ASSESSMENT OF LAND USE LAND COVER CHANGE IMPACT ON LAND SURFACE TEMPERATURE USING GEOSPATIAL TECHNIQUES: A CASE OF BEKOJI TOWN, OROMIA REGION, ETHIOPIA.

Muhammed Kedir

A Thesis Submitted to the Department of Architecture Engineering

College of Civil Engineering and Architecture (CoCEA)

Presented in Partial Fulfillment of the requirement for the Degree of Master's in Geo-informatics Engineering

Office Of Graduate Studies

Adama Science and Technology University

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Under the Supervision of

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Declaration for thesis

I hereby declare that this Master Thesis entitled" Assessment of Land Use Land Cover Change Impacts on Land Surface Temperature Using Geospatial Techniques: a Case of Bekoji Town, Oromia Region, Ethiopia." is my original work. That is, it has not been submitted for the award of any academic degree, diploma, or certificate in any other university. All sources of materials that are used for this thesis have been duly acknowledged through citation.

Muhammed_Kedir ______________________ _______________

Name of student Signature Date

Recommendation of Advisors

We, the advisor(s) of this thesis, hereby certify that we have read, and revised the version of the thesis entitled" Assessment of Land Use Land Cover Change Impacts on Land Surface Temperature Using Geospatial Techniques: A Case of Bekoji Town, Oromia Region, Ethiopia.". Prepared under our guidance by Muhammed Kedir submitted in partial fulfillment of the requirements for the degree of Master's of Science in Geo-informatics Engineering. Therefore, we recommend the submission of a revised version of the thesis to the department following the applicable procedures.

Getachew B/Meskel (Ph.D.) ____________________ ________________

Major Advisor Signature Date

________________ ________________ ________________

Co- advisor Signature Date

Approval Page for Thesis

We, the advisors of the thesis, entitled" Assessment of Land Use Land Cover Change Impacts on Land Surface Temperature Using Geospatial Techniques: A Case of Bekoji Town, Oromia Region, Ethiopia.". and developed by Muhammed Kedir, hereby certify that the recommendation and suggestions made by the board of examiners are appropriately incorporated into the final version of the thesis.

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Co-advisor	Signature	Date

Approval of Board

We, the undersigned, members of the Board of Examiners of the thesis by Muhammed Kedir have read and evaluated the thesis entitled "Assessment of Land Use Land Cover Change Impacts on Land Surface Temperature: A Case of Bekoji Town, Oromia Region, Ethiopia and examined the candidate during open defence. This is, therefore, to certify that the thesis is accepted for partial fulfillment of the requirement of the degree of Master of Science in Geo-informatics Engineering.

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Final approval and acceptance of the thesis is contingent upon submission of its final copy to the Office of Postgraduate Studies (OPGS) through the Department Graduate Council (DGC) and College Graduate Committee (SGC).

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Department Head Signature Date

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College Dean Signature Date

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Office of Postgraduate Studies, Dean Signature Date

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List of acronyms and abbreviations

Acronym/abbreviations	Full Name
GIS	Geographic Information Systems
LULCC	Land Use and Land Cover Change
LST	Land Surface Temperature
MODIS	Moderate Resolution Imaging Spectroradiometer
NDBAI	Normalized Difference Bare Index
NDBI	Normalized Difference Built-up Index
NDVI:	Normalized Difference Vegetation Index
NDWI	Normalized Difference Water Index
NIR	Near Infrared Refetactance
SAR	Synthetic Aperture Radar
SWIR	Shortwave Infrared Reflectance
UHI	Urban Heat Island

Abstract

Rapid urbanization and land use and land cover (LULC) changes have emerged as critical environmental challenges, particularly in rapidly growing urban centers such as Bekoji Town in the Oromia Region of Ethiopia. This study investigates the impact of LULC dynamics on land surface temperature (LST) over a 30-year period, utilizing multi-temporal Landsat satellite imagery from 1994, 2004, 2014, and 2024. A supervised classification technique employing the Maximum Likelihood Algorithm (MLA) was used to categorize LULC into five classes: built-up areas, agricultural land, vegetation, grassland, and bare land. LST was extracted using the split-window algorithm, and normalized indices Normalized Difference Vegetation Index (NDVI) and Normalized Difference Built-up Index (NDBI)were calculated to assess the relationship between surface temperature and land cover types.The findings reveal a significant transformation of land use, with built-up areas expanding from 9.4% in 1994 to 22.5% in 2024 and Vegeatation land decreased from 36.4% to 18.8%. These changes were accompanied by a marked increase in LST, with minimum surface temperatures rising by 2.84°C and maximum temperatures by 2.97°C. Statistical analyses demonstrated a strong negative correlation between NDVI and LST, indicating the cooling effect of vegetation, and a positive correlation between NDBI and LST, reflecting the contribution of impervious surfaces to heat accumulation. This study underscores the environmental implications of unplanned urban expansion highlights the need for sustainable land use policies. The integration of geospatial techniques for analyzing urban heat dynamics and provides valuable insights for urban planners, environmental managers, and policymakers aiming to enhance climate resilience and sustainable development. As a whole, geospatial analysis clearly indicates that changes in land cover significantly influence LST in Bekoji town. Built-up areas consistently recorded higher temperatures, while vegetated areas showed cooler surface conditions. This relationship underscores the importance of sustainable urban planning and the integration of green infrastructure to mitigate adverse thermal and environmental effects. The study advocates for reforestation, green buffer zones, and policy interventions to balance urban growth with environmental health.

Keywords: Land Use Land Cover; Land Surface Temperature; Remote Sensing; GIS; NDVI; NDBI; Bekoji Town.

CHAPTER ONE
1. INTRODUCTIO

1.1. Background of the Study

Since its discovery by Luke Howard in 1818, the phenomenon known as Urban Heat Island (UHI) has gained significant attention considering the current acceleration of urbanization worldwide. Forecasts for urbanization show a global trend of increasing urban growth, especially in developing nations driven by economic expansion (ESSAP, 1993). By 2050, it is predicted that 68% of people will live in cities, a significant increase from the current 55% (United Nations, 2018). Alongside rising greenhouse gas concentrations in the atmosphere, urbanization characterized by the expansion of built-up regions and infrastructure has emerged as a major human-caused driver of climate change (IPCC, 2007, 2013). At both the local and regional levels, changes in land use/cover (LULC), particularly the quick switch from pervious to impervious surfaces, pose environmental issues (Rousta et al., 2018; Zhou et al., 1998). Two notable effects of LULC changes in urban environments include variations in Land Surface Temperature (LST) and the creation of urban heat islands (Mohammad & Goswami, 2018). Temperature fluctuations across distinct land cover categories are caused by surface reflectance and roughness, which are influenced by land surface temperature (LST), a crucial parameter in studies of surface energy balance and climate change (Tomlinson et al., 2011; Li et al., 2017; Hu & Jia, 2009).

In the Eastern African context, the main cause of LULC changes is the increase in human and livestock populations, which results in the overuse of land for agricultural purposes. As a result of this change, naturally vegetated land is transformed into built-up areas, pasture grounds, farmlands, and urban regions. Soil erosion, deforestation, land degradation, biodiversity loss, and major contributions to climate change-related global warming are among the repercussions (Pomeroy et al., 2003; Maitima et al., 2009).

Ethiopia is a country in East Africa that is seeing a rapid increase in land use and land cover change, which is mainly caused by population expansion and changing local community views on sustainable land management (Hurni et al., 2005; Belay et al.,). Complicating the dynamic state of the nation's landscapes are additional difficulties such as surface flooding, runoff, and sedimentation. Particularly in the Amhara National Regional State, population pressure causes marked land degradation, resulting in the loss of forest, shrubland, bushland, and grasslands to make room for farming, grazing land development, and habitation (Bekele, 2005). By 2050, Ethiopia is expected to have the most urbanized population in the world, with an estimated 814 million people living there (current urban population rate stated). The country has an urbanization rate of 1.1%. Beyond the bounds of traditional cities, this unheard-of urban expansion is displacing marshes, vegetation, and agricultural regions and exerting pressure on the surrounding natural resources. The implications of this rapid urbanization include altered precipitation patterns, heatwaves, urban heat islands, and climate change (Bai et al., 2018; Estoque & Murayama, 2013; Malik et al., 2020; Mohammad et al., 2019). Researchers are now better equipped to explore the complex link between UHI and landscape dynamics thanks to developments in thermal remote sensing, Geographic Information Systems (GIS), and statistical techniques. Several studies have produced insights that help policymakers understand the dynamics of UHI and help create strategies that work (Quattrochi and Luvall, 1999; Yuan and Bauer, 2007; Rizwan et al., 2008; Junxiang et al., 2011; Kumar et al., 2012; Radhi et al., 2013; Myint et al., 2013; Zhou et al., Adams and Smith, Coseo and Larsen, Song et al., Chun and Guldmann, Rotem-Mindali et al., 2015). Remote sensing and GIS technology integration have become essential for detecting LULC changes and retrieving LST data (Choudhury et al., 2019). Land use land cover (LULC) has a pivotal role in shielding the physical environment from incoming solar radiation, and it can also be used in enhancing the esthetical value of the environs (Cheng and Zhang 2017). Conversely, it has been shifting from one type to another due to man's interference over time and causes environmental degradation (Beyene 2019; Balew and Korme 2020). The rapid growth of the human population is a prime cause of LULC change (Moisa et al. 2021; Negash et al. 2021). A study by Negassa et al. (2020) in western parts of Oromia reported that people are converting forestland cover to agriculture, grazing, and settlement. LULC change due to anthropogenic activities causes the rise of surface temperature (Rahman et al. 2012; Bharath et al. 2013; Song et al. 2018; Rahaman et al. 2020). Climate and weather conditions can significantly affect the thermal condition of the environment which in turn affects the land surface temperature (LST). Because of anthropogenic activities, the forest cover change is declining from time to time. Vegetation indices such as Fractional Vegetation Cover (FVC) and Normalized Difference Vegetation Index (NDVI) can indicate the presence and abundance of vegetation cover (Iang and Tian 2010). The LST and NDVI have a negative relationship, and vegetation cover can lower the LST, and it has a cooling effect on the temperature of an area (Gallo and Tarpley 1996; Weng 2001). Greenery plays a significant role in alleviating the impact of surface temperature by falling temperature and rising humidity (Sandra et al. 2011; Wedajo et al. 2019).

