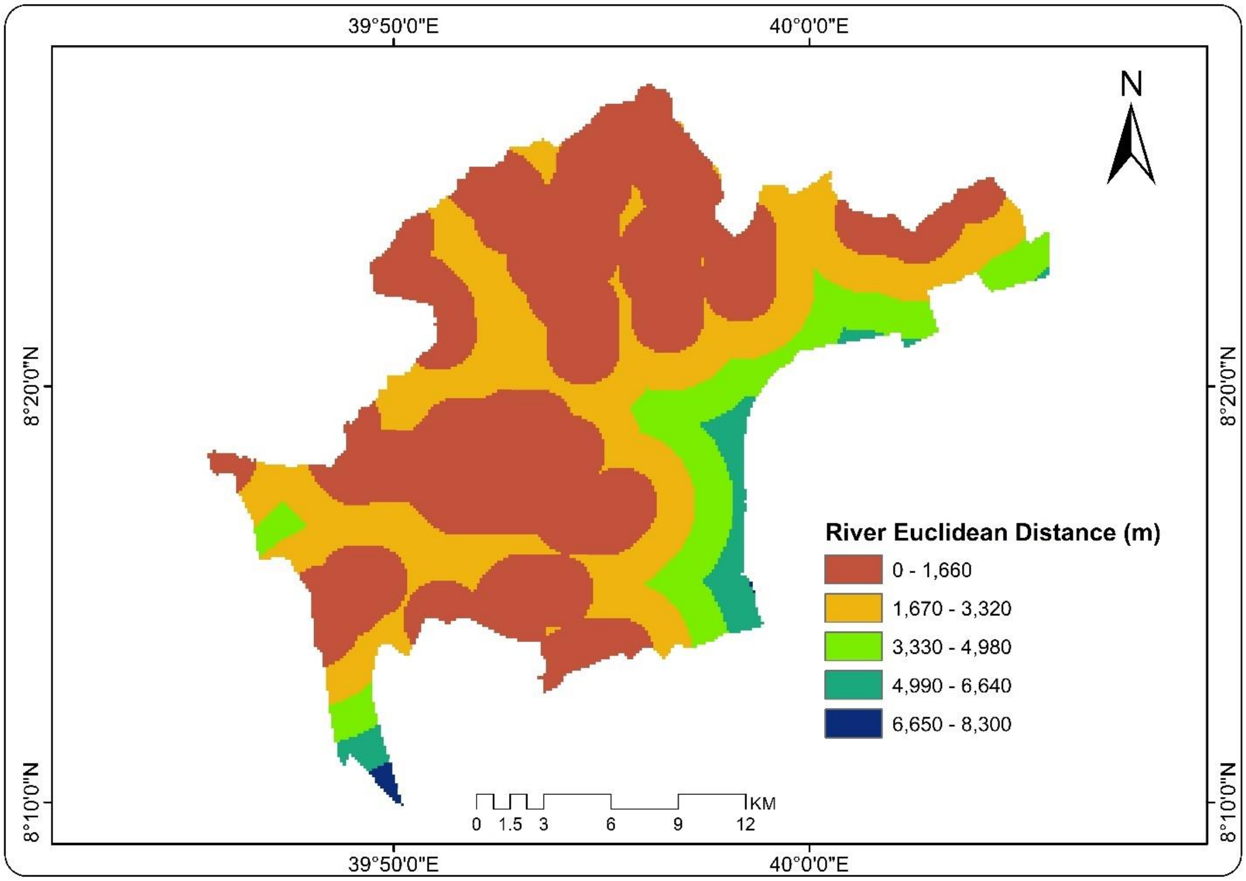

Figure 4-15: Distance from river

Proximity to road

Accessibility to roads is the key to determining the cause and intensity of forest fires (Narayanaraj, 2012). Roads will strive to enhance the accessibility of the forest by humans, thus the ignition potential for fire by human actions such as farming, wood cutting, illegal burning, or accidents (Cardille et al., 2001). Roads in most cases are indicators of disturbance that enhance the rate and severity of fire (Kolanek et al., 2021).

Only roads cutting across the Arba Gugu forest were considered for this research. Two roads cut across the middle of the study area and converge at Arba Gugu town from the east, as shown by Figure 4-16. This area with intense human activity and vehicle movement is depicted as an area of high risk for forest fire occurrence due to the fact that there is a high likelihood of ignition. No highway frontage exists along the western edge of the study area.

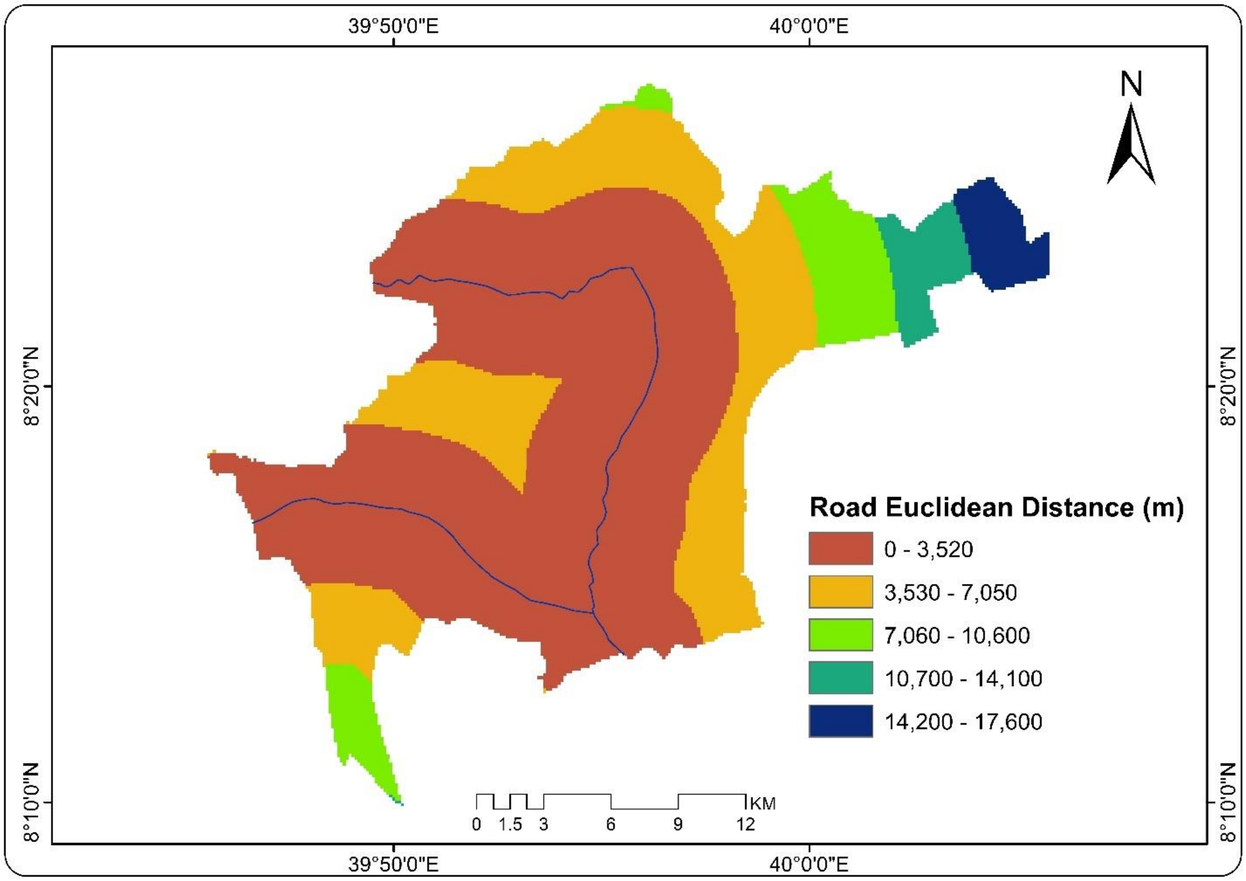

Figure 4-16: Proximity to road

Elevation (m)

Elevation is one of the leading causes of forest fire occurrence and behavior (Mansoor et al., 2022). Climatic variables such as cover, temperature, and humidity all change with elevation and are all essential parameters in the case of fire susceptibility determination (Pausas & Paula, 2012). As noted from Figure 4-17, the elevation of Arba Gugu forest area ranges from 1800 to 3800 meters above mean sea level. The highest elevation is situated in the northern part of the study area and ranges from approximately 1800 to 2300 meters. Such lower grounds, being relatively warmer and drier, are most prone to more frequent and high frequency of fire. The western region of the study area possesses higher grounds of 2800 to 3800 meters.

