



COLLEGE OF NATURAL AND COMPUTATIONAL SCIENCES

SCHOOL OF EARTH SCIENCES

REMOTE SENSING AND GEO-INFORMATICS

**ASSESSING THE IMPACTS OF LAND-USE AND LAND-COVER
CHANGE ON CLIMATE VARIABILITY IN GIMBO DISTRICT,
SOUTHWEST PEOPLE'S REGION, ETHIOPIA**

MSc. Thesis

By

TAMIRU ASSEFA

ID NO: GSR/4250/16

ADVISOR: Prof. K. V. SURYABHAGAVAN

ADDIS ABABA, ETHIOPIA

MAY, 2025

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**A THESIS SUBMITTED TO THE SCHOOL OF EARTH SCIENCES, ADDIS ABABA
UNIVERSITY IN PARTIAL FULFILMENT OF THE REQUIREMENT FOR THE
DEGREE OF MASTER OF SCIENCE IN REMOTE SENSING AND
GEOINFORMATICS**

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DEPARTMENT OF REMOTE SENSING AND GEOINFORMATICS

ADDIS ABABA UNIVERSITY

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MAY, 2025

Declaration

I, Tamiru Assefa, hereby declare that this thesis titled “Assessing the impacts of land-use and land-cover change on climate variability in Gimbo district, southwest people’s region, Ethiopia” is the result of the original research work. All sources of information and references used in the thesis preparation have been acknowledged.

This thesis has not been submitted in whole or in part for the award of a degree or diploma in this or any other university.

Signed -----

Tamiru Assefa -----

May, 2025

Acknowledgments

First and foremost, I would like to express my deepest gratitude to Dr. Biniyam Tesfaw, head of the Department of Remote Sensing and Geo-informatics, for his valuable support and encouragement throughout this study, to my supervisor, Prof. Surya, for his thoughtful guidance, patience, and steady support throughout this journey. His encouragement and advice made a real difference in helping me stay focused and move forward, even during challenging times. I'm also grateful to the faculty and staff of Addis Ababa University, especially those in the Department of Remote Sensing and Geo-Informatics, for their support, feedback, and willingness to assist whenever i needed help.

Thank you.

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List of Abbreviations

CART	Classification and Regression Trees
CRGE	Climate Resilient Green Economy
CSA	Climate Smart Agriculture
ESIF	Ethiopian Strategic Investment Framework
FN	False Negative
FP	False Positive
GEE	Google Earth Engine
GTB	Gradient Tree Boosting
K	Kappa Coefficient
KNN	K-Nearest Neighbor
LST	Land Surface Temperature
LT-LEDS	Long-Term Low Emission Development Strategy
LULC	Land Use and Land Cover
MK	Mann-Kendall test
MLR	Multiple Linear Regression
NAP	National Adaptation Plan
OLI	Operational Land Imager
OOA	Overall Accuracy
PA	Producer's Accuracy
PWS	Prewhitened Sen's Slope
Pe	Expected Agreement
Po	Observed Agreement
RF	Random Forest
SVM	Support Vector Machine
TIRS	Thermal Infrared Sensor
TM	Thematic Mapper
TN	True Negative
TP	True Positive
UA	User's Accuracy
USGS	United States Geological Survey
ZMK	Z-transformed Mann-Kendall
masl	Meters above sea level

Abstract

Land use and land cover change are major drivers of climate variability; however, their interaction is understudied in many regions, including southwest Ethiopia. This study investigates land use and land cover (LULC) dynamics and their influence on climate variability in the Gimbo district, a biodiversity hotspot undergoing rapid land use transitions due to population growth and agricultural expansion. Utilizing multi-temporal Landsat imagery (1989–2024) and TerraClimate datasets (temperature and rainfall), this research integrates remote sensing and statistical methods to assess changes in land surface temperature (LST) and climate trends. Six land use and land cover classes—water bodies (WB), wetlands (WL), forest land (FL), built-up area (BUA), agricultural land (AL), and tea plantation (TP)—were classified using five machine learning algorithms: Classification and Regression Tree (CART), Random Forest (RF), Support Vector Machine (SVM), Gradient Tree Boost (GTB), and K Nearest Neighbor (KNN). Cloud masking and spatial subsetting were applied to preprocess images. Accuracy assessments were conducted using overall accuracy (OAA), kappa coefficient, and F1 scores. LULC change detection was quantified through gain-loss analysis, while climate trends were evaluated using Mann-Kendall tests and Sen's slope estimator. Pearson correlation and multiple linear regression (MLR) assessed the relationship between LULC change and climate variables. Results indicated that SVM performed best in 1989 (OAA = 84.62%, kappa coefficient = 0.81), 2010 (OAA = 89.59%, kappa coefficient = 0.87), and 2019 (OAA = 91.62%, kappa coefficient = 0.90) classifications, while RF outperformed the others in 2024, achieving an OAA of 93.37% and kappa of 0.92. Overall, SVM maintained the highest average classification accuracy (OAA = 89.11%). The LULC change detection results revealed that wetlands declined by 5.6 percentage points, representing a relative decline of 62% at an annual rate of 2.79%. Forest land saw a decrease of 25.72 percentage points, corresponding to a relative decline of 41% at a rate of 1.49% per year. Agricultural land increased by +28.84 percentage points with a relative rise of 111.5% at 2.14% per year, built-up areas grew by +0.83 percentage points with a 73.45% relative increase at 1.49% per year, and tea plantations increased by +1.67 percentage points with a 293% gain at 3.89% from 1989 to 2024. Climate analysis highlighted a statistically significant increase in mean minimum annual temperature (0.0254 °C/year, $p = 0.0000201$) and average annual maximum temperature (0.02355 °C/year, $p = 0.00442$). At the same time, MLR results showed that mean annual maximum temperature was strongly correlated with agricultural land expansion, forest loss, and tea plantation expansion, with $p < 0.05$. Additionally, the average annual land surface temperature (LST) increased by 0.33 °C ($P = 0.000062$), while the mean annual rainfall exhibited a non-significant trend (0.0255 mm/year, $p > 0.05$). The study underscores how rapid agricultural expansion and deforestation have intensified local warming, emphasizing the need for climate-smart land management interventions. Finally, it recommends enforcing policies, strategies, and proclamations to conserve wetlands and forests while integrating high-resolution satellite data to enhance future LULC-climate analyses.

Keywords: Land-use and land-cover (LULC), Climate variability, Machine learning, Trend analysis, multiple linear regression

Chapter One

Introduction

1.1 Background

Climate variability, land-use, and land-cover change are interlinked phenomena that profoundly affect environmental and socio-economic systems in regions with fragile ecosystems where communities heavily rely on natural resources. The relationship between climate and land-use and land-cover is complex, with evidence showing that human-triggered climate change is a direct consequence of alterations in land-use and land-cover (Bununu et al., 2023). Over the last three decades, extensive land-use and land-cover changes, such as deforestation, agricultural expansion, and urbanization, have significantly transformed the landscape and local conditions of the study area. Gimbo's distinct challenge, its varied elevation range, and its ecological importance make it an ideal location to study the interplay between land-use and land-cover change and climate variability. However, despite growing attention to studying land-use and land-cover change in Ethiopia, there is a lack of localized studies focusing on the study area, leaving critical knowledge gaps. The southwest region of Ethiopia, known for its rich biodiversity, has experienced significant land-use and land-cover changes due to population growth, deforestation, agricultural expansion, and urban development. These changes have contributed to shifts in rainfall patterns, land surface temperature, and other climatic factors. For instance, research in Keffa zone has linked deforestation with an increase in temperature and irregular distribution (Lemma et al., 2021). Similarly, a study conducted in the Gojeb River catchment highlighted how agricultural expansion and vegetation loss affected rainfall patterns (Danganchew et al., 2020). On the other hand, a study in the upper Omo-Gibe basin found that such changes are aggravated by anthropogenic activities, stressing the need for a deeper understanding of these interactions (Lukas et al., 2023).

Furthermore, forest loss in Jimma and its surroundings revealed a reduction of 1,427 hectares of vegetation cover, contributing to increased land surface temperatures and altered rainfall patterns, consistent with broader climatic trends observed across Ethiopia (Dessu et al., 2020). This evidence underscores the need to assess climate variability in the study area within the larger context of land-use and land-cover change. Advanced tools such as machine learning algorithms, the Mann-Kendall trend test, Sen's slope estimator, and multiple linear regression provide a unique opportunity to explore the complex relationship between land-use, land-cover change, and climate.

The Mann-Kendall test, widely used to detect climatic trends, has identified significant changes in rainfall and temperature patterns in southern and southwestern Ethiopia (Gasura & Wana, 2021) and (Habte et al., 2021). In northwestern Ethiopia in the Amhara region, Mann-Kendall analysis results have revealed pronounced variability in land surface temperatures over two decades (Bayable & Alemu, 2021). Similarly, research in the Gidabo River basin using statistical, hydrological, and modeling techniques has shown a notable increase in surface runoff associated with land-use and land-cover changes (Aragaw et al., 2021), while research in the Gonder Zuria district has highlighted a seasonal decline in rainfall and temperature trends (Mareligne & Gashu, 2023).

Machine learning algorithms have proven valuable for land-use and land-cover classification and predicting future changes. In the upper Omo Gibe river basin, the random forest algorithm coupled with CA-ANN classified land cover types and predicted future land-use and land-cover trends (Lukas et al., 2023).

The study aimed to investigate the localized impacts of land-use and land-cover change on climate variability in the Gimbo district, an area that has been understudied in this context. Using multispectral Landsat imagery from 1989 to 2024, land-use and land-cover changes were classified using supervised machine learning algorithms such as Classification and Regression Tree (CART), Random Forest (RF), support vector Machine (SVM), Gradient Tree Boost (GTB) and K Nearest Neighbor (KNN) in the Google earth engine platform. Temporal trends of climate variables such as minimum and maximum temperature, land surface temperature, and precipitation were analyzed using the Mann-Kendall trend test and Sen's slope estimator to understand the extent of variability. Furthermore, the Pearson correlation coefficient and multiple linear regression (MLR) were employed to quantify the relationship and impacts of land-use, land-cover change, and climate variability. By addressing the research gap, the study provides valuable insights to guide policymakers and stakeholders in implementing climate-smart sustainable land management practices and climate adaptation actions in line with the environmental policy of Ethiopia, 1997 and the CRGE strategy 2011, NAP Eth 2019, and LT-LEDS, 2020–2050.

1.2 Problem statement

The Gimbo district of the Southwest People's region in Ethiopia is experiencing rapid land-use and land-cover (LULC) changes driven by anthropogenic activities such as deforestation, agricultural expansion, urbanization, and the establishment of large-scale commercial plantations. These changes have profound environmental and climatic implications, including rising temperatures, disrupted rainfall patterns, soil degradation, and reduced agricultural productivity, particularly in areas like Rhoi, Hamani, and Shocha. Additionally, practices such as planting eucalyptus in wetlands and the use of herbicides (24D and Roundup) threaten the health of wetland ecosystems. Despite studies in nearby areas like Jimma and Bonga demonstrating the climatic impacts of deforestation and agricultural expansion (Dessu et al., 2020), there is a lack of localized research in the study area. This study aims to address these gaps by investigating the climatic impacts of LULC changes, providing essential insights for sustainable land management and climate resilience interventions in the district.

1.3 Objectives

1.3.1 General Objective

To assess the impact of land use and land-cover change on climate variability in the Gimbo district, southwest Ethiopia, from 1989 to 2024

1.3.2 Specific Objectives

1. To evaluate and compare the performance of supervised machine learning algorithms for land-use and land-cover classification
2. To quantify the temporal and spatial change in land-use and land-cover using multi-temporal Landsat imagery
3. To analyze trends in climate variability, focusing on air temperature, land surface temperature, and rainfall.

1.4 Research questions

1. Which supervised machine learning algorithm achieved the highest accuracy for LULC classification?
2. What are the temporal and spatial changes in land-use and land-cover in the study area from 1989 to 2024?
3. What are the temporal trends in climate variables?

1.5 Significance of the study

The study will address challenges in land management and climate change by examining how land-use and land-cover (LULC) changes influence local climate variability in the Gimbo district. It bridges a critical gap in site-specific research, providing valuable insights for sustainable land management and climate change. Advanced machine learning techniques, such as Random Forest (RF), Support Vector Machine (SVM), and Classification and Regression Tree (CART), combined with the Google Earth Engine (GEE) platform, were employed to generate LULC maps. Additionally, the study compares the performance of supervised machine learning algorithms to identify the most suitable classifiers for analyzing LULC changes, assesses the spatial and temporal land-use and land-cover change, and climate trend analysis. The findings will support decision-makers by demonstrating how land-use and land-cover change impacts local climate patterns, including temperature, rainfall, and land surface temperature. Ultimately, the study provides actionable local-level guidance for developing climate-resilient land management interventions, promoting sustainable development, and mitigating the adverse effects of climate change.

1.6 Scope of the study

The study aimed to assess the impacts of land-use and land-cover change on climate variability in the Gimbo district, Southwest Ethiopia People's Region from 1989 to 2024. It specifically examines changes in climate variables, including temperature and rainfall. The research used Landsat 5 TM, Landsat 8 OLI/TIRS, and TerraClimate data as input to examine LULC change and climate trend analysis. Machine learning algorithms were used for LULC classification, while Mann-Kendall and Sen's slope estimator for detecting the presence of trend and magnitude of the climate variables, Pearson correlation coefficient, and multiple linear regression were used to assess the relationship between LULC change and climate variables.

1.7 Limitations

The study provides valuable insights into the impacts of LULC change on climate variability, but it has several limitations. First, it did not incorporate socio-economic data, such as population growth or land tenure dynamics, which are critical in explaining the underlying drivers of LULC change. Additionally, ground truth data for earlier years (1989 and 2010) were unavailable. Second, the presence of cloud cover in some of the satellite images, particularly during the wet

seasons, obscured surface features and potentially affected the accuracy of land cover classification. Furthermore, the spatial resolution of Landsat imagery (30 meters) was insufficient to detect small-scale land cover changes, such as settlement expansion or fragmented agricultural plots, which are common in heterogeneous landscapes like Gimbo. Lastly, the use of proxy climate data, due to the limited availability of long-term ground-based meteorological records in the district, introduced bias in the climate analysis. Future research would benefit from integrating socio-economic datasets, higher-resolution satellite imagery, and locally recorded climate observations to enhance the accuracy and interpretability of findings.

1.8 Organization of the thesis

The thesis is structured into seven chapters, adhering to institutional guidelines and academic conventions. It begins with title pages, acknowledgment, and an abstract that concisely summarizes the research objectives, methodology, key findings, and discussion. A table of contents, list of tables, and list of figures follow to facilitate navigation. Chapter One introduces the research by outlining the background, research problem, objectives, research questions, significance of the study, scope, and limitations. Chapter two reviews existing literature and identifies gaps that this research addresses. Chapter three details materials and methods describing the research design, data source, collection procedures, and analytical techniques. Chapter four systematically presents the main findings supported by tables, figures, and graphs, Chapter five presents the interpretation of the results of the research questions and existing literature. Chapter 6 summarizes the key insights, limitations, and proposes actionable direction for future research, finally, the thesis concludes with references used during the study.

Chapter Two

2. Literature review

2.1 LULC changes and climate variability

Land-use and land-cover (LULC) changes refer to alterations in the landscape driven primarily by human activities such as agriculture, urbanization, deforestation, and afforestation. These modifications can significantly influence natural environments and climate systems at both local and regional levels (Alemayehu et al., 2023; Nsubuga & Rautenbach, 2018; Shao et al., 2018). Understanding the interplay between LULC changes and climate variability is crucial for developing sustainable environmental management strategies. In tropical countries like Ethiopia, LULC change is primarily driven by agricultural expansion, population pressure, and commercial activities, such as tea and coffee plantations. Southwest Ethiopia, a biodiversity hotspot with rich forest cover, is under pressure from these activities, raising concerns about the impacts on climate and ecosystems. Gimbo district is one of the areas in Southwest Ethiopia where such changes have been observed over the last few decades.

2.1.1 Deriving factors

Several factors are responsible for the changes in land cover. Population growth and the demand for more farmland are at the top of the list. For example, in the Adama Zuria district, the increase in agricultural and settlement areas came at the expense of natural shrub lands and forests (Jote et al., 2021). The same trend is likely happening in Gimbo, where forests are being cleared for agriculture, impacting the environment. In the Central Rift Valley, agricultural land expansion has led to deforestation and environmental degradation, which endangers both the ecosystem and local farming communities (Molla, 2015).

2.1.2 Impacts on communities

Alterations in land use not only influence the environment but also significantly affect the local populations. As forests cleared, communities lose their sources of firewood, building materials, and other essential resources. Additionally, land degradation hampers agricultural production, resulting in diminished harvests and food shortages, as observed in various areas of Ethiopia (Belete, 2020). In the Atwima Nwabiagya district of Ghana, rapid urban growth and agricultural

expansion have led to comparable consequences, causing deforestation, soil degradation, and diminished farming output (Kullo et al., 2021).

2.1.3 Environmental consequences

The environmental consequences of LULC changes are significant. As forests are converted into farmland, loss of biodiversity, increased soil erosion, and habitat destruction will occur. In the Arsi Negele district, agricultural expansion led to a sharp decline in shrub lands and woodlands, further damaging the environment (Molla, 2015). A study conducted in the Gumara watershed, which is part of the Lake Tana basin in the northern highlands of Ethiopia, indicates that changes in land-use and land-cover (LULC) have significantly affected local climate variability. Urbanization, marked by a rapid increase in built-up areas, has reduced natural vegetation cover, leading to higher surface runoff, reduced infiltration, and water scarcity. Deforestation and agricultural expansion have contributed to rising temperatures and altered rainfall patterns. Specifically, the increase in impervious surfaces due to urbanization has increased temperature and decreased rainfall, particularly during key agricultural seasons. These LULC changes exacerbate climate variability, intensifying droughts and impacting water resources and agricultural productivity (Halefom et al., 2019).

2.2 Climate variability in southwest Ethiopia

Climate variability in Southwest Ethiopia is characterized by significant changes in temperature and rainfall patterns, impacting agricultural practices and water resources. Studies indicate a notable increase in annual maximum and minimum temperature rises of 0.71°C and 0.65°C respectively from 1983 to 2016 (Habte et al., 2021). Conversely, rainfall trends show high spatial variability, with some areas experiencing declines in precipitation, particularly under future climate scenarios projected by regional climate models (Yechale, 2023), (Tesfaye et al., 2022). Farmers have recognized these changes, adapting through strategies such as crop diversification, soil conservation, and altering planting dates (Girma et al., 2018). However, the effectiveness of these adaptations is limited by factors such as knowledge gaps and resource availability. The overall decline in water resources due to climate change exacerbates challenges for subsistence agriculture, necessitating robust climate-resilient policies (Yechale, 2023).

2.3 Impact of land-use and land-cover changes on climate variability

Land-use and land-cover (LULC) changes significantly affect climate variability by influencing hydrological processes, local climates, and agricultural productivity. Globally, urbanization and agricultural expansion have led to increased built-up areas and reduced agricultural land, contributing to altered precipitation patterns and temperature shifts. For instance, in the Aurangabad district of India, these changes have resulted in decreased precipitation and temperature changes (Masroor et al., 2022). In the Damodar catchment, land cover changes between 1972 and 2001 were linked to increased reservoir inflows, with climate variability playing a more significant role than land-cover (Kumar et al., 2023). Moreover, while climate trends have little impact on cropland changes globally, extreme weather conditions, particularly in hotter regions, are closely linked to higher rates of cropland loss (Kennedy et al., 2023). Additionally, land-cover transitions have sometimes led to overestimations of climate impacts on phenology, as seen in the Northern Hemisphere, where changes in land cover affected green-up dates (Pan et al., 2023). In Ethiopia, LULC changes have similarly exacerbated climate variability and environmental degradation. The conversion of natural vegetation to cultivated land has led to increased soil erosion, altered hydrological responses, and reduced groundwater recharge, all contributing to more surface runoff (Negese, 2021; Ebabu et al., 2022). These changes are compounded by climate change, including rising temperatures and unpredictable rainfall, which threaten agricultural productivity and food security (Bezu, 2020). Over the past few decades, Ethiopia has experienced a 0.37°C increase in annual temperature, while rainfall patterns remain unpredictable, leading to severe droughts and floods (Bezu, 2020). Ineffective land-use policies and governance gaps have further intensified these challenges, underscoring the urgent need for sustainable land management practices that mitigate both land use changes and climate impacts (Arficho & Thiel, 2020).

2.4 Machine learning approaches in land use-land cover change using GEE in Ethiopia

Machine learning approaches utilizing Google Earth Engine (GEE) have significantly advanced the analysis of land-use and land-cover changes in Ethiopia. Studies have employed various algorithms, notably Random Forest (RF) and Support Vector Machines (SVM), to classify LULC types and detect changes over time. For instance, the RF algorithm demonstrated high accuracy in

the upper Tekeze basin, achieving overall accuracy rates of 83% and 75% Kappa values, while the CART model outperformed others in the Welmel watershed, indicating its effectiveness in LULC classification (Tekla et al., 2024; Fentaw & Abegaz, 2024). Additionally, a hybrid approach combining SVM with other methods has been proposed to enhance classification efficiency and accuracy (Shivamurthy et al., 2024). These machine learning techniques not only facilitate the monitoring of LULC dynamics but also inform sustainable land management practices, crucial for mitigating land degradation and preserving ecosystems in the region (Wondrade, 2023).

Chapter Three

3. Materials and methods

3.1 Description of the study area

The study area is situated in the Kafa zone of the Southwest Ethiopia people's region, 419 km southwest of Addis Ababa. Geographically lying between 07°12'32.56" – 07°29'32.32" N latitude and 36°01'15.83" – 36°29'51.44" E longitude, it spans a total area of 743.50 km² (Figure 1). The topography is highly diverse, characterized by elevations ranging from 1,291–2,615 meters above sea level (m a.s.l.) with a mean elevation of 1,972 m a.s.l. Slopes vary from 0° to 63.87°, with an average of 10.87°, indicating predominantly gentle to moderately steep terrain.

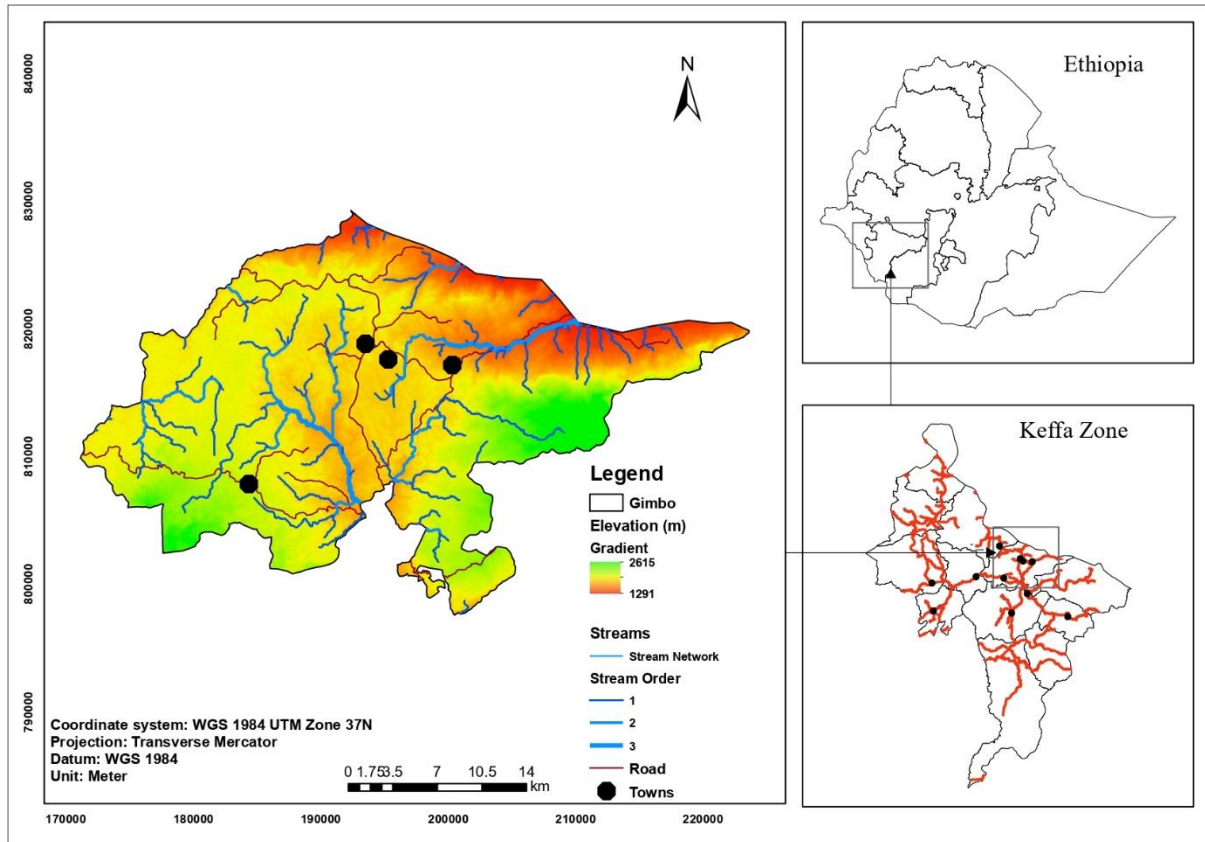


Figure 1. Location map of the study area

3.1.1 Climate and natural resources

The district has a tropical highland climate characterized by two main rainy seasons. The primary rainy period lasts from June to September, while a shorter rainy phase occurs in March and April. The average annual rainfall varies between 1,710 mm and 1,892 mm, while the mean temperature ranges from 18.1°C to 19.4°C (Matheos, 2001), fostering dense forest ecosystems that are part of the Kafa Biosphere Reserve. These forests, especially those containing wild Arabica coffee (*Coffea arabica*), hold global significance due to their biodiversity and role in conservation initiatives. The area is also abundant in natural resources, including non-timber forest products such as honey, spices, medicinal plants, and wild fruits (district office of agriculture report 2024).

3.1.2 Economy and livelihoods

Agriculture serves as the foundation of the district's economy, with a majority of the population involved in subsistence farming. The primary crops grown include maize, teff, sorghum, tea, and coffee, with coffee & tea being the most significant cash crops. Additionally, the district's forests generate income through non-timber forest products (NTFPs). Many households also engage in livestock rearing, especially cattle and goats, which adds an extra source of income. Given the advantageous altitude and climate of the district, sustainable agroforestry practices are gaining importance, integrating agricultural cultivation with forest preservation (CSA, 2014).

3.1.3 Population

As of the projected population in 2022 by CSA, Gimbo district is home to 130,328 people, with an annual growth rate of 2.5%. The population is composed of 64,139 males and 66,189 females, with a population density of approximately 158.1 people per square kilometer. Traditional social structures are still influential, especially in rural areas, where community governance is often intertwined with local agricultural practices.

3.2 Research design

The research employed mixed approaches, integrating quantitative, descriptive, and geospatial techniques to evaluate the impact of LULC changes on climate variables, specifically temperature, rainfall, and land surface temperature in the study area. Temporal Landsat imagery (1989, 2010, 2019, and 2024) was processed using Google Earth Engine and Arc Map to classify LULC types and quantify spatiotemporal changes. Climate data were sourced from the TerraClimate dataset.

Statistical analysis included Pearson correlation to assess the relationship between LULC changes and climate variables, while MLR was used to quantify the impacts of LULC dynamics on climate variability over time. To provide a clear understanding of the methodological framework employed to assess the impacts of LULC change on climate variability, a flow chart (Figure 2) is presented. This flow chart outlines the sequential steps from data collection to data analysis and validation.

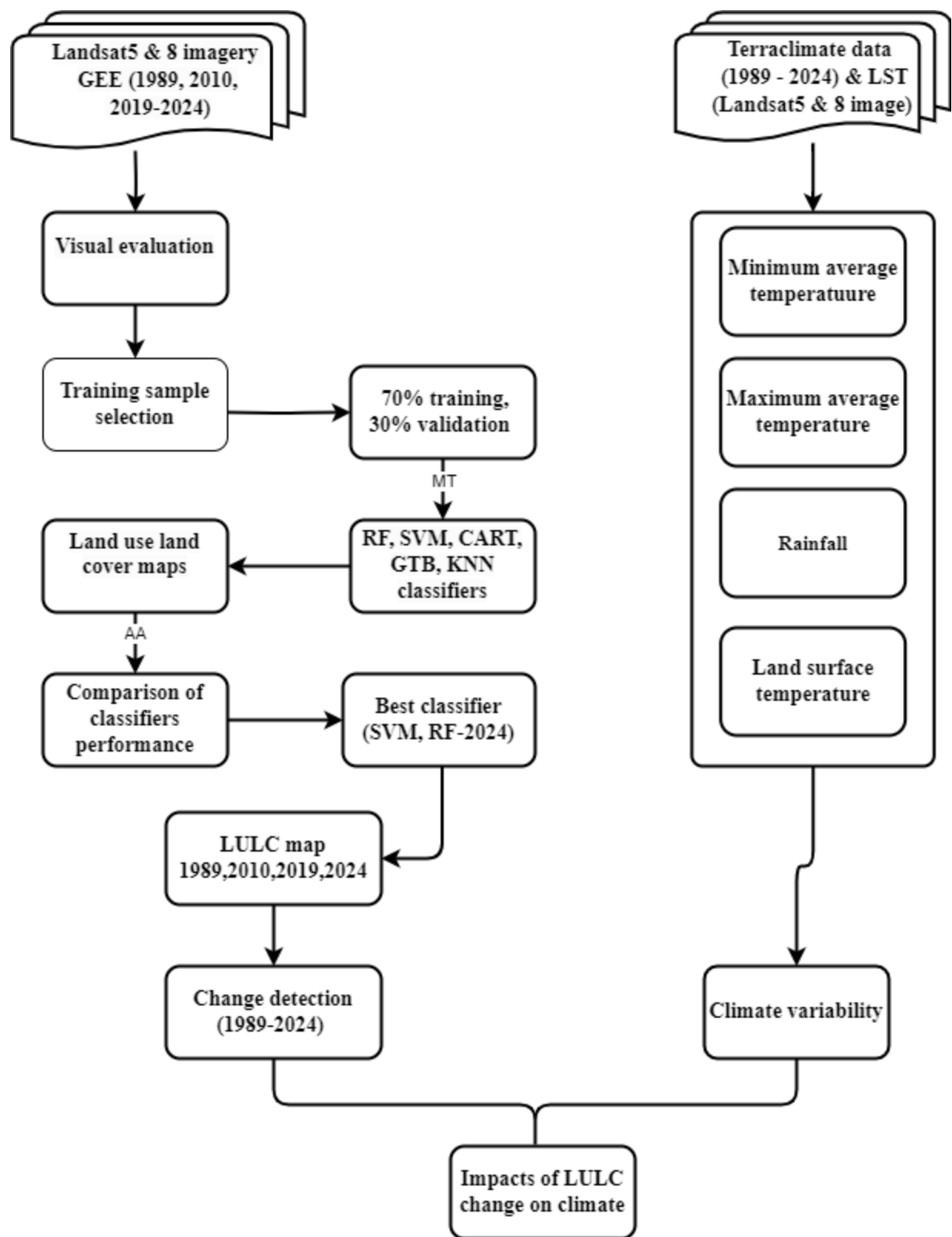


Figure 2. Methodology flow chart

3.3 Data

3.3.1 Satellite dataset

Multi-temporal satellite imagery from the USGS Earth Explorer Landsat archive (1989–2024) was processed in Google Earth Engine (<https://earthengine.google.com/>), a cloud-based platform for processing geospatial data. Landsat 5 Thematic Mapper (TM) and Landsat 8 Operational Land Imager (OLI) with a spatial resolution of 30 meters and a 16-day revisit cycle were utilized to assess land use and land cover changes in the area. Detailed specifications of the Landsat imagery are provided in Table 1.

Table 1. Landsat images and their specifications used for the study

Satellite data	Acquisition date	Sensor	Pixel size	Bands used	Path/Row	Source
Landsat 5	01/01/1989 to 12/31/1989	TM	30 m	B2,B3,B4,B5,B7	170/055	USGS
Landsat 5	01/01/2010 to 12/31/2010	TM	30 m	B2,B3,B4,B5,B7	170/055	USGS
Landsat8	01/01/2019 to 12/31/2019	OLI/TIRS	30 and 15 m	B2–B7	170/055	USGS
Landsat8	01/01/2024 to 12/31/2024	OLI/TIRS	30 and 15 m	B2–B7	170/055	USGS

3.3.2 Climate data

Due to incomplete records from meteorological stations (>10%) in the study area, the TerraClimate dataset was used to evaluate climate variability (Table 2). This dataset provided monthly minimum and maximum average temperatures, along with total monthly precipitation, at a high spatial resolution ($1/24^\circ$, ~4 km) for global land surfaces, covering the period from 1958 to the present (Abatzoglou et al., 2018). Additionally, land surface temperature data were obtained from the thermal bands of Landsat 5 TM and Landsat 8 TIRS imagery (Table 3).

Table 2. Climate data used (1989-2024)

Period	Metric	Value	Temporal resolution	Data source
1989 – 2024	min temp (°C)	annual average of daily minimum temperatures	monthly, seasonal, annual	TerraClimate website
1989 – 2024	max temp (°C)	annual average of daily minimum temperatures	monthly, seasonal, annual	TerraClimate website
1989 – 2024	rainfall (mm)	total monthly rainfall	monthly, seasonal, annual	TerraClimate website
1989 – 2024	LST (°C)	mean land surface temperature	annual	USGS Earth Explorer (Landsat 5, Landsat 8 thermal bands)

Table 3. Technical specifications of TM (Landsat 5) and TIRS (Landsat 8) for LST analysis

Parameter	Landsat 5 (TM)	Landsat 8 (TIRS)
Thermal Sensor	Thematic Mapper (TM)	Thermal Infrared Sensor (TIRS)
Thermal Bands	Band 6	Band 10
Wavelength Range (µm)	10.4 – 12.5	10.6 – 11.19
Central Wavelength (µm)	11.45	10.9
Spatial Resolution	120 m (resampled to 30 m)	100 m (resampled to 30 m)
Radiometric Resolution	8-bit	12-bit
Temporal Resolution	16 days	16 days
Swath Width	185 km	185 km
Operation Period	1984 – 2013	2013 – present

3.3.3 Land surface temperature (LST)

Land surface temperature (LST) was derived from Landsat imagery thermal infrared data in the Google Earth Engine, a cloud-based geospatial data processing platform, for processing large-scale remote sensing dataset. For Landsat 5, thermal band 6 (TIR) was used, while for Landsat 8, thermal band 10 from the thermal infrared sensors (TIRS) was employed to retrieve the mean LST values. The retrieval process involved the following sequential steps, as outlined in equations (1-6)

DN values were converted to radiance value using equation 1 (Xu et al., 2011).

$$\left[L\lambda = L_{\min} + \left(L_{\max} - \frac{L_{\min}}{Q_{\max}} \right) * Q_{\text{dn}} \right] \quad (1)$$

where L_λ the spectral radiation value measured in $w/m^2sr\lambda$, L_{min} and L_{max} are the minimum and maximum radiance of thermal bands obtained from the metadata of Landsat image, Q_{max} is the maximum quantized pixel value obtained from the metadata and Q_{dn} is the digital number for Landsat 5 TM 255 and for Landsat 8 TIRS is 65535.

Radiance values were converted into brightness temperature using equation 2 (Chander et al., 2009).

$$T_B = \frac{K2}{(\ln \frac{K1}{L_\lambda} + 1)} \quad (2)$$

where the brightness temperature at the sensor (T_B) is expressed in Kelvin (K) and is calculated using thermal conversion constants specific to the spectral bands. For Landsat 5 TM band 6, the thermal conversion constants $K1$ and $K2$ are 607.76 and 1260.56, respectively, for Landsat 8 TIRS band 10, these constants are 666.09 and 1282.71, & obtained from the metadata, and $\ln$ is the natural logarithm.