The LST has been increasing year to year globally (Tafesse and Suryabhagavan 2019). There are various factors that contribute to the increasing trend of the LST. Among these, huge agricultural investment is one of the major possible causes of the rise and variability of surface temperature (Tena et al. 2016). Strong negative correlations between NDVI and LST are highlighted, whereas NDBI and LST tend to show positive correlations. Bareland, represented by NDBAI, often exhibits moderate to high LST due to low thermal capacity. Furthermore, NDWI demonstrates the cooling effects of water bodies. The integration of these indices with LULC analysis provides a robust framework for understanding landscape thermal behaviors (Zhang et al. (2017) and Li et al. (2019). This study attempts to evaluate the complex relationship between urban LULC changes and LST in Bekoji town using thermal bands of Landsat imageries. This study aims to offer significant insights into forecasting future land warming trends through the utilization of remote sensing and GIS methods. Considering continued urbanization and climate change, the results are expected to provide useful information for environmental specialists, natural resource managers, and urban planners, encouraging the management of natural landscapes for sustainability and health.

In general, geospatial technology, encompassing remote sensing and Geographic Information Systems (GIS), offers a promising solution to this problem. Remote sensing provides consistent and extensive data on LULC and LST over large areas and multiple periods, while GIS facilitates the analysis and visualization of these data. However, the integration of these technologies to assess LULC changes on LST has been fully realized or standardized. Several studies have been conducted in the country (Balew and Korme 2020). Hence, Assessment of land use land cover change impact on land surface temperature using geospatial technology was investigated for Bekoji town.

1.2 Statement of the Problem

The primary problems addressed by this study were urban expansion, deforestation, and agricultural problems serious issues. Bekoji town is growing at a fair rate and change of detection land use land cover. This growth and expansion have been radical, particularly since

1994. Several factors like climate, accessibility, and other social factors for the growth and development of Bekoji town. LULC changes often go unchecked, leading to increasing LSTs that contribute to environmental degradation and challenges for sustainable land-use planning. There is a growing need to assess the relationship between LULC and LST, particularly in study areas experiencing rapid development or environmental stress. Limited research on localized impacts of LULC changes on LST poses a challenge for sustainable land-use planning in 2024. Geospatial technology to accurately assess the LULC changes on LST for the study area and in the study area urban expansion, deforestation, and agricultural problems major issues, how to change of detection of land use land cover and as wheel as a change of temperature through different year of the study. With rapid urbanization and environmental changes, understanding the relationship between LULC changes and LST is critical for sustainable development and climate resilience. The absence of detailed geospatial analysis in the study area or Bekoji town leads to limited insights into the factors affecting local temperature patterns.

Earth's environment is a complex system with various interacting components, including physical, biological, chemical, and human factors, all undergoing continuous changes (Emilio, 2008). The alteration of land Use/land-cover patterns are attributed to factors like population growth, industrialization, and various activities conducted by nature and humans. Land-use land cover change emerges as a key contributor to the rise in land surface temperature. Presently, the challenges of global warming and environmental issues are a significant concern in both developing and developed nations. Practices like excessive grazing the clearing of forests, and unplanned land use for settlement contribute to the warming of our environment. The rapid urbanization and land-use/land-cover changes in Ethiopia have led to significant alterations in the land surface temperature, contributing to the emergence of urban heat islands and potential adverse effects on the local climate (Guha, Govil, & Mukherjee, 2017).

1.3 Objectives of the Study

1.3.1 The general objective

The main objective of the study was to assess land use land cover change impact on land surface temperature of Bekoji town using geospatial technology Bekoji town, Oromia Region, Ethiopia.

1.3.2 The specific objectives

1. To assess the spatiotemporal changes of LULC of Bekoji town over 1994, 2004,2014 and 2024
2. To assess LST spatiotemporal patterns of Bekoji town from 1994, 2004,2014 and 2024
3. To analyze the correlation between LST, NDVI & NDBI of Bekoji town from 1994, 2004,2014 and 2024
4. To identify factors influencing changes in LULC and LST of Bekoji town

1.4 Research Questions

1. How do you assess the historical spatiotemporal changes of LULC of Bekoji town?
2. What are the spatiotemporal patterns of land surface temperature of Bekoji town?
3. What is the correlation between LULC, LST, NDVI, and NDBI of Bekoji town?
4. What are the factors influencing changes in LULC and LST of Bekoji town?

1.5 Significance of Study

This study was beneficiaries for urban planners, environmental managers, land use policymakers, and other stockholders involved. Understanding how urbanization and other LULC changes contribute to increased temperatures in town can inform the development of mitigation strategies, such as green infrastructure and urban planning policies aimed at reducing heat islands. The findings from this study can guide urban planners and policymakers in making data-driven decisions to promote sustainable development. Temperature increases due to LULC changes, planners can implement measures to enhance urban resilience, such as increasing green spaces, promoting energy-efficient building designs, and improving land use zoning. This study can contribute to climate change mitigation by highlighting how land management practices affect local and regional climates.

The assessment helps in understanding how LULC changes, such as deforestation and agricultural expansion, affect local climates and ecosystems. This knowledge is essential for developing conservation strategies that protect biodiversity, maintain ecosystem services, and ensure sustainable land use practices. The studies directly related to environmental management and urban development in terms of practical ramifications. Using cutting-edge remote sensing and Geographic Information System (GIS) techniques, the thesis achieves a high degree of methodological rigor that serves as a useful model for future research. The research findings can provide guidance for making decisions on land-use management, climate-resilient infrastructure planning, and sustainable urban development. Additionally, by providing evidence-based insights that might direct policymakers in the region, the study adds to the larger conversation about policy.

This study provides significant contributions across multiple domains including land use planning, environmental management, urban development, and geospatial data application. Contribution to Land Use Planning and Management:the findings offer crucial insights into how changes in land use and land cover (LULC) influence land surface temperature (LST) in Bekoji town. By identifying the spatial and temporal patterns of LULC transitions, such as urban expansion and vegetation loss, the study helps urban planners:recognize urban heat island (UHI) formation zones.Strategically design green spaces and sustainable land zoning.Contribution to Environmental Sustainability: correlating LULC dynamics with LST variations, the study underlines the environmental consequences of unchecked urbanization and deforestation. It contributes to environmental policy and conservation efforts by supporting reforestation and afforestation initiatives.Promoting climate-resilient land management practices.Providing a geospatial framework for environmental impact assessments.Contribution to Land Administration:this research aids in the modernization of land administration by incorporating geospatial techniques and monitor land changes. It supports:Transparent land tenure systems by mapping and analyzing land use transformations.Evidence-based land allocation and resource distribution.Enhances technical capacity in using satellite data for thermal and land analysis.Provides a workflow for LST extraction and LULC classification.

1.6. Scope of the Study

This study focused on the relationship between land use land cover changes and land surface temperature in Bekoji town, from 1994,2004,2014 and 2024. The analysis utilizes remote sensing data from satellite imagery (such as Landsat and MODIS) and GIS tools to assess LULC changes and their effects on the LST of Bekoji town. The study covered multiple land cover types, including agricultural land, built areas, vegetation, water bodies, and grasslands, providing a comprehensive understanding of the dynamics at play. The study employed supervised classification techniques to categorize LULC types. Validation of classification results was conducted using ground truth data and accuracy assessment metrics. LST was derived from thermal infrared bands of satellite images using established algorithms. The study's content covers a wide range of topics, with a focus on the unique impact that LULC changes have on land surface temperature. To identify various land cover types, measure changes over time, and correlate these changes with variations in LST, the research entails the collection and analysis of satellite imagery. Furthermore, to better understand the subtleties of the microclimate, the study investigates how elevation affects the way that LULC changes affect LST.To better understand how particular urban features, such as built-up areas, vegetation cover, and water bodies, affect temperature changes, the content also contains a comparative examination of various land use categories.

1.7 Organization of the thesis

This thesis is presented into five chapters. The first chapter introduces the proposed topic, estimation of land surface temperature and urban heat island effect. It also includes the problem statements, research questions, objectives, scope and significances of the study. The second chapter literature review. This section has many relevant topics, such as definition, factors for change and effect of land surface temperature and urban heat island, thermal remote sensing data types, land-use/land-cover and their effect on land surface temperature variation,spatial characteristics and impact of urbanization and urban green land cover on land surfacetemperature, role of advanced technologies like remote sensing and GIS for urban heat island studies.The third chapter illustrates material and methodology used to assess the major problems like detail description of the study area, data used, software packages, techniques applied for image processing, enhancement, classification and accuracy assessment and methods used for urban green land cover extraction, derivation of normalized vegetation index NDVI,NBBI and retrieval of land surface temperature and statistical correlation measures. The fourth chapter presents result and discussion of the present study.The fifth chapter has conclusion and recommendations are presented.

1.8 Definition terms

Land Use Land Cover (LULC): A combined term describing both how humans use the land and the physical characteristics of the land's surface. LULC classification helps assess environmental changes and their effects on temperature.

Land Surface Temperature (LST): The temperature of the land's surface as measured from satellites or ground-based observations. LST is influenced by land cover, vegetation, and human activities, and it plays a key role in the study of climate and environmental changes.

Geospatial Techniques: A set of technologies and tools used to collect, analyze, and interpret data related to the Earth's surface. This includes Geographic Information Systems (GIS), Remote Sensing (RS), and Global Positioning Systems (GPS).

Urban Heat Island (UHI): A phenomenon where urban areas experience higher temperatures than surrounding rural areas due to human activities, reduced vegetation, and heat absorption by built-up surfaces.

Spatial Resolution: The level of detail in a spatial dataset, typically expressed as the size of the smallest identifiable unit(e.g.,30mforLandsatimagery).

CHAPTER TWO
2. LITERATURE REVIE

2.1 Concept of LULC

Key elements in the complex interaction between human activity and the surface of the Earth are land use and land cover (LULC). "Land cover" encompasses the natural condition of the surface, including solid surfaces, creatures, water bodies, and soil, whereas "land use" refers to human activities and their frequently undetectable effects (Lo, 1986; Jansen & Di Gregorio, 2003). LULC research explores how these characteristics change globally, highlighting the phenomenon's unparalleled scope, effects on Earth's systems, and need for a better comprehension of its underlying causes (Lambin et al., 2001; Foley et al., 2005).

2.2 Effects of LULC change

LULC modifications have substantial environmental effects, especially in metropolitan areas. Urban Heat Islands (UHIs) are the product of LULC adjustments in urban environments, which also affect Land Surface Temperature (LST) (Mohammad & Goswami, 2018). Changes in LULC distribution have an impact on LST, and this complex link between LULC and LST is crucial to comprehending UHI impacts (Walawender et al., Song et al.,). According to Zhang et al. (2013), LULC changes also work in tandem with greenhouse gas concentrations as key anthropogenic drivers of climate change.