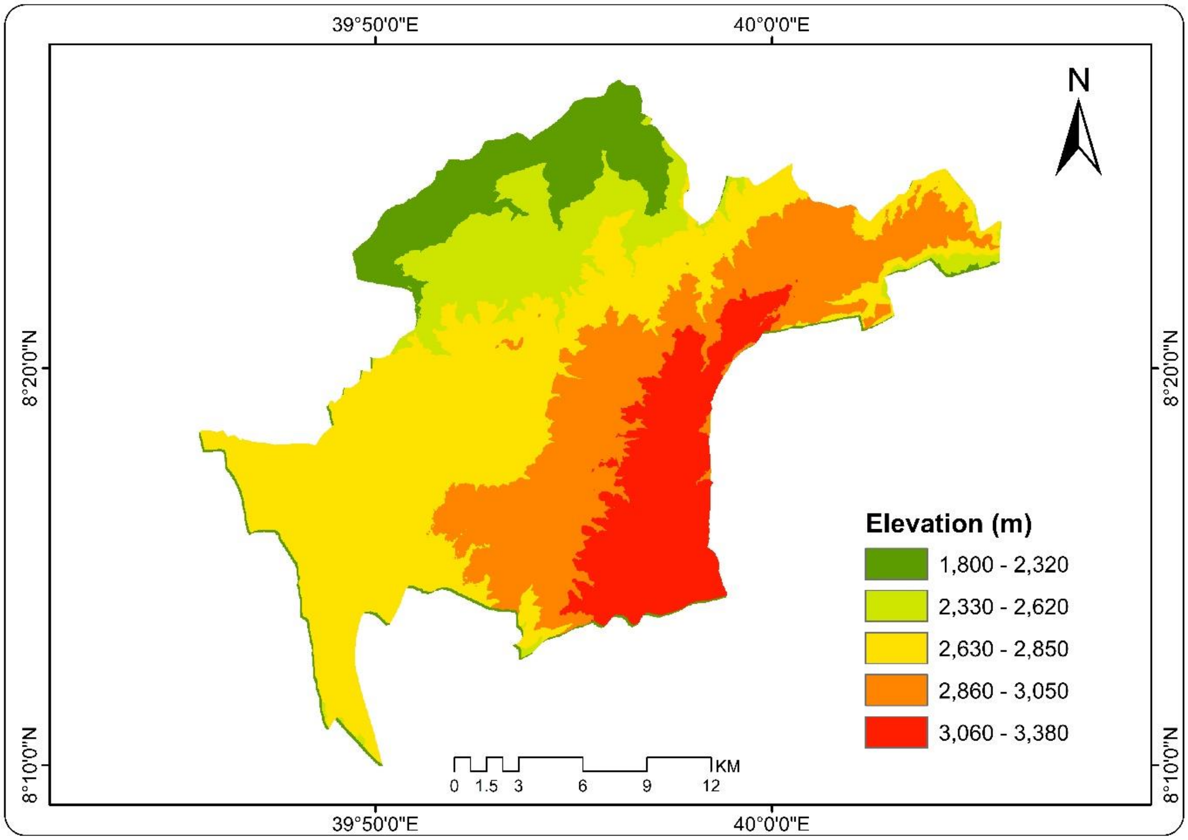

Figure 4-17: Elevation

Slope

Slope is another critical topography that influences the ignition, spread, and magnitude of forest fires (Roman-Cuesta et al., 2009). Steep slopes enhance fire spread as they preheat vegetation upslope through convection and radiation. The fire is faster in the uphill direction due to the fact that flames are closer to the fuel surface, thus facilitating more easily igniting vegetation (Rothermel, 1972; Sharples, 2009).

As evident in Figure 4-18, the study area for Arba Gugu has extremely variable topography. The northern, western, and southern edges contain very steep slopes that range from 27° to 89°. Due to their height, the steep slopes have a greater chance of extremely rapid fire spread if they were to be ignited, which would be tougher to manage. Conversely, the study area's central and eastern sectors have lower slope gradient. Such low slope gradient sectors usually experience slower fire spread, with more time available for fire intervention and perhaps restricting fire intensity.

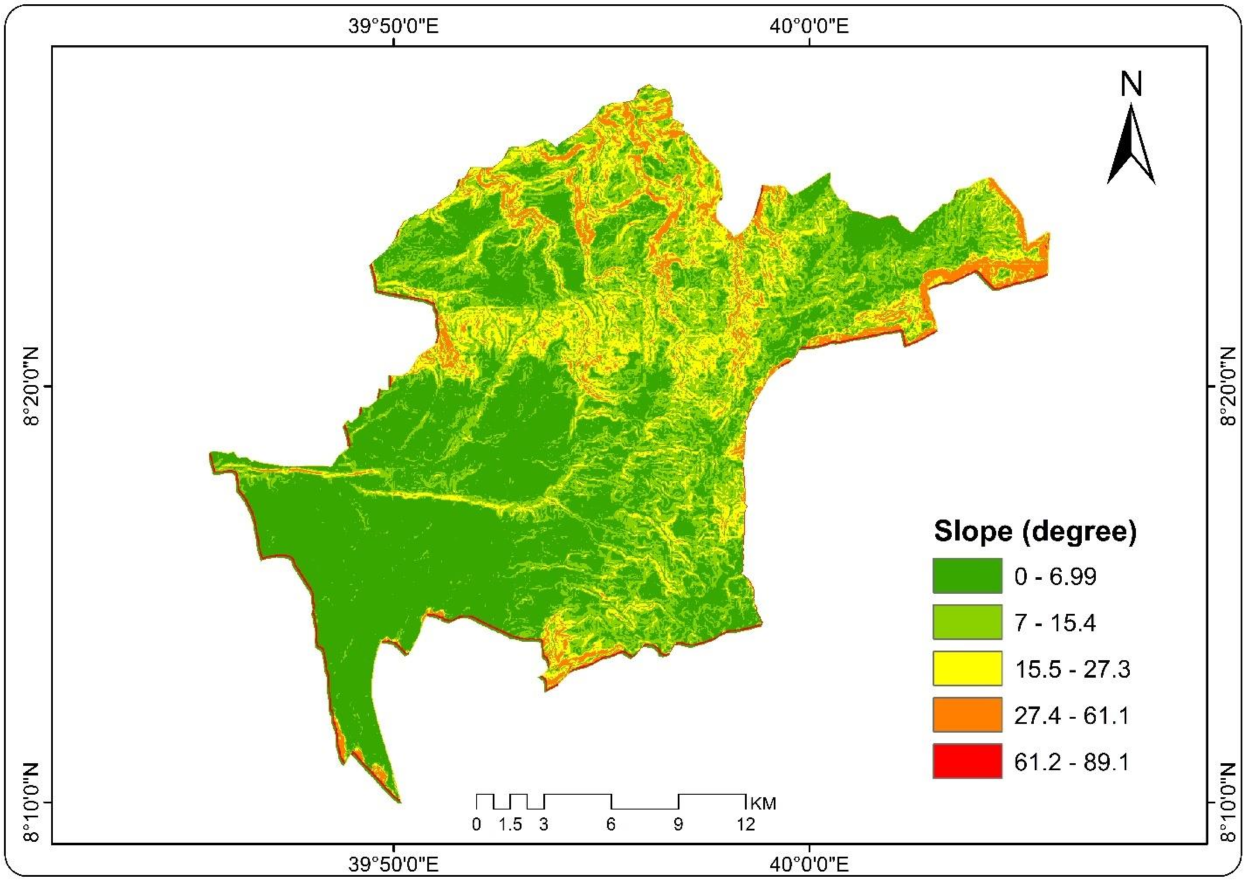

Figure 4-18: Slope

Aspect

Direction in which a slope faces is another key topographic element that influences forest fire initiation and spread (Linn et al., 2007). Aspect controls the solar radiation a surface receives, which in turn governs microclimatic conditions such as temperature, soil moisture, and vegetation dryness (Huryn, 2016). Generally, south- and southwest-facing slopes within the Northern Hemisphere receive more direct sunlight, are warmer and drier, and therefore more prone to wildfire initiation and enhanced fire spread (McCune, 1988; Kirkpatrick & Brown, 1991).