Normalized difference vegetation index was calculated from the reflectance of near infrared and red bands using equation 3, proportional vegetation was also calculated using equation 4, and emissivity using equation 5.

$$NDVI = \frac{NIR - R}{NIR + R} \quad (3)$$

$$PV = \frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \quad (4)$$

$$\varepsilon = \varepsilon_{veg} * PV + \varepsilon_{soil}(1 - PV) \quad (5)$$

where ε_{soil} (0.004) is the emissivity of soil, PV is the fractional vegetation or the proportional vegetation cover, ε_{veg} (0.986) is the emissivity of vegetation cover. And LST was calculated using equation 6 adopted from (Sobrino et al., 2004)

$$LST = \frac{TB}{\left[1 + \left(\frac{\lambda * TB}{p}\right) \ln(\varepsilon)\right] - 273.15} \quad (6)$$

where LST is the land surface temperature, λ is the wave length of the emission radiance (11.5 μm for Landsat 5 TM, and 10.8 μm for Landsat 8 OLI), p is derived from hook's law; $= \frac{h*c}{\sigma}$, h is the planks constant ($6.626 * 10^{-34}$ mK), c is the speed of light ($2.998 * 10^8$ m/s), σ Boltzmann constant ($1.38 * 10^{-23}$ JK), $\ln$ is the natural logarithms, ε is the emissivity of land surface.

Data from 1989–2024 were processed to convert spectral radiance into brightness temperature using the Planck function. Surface emissivity corrections were then applied based on NDVI and proportional vegetation cover (PV) to account for land cover specific emissivity variations. The resulting LST values provided a spatial and temporal representation of surface heat variations associated with LULC change. To quantify LULC-driven climate impacts mean LST value is correlated with the LULC classes using Pearson correlation and multiple linear regression.

3.4 Data pre-processing

Before analysis, raw satellite imagery sourced from USGS Earth Explorer via the Google Earth Engine platform underwent preprocessing to ensure data quality and consistency. First, cloud and cloud shadow masking was applied using the QA_PIXEL band to minimize atmospheric interference, spatial cropping (sub-setting) was performed to focus the analysis on the study area boundary, a median composite image was generated, combining the cloud-masked and clean imagery to represent the typical land surface characteristics for each year, thereby minimizing the impact of cloud cover. The final composite image was subsequently used as input for land-use and land-cover classification. Additionally, climate data, such as temperature and precipitation, sourced from the TerraClimate website, were processed to identify outliers using Z-score.

3.5 Classification Algorithms

3.5.1 Classification and Regression Tree (CART)

Classification and Regression Tree (CART) is a decision tree-based algorithm that employs recursive partitioning to divide the feature space into binary regions based on spectral reflectance values, aiming to minimize impurity at each node (Breiman et al., 1986). In the study, the classifier was trained using the smileCart implementation available in Google Earth Engine (GEE). The training dataset, created from land-use and land-cover classes sampled within the study area, was

split into 70% training and 30% validation subsets (Yang et al., 2017). The CART model iteratively evaluated reflectance bands (SR_B2 to SR_B7) to identify optimal split points for each node, building a structured decision tree. During classification, each pixel in the composite image was assigned to a class based on decision rules derived from the training data. The model's performance was evaluated using an error matrix, overall accuracy, and the kappa coefficient to measure the agreement between predicted and reference data.

3.5.2 Random Forest (RF)

Random Forest (RF) is an ensemble learning algorithm that constructs multiple decision trees and aggregates their outputs to improve classification accuracy (Breiman, 2001). Among the various algorithms used for land-use and land-cover (LULC) classification in Google Earth Engine (GEE), RF has demonstrated superior performance, yielding higher overall accuracy and kappa coefficients (Aigbokhan et al., 2022; Aldiansyah & Saputra, 2023). In the study, the smile Random Forest algorithm was employed to train the classifier using 50 trees. The training process involved sampling reflectance bands (SR_B2 to SR_B7) along with LULC classes from the study area. The RF model constructed multiple decision trees, each trained on a randomly selected subset of the data and features, effectively reducing overfitting. The classification of the composite image was determined through majority voting across the ensemble of trees.

3.5.3 Support Vector Machine (SVM)

Support vector machine is the most commonly used supervised classification algorithm, identifying an optimal hyperplane to separate classes in a high-dimensional feature space (Cortes & Vapnik, 1995). The critical parameters for using SVM include kernel type, error penalty, and gamma term (Yang, 2011). The SVM was configured with the kernel type set to radial basis function (RBF), an error penalty value of $C = 100$, and a gamma value of 0.1. The training process involved mapping reflectance bands (SR_B2 to SR_B7) into a transformed space using the sampled LULC data to maximize class separability. SVM iteratively adjusted the hyperplane to minimize classification errors while maintaining a margin between different classes (Wang, 2022). The classifier's performance was validated using a reference dataset, and metrics such as overall accuracy and kappa coefficient were employed to quantify its effectiveness.

3.5.4 K-Nearest Neighbors (KNN)

K-Nearest Neighbor (KNN) is a non-parametric algorithm that classifies data points based on the majority vote of their k nearest neighbors in the feature space (Cover & Hart, 1967). The smile KNN implementation was configured with $k = 10$, using reflectance data to determine spectral similarity. Training data, sampled from the study area, was divided into training (70%) and validation subsets (30%) to ensure accurate model evaluation. The algorithm classified the composite image by assigning each pixel to the LULC class most common among its 10 nearest neighbors.

3.5.5 Gradient Tree Boost (GTB)

GTB (Gradient Tree Boost) is an iterative ensemble approach in which decision trees are sequentially learned to correct the residuals from the predictions of previous trees (Friedman, 2001). The smile Gradient Tree Boost model was trained with 100 trees from reflectance bands (SR_B2 to SR_B7) of the whole study area. The model was fit to the training set (70%) and then independently evaluated on the validation set (30%) as reported for McCarty et. al, 2020). Then the trained GTB classifier was used on this composite image to obtain a LULC map with strong predictive precision (Friedman, 2001).

3.6 Data analysis

3.6.1 Land-use and land-cover classification

The study used the USGS Level I and Level II land-use and land-cover classification system to categorize land use and land-cover types in the study area (Table 5). The different categories of land-use and land-cover in the study area were classified using pixel-based spectral image classification algorithms, specifically the supervised machine learning algorithms such as Random Forest (RF), Support Vector Machine (SVM), Classification and Regression Tree (CART), KNN, and GTB within the Google Earth Engine platform. Six LULC classes were identified in consultation with the district office of agriculture and natural resources to ensure alignment with the local socio-economic and ecological context. In ArcMap 10.8, post-classification refinement techniques, majority filtering, and boundary cleaning were used to enhance the quality of the classified map. The accuracy was evaluated using reference points collected from Google Earth

Pro, stratified across 1989, 2010, and 2019, and reference points collected during the field survey were used to assess the accuracy of the 2024 LULC classification.

Table 4. USGS Level I and Level II classes

LULC Classes	Description
Water Bodies	Flowing bodies of water, including rivers and streams
Wetlands	Freshwater wetlands such as marshes and floodplains
Forests Land	Evergreen forests at higher elevations, characterized by trees that retain foliage year-round and are adapted to cooler temperatures and higher rainfall
Built-up area	Areas with dense human settlements, including cities, towns, and villages
Agricultural Land	Land used for growing crops or raising livestock, including small-scale farms
Tea plantation (TP) (user-defined)	Land specifically used for the cultivation of tea (<i>Camellia sinensis</i>), typically on a commercial-scale, perennial plantation. Includes both large estates and smallholder out-growers. Characterized by regularly spaced rows or terraces of tea bushes and intensive management, distinct from natural vegetation or other crop types

3.6.2 Land-use and land-cover change detection

To quantify the spatial and temporal changes in land use and land cover, change detection analysis was performed using classified maps from multiple periods. Pixel-based numerical values were extracted for each LULC class, and cross-tabulation metrics were generated to identify the transition pattern between classes. These matrices provided insights into gains, losses, and net changes for each category across the years. The annual transformation rate for each LULC class was calculated using Equation 7 (Puyravaud, 2003).

$$r = \frac{1}{t_2 - t_1} * \ln \frac{A_2}{A_1} * 100 \quad (7)$$

where r represent rate of LULC change and A1, A2 are area of LULC at time t1 and t2 respectively

3.6.3 Climate variability and analysis

3.6.3.1 Trend analysis

The non-parametric Mann-Kendall test and Sen's slope estimator were employed to detect the pattern or trend of climatic variables such as temperature and rainfall on a monthly, seasonal, and annual basis, for the study period from 1989 to 2024.

3.6.3.2 Mann-Kendall trend analysis

The Mann-Kendall (MK) test is a non-parametric statistical test used to detect the presence of monotonic trends in time series data. It ranks and compares data points to detect trends, demonstrating robustness against outliers and the ability to handle missing values (Joshi & Bhatt, 2024). The Mann-Kendall statistics were computed using equation 8.

$$S = \sum_{k=1}^{n-1} \sum_{j=k+1}^n \text{sgn}(x_j - x_k) \quad (8)$$

$$\text{sign}(x_j - x_k) = \begin{cases} 1 & \text{if } x_j - x_k > 0 \\ 0 & \text{if } x_j - x_k = 0 \\ -1 & \text{if } x_j - x_k < 0 \end{cases}$$

Where; S the Mann-Kendall statistics, x_j and x_k are the sequential rainfall and temperature values at time j and k respectively. And variance of the S was computed based on the equation 9 provided (Masroor et al., 2022)

$$\text{Var}(S) = \frac{n(n-1)(2n+5) - \sum_t t(t-1)(2t+5)}{18} \quad (9)$$

Additionally, statistical significance tests were performed to assess variations in accuracy over time using equation 10.

$$Z = \begin{cases} \frac{s-1}{\sqrt{\text{var}(s)}} & \text{if } S > 0 \\ 0 & \text{if } S = 0 \\ \frac{s+1}{\sqrt{\text{var}(s)}} & \text{if } S < 0 \end{cases} \quad (10)$$

To test for a monotonic trend at a significance level p , the absolute value of the Z-statistic was compared to the critical value $Z_{\alpha/2}$ from the standard normal distribution table (Masroor et al., 2022).

3.6.3.3 Sen's slope estimator

Alongside the Mann-Kendall test, Sen's slope estimator was employed to determine the rate of change in climatic variables over time. This non-parametric technique offers reliable estimates of trend magnitudes, enabling accurate assessment of how climatic factors such as precipitation & temperature respond to land-use and land-cover (LULC) changes. The analysis focused on

evaluating the direction and strength of these trends to assess whether LULC change causes shifts in these climatic variables (Sen, 1968).

The Sens' slope is T_i is calculated using equation 11.

$$T_i = \frac{x_j - x_k}{j - k} \quad (11)$$

Where T_i represent the Sen's slope and x represent the data points, j and k represent the index time in which $j > k$

The median of these n values T_i was used as Sen's slope estimator, using equation 12

$$Q_i = \begin{cases} T \frac{N+1}{2} & N \text{ is odd} \\ \frac{1}{2} \left(T \frac{N}{2} + T \frac{N}{2} + 1 \right) & N \text{ is even} \end{cases} \quad (12)$$

3.6.4 Correlation analysis

The relationship between land-use and land-cover change classes and climate factors was examined using Pearson correlation analysis. This method determined the strength and direction of the relationship between LULC changes and climate variables, including temperature, rainfall, and land surface temperature. The Pearson correlation coefficient was computed using equation 13 (Pearson, 1985).

$$r = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{(\sum (x_i - \bar{x})^2) \sum (y_i - \bar{y})^2}} \quad (13)$$

The Pearson correlation coefficient ranges from -1 to 1, where $r = 1$ indicates a perfect positive linear relationship, $r = -1$ indicates a perfect negative linear relationship, and $r = 0$ suggests no linear relationship.

where x_i and y_i are individual data points, $\bar{x}$ and $\bar{y}$ are the mean values of x and y , and n is the total number of data points.

3.6.5 Multiple Linear Regression

To assess the impact of land use and land cover changes on climate variables such as temperature, precipitation, and land surface temperature, multiple linear regressions were applied. The regression model was expressed by equation 14, adopted from (Tranmer et al., 2020)

$$y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \beta_3 x_{3i} + \dots + \beta_n x_{ni} + \mathcal{E}_i \quad (14)$$

Where y represents the dependent variables (climate variables), β_0 is the intercept, $x_{1i}, x_{2i}, x_{3i} \dots x_{ni}$ represent the land use and land cover classes, $\beta_1, \beta_2, \beta_3 \dots \beta_n$ are regression coefficients, and $\mathcal{E}_i$ is the error term.

3.6.6 Accuracy assessment

To evaluate the performance of the classification algorithms and ensure the reliability of the results for all study years (1989, 2010, 2019, and 2024), the accuracy of the classified images was assessed based on the recommendations for a minimum number of samples for each land use class, where the area is less than 4000 km² and the number of classes is fewer than 12 (Lillesand et al., 2008). The assessment involved comparing the classified images with reference data & accuracy was evaluated using metrics such as overall accuracy, confusion matrix, precision, recall, F1 score, and Kappa coefficient. The Kappa statistic measures the agreement between two categorizations of a dataset, correcting for chance agreement. In landscape ecology and wildlife habitat analysis, it is particularly useful for assessing the accuracy of predictive models by comparing model outputs with field-surveyed data, taking into account both overall accuracy and category-specific agreements (Jenness & Wynne, 2005). The accuracy assessment was computed with the following matrices using equations 15–21.

$$OAA = \frac{\sum(TP + TN)}{\sum(TP + TN + FP + FN)} \quad (15)$$

$$PA = \frac{TP}{TP + FN} \quad (16)$$

$$UA = \frac{TP}{TP + FP} \quad (17)$$

$$\hat{K} = \frac{p_o - p_e}{1 - p_e} \quad (18)$$

$$Precision = \frac{TP}{TP + FP} \quad (19)$$

$$Recall = \frac{TP}{TP + FN} \quad (20)$$

$$F1\ score = 2 * \frac{Precision * recall}{Precision + recall} \quad (21)$$

where K refers to the Cohen's kappa coefficient, p_o observed agreement, p_e expected agreement by chance, and $1 - p_e$ maximum possible agreement beyond chance.

Chapter Four

4. Results

This chapter presents the outcomes of data analysis, structured to address the study's core objectives: compare the performance of classifiers used for land-use and land-cover change, quantify the spatiotemporal land-use and land-cover change, analyze patterns or trends of climate variables, and assess the significance of the findings about the research questions. Data was processed, cleaned, and analyzed using quantitative techniques, and the following sections present the results in a structured format, supported by visualizations and performance metrics.

4.1 Sample distribution for training and validation of the 1989 LULC classification

For the 1989 LULC classification, a total of 1,174 samples were used, with 70% (822 samples) allocated for training and 30% (352 samples) for validation (Table 5). The samples were distributed across six LULC classes as waterbody (160 samples; 112 training, 48 validation), wetland (160; 112 training, 48 validation), forest land (169; 118 training, 51 validation), built-up area (240; 168 training, 72 validation), agricultural land (256; 179 training, 77 validation), tea plantation (TP) (189; 132 training, 57 validation) (Figure 3).

Table 5. Training and validation samples (1989)

LULC classes	Total samples	Training samples (70%)	Validation samples (30%)
Waterbody	160	112	48
Wetland	160	112	48
Forest land	169	118	51
Built-up area	240	168	72
Agricultural land	256	179	77
Perennial crop (TP)	189	132	57
Total	1174	821	353

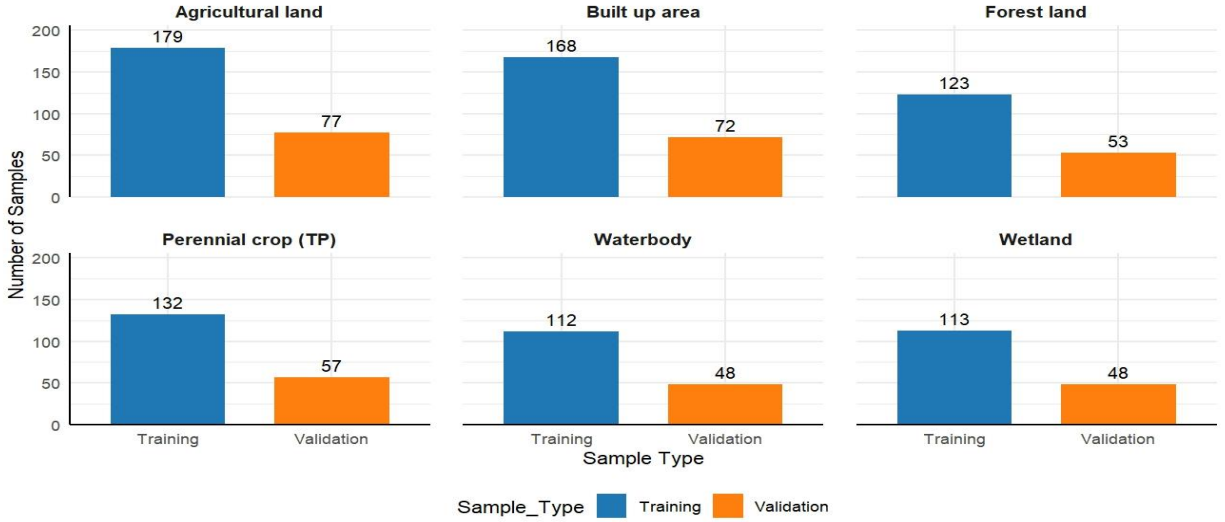


Figure 3. LULC training and validation sample distribution (1989)

4.1.1 Accuracy assessment for five classification algorithms (1989)

The accuracy assessment result of algorithms shows that Support Vector Machine (RBF kernel with gamma values) achieved the highest overall accuracy (OAA) of 84.62% and kappa coefficient ($\kappa = 0.81$), indicating strong agreement with reference data. Random Forest (RF) and Gradient Tree Boosting (GTB) followed closely with OAA of 83.48% and 82.91%, and kappa values of 0.80 and 0.79, but CART and KNN show the least with OAA of 80.06 % and 79.2 %, and Kappa values of 0.76 and 0.77, respectively (Table 6, Figure 4). In class-specific metrics, GTB produced the highest F1 score (0.85) for water body (WB), SVM outperformed other models in wetland, agricultural land (AL), built-up area (BUA), and tea plantation (TP) with F1 scores of 0.79, 0.90, 0.84, and 0.86, respectively. For forest land (FL), both RF and GTB achieved the highest F1 score of 0.89. In contrast, KNN showed the lowest OAA (79.20%) and comparatively lower F1 scores across most land cover types. Overall, the results indicate that SVM, RF, and GTB provide more reliable and accurate classification results for land-use and land-cover mapping, with SVM offering the most balanced performance across multiple classes.

Table 6. Accuracy assessment for five classification algorithms (1989)

Metrics	CART	RF	SVM	KNN	GTB
OAA (%)	80.06	83.48	84.62	79.2	82.91
kappa	0.76	0.8	0.81	77	79.32
WB PA (%)	72.22	82.22	71.11	73.33	84.44
WB UA (%)	86.67	86.05	86.49	76.74	86.36
WB F1	0.79	0.84	0.78	0.75	0.85
WL PA (%)	74.6	77.59	84.48	70.69	74.14
WL UA (%)	81.03	76.27	74.24	70.69	78.18
WL F1	0.78	0.77	0.79	0.71	0.76
FL PA (%)	90.38	90.91	94.55	90.91	90.91
FL UA (%)	85.45	86.21	81.25	80.65	87.72
F1 score	0.88	0.89	0.87	0.85	0.89
BUA PA (%)	79.37	82.35	79.41	76.47	77.94
BUA UA (%)	73.53	83.58	88.52	80	81.54
F1 score	0.76	0.83	0.84	0.78	0.80
AL PA (%)	84.51	82.50	87.50	78.75	83.75
AL UA (%)	75	86.84	93.33	86.3	83.75
F1 score	0.79	0.85	0.90	0.82	0.84
TP PA (%)	79.17	86.67	88.89	86.67	88.89
TP UA (%)	84.44	81.25	83.33	78.00	0.80
F1 score	0.82	0.84	0.86	0.82	0.84

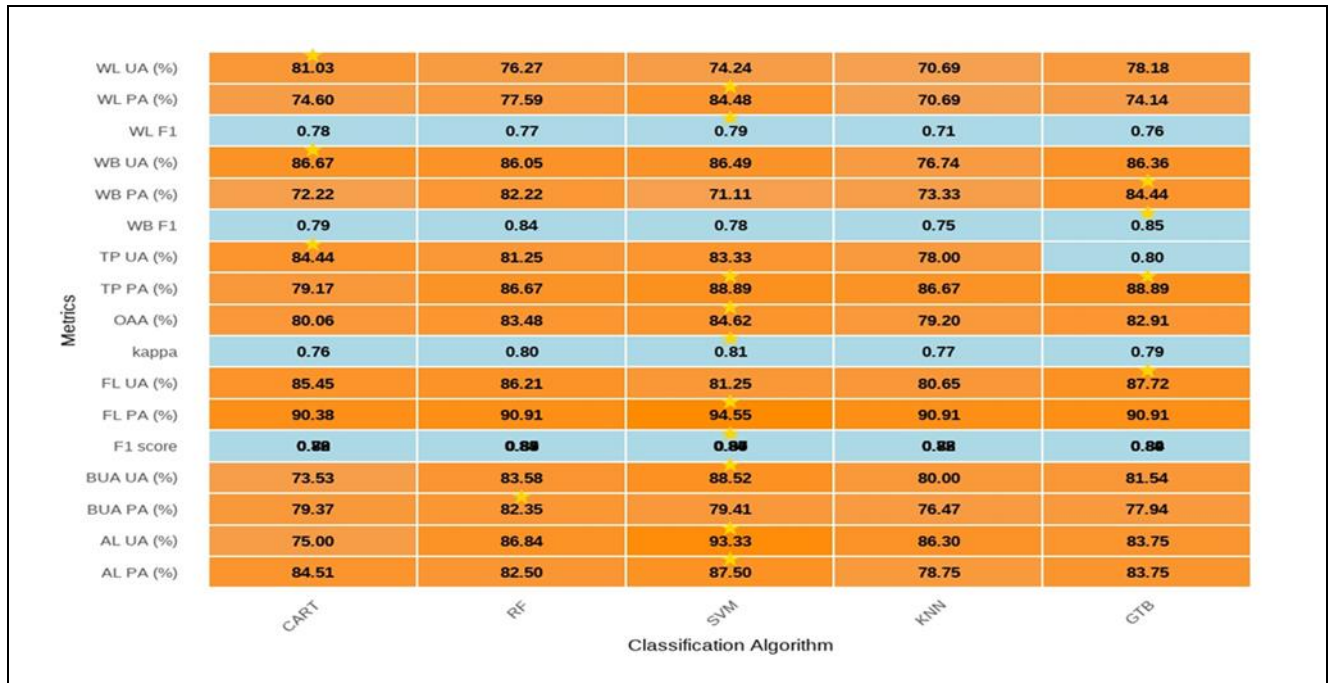


Figure 4. Accuracy assessment of algorithms (1989)

4.1.2 Performance comparison of classifiers for LULC mapping (1989)

A comparative performance evaluation of five classification algorithms (CART, RF, SVM, GTB, and KNN) suggests that SVM is the top performer, achieving the highest overall accuracy (OAA = 84.62%) and kappa coefficient ($\kappa = 0.81$), which indicates superior overall classification and strong agreement with reference data. It also recorded the best F1 scores across four of the six land cover classes: water body (WL = 0.79), built-up area (BUA = 0.84), agricultural land (AL = 0.90), and tea plantation (TP = 0.86). GTB demonstrated leading performance in the water body (WB) category with an F1 score of 0.85 and tied with RF in forest land (FL), with each achieving an F1 score of 0.89. RF consistently ranked second across most metrics, highlighting its reliability as a strong alternative to SVM and GTB. In contrast, KNN ranked the lowest in overall accuracy (79.2%) and exhibited the weakest performance across multiple classes (Table 7, Figure 5). The findings confirm that SVM delivered the most balanced and accurate classification results, with GTB and RF also showing strong performance in specific LULC categories.

Table 7. Performance comparison of classification algorithms for LULC mapping (1989)

Metrics	CART	RF	SVM	KNN	GTB	Best performer
OAA	80.06	83.48	84.62	79.2	82.91	SVM
Kappa c.	76	80	81	77	79.32	SVM
WB F1	79	84	78	75	85	GTB
WL F1	78	77	79	71	76	SVM
FL F1	88	89	87	85	89	SVM and GTB
BUA F1	76	83	84	78	80	SVM
AL F1	79	85	90	82	84	SVM
TP F1	82	84	86	82	84	SVM

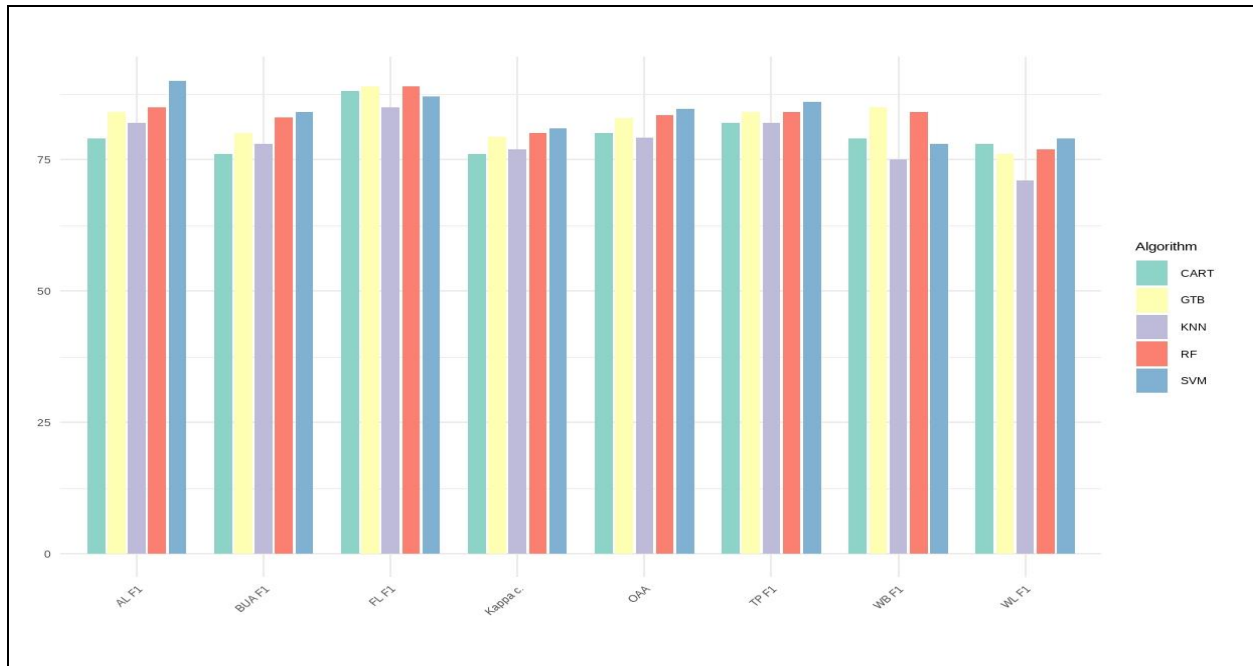


Figure 5. Performance comparison of classifiers (1989)

4.1.3 Algorithm performance ranking based on key metrics (1989)

Table 8 and Figure 6 present a comparative ranking of classification algorithms based on key performance metrics for LULC classification using the 1989 dataset. SVM was identified as the top-performing algorithm, achieving the lowest total ranking score (13), indicating consistently superior performance across metrics. It ranked first in overall accuracy (OAA), kappa coefficient, and four class-specific F1 scores: wetland (WL), built-up area (BUA), agricultural land (AL), and tea plantation (TP). GTB ranked highest in water body (WB) and shared the top position in forest land (FL) classification alongside RF. RF achieved a strong second-place overall ranking (total score = 16), showing balanced performance across nearly all metrics. CART and KNN, with total scores of 28 and 34, respectively, ranked as the least effective classifiers, with KNN performing the poorest across most categories. The rankings reinforce the conclusion that SVM is the most effective algorithm for LULC classification in this study, followed closely by RF and GTB. The resulting LULC classification map generated using the Support Vector Machine (SVM) algorithm and the validation points used for accuracy assessment is presented in Figures 7 and 8.

Table 8. Algorithm performance ranking based on key metrics (1989)

Metrics	CART	RF	SVM	KNN	GTB	Best performer
OAA	4	2	1	5	3	SVM
Kappa c.	4	2	1	5	3	SVM
WB F1	3	2	4	5	1	GTB
WL F1	2	3	1	5	4	SVM
FL F1	2	1	3	4	1	RF and GTB
BUA F1	5	2	1	4	3	SVM
AL F1	5	2	1	3	4	SVM
TP F1	3	2	1	3	2	SVM
Total	28	16	13	34	21	SVM

1. Best performer, 2. Second highest, 3. Average performer, 4. Second lowest, 5. Lowest

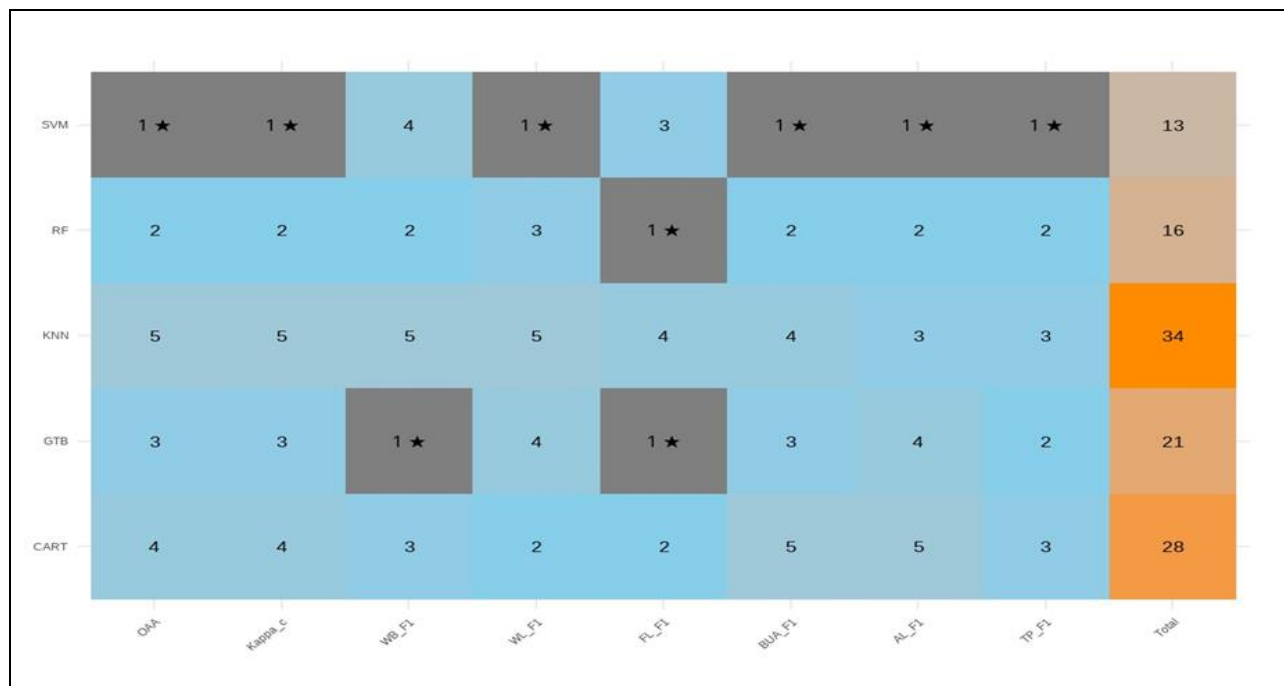


Figure 6. Ranking of classifiers (1989)

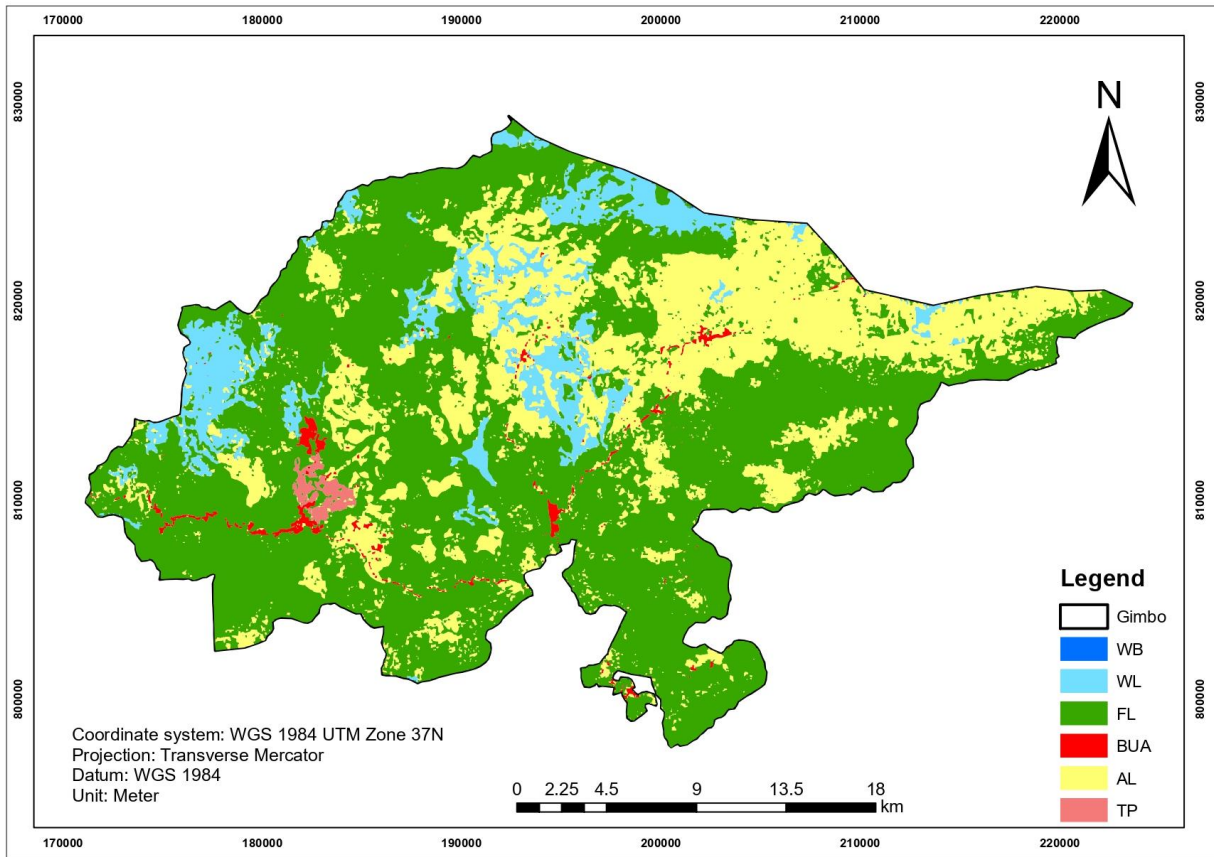


Figure 7. LULC map 1989 (SVM)

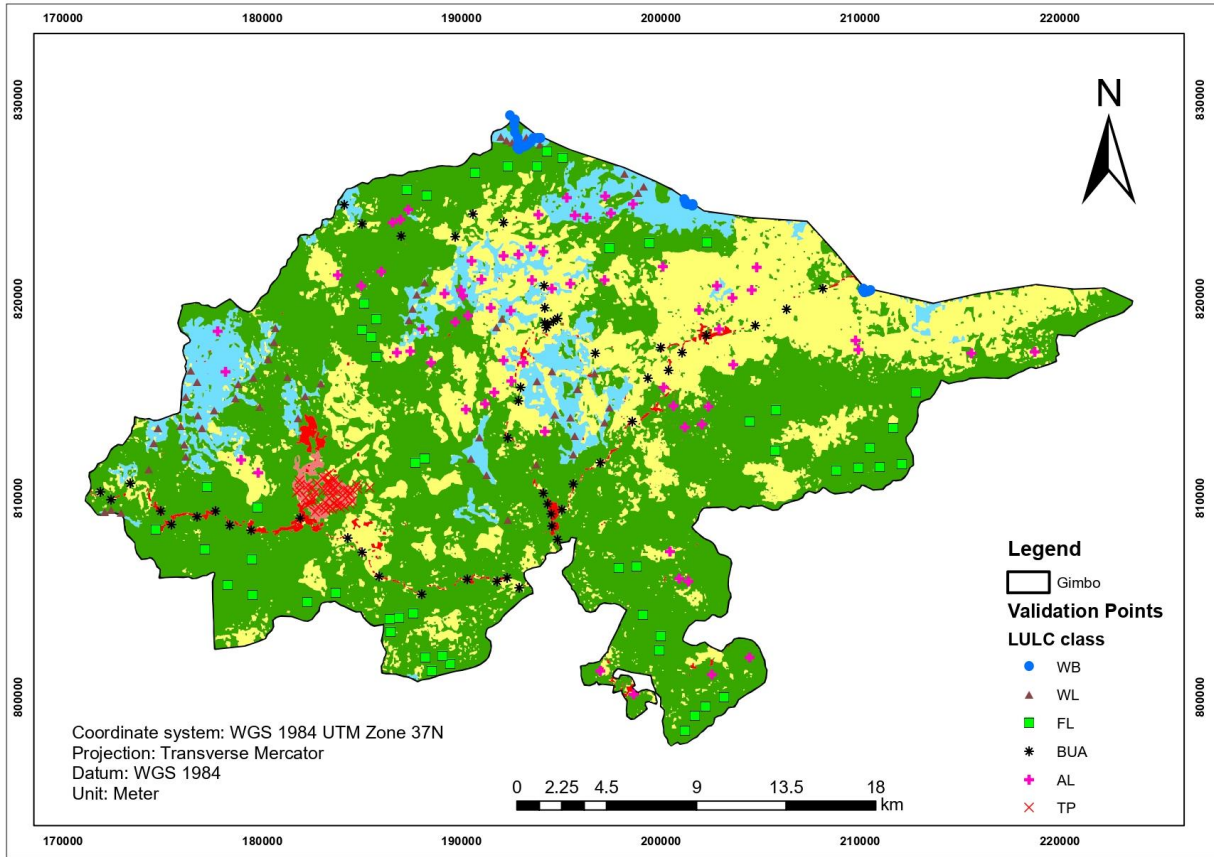


Figure 8. Validation points for the 1989 LULC map

4.1.4 Training and validation sample (2010)

In 2010, a total of 1,182 sample points were collected across six classes, following a proportional 70/30 split for training (827) and validation (355) datasets (Table 9). Agricultural land (256 samples), built-up area (240 samples), tea plantation (189), forestland (176), wetland (161), and waterbody (160) ensured balanced representation. Figure 9 illustrates the sample distribution across classes, emphasizing proportional equity.