2.3 Driving Forces of LULC Change

It's essential to comprehend the motivations for LULC revisions. Research examines how changes in LULC and population growth affect the development of Urban Heat Islands (Zhang et al., 2013). Furthermore, it is clear how LULC changes are entwined with land-use change and urbanization, affecting the Normalized Difference Vegetation Index (NDVI) and Land Surface Temperature (LST) in urban regions (Li et al., 2011). One important environmental factor affecting the local microclimate, especially the modification of LST, is Land Use and Land Cover Change (LULCC). This phenomenon reflects socioeconomic changes associated with human activity and arises from a confluence of anthropogenic and natural elements in globalized land systems (Popp et al., 2017). Urban LST estimation becomes more difficult in areas where natural and semi-natural land coverings are being replaced by impermeable surfaces due to surface heterogeneity (Akinbobola, 2019).

Understanding the environmental dynamics of a place requires accurate identification, with LULC emerging as a crucial characteristic. The quick transition from previous to impermeable surfaces caused by LULC changes has a significant impact on the local and regional environments, highlighting the significant impact of LULC on surface temperature, especially in metropolitan areas (Rousta et al., 2018; Zhou et al., 1998; Weng et al., 2004). Answering important issues concerning the changing land cover, the types of changes, and the speeds at which these changes happen requires an understanding of the notion, consequences, and causes behind LULC. Understanding the dynamic relationships between land use and land cover changes over time and forecasting future change patterns depend on simulation modeling (Brown et al., 2000; Loveland and Acevedo, 2006). Finding and evaluating LULC changes are essential techniques for evaluating ecological and environmental degradation (Beevi et al., 2015; Hadeel et al., 2011).

2.4 Concept of Land Surface Temperature (LST)

The result of all surface-atmosphere interactions and energy fluxes between the atmosphere and the ground are combined to form the land surface temperature (LST), a complete measurement. According to Duan et al. (2019), it is essential to comprehend the dynamics of the urban thermal environment. Numerous surface characteristics, including building materials, the composition of urban vegetation, land cover, elevation, and climate, all have an impact on LST. An important area of urban climatology is the relationship between rising land surface temperatures and increased heat-transmitting anthropogenic emissions, reduced water-pervious surfaces, and increased land surface covering with high heat conductivities (Sara Afrasiabi Gorgani, 2016). According to Sobrino and Raissouni (2000), land surface temperature is a function of surface qualities and is greatly influenced by the structure of urban vegetation and the materials used in construction. The relationship between vegetation quality and LST, which is influenced by soil types, land use, and urbanization, complicates our understanding of urban heat islands. The inverse connection highlights the complex dynamics affecting LST.

2.5 Remote Sensing in LULC

For a thorough grasp of the dynamics of the Earth's surface, remote sensing techniques are essential for evaluating changes in land use and cover (Chao et al., 2020). The Land Surface Temperature is a fundamental indication that allows different elements of land usage and land cover changes to be measured by satellite-based thermal remote sensing. Tracking spectrally sensitive changes on the surface of the Earth is made possible by remote sensing's wide coverage, equivalent geographic scales, and temporal consistency (Jensen, 2007). Renowned for their worldwide reach since 1972, NASA's Landsat missions play a significant role in the detection of changes in land cover and use. They provide freely accessible, moderate-to-high-resolution data (Helmer et al., 2000; Lu and Weng, 2004; Gao and Zhang, 2009; Kumar and Acharya, 2016). To analyze LULC changes and LST, remote sensing (RS) and geographic information systems (GIS) are essential tools (Ayele et al., 2018; Hc et al., 2020). Using synoptic LULC data from satellite-based RS, one may map and identify changes in land surface temperature as well as land use (Chew et al., 2016; Malik et al., 2020). The thermal sensor on Landsat makes it easier to calculate LST, a crucial statistic that represents ground temperature, and is primarily used to identify Urban Heat Islands (UHI) (Rajeshwari and Mani, Choudhury & Das Arijit Das, 2019). According to Ullah et al. (2019), remote sensing indices like the NDVI and NDBI are essential for determining how land use change would affect LST. Using LST from remote sensing data made possible by satellite sensors such as MODIS, ASTER, and Landsat is essential for UHI research because it provides extensive spatial coverage over a range of temporal scales (Imhoff et al., 2010). Geographical technology and remote sensing are key tools in contemporary environmental analysis for locating land use change (LULC) and extracting subtle variations in land surface temperature (Choudhury et al., 2019). The quick computation of LST is made possible using satellite imagery from Landsat, NOAA-AVHRR, and MODIS (Frey et al., 2012). To ensure accurate LST determination, atmospheric correction procedures particularly the split-window method frequently employed for Landsat-8 LST retrieval address atmospheric influences (Honnerová et al., 2016). Many agree that Land Surface Temperature (LST) is important for evaluating temperature changes in urban areas and that this has consequences for regional climate and human-environment interactions (Zhang et al., 2017). A wealth of research on the temporal dynamics of vegetation and climate indices in different places is reflected in the Scopus database. Knowing LST trends becomes essential to understanding climate change effects (Sadiq Khan et al., 2020). The distribution and change of LST are significantly influenced by natural vegetation, and one commonly used metric for calculating LST is the normalized difference vegetation index, or NDVI (Guha et al., 2018). Understanding the effects of climate change requires in-depth research using remote sensing datasets, as the conversion of natural vegetation to impermeable surfaces in urban land cover drastically changes the microclimate (Sadiq Khan et al., 2020). Determining local solar radiation, atmospheric parameters, and surface features, the surface thermal environment (LST) is a manifestation of the heat exchange equilibrium between the ground and the atmosphere. According to Yang et al. (2017), LST changes significantly because of the growing urbanization of areas. Natural surfaces such as vegetation and water bodies are replaced by impermeable artificial surfaces, which causes geographic variations in energy exchange. According to Dewan & Yamaguchi (2009) and Gogoi et al. (2019), land surface temperature (LST) is a critical indication of the energy balance at the ground surface and varies greatly depending on changes in land use and cover. Because urban surface alterations alter local thermal conditions, there are health concerns for people (Grimmond, 2007).

2.6 Land use and Land cover change in Ethiopia

Land cover changes driven by agricultural expansion have also been linked to variations in LST. Research has shown that intensive agricultural practices can lead to localized temperature increases, emphasizing the importance of sustainable agricultural methods to mitigate temperature effects (Alemayehu et al., 2022). Agricultural expansion remains a leading driver of LULCC in Ethiopia. The government's policies promoting large-scale agriculture have led to the conversion of forests and grasslands into croplands. Between 2017 and 2021, over 250,000 hectares of forest land were converted to agricultural land in Oromia and SNNPR regions (Kebede et al. (2021). Agricultural development is a primary driver of LULC change in Ethiopia. Studies indicate that areas converted from forest or grassland to cropland experience increased LST. Abate et al. (2021) found that the conversion of natural vegetation to agricultural land led to significant increases in LST, highlighting the need for sustainable agricultural practices to mitigate these effects. Agricultural activities have significantly altered land cover in Ethiopia. Research shows that the conversion of forest and grassland to cropland increases LST. For instance, Abate et al. (2021) found that areas with extensive agricultural practices exhibited higher surface temperatures due to reduced vegetation cover.

Urban areas have been associated with significantly higher surface temperatures compared to rural regions due to the urban heat island effect. Studies indicate that increased impervious surfaces and reduced vegetation in urban settings contribute to elevated LST, highlighting the need for sustainable urban planning (Tesfaye et al., 2023). Urban growth has accelerated in cities like Addis Ababa, contributing significantly to land cover changes. Research by Tesfaye et al. (2023) indicates that urban areas in Addis Ababa expanded by 60% from 2017 to 2022, primarily encroaching on agricultural lands and forests. Rapid urbanization has also been linked to rising LST. Tesfaye et al. (2023) highlighted that urban areas in Addis Ababa have shown a marked increase in LST due to the heat island effect. The study found that urbanization resulted in significant land cover changes, with impervious surfaces (e.g., roads, buildings) replacing vegetation, leading to elevated temperatures.

Urbanization is a critical driver of LST increases. Tesfaye et al. (2023) highlighted that urban areas in Addis Ababa have experienced significant temperature rises due to the heat island effect. The study noted that impervious surfaces, such as roads and buildings, contributed to elevated LST, emphasizing the need for urban planning that incorporates green spaces to mitigate heat impacts.

Deforestation has reached alarming rates, driven by agricultural expansion, logging, and infrastructure development. A review by Hussen et al. (2022) emphasized that Ethiopia lost approximately 5 million hectares of forest cover from 2017 to 2022, leading to biodiversity loss and increased carbon emissions. Deforestation has been associated with increased land surface temperatures. A study by Hussen et al. (2022) revealed that forested areas in Ethiopia, particularly in the Southern Nations, Nationalities, and Peoples' Region (SNNPR), showed lower LST compared to deforested areas. The loss of tree cover not only increases surface temperatures but also impacts local microclimates. Deforestation is another critical factor affecting LST. Hussen et al. (2022) reported that forested areas in southern Ethiopia exhibited lower LST compared to deforested regions. The loss of tree cover was shown to contribute to increased surface temperatures, adversely impacting local climates and ecosystems. Deforestation, particularly in the Ethiopian Highlands, has led to increased LST. Loss of forest cover reduces shading and evapotranspiration, resulting in higher surface temperatures. Studies stress the need for reforestation and sustainable land management practices to counteract these effects (Hussen et al., 2022).

2.7 Changes in LULC

Particularly urban expansion and agricultural land conversion, have a direct impact on LST by altering surface properties such as albedo and evapotranspiration rates. Analyzed LULC and LST in Addis Ababa using Landsat 8 data and found that urban areas exhibited significantly higher LST compared to agricultural and vegetated areas. This increase was attributed to the transformation of natural landscapes into impervious surfaces such as buildings and roads, which reduce evapotranspiration and increase heat absorption (Gebre et al. (2019). Explored

LULC changes in the Lake Tana Basin, one of the key agricultural areas in Ethiopia. Their findings showed that deforestation and conversion of wetlands into cropland led to an increase in LST, which significantly affected the local microclimate. The study highlighted that the reduction in tree cover, and wetland areas contributed to increased daytime surface temperatures, suggesting the importance of conservation for climate regulation (Yirsaw et al. (2021).

2.8 Urban Heat Island Effect in Ethiopian Cities

Urban heat islands are a growing concern in Ethiopian cities due to rapid urbanization and a lack of green infrastructure. Studied the UHI effect in Addis Ababa by using Landsat thermal infrared imagery. Their research indicated that urban areas with extensive concrete structures exhibited significantly higher LST compared to suburban and rural areas with more green cover. The study suggested that increasing green spaces in Addis Ababa could mitigate the UHI effect, improve air quality, and enhance urban resilience to climate change *(Woldeyohannes et al. (2019)*. Another study explored the seasonal variation of UHI in Hawassa City using MODIS and Landsat 8 data. Their findings revealed that LST values were higher during the dry season, with urban areas showing greater temperature variability than surrounding rural areas. The study emphasized the role of vegetation in controlling LST, especially in urban environments, suggesting that city planning should integrate more green infrastructure to alleviate extreme temperatures *(Gebru et al. (2022)*. Rapid urbanization has led to the emergence of urban heat islands in cities like Addis Ababa. Tesfaye et al. (2023) used remote sensing to map urban LULC changes and assess their impacts on LST, revealing that urban areas exhibit significantly higher temperatures compared to surrounding rural regions.