As shown in Figure 4-19, the northern part of the Arba Gugu study area is dominated by north- and northwest-aspect slopes. These aspects would otherwise be less solar irradiated and, as a result, have cooler and more humid conditions, which are prone to reduce fire susceptibility. The southern part of the study area, conversely, has south- and southwest-aspect slopes. Such slopes get more solar radiation, which leads to higher temperatures, less soil moisture, and drier vegetation all the factors that play an important role in enhancing the likelihood of igniting forest fire and higher intensity of fire behavior (Badakhshan et al., 2024).

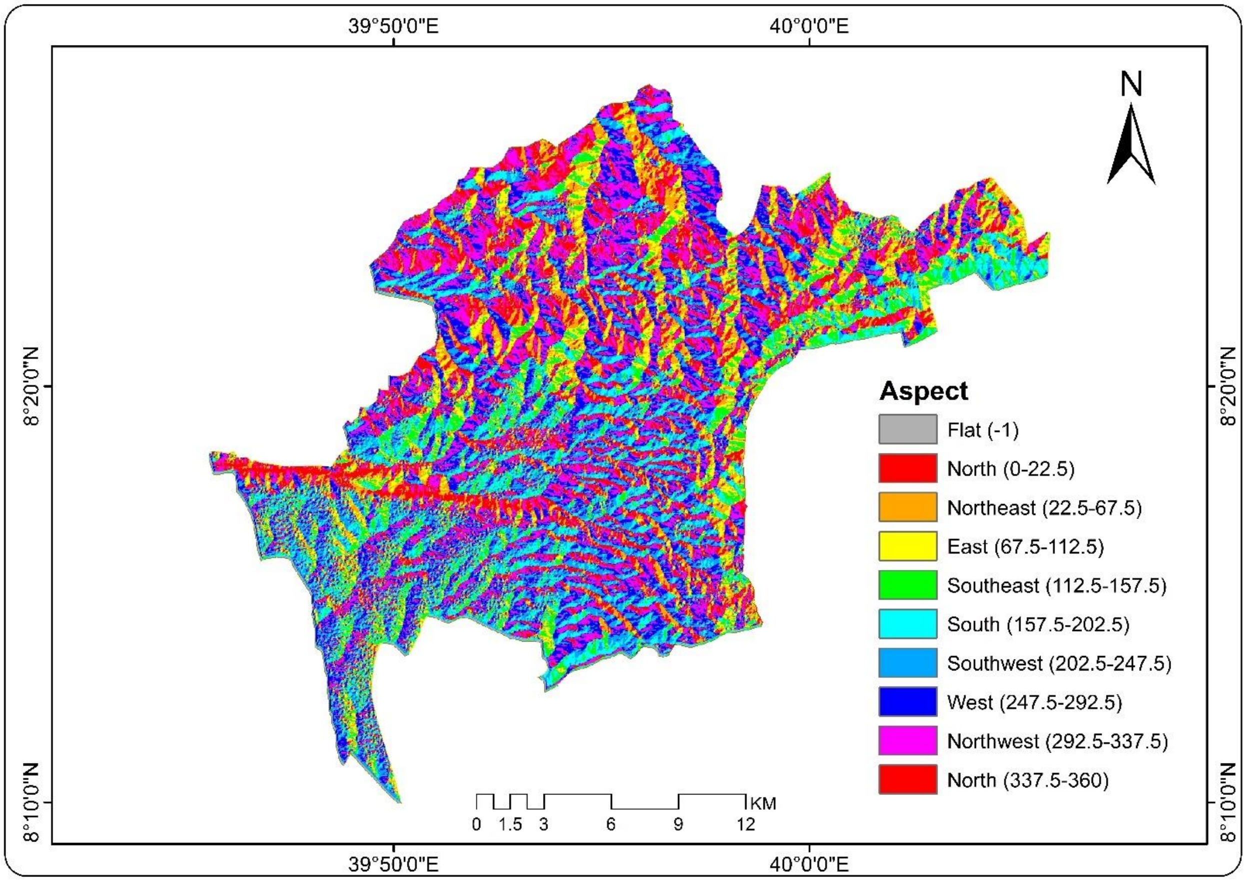

Figure 4-19:Aspect

4.6.2. Parameter reclassification for weighted overlay analysis

While forest fire risk is being modeled using the Analytic Hierarchy Process (AHP), the environmental variables must be standardized to similar classes that represent various levels of fire susceptibility. Figure 4-20 illustrates the transformation of four key parameters humidity, rain, highest temperature, and lowest temperature into five suitability classes, which serve as inputs for the weighted overlay analysis.

Humidity is one of the critical climatic factors influencing the likelihood of starting forest fires. Humidity across the study region has been divided into five classes in Figure 4-20 (a). The lowest humidity (10.1–10.5 g/m^3) falls under the N1 category in the northwest region of the study area, which has very high fire risk. Low atmospheric humidity dries vegetation and surface fuels, with perfect conditions for the initiation of fires (Viegas, 1998). Conversely, areas in the southern parts with higher values of humidity (11.5–11.8 g/m³, S5) are less prone to fire ignition due to higher fuel moisture content, reducing flammability.

Rainfall plays a critical role in regulating the moisture balance of ecosystems. The amount of precipitation was recoded into five classes as shown in Figure 4-20 (b), where low rainfall (1,040–1,100 mm, S5) occurs largely along the southern edge of the study area, marking areas highly susceptible to fire ignition. Low rainfall leads to dry conditions favorable to fire establishment (Flannigan et al., 2009). Alternatively, areas receiving more precipitation (1,410–1,510 mm, N1) in the north have fewer opportunities for fires, as frequent rain maintains greater fuel moisture.

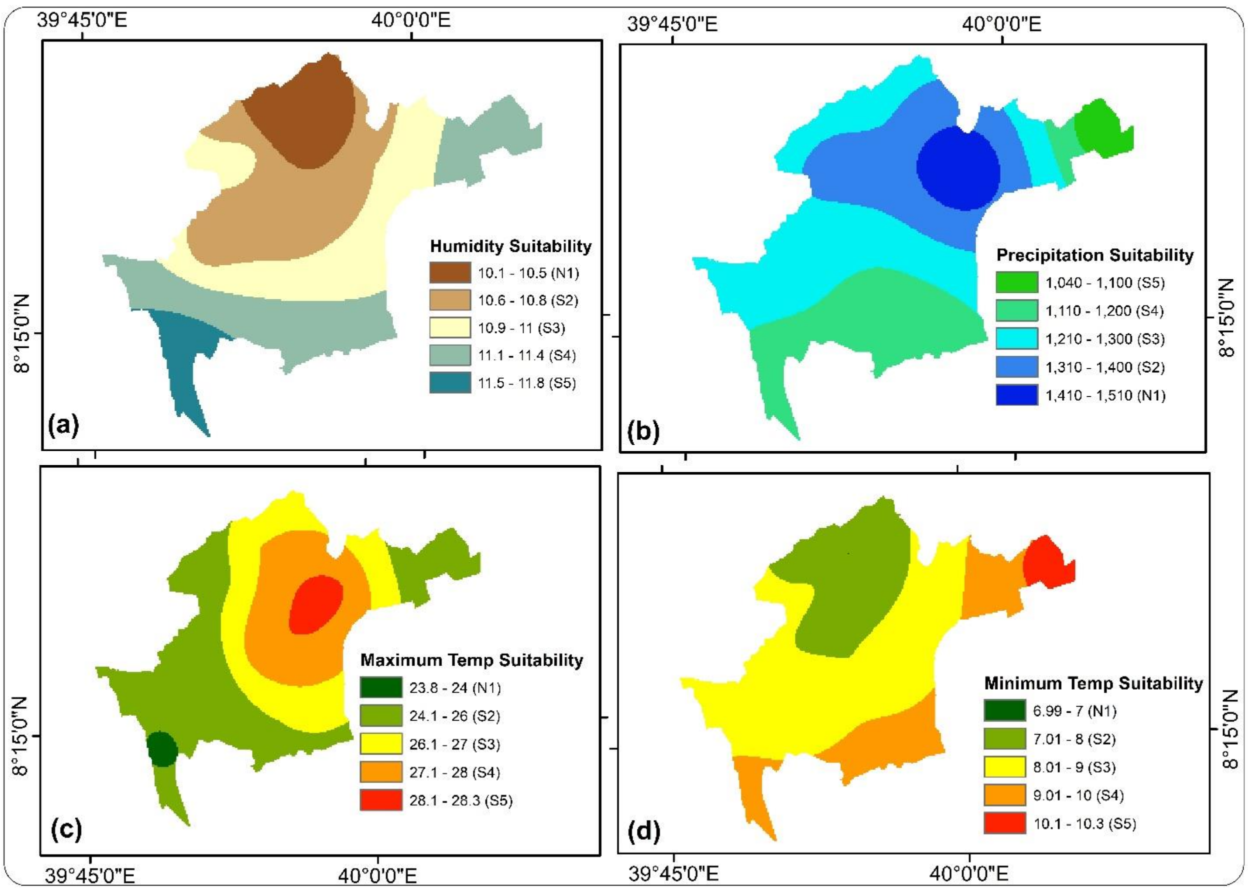

Figure 4-20: Reclassification of parameters; (a) Humidity, (b) Precipitation, (c) Maximum temperature, (d) Minimum temperature