Table 9. Training and validation samples (2010)

LULC classes	Total samples	Training samples (70%)	Validation samples (30%)
Waterbody	160	112	48
Wetland	161	113	48
Forest land	176	123	53
Built-up area	240	168	72
Agricultural land	256	179	77
Perennial crop (TP)	189	132	57
Total	1182	827	355

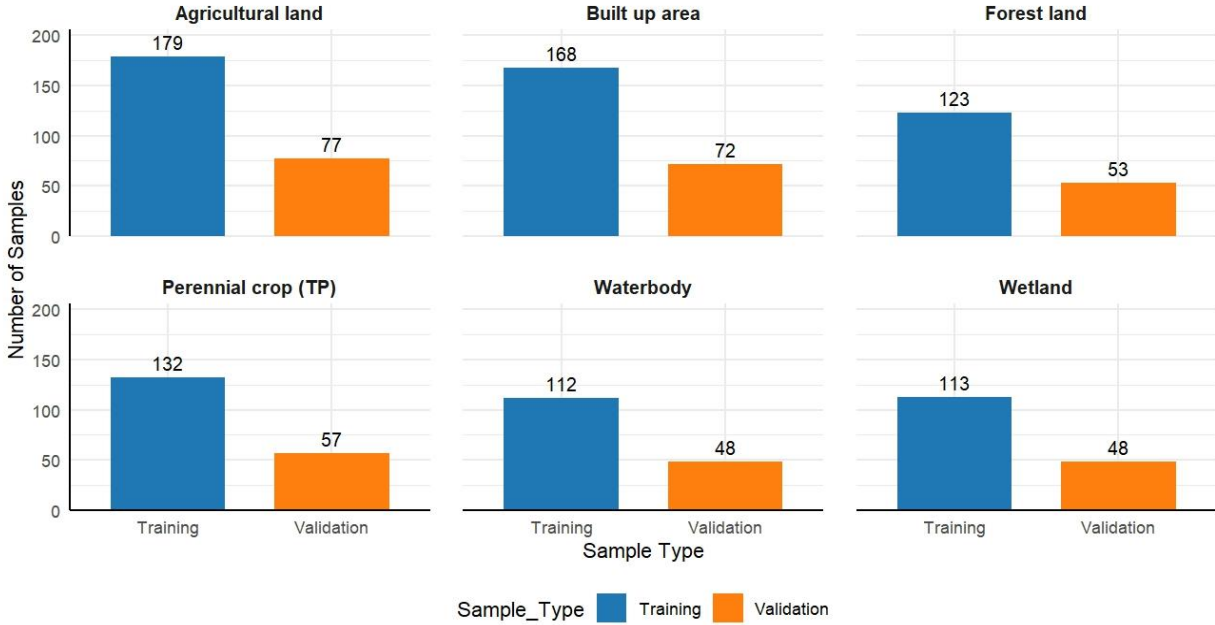


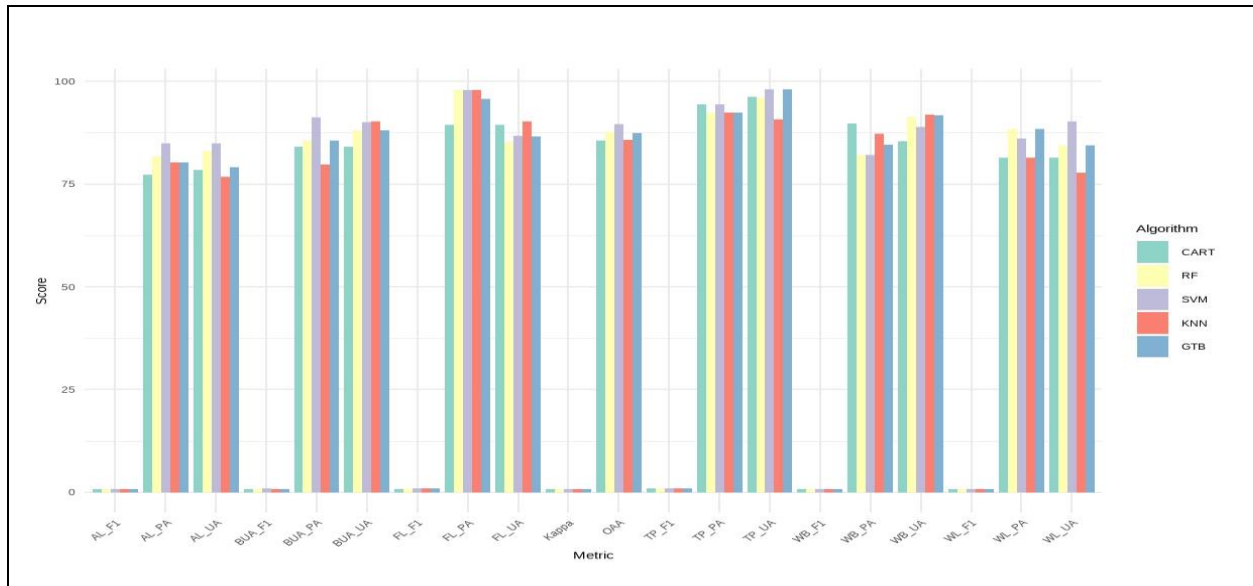
Figure 9. LULC sample distribution (2010)

4.1.5 Algorithms accuracy assessment (2010)

The accuracy assessment of CART, RF, SVM, KNN, and GTB used in 2010 reveals that SVM consistently outperforms other classifiers across most evaluation metrics (Table 10, Figure 10). It achieves the highest Overall Accuracy (OAA) at 89.59 % and the highest kappa value of 0.87, indicating strong agreement beyond chance. SVM also demonstrates superior performance in class-specific metrics, particularly in the built-up area (BUA), agriculture land (AL), and tea plantation (TP) categories, with F1 scores of 0.91, 0.85, and 0.96, respectively. Although KNN shows competitive F1 scores in some classes, like forest land (FL) and water body (WB), it falls behind in overall accuracy. RF and GTB exhibit balanced performance with identical kappa values (0.85) and high F1 scores across multiple classes, suggesting their robustness. CART lags slightly in both overall and class-wise metrics. Overall, SVM emerges as the most accurate and reliable algorithm among others.

Table 10. Algorithms' accuracy assessment (2010)

Metrics	CART	RF	SVM	KNN	GTB
OAA (%)	85.49	87.70	89.59	85.80	87.38
kappa	0.81	0.85	0.87	0.83	0.85
WB PA (%)	89.74	82.05	82.05	87.18	84.62
WB UA (%)	85.37	91.43	88.89	91.89	91.67
WB F1	0.88	0.86	0.85	0.89	0.88
WL PA (%)	81.40	88.37	86.05	81.40	88.37
WL UA (%)	81.40	84.44	90.24	77.78	84.44
WL F1	0.81	0.86	0.88	0.80	0.86
FL PA (%)	89.36	97.87	97.87	97.87	95.74
FL UA (%)	89.36	85.19	86.79	90.20	86.54
F1 score	0.89	0.91	0.92	0.94	0.91
BUA PA (%)	84.06	85.51	91.30	79.71	85.51
BUA UA (%)	84.06	88.06	90	90.16	88.06
F1 score	0.84	0.87	0.91	0.85	0.87
AL PA (%)	77.27	81.82	84.85	80.30	80.30
AL UA (%)	78.46	83.08	84.85	76.81	79.10
F1 score	0.78	0.82	0.85	0.79	0.80
TP PA (%)	94.34	92.45	94.34	92.45	92.45
TP UA (%)	96.15	96.08	98.04	90.74	98.00
F1 score	0.95	0.94	0.96	0.92	0.95

**Figure 10.** Accuracy assessment of classifiers (2010)

4.1.6 Performance comparison of classification algorithms for LULC mapping (2010)

In 2010, SVM achieved the highest overall performance in land-use and land-cover (LULC) mapping with the highest overall accuracy (OAA) of 89.59 % and a kappa coefficient of 0.87, reflecting a high degree of classification agreement beyond chance. RF and GTB delivered strong

and balanced results but were slightly outperformed by SVM in most performance metrics. SVM also attained the highest F1 scores in four out of six land cover categories, including wetland (0.88), built-up area (0.91), and agricultural land (0.85), and tea plantation (0.96), K-NN outperformed other algorithms in water bodies (F1 = 0.89) and forest land (F1 = 0.94) but its overall accuracy was comparatively lower. CART showed the weakest performance across the evaluated criteria. The findings suggest that SVM is the most accurate and consistent classifier for LULC mapping based on the 2010 dataset (Table 11 and Figure 11).

Table 11. Performance comparison of classification algorithms for LULC mapping (2010)

Metrics	CART	RF	SVM	KNN	GTB	Best performer
OAA	85.49	87.70	89.59	85.80	87.38	SVM
Kappa c.	81.47	85	87	83	85	SVM
WB F1	88	86	85	89	88	KNN
WL F1	81	86	88	80	86	SVM
FL F1	89	91	92	94	91	KNN
BUA F1	84	87	91	85	87	SVM
AL F1	78	82	85	79	80	SVM
TP F1	95	94	96	92	95	SVM

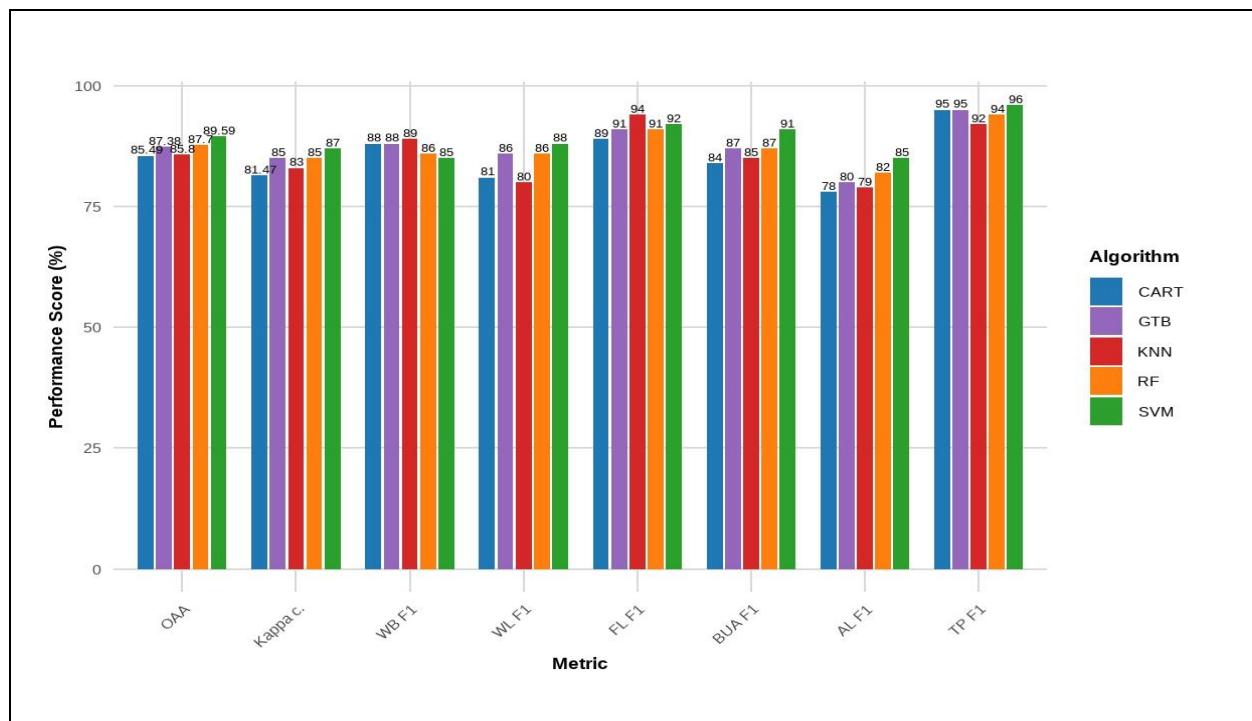


Figure 11. Performance comparison of classifiers (2010)

4.1.7 Algorithm performance ranking based on key metrics (2010)

Support Vector Machine (SVM) algorithm consistently achieved the highest rankings, securing first place in five out of eight metrics and accumulating the lowest total score of 12, indicating superior overall performance, Random Forest (RF) and Gradient Tree Boosting (GTB) followed with total scores of 19 and 20, respectively, reflecting balanced but slightly lower performance, KNN, despite ranking first in the classification of water body and forest land, obtained a total score of 24, suggesting inconsistency across other classes. CART ranked lowest overall with a score of 30, indicating the weakest performance among the algorithms evaluated (Table 12, Figure 12). These rankings reinforce the conclusion that SVM is the most effective and reliable classifier for land-use and land-cover (LULC) mapping for 2010 in the study area, and the resulting LULC map generated using SVM and the validation points used for accuracy assessment is presented in Figures 13 and 14.

Table 12. Algorithm performance ranking based on key metrics

Metrics	CART	RF	SVM	KNN	GTB	Best performer
OAA	5	2	1	4	3	SVM
Kappa c.	5	2	1	4	3	SVM
WB F1	2	3	4	1	2	KNN
WL F1	3	2	1	4	2	SVM
FL F1	4	3	2	1	3	KNN
BUA F1	4	2	1	2	2	SVM
AL F1	5	2	1	4	3	SVM
TP F1	2	3	1	4	2	SVM
Total	30	19	12	24	20	SVM

1. Best performer, 2. Second highest, 3. Average performer, 4. Second lowest, 5. Lowest

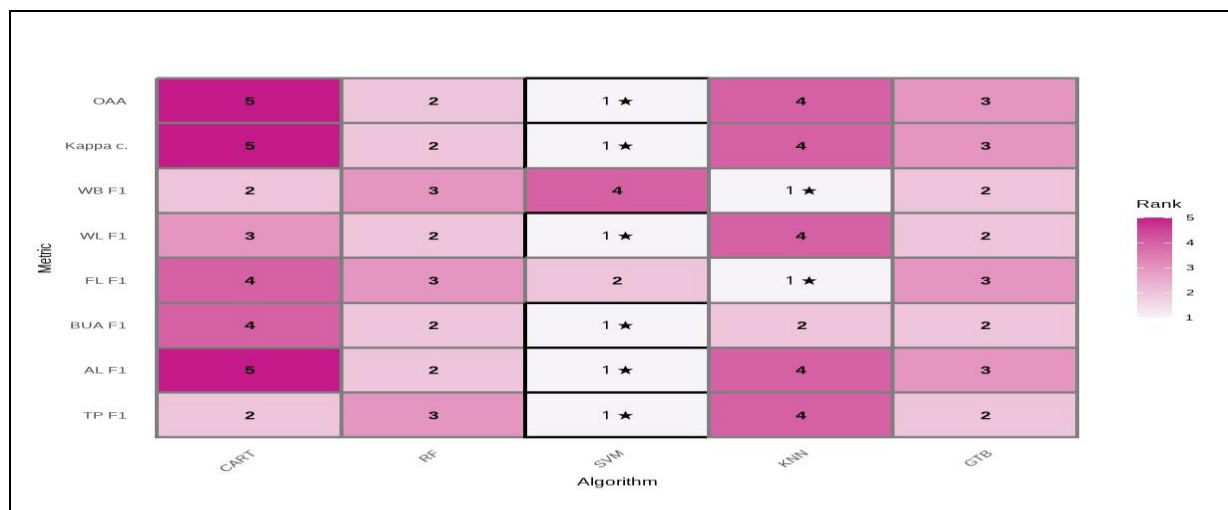


Figure 12. Performance ranking of classifiers (2010)

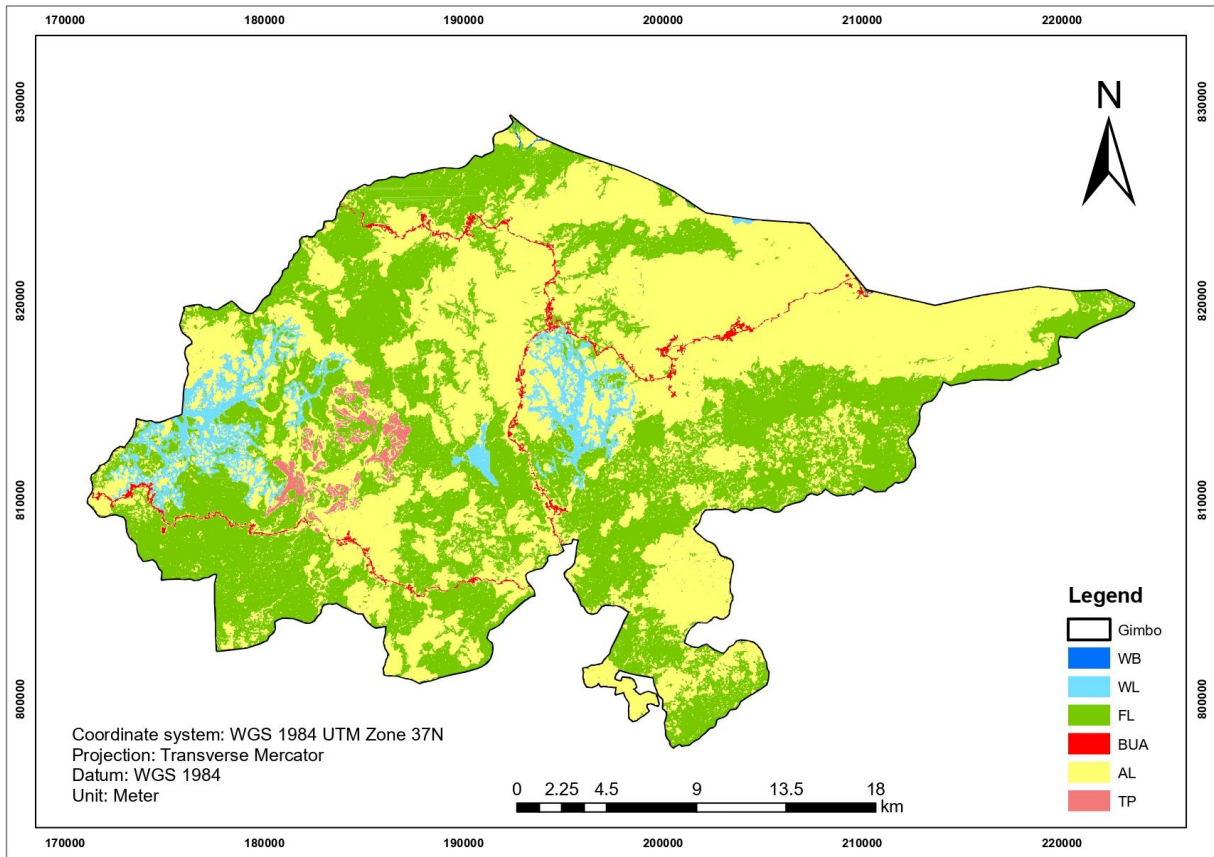


Figure 13. LULC map 2010 (SVM)

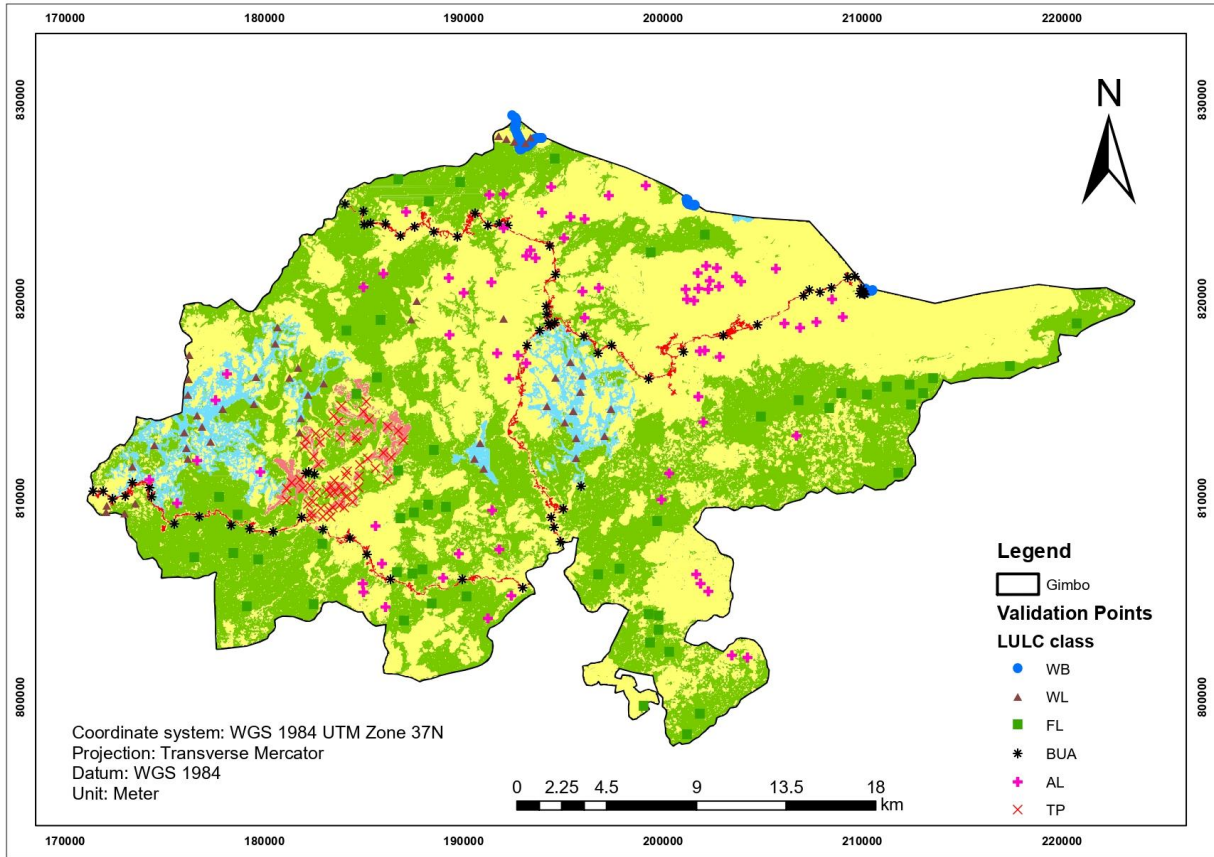


Figure 14. Validation points for the 2010 LULC map

4.1.8 Training and validation samples (2019)

In 2019, stratified random sampling techniques were used to allocate 1,173 samples across six classes, 821 for training and 352 for validation, based on a 70/30 split ratio (Table 13). The class-specific samples include agricultural land (256), built-up area (240), tea plantation (189), forest land (168), waterbody (160), wetland (160), and Figure 15 visualizes the class-specific sample distribution.

Table 13. Training and validation samples (2019)

LULC classes	Total samples	Training samples (70%)	Validation samples (30%)
WB	160	112	48
WL	160	112	48
FL	168	118	50
BUA	240	168	72
AL	256	179	77
PC/TP	189	132	57
Total	1173	821	352

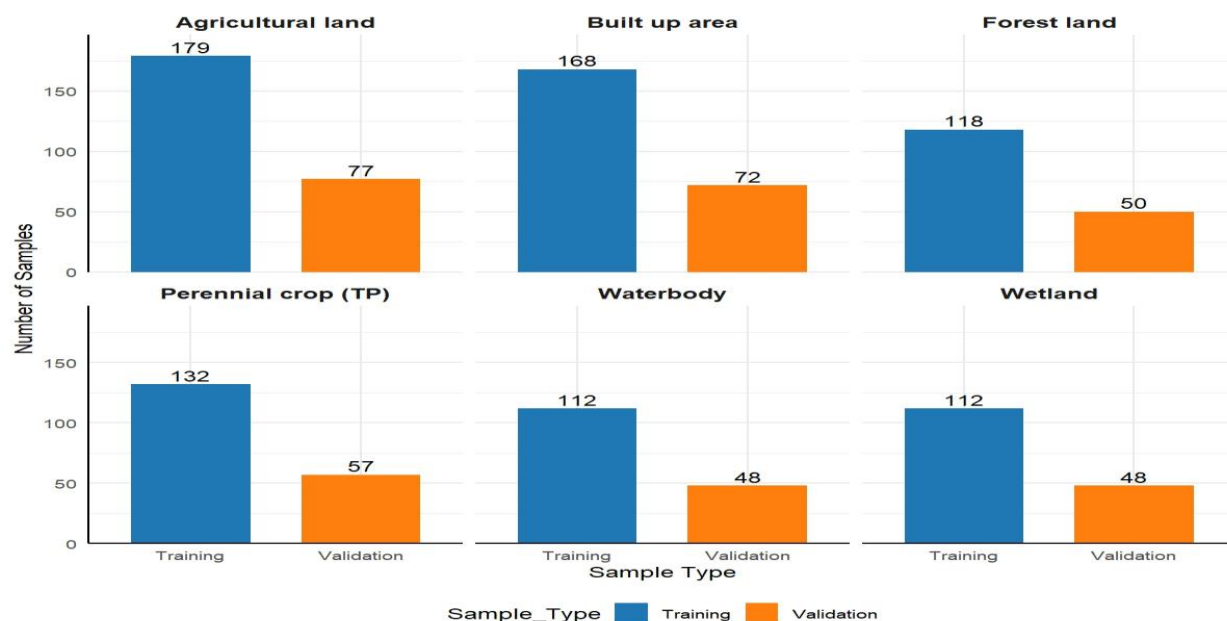


Figure 15. LULC sample distribution (2019)

4.1.9 Algorithms accuracy assessment (2019)

The accuracy assessment of CART, Random Forest (RF), Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Gradient Tree Boosting (GTB) for land-use and land-cover (LULC) mapping in 2019 reveals that Support Vector Machine (SVM) demonstrated the best overall performance (Table 14, Figure 16). SVM achieved the highest overall accuracy (OAA) of 91.62 % and a kappa coefficient of 0.90, indicating strong agreement and classification reliability. In terms of class-specific performance, SVM produced the highest F1 scores in built-up area (0.87) and agricultural land (0.90), and tied with RF in wetland (0.91). RF closely followed with an OAA of 90.72 % and strong F1 scores across all classes, including the highest F1 score for Water Body (0.94). Tea plantation classification showed exceptional consistency, with all algorithms achieving high precision and recall, and SVM, RF, and GTB each recording an F1 score of 0.98 or higher. While KNN showed moderate performance in most classes, it underperformed in overall accuracy. CART consistently scored the lowest across most metrics. The results confirm that SVM is the most effective and consistent classifier for LULC classification in 2019, followed closely by RF, while CART remains the least.

Table 14. Accuracy assessment for five classification algorithms (2019)

Metrics	CART	RF	SVM	KNN	GTB
OAA (%)	85.63	90.72	91.62	85.93	88.62
kappa	0.826	0.89	0.90	0.83	0.86
WB PA (%)	94.23	92.31	90.38	86.54	94.23
WB UA (%)	92.45	96	95.92	88.24	92.45
WB F1	0.93	0.94	0.93	0.87	0.93
WL PA (%)	71.74	93.48	91.30	84.78	82.61
WL UA (%)	86.84	89.58	91.30	84.78	88.37
WL F1	0.79	0.91	0.91	0.85	0.85
FL PA (%)	95.65	97.83	97.83	91.30	93.48
FL UA (%)	93.62	90	88.24	87.50	89.58
F1 score	0.95	0.94	0.93	0.89	0.91
BUA PA (%)	76.12	82.09	82.09	79.10	76.12
BUA UA (%)	75	84.62	93.22	79.10	82.26
F1 score	0.76	0.83	0.87	0.79	0.79
AL PA (%)	82.43	86.49	93.24	83.78	89.19
AL UA (%)	76.25	88.89	86.25	82.67	83.54
F1 score	0.79	0.88	0.90	0.83	0.86
TP PA (%)	97.96	97.96	97.96	93.88	97.96
TP UA (%)	100	97.96	97.96	97.87	97.96
F1 score	0.99	0.98	0.98	0.96	0.98

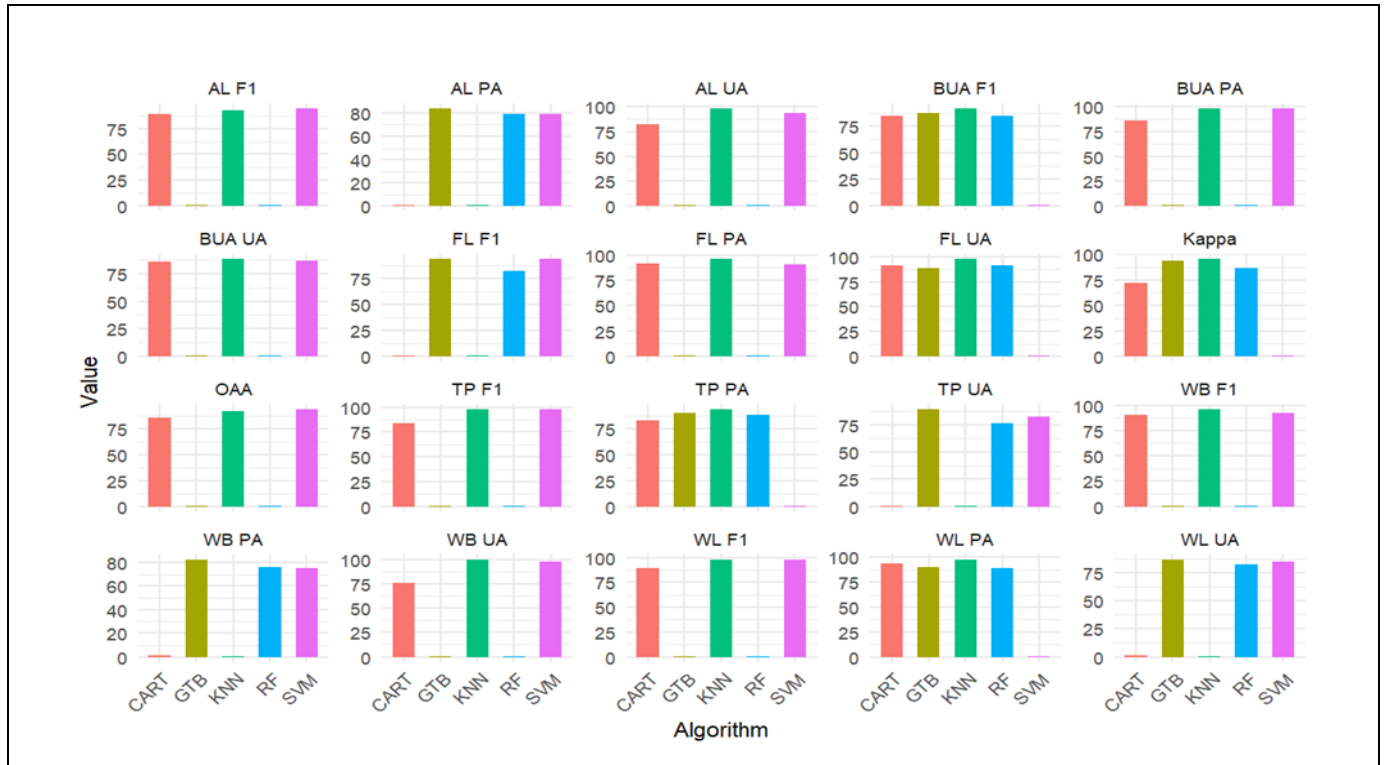


Figure 16. Accuracy assessment of classifiers (2019)

4.1.10 Performance comparison of classification algorithms for LULC mapping (2019)

The comparative evaluation result of algorithms for LULC mapping in 2019 indicates Support Vector Machine (SVM) as the top-performing classifier. It achieved the highest overall accuracy of 91.62% and a kappa coefficient value of 0.90, indicating strong classification reliability and agreement (Table 15, Figure 17). It also recorded the best F1 scores in three land cover classes: built-up area (0.87), agricultural land (0.90), and shared the highest score for wetland (0.91) with Random Forest (RF). RF closely followed with an overall accuracy of 90.72% and led in water body classification with the highest F1 score (0.94). CART classifier, despite being the lowest overall performer in earlier comparisons, achieved the highest F1 scores for forest land (0.95) and tea plantation (0.99), suggesting its suitability for some classes. K-Nearest Neighbors (KNN) and Gradient Tree Boosting (GTB) demonstrated moderate performance across most metrics but did not lead in any category. The findings reaffirm SVM's consistent effectiveness for LULC classification, while also highlighting the contextual strengths of CART and RF in specific land cover types.