2.9 Impacts of LULC on Environmental and Social Factors

Changes in LULC, such as deforestation and urbanization, directly impact soil moisture levels and evapotranspiration rates. By using Sentinel-1 SAR (Synthetic Aperture Radar) data, they provided insights into how reduced vegetation cover leads to decreased soil water content, which can exacerbate issues related to land degradation and reduced agricultural productivity *(Abdelrahman et al. (2022)*. The insights gained from LULC and LST assessments are critical for urban planning and climate adaptation in Ethiopia. Assessed the impact of green spaces on urban heat mitigation in Addis Ababa, using GIS to identify key areas where green infrastructure could reduce LST effectively. Their findings showed that increasing urban parks and green corridors could significantly decrease LST, thereby enhancing the quality of life for urban residents *(Tekle and Feyisa (2021)*. The insights gained from LULC and LST assessments are critical for urban planning and climate adaptation in Ethiopia. The impact of green spaces on urban heat mitigation in Addis Ababa, using GIS to identify key areas where green infrastructure could reduce LST effectively. Their findings showed that increasing urban parks and green corridors could significantly decrease LST, thereby enhancing the quality of life for urban residents *(Tekle and Feyisa (2021)*. Implications of LULC-driven LST changes for agriculture in Ethiopia. The study found that increasing LST due to the conversion of vegetated areas to farmland adversely affected soil moisture and crop yields, particularly in the lowlands. They recommended integrating agroforestry practices to help mitigate rising temperatures and improve agricultural sustainability, which is vital for the country's food security *Molla and Abebe (2023)*. Despite advancements in remote sensing and GIS technologies, challenges remain in assessing LULC and LST in Ethiopia. One significant challenge is the lack of high-resolution reference data for validating LULC classifications. It was pointed out that field data collection is often limited by the country's rugged terrain and resource constraints, leading to gaps in the validation process that can affect the accuracy of LULC maps *(Foody et al. (2021)*. Another challenge is related to cloud cover, which is a persistent issue for optical remote sensing in Ethiopia's highland areas. Addressed this challenge by incorporating Synthetic Aperture Radar (SAR) data from Sentinel-1, which is unaffected by cloud cover, for LULC mapping. The use of SAR data improved the reliability of LULC assessments, especially during the rainy season when cloud-free optical images are rare *(Haile et al. (2022)*. Highlighted the importance of incorporating ground-based temperature measurements to validate satellite-derived LST, which is often influenced by atmospheric conditions and surface emissivity. Future research should focus on developing hybrid models that combine satellite, drone, and ground-based data for more comprehensive LST assessments *(Ayele et al. (2023)*.

2.10 Applications of Geospatial Technologies

The availability of high-resolution satellite imagery, such as Sentinel-2 and Landsat 8, has enhanced the capacity for environmental monitoring and land use assessments. For instance, researchers have utilized these data sources to analyze land use and land cover changes, particularly in agricultural areas and urban environments (Meles et al., 2022). The integration of GIS with technologies such as drones and mobile applications has facilitated real-time data collection and analysis. Studies have shown that drones equipped with GPS and remote sensing capabilities have improved agricultural monitoring and land surveying (Alemayehu et al., 2023). The development of user-friendly software tools and platforms, such as QGIS and Google Earth Engine, has democratized access to geospatial data analysis, allowing researchers and practitioners to conduct sophisticated analyses without requiring extensive technical expertise (Zewdie et al., 2024). Geospatial technology has been employed to enhance agricultural productivity and food security. Researchers have used remote sensing to monitor crop health, assess soil moisture levels, and predict yields. For example, Tadele et al. (2023) utilized remote sensing data to analyze the impacts of climate change on crop production in the Ethiopian highlands. Urbanization in Ethiopia has accelerated, leading to increased pressure on infrastructure and services. GIS has been used to analyze urban growth patterns and inform land use planning. Studies have highlighted the application of geospatial analysis in assessing urban heat islands and optimizing land use to enhance urban resilience (Tesfaye et al., 2024). Geospatial technology plays a critical role in disaster risk reduction and management. Remote sensing data have been utilized for flood mapping, drought assessment, and monitoring of environmental hazards. For instance, research by Hussein et al. (2022)

2.11 Challenges in LULC and LST Studies in Ethiopia

Demonstrated the use of satellite imagery to assess flood risks in the context of climate change, informing disaster preparedness efforts. The monitoring of deforestation, land degradation, and biodiversity has been significantly enhanced through geospatial technology. Studies have shown the application of remote sensing to track changes in land cover and assess their ecological impacts, thereby informing conservation efforts (Dessalegn et al., 2023).

2.12 Challenges in the Application of Geospatial Technology

Despite the progress made, several challenges hinder the effective application of geospatial technology in Ethiopia. There are challenges related to data quality, accessibility, and coverage. In many rural areas, the lack of reliable ground truth data hampers the accuracy of remote sensing analyses (Zewdie et al., 2024). The shortage of trained personnel in geospatial technology remains a barrier to widespread adoption. There is a need for capacity building and training programs to enhance local expertise (Alemayehu et al., 2023). Fragmentation among institutions and a lack of coordinated efforts in geospatial data sharing can impede effective planning and decision-making processes (Meles et al., 2022). Karaku's study analyzed Landsat satellite images from 1989 to 2015 to explore the correlation between LULC, NDVI, and LST, revealing the intensity of UHI. The study clearly indicated a rise in urban and agricultural areas alongside a decline in barren land over time. Changes in Land Surface Temperature (LST) were linked to factors like construction materials, greenery, geography, and topography. Urban and barren lands exhibited the highest LST, with urban areas showing fluctuating temperatures while rural areas tended to cool.

The increase in urban areas led to a noticeable UHI effect. (Suzana Binti Abu Bakar et al., 2016) Explored the link between LST and LU/LC on Langkawi Island. They analyzed satellite imagery from 2002 to 2015, employing indices like NDVI, NDBI, and MNDWI alongside classifiers like MLC and SVM. SVM exhibited higher accuracy (90%) compared to MLC (86.62%). Results indicated a rise in temperature with increased impervious surfaces and a decline in vegetated areas. The study suggests using NDVI, NDBI, and MNDWI as indicators to monitor Land Surface Temperature influenced by LU/LCC. In 2018, Matiwos Belayhun Haylemariyam utilized Landsat satellite imagery from 1993 and 2017 to assess land use changes and their Effect on land surface temperature in Dire Dawa City, Ethiopia. The analysis identified five major land use types and found that built-up and shrub areas expanded, while barren land decreased. Built-up areas and barren land exhibited the highest land surface temperatures, while shrub and sparse vegetation had lower temperatures due to their vegetative cover. The study also highlighted a negative correlation between the NDVI and LST. Empirical studies confirm significant land cover changes across Ethiopia. Between 2017 and 2021, over 250,000 hectares of forest were converted to agricultural land in Oromia and the Southern Nations, Nationalities, and Peoples' Region (Kebede et al., 2021). This large-scale deforestation contributed to increased land surface temperatures (LST) in affected areas. Studies such as Abate et al. (2021) found a direct correlation between the conversion of natural vegetation to croplands and increased LST, underscoring the environmental costs of unsustainable agricultural practices. Similarly, urban areas, particularly Addis Ababa, expanded by 60% between 2017 and 2022, encroaching on agricultural and forested lands (Tesfaye et al., 2023). These transformations were shown to elevate local temperatures, emphasizing the role of LULCC in altering regional climates.

2.13 Research Gaps

Various researchers have analyzed the temperature of the Earth's surface, but their methodologies and findings differ. However, most of these studies have focused on a specific urban area and have not been able to distinguish the spatiotemporal fluctuations in LULC dynamics and their effects on LST across multiple urban areas. Some studies used a limited number of sample points for correlation analysis, resulting in inflated maximum values due to poor sample distribution. While these researchers utilized Data from remote sensing to generate surface temperature maps, they failed to statistically analyze which LU/LC factors contribute most to the increase in LST. Additionally, they lacked confidence intervals to validate their results. Many studies focus only on examining the relationships between LULC, LST, and NDVI.Therefore, this study aims to address these gaps by integrating various geospatial software and statistically analyzing the data.Limited Localized Studies in Secondary Urban Centers: most existing research in Ethiopia focuses on major urban centers such as Addis Ababa or Adama. There is a lack of localized, data-driven assessments of LULC-induced thermal impacts in small but rapidly growing towns like Bekoji. This gap hampers region-specific urban planning and policy formulation. Inadequate Use of Multi-Temporal and Multi-Source Satellite Data:previous studies often rely on single-time datasets or limited time frames. There is insufficient use of multi-temporal satellite imagery (spanning two decades) to capture long-term LULC dynamics and their thermal effects. This study bridges that gap by using Landsat data from 1994, 2004,2014 and 2024. Insufficient Integration of LST with Specific LULC Categories:while many studies map LULC or LST independently, few analyze the direct relationship between specific land cover types (e.g., built-up vs. vegetation) and their corresponding LST values. This study explicitly quantifies and compares LST changes across classified LULC types.Limited Application of Remote Sensing for Policy and Planning: remote sensing and GIS tools remain underutilized in informing land use policy and climate resilience strategies at the town level in Ethiopia. This research demonstrates how geospatial analysis can serve as a decision-support tool for urban planners and environmental managers. Minimal Assessment of Ecosystem Service Loss Due to LULC Change:there is a research gap in linking LULC changes with ecosystem service losses, such as the reduction in natural cooling, carbon sequestration, and biodiversity. This study indirectly addresses this by evaluating how the loss of vegetated cover affects LST.By addressing these gaps, the study contributes to a deeper understanding of how human-induced land changes alter the thermal environment of rapidly urbanizing towns, supporting evidence-based planning and sustainable land management in our country.

CHAPTER THREE

3. MATERIAL AND METHODS

3.1 Description of the Study Area

3.1.1 Location

Bekoji is in the central part of Ethiopia in the Oromia Regional state. It is positioned with geographic coordinates between longitude 39° 13'00" E to 39° 17'00" E and latitude 7° 30'60'N to 7° 33'60" N. The average distance from the capital city of Addis Ababa is 223km to the south and 56km from Asella, the capital town of the Arsi zone.