Maximum temperature is another crucial parameter influencing the combustibility of vegetation. Figure 4-20 (c) indicates that Arba Gugu's central region experiences the maximum temperatures (28.1–28.3°C, S5). Rising temperatures accelerate drying of fuels and lower ignition levels, hence increasing fire risk (Moritz et al., 2012). Regions with minimum maximum temperatures (23.8–

24°C, N1) are most likely to have low fire risk due to the retention of higher moisture content in vegetation.

Minimum temperature also controls nighttime recovery of moisture in fuels. Figure 4-20 (d) shows the maximum minimum temperatures at the northeastern and southern edges (10.1–10.3°C, S5), referring to the possibility that fuels are dry even at night, favoring fire-prone conditions. The lower minimum temperatures (6.99–7°C, N1) northward have lesser exposure to fire with cooler and more humid nighttime weather (Bradstock, 2010). Higher minimum temperatures inhibit the recovery of relative humidity and fuel moisture at night and thus extend the fire-conducive period. The other parameter aspect, wind direction, wind speed, and slope were reclassified into five suitability classes based on their effect on forest fire risk. The spatial distribution of the reclassified parameters in the study area is presented in Figure 4-21.

Aspect, as in the direction of a slope, also plays an important role in controlling fire behavior by affecting solar radiation and moisture retention. As illustrated in Figure 4-21 (a), aspect has been classified into classes and south slopes (114–202°, S5) ranked as being most vulnerable to fire due to increased solar radiation and hence drier fuel conditions (Wagtendonk & Root, 2003). Conversely, north-facing slopes (1–22.5°, S2) are wetter and less flammable. This is in agreement with evidence that north and northwest aspects have higher frequencies of fires because of lower fuel moisture.

Wind direction is another determinant of fire spread. Wind direction ranges in Figure 4-21 (b) were reclassified, with 101–122° winds (S5) posing the highest risk of fire spread. This classification suggests that southeast winds may be orientated in accordance with terrain and fuel continuity to facilitate fire spread. Sharples (2009) has done research highlighting the manner in which wind direction can be orientated along slope and thus enhance the velocity and intensity of fire spread. Meanwhile, 79.8–87.5° wind (N1) experiences the worst possible conditions for fire spread.

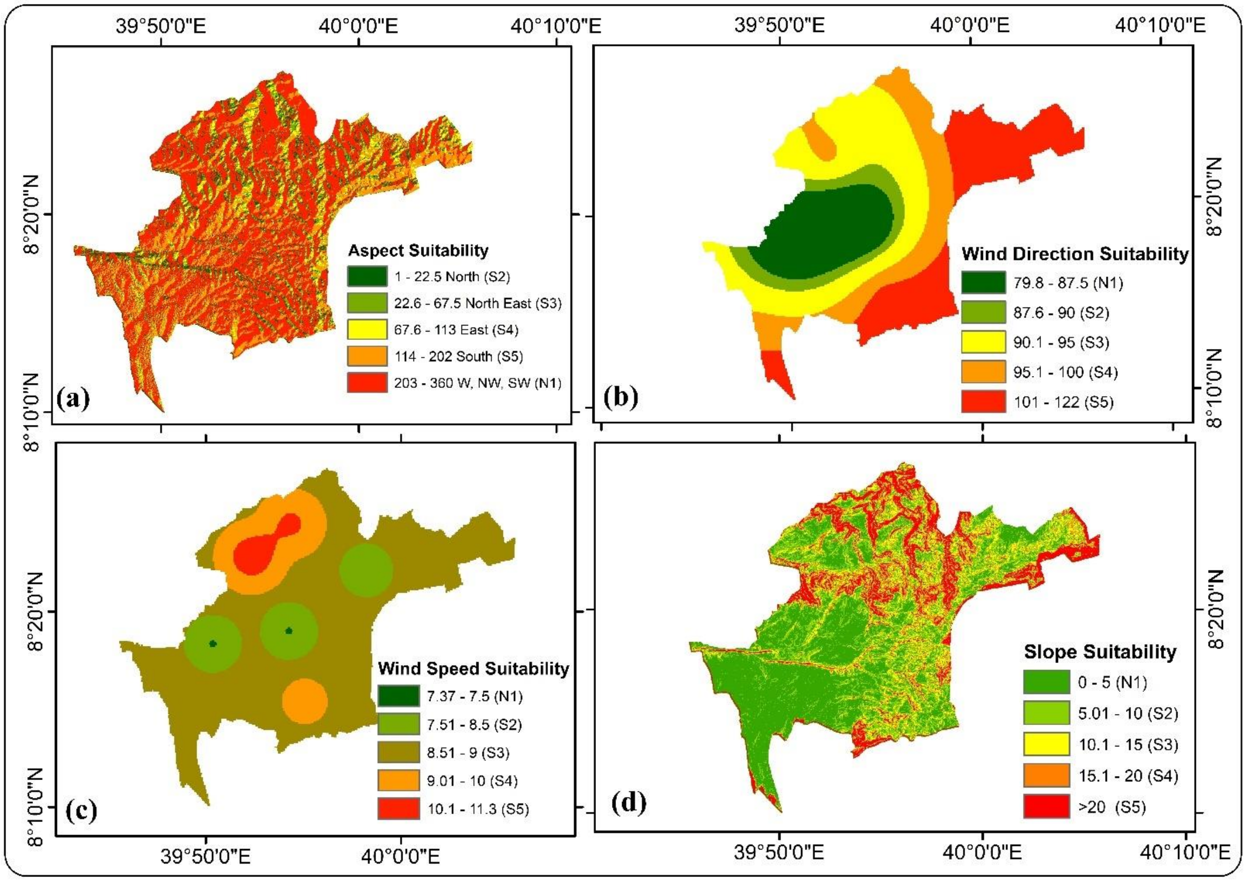

Figure 4-21: Reclassification of parameters; (a) Aspect, (b) Wind Direction, (c) Wind Speed, (d) Slope

Wind speed controls the rate of fire spread and the jumping of barriers by fires or not. In Figure 4-21 (c), wind speeds have been categorized into five types, with the most hazardous speeds (10.1–11.3 m/s, S5) being rated as most hazardous for fire behavior. Long-term high wind speeds can enhance oxygen supply to the fire, increase the height of the flame, and carry embers long distances to start spot fires in front of the fire front (Albini, 1976). Regions of low wind speeds (7.37–7.5 m/s, N1) were identified as low-risk areas.

Slope affects the speed at which fire can move. Figure 4-21 (d) shows steeper slope (>20°, S5) is highly susceptible to rapid fire movement because fire preheats and dries the upslope fuels (Rothermel, 1972). The steeper the slope, the faster the fire can spread uphill. Level ground (0–5°, N1) was classified as low-risk locations because fires will move comparatively slower along flat surfaces.

Elevation affects microclimatic conditions, fuel composition, and plant structure, which in turn affect fire behavior (Heyerdahl et al., 2001). Figure 4-22 (a) illustrates lower elevations (0–2,500 m, N1) that occur primarily in the northwest as least susceptible to fires due to more agreeable humidity and temperature conditions that favor the retention of moisture. Higher elevations (3,010–3,380 m, S5) occurring primarily in the east are more fire-susceptible. Under such increases, less atmospheric pressure and increased winds increase drying of vegetation and increased fire potential for spread (Westerling et al., 2006).