Table 15. Performance comparison of classification algorithms for LULC mapping (2019)

Metric	CART	RF	SVM	KNN	GTB	Best performer
OAA	85.63	90.72	91.62	85.93	88.62	SVM
Kappa c.	82.6	89	90	83	86	SVM
WB F1	93	94	93	87	93	RF
WL F1	79	91	91	85	85	SVM and RF
FL F1	95	94	93	89	91	CART
BUA F1	76	83	87	79	79	SVM
AL F1	79	88	90	83	86	SVM
TP F1	99	98	98	96	98	CART

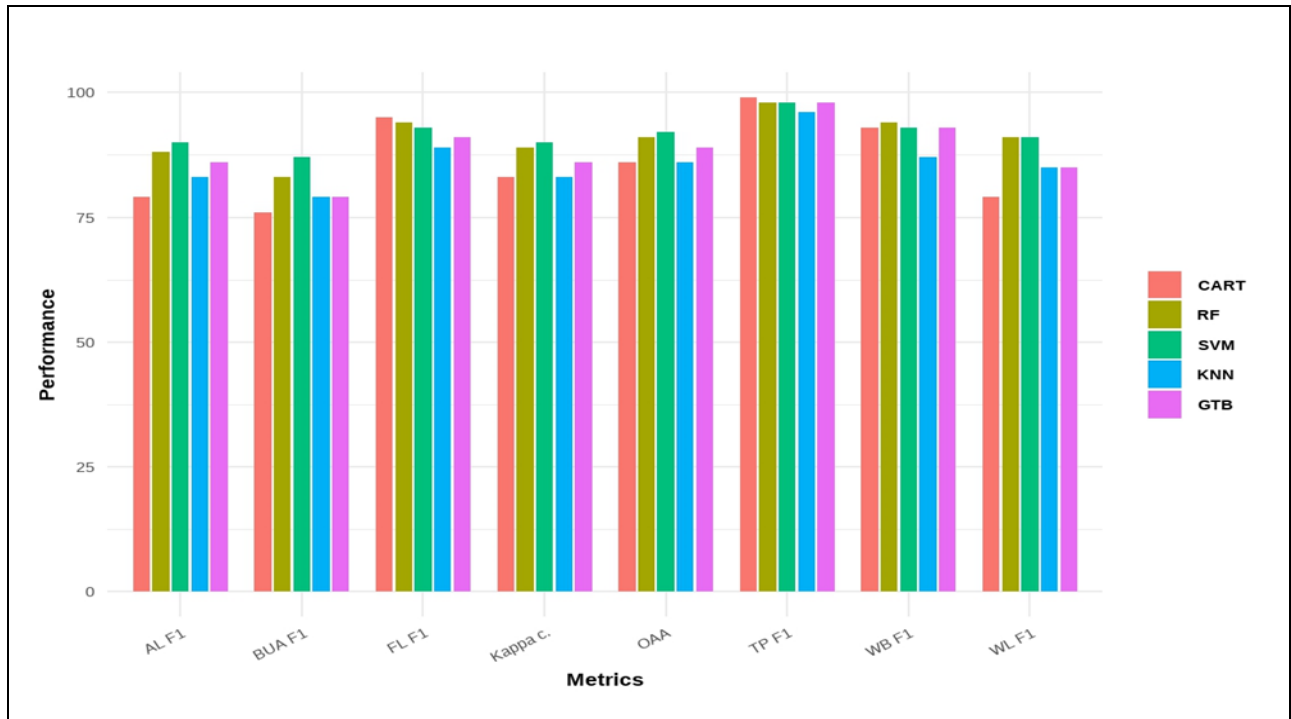


Figure 17. Performance comparison of classifiers (2019)

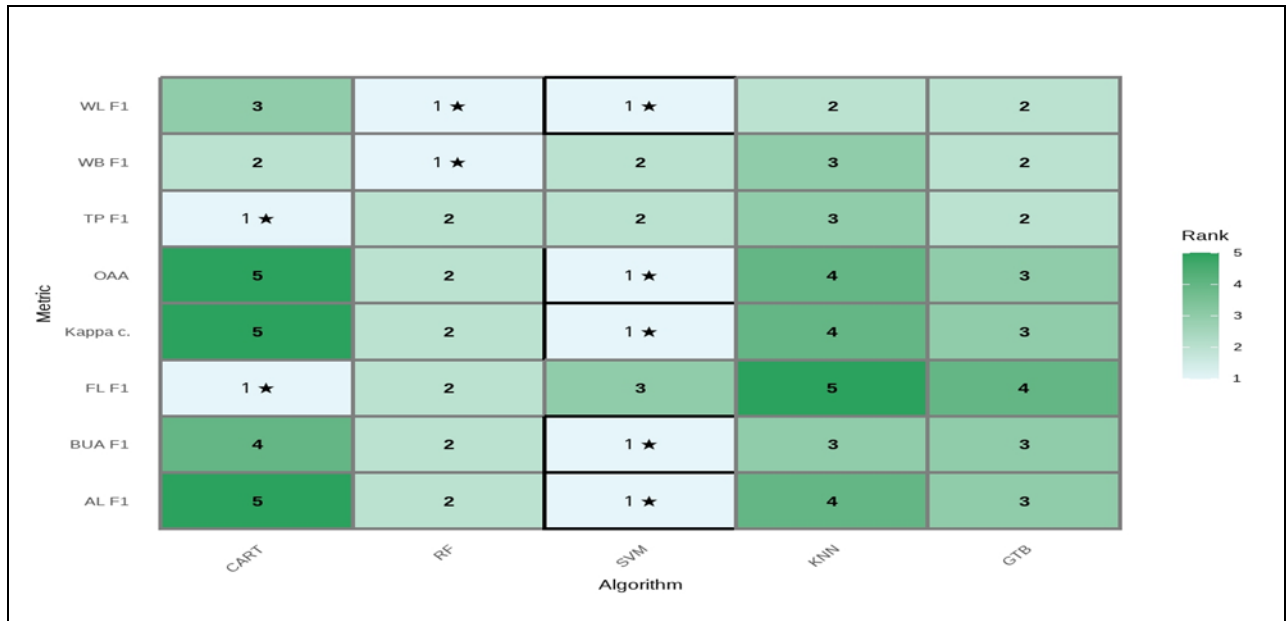
4.1.11 Algorithm performance ranking based on key metrics (2019)

The performance ranking of classification algorithms for the year 2019, based on key metrics (overall accuracy, kappa coefficient, and class-specific F1 scores), confirms Support Vector Machine (SVM) as the best-performing algorithm (Table 16, Figure 18). SVM achieved the lowest total ranking score of 12, indicating consistently high performance across multiple metrics. It ranked first in Overall Accuracy, kappa coefficient, built-up area F1, and agricultural land F1, and tied for first in wetland F1 with Random Forest (RF). RF followed closely with a total score of 14 and stood out in water body classification, where it ranked first, and second in other categories. The Classification and Regression Tree (CART), despite generally weaker overall performance, excelled in classifying forest land and tea plantation, earning the top rank in those categories. Gradient Tree Boosting (GTB) and K-Nearest Neighbors (KNN) were moderate performers, with total scores of 22 and 28, respectively, and did not lead in any specific metric. Overall, the rankings reinforce SVM's superiority as a robust and reliable classifier for LULC mapping, while also highlighting the contextual strengths of RF and CART in specific land cover types, and the resulting map for 2019 using SVM and the validation points used is presented in Figures 19 and 20.

Table 16. Algorithm performance ranking based on key metrics (2019)

Metrics	CART	RF	SVM	KNN	GTB	Best performer
OAA	5	2	1	4	3	SVM
Kappa c.	5	2	1	4	3	SVM
WB F1	2	1	2	3	2	RF
WL F1	3	1	1	2	2	RF,SVM
FL F1	1	2	3	5	4	CART
BUA F1	4	2	1	3	3	SVM
AL F1	5	2	1	4	3	SVM
TP F1	1	2	2	3	2	CART
Total	26	14	12	28	22	SVM

1. Best performer, 2. Second highest, 3. Average performer, 4. Second lowest, 5. Lowest

**Figure 18.** Algorithm performance ranking (2019)

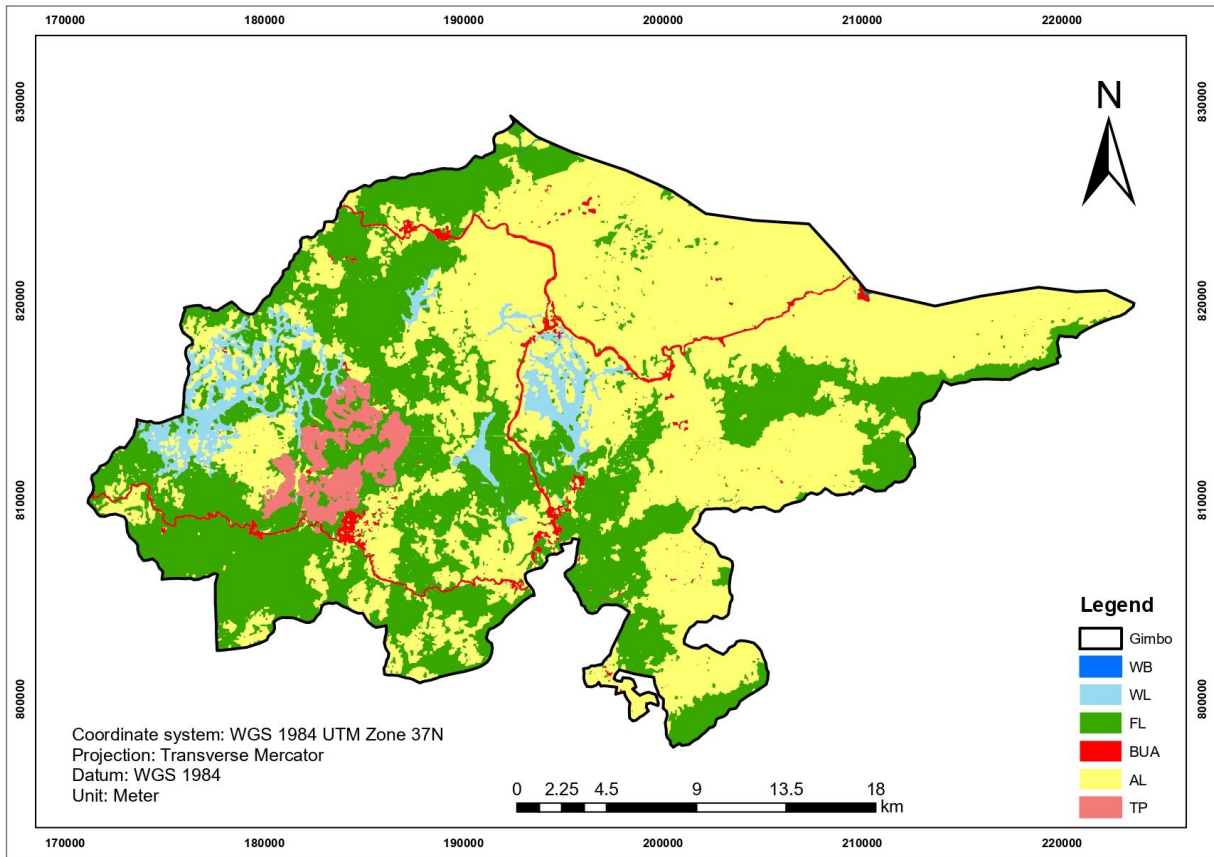


Figure 19. LULC map 2019 (SVM)

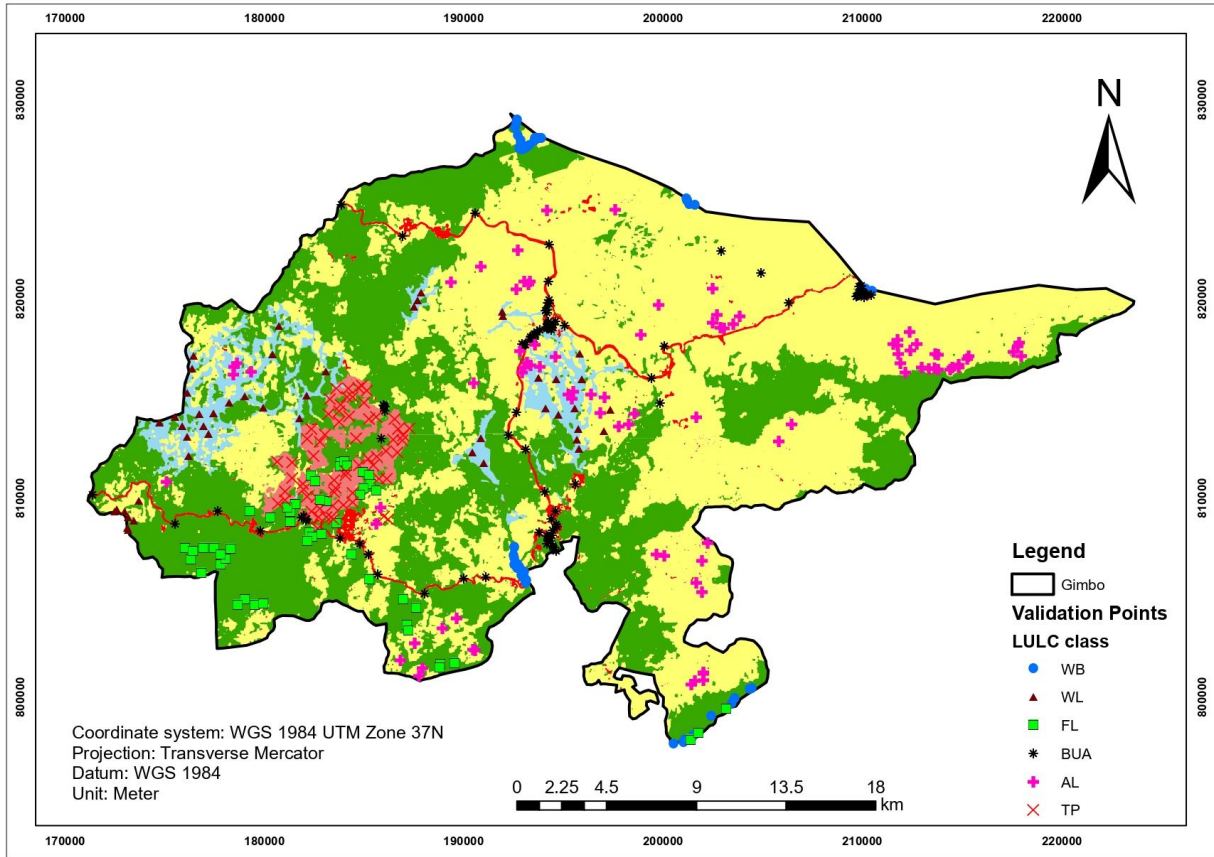


Figure 20. Validation points for the 2019 LULC map

4.1.12 Training and validation points for 2024

A total of 1,197 samples were collected in 2024 for land-use and land cover (LULC) classification using stratified sampling, as shown in Table 17. Of these, 838 samples (70 %) were used for training and 359 samples (30%) for validation. These samples were distributed in six LULC classes, such as built-up area (275), agricultural land (276), tea plantation (189), forest land (169), water body (160), and Wetlands (128). Figure 21 shows the distribution of these samples across classes.

Table 17. Training samples for 2024

LULC classes	Total samples	Training samples (70%)	Validation samples (30%)
Waterbody	160	112	48
Wetland	128	90	38
Forest land	169	118	51
Built up area	275	192	83
Agricultural land	276	193	83
Perennial crop (TP)	189	132	57
Total	1197	837	360

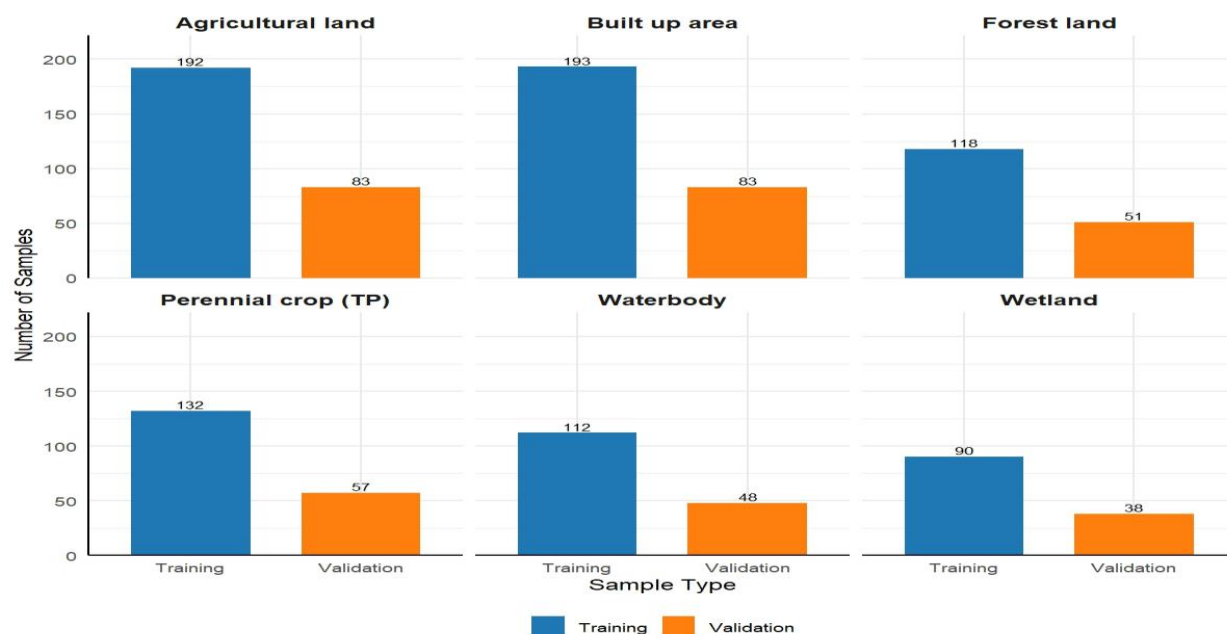


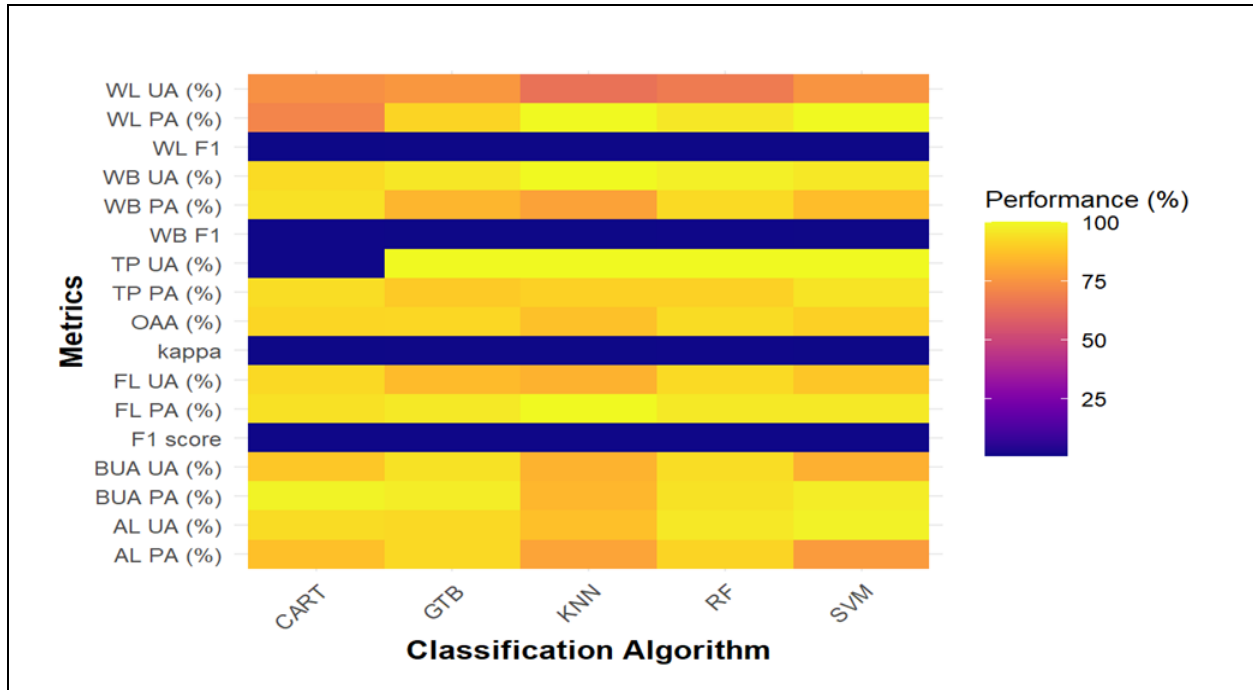
Figure 21. LULC sample distribution (2024)

4.1.13 Accuracy assessment of classifiers for 2024

The accuracy assessment for the 2024 LULC classification indicates that Random Forest (RF) achieved the highest overall performance among the five evaluated algorithms, with an overall accuracy (OAA) of 93.37% and a kappa coefficient of 0.92, reflecting strong agreement and classification reliability (Table 18, Figure 22). Gradient Tree Boosting (GTB) followed closely with an OAA of 92.27% and a kappa of 0.91, while CART also performed well, achieving an OAA of 91.99% and a kappa of 0.90. In class-specific evaluations, RF recorded the highest F1 scores in water bodies (0.95), forest land (0.95), and agricultural land (0.94), demonstrating strong generalization across diverse land cover types. GTB performed particularly well in built-up area classification, achieving the highest F1 score (0.96), and showed consistently high scores in agricultural land and tea plantations. Although SVM did not lead in any specific class, it maintained stable performance with an OAA of 90.61% and high F1 scores in several categories. KNN showed relatively lower performance overall, with the lowest OAA (87.02%) and reduced accuracy in multiple classes. The results indicate that RF as best classifier for LULC mapping in 2024, with GTB and CART also emerging as competitive alternatives depending on class-specific needs.

Table 18. Accuracy assessment for five classification algorithms (2024)

Metrics	CART	RF	SVM	KNN	GTB
OAA (%)	91.99	93.37	90.61	87.02	92.27
kappa	0.90	0.92	0.89	0.84	0.91
WB PA (%)	94.74	92.98	85.96	78.95	84.21
WB UA (%)	93.1	98.15	96.08	100	96
WB F1	0.94	0.95	0.91	0.88	0.90
WL PA (%)	70.83	95.83	100.00	100	91.67
WL UA (%)	73.91	67.65	75.00	64.86	75.86
WL F1	0.72	0.79	0.86	0.79	0.83
FL PA (%)	94.55	96.36	96.36	100	96.36
FL UA (%)	92.86	92.98	88.33	83.33	85.48
F1 score	0.94	0.95	0.92	0.91	0.91
BUA PA (%)	98.72	94.87	97.44	84.62	97.44
BUA UA (%)	88.51	93.67	82.61	83.54	95
F1 score	0.93	0.94	0.89	0.84	0.96
AL PA (%)	86.75	91.55	77.11	79.52	92.77
AL UA (%)	93.51	96.20	98.46	86.84	92.77
F1 score	0.90	0.94	0.86	0.83	0.93
TP PA (%)	93.85	90.77	95.38	90.77	89.23
TP UA (%)	100	100	100.00	100	100
F1 score	0.97	0.95	0.98	0.95	0.94

**Figure 22.** Accuracy assessment of classifiers (2024)

4.1.14 Performance comparison of classification algorithms (2024)

In 2024, the evaluation of results indicates that Random Forest (RF) algorithms emerged as the most effective model across multiple performance metrics for land-use and land-cover (LULC) mapping, as presented in Table 19 and Figure 23. It achieved the highest overall accuracy (OAA) of 93.37% and a Kappa coefficient of 0.92, reflecting strong classification reliability and consistency. Furthermore, RF recorded the best F1-score (0.95), indicating balanced performance across all classes. It also excelled in classifying forest land (F1 = 0.95) and agricultural land (F1 = 0.94). On the other hand, Support Vector Machine (SVM) showed superior performance in tea plantations (F1 = 0.98) and wetlands (F1 = 0.86), and the Gradient Boosted Trees (GTB) algorithm achieved the highest F1-score in built-up areas (F1 = 0.96). The results support the suitability of RF for LULC classification tasks, offering a strong balance between accuracy and class-specific precision.

Table 19. Performance comparison of classification algorithms (2024)

Metrics	CART	RF	SVM	KNN	GTB	Best performer
OAA	91.99	93.37	90.61	87.02	92.27	RF
Kappa c.	90	92	89	84	91	RF
WB F1	94	95	91	88	90	RF
WL F1	72	79	86	79	83	SVM
FL F1	94	95	92	91	91	RF
BUA F1	93	94	89	84	96	GTB
AL F1	90	94	86	83	93	RF
TP F1	97	95	98	95	94	SVM

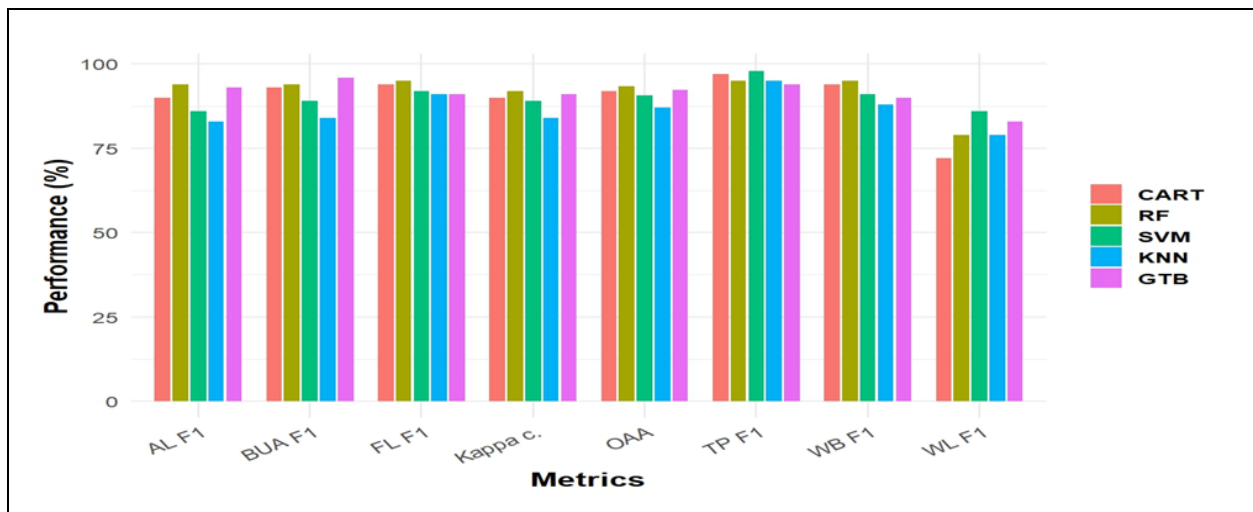


Figure 23. Performance comparison of MLA (2024)

4.1.15 Algorithm performance ranking based on key metrics (2024)

Algorithm performance ranking based on classification metrics confirmed the superior performance of the Random Forest (RF) model for land-use and land-cover (LULC) mapping in 2024 (Table 20, Figure 24). RF consistently ranked highest across the majority of metrics, securing first place in overall accuracy (OAA), Kappa coefficient, F1-score (WB F1), forest land (FL F1), and agricultural land (AL F1), resulting in the lowest total rank score of 13. Gradient Tree Boosting (GTB) followed with a total rank of 20, outperforming others in the built-up area (BUA F1) classification. Support Vector Machine (SVM) demonstrated particular strength in classifying wetland (WL F1) and tea plantation (TP F1), ranking first in both. However, it accumulated a total rank of 24 due to lower performance in other metrics. In contrast, K-Nearest Neighbors (KNN) consistently underperformed, with the highest total score of 34. Overall, the ranking analysis highlights RF as the most balanced and effective algorithm for multi-class LULC classification tasks, outperforming alternatives in both overall accuracy and class-specific performance, and the resulting map generated and validation point used are presented in Figures 25 and 26.

Table 20. Algorithm performance ranking based on key metrics

Metrics	CART	RF	SVM	KNN	GTB	Best performer
OAA	3	1	4	5	2	RF
Kappa c.	3	1	4	5	2	RF
WB F1	2	1	3	5	4	RF
WL F1	4	3	1	3	2	SVM
FL F1	2	1	3	3	3	RF
BUA F1	3	2	4	5	1	GTB
AL F1	3	1	4	5	2	RF
TP F1	2	3	1	3	4	SVM
Total	22	13	24	34	20	RF

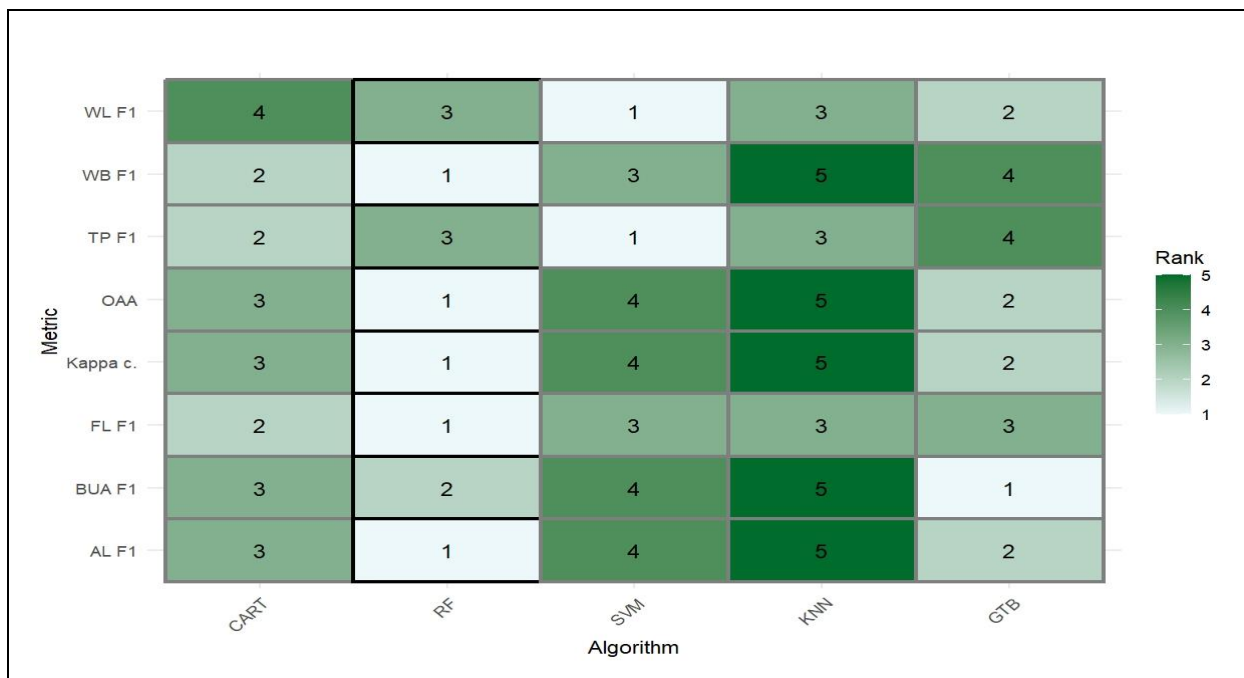


Figure 24. Performance ranking (1=best)

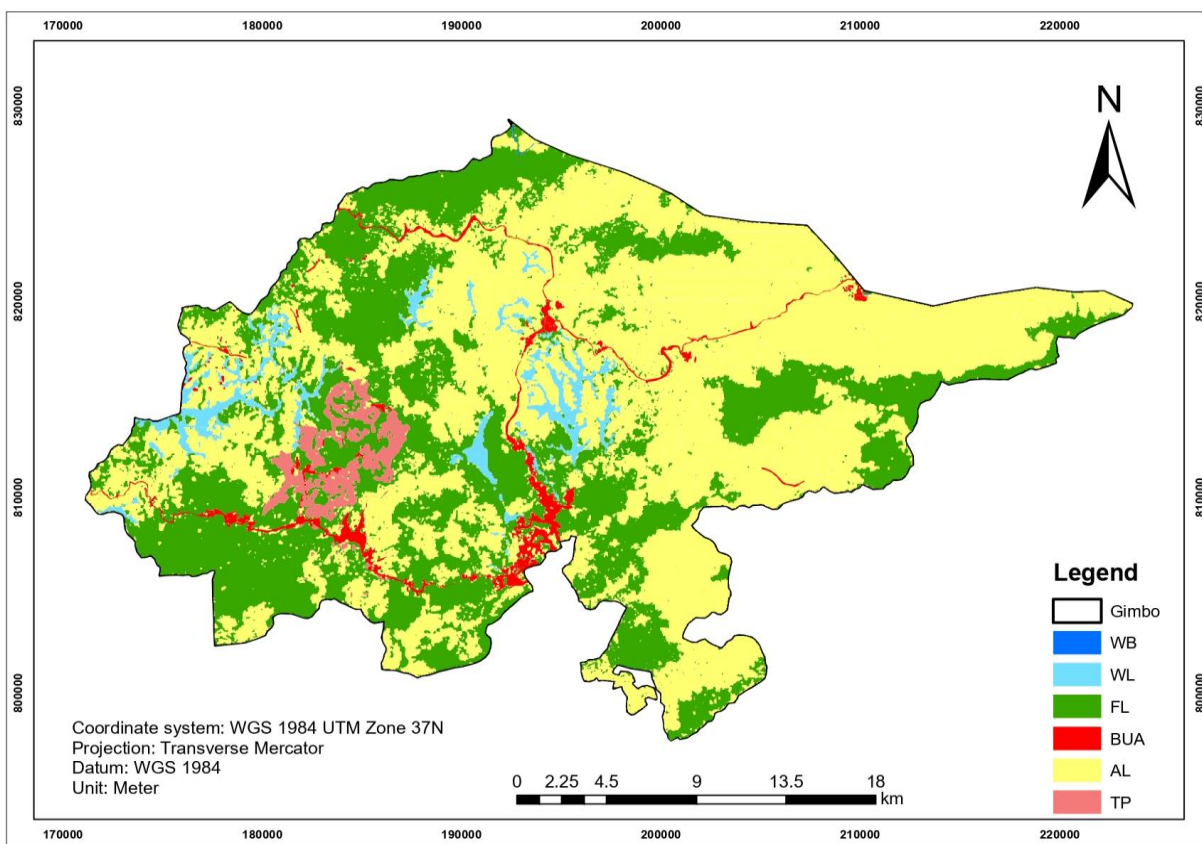


Figure 25. LULC map 2024 (RF)

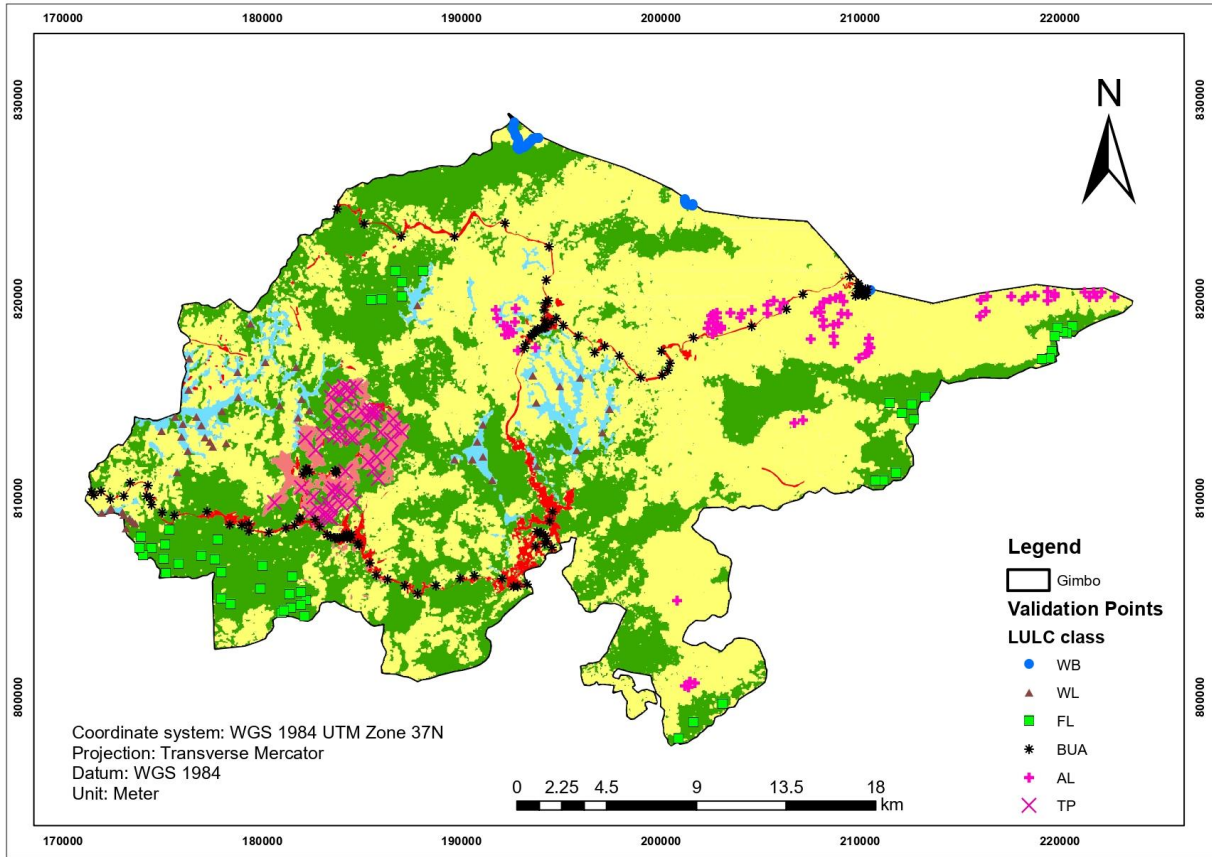


Figure 26. Validation points the 2024 LULC map

4.1.16 Performance comparison of algorithms (1989, 2010, 2019, and 2024)

Table 21 and Figure 27 presents the comparison of CART, Random Forest (RF), Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Gradient Tree Boosting (GTB) evaluated across four time points (1989, 2010, 2019, and 2024) using three performance metrics; average overall accuracy (OAA), average kappa coefficient, and mean F1 score. Across all years, SVM consistently achieved the highest average performance, ranking with an average OAA score of 89.29%, average kappa of 86.75, and average mean F1 score of 89.00%. RF followed closely with an average overall score of 88.02, and GTB ranked third with 86.96%. In contrast, CART and KNN lagged behind for this study, with KNN consistently ranking lowest across all metrics. In the early years (1989–2019), Support Vector Machine (SVM) dominated, but in 2024 RF surpassed SVM with the highest OAA (93.37%) and kappa (0.92), indicating that RF has become increasingly effective over time. These findings highlight SVM as the most stable and accurate algorithm overall, while RF demonstrates significant improvement and competitiveness in recent

years. Therefore, the results indicate that Support Vector Machine's stability and accuracy over time, while underscoring RF's rising competitiveness in recent years (Patil & Panhalkar, 2023), and Figure 28 presents LULC maps of 1989, 2010, 2019, and 2024.