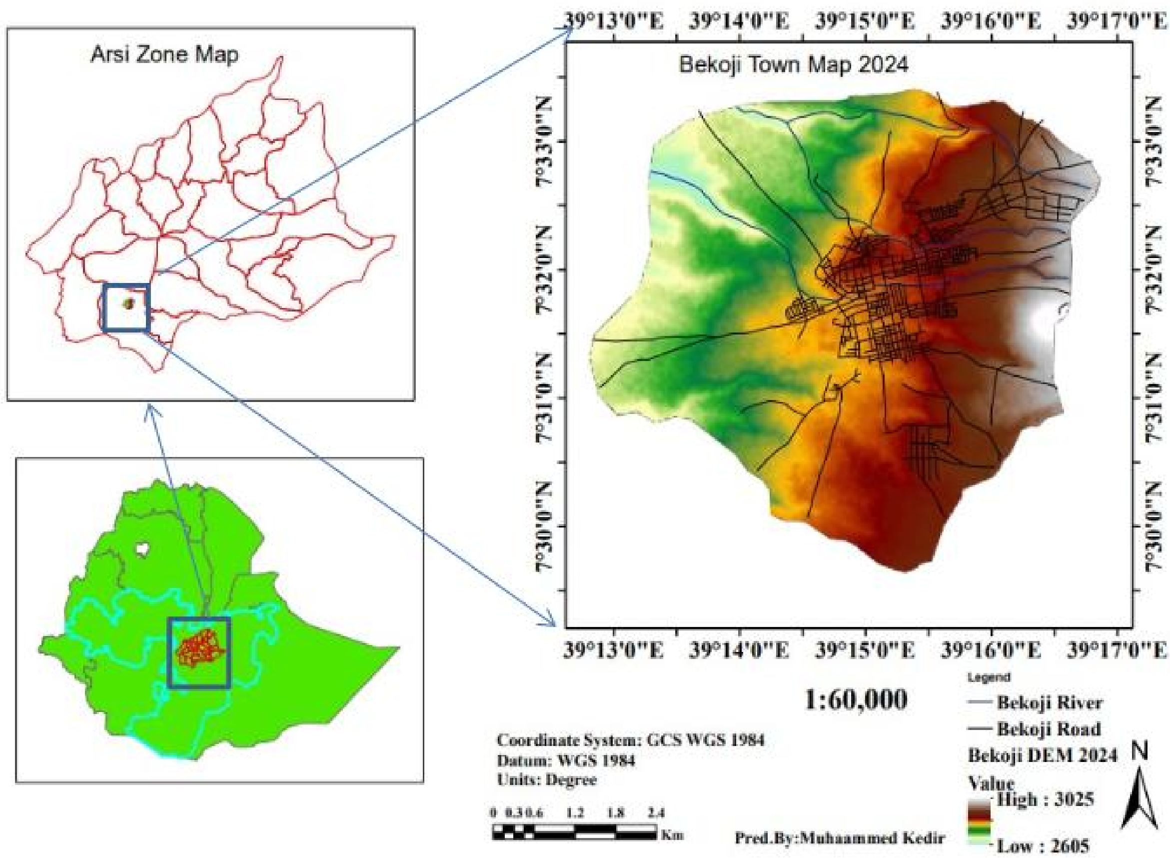


Figure 3.1 Study area Map of Bekoji Town

3.1.2 Climate Condition of Bekoji Town

Bekoji location experiences a moderate climate with noticeable seasonal variations throughout the year. January begins with mild daytime temperatures averaging 21.2°C and cool nights around 6.3°C. Rainfall is minimal at just 10 mm, and sunshine is relatively abundant with nearly 12 hours per day. As the months progress into February and March, temperatures gradually rise, with highs reaching 25°C in March and lows climbing to 9.3°C. Rainfall also starts to increase, reaching 50 mm in March, and sunshine decreases slightly to 10.5 hours per day. April through June marks a transition into the wetter season. Rainfall intensifies significantly from 90 mm in May to 180 mm in June, while temperatures begin to decline slightly. June experiences average highs of 19.5°C and lows of 10.4°C. Humidity also rises sharply, reaching 73% in June. The peak of the rainy season occurs in July, August, and September. Rainfall peaks at 290 mm in September, and humidity remains high, fluctuating between 77% and 79%. Despite this, temperatures are relatively cool, with August averaging highs of 17.2°C and lows of 10.3°C. Sunshine hours are at their lowest, dipping to just over 6 hours per day in July and August. By October, the region begins to dry out with rainfall dropping to 70 mm, and temperatures start to rise again. November and December mark a return to drier and sunnier conditions, with rainfall reducing to just 10 mm in December. The year ends with average highs around 21.3°C and lows near 6.7°C, like January. Overall, this climate features a distinct wet season from May to September, cooler temperatures during the rainy months, and a dry season with more sunshine and milder conditions from October to April.

Table 3.1 Climate Condation of Bekoji town.

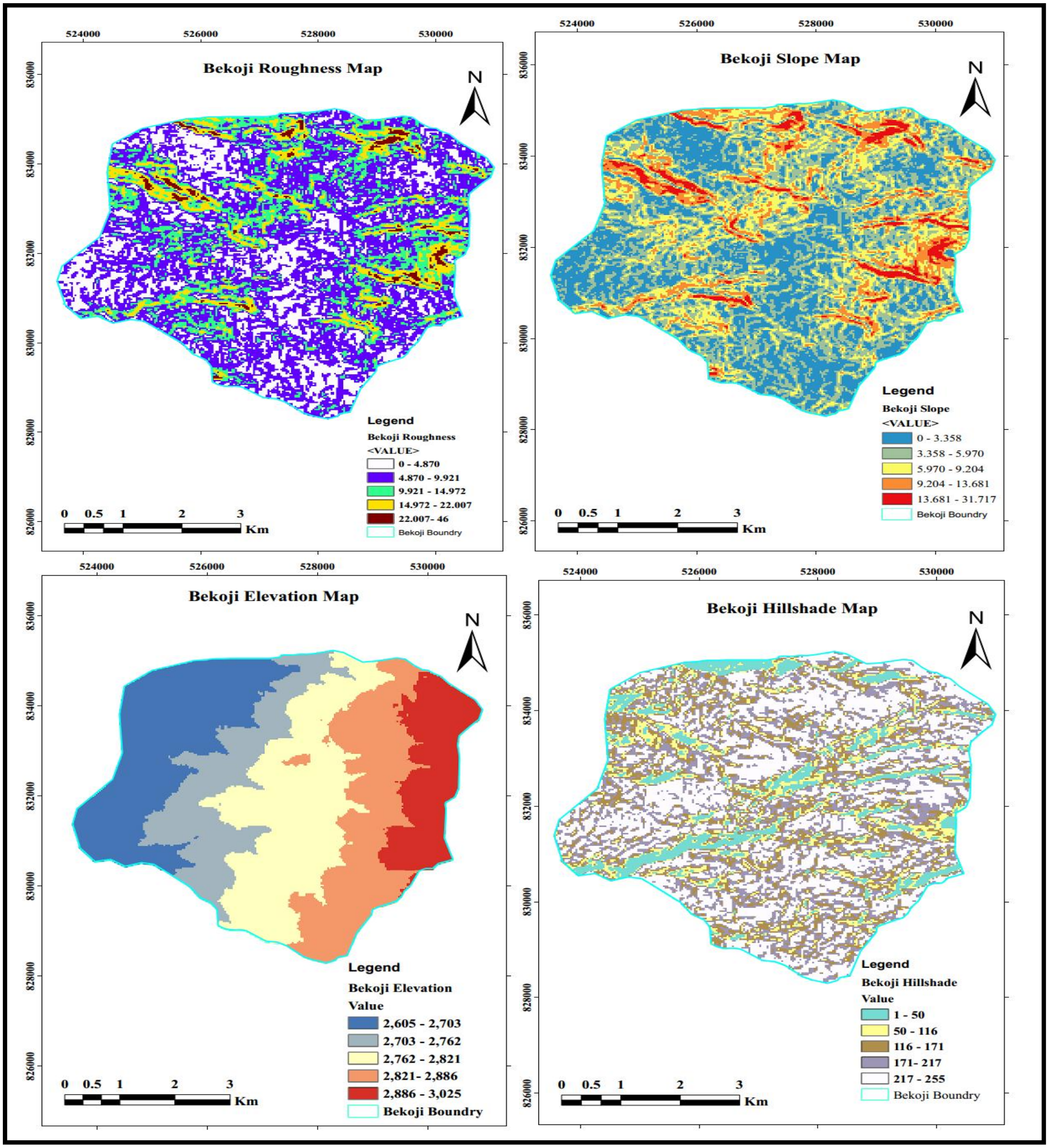
Climate Parameter	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Avg. High Temp (°C)	21.2	22.4	25	24.2	22.8	19.5	16.1	17.2	19.7	21.4	22.2	21.3
Avg. Low Temp (°C)	6.3	7.1	9.3	12.7	11.1	10.4	10.1	10.3	9.8	8.9	7.5	6.7
Rainfall (mm)	10	15	50	90	130	180	220	250	160	70	20	10
Humidity (%)	52	53	50	58	64	73	79	77	70	65	60	55
Sunshine (hrs/day)	11.9	11.5	10.5	9.2	8.6	7.5	6.1	6.3	7.2	8.8	10.2	11.9

Source: "CLIMWAT Climatic database"Food and Agriculture Organization of United Nations. Retrieved 21 June 2024.

3.1.3 Population

They have 110,000 population 61,000 female and 59,000 mean (Ethiopia Statistical Agency 2021). Based on figures from the Central Statistical Agency in 2005, this town has an estimated total population of 16,730, of whom 7,999 are men and 8,731 are women. The 1994 national census reported this town had a total population of 9,367, of whom 4,338 were men and 5,029 were women.

3.1.4 Topographic of Bekoji Town



3.2 Roughness,Slope,Elevation and hillshade map of Bekoji twon.

Bekoji elevation map as indicate in Figure; between 2605m and 3025m above mean sea level. This elevation map in below figure indicate uses a color band to indicate height above sea level, from (lowest, 2,065–2,703 m) to (highest, 2,886–3,025 m). It helps in understanding the vertical dimension of the landscape, which is vital for hydrology, climate zoning, and ecological studiesBekoji roughness map illustrates terrain roughness. Areas (value < 4.870) represent smoother terrains, while areas (value > 12.007) are the roughest. Bekoji Slope map categorizes land based on gradient steepness. The areas (0.0–3.585 degrees) indicate flat or gently sloped terrain, ideal for agriculture and infrastructure. The areas (13.681–31.717 degrees) signify steep slopes, which may be susceptible to landslides or soil degradation if not managed properly. Bekoji hill shade map enhances terrain visualization by simulating light and shadow based on topography. Lighter areas represent ridges and slopes facing the light source, while darker areas indicate valleys or shaded slopes. This map is particularly useful for visual interpretation of landforms and supports the analysis provided by slope and elevation data.