Land use and vegetation type directly regulate fuel load and connectivity, which are the most crucial parameters in wildfire initiation and expansion (Chuvieco et al., 2003). In Figure 4-22 (b), settlements (S) were assigned the highest fire vulnerability, since human uses increase the probability of ignition both by chance and by design. Shrubland areas (S2) were also shown to be of high risk due to the big surface-to-volume ratio of the shrub fuels that dry fast and burn hot (Miller & Urban, 2000). Crop areas (N1), however, were shown to be least at risk because active land management activities minimize available fuel and potential fire spread.

Human accessibility is often correlated with fire occurrence, as roads facilitate movement for activities that can lead to inadvertent ignition (Cardille et al., 2001). Figure 4-22 (c) shows that areas nearest to roads (0–3,520 meters, S5) were extremely prone to fire. Greater human activity near roads — including transportation, tourism, and agricultural activities — increases the potential for ignition sources. Conversely, off-road areas farther away from roads (14,200–17,600 meters, N1) were found to be low risk and show lower human activity and presence.

Rivers and water bodies can modify microclimatological conditions by introducing humidity in the surrounding area and acting as physical barriers that retard fire advance (Pereira et al., 2014). As Figure 4-22 (d) shows, regions closest to rivers (0–1,660 meters, N1) exhibit lowest fire hazard with additional humidity and potential barrier effect. Areas more distant (6,650–8,300 meters, S5) were also mentioned as being very vulnerable, where low humidity and absence of natural firebreaks facilitate easier ignition and spread of fires.

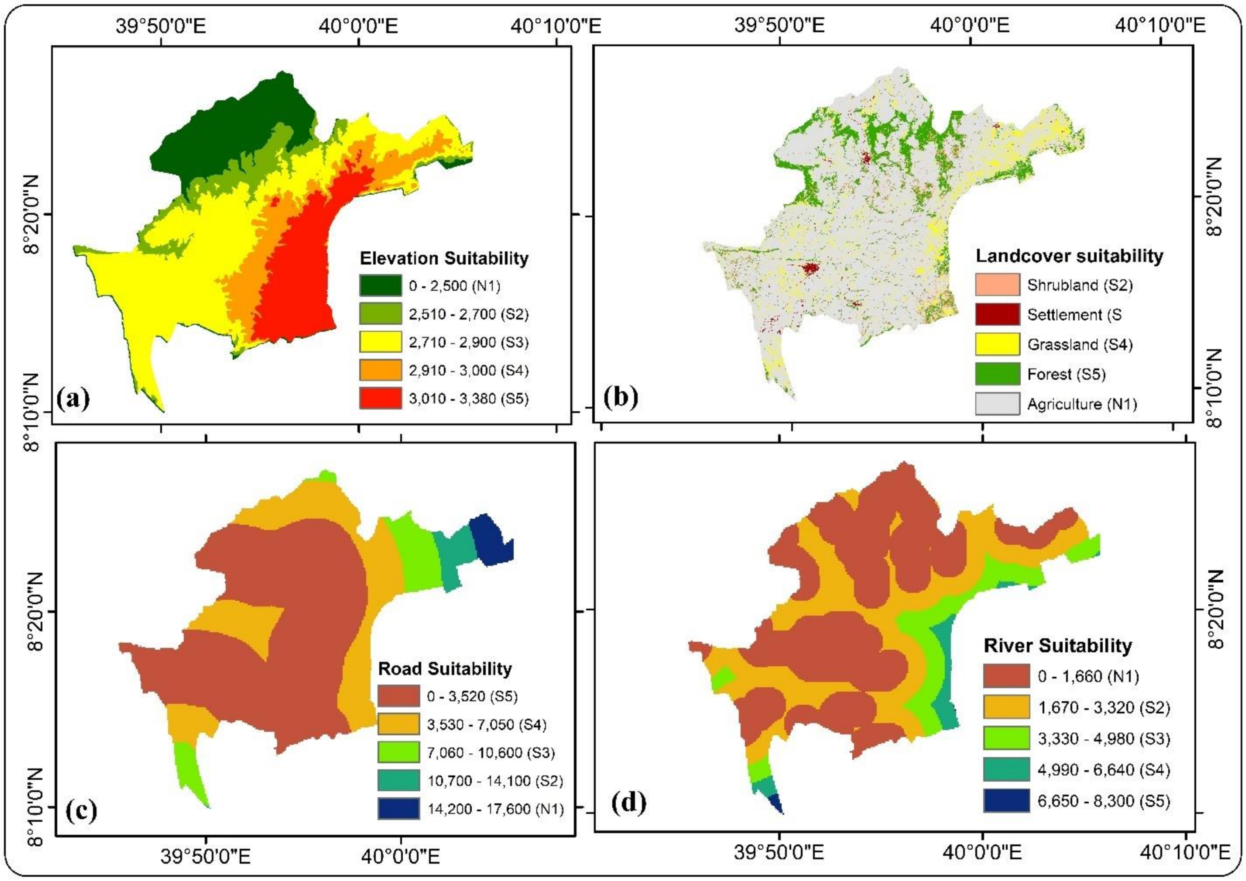

Figure 4-22: Reclassification of parameters; (a) Elevation, (b) Land cover, (c) Road, (d) River

4.7.Application of AHP

4.7.1. Confusion Matrix

Saaty (1980) developed the Analytic Hierarchy Process (AHP), which has been utilized in this study to elicit the relative importance of twelve environmental and anthropogenic variables influencing forest fire susceptibility. These included: elevation, wind speed, wind direction, maximum temperature, minimum temperature, slope, humidity, aspect, land use, distance to roads, distance to rivers, and precipitation. AHP is particularly helpful in managing multi-criteria decision-making problems (Annex 1), especially when qualitative and quantitative factors need to be evaluated in an orderly fashion (Saaty, 2008; Vargas, 1990).

To utilize AHP, an expert opinion and literature-based pairwise comparison matrix was created (Malczewski, 1999; Feizizadeh & Blaschke, 2013). Each pair of the criteria were ranked comparatively to each other on a 1–9 Saaty scale. Judgments were then put into a reciprocal matrix, and column totals were computed. Normalization involved dividing each matrix element with the corresponding column total so that the values in each column summed to 1 (Saaty, 1980). The mean of the normalized values in each row was subsequently calculated to determine the priority vector or final weight of each factor.

Moreover, climatic factors like maximum temperature and wind speed were high in their impact, complementing findings of Flannigan et al. (2000), who have noted that heightened temperature and strong winds increase vegetation dryness and allow for easier fire spread. Terrain factors like elevation and slope also had considerable impacts, as per González-Olabarria et al. (2011) research demonstrating that topography affects the course of fire and hazard due to its control over vegetation type and moisture gradients.

4.7.2. Consistency ratio

For verification of consistency in the pairwise comparisons, consistency analysis was conducted. Consistency Index (CI) was 0.12, and Random Index (RI) for twelve criteria is 1.54, as calculated from the standard RI table given by Saaty (1980). The Consistency Ratio (CR) was subsequently calculated as 0.08. As defined by Saaty (1980) and more recently emphasized by Forman and Selly (2001), a CR value less than 0.10 signifies an acceptable level of consistency in the pairwise comparison, that is, the expert judgments are consistent and dependable. Since the obtained CR value is below the threshold, it means that the pairwise comparison matrix is consistent and its resulting weights can be used in future multi-criteria decision-making. Maintaining an acceptable consistency ratio is extremely critical in AHP as inconsistencies may drastically mislead the priority outcomes and weaken the validity of the final model of decision (Vargas, 1990; Ishizaka & Labib, 2009).

Table 4-11: Consistency ratio

CI	0.12
RI	1.54
CR	0.08

4.7.3. Weighted overlay result

The weighted overlay analysis classified the study area into five forest fire hazard zones, viz. very low, low, moderate, high, and very high (Figure 4.23). The results show that the central and eastern parts of the study area are predominantly under high to very high-risk zones. These zones correspond to areas under control of conditions such as elevated temperature, reduced moisture, steep slopes, and some types of land use that are highly prone to ignition and fire spread. The above finding conforms to the work of Chuvieco and Congalton (1989) and Martínez et al. (2009), who emphasized that climatic variables, topography, and vegetation are major drivers controlling wildfire vulnerability.