Table 21. Comparison of classification algorithms' performance (1989 – 2024)

Metrics	Year	CART (%)	RF (%)	SVM (%)	KNN (%)	GTB (%)
OAA (%)	1989	80.06	83.48	84.62	79.2	82.91
	2010	85.49	87.7	89.59	85.8	87.38
	2019	85.63	90.72	91.62	85.93	88.62
	2024	91.99	93.37	90.61	87.02	92.27
Average Score (OAA)	All years	85.7925	88.8175	89.11	84.4875	87.795
Kappa Coefficient	1989	76	80	81	77	79.32
	2010	81.47	85	87	83	85
	2019	83	89	90	83	86
	2024	90	92	89	84	91
Average Score (Kappa)	All years	82.6175	86.5	86.75	81.75	85.33
Mean F1 score	1989	80	84	84	79	83
	2010	86	88	90	87	88
	2019	87	91	92	87	89
	2024	90	92	90	87	91
Average score (MeanF1)	All years	85.75	88.75	89	85	87.75
Average Score (OAA, Kappa, Mean F1)	All years	84.72	88.0225	88.28667	83.74583	86.95833
Rank (best=1)	All years	4	2	1	5	3

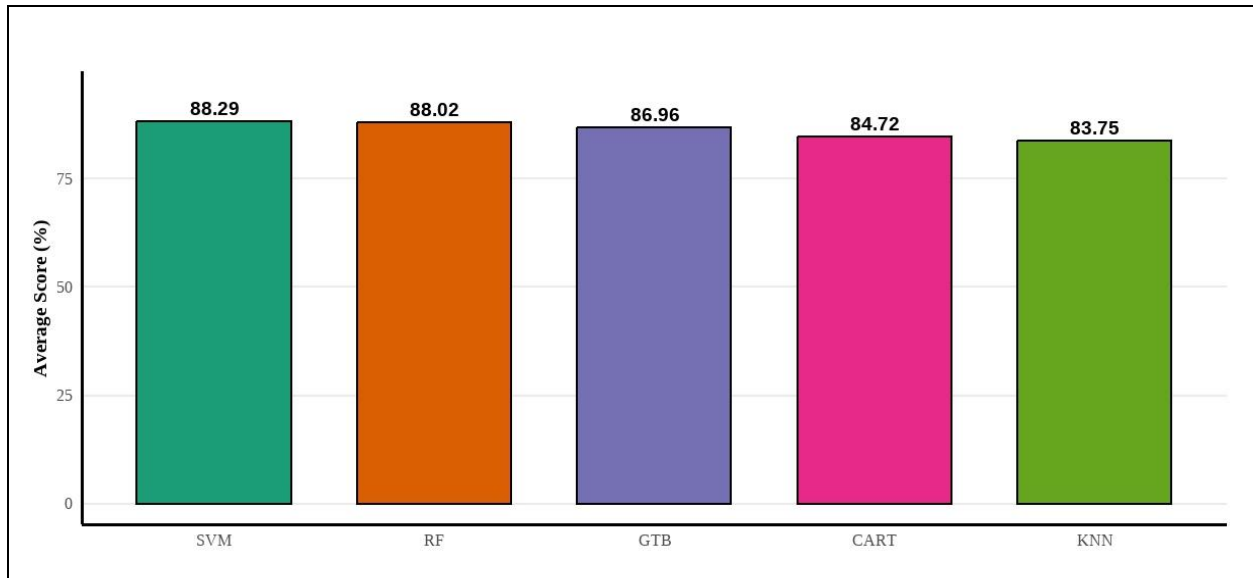


Figure 27. Performance comparison of classification algorithms

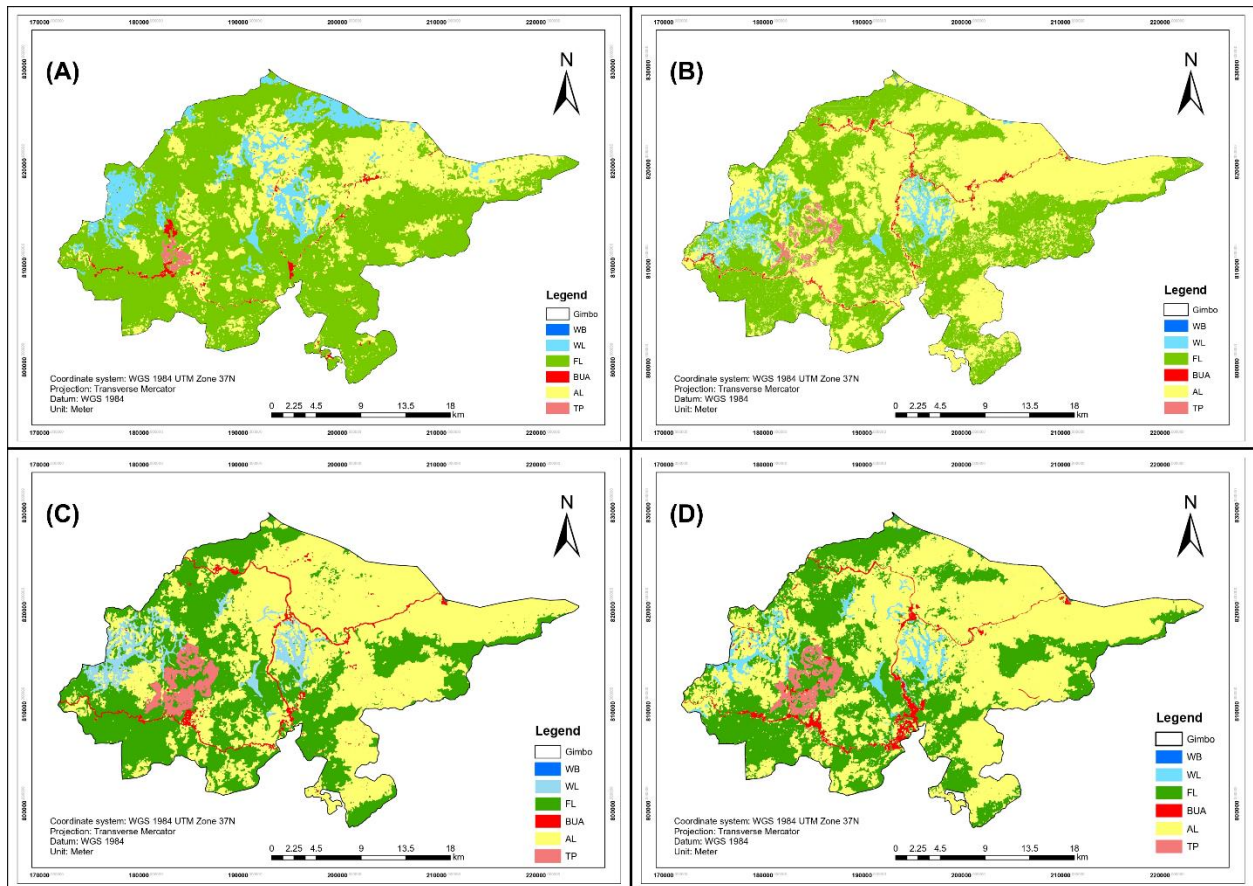


Figure 28. LULC maps of the study area for (A) 1989, (B) 2010, (C) 2019, and (D) 2024

4.2 Spatial and temporal analysis of land-use and land-cover change

The land-use and land-cover distribution for the years 1989, 2010, 2019, and 2024 reveal significant changes in land-cover patterns over the years (Table 22, Figure 29). Water Bodies (WB) showed a slight decline in area, from 22.76 ha (0.029%) in 1989 to 21.24 ha (0.0287%) in 2024, indicating minimal change, wetlands (WL), 7031.71 ha (8.99%) from 1989 to 2646.89 ha (3.39%) in 2024 converted to other land use, particularly agriculture, forest land (FL) shrank from 49544.76 ha (63.40%) in 1989 to 29442.67 ha (37.68%) in 2024, signifying major forest loss over time. In contrast, agricultural land (AL), expanded from 20215.09 ha (25.87%) in 1989 to 42752.69 ha (54.71%) in 2024 driven by population growth and increased demand for farmland, built-up area (BUA) increased from 880.76 ha (1.13%) in 1989 to 1530.52 ha (1.96%) in 2024, reflecting urban expansion and infrastructural development, and tea Plantations (TP) rise from 448.42 ha (0.57%) in 1989 to 1749.27 ha (2.24%). Overall, the LULC change analysis indicates a clear deforestation and wetland loss trend, followed by a significant expansion of agricultural land, built-up areas, and tea plantations. The declining forest and wetland cover raises threats for environmental sustainability, biodiversity loss, and climate change implications, emphasizing the need for effective land management and conservation interventions.

Table 22. LULC distribution for 1989, 2010, 2019, and 2024

LULC classes	1989		2010		2019		2024	
	Area (ha)	Area (%)	Area (ha)	Area (%)	Area (ha)	Area (%)	Area (ha)	Area (%)
WB	22.76	0.03	22.36	0.03	22.27	0.03	21.24	0.027
WL	7031.71	9.00	3815.45	4.88	3533.42	4.52	2646.89	3.39
FL	49544.76	63.40	35935.74	45.99	31133.57	39.84	29442.90	37.68
BUA	880.76	1.13	1013.90	1.30	1122.67	1.44	1530.52	1.96
AL	20215.09	25.87	36537.91	46.76	40639.16	52.01	42752.69	54.71
TP	448.42	0.57	818.14	1.05	1692.41	2.17	1749.27	2.24
Total	78143.50	100.00	78143.50	100.00	78143.50	100.00	78143.50	100.000

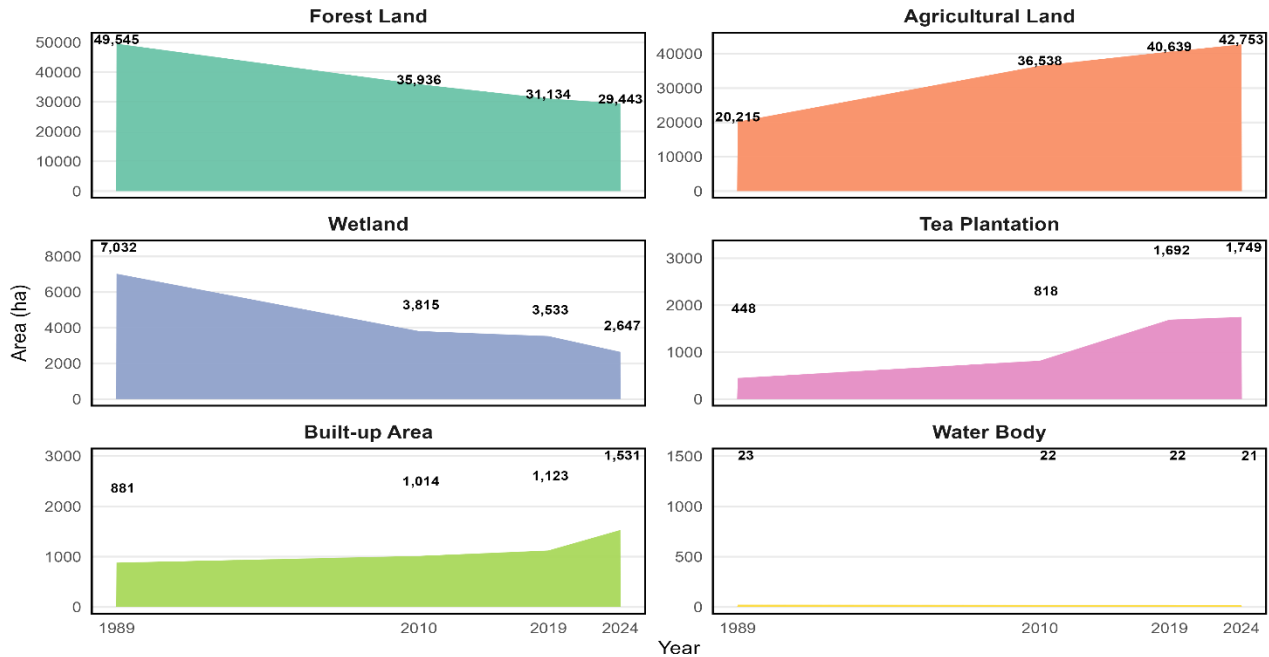


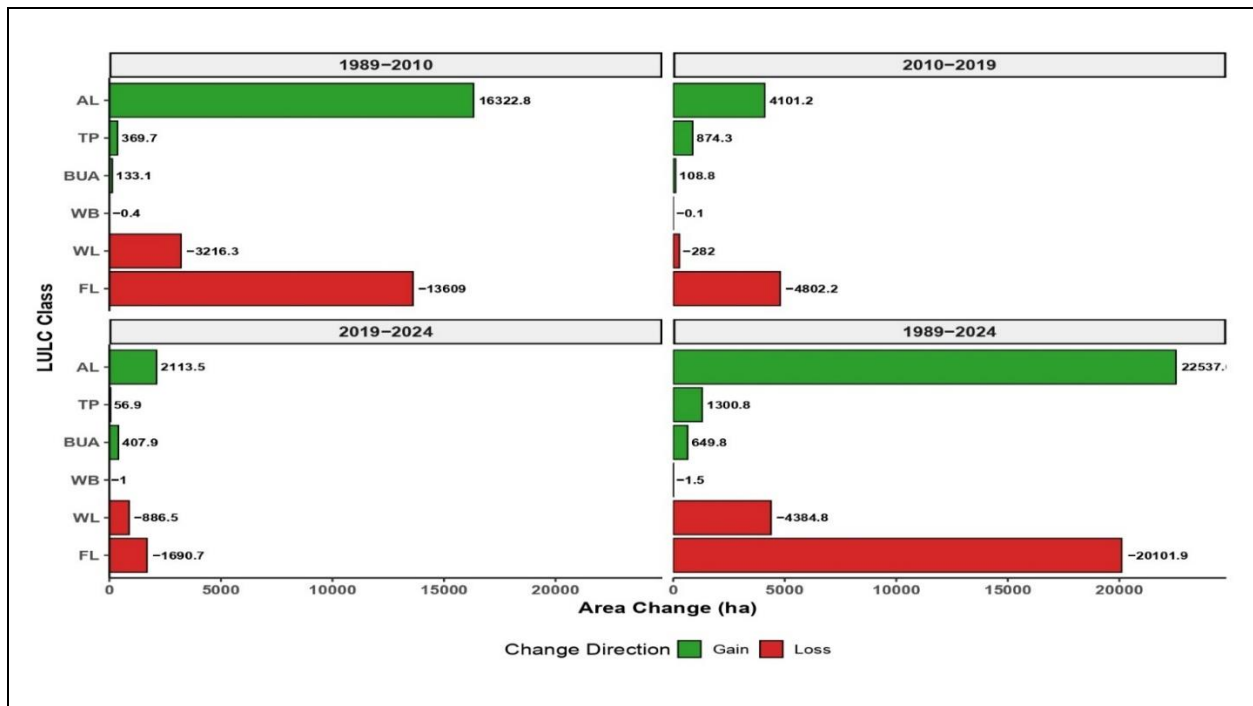
Figure 29. LULC distribution (189, 2010, 2019, and 2024)

4.2.1 Land-use and land-cover (LULC) change analysis (area in hectares) (1989–2024)

The land-use and land-cover change (LULC) from 1989 to 2024 reveals significant changes across different land-use and land-cover classes (Table 23, Figure 30). Water bodies (WB) experienced a slight decline of 1.522 hectares over the 35 years, with minor fluctuations. Wetlands (WL) by 4,384.81 hectares from 1989 to 2024, with the most significant loss occurring between 1989 and 2010 (-3,216.26 hectares), forestland (FL) shrank by 20,103.1 hectares over the same period, with the sharpest decline (-13,609 hectares) occurring between 1989 and 2010. In contrast, agricultural land (AL), Tea plantations (TP), and built-up area (BUA) show expansion by 22,537.6 hectares, 1,300.84 hectares, and 649.75 hectares from 1989 to 2024 respectively, with the most rapid growth between 1989 and 2010 (+16,322.82 hectares), increase 874.28 hectares between 2010 and 2019, and 407.85 hectares between 2019 and 2024, respectively. Overall, the LULC changes highlight a marked decline in natural ecosystems, particularly wetlands and forests, while agricultural expansion and built-up areas have significantly increased.

Table 23. Land-use and land-cover (LULC) change analysis (area in hectares) (1989–2024)

LULC classes	1989	2010	2019	2024	$\Delta(1989-2010)$	$\Delta(2010-2019)$	$\Delta(2019-2024)$	$\Delta(1989-2024)$
WB	22.76	22.36	22.27	21.24	-0.40	-0.09	-1.03	-1.52
WL	7031.71	3815.45	3533.42	2646.89	-3216.26	-282.03	-886.52	-4384.81
FL	49544.76	35935.74	31133.57	29442.9	-13609.02	-4802.17	-1690.67	-20101.86
BUA	880.76	1013.90	1122.67	1530.52	133.14	108.77	407.85	649.75
AL	20215.09	36537.91	40639.16	42752.7	16322.82	4101.25	2113.53	22537.60
TP	448.42	818.14	1692.41	1749.27	369.71	874.28	56.85	1300.84
Total	78143.5	78143.5	78143.5	78143.5				

**Figure 30.** Land-use and land-cover gain and loss by class (1989–2024)

4.2.2 Rate of change

4.2.2.1 Rate of LULC changes (1989–2010)

Between 1989 and 2010 (Table 24, Figures 31, 32, 33), water bodies (WB) experienced a minor decline of 0.40107 ha, with a negligible annual rate of change of -0.08%. Wetland (WL) and forest land (FL) show a substantial reduction of 3216.26 ha and 13609 ha with an annual rate of -2.91% and -1.53%, respectively, indicating deforestation and land conversion. In contrast, built-up areas (BUA) expanded by 133.1493 ha at an annual rate of 0.67%, while agricultural land (AL) and tea

plantations (TP) showed significant increases of 16322.82ha (2.82%) and 369.7144 ha (2.86%), respectively, suggesting agricultural expansion.

Table 24. LULC change (1989–2010)

OID	LULC	1989	2010	Δ LULC	1989%	2010%	Δ LULC%	rate (r)
1	WB	22.76	22.36	-0.40	0.029129	0.02862	-1.76	-0.08%
2	WL	7031.71	3815.45	-3216.26	9.00	4.88	-45.7	-2.91%
3	FL	49544.76	35935.74	-13609.02	63.40	45.99	-27.5	-1.53%
4	BUA	880.76	1013.90	133.14	1.13	1.30	15.1	0.67%
5	AL	20215.09	36537.91	16322.82	25.87	46.76	80.7	2.82%
6	TP	448.42	818.14	369.71	0.57	1.05	82.4	2.86%

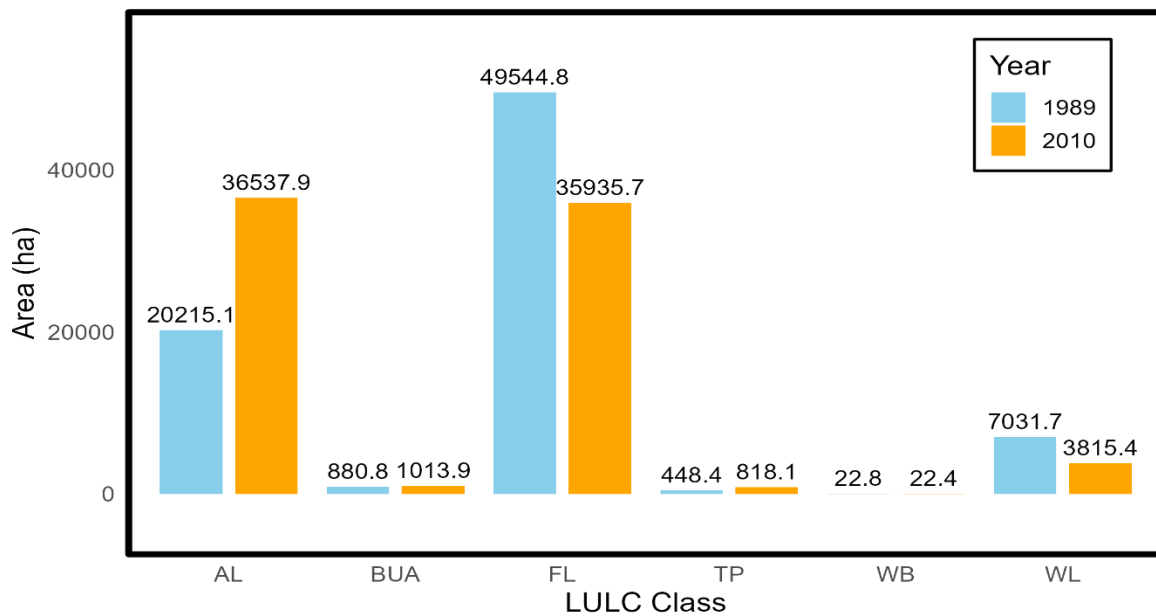


Figure 31. LULC comparison (1989–2010)

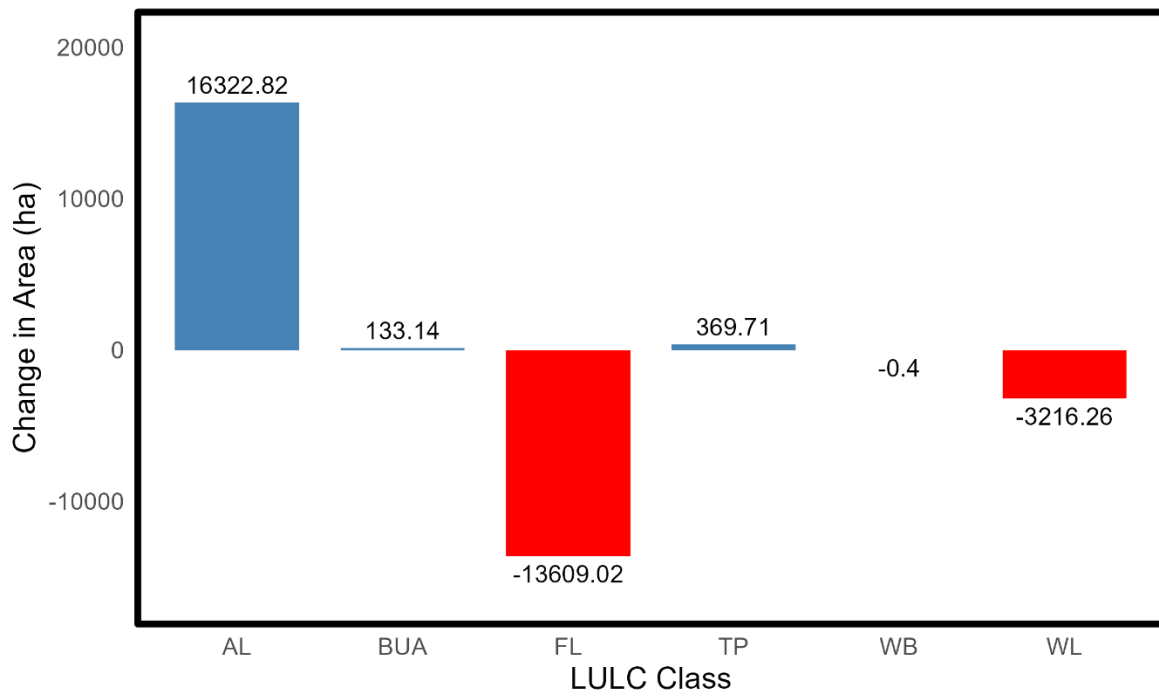


Figure 32. Net LULC Change (1989–2010)

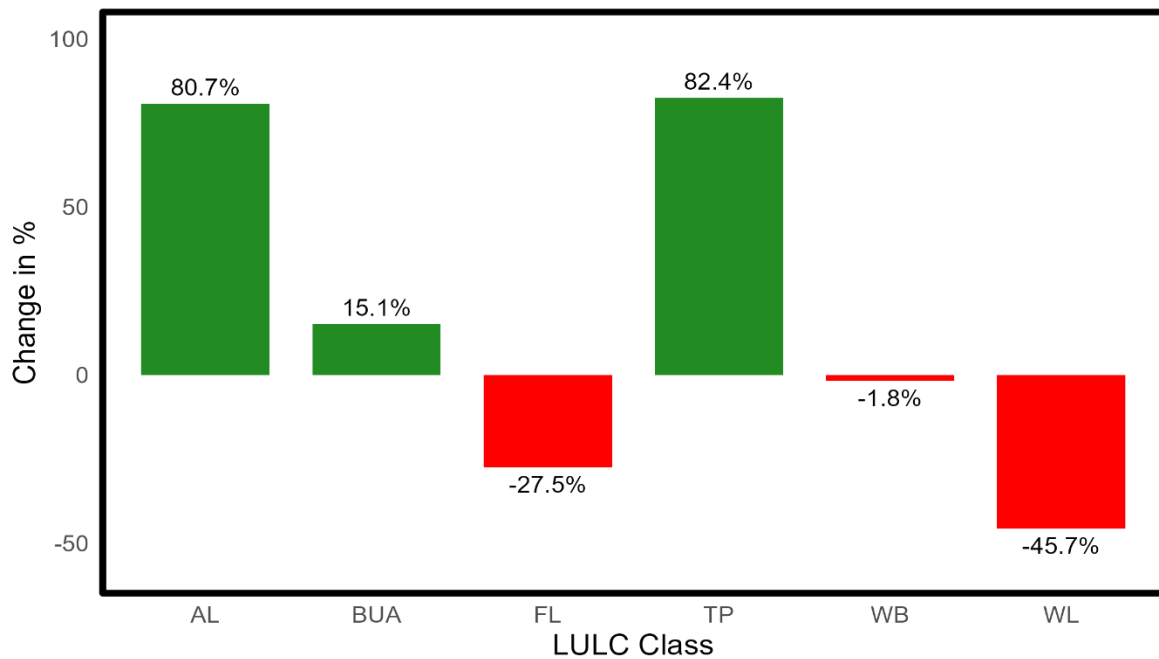


Figure 33. LULC Change (%) (1989–2010)

4.2.2.2 LULC changes (2010–2019)

LULC change (2010 and 2019) as shown in (Table 25, and figure 34, 35, and 36), waterbody (WB) remained relatively stable, with only a slight reduction of -0.09 ha with an annual rate of -0.04%, wetlands (WL) declined by -282.033 ha (-0.85%), and forest land (FL) by -4802.17 ha (-1.59%). In contrast, agricultural land (AL), tea plantations (TP), and built-up areas expanded at rates of 1.18%, 8.08%, and 1.13%, indicating an increase in human activity.

Table 25. LULC change (2010–2019)

OID	LULC classes	2010	2019	Δ	2010%	2019%	Δ LULC%	Rate ®
1	WB	22.36	22.27	-0.09	0.029	0.028	-0.40	-0.04%
2	WL	3815.45	3533.42	-282.03	4.88	4.52	-7.39	-0.85%
3	FL	35935.74	31133.6	-4802.17	45.99	39.84	-13.36	-1.59%
4	BUA	1013.90	1122.67	108.759	1.30	1.44	10.73	1.13%
5	AL	36537.91	40639.2	4101.25	46.76	52.01	11.22	1.18%
6	TP	818.14	1692.41	874.27	1.05	2.17	106.86	8.08%

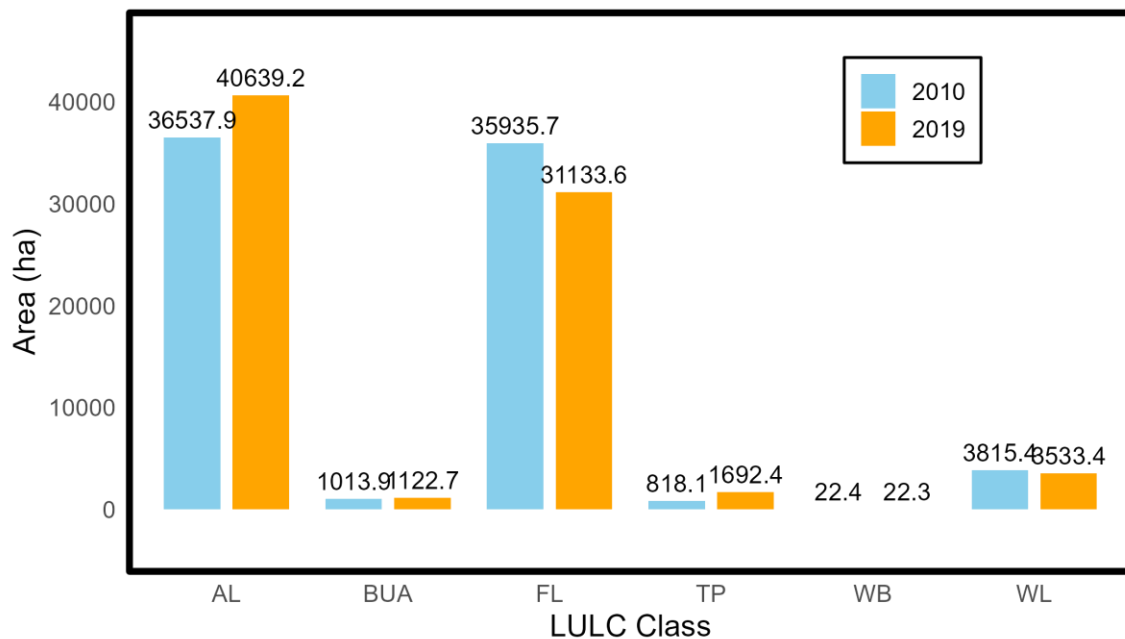


Figure 34. LULC area comparison (2010–2019)

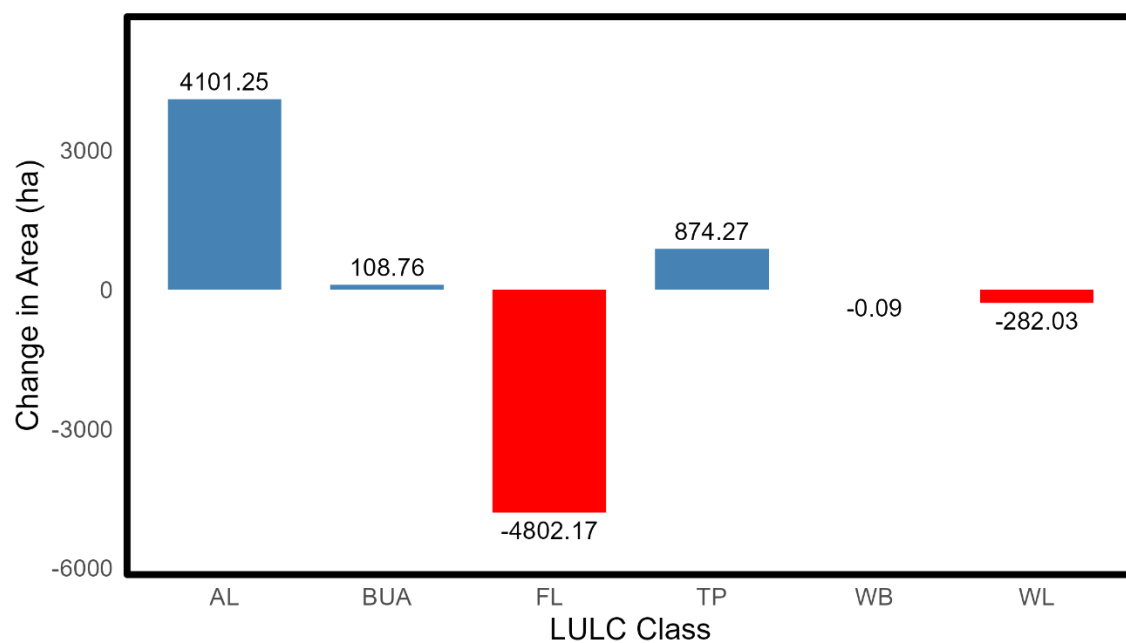


Figure 35. Net LULC change (2010–2019)

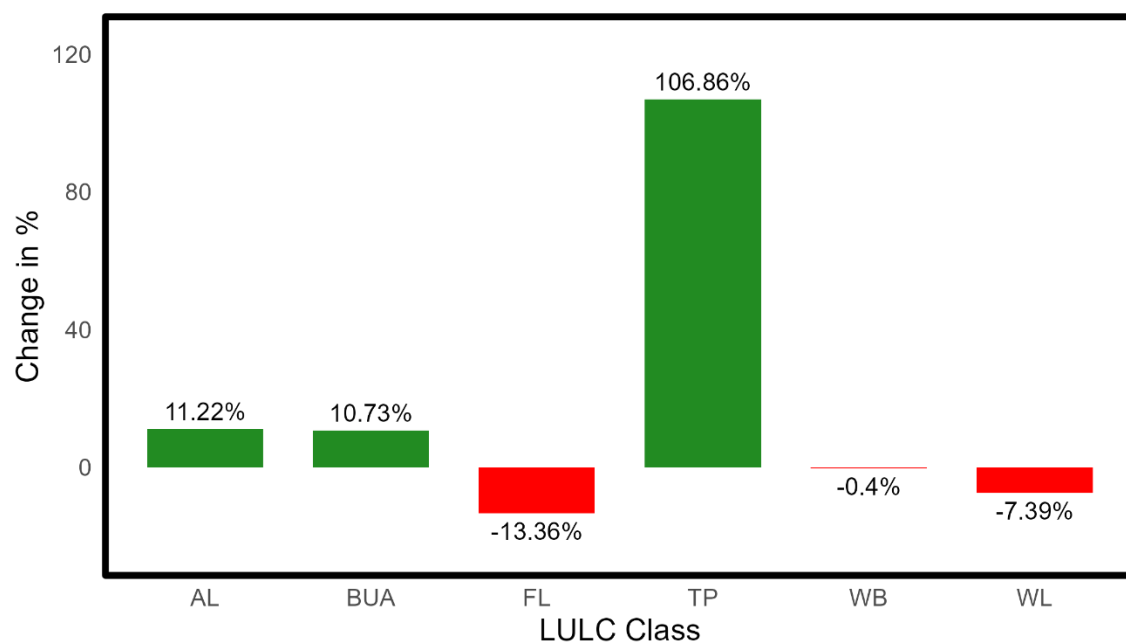


Figure 36. Δ LULC% (2010–2019)

4.2.2.3 LULC changes (2019 – 2024)

As presented in Table 26, Figures 37 and 38, between 2019 and 2024, water body slightly declined by 1.03 ha with an annual rate of -0.95% , wetlands (WL) by -886.522 ha (-5.78%), and forest land (FL) decreased by -1691.9 ha (-1.12%). Meanwhile, agricultural land, tea plantations, and built-up area expanded by 1.01% , 0.66% , and 6.20% , showing a continued land conversion.