3.2 Research Design

This study adopted a quantitative research design, combining geospatial technologies with statistical techniques. The approach includes remote sensing for land use/land cover (LULC) classification, land surface temperature (LST) estimation, and NDVI, and NDBI analysis. Field surveys are integrated to validate remote sensing data and enhance analytical accuracy. Land use and land cover (LULC) categories were the primary units of analysis, with parcels differentiated based on specific classifications such as agricultural land, forests, urban areas, and water bodies. Satellite image pixels form the spatial data units used for studying LULC patterns and Land Surface Temperature (LST) relationships, providing a high-resolution basis for analysis. Points selected on the ground serve as benchmarks for verifying and validating remote sensing classifications, ensuring data accuracy and consistency. Stratified Random Sampling: To ensure comprehensive coverage, the study area is stratified into distinct LULC classes using remote sensing imagery. Random samples are then drawn from each stratum, allowing for a proportional representation of all LULC types and reducing bias. Ground verification points are selected systematically, ensuring consistent spatial coverage across various terrain types and LULC categories. This method guarantees thorough validation of remote sensing classifications. Remote Sensing Data: For LULC and LST analysis, the total pixels within the study area are sampled. This sample size strikes a balance between computational efficiency and representativeness. Ground Truthing Data: ground verification points are identified based on the spatial distribution of LULC categories and their accessibility. Ground Validation Points; Minimum of 25 points per LULC category and 250 total validation points.

3.3 Data Source

Primary data refers to firsthand information collected directly from the field: Ground truth data is gathered through meticulous field surveys using GPS devices. This data plays a critical role in understanding real-world conditions and ensures accuracy in analyses. Validation data is crucial for verifying classifications like Land Use Land Cover (LULC) and Land Surface Temperature (LST), making sure the results align with ground reality.

Secondary data encompasses pre-existing datasets that complement primary data: High-resolution satellite imagery such as Landsat, Sentinel-2, and MODIS is instrumental in mapping and environmental analysis- economic data from Population Data is gathered from: The Municipality of Bekoji, which provides localized statistics, and The Ethiopian Statistical Agency, which offers broader socio-economic datasets. Socio-economic datasets provide context, enabling a more comprehensive understanding of LULC and LST interactions (Foody, 2002). The integration of ground truth data with satellite imagery ensures the reliability and applicability of the findings for environmental management and planning. Fined by the Bekoji Town Municipality, providing accurate delineations for spatial analysis.

3.3.1 Land Use Land Cover Data

LULC data derived from remote sensing platforms like Landsat, Sentinel-2, and MODIS have been widely employed in environmental studies. Organizations such as the United States Geological Survey (USGS) and ESA provide access to pre-processed LULC datasets that aid in categorizing land into different classes, including agricultural, urban, and forested areas. These classifications are crucial for understanding land use patterns and their impacts on ecological and socio-economic systems. The Copernicus Land Monitoring Service further enhances LULC analysis by providing detailed European datasets, which serve as benchmarks for global comparisons (European Commission, 2018).

3.3.2 Land Surface Temperature Data

LST estimation relies on thermal infrared sensors, such as those aboard MODIS and Landsat 8. These sensors measure surface radiance, which is then converted into temperature values using established algorithms (Sobrino et al., 2004). NASA's Earth Observing System and the Copernicus program provide reliable LST data, which can be supplemented with ground-based temperature monitoring networks for validation. Accurate LST data is critical for investigating phenomena such as urban heat islands and the effects of climate change on local and regional scales (Weng, 2009).

3.3.3 Normalized Difference Vegetation Index (NDVI)

NDVI is a widely used indicator derived from satellite imagery to assess vegetation health and density. Calculated using the near-infrared and red bands, NDVI values range from -1 to +1, with higher values indicating healthier vegetation. Platforms like Landsat, Sentinel-2, and MODIS provide robust NDVI data, which is instrumental in monitoring seasonal vegetation changes and assessing the impacts of LULC changes on ecological systems (Rouse et al., 1974). Data platforms such as Google Earth Engine have simplified obtaining and analyzing NDVI data.

3.3.4 Topographic Data

Digital Elevation Models (DEMs) are essential for understanding the topographic characteristics of a region, such as elevation, slope, and terrain shape. DEMs derived from the Advanced Space Borne Thermal Emission and Reflection Radiometer (ASTER) and the Copernicus program provide high-resolution elevation data. These models are critical for analyzing the influence of topography on LULC and LST dynamics (Gesch, 2007).

3.3.5 Ground Truth Data

Field surveys and ground truth data collection are indispensable for validating satellite-derived LULC classifications. Ground data, including vegetation types, land use practices, and surface temperatures, enhance the accuracy of remote sensing analyses. Supplementary data from climate records, topographic maps, and socio-economic datasets provide context, enabling a more comprehensive understanding of LULC and LST interactions (Foody, 2002). The integration of ground truth data with satellite imagery ensures the reliability and applicability of the findings for environmental management and planning. Fined by the Bekoji Town Municipality, providing accurate delineations for spatial analysis.

3.4 Data Collection

High-resolution satellite imagery has become an essential tool for assessing LULC and LST. Landsat 8, with its Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS), offers a 30-meter spatial resolution for multispectral data and a 100-meter resolution for thermal data, making it suitable for detailed LULC classification and LST estimation. Similarly, Sentinel-2, operated by the European Space Agency (ESA), provides high spatial resolution (10 meters for visible and near-infrared bands) and a rapid revisit time, facilitating the detection of temporal changes in land use patterns. MODIS, aboard NASA's Terra and Aqua satellites, complements these datasets with its daily global coverage, providing critical time-series data for long-term studies (Justice et al., 2002).

Table 3.2 Data Source

Data types	Source	Definition
Landsat image	USGS	For LU/LC, LST, NDVI Analysis
Structural plan	Bekoji town Land Administration office	To generate a road and river
Administrative Boundary	Bekoji town Municipality	To subset/extract the area of the study
GPS data	Field survey	Ground verification
Temperature Data	National metrology	For validation purposes

3.5 Software used

GPS devices for accurate location data collection. High-performance computers for processing large geospatial datasets and running analytical software. ArcGIS 10.8: Used for proximity analysis, reclassification, and NDVI (Normalized Difference Vegetation Index) mapping.

QGIS 3.30: Applied for LULC classification and LST mapping, providing open-source support for geospatial analyses. ERDAS: Specialized in advanced satellite image processing and correction. Google Earth Pro: Utilized for visual interpretation and cross-validation of spatial features.

Table 1.3 Software used

Software	Application
ArcGIS 10.8	Proximity analysis, reclassification, NDVI mapping
QGIS 3.40	Image classification, LULC mapping, LST mapping
ERDAS	Processing satellite imagery.
Google earth pro	Used as a base map in visual image interpretation and for the ground truthing and validation of suitability Map

3.6 Methodology

The study utilizes Landsat images of Bekoji Town from four different time periods: TM 1994, ETM+ 2004, 2014 and OLI/TIRS 2024. The objective is to analyze changes in Land Use/Land Cover (LU/LC) and Land Surface Temperature (LST) over time. Image Prepossessing: All Landsat images undergo image prepossessing to ensure consistency and usability for further analysis. The prepossessing is followed by different processing paths depending on the data type: thermal infrared band, band rationing, and multi-spectral bands. Thermal Infrared Band Analysis:Using Band 8 and Band 10, the thermal infrared data is converted through the following steps:Conversion to Top of Atmosphere Radiance.Conversion to Top of Brightness Temperature.Calculation of Land Surface Impassivity.These steps culminate in the generation of LST maps for the years 1994, 2004, and 2024. Band Rationing: This step involves computing important vegetation and built-up indices:NDVI (Normalized Difference Vegetation Index) and NDBI (Normalized Difference Built-up Index):These indices are later used to determine the correlation between LST and LU/LC indices, forming a basis for statistical analysis and ultimately leading to a comparison of LST and LU/LC conversions. Multi-spectral Band Analysis: This section focuses on image classification using multi-spectral data:Supervised classification is performed with the maximum likelihood method.Accuracy assessment is conducted using Google Earth for validation.The classified data leads to the creation of LU/LC maps for 1994, 2004,2014 and 2024.Change Detection and Analysis:With LU/LC maps from the three time periods, a change analysis is carried out:LU/LC conversion from 1994 to 2004 and LU/LC conversion from 2004 to 2024. These results are integrated with the LST analysis and statistical correlation, enabling a comprehensive comparison of LST and LU/LC conversions over the 30-year period.This systematic approach offers a holistic view of environmental and urban transformations in Bekoji Town. The integration of LST and LU/LC analyses over multiple decades helps assess the impacts of land use changes on surface temperature, informing better urban planning and climate resilience strategies.