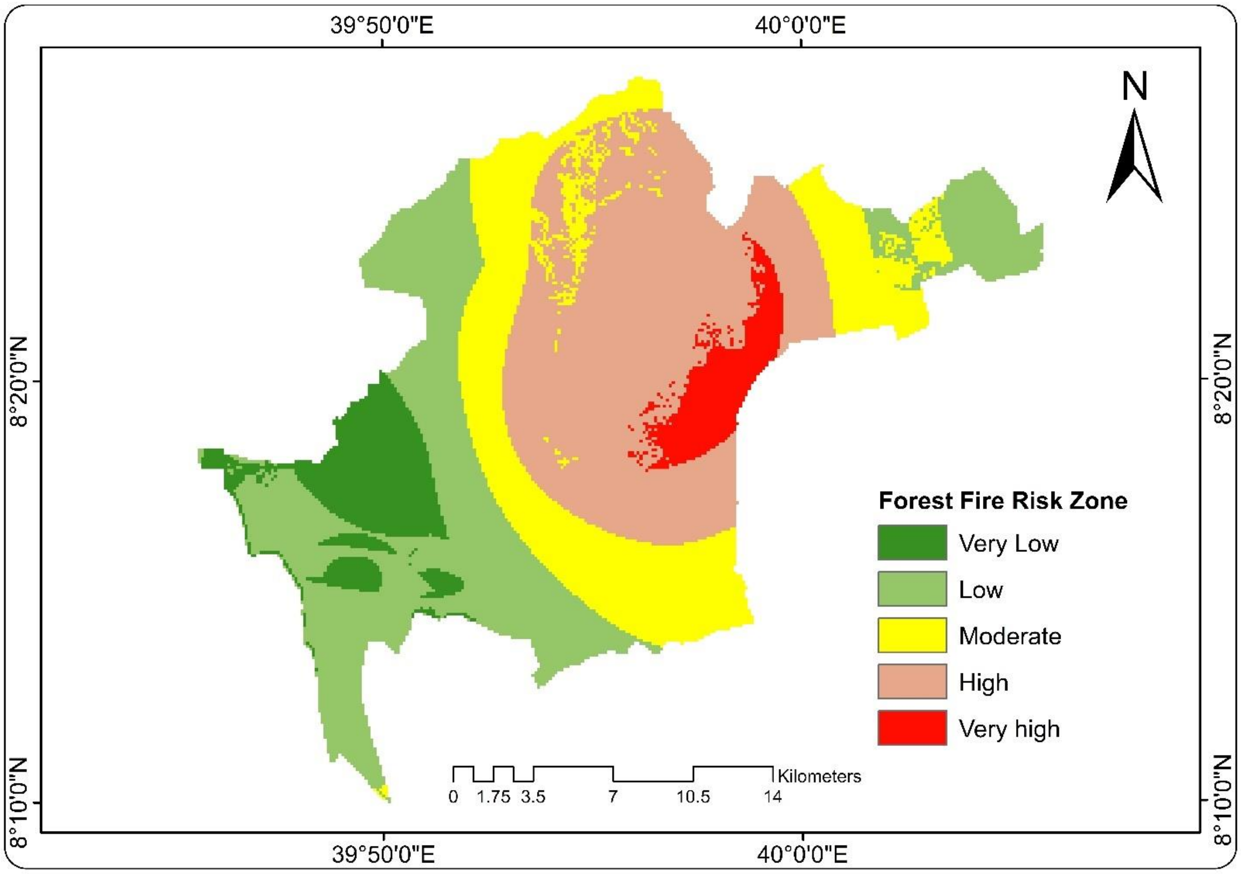

Figure 4-23: Forest fire risk zone in the study area

On the other hand, the very low and low fire danger zones are mostly in the periphery and southwestern part of the study area. They can be correlated with higher humidities, sloping gradient slopes, lower temperatures, and fire-ignition-tendency land use types like agricultural land or wetlands. These fire-emergence suppressing conditions have also been postulated by Vasilakos et al. (2007) and Jaiswal et al. (2002), who have also found moisture content and topographic stability to be essential mitigative factors for wildfire risk.

Intermediate risk belt belts also appear to encircle high-risk belts. The belts reflect environmental condition change sensitivity whereby minor levels of change, i.e., short-term drying or wind speed increases, are capable of increasing fire danger. Similarly transitional risk architecture has also been reported by the study by Kalabokidis et al. (2007) and Bajocco et al. (2010), once more reflecting landscape fire vulnerability dynamicity.

Table 4-12: Forest fire risk zone area and percentage share

SN	Risk Zone	Area	Percent
1	Very Low	3842.048	8.26
2	Low	13721.6	29.51
3	Moderate	11190.27	24.07
4	High	15615.59	33.58
5	Very High	2126.643	4.57

4.8. Socio-economic and livelihood impacts of forest fire

4.8.1. Frequency and Causes of Forest Fires

Within the Arba Gugu area, forest fires are reported to be a frequent occurrence, and it primarily occurs during the dry season. As one of the residents explained, "Forest fires are common, especially during the dry season" That is so based on trends experienced in other regions where fire frequency takes place more frequently in dry months due to high temperatures and low humidity (Archibald et al., 2021). Human activities are mainly responsible for forest fires in this region, e.g., "careless burning of farm residue" and "land clearing," which are common practices in agricultural societies. A local government officer noted, "Forest fires are mostly caused by human activities like careless burning of farm residues and random lightning strikes." This response is in agreement with research by Cochrane (2018), who also referenced anthropogenic drivers, namely land use practices like fire use for clearing agricultural land, as the main cause of fires in Africa.

4.8.2. Agricultural Impacts of Forest Fires

Bushfires have also had deep effects on farm crops in the region, with the majority of farmers reporting vast losses on charred crops. One of the farmers described, "Forest fires have burned huge portions of our crops, especially in seasons when it is dry, and thus resulted in reduced yields." This is a direct confirmation of literature citing the destructive impact of forest fires on crop yield, especially in tropical regions where crops and soil fertility are incinerated (Smith et al., 2018). Their impacts after the fire usually end up destroying the soil, explained one of the farmers, recounting, "Soil fertility has been lost, water sources have been affected, and the microclimate is warmer and drier, and crops become more difficult to cultivate." This corroborates with Kauffman et al.'s (2021) research, where it was discovered that forest fires drive environmental change in the long term by reducing soil loss by erosion and water, which ultimately affects agricultural productivity. A shift in farming activities is also taking place, whereby the majority of farmers have shifted to more fire-resistant crops, as one of the interviewees states: "We now prefer planting drought-resistant crops, and we avoid planting those that are more prone to fire damage, like maize." This is in agreement with literature-defined adaptation interventions, which include the promotion of fire- and drought-resistant crops in fire- and drought-prone areas (Lilly et al., 2020).

One of the other key informants also stated the overall agriculture effects, including in the following quotation: "Most of the households have been affected by reduction in crop production due to recurrent bush fires. The fires reduce the soil fertility for useful farming." The above quotation illustrates the overall trend experienced in fire-stricken areas where soil fertility is greatly decreased once fires have taken place, leading to decreased agricultural production (Pereira et al., 2020).

4.8.3. Livelihood Impacts of Forest Fires

Forest fires in Arba Gugu of Guna Woreda have had far-reaching impacts on the surrounding community, particularly their socioeconomic status. Even though agricultural loss is often the most obvious loss, the whole extent of losses extends much further to touch household income, food security, property ownership, as well as community resilience. Through both focus group discussions (FGDs) and key informant interviews (KIIs), this study uncovered the various ways forest fires erode livelihood.

Firstly, agriculture the leading livelihood activity of the area is heavily impacted by fire outbreaks. Loss of cropland, soil erosion, and destruction of farm infrastructure directly affect food crops and household incomes. The farmers of the area indicated that the fires typically start during the dry season when opportunities for rapid spread are imminent. The fires destroy crops already grown and diminish the soil's fertility, thereby making the production of high yields in subsequent seasons more difficult. Agricultural equipment, stored grain, and animal feed burning are also contributing to the economic cost through some households selling off whatever they have left or surviving on relief assistance.

Aside from agriculture, the majority of residents engage in secondary livelihoods such as collecting firewood, charcoal production, and the harvesting of forest-based products including honey, wild fruits, and medicinal plants. These forest-based livelihoods are especially critical for women and youth with no access to land or waged labor. One of the interviewees described, "Besides agriculture, people are also relying on the harvesting of firewood and small businesses. The burning of the trees to which we must turn in order to harvest firewood also leaves less room for enterprises." The observation is the sign of the link between forest health and rural household economies. Through Morris et al. (2021), it is evident that forest decline by means of fires heavily impacts not only revenues but also natural resource sustainable utilization.