Table 26. LULC change (2019–2024)

OID	LULC	2019	2024	Δ	2019%	2024%	Δ LULC%	rate (r)
1	WB	22.27	21.24	-1.03	0.029	0.027	-4.63	-0.95%
2	WL	3533.42	2646.89	-886.52	4.52	3.39	-25.09	-5.78%
3	FL	31133.57	29442.90	-1690.67	39.84	37.68	-5.43	-1.12%
4	BUA	1122.67	1530.52	407.85	1.44	1.96	36.33	6.20%
5	AL	40639.16	42752.69	2113.53	52.01	54.71	5.20	1.01%
6	TP	1692.41	1749.27	56.85	2.17	2.24	3.36	0.66%

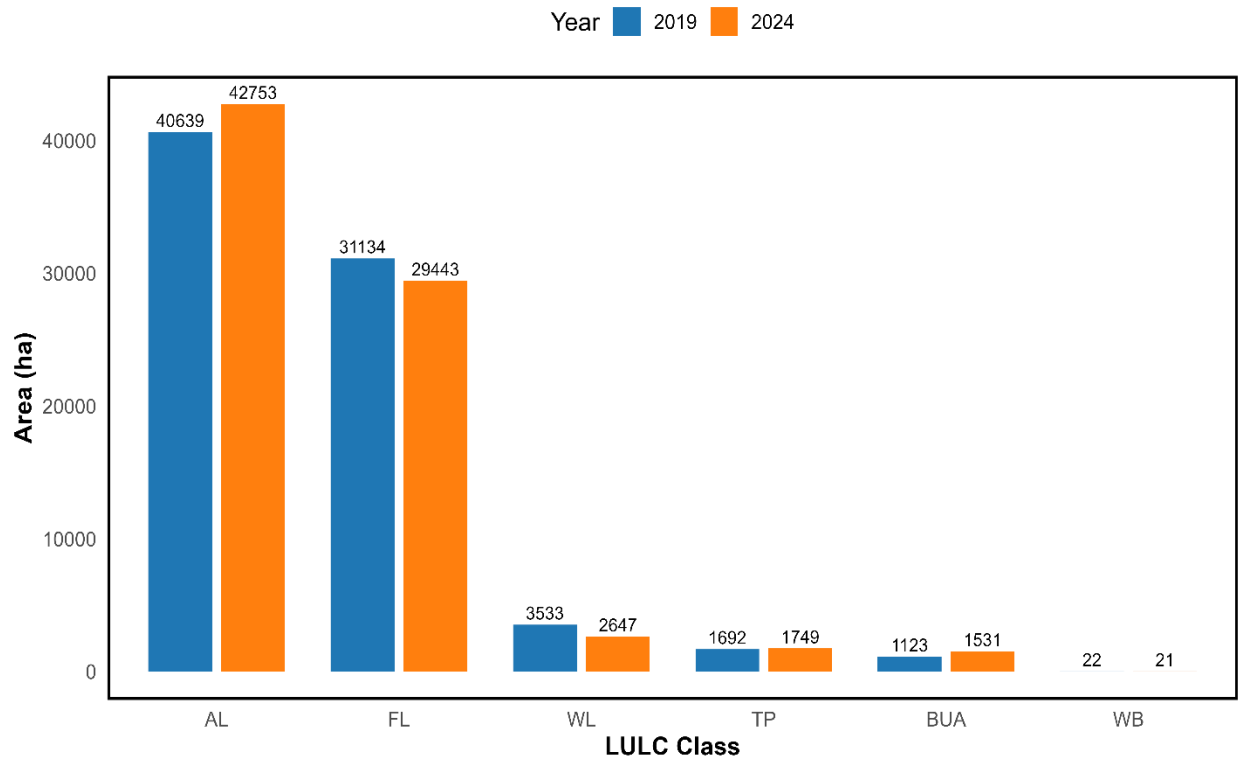


Figure 37. LULC areas (2019-2024)

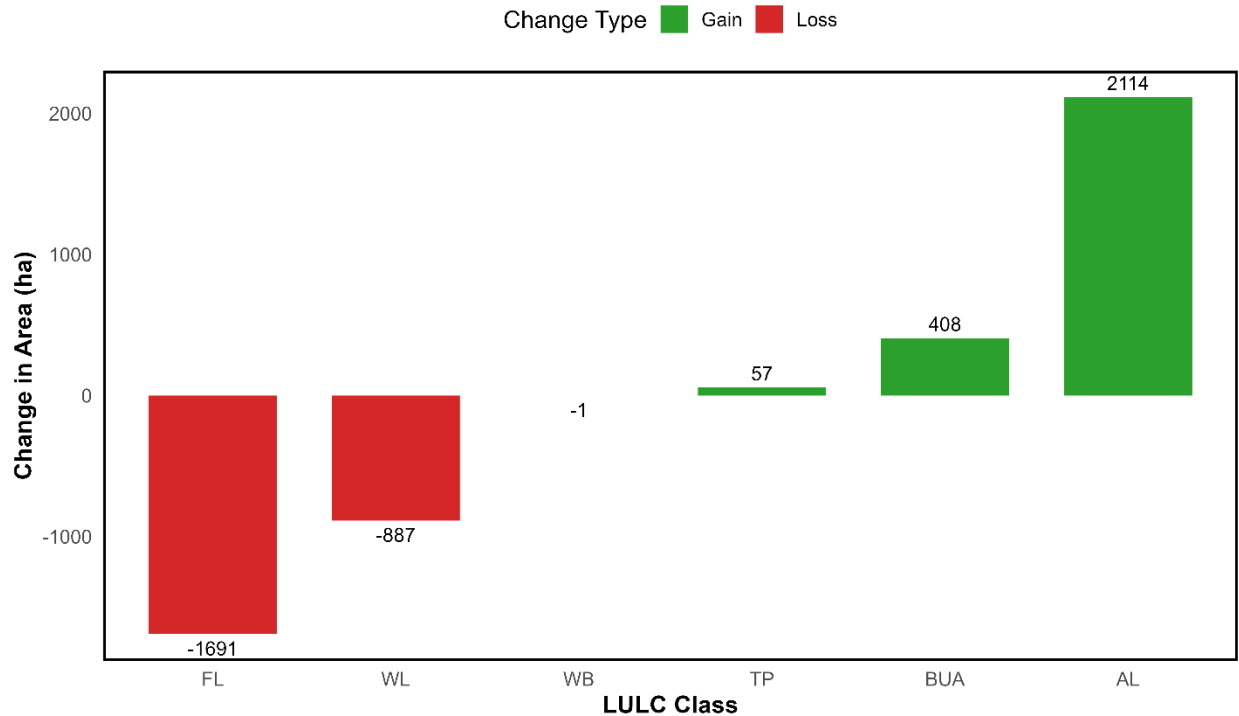


Figure 38. Net LULC classes (2019 – 2024)

4.2.2.4 Overall LULC changes (1989–2024)

Table 27 and figures 39, 40, and 41 show that from 1989 to 2024, significant changes have occurred in land use and land cover (LULC), reflecting shifting environmental and human influences. Water bodies (WB) experienced a slight decline by -1.5 ha, with a -0.20 % rate of change, wetlands (WL) by 4,384.81 ha, shrinking from 8.99 % to 3.39 % a rate of 2.79 % per year, forest land (FL) by 20,103.1 ha, dropping from 63.40 % to 37.68 %, indicating annual deforestation rate of 1.49 %. In contrast, agricultural land (AL) nearly doubled, increasing by 22,537.6 ha and growing from 25.87 % to 54.71%, tea plantations (TP) expanding by 1,300.84 ha, with their share rising from 0.57 % to 2.24 % at a rapid annual rate of 3.89 %, built-up areas (BUA) expanded considerably growing by 649.75 ha with a rate rising from 1.13 % to 1.96 %, marking an annual increase of 1.58 %. These changes reveal the shift from natural ecosystems to human-dominated landscapes, emphasizing the need for sustainable land management strategies.

Table 27. LULC change (1989–2024)

OID	LULC classes	1989	2024	Δ	1989%	2024%	Δ LULC%	rate ®
1	WB	22.76	21.24	-1.52	0.03	0.027	-6.68	-0.20%
2	WL	7031.71	2646.89	-4384.81	9.00	3.39	-62.36	-2.79%
3	FL	49544.76	29442.90	-20101.86	63.40	37.68	-40.57	-1.49%
4	BUA	880.76	1530.52	649.75	1.13	1.96	73.77	1.58%
5	AL	20215.09	42752.69	22537.60	25.87	54.71	111.49	2.14%
6	TP	448.42	1749.27	1300.84	0.57	2.24	290.10	3.89%

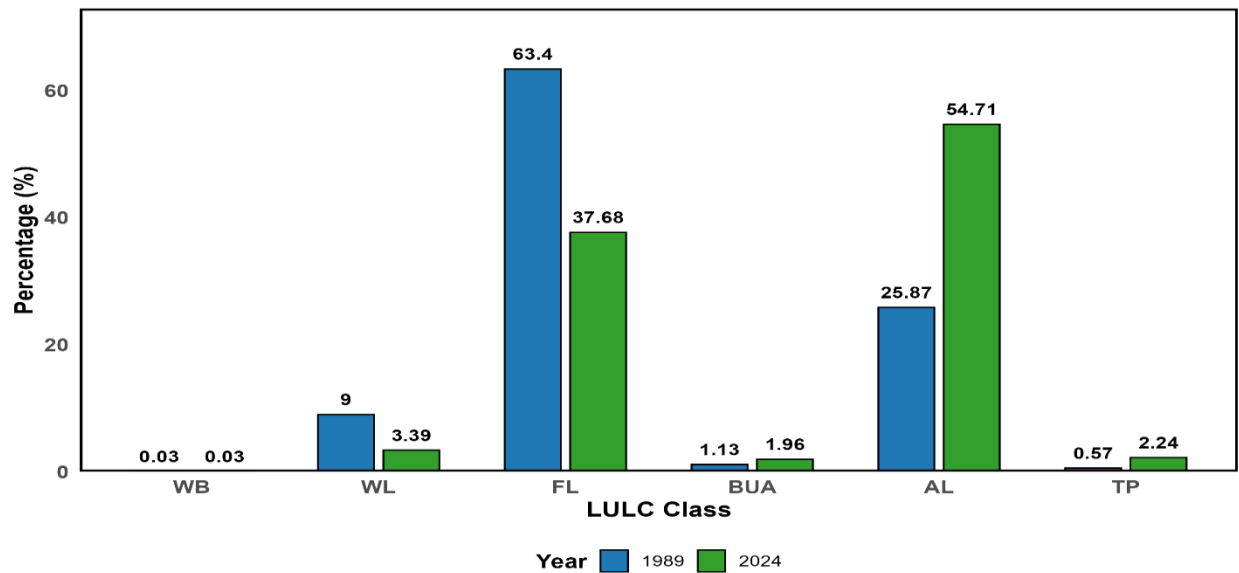


Figure 39. LULC Percentage distribution (1989 & 2024)

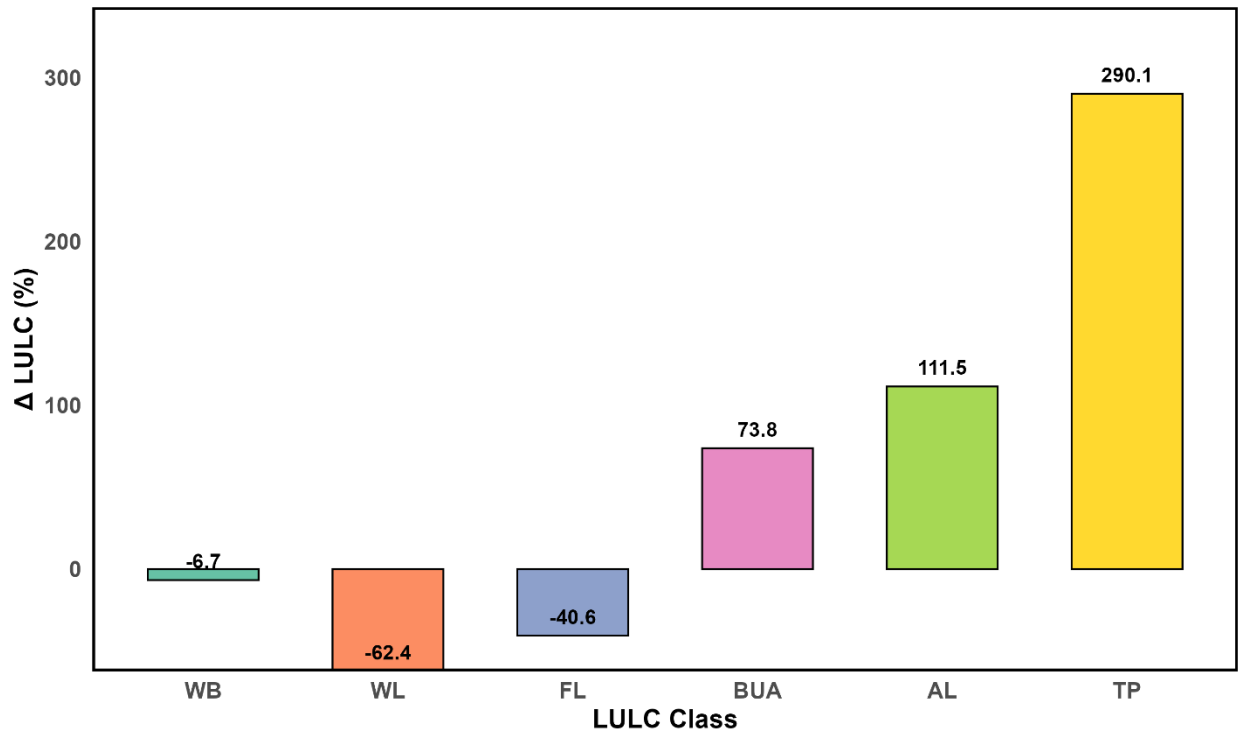


Figure 40. ΔLULC% (1989–2024)

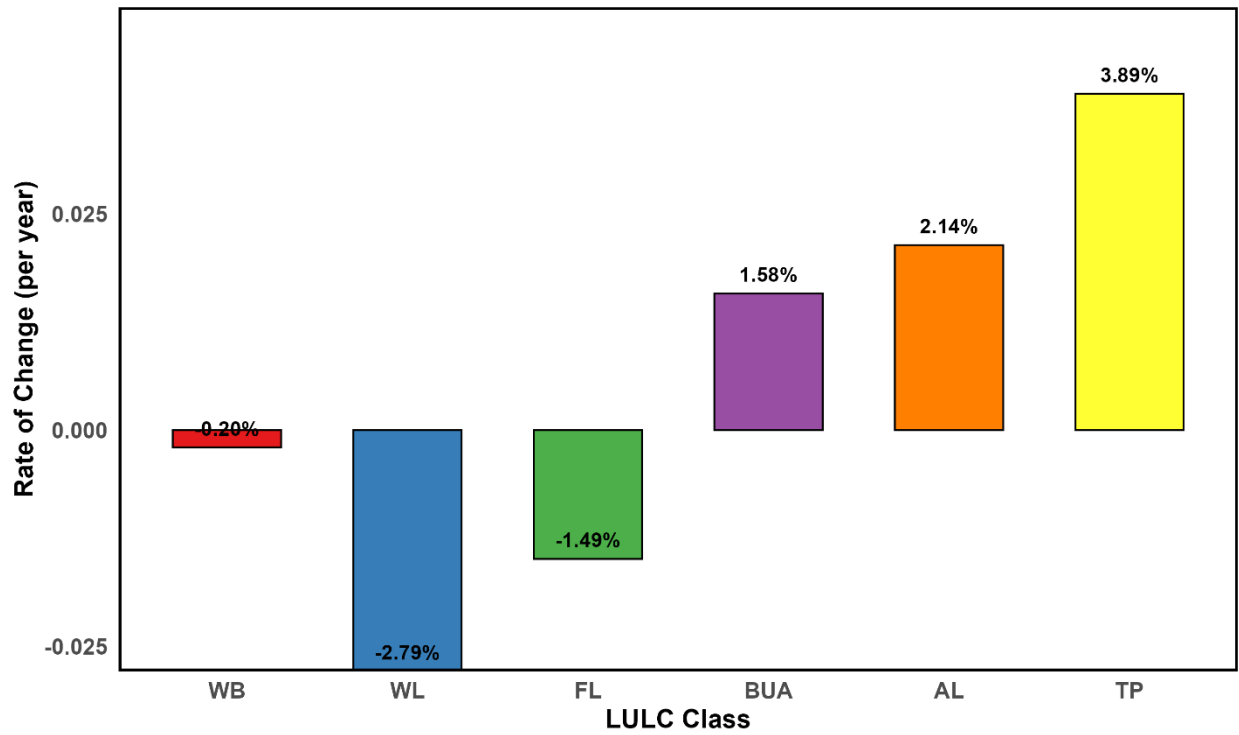


Figure 41. Rate of change per year (1989–2024)

4.2.2.5 LULC transition pattern and conversion analysis

The LULC transition matrix from 1989 to 2024 in Gimbo District indicates notable land cover changes (Table 28). The most significant conversion was from forest land to agricultural land, accounting for approximately 20,010.87 hectares, which represents 67.96% of the total area that transitioned out of forest land. Additionally, the conversion of wetlands to agricultural land was also substantial, with 4,828.95 hectares, or 67.74% of all wetland losses. Other important transitions include forest to built-up areas (663.03 ha), forest to wetland (673.47 ha), and agricultural land to built-up (553.23 ha). These results highlight the spatial dynamics of land conversion, where forest and wetland areas are primarily being lost to agricultural expansion and urbanization.

Table 28. LULC Transition matrix (1989–2024) (ha)

From \ To	1 (WB)	2 (WL)	3 (FL)	4 (BUA)	5 (AL)	6 (TP)
1 (WB)	11.88	0	5.13	0	4.86	0
2 (WL)	1.44	1747.61	399.51	39.94	4828.95	3.42
3 (FL)	7.65	673.47	27564.6	663.03	20010.87	776.88
4 (BUA)	0	11.07	126.72	240.03	276.83	119.61
5 (AL)	0.27	214.74	1293.3	553.23	17619.12	499.86
6 (TP)	0	0	53.64	34.29	12.06	349.5
Total	21.24	2646.89	29442.9	1530.52	42752.69	1749.27

4.3 Temporal analysis of climatic variables (1989–2024)

The Mann-Kendall (MK) test and Sen's slope estimator were used to analyze the monthly, seasonal, and annual averages of climate variables, including precipitation and temperature extremes. The analysis involved computing statistical measures, including minimum, maximum, mean, standard deviation (SD), Z-value of the Mann-Kendall (ZMK) test, Sen's slope, and p-values at a 95% confidence interval. The Z-values from the MK test were used to identify whether trends were increasing or decreasing. Sen's slope was used to show the magnitude of these trends. The overall findings of the test are discussed in detail for each climate variable.

4.3.1 Monthly minimum temperature (1989–2024)

The MK test for minimum temperature revealed a general warming trend throughout the study period, with varying levels of statistical significance, as shown in Table 29 and Figures 42 and 43. In January, temperatures showed minor fluctuations with a mean of 10.47°C and a standard deviation of 1.10, indicating a slight but non-significant warming trend (ZMK=1.10, $p=0.27$) and an annual increase of 0.0245°C. February, showed a near-significant warming trend (ZMK=1.76, $p=0.08$) with a warming rate of 0.0311°C/year. A statistically significant warming trend was observed in March (ZMK=2.87, $p=0.0041$), with temperatures increasing by 0.0354°C/year, indicating a notable shift in climatic conditions. April exhibited stable temperatures with no significant trend (ZMK=1.26, $p=0.21$) and a negligible annual increase of 0.0106°C/year. In contrast, May recorded a significant warming trend (ZMK=2.47, $p=0.013$), with temperatures rising by 0.0201°C/year, which have implications for the agricultural growing season.

In June, a moderate warming trend was observed (ZMK=1.92, $p=0.054$, slope: 0.0152°C/year), while July showed a significant warming trend (ZMK=2.47, $p=0.013$) with an increase of 0.0194°C/year. August also exhibited a warming trend, although it was not statistically significant (ZMK=1.45, $p=0.147$, slope: 0.0087°C/year). In September, a significant warming trend recorded (ZMK=2.21, $p=0.027$) with a temperature increase of 0.0172°C/year, while October showed a similar trend (ZMK=2.00, $p=0.045$) with a rise of 0.0267°C/year. November approached significance (ZMK=1.95, $p=0.051$) with a warming rate of 0.0255°C/year. Lastly, December exhibited a significant warming trend (ZMK=2.26, $p=0.024$), with temperatures increasing by 0.0278°C/year (mean: 10.44°C, standard deviation: 1.14). Overall, the findings indicate a persistent warming trend in the district, with potential implications for climate variability and agricultural activities.

Table 29. Monthly MK result for minimum temperature (°C)

Months	Minimum	Maximum	Mean	STD	ZMK	P value	Sen's slope	PWS
January	8.27	12.93	10.47	1.1	1.1	0.2699	0.0245	0.0245
February	7.9	13.66	11.32	1.24	1.76	0.0789	0.0311	0.0311
March	11.03	14.5	12.77	0.88	2.87	0.0041	0.0354	0.035
April	10.91	14.08	13.16	0.64	1.26	0.2092	0.0106	0.0072
May	11.19	14.17	12.9	0.63	2.47	0.0134	0.0201	0.0172
June	11.72	13.63	12.64	0.47	1.92	0.0545	0.0152	0.0101
July	11.42	13.74	12.52	0.49	2.47	0.0134	0.0194	0.0158
August	10.62	13.92	12.42	0.55	1.45	0.1466	0.0087	0.0055
September	10.74	13.36	12.28	0.52	2.21	0.0271	0.0172	0.0149
October	8	12.99	11.48	0.94	2	0.0454	0.0267	0.0266
November	8.86	13.48	11.15	0.95	1.95	0.0514	0.0255	0.0259
December	8	13.8	10.44	1.14	2.26	0.0237	0.0278	0.0278

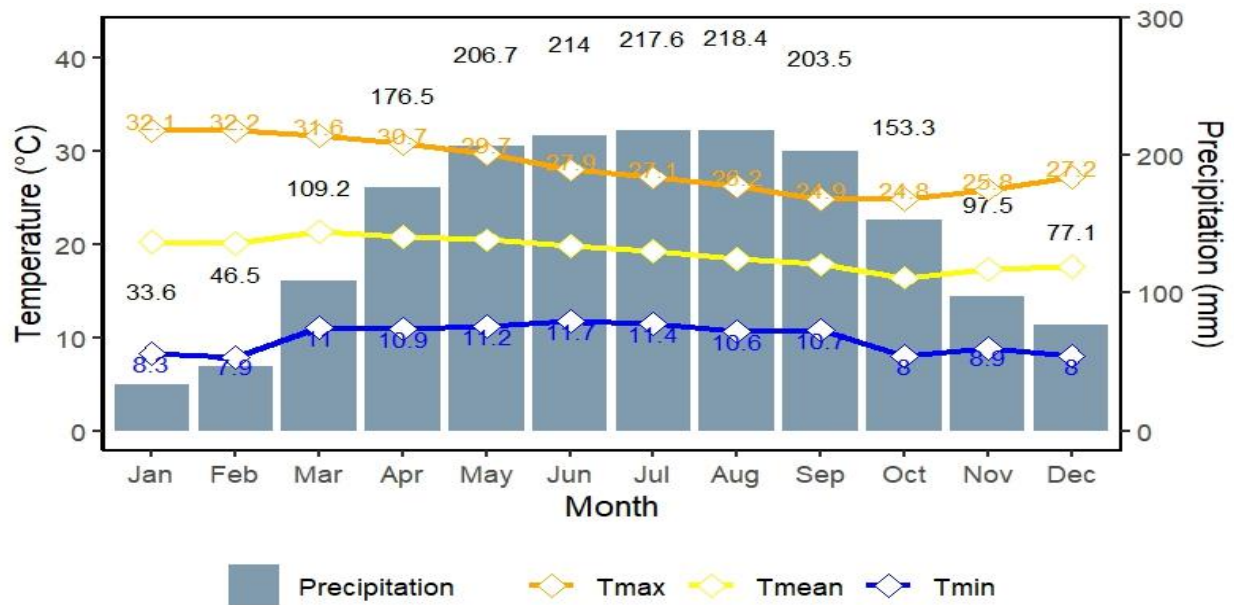


Figure 42. Monthly minimum temperature trend

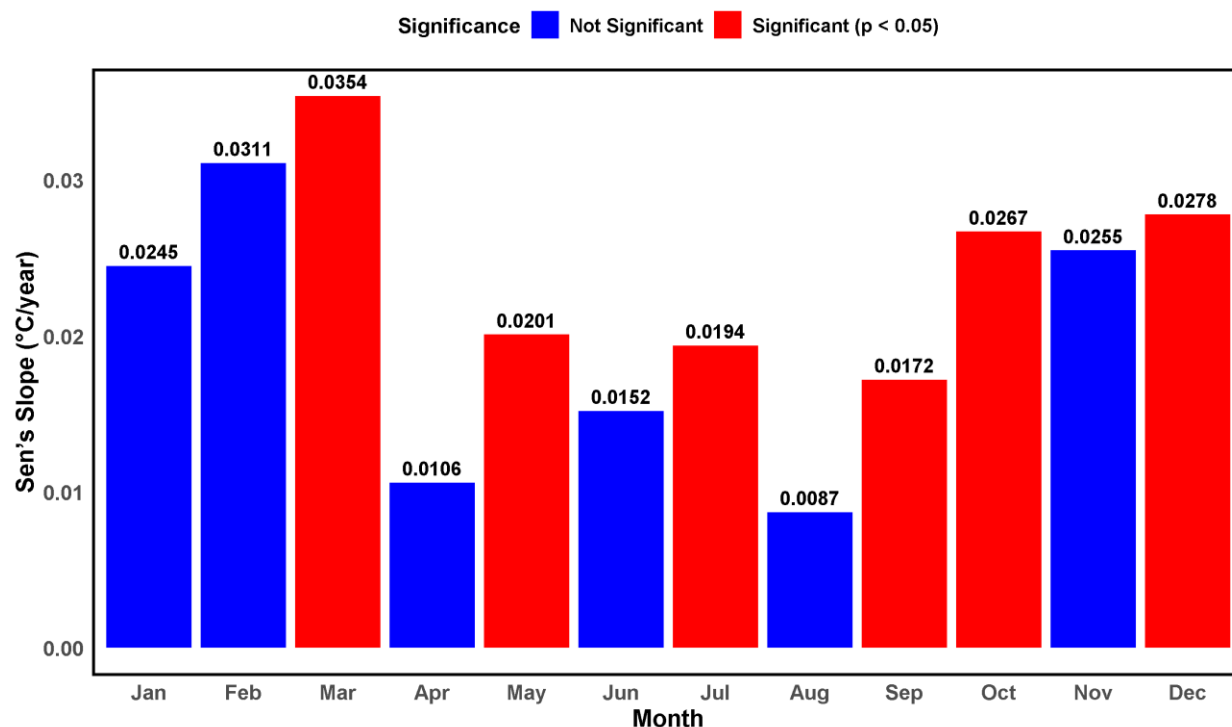


Figure 43. Monthly Sen's slope of minimum temperature trend (1989–2024)

4.3.1.1 Seasonal minimum temperature

4.3.1.1.1 Fall season (February, March, April, May)

The analysis of the minimum temperature for the fall season from 1989 to 2024 reveals a statistically significant increasing trend, as shown in Table 30 and Figures 44 and 45, which detailed the temperature data and trend. During this period, the minimum temperature ranged from 11.17°C to 13.79°C, with a mean value of 12.55°C and a standard deviation of 0.58°C, indicating a consistent warming trend. The Sen's slope estimate of 0.024°C/year quantifies the gradual warming trend, highlighting the consistent increase in minimum temperatures over the years. Furthermore, the Mann-Kendall test result with a Z-value of 2.87 and a p-value of 0.004 confirm that the warming trend is statistically significant at the 95% confidence level, indicating high likelihood that the trend is not due to random variation.

4.3.1.1.2 Winter season (June, July, August, September)

The minimum temperature range is from 11.47 °C to 13.51 °C, resulting in a mean temperature of 12.49 °C with a standard deviation of 0.38 °C (Table 30, Figures 44, 45). The Sen's slope estimate (0.017 °C/year) suggests a steady increase in temperature over the years. The Mann-Kendall test

results provide a Z-value of 3.01 and a p-value of 0.0026, confirming that the increasing trend is statistically significant at the 95% confidence level.

4.3.1.1.3 Summer season (October, November, December, January)

The minimum temperature for summer exhibits a relatively pronounced warming trend among the three seasons. The minimum temperature ranges from 9.63°C to 12.29°C, with a mean value of 10.91°C and a standard deviation of 0.60°C. The Sen's slope estimate (0.029°C/year) indicates a relatively higher rate of temperature increase compared to the fall and winter seasons. The Mann-Kendall test results in a Z-value of 3.09 and a p-value of 0.00199, signifying a statistically significant warming trend at the 95% confidence level (Table 30, Figures 44 and 45). Across all three seasons, the findings suggest a consistent and statistically significant increase in seasonal temperatures over the study period, reinforcing the presence of climate variability and warming trends in the area.

Table 30. Seasonal minimum temperature

Seasons	Min Tem (°C)	MaxTem (°C)	Mean Tem (°C)	Standard Deviation (°C)	Sen's Slope (°C/year)	Z-Value	p-Value	Trend Direction	Significance ($\alpha=0.05$)
Belg	11.17	13.79	12.55	0.58	0.024	2.87	0.004	Increasing	Significant
Kiremt	11.47	13.51	12.49	0.38	0.017	3.01	0.0026	Increasing	Significant
Bega	9.63	12.29	10.91	0.6	0.029	3.09	0.00199	Increasing	Significant

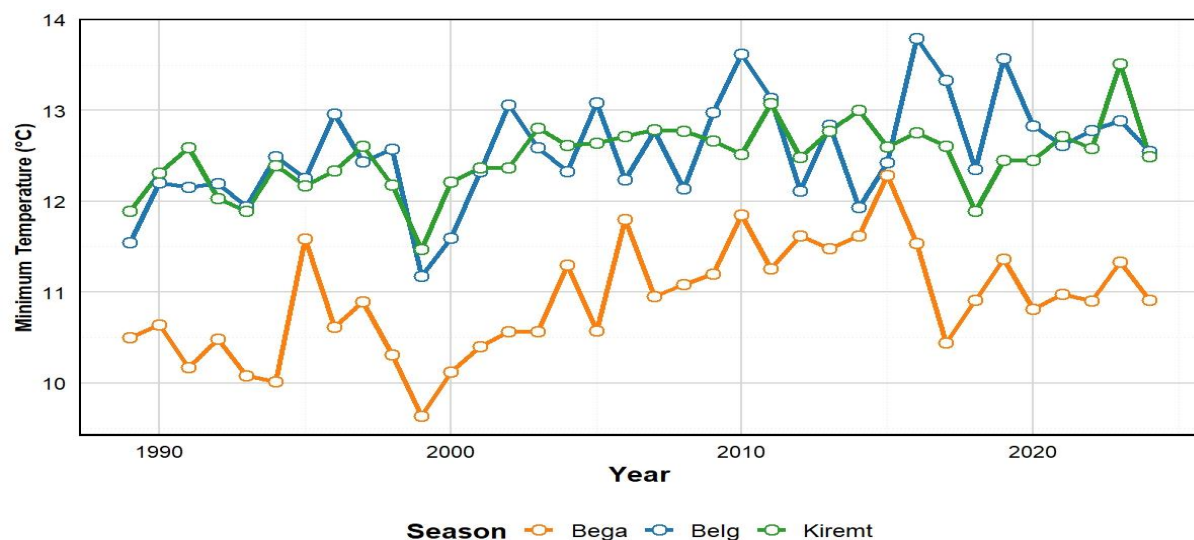


Figure 44. Seasonal minimum temperature trend (1989–2024)

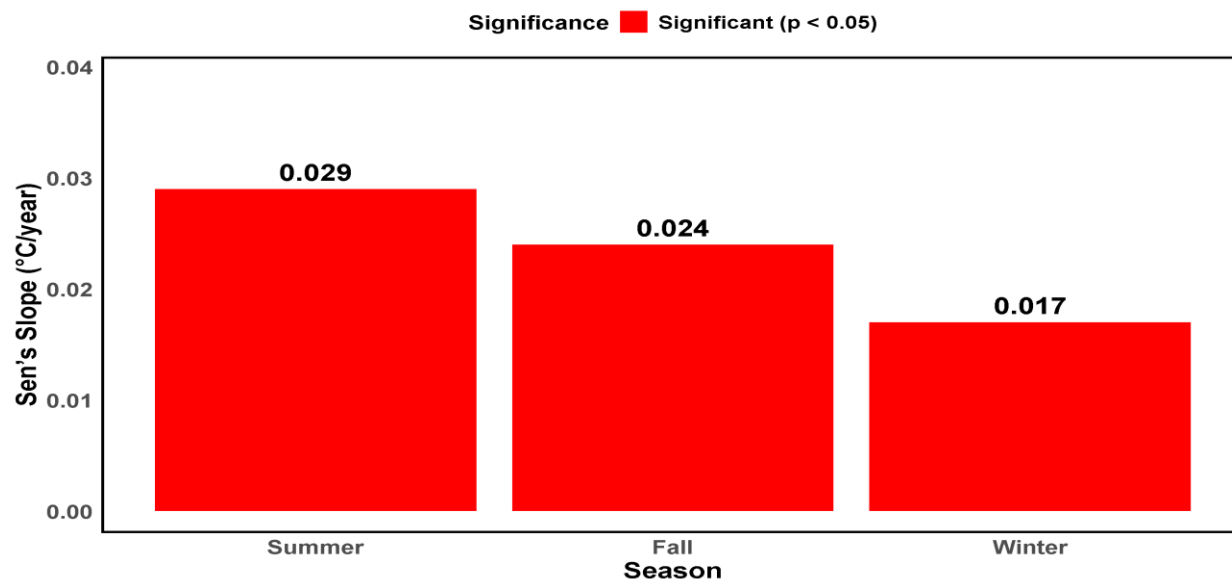


Figure 45. Sen's slope of seasonal minimum temperature (1989–2024)

4.3.1.2 Annual minimum temperature

The Mann-Kendall trend test and Sen's slope estimate for the annual minimum temperature from 1989–2024, as summarized in Table 31, Figure 46, reveal a statistically significant increasing trend at a 95 % confidence interval (ZMK= 4.2633, $P < 0.05$, Sen's slope = 0.0254°C). This consistent warming trend is evidenced by the annual temperature increase of 0.0254°C , which suggests evidence of a consistent warming trend.

Table 31. MK test for annual minimum temperature

Statistics	Values
ZMK	4.2633
P value	2.01E-05
Sen's slope	0.0254°C

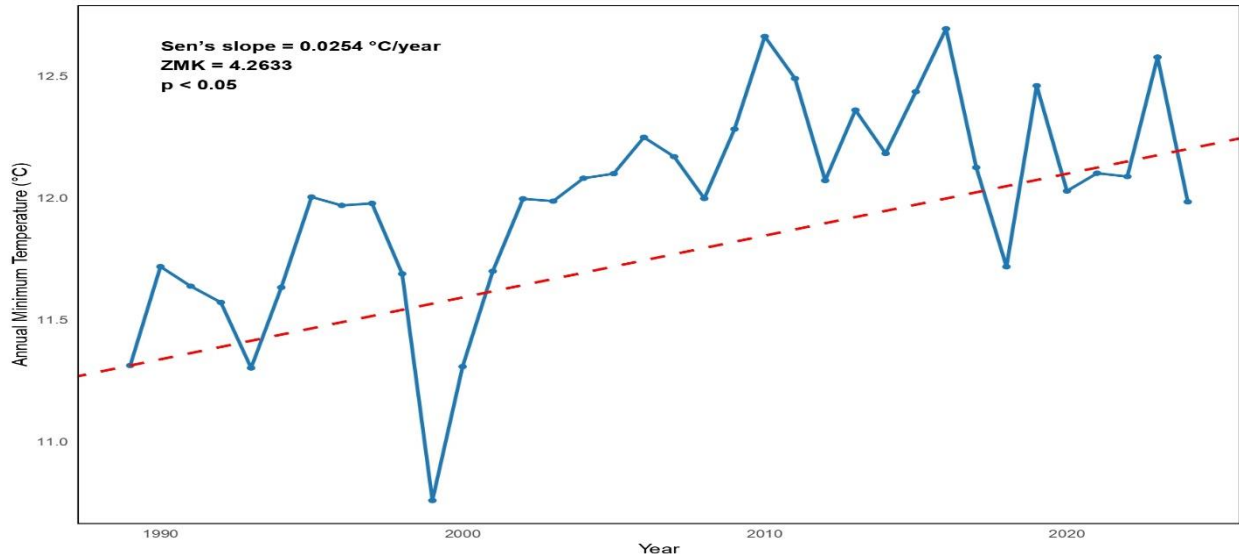


Figure 46. Average annual minimum temperature (1989–2024)

4.3.2 Maximum temperature

4.3.2.1 Monthly maximum temperature (1989–2024)

An increase in temperature is one of the indications of global climate change (Marsoor, 2021). The MK and Sen's slope estimates indicate significant positive trends in several months, suggesting an overall warming pattern, as detailed in Table 32 and Figures 47 and 48. For January, the minimum range is from 27.02°C to 32.14°C, respectively, with a mean of 28.81°C and a standard deviation of 0.95. The MK Z-value of 2.33, ($p = 0.0198$) and Sen's slope of 0.0278 °C/year indicating a statistically significant upward trend. February exhibited the highest variability with a standard deviation of 1.34. The ZMK value was 2.17 ($p = 0.0303$) and a Sen's slope was 0.0525°C/year with a pre-whitened slope of 0.0341°C/year indicating a statistically significant trend. March and April also demonstrated statistically significant trends, with ZMK value of 2.82 and 2.96, and p-value of 0.004 and 0.0031 respectively. The Sen's slopes were 0.0384°C/year and 0.0349°C/year, indicating an increase during these months. The months of May through October showed consistent positive trends, with significant warming patterns in May ($Z = 2.63$, $p = 0.0086$, Sen's slope = 0.0262°C/year) and July ($Z = 2.07$, $p = 0.0384$, Sen's slope = 0.0183°C/year). However, the trends in August and September, were positive, but not statistically significant ($p > 0.05$). In November, the trend was weaker, with an MK Z-value of 0.34 ($p = 0.7335$), indicating no significant change during this month. December showed marginal significance with a Sen's slope of 0.0212°C/year ($p = 0.0789$).