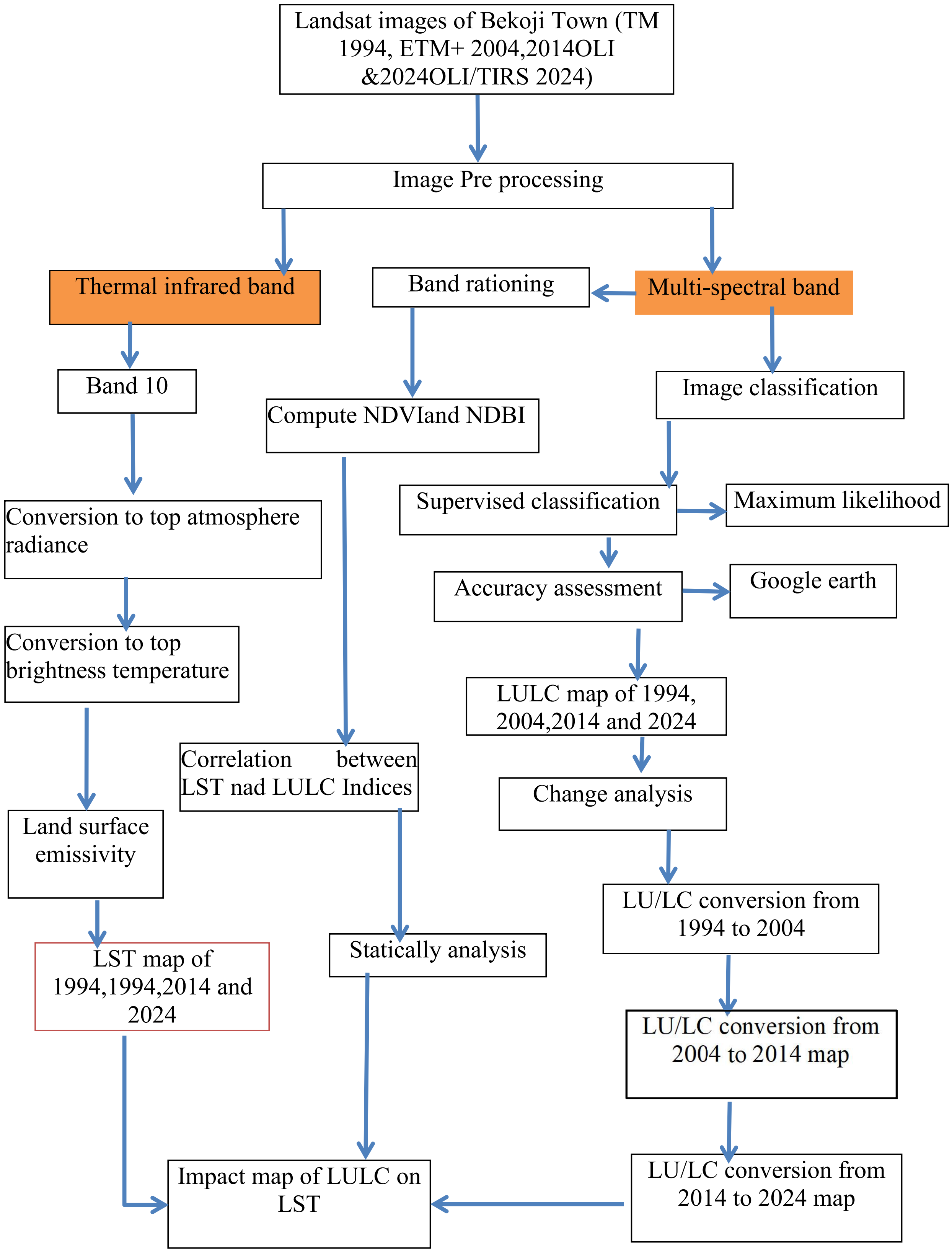


Figure 3.3 Methodological Frame work

3.7 Data Preprocessing, Classification LULC, and LST Estimation Techniques

Perform radiometric and atmospheric corrections on satellite imagery to minimize distortions and enhance accuracy. Process Digital Elevation Model (DEM) data to analyze slope and elevation characteristics, ensuring terrain-related variables are adequately addressed.

3.7.1 Supervised Classification for LULC

Image classification is a fundamental technique for land cover mapping. In the context of LULC analysis, supervised classification methods, such as Maximum Likelihood Classification (MLC), have been widely used due to their high accuracy in categorizing land cover types. MLC involves the statistical analysis of training datasets to classify pixels into specific land use categories such as vegetation, agricultural land, grasslands, settlements, and bare land. Previous studies have confirmed that supervised classification methods provide reliable LULC maps, with MLC being particularly effective in differentiating complex land cover types (Lillesand et al., 2015). The LULC was classified using a supervised classification method with the maximum likelihood algorithm. The LULC of the study area was classified into agricultural land, vegetation, grassland, settlement, and bare land.

3.7.2 Accuracy assessment

The accuracy of classification results is crucial for ensuring the reliability of the land cover maps. Accuracy assessment is typically performed using a confusion matrix, which compares classified results with ground-truth data. The matrix generates user and producer accuracy metrics, allowing researchers to assess the effectiveness of their classification techniques. The overall accuracy and Kappa statistics (Khat) are commonly calculated to quantify the agreement between the classified image and the ground truth (Congalton & Green, 2009). The user accuracy is calculated as the total number of correctly classified pixels that belong to a class divided by the sum of the values of the rows of the same class (Eq. 3). Consequently, the producer accuracy is calculated as the total number of correctly classified pixels that belong to a class divided by the sum of the values of the column of the same class (Disparate and Virdis 2015) (Eq. 4). The overall accuracy is calculated as given as follows:

$$Overall\ accourcy = \frac{sum\ of\ the\ diagonal\ elements}{total\ number\ of\ accuracy\ site(pixels)} * 100 \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

$$Khat = \frac{Obs - exp}{1 - exp} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(2)$$

$$UAC = \frac{Xii}{X_{+i}} * 100 \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.(3)$$

$$PAC = \frac{Xii}{X_{i+}} * 100 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(4)$$

3.7.3 Land Use Land Cover Categories

Built-up areas represent regions dominated by human-made structures such as buildings, roads, and other infrastructure. These surfaces typically have low albedo, high thermal mass, and limited evapotranspiration, leading to elevated LST. Analyzing built-up expansion is essential for understanding urban heat island (UHI) effects and the thermal footprint of urbanization in Bekoji town.Agricultural land includes croplands and areas under cultivation. These zones experience seasonal land cover changes and varying evapotranspiration rates, influencing local temperature dynamics. Monitoring changes in agricultural land helps assess the trade-offs between food production, land conversion, and thermal regulation capacity.Vegetated areas, especially forests and woodlands, play a crucial role in moderating LST through shading and high evapotranspiration. They generally exhibit the lowest surface temperatures among LULC classes. Including this class helps highlight the cooling benefits of natural vegetation and the thermal consequences of deforestation or degradation.Grasslands consist of open areas with herbaceous vegetation and are common in semi-urban or peri-urban landscapes like Bekoji. While they offer moderate evapotranspiration, their LST is higher than dense forests but lower than built-up or bareland areas. Tracking grassland helps in understanding transitional land use zones and their role in thermal regulation. Bareland refers to areas with minimal or no vegetation cover, including exposed soil, rock, or sand. These areas absorb more solar radiation and have little to no evapotranspiration, resulting in high LST values. Including bareland is critical to understanding the thermal behavior of degraded or undeveloped lands and identifying areas vulnerable to land degradation.Including these five LULC categories allows for a comprehensive assessment of how different land cover types influence LST. Each class represents distinct physical and biophysical properties that affect heat absorption, storage, and radiation, making them essential for evaluating land-climate interactions in Bekoji town.

3.7.4 LULC change detection

The magnitudes of change were determined by the amount of changed area, the extent of change, and the rate of change. The rate of change was calculated to demonstrate the magnitude of the changes between a given period (Eq. 5)

$$Rate\ of\ Change\left(\frac{Km^2}{Year}\right) = \frac{A2 - A1}{Z} \quad \text{......................................}(5)$$

3.7.5 LST Estimation Technique

Estimating LST from remote sensing data is essential for understanding temperature variations across different land cover types. Several algorithms, including the split-window technique and single-channel methods, are used to retrieve LST from thermal infrared bands. The split-window technique, which utilizes two thermal bands (usually from Landsat's thermal infrared sensor), has been widely applied due to its ability to mitigate atmospheric effects on thermal radiance (Sobrino et al., 2004).

3.7.5.1 Conversion of digital numbers to the top of atmosphere (TOA) spectral radiance

The process of converting digital numbers (DN) from satellite data into usable radiance values is essential for accurate LST estimation. This conversion requires specific algorithms depending on the satellite sensor being used. For Landsat 8, the conversion involves using multiplicative rescaling factors to transform DN values into top-of-atmosphere (TOA) radiance (Chavez, 1996).

To calculate, the LST (Eq. 6) is the first process that must be followed for Landsat 8 Thermal Infrared Sensor TIRS to convert DN to radiance.

$$L\lambda = (ML * QCal) + AI \text{...}(6)$$

Where Lλ is the top of atmosphere (TOA) spectral radiance ($Wm^{-2}\ sr^{-1}\ \mu m^{-1}$). ML is the band-specific multiplicative rescaling factor from the metadata. AL is the band-specific additive rescaling factor from the metadata. Q Cal is the quantized and calibrated standard product pixel values (DN). For converting Digital Number (DN) to radiance (Eqs. 7, 8) for Landsat 5TM and Landsat 7 ETM+, the gain and bias method was used.

$$L\lambda = gain * Qcal + bias \quad \text{...}(7)$$

$$L\lambda = \frac{LMAX\lambda - \mathrm{LMIN}\lambda}{QCALMAX - QCALMIN} * (DN - QCALMIN) + LMIN\lambda \quad \text{................}(8)$$

pixel value in Digital Number (DN). LMIN λ is the spectral radiance that is scaled to QCALMIN in watts/ (meter squared*ster* μm). LMAXλ=is the spectral radiance that is scaled to QCALMAX in watts/ (meter squared*ster* μm). QCALMIN is the minimum quantized calibrated pixel value corresponding to LMINλ in DN. QCALMAX is the maximum quantized calibrated pixel value corresponding to LMAXλ in DN=255.

3.7.5.2 Conversion of radiance to brightness temperature

After the DNs are converted to radiance, the thermal band's spectral radiance should be converted to brightness temperature

$$BT = \frac{K2}{\ln\left(\frac{ki}{Li} + 1\right)} = 273.15 \quad \text{………………………………………… (9}$$

(Eq. 9). This is usually accomplished using thermal constants delivered in the metadata, where BT is the effective at-sensor brightness temperature (K); K2 is the calibration constant 2. K1 is the calibration constant 1. Lλ is spectral radiance at the sensor's aperture (W/ (m2*sr* μm)), and Ln is the natural logarithm. Land surface emissivity estimation using NDVI. The NDVI will be used to categorize the distributions of vegetation covers and their greenness as well. Consequently, it also explores the transformation of NDVI into values associated with the cover portion using an empirical relationship. Land surface emissivity estimation using NDVI. The NDVI was used to categorize the distributions of vegetation covers and their greenness as well. Consequently, it also explores the transformation of NDVI into values associated with the cover portion using empirical relationships

3.7.5.3 Land surface emissivity estimation using NDV

Land surface emissivity (LSE) is another critical factor in LST estimation, as it affects the accuracy of temperature readings. LSE is influenced by the amount and type of vegetation present, and it is often estimated using the Normalized Difference Vegetation Index (NDVI). NDVI is a widely used vegetation index that distinguishes between vegetated and non-vegetated surfaces by measuring the difference between the near-infrared and red bands (Tucker, 1979).

The NDVI will be used to categorize the distributions of vegetation covers and their greenness as well. Consequently, it also explores the transformation of NDVI into values associated with the cover portion using empirical relationships with vegetation indices, as a basis function.

The calculation of the NDVI is important because, subsequently, the proportion of the vegetation (PV) must be calculated, which is closely correlated to the NDVI (Eq. 10). In addition, emissivity (ε) should be calculated, which is related to the PV.

$$NDVI = \frac{NIR - R}{NIR + R} \text{ ....} 10$$

Where NDVI is the Normalized Difference Vegetation Index, NIR is the near-infrared band, and R is the red band. Landsat 8 data used Bands 5 (Infrared) and 4 (red), whereas Landsat 5 and 7 used Bands 4 and 3, to calculate the NDVI values. From the NDVI values acquired, the next step in obtaining Land Surface Emissivity (LSE), namely the calculation of the proportion of vegetation (Pv), will be achieved.