In addition to loss of earnings, the households also lose important physical resources. Livestock, for example, is one of the most important assets of wealth in the area not only used for subsistence and labor but even as a kind of financial shock absorber in hard times. Yes, several families lost livestock, stored crops, and farming equipment in the fires," one of the farmers stated. The destruction of livestock, especially cattle, goats, and chickens, is especially detrimental to agro-pastoral communities that depend on them for milk, meat, ploughing, and money. Chelliah et al. (2019) highlight this, as they note that loss of livestock due to fires or death might further impoverish households and constrain their resilience to subsequent shocks.

Food security is further negatively impacted by the fires. Reduced crop yields result in increased market prices, while reduced availability of forest food such as edible roots, fruits, and wild vegetables further declines household nutrition. One of the residents explained, "Food security has declined because the production of crops has been reduced, and it has driven food prices up. There are some families who are reliant on government and NGOs relief." This is indicative of a larger pattern among fire-prone regions, where successive losses amount to long-term food insecurity. IOM (2022) explains how wildfires burn away seasonal sources of food, lower purchasing power, and force needy households to have to rely even more on external assistance.

At the institutional level, informants were keen to indicate that loss due to fires is the same as complete economic insecurity at a community level. A local government official explained, "Most families are financially unreliable because of the loss of crops, livestock, and farmland, so it is difficult to recover." This corroborates the finding that poor families with already scarce social protection find it difficult to recover from forest fires. Pelling et al. (2015) argue that the absence of structured recovery mechanisms, such as insurance or microfinance schemes, exposes societies affected by fire to long-term backwardness that accumulates with each occurrence.

In summary, the socioeconomic impacts of forest fires in the Arba Gugu area are intricate and deeply entrenched in the everyday way of life of the people. The fires destroy not only material property like land, agriculture, and livestock but also the intangible survival tactics on which individuals rely on the renewability of forest resources. The fires worsen hunger, desiccate sources of income, and destabilize homes, mostly among the most vulnerable. In response to such effects, comprehensive fire management approaches including reforestation, community preparedness, and diversification of livelihoods, and post-fire recovery assistance depending on the local conditions are urgently required.

4.9.Discussion

The finding of this study was a steep and persistent decline in forest cover in the Arba Gugu area from 1994 to 2024, mainly caused by agriculture expansion and settlement expansion. This deforestation trend mirrors most other studies in these kinds of ecosystems. As an example, Lambin et al. (2001) discussed that agricultural expansion is the primary driver of deforestation in the developing world due to the fact that increasing populations demand agriculture land for area that leads to the conversion of forests. Similarly, Hosonuma et al. (2012) discussed that agricultural expansion, forest extraction, and infrastructure expansion are the primary drivers of forest cover loss in the tropics, following the same trend seen in the Arba Gugu landscape.

In addition, past expansion in settlement size, particularly between 2014 and 2024, during which settlements expanded by 787.69%, supports the Seto et al. (2012) statement that urbanization is changing landscapes worldwide at a very fast pace and has related impacts on land cover change, ecosystem services, and sustainability. Urbanization of Abajema Town and other newer towns such as Moye, Efo, and Aseko illustrate such rural-urban transition world trends and further serve to underscore the imperative for an integrated urban planning to develop land cover change sustainably.

The change rate for the grassland and the shrubland also agrees with that which has been found for comparable environments. The study quantified a precipitous decline in shrubland from 1994 to 2004, which was re-established from 2014 to 2024. Meyfroidt and Lambin (2011) enumerate the following dynamic processes under which land abandonment and secondary succession lead to re-colonization of shrubland when agricultural profitability is devalued or depopulation through rural out-migration. In addition, the widespread extension of grassland in the study confirms what Gibbs et al. (2010) had reported, that grassland would dominate forests and shrublands in landscapes under heavy agricultural pressure, especially when the soils worsen and are no longer viable for cultivation.

In this study, forest fire risk mapping using the Analytic Hierarchy Process (AHP) included several biophysical, climatic, and anthropogenic variables to determine the risk zones in the Arba Gugu forest case. The outcome showed that the risk zones were particularly in the high maximum temperature, low humidity, steep, southwest- and south-aspect, and proximity to roads and settlements regions. The method and findings are in close agreement with previous studies. For instance, Chuvieco and Congalton (1989) and Martínez et al. (2009) emphasized the ability of multi-criteria evaluation methods like AHP in incorporating the complex interaction of climatic, topographic, and anthropogenic drivers governing wildfire vulnerability. They also identified temperature, slope, and distance to human settlements as some of the most relevant variables governing fire risk.

The dominant role of temperature and humidity in increasing fire hazard, as revealed by the Arba Gugu study, is also corroborated by the global observations of Flannigan et al. (2009) and Westerling et al. (2006), who found that warmer temperatures and reduced precipitation and humidity are leading factors explaining higher frequency and magnitude of fire, especially under climate change. Also, the discovery that south- and southwest-facing slopes were more vulnerable lends credibility to the assertions of Badakhshan et al. (2024) and Wagtendonk and Root (2003), whose finding was that sun-facing slopes receive a greater quantity of solar radiation and hence increase fuel drying and the probability of fire.

Human factors place significant weight on proximity to roads and settlements, resonating with Narayanaraj (2012) and Cardille et al. (2001), whose work indicated that proximity to people and roads is a sign of high rates of ignition for both accidental and deliberate causes. Similarly, the effect of river distance was also properly represented, as with Pettit and Naiman (2007), where riparian zones were said to act as natural firebreaks due to being more humid.

The findings of this study underscore the critical need to institutionalize data-driven decision-making in forest and land use management. Integrating geospatial technologies such as remote sensing and GIS into forest governance can provide high-resolution, up-to-date data on land cover change, fire risk, and human encroachment (De Sy et al., 2012). These technologies allow for real-time monitoring of deforestation, facilitating prompt enforcement and adaptive planning. Furthermore, platforms that democratize environmental data access can improve transparency, foster accountability, and support evidence-based policy formulation (Herold & Skutsch, 2011). Establishing a centralized environmental monitoring framework, possibly linked to national REDD+ programs, would also align with international commitments to climate change mitigation and sustainable development.

Enhancing public awareness and local education is essential for sustainable forest management. Local communities play a vital role in land use decisions, yet often lack access to information on the long-term ecological and economic consequences of deforestation and land degradation. As noted by Pretty and Smith (2004), community-based education and participatory approaches significantly improve resource stewardship by fostering a sense of ownership and responsibility. Environmental education in schools and community training programs can shift attitudes and behaviors, especially when linked to livelihood alternatives such as agroforestry or ecotourism. Moreover, engaging communities in co-management structures, as advocated by Ribot et al. (2006), increases the legitimacy and effectiveness of conservation initiatives. Therefore, policy frameworks should embed environmental education and stakeholder participation as pillars of forest governance strategies.

The findings of this study align closely with several key international frameworks aimed at promoting sustainable forest management, climate resilience, and biodiversity conservation. Notably, the observed deforestation trends and land cover transitions in the Arba Gugu area underscore the urgency of implementing the goals of the United Nations Sustainable Development Goals (SDGs), particularly SDG 13 (Climate Action), SDG 15 (Life on Land), and SDG 11 (Sustainable Cities and Communities). The study's emphasis on the drivers of forest loss—agriculture, settlement expansion, and fire risk—also resonates with the objectives of the UNFCCC REDD+ mechanism (Reducing Emissions from Deforestation and Forest Degradation), which encourages developing countries to conserve forest carbon stocks while enhancing forest governance (UNFCCC, 2010). Additionally, the patterns of land abandonment and shrubland recovery support the principles of the Convention on Biological Diversity's Aichi Targets and the post-2020 Kunming-Montreal Global Biodiversity Framework, particularly in promoting ecosystem restoration and halting biodiversity loss (CBD, 2022). By providing spatially explicit data on deforestation and fire risk zones, this study offers practical insights that can contribute to national reporting obligations and policy alignment under these global initiatives, demonstrating how local-level analyses are essential for achieving broader international environmental goals.

CHAPTER FIVE

5. CONCLUSION AND RECOMMENDATION

5.1.Conclusion

This study assessed the dynamics of Land Use and Land Cover (LULC) trends, modeled forest fire risk zones, and analyzed the socio-economic impacts of forest fires in Arba Gugu from 1994-2024. Impacts were found to include widespread and ongoing loss of forest cover, with an estimated loss of nearly 59% over the study period, largely due to agricultural growth and settlement expansion. Agriculture remained the dominant land use, increasing by close to 40%, while settlements expanded considerably, particularly between 2014 and 2024, showing rapid urbanization. Shrubland reduced tremendously initially but began recovering in the recent years, while grassland increased, showing land degradation and changed land management.