Table 32. Monthly MK result for maximum temperature

Months	Min	Max	Mea	STD	ZMK	P-Value	Sen's Slope (°C/year)	PWS (°C/year)
January	27.02	32.14	28.81	0.95	2.33	0.0198	0.0278	0.0278
February	26.57	32.2	29.37	1.34	2.17	0.0303	0.0525	0.0341
March	27.45	31.59	29.36	0.93	2.82	0.0048	0.0384	0.0309
April	26.22	30.7	28.74	0.88	2.96	0.0031	0.0349	0.0286
May	26.7	29.67	27.89	0.68	2.63	0.0086	0.0262	0.021
June	25.05	27.93	26.2	0.65	2.03	0.0424	0.0217	0.0217
July	23.6	27.1	24.85	0.74	2.07	0.0384	0.0183	0.0172
August	23.34	26.22	24.78	0.67	1.78	0.0744	0.0169	0.0169
September	24.6	27.46	25.83	0.6	1.59	0.111	0.012	0.012
October	25.45	28.79	27.18	0.69	2.11	0.0348	0.0185	0.0149
November	25.63	29.46	27.55	0.74	0.34	0.7335	0.0042	0.0042
December	25.32	31.21	28.02	1.02	1.76	0.0789	0.0212	0.0212

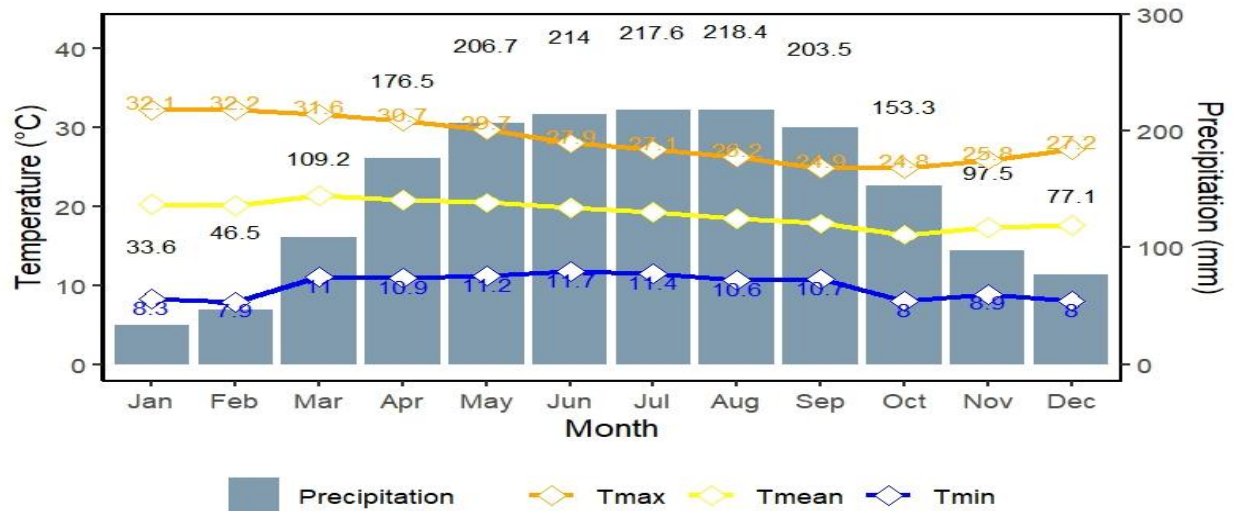


Figure 47. Monthly minimum, maximum temperature, and precipitation trend

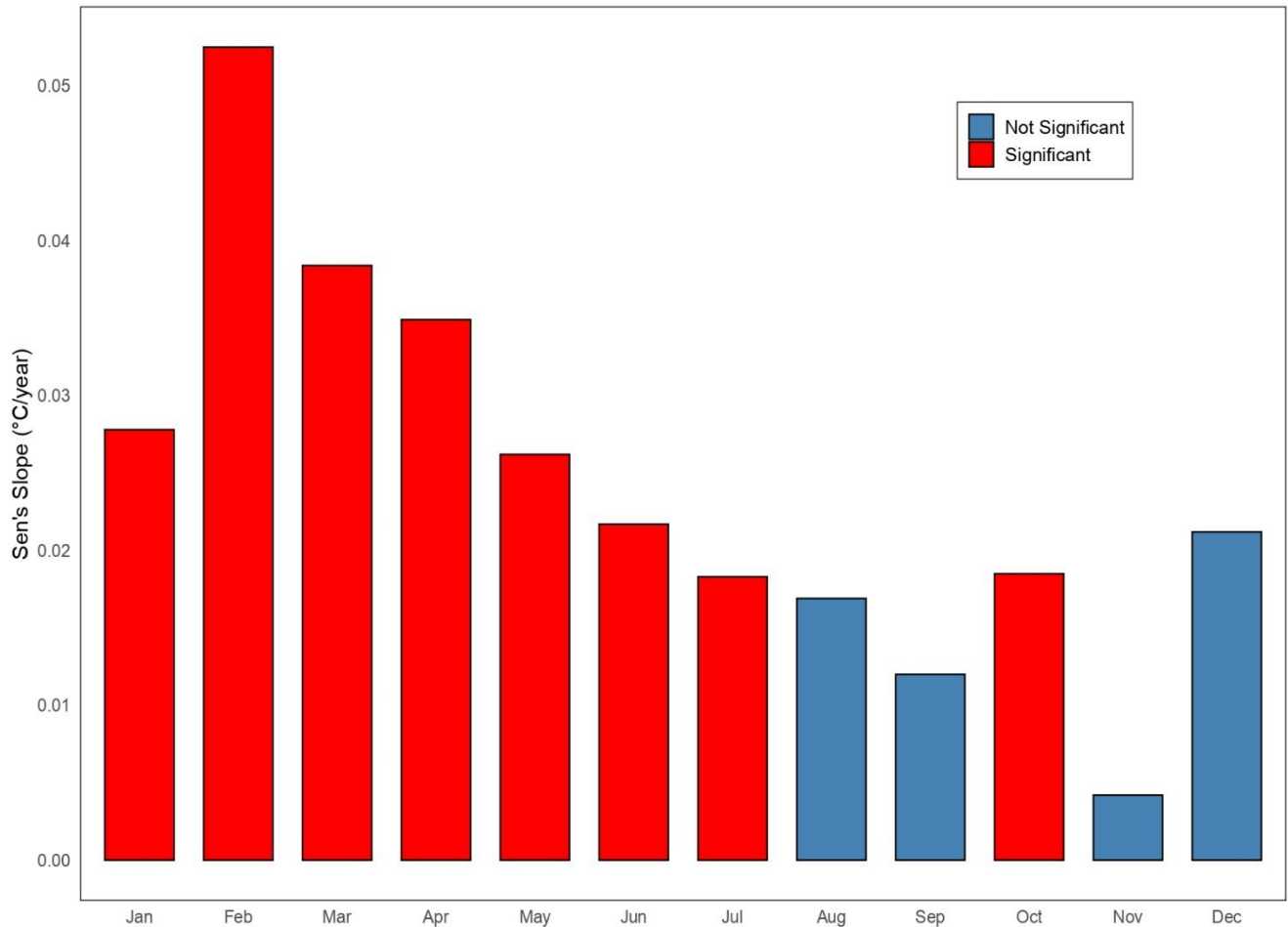


Figure 48. Monthly Sen's Slope of Maximum Temperature (1989–2024)

4.3.2.2 Seasonal maximum temperature

4.3.2.2.1 Fall (February–May)

During this season, the maximum temperature ranges from 26.79°C to 29.81°C, with an average temperature of 28.84°C and a standard deviation of 0.69°C. The temperature trend shows an increasing pattern, with Sen's slope estimating an increase of 0.037°C per. The Z-value of 3.04 and a p-value of 0.0024 indicating a statistically significant warming trend at a 95 % confidence interval (Table 33, Figure 49).

4.3.2.2.2 Winter (June–September)

The maximum temperatures range from 24.39°C to 26.91°C, an average of 25.42°C and a standard deviation of 0.57°C (Table 33, Figure 49). The Sen's Slope value of 0.016°C per year indicates a gradual increase in temperature overtime. A Z-value of 2.25 and a p-value of 0.0246 confirm that

the increasing trend is statistically significant at a 95 % confidence interval, indicating a reliable upward trend in temperature.

4.3.2.2.3 Summer (October–January)

The minimum temperature is recorded at 26.6°C, while the maximum temperature reaches 29.2°C, with a mean temperature of 27.89°C and a standard deviation of 0.52°C (Table 33, Figure 49). The temperature trend is increasing by 0.017°C per year. A Z-value of 2.14 and a p-value of 0.0325 indicate that the warming trend is statistically significant at a 95 % confidence interval.

Table 33. Seasonal maximum temperature

Seasons	Minimum Temperature (°C)	Maximum Temperature (°C)	Mean Temperature (°C)	Standard Deviation (°C)	Sen's Slope (°C/year)	Z-Value	p-Value	Trend Direction	Significance ($\alpha=0.05$)
Belg	26.79	29.81	28.84	0.69	0.037	3.04	0.0024	Increasing	Significant
Kiremt	24.39	26.91	25.42	0.57	0.016	2.25	0.0246	Increasing	Significant
Bega	26.6	29.2	27.89	0.52	0.017	2.14	0.0325	Increasing	Significant

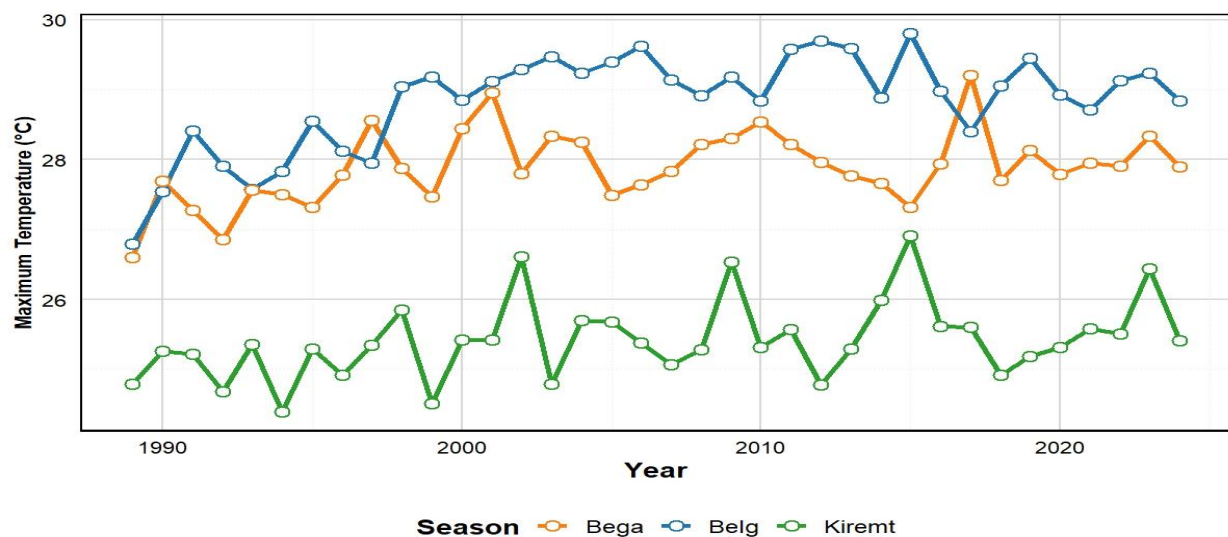


Figure 49. Seasonal maximum temperature trend (1989–2024)

4.3.2.3 Annual maximum temperature (1989–2024)

The annual average maximum temperature from 1989–2024 (Table 34, Figure 50) has demonstrated a significant increasing trend with (ZMK= 2.8468, $P<0.05$, Sen's slope = 0.02355°C/year), indicating an upward pattern. The Sen's slope estimate further confirmed that

the annual maximum temperature has been rising by 0.02355°C with a p-value of 0.00442 at a 95 % confidence interval, suggesting the observed rise in temperature is statistically significant, highlighting a warming trend in the study area.

Table 34. Annual maximum temperature during 1989–2024

Statistics	Value
ZMK	2.8468
P value	0.00442
Sen's slope	0.02355

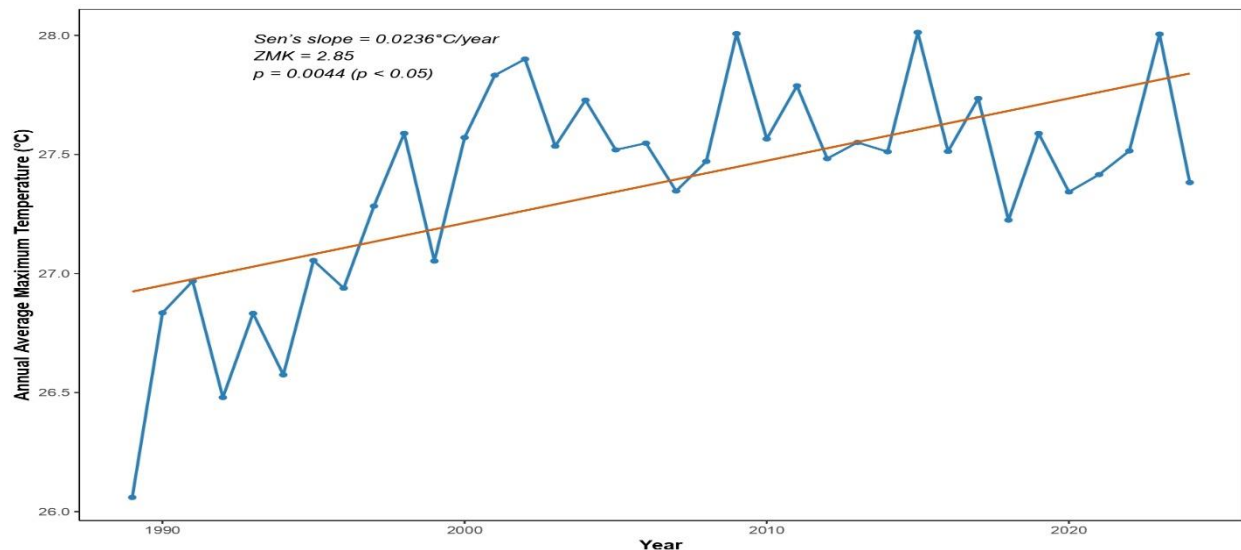


Figure 50. Average annual maximum temperature (1989–2024)

4.3.3 Precipitation (1989–2024)

4.3.3.1 Monthly precipitation

The main rainy season, which starts in June and lasts in September, contributes a substantial amount of rainfall. The rainfall data for the months of the year reveals a diverse range of patterns in terms of minimum, maximum, mean, and standard deviation, alongside statistical trends (Table 35, and Figures 51 and 52). January recorded a statistically significant decreasing trend with ZMK value -2.13 and p value = 0.00336 and with the lowest mean rainfall of 33.59 mm, a standard deviation of 24.72 mm, and showed a negative Sen's slope of -0.881, indicating a slight decrease over time. February, with a mean of 46.47 mm, had a relatively higher minimum (1 mm) and maximum (200.46 mm), but the trend was insignificant, as shown by the p-value of 0.4375 and a

minor Sen's slope of -0.5672. The month of March had a higher mean of 109.17 mm and a negative Sen's slope of -1.4243, indicating a downward trend with a p-value of 0.0548, which was just on the threshold of statistical significance. April, with a mean of 176.49 mm, showed minimal change, evidenced by a Sen's slope of -0.4262 and a high p-value of 0.7335, suggesting no clear trend. May experienced the highest mean rainfall of 206.74 mm, and its positive Sen's slope of 1.0328 suggests a slight increasing trend, although the p-value of 0.1864 indicates statistical insignificance. June also showed considerable rainfall (mean of 213.97 mm), with a small negative trend in Sen's slope at -0.8742, but a p-value of 0.2819 indicating no strong evidence of a significant change. The months of July and August had similar patterns, with means of 217.6 mm and 218.37 mm, respectively, and p-values of 0.9349 and 0.8809, indicating no significant trends. September's rainfall was slightly lower at 203.47 mm, but with a positive trend (Sen's slope of 0.9649), indicating an increasing trend, though the p-value of 0.2052 remains inconclusive. October's mean rainfall of 153.27 mm, along with a positive Sen's slope of 1.7178, suggests an upward trend, with a p-value of 0.2052 indicating a potential insignificant change. November saw moderate rainfall (mean of 97.48 mm) and a positive Sen's slope of 0.9706, with no significant trend (p-value of 0.2152). December had the least rainfall (mean of 77.11 mm), and although the Sen's slope was negative (-0.247), it indicated no meaningful trend, with a p-value of 0.8809. Overall, while some months show slight increasing and decreasing trends, the statistical significance of these changes varies across the year.

Table 35. Monthly MK results of precipitation

Months	Minimum	Maximum	Mean	STD	ZMK	P value	Sen's slope	PWS
January	0	87.78	33.59	24.72	-2.13	0.03	-0.88	-0.95
February	1	200.46	46.47	39.86	-0.78	0.44	-0.57	-0.45
March	42.23	223.71	109.17	45.67	-1.92	0.05	-1.42	-1.09
April	37.19	368.2	176.49	70.97	-0.34	0.73	-0.43	-0.43
May	28.46	307.06	206.74	59.76	1.32	0.19	1.03	0.59
June	114.93	345.23	213.97	56.24	-1.08	0.28	-0.87	-0.87
July	142.11	336.91	217.6	42.56	-0.08	0.93	-0.02	-0.02
August	124.58	389.66	218.37	58.94	0.15	0.88	0.19	0.19
September	119.12	307.07	203.47	45.42	1.27	0.21	0.96	0.96
October	14.56	285.68	153.27	68.23	1.27	0.21	1.72	1.87
November	10.22	360.48	97.48	74.28	1.24	0.22	0.97	0.97
December	0	251.54	77.11	66.39	-0.15	0.88	-0.25	-0.25

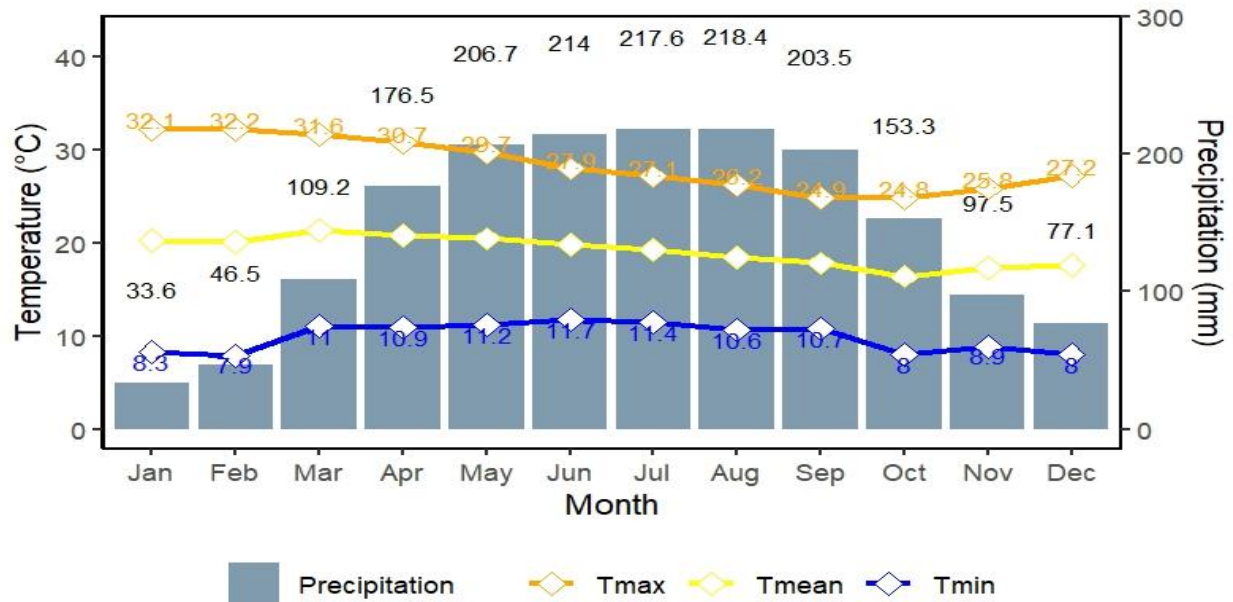


Figure 51. Monthly precipitation trend

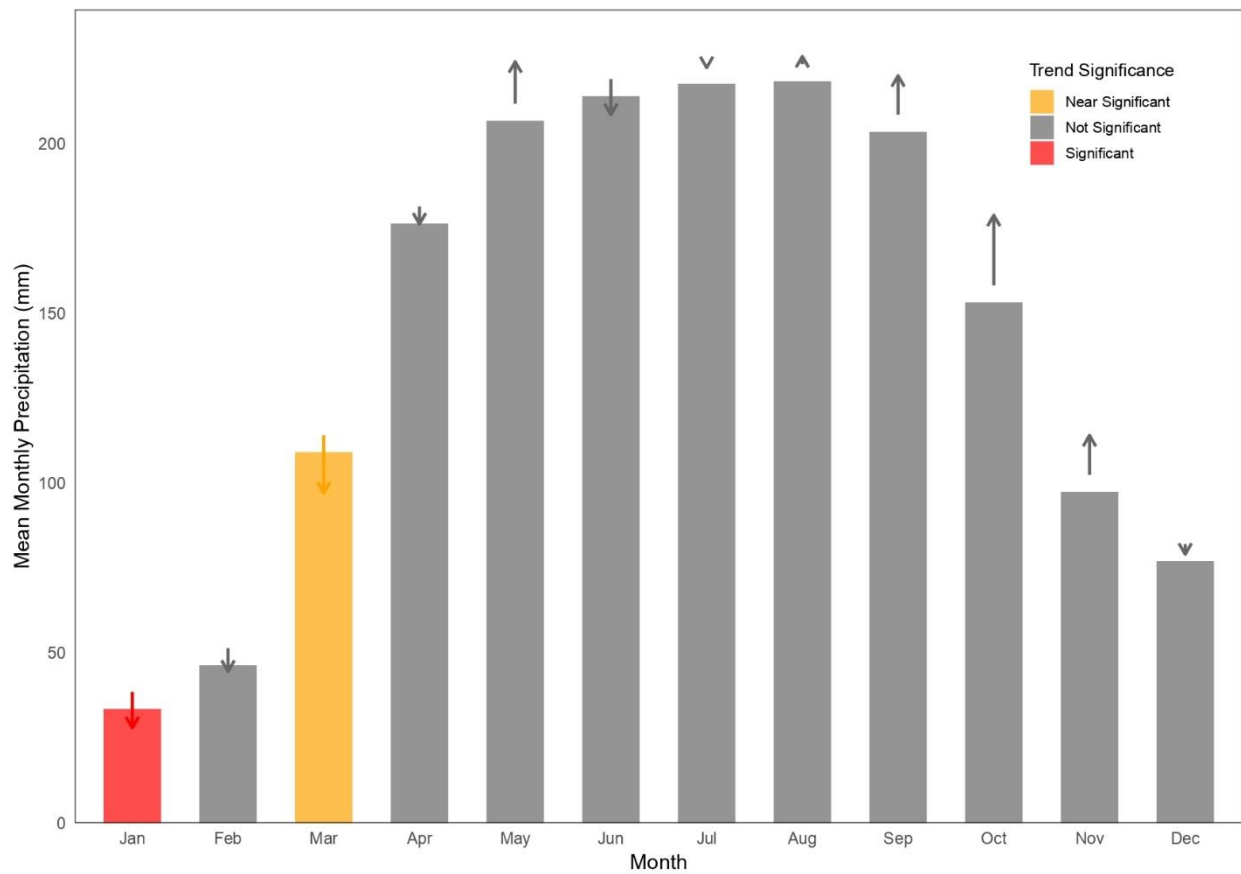


Figure 52. Monthly Sen's Slope of precipitation (1989–2024)

4.3.3.2 Seasonal rainfall

The seasonal rainfall trends for the fall, winter, and summer seasons reveal no significant changes in rainfall patterns over time (Table 36, Figure 53). During the fall, rainfall ranged from 592.11 mm to 1337.58 mm, with an average value of 853.42 mm and a standard deviation of 130.39 mm. Although the Sen's slope (0.264 mm/year) suggests a slight increase, the Z-value (0.15) and p-value (0.8809) indicate that the trend is not statistically significant. Similarly, in winter season, rainfall varied between 145.08 mm and 706.25 mm, with an average of 361.44 mm and a standard deviation of 117.87 mm. The Sen's slope (0.088 mm/year) implies a minor increase, but the Z-value (0.068) and p-value (0.9457) confirm that this change is not statistically significant, indicating no clear trend. For summer, rainfall ranged from 281.44 mm to 846.64 mm, with a mean of 538.87 mm and a standard deviation of 118.98 mm. The Sen's slope (-1.965 mm/year) suggests a decreasing trend, but with a Z-value of -0.967 and a p-value of 0.3335, but the trend is not statistically significant. Overall, none of the three seasons exhibit a statistically significant trend at $\alpha = 0.05$, indicating that rainfall patterns in the study area have remained relatively stable over time, without clear evidence of increasing or decreasing trends significantly.

Table 36. Seasonal rainfall

Seasons	Minimum RF (°C)	Maximum RF (°C)	Mean RF (°C)	Standard Deviation (°C)	Sen's Slope (°C/year)	Z-Value	p-Value	Trend Direction	Significance ($\alpha=0.05$)
Fall	592.11	1337.58	853.42	130.39	0.26	0.15	0.88	No clear trend	Not Significant
Winter	145.08	706.25	361.44	117.87	0.09	0.07	0.95	No clear trend	Not Significant
Summer	281.44	846.64	538.87	118.98	-1.97	-0.97	0.33	Decreasing	Not Significant

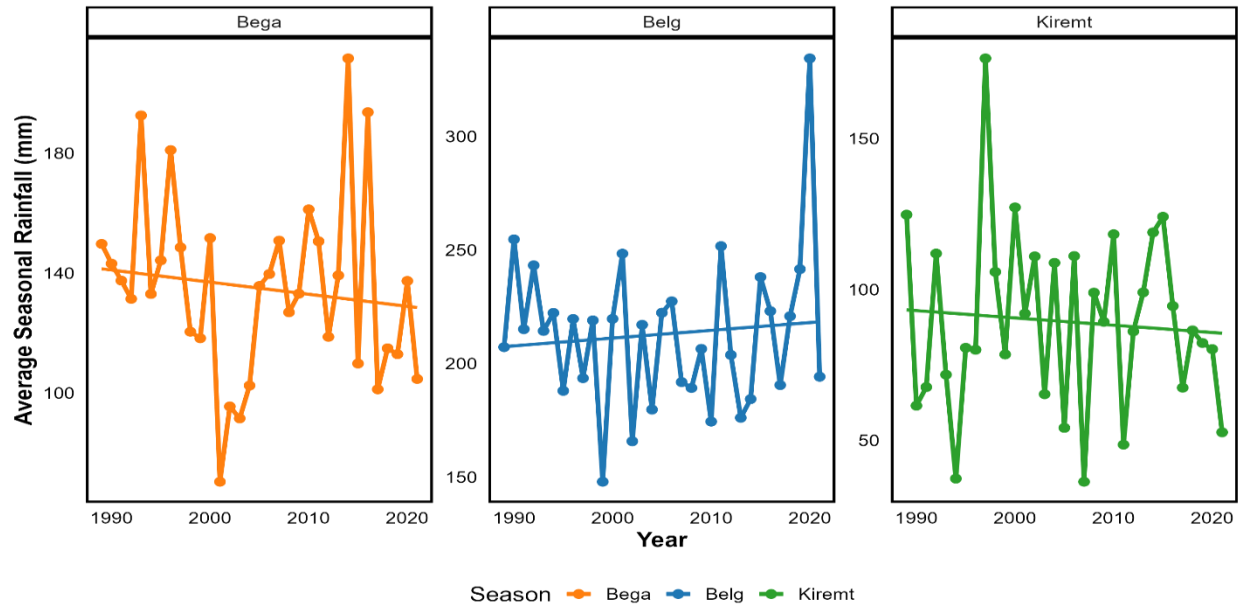


Figure 53. Seasonal rainfall trend (1989–2024)

4.3.3.3 Annual average rainfall

The Mann-Kendall trend test of the annual average rainfall from 1989 to 2024 and the value of Z-statistic (ZMK) were 0.02724 with a corresponding p-value of 0.989, indicating a statistically insignificant trend in rainfall. Additionally, the Sen's slope estimator resulted in 0.0255 mm/year, suggesting a very slight and non-significant increase in rainfall (Table 37, Figure 54). These findings indicate that the annual average rainfall has remained relatively stable over the past three and a half decades, with no evidence of a consistent increasing or decreasing trend.

Table 37. MK test annual rainfall result from 1989 to 2024

Statistics	Value
ZMK	0.03
P value	0.99
Sen's slope	0.03mm/year

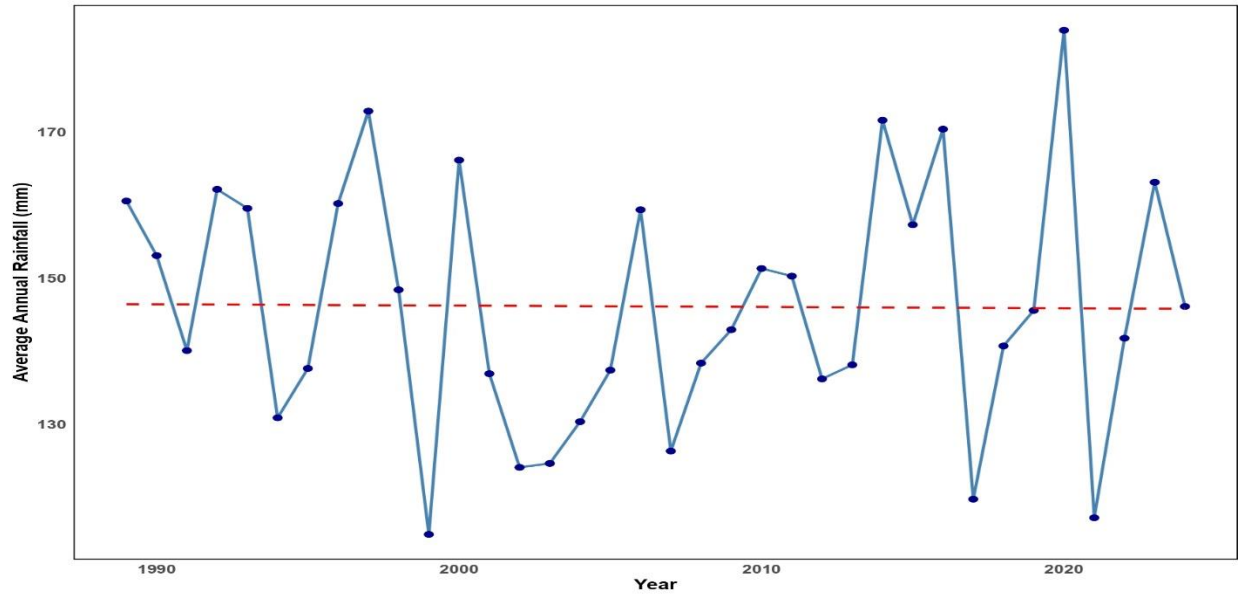


Figure 54. Average annual precipitation (1989–2024)

4.3.4 Minimum, maximum, and mean LST

The annual land surface temperature (LST) from 1989 to 2024 shows notable trends in temperature changes. The minimum LST ranged from 11.23 °C to 20.99 °C, while the maximum LST varied between 26.25 °C and 47.61 °C (Table 38). The mean LST showed an increase from 11.76 °C in the minimum to 29.71 °C in the maximum, with an overall mean LST of 22.8 °C. The standard deviation for the minimum LST was 2.59 °C, while the maximum LST exhibited a higher variation, with a standard deviation of 4.99 °C. The Mann-Kendall test showed significant upward trends in both minimum and maximum LST, with p-values of 0.0052 and 0.0011, respectively, indicating the trends are statistically significant. The Sen's slope estimates further confirmed these upward trends, with values of 0.13 °C for the minimum, 0.25 °C for the maximum, and 0.33 °C for the overall mean, all of which had p-values below 0.05, underscoring temperature increases over the years. The findings suggest a clear warming trend in the area.

Table 38. Minimum, maximum and mean LST

LST category	Min (°C)	Max (°C)	Mean (°C)	Std. dev.	Mann-Kendall Z	Mann-Kendall p-value	Sen's Slope	Sen's Slope p-value
Min LST	11.23	20.99	15.11	2.59	2.79	0.0052	0.13	0.0052
Max LST	26.25	47.61	38.67	4.99	3.26	0.0011	0.25	0.0011
Mean LST	11.76	29.71	22.8	5.62	4	0.000062	0.33	0.000062

4.4 The spatiotemporal impacts of land-use and land-cover changes on climate variability (1989–2024)

The spatio-temporal analysis of land use and land cover (LULC) changes from 1989 to 2024 shows significant climate variability across different LULC classes. Water Bodies (WB) experienced a slight reduction (−6.68%), with mean minimum temperature increasing by 3.23 °C, mean maximum temperature by 3.90 °C, and land surface temperature by 3.01 °C, rainfall (RF) declined until 2019 but increased substantially in 2024 (+168.94 mm). Wetlands (WL) underwent a drastic reduction (−62.36%), correlating with a 1.64 °C rise in mean minimum temperature and 2.34 °C in mean maximum temperature. LST slightly declined (−0.12 °C), while rainfall increased by 94.39 mm in 2024 after years of decline. Forest land (FL) significantly shrank (−40.57%), leading to minimum temperature rising by 2.14 °C, maximum temperature by 2.71 °C, and LST by 1.65 °C, intensifying warming effects. Rainfall initially decreased but recovered in 2024 (+60.78 mm). Built-up areas (BUA) expanded massively (+73.77%), causing a 2.02 °C rise in minimum temperature, 2.87 °C in maximum temperature, and a significant LST increase (+1.29 °C). Rainfall initially declined but rebounded by 2024 (+18.38 mm). Agricultural land (AL) expanded (+111.49%), leading to minimum temperature and maximum temperature increases of 1.98 °C and 2.17 °C, respectively, while LST decreased slightly (−0.85 °C). RF initially declined but recovered slightly (+12.94 mm). Tea plantations (TP) expanded dramatically (+290.09%), with minimum temperature increasing by 1.84 °C and maximum temperature by 2.98 °C, while LST rose only slightly (+0.04 °C). Rainfall increased by 120.04 mm. Overall, deforestation, wetland loss, tea plantation, and built-up area expansion have driven warming and rainfall fluctuations (Table 39, Figure 55).

Table 39. Land-use and land-cover and climate variables change (1989–2024)

Year	LULC class	Area(ha)	LULC (%)	ΔLULC (%)	Mean Tmin (°C)	ΔMean Tmin (°C)	Mean Tmax (°C)	ΔMean Tmax (°C)	Mean LST (°C)	ΔMean LST (°C)	Mean RF (mm)	ΔMean RF (mm)
1989	WB	22.76	0.03	-	9.27	-	28.69	-	25.91	-	1959.62	-
2010	WB	22.36	0.03	-1.76	12.39	3.12	31.96	3.27	28.88	2.97	1869.26	-90.36
2019	WB	22.27	0.03	-0.40	11.39	-1.00	32.73	0.77	29.79	0.91	1780.97	-88.29
2024	WB	21.24	0.03	-6.68	12.50	1.10	32.60	-0.13	28.92	-0.88	2128.56	347.60
1989	WL	7031.71	9.00	-	8.90	-	28.24	-	29.15	-	1977.27	-
2010	WL	3815.45	4.88	-45.74	11.23	2.33	30.30	2.06	26.77	-2.38	1878.18	-99.09
2019	WL	3533.42	4.52	-7.39	10.51	-0.72	30.78	0.48	29.80	3.03	1845.15	-33.02
2024	WL	2646.89	3.39	-25.09	10.53	0.03	30.58	-0.20	29.03	-0.77	2071.66	226.51
1989	FL	49544.76	63.40	-	8.28	-	27.23	-	24.39	-	1910.06	-
2010	FL	35935.74	45.99	-27.47	11.00	2.72	29.78	2.55	25.85	1.46	1790.24	-119.82
2019	FL	31133.6	39.84	-13.36	10.35	-0.65	30.36	0.58	26.40	0.54	1758.53	-31.71
2024	FL	29442.9	37.68	-5.43	10.42	0.07	29.94	-0.42	26.04	-0.36	1970.84	212.31
1989	BUA	880.76	1.13	-	8.39	-	27.50	-	28.86	-	1974.41	-
2010	BUA	1013.9	1.30	15.12	11.56	3.17	30.62	3.13	26.35	-2.51	1859.80	-114.61
2019	BUA	1122.67	1.44	10.73	10.63	-0.93	31.07	0.45	31.12	4.77	1788.48	-71.32
2024	BUA	1530.52	1.96	36.33	10.40	-0.22	30.36	-0.71	30.16	-0.97	1992.79	204.31
1989	AL	20215.09	25.87	-	9.17	-	28.47	-	30.12	-	1949.52	-
2010	AL	36537.91	46.76	80.75	11.59	2.41	30.64	2.17	31.23	1.11	1833.18	-116.34
2019	AL	40639.2	52.01	11.22	10.73	-0.85	31.38	0.74	30.67	-0.56	1725.27	-107.90
2024	AL	42752.69	54.71	5.20	11.15	0.42	30.64	-0.74	29.27	-1.40	1936.58	211.30
1989	TP	448.42	0.57	-	7.72	-	26.65	-	27.85	-	1950.79	-
2010	TP	818.14	1.05	82.45	10.85	3.14	29.90	3.25	26.54	-1.31	1869.17	-81.62
2019	TP	1692.41	2.17	106.86	10.23	-0.63	29.88	-0.02	28.88	2.34	1835.27	-33.91
2024	TP	22.76	2.24	3.36	9.55	-0.67	29.63	-0.25	27.90	-0.99	2070.84	235.57

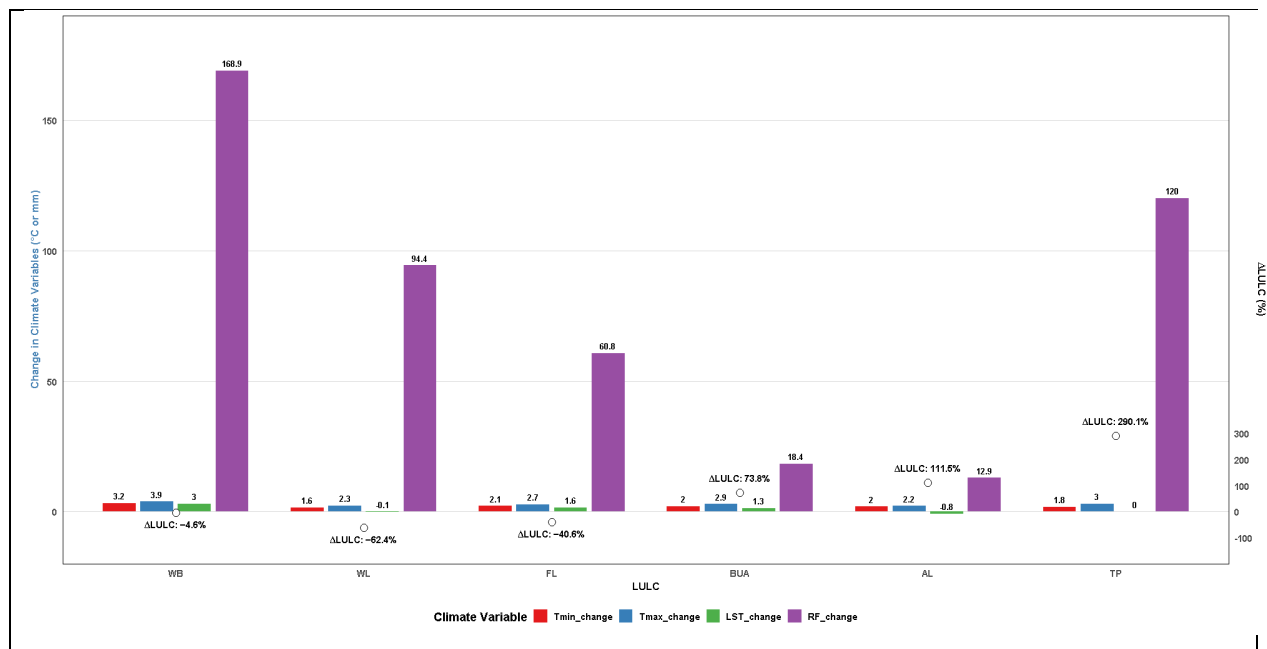


Figure 55. Change in LULC and climate variables

4.6 Impacts of land-use and land-cover change

The multiple linear regression (MLR) results indicate that land-use and land-cover (LULC) changes (1989–2024) significantly influence climate variability, specifically the mean maximum temperature. The model has strong explanatory power, with an R-squared value of 0.73, suggesting that approximately 73% of the variability in mean maximum temperature is explained by changes in forest land (FL), agricultural land (AL), and tea plantations (TP), indicating a substantial impact of these variables on temperature dynamics. A 1% increase in forest loss from 1989–2024 is associated with a 0.30°C increase in mean maximum temperature, which demonstrates the warming effect caused by deforestation (coefficient = 0.30, $p < 0.05$). Similarly, expansion of agricultural land by 1% result in a 0.16°C rise in mean maximum temperature (coefficient = 0.16, $p < 0.05$), confirming the warming effect of this expansion. Interestingly, the model shows that a 1% increase in tea plantations corresponds to a 0.89°C increase in mean maximum temperature (coefficient = 0.89, $p < 0.05$), and all variables are statistically significant at the 95% confidence interval, and the overall model fit is strong ($F = 28.53$, $p < 0.000000004$), indicating robust relationships between LULC changes and mean maximum temperature dynamics.

Chapter V

5. Discussion

5.1 Performance of algorithms

The evaluation of classification algorithms (CART, RF, SVM, KNN, and GTB) for land-use and land cover mapping from 1989 to 2024 revealed a trend where certain algorithms consistently outperformed others in specific years. Support Vector Machine (SVM-Kernel Radial Basis Function) consistently outperformed other models in 1989, 2010, and 2019, achieving the highest overall accuracy (84.62–91.62%) and Kappa coefficients ($K = 0.81–0.90$); this superiority aligns with its robustness in handling high-dimensional data and nonlinear class boundaries, particularly for heterogeneous classes like agricultural land (Patil & Panhalkar, 2023). In contrast, RF emerged as the best performer in 2024 with an overall accuracy of 93.37% and a Kappa coefficient of 0.92, attributed to its ensemble learning approach, which effectively handles the complexity of spectral signatures and minimizes overfitting by aggregating results from multiple decision trees (Kasahun et al., 2024). GTB demonstrated strong class-specific accuracy, particularly for water bodies ($F1 \text{ score} = 0.94$ in 2019) and forest land ($F1 = 0.95$ in 2024), attributable to its iterative error correction. While the majority of LULC studies in Ethiopia and elsewhere have reported RF as the best performer for general land-use and land-cover mapping (Islam et al., 2023; Kasahun et al., 2024; Zafar et al., 2023), the result of this study aligns more closely with (Basheer et al., 2022; Patil et al., 2023), who reported SVM as the best performer.

5.2 Land-use and land-cover change dynamics

The spatial and temporal analysis of land-use and land-cover change over the last 35 years revealed a decline in forest resource (-40.57%), wetlands (-62.36%) and waterbody (-4.64%). In contrast to the decline in natural resources, agricultural land increased by 111.49% and tea plantations by 290.9% driven by population growth. Built-up area grew by 73.77 % as the district town expanded significantly over the years. These trends align with previous studies that have documented similar patterns of land-use and land-cover changes (Bikeko & Venkatesham, 2024; Desta et al., 2022; Mulatu et al., 2025; Warku et al., 2022; Wayesa et al., 2025).

5.3 Drivers and environmental implications of LULC change

The LULC transitions between 1989 and 2024 reflect increasing anthropogenic pressures on natural ecosystems in the study area. The substantial conversion of forest land to agriculture (20,010.87 ha) indicates the role of farming as a major driver of deforestation, driven by population growth and the need for cultivable land. Similarly, the transition of 4,828.95 hectares of wetlands to agriculture indicates ecosystem degradation and potential hydrological disruption. Urban expansion was also observed at the cost of 663.03 hectares of forest and 553.23 hectares of agricultural land. While tea plantations expanded modestly, primarily from agricultural land (499.86 ha), their growth reflects a diversification of land use. Overall, the trend reveals a shift from ecologically sensitive land covers to economically driven land uses, highlighting the need for integrated land management policies to balance development and conservation.

5.4 Climate variability and linkage to LULC change

The analysis of climate variability indicated a notable warming trend throughout the study period, accompanied by significant variation on a monthly, seasonal, and annual basis. The monthly minimum temperatures showed the most significant rise in March (+0.0354 °C, ZMK = 2.87, $p < 0.05$, STD = 0.88), followed by May (+0.0201 °C, ZMK = 2.47, $p < 0.05$, STD = 0.63), September (+0.0172 °C, ZMK = 2.21, $p < 0.05$, STD = 0.52), October (+0.0267 °C, ZMK = 2, $p < 0.05$, STD = 0.94), and December (+0.0278 °C, ZMK = 2.26, $p < 0.05$, STD = 1.14). The maximum temperature indicated a notable increase from January to July, as well as in October. In particular, January experienced an increase of (+0.0278 °C, ZMK = 2.33, $p < 0.05$, STD = 0.95), while February saw a rise of (+0.0525 °C, ZMK = 2.17, $p < 0.05$, STD = 1.34). March recorded a warming of (+0.0384 °C, ZMK = 2.82, $p < 0.05$, STD = 0.93), and April showed an increase of (+0.0349 °C, ZMK = 2.96, $p < 0.05$, STD = 0.88). May's temperature increased by (+0.0262 °C, ZMK = 2.63, $p < 0.05$, STD = 0.68), while June had a rise of (+0.0217 °C, ZMK = 2.03, STD = 0.65). July experienced an increase of (+0.0183 °C, ZMK = 2.07, $p < 0.05$, STD = 0.74), and October recorded a warming of (+0.0185 °C, ZMK = 2.11, $p < 0.05$, STD = 0.69). This warming trend is associated with changes in land use and land cover.

Seasonal analysis further underscored a distinct trend in minimum temperature with the highest rise occurring in summer ($+0.029\text{ }^{\circ}\text{C}$, $\text{ZMK} = 3.09$, $P < 0.05$, $\text{STD} = 0.6$), followed by fall ($+0.027\text{ }^{\circ}\text{C}$, $\text{ZMK} = 2.87$, $P < 0.05$, $\text{STD} = 0.58$), and winter ($+0.017\text{ }^{\circ}\text{C}$, $\text{ZMK} = 3.01$, $P < 0.05$, $\text{STD} = 0.38$). For maximum temperature, Fall has recorded the highest increase ($+0.037\text{ }^{\circ}\text{C}$, $\text{ZMK} = 3.04$, $P < 0.05$, $\text{STD} = 0.69$), followed by summer ($+0.017\text{ }^{\circ}\text{C}$, $\text{ZMK} = 2.14$, $P < 0.05$, $\text{STD} = 0.52$) and winter ($+0.016\text{ }^{\circ}\text{C}$, $\text{ZMK} = 2.25$, $P < 0.05$, $\text{STD} = 0.57$). At the annual scale, the minimum and maximum temperature increased by $0.0254\text{ }^{\circ}\text{C}$ per year and $0.02355\text{ }^{\circ}\text{C}$ per year, respectively, and showed a rise of $0.33\text{ }^{\circ}\text{C}$ in land surface temperature ($\text{ZMK} = 4.0$, $p < 0.05$, $\text{STD} = 5.62$). In contrast, the monthly rainfall variability showed very little statistically significant pattern or trend, indicating intra-annual variability. January exhibited the only significant decline (-0.88 mm/year , $\text{ZMK} = -2.13$, $p < 0.05$, $\text{STD} = 24.72$).

Seasonal analysis of rainfall data also indicates a non-significant long-term trend across the study period. The winter (main rainy season) showed a near-stable trend ($+0.088\text{ mm/year}$, $\text{ZMK} = 0.068$, $p = 0.9457$), fall (short rains) season showed minimal change ($+0.264\text{ mm/year}$, $\text{ZMK} = 0.15$, $p = 0.8809$), summer (dry season) recorded a slight but non-significant decline (-1.965 mm/year , $\text{ZMK} = -0.967$, $p = 0.3335$). These findings align with studies in Ethiopia that report high inter-annual rainfall variability, suggesting a similar pattern (Bikeko & Venkatesham, 2024; Gemedi et al., 2021; Ware et al., 2023).

The annual precipitation remained stable over the 35 years with an increase of 0.0255 mm/year ($\text{ZMK} = 0.02724$, $p = 0.989$), showing a statistically insignificant trend ($p > 0.05$), suggesting that changes in annual trend are not substantial over the study period. The stability of rainfall relative to minimum and maximum temperature is driven by different factors in the study area. High intra-annual variability, from erratic monthly fluctuations observed in April with a STD of 70.97 mm , and November with a STD of 74.28 mm .

The Pearson correlation analysis revealed that land-use and land-cover change correlate strongly with local temperature trends. Forest land showed a strong negative correlation with mean minimum ($r = -0.68$) and maximum temperature ($r = -0.70028$), indicating that the continued decline of forest contributes to the local warming trend. This relationship is supported by the multiple linear regression results, where forest degradation ($\beta = 0.296$, $p < 0.05$) contributes to local warming. The statistical findings reflect the cooling role of forests in the microclimate,

indicating their removal leads to increased temperatures. In addition, agricultural land demonstrated a strong positive correlation with mean minimum temperature ($r = 0.70$) and maximum temperature ($r = 0.69$) and the regression result confirmed its warming influence ($\beta = 0.165, p < 0.05$), suggesting that agricultural expansion has contributed to rising temperatures. Tea plantations also demonstrated a strong positive correlation with land surface temperature ($r = 0.74$), a moderate positive correlation with minimum and maximum temperature ($r = 0.54$ and $r = 0.47$) and a high regression coefficient ($\beta = 0.892, p < 0.05$), highlighting their significant role in air and surface heating. Built-up areas, while expanding moderately, were positively correlated with both minimum temperature ($r = 0.52$) and land surface temperature ($r = 0.60$), consistent with the urban heat island effect observed globally. Collectively, these findings provide strong statistical evidence that deforestation, agricultural land expansion, and the growth of tea plantations and built-up areas contribute significantly to rising temperature in the study area. Among the predictors, forest loss, agricultural land expansion, and tea plantations are the most significant factors influencing the increase in mean maximum temperature dynamics. In contrast, rainfall variability showed weak correlation with land-use and land-cover change, suggesting that broader climatic drivers may play a more dominant role in influencing rainfall pattern. This study aligns with findings from earlier sections and prior studies (Warku et al., 2022; Bikeko & Venkatesham, 2024).

Chapter VI

Conclusion and recommendations

6.1 Conclusion

The study has investigated the impacts of land-use and land-cover change on climate variability in the Gimbo district, southwest Ethiopia, from 1989 to 2024. Land-use and land-cover change detection was conducted using machine learning algorithms in the Google Earth Engine platform, and the climate variability trend analysis was also done using the non-parametric Mann-Kendall test and Sen's slope estimator. The relationship and strength between land-use, land cover changes, and climate variables were examined using the Pearson correlation. The Multiple Linear Regression (MLR) was also used to quantify the impacts of land-use and land-cover change on the climate variables. The performance comparison of algorithms' results shows that SVM outperformed other classifiers in overall accuracy and kappa coefficients, followed by RF and GTB. On the other hand, the land-use and land-cover changes reveal a significant environmental transformation characterized by the expansion of agricultural land, tea plantations, and built-up areas, at the expense of forest land and wetland areas, and the dramatic transitions observed necessitate urgent action. Such an increase in agricultural land, forest loss, and tea plantations caused an increase in minimum and maximum temperatures, with insignificant rainfall variations, and the MLR result confirmed that such LULC changes influence the mean maximum temperature significantly. Prioritizing forest and wetland conservation, climate-smart agriculture, and green urban planning could mitigate climate impacts. To address these challenges, future efforts must integrate high-resolution remote sensing, community engagement, and cross-sectoral governance to foster resilient landscapes. Finally, further analysis is required using high-quality data for land-use and land cover change and climate variability analysis.

6.2 Recommendations

To effectively address the climate trends associated with land-use and land-cover change (LULCC), priority should be given to forest conservation and restoration. This can be achieved through community-based initiatives and the strict enforcement of land-use regulations, as outlined in the rural land administration and use proclamation No. 1324/2024. Encouraging climate-smart agriculture and sustainable irrigation practices can help mitigate the warming effects of

agricultural expansion. These practices also play a crucial role in ensuring food security (CRGE strategy, 2011). Urban planning should incorporate green infrastructure and tree-planting programs to alleviate the urban heat island effect, which is a significant aspect of land-use and land-cover change. Strengthening cross-sectoral governance among environmental, agricultural, and urban development agencies is essential. Additionally, fostering community engagement is crucial to enhance participatory land management. These interventions align with the environmental policy of Ethiopia, 1997; Ethiopia's climate-resilient green economy strategy, 2011; the participatory community-based watershed development strategy, 2018; and the climate-smart agriculture strategy, 2021. They can help achieve a balance between developmental needs and ecological sustainability in the study area and similar environments.

References

- Abatzoglou, J. T., Dobrowski, S. Z., Parks, S. A., & Hegewisch, K. C. (2018). TerraClimate, a high-resolution global dataset of monthly climate and climatic water balance from 1958–2015. *Scientific Data*, 5, Article 170191. <https://doi.org/10.1038/sdata.2017.191>
- Aigbokhan, O., Pelemo, O. J., Ogoliegbune, O. M., Essien, N. E., Ekundayo, A. A., & Adamu, S. (2022). Comparing machine learning algorithms in land use land cover classification of Landsat 8 (OLI) imagery. *Asian Research Journal of Mathematics*, 18(3), 62–74. <https://doi.org/10.9734/arjom/2022/v18i330367>
- Aldiansyah, S., & Saputra, R. (2023). Comparison of machine learning algorithms for land use and land cover analysis using Google Earth Engine (Case study: Wanggu watershed). *International Journal of Remote Sensing and Earth Sciences (IJReSES)*, 19(2), 197–210. <https://doi.org/10.30536/j.ijreses.2022.v19.a3803>
- Alemayehu, Z. Y., Minale, A. S., & Legesse, S. A. (2023). Land use and land cover dynamics nexus to local climate variability in Suha watershed, upper Blue Nile basin, Northwest Ethiopia. *Sustainable Environment*, 9(1), Article 2278828. <https://doi.org/10.1080/27658511.2023.2278828>
- Aragaw, H., Goel, M., & Mishra, S. (2021). Hydrological responses to human-induced land use/land cover changes in the Gidabo River basin, Ethiopia. *Hydrological Sciences Journal*, 66(5), 640–655. <https://doi.org/10.1080/02626667.2021.1890328>
- Arficho, M., & Thiel, A. (2020). Does land-use policy moderate impacts of climate anomalies on LULC change in dry-lands? An empirical enquiry into drivers and moderators of LULC change in Southern Ethiopia. *Sustainability*, 12(15), Article 6261. <https://doi.org/10.3390/su12156261>
- Basheer, S., Wang, X., Farooque, A. A., Nawaz, R. A., Liu, K., Adekanmbi, T., & Liu, S. (2022). Comparison of Land Use Land Cover Classifiers Using Different Satellite Imagery and Machine Learning Techniques. *Remote Sensing*, 14(19), 4978. <https://doi.org/10.3390/rs14194978>
- Bayable, G., & Alemu, G. (2021). Spatiotemporal variability of land surface temperature in north-western Ethiopia. *Environmental Science and Pollution Research*. <https://doi.org/10.1007/s11356-021-15763-9>
- Belete, T. (2020). Challenges and prospects in the adoption of modern agricultural inputs in Gimbo District, Kaffa Region, Southern Ethiopia. *Public Policy and Administration Research*, 10(8), 1–9. <https://doi.org/10.7176/ppar/10-8-01>

- Bezu, A. (2020). Analyzing impacts of climate variability and changes in Ethiopia: A review. *American Journal of Modern Energy*, 6(3), 65–76. <https://doi.org/10.11648/j.ajme.20200603.1>
- Bikeko, S. S., & Venkatesham, E. (2024). Land use land cover change as a causal factor for climate variability and trends in the Bilate Watershed, Ethiopia. *Environmental Monitoring and Assessment*, 196, Article 1250. <https://doi.org/10.1007/s10661-024-13435-y>
- Breiman, L. (2001). Random forests. *Machine Learning*, 45(5–32). <https://doi.org/10.1023/A:1010933404324>
- Breiman, L., Friedman, J. H., Olshen, R. A., & Stone, C. J. (1986). Classification and regression trees. Wadsworth & Brooks/Cole.
- Bununu, Y. A., Bello, A., & Ahmed, A. (2023). Land cover, land use, climate change and food security. *Sustain Earth Reviews*, 6(16). <https://doi.org/10.1186/s42055-023-00065-4>
- Chander, G., Markham, B. L., & Helder, D. L. (2009). Summary of current radiometric calibration coefficients for Landsat MSS, TM, ETM+, and EO-1 ALI sensors. *Remote Sensing of Environment*, 113(5), 893–903. <https://doi.org/10.1016/j.rse.2009.01.007>
- Cortes, C., & Vapnik, V. (1995). Support-vector networks. *Machine Learning*, 20(273–297). <https://doi.org/10.1007/BF00994018>
- Cover, T. M., & Hart, P. E. (1967). Nearest neighbor pattern classification. *IEEE Transactions on Information Theory*, 13(1), 21–27. <https://doi.org/10.1109/TIT.1967.1053964>
- Dagnachew, M., Kebede, A., Moges, A., & Abebe, A. (2020). Effects of climate variability on Normalized Difference Vegetation Index (NDVI) in the Gojeb River catchment, Omo-Gibe Basin, Ethiopia. *Advances in Meteorology*, Article 8263246. <https://doi.org/10.1155/2020/8263246>
- Dessu, T., Korecha, D., Hunde, D., & Worku, A. (2020). Long-term land use land cover change in urban centers of Southwest Ethiopia from a climate change perspective. *Frontiers in Climate*, 2. <https://doi.org/10.3389/fclim.2020.577169>

Desta, M. K., Gitima, G., Jakubus, M. B., & Bitew, A. (2022). Spatiotemporal land use and cover changes across agroecologies and slope gradients using geospatial technologies in Zoa watershed, Southwest Ethiopia. *Heliyon*, 8(9), e10696. <https://doi.org/10.1016/j.heliyon.2022.e10696>

Ebabu, K., Taye, G., Tsunekawa, A., Haregeweyn, N., Adgo, E., Tsubo, M., Fenta, A. A., Meshesha, D. T., Sultan, D., Aklog, D., Admasu, T., van Wesemael, B., & Poesen, J. (2022). Land use, management, and climate effects on runoff and soil loss responses in the highlands of Ethiopia. *Journal of Environmental Management*, 316, Article 116707. <https://doi.org/10.1016/j.jenvman.2022.116707>

Farhadi, Z., Bevrani, H., Feizi-Derakhshi, M.-R., Kim, W., & Ijaz, M. F. (2022). An ensemble framework to improve the accuracy of prediction using clustered random-forest and shrinkage methods. *Applied Sciences*, 12(20), 10608. <https://doi.org/10.3390/app122010608>

Fentaw, A. E., & Abegaz, A. (2024). Analyzing land use/land cover changes using Google Earth Engine and random forest algorithm and their implications to the management of land degradation in the Upper Tekeze Basin, Ethiopia. *The Scientific World Journal*, 2024, Article 3937558. <https://doi.org/10.1155/2024/3937558>

Friedman, J. H. (2001). Greedy function approximation: A gradient boosting machine. *Annals of Statistics*, 29(5), 1189–1232. <https://doi.org/10.1214/AOS/1013203451>

Gashure, S., & Wana, D. (2021). Spatiotemporal climate variability and trends in UNESCO designated Cultural Landscapes of Konso, Ethiopia. *African Geographical Review*, 42(2), 107–124. <https://doi.org/10.1080/19376812.2021.1997611>

Gemeda, D. O., Feyssa, D. H., & Garedew, W. (2021). Meteorological data trend analysis and local community perception toward climate change: A case study of Jimma City, Southwestern Ethiopia. *Environment, Development and Sustainability*, 23, 5885–5903. <https://doi.org/10.1007/s10668-020-00851-6>

Girma, E., Johansson, T., Garedew, W., & Yisihak, T. (2018). Climate variability and small-scale farmer adaptation strategy in Setema-Gatira area of Jimmaa, Southwestern Ethiopia. *American*

Habte, A., Mamo, G., Worku, W., Ayalew, D., & Gayler, S. (2021). Spatial variability and temporal trends of climate change in Southwest Ethiopia: Association with farmers' perception and their adaptation strategies. *Advances in Meteorology*, 2021, 1–17. <https://doi.org/10.1155/2021/3863530>

Halefom, A., Teshome, A., & Sisay, E. (2019). Impacts of land use/land cover detection on climate variability of Gumara Watershed, Ethiopia. *International Journal of Water*, 13(2), 101–121. <https://doi.org/10.1504/IJW.2019.10020973>

Islam, F., Tariq, A., Waseem, L. A., Bibi, T., & Rehman, N. (2023). Comparison of three machine learning algorithms using Google Earth Engine for land use land cover classification. *Rangeland Ecology & Management*, 92, 45–56. <https://doi.org/10.1016/j.rama.2023.10.007>

Jenness, J., & Wynne, J. J. (2005). Cohen's Kappa and Classification Table Metrics 2.0: An ArcView 3x extension for accuracy assessment of spatially explicit models [Computer software].

Joshi, J. P., & Bhatt, B. (2024). Time series trend analysis of temperature and rainfall using Mann-Kendall method: A study of Vadodara City, Gujarat, India. *Asian Journal of Geographical Research*, 7(2), 123–139. <https://doi.org/10.9734/ajgr/2024/v7i223>

Jote, D., Wondimu, G., & Delata, L. (2021). The impacts of land use land cover dynamics on land management: The case study of Adama Zuria District, Oromia Region, Ethiopia. *Journal of Environment and Earth Science*, 11(5), 1–12. <https://doi.org/10.7176/jees/11-5-01>

Kasahun, M., & Legesse, A. (2024). Machine learning for urban land use/cover mapping: Comparison of artificial neural network, random forest and support vector machine, a case study of Dilla town. *Heliyon*, 10(20), e39146. <https://doi.org/10.1016/j.heliyon.2024.e39146>

Kennedy, J., Hurtt, G. C., Liang, X.-Z., & Chini, L. (2023). Changing cropland in changing climates: Quantifying two decades of global cropland changes. *Environmental Research Letters*, 18(6), Article 064032. <https://doi.org/10.1088/1748-9326/acca97>

- Kullo, E., Forkuo, E., Biney, E., Harris, E., & Quaye-Ballard, J. (2021). The impact of land use and land cover changes on socioeconomic factors and livelihood in the Atwima Nwabiagya district of the Ashanti region, Ghana. *Environmental Challenges*, 5, Article 100226. <https://doi.org/10.1016/j.envc.2021.100226>
- Kumar, S., Mishra, A., & Singh, U. K. (2023). Assessment of land cover changes and climate variability effects on catchment hydrology using a physically distributed model. *Sustainability*, 15(13), Article 10304. <https://doi.org/10.3390/su151310304>
- Lemma, D., Teshome, K., Gebretsadik, S., Debela, K., & D. (2021). Forest cover change detection in relation to climate variability and LULC changes using GIS and RS techniques: A case of the Kafa Zone, Southwest Ethiopia. *Journal of Water and Land Development*, 2021. <https://doi.org/10.24425/jwld.2021.139025>
- Li, S., & Jiang, G. (2018). Land surface temperature retrieval from Landsat-8 data with the generalized split-window algorithm. *IEEE Access*, 6, 18149–18162. <https://doi.org/10.1109/ACCESS.2018.2818741>
- Lillesand, T. M., Kiefer, R. W., & Chipman, J. W. (2008). *Remote sensing and image interpretation* (6th ed.). Wiley.
- Lukas, P., Melesse, A., & Kenea, T. (2023). Prediction of future land use/land cover changes using a coupled CA-ANN model in the Upper Omo-Gibe River Basin, Ethiopia. *Remote Sensing*, 15(4), Article 1148. <https://doi.org/10.3390/rs15041148>
- Maregn, A., & Gashu, G. (2023). Analysis of observed and perceived climate change and variability in Gondar Zuria Woreda, Northwestern Ethiopia. *Ethiopian Renaissance Journal of Social Sciences and Humanities*, 10(1). <https://doi.org/10.4314/erjssh.v10i1.4>
- Masroor, M., Avtar, R., Sajjad, H., Choudhari, P., Kulimushi, L. C., Khedher, K. M., Komolafe, A. A., Yunus, A. P., & Sahu, N. (2022). Assessing the influence of land use/land cover alteration on climate variability: An analysis in the Aurangabad district of Maharashtra state, India. *Sustainability*, 14(2), Article 642. <https://doi.org/10.3390/su14020642>

- Matheos, E. (2001). Inventory of woody species in Bonga Forest (Institute of Biodiversity Conservation and Research Technical Report No. 1). Addis Ababa, Ethiopia.
- McCarty, D. A., Kim, H. W., & Lee, H. K. (2020). Evaluation of light gradient boosted machine learning technique in large scale land use and land cover classification. *Environments*, 7(10), Article 84. <https://doi.org/10.3390/environments7100084>
- Molla, M. (2015). Land use/land cover dynamics in the Central Rift Valley Region of Ethiopia: Case of Arsi Negele District. *African Journal of Agricultural Research*, 10(3), 434–449. <https://doi.org/10.5897/AJAR2014.8728>
- Mulatu, K., Hundera, K., & Senbeta, F. (2025). Analysis of forest cover change in the southwest Ethiopia: Key drivers, impacts, and conservation implications. *International Journal of Forestry Research*, Article 5523008. <https://doi.org/10.1155/ijfr/5523008>
- Negese, A. (2021). Impacts of land use and land cover change on soil erosion and hydrological responses in Ethiopia. *Applied and Environmental Soil Science*, 2021, Article 6669438. <https://doi.org/10.1155/2021/6669438>
- Nsubuga, F. N. W., & Rautenbach, H. (2018). Climate change and variability: A review of what is known and ought to be known for Uganda. *International Journal of Climate Change Strategies and Management*, 10(5), 752–771. <https://doi.org/10.1108/IJCCSM-04-2017-0090>
- Obodai, J., Adjei, K. A., Odai, S. N., & Lumor, M. (2019). Land use/land cover dynamics using Landsat data in a gold mining basin—the Ankobra, Ghana. *Remote Sensing Applications: Society and Environment*, 13, 247–256. <https://doi.org/10.1016/j.rsase.2018.10.007>
- Pan, Y., Peng, D., Chen, J., Myneni, R. B., Zhang, X., Huete, A., Fu, Y. H., Zheng, S., Yan, K., Yu, L., Zhu, P., Shen, M., Ju, W., Zhu, W., Xie, Q., Huang, W., Chen, Z., Huang, J., & Wu, C. (2023). Climate-driven land surface phenology advance is overestimated due to ignoring land cover changes. *Environmental Research Letters*, 18(4), Article 044034. <https://doi.org/10.1088/1748-9326/acca34>

- Patil, A., & Panhalkar, S. (2023). A comparative analysis of machine learning algorithms for land use and land cover classification using Google Earth Engine platform. *Journal of Geomatics*, 17(2), 96–104. <https://doi.org/10.58825/jog.2023.17.2.96>
- Pearson, K. (1895). Note on regression and inheritance in the case of two parents. *Proceedings of the Royal Society of London*, 58, 240–242. <https://doi.org/10.1098/rspl.1895.0041>
- Puyravaud, J. P. (2003). Standardizing the calculation of the annual rate of deforestation. *Forest Ecology and Management*, 177(1–3), 593–596. [https://doi.org/10.1016/S0378-1127\(02\)00335-3](https://doi.org/10.1016/S0378-1127(02)00335-3)
- Sen, P. K. (1968). Estimates of the regression coefficient based on Kendall's tau. *Journal of the American Statistical Association*, 63(324), 1379–1389. <https://doi.org/10.1080/01621459.1968.10480934>
- Shao, G., Guan, Y., Zhang, D., Yu, B., & Zhu, J. (2018). The impacts of climate variability and land use change on streamflow in the Hailiutu River Basin. *Water*, 10(6), Article 814. <https://doi.org/10.3390/w10060814>
- Shivamurthy, V., Pawale, S., Shetty, Y. C., & Bhat, S. T. (2024). Comprehensive hybrid approach for LULC classification using GEE-API and ML. In *EGU General Assembly 2024. Copernicus Meetings*. <https://doi.org/10.5194/egusphere-egu24-19017>
- Sobrino, J. A., Jiménez-Muñoz, J. C., & Paolini, L. (2004). Land surface temperature retrieval from Landsat TM 5. *Remote Sensing of Environment*, 90(4), 434–440. <https://doi.org/10.1016/j.rse.2004.02.003>
- Tesfaye, B. T., Galato, S. D., Tussie, G. D., & Zeleke, G. (2024). Analysis of land use and land cover trends using Google Earth Engine and machine learning algorithms: The case of Welmel Watershed, Southeastern Ethiopia. *SSRN*. <https://doi.org/10.2139/ssrn.4687267>
- Tesfaye, D. G., Dadi, D., Funk, C., Garedew, W., Eyelade, D., & Worku, A. (2022). Downscaled climate change projections in urban centers of Southwest Ethiopia using CORDEX Africa simulations. *Climate*, 10(10), Article 158. <https://doi.org/10.3390/cli10100158>

- Tranmer, M., Murphy, J., Elliot, M., & Pampaka, M. (2020). Multiple linear regression (2nd ed.). Cathie Marsh Institute. <https://hummedia.manchester.ac.uk/institutes/cmist/archive-publications/working-papers/2020/2020-1multiple-linear-regression.pdf>
- Wang, Q. (2022). Support vector machine algorithm in machine learning. In 2022 IEEE International Conference on Artificial Intelligence and Computer Applications (ICAICA) (pp. 750–756). IEEE. <https://doi.org/10.1109/ICAICA54878.2022.9844516>
- Ware, M. B., Matewos, T., Guye, M., Legesse, A., & Mohammed, Y. (2023). Spatiotemporal variability and trend of rainfall and temperature in Sidama Regional State, Ethiopia. *Theoretical and Applied Climatology*, 153, 213–226. <https://doi.org/10.1007/s00704-023-04463-8>
- Warku, F., Korme, T., & Wedajo, G. K. (2022). Impacts of land use/cover change and climate variability on groundwater recharge for upper Gibe watershed, Ethiopia. *Sustainable Water Resources Management*, 8(2), Article 58. <https://doi.org/10.1007/s40899-021-00588-8>
- Wayesa, G., Kidane, M., Tolessa, T., & Mammo, S. (2025). Impacts of land use/land cover dynamics on ecosystem services in Jimma Rare District, Western Ethiopia. *Sustainable Environment*, 11(1), 2436231. <https://doi.org/10.1080/27658511.2024.2436231>
- Wondrade, N. (2023). Integrated use of GIS, RS, and USLE model for LULC change analysis and soil erosion risk mapping in the Lake Hawassa Watershed, Southern Ethiopia. *Geocarto International*, 38(1), Article 2210106. <https://doi.org/10.1080/10106049.2023.2210106>
- Xu, H., Chen, Y., Dan, S., Peng, J., & Zhang, Q. (2011). Dynamical monitoring and evaluation methods to urban heat island effects based on RS & GIS. *Procedia Environmental Sciences*, 10(B), 1228–1237. <https://doi.org/10.1016/j.proenv.2011.09.197>
- Yang, X. (2011). Parameterizing support vector machines for land cover classification. *Photogrammetric Engineering & Remote Sensing*, 77(1), 27–37. <https://doi.org/10.14358/PERS.77.1.27>

- Yang, C., Wu, G., Ding, K., Shi, T., Li, Q., & Wang, J. (2017). Improving land use/land cover classification by integrating pixel unmixing and decision tree methods. *Remote Sensing*, 9(12), Article 1222. <https://doi.org/10.3390/rs9121222>
- Yechale, K. B. (2023). The impacts of climate change on hydrological processes of Gilgel Gibe catchment, Southwest Ethiopia. *PLOS ONE*, 18(6), Article e0287314. <https://doi.org/10.1371/journal.pone.0287314>
- Zafar, Z., Zubair, M., Zha, Y., Fahd, S., & Nadeem, A. A. (2023). Performance assessment of machine learning algorithms for mapping of land use/land cover using remote sensing data. *Remote Sensing Applications: Society and Environment*, 29, Article 100989. <https://doi.org/10.1016/j.rsase.2022.100989>