Forest fire hazard modeling, using the Analytic Hierarchy Process (AHP), concluded that temperatures in regions with increased levels, decreased humidity, steep slopes, and near roads and settlements were most vulnerable to forest fires. Central and eastern parts of the study region were most vulnerable and agreed with climatic, topographic, and anthropogenic conditions. The multiple criteria were effectively included by the modeling process and satisfactory consistency ratio, as well as results reliability, was ensured.

In socio-economic and livelihood aspects, forest fires have been shown to have negatively affected local communities in many respects. Reduced forest cover coupled with frequent fire episodes has led to significant reductions in agricultural productivity, the most notable of which is crops as well as pasturelands for livestock. Such loss has led to increased food insecurity, more so by vulnerable groups including pastoralists, small-scale farmers, and women. Moreover, there has been loss of property such as equipment, livestock, and harvested crops, further threatening the economic sustenance of households. The impact on food security has been acute, with many households becoming more dependent on external support, including NGOs and the government.

In their battle against such challenges, communities have practiced many coping mechanisms, including fire suppression efforts and cultivation of drought-resistant plants. These interventions have not managed to reverse the effects of forest fires in the long term completely. The study deems more sophisticated and integrative fire management methods, including more community-based programs on resilience and more access to post-fire recovery programs. In addition, climate-resilient and sustainable land management measures are essential in the mitigation of the prevailing environmental and socio-economic issues affecting the Arba Gugu communities.

5.2.Recommendations

The following are the recommendations based on what the research has found;

- Because of the near 59% loss of forests, extreme measures such as reforestation, community-based forest management (CBFM), and preserving the remaining forests must become priorities.
- To check the rapid settlement and agricultural development, municipal governments ought to have sustainable land use practices and regulate urban development through zoning.
- There should be ongoing community education schemes on forest stewardship, sustainable agriculture, and fire prevention.

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Annexes

Annex 1: Pairwise comparison

	Elevation	Wind speed	Wind direction	Max_Temp	Min_Temp	Slope	Humidity	Aspect	Landuse	Proximity to road	Distance from river	Precipitation
Elevation	1.0	9	6	5	6	3	6	6	7	5	5	7
Wind speed	0.11	1.00	5	4	7	3	5	5	7	4	7	5
Wind direction	0.17	0.20	1.00	9	9	9	2	6	6	2	7	5
Max_Temp	0.20	0.25	0.11	1.00	7	5	2	7	7	2	8	5
Min_Temp	0.17	0.14	0.11	0.14	1.00	7	6	7	9	4	9	5
Slope	0.33	0.33	0.11	0.20	0.14	1.00	5	2	2	5	9	7
Humidity	0.17	0.20	0.50	0.50	0.17	0.20	1.00	2	7	3	9	9
Aspect	0.17	0.20	0.17	0.14	0.14	0.50	0.50	1.00	7	3	9	9
Landuse	0.14	0.14	0.17	0.14	0.11	0.50	0.14	0.14	1.00	3	9	7
Proximity to road	0.20	0.25	0.50	0.50	0.25	0.20	0.33	0.33	0.33	1.00	9	7
Distance from river	0.20	0.14	0.14	0.13	0.11	0.11	0.11	0.11	0.11	0.11	1.00	9
Precipitation	0.143	0.200	0.200	0.200	0.200	0.143	0.111	0.111	0.143	0.143	0.111	1.00
Total	**3.00**	**12.06**	**14.01**	**20.95**	**31.12**	**29.65**	**28.20**	**36.70**	**53.59**	**32.25**	**82.11**	**76.00**

Annex 2: Normalization of comparison matrix

	Elevation	Wind speed	Wind direction	Max_Temp	Min_Temp	Slope	Humidity	Aspect	Landuse	Proximity to road	Distance from river	Precipitation	Weight
Elevation	0.33	0.75	0.43	0.24	0.19	0.10	0.21	0.16	0.13	0.16	0.06	0.09	6.09
Wind speed	0.04	0.08	0.36	0.19	0.22	0.10	0.18	0.14	0.13	0.12	0.09	0.07	8.53
Wind direction	0.06	0.02	0.07	0.43	0.29	0.30	0.07	0.16	0.11	0.06	0.09	0.07	8.53
Max_Temp	0.07	0.02	0.01	0.05	0.22	0.17	0.07	0.19	0.13	0.06	0.10	0.07	9.74
Min_Temp	0.06	0.01	0.01	0.01	0.03	0.24	0.21	0.19	0.17	0.12	0.11	0.07	10.96
Slope	0.11	0.03	0.01	0.01	0.00	0.03	0.18	0.05	0.04	0.16	0.11	0.09	10.96
Humidity	0.06	0.02	0.04	0.02	0.01	0.01	0.04	0.05	0.13	0.09	0.11	0.12	10.96
Aspect	0.06	0.02	0.01	0.01	0.00	0.02	0.02	0.03	0.13	0.09	0.11	0.12	10.96
Landuse	0.05	0.01	0.01	0.01	0.00	0.02	0.01	0.00	0.02	0.09	0.11	0.09	10.96
Proximity to road	0.07	0.02	0.04	0.02	0.01	0.01	0.01	0.01	0.01	0.03	0.11	0.09	10.96
Distance from river	0.07	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.12	1.22
Precipitation	0.05	0.02	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.14
Total	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	100

Annex 3: FGD and KII

ASTU UNIVERSITY

School of Civil Engineering and Architecture (SOCEA)

Department of Geomatics Engineering

FGD and KII guiding question

I am a researcher conducting a study on the socioeconomic impacts of forest fires on local communities, specifically focusing on 'Assessing Forest fire effects on the surrounding environment: The case of Arba Gugu forest in Guna Woreda, Oromia regional state, Ethiopia'. This research aims to gather firsthand information and insights from community members like you, which will help inform better support systems, prevention strategies, and policies that could benefit the affected communities in the future. I want to assure you that your participation in this discussion is entirely voluntary. You have the right to decline to answer any question or to stop the interview at any time if you feel uncomfortable, without facing any negative consequences. Additionally, everything you share during this conversation will be treated with the highest level of confidentiality. Your name and any personal or identifying information will not be recorded in the final report or shared with anyone outside the research team. The information will only be used for academic and research purposes to better understand the challenges faced by communities like yours. Your honest and thoughtful responses are very important and will be greatly appreciated. If you are comfortable, I would like to begin our discussion.

Mekdes Teshome

Cell phone: +251 91 329 9610

FOCUS GROUP DISCUSSION (FGD) QUESTIONS

(Target: local farmers, community members, women's groups, youth groups, pastoralists)

A. General Understanding and Experience

1. How common are forest fires in the Arba Gugu area, based on your experience?
2. Can you describe how forest fires typically start in this region?
3. How do you usually find out about fires in the area?

B. Agricultural Impacts

4. How have forest fires affected your farmland and crop yields in recent years?
5. What changes have you noticed in soil fertility, water availability, or microclimate following fires?
6. Have forest fires influenced your choices of crops or farming practices? If so, how?
7. Do forest fires affect livestock grazing areas? Can you give examples?

C. Livelihood Impacts

8. Besides farming, what other sources of income do people rely on, and how have fires affected them?
9. Have forest fires led to any loss of assets like tools, livestock, or stored harvests?
10. How have forest fires impacted food security in your household and community?

D. Coping Mechanisms and Community Response

11. How do you and your community usually respond to forest fires?
12. Have you received any support (from the government, NGOs, or other groups) after a fire incident?
13. What strategies do you use to protect your farm, livestock, and household from the impacts of fires?

KEY INFORMANT INTERVIEW (KII) QUESTIONS

(Target: local government officials, agricultural officers, forest rangers, community elders)

A. Context and Occurrence

1. Can you describe the history and frequency of forest fires in the Arba Gugu area?
2. What are the main drivers of forest fires here, from your perspective?

B. Socioeconomic and Agricultural Impact

3. Based on your knowledge or records, how have forest fires affected local agricultural productivity?
4. How do forest fires influence the economic stability of farming and pastoral households?
5. Are there any particular groups (e.g., women, landless farmers, pastoralists) that are more vulnerable to the effects of fires?

Mekdes Teshome

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