3.7.5.4 Calculating the proportion of vegetation

The proportion of vegetation (Pv) is calculated according to Eq. 11:

$$PV = \left[\frac{NDVI - NDVImin}{NDVImax - NDVI\ min}\right]2 \quad \text{.................................} 11$$

3.7.5.5 Land surface emissivity (LSE) assessment

Land surface emissivity (ε) is significant to estimate LST because states that, the proportionality factor to predict emitted radiance represents the efficiency of transmitting thermal energy across the surface into the atmosphere represented by land surface emissivity. The emissivity is calculated using Eq. 12:

$$\varepsilon = 0.004 * PV + 0.986 \text{ ....} 12$$

The calculated radiant surface temperatures will be corrected for emissivity using Eq. 13

$$LST = \frac{TB}{1 + \left(\lambda \frac{TB}{p}\right) In\varepsilon} - 273.15 \text{ ....} 13$$

Where LST is the land surface temperature (in Kelvin); and TB is the radiant surface temperature (in Kelvin). λ is the wavelength of emitted radiance (11.5 μm). ρ is h × c/σ (1.438 × 10−2 mK); h is the Planck's constant (6.26×10−34 J s); c is the velocity of light (2.998× 108 m/s); σ is Stefan Boltzmann's constant (1.38×10−23 J K−1); and ε is land surface emissivity.

3.8 Data Validity and Reliability

3.8.1 Validity

Validity reflects the extent to which the data and methods truly represent the phenomenon under investigation. Rigorous ground true-thing and field validation using systematic sampling techniques guarantee the authenticity of collected data. These methods ensure that the classifications and interpretations align closely with real-world conditions. The application of established indices, such as NDVI (Normalized Difference Vegetation Index) for vegetation analysis, NDBI (Normalized Difference Built-up Index) for urban area identification, and NDBAI (Normalized Difference Bare Land Index) for detecting bare land mapping, enhances the validity of Land Use Land Cover (LULC) classifications. These indices provide scientifically robust metrics for accurate representation of landscape features.

3.8.2 Reliability

Reliability ensures that the results are consistent and reproducible, regardless of variations in data or tools: Utilizing multiple data sources such as Landsat, Sentinel-2, and MODIS provides a comprehensive data set, reducing the chance of bias or data gaps. Employing advanced software tools like Arc-GS and QGIS ensures precise analysis through proven methodologies and robust algorithms. Reliability is further reinforced through accuracy assessments, including The confusion matrix, which evaluates the agreement between predicted and actual classifications, and Kappa statistics, which measure the consistency and reliability of classification results. By combining systematic validation techniques with the integration of diverse data sources and advanced tools, the study ensures both validity and reliability, producing accurate results.

3.9 Method of Data Analysis

Using data analysis tools, the remotely sensed data was collected from Satellite data from platforms such as Landsat, provided by organizations like NASA and USGS, which offer valuable information for monitoring land surface changes and estimating temperature variations. These datasets, accessible through GIS software, enable researchers to analyze spatial and temporal variations in land use and temperature. Several satellite platforms, including Landsat 5, 7, and 8, offer thermal infrared bands crucial for estimating LST. These datasets, when validated against ground station data, ensure the accuracy of remote sensing applications (Sobrino et al., 2004).

Statistical analysis used regression and correlation analyses to assess the relationships between LULC types and LST, helping to quantify the impact of land cover changes on temperature. Regression models, to correlate NDVI values with climatic variables, land use changes, and agricultural productivity. To quantify the relationship between LULC types and LST, statistical methods such as regression and correlation analysis are often employed. These methods enable researchers to assess the extent to which land cover changes affect surface temperatures. For example, studies have shown significant correlations between vegetation cover (as measured by NDVI) and LST, where areas with higher vegetation cover tend to have lower temperatures due to the cooling effect of plants (Kloog et al., 2012). Additionally, regression models can be used to examine the relationship between climatic variables, land use changes, and agricultural productivity, providing insights into the broader impacts of LULCC on local climates. Descriptive statistics: generate frequency distributions, percentages, and summary tables to describe LULC classes comprehensively. Produce visual maps that highlight spatial patterns of LULC and LST. Inferential Statistics: Perform regression analysis to evaluate the relationship between LULC changes and LST variations. Use ANOVA to test statistically significant differences in LST across various LULC classes. Geospatial Analysis: Conduct NDVI, and NDBI analysis to assess vegetation health and changes over time. Perform time-series analysis to monitor and quantify LULC and LST dynamics, providing insights into long-term trends.

3.10 Ethical consideration

This study considered ethical Geo-informatics often deals with sensitive data, such as satellite imagery, location data, and personal geographic information. Ethical practices require strict adherence to privacy laws like GDPR (General Data Protection Regulation). Developing tools and solutions that prioritize environmental sustainability. Avoid actions that might harm ecosystems or contribute to environmental degradation. Providing truthful, evidence-based evaluations of projects, especially those with significant ecological impacts. Presenting Geo-spatial data and findings truthfully without manipulation to serve political, commercial, or ideological agendas. Designing spatial algorithms and systems that are fair and do not perpetuate biases against certain regions, communities, or groups. Avoiding Plagiarism, and maintaining academic integrity in publications, thesis, or project submissions. Using Geo-spatial technology to benefit society, such as in disaster prediction, mitigation, and recovery. Prioritizing projects that address global challenges like climate change, urbanization, or resource management. Engaging stakeholders honestly and ensuring their informed consent in projects involving their data or resource.

CHAPTER FOUR

4. RESULTS AND DISCUSSION

4.1. Temporal changes in LULC of Bekoji town

In this research, below the figure (4.1) as indicate Built up highly increasing from 9.4% in 1994 to 22.5% in 2024 and vegetation decrease from 36.4% in 1994 to 18.8 % in 2024.

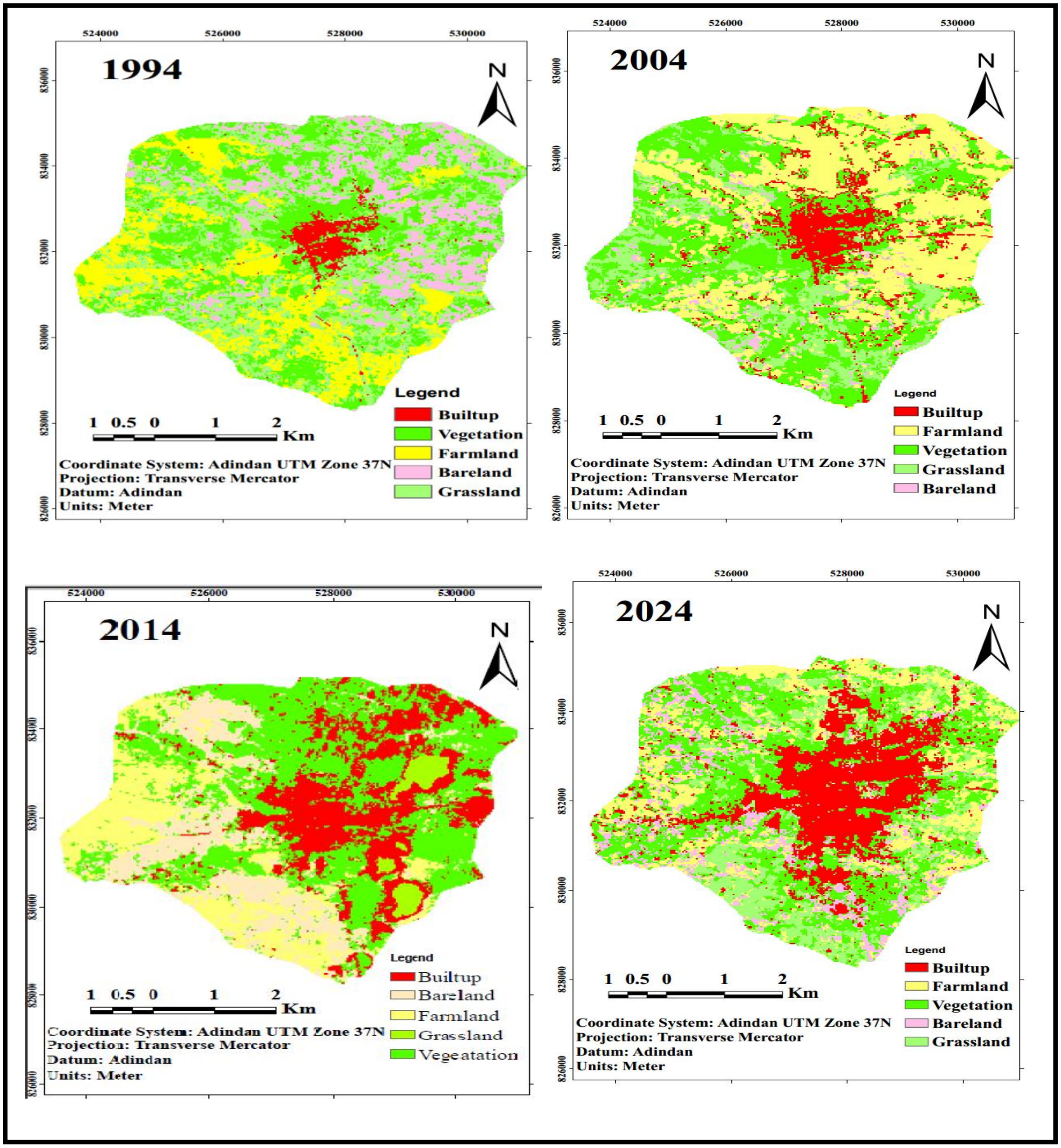


Figure 4.1 LULC map of Bekoji town 1994.2004,2014 and 2024

4.1.1 Accuracy assessment of classified LULC of Bekoji town

Analyzing land cover data obtained from remote sensing requires careful consideration of accuracy evaluation, which includes the use of Kappa coefficients, Overall Accuracy (OA), User's Accuracy (UA), and Producer's Accuracy (PA). As far as the map maker is concerned, PA indicates accuracy, and users' perspectives of accuracy are represented by UA. A measure of accuracy in reference site mapping is called OA. Between categorized and reference data, kappa coefficients quantify the degree of agreement.

By using the following formulas, the evaluation of land use/land cover (LU/LC) accuracy for the years 1994, 2004,2014 and 2024 of Bekoji town showed overall classification accuracies of 90.01%, 89.00%, 90.00%,90.01% respectively. In subsequent years, the Kappa values were 0.8848 for 1994, 0.8857 for 2004,0.8861 for 2014 and 0.9000 for 2024. Overall Accuracy (OA): Measures the percentage of correctly classified pixels out of all pixels in the dataset.

The Kappa Coefficient Computes the predicted agreement using random chance while accounting for the distribution of pixels between classes. Whereas the Kappa coefficient, or K, has a value between 0 and 1, where 0 denotes no improvement over random chance and 1 denotes complete agreement. The total number of samples (N) in the confusion matrix, the number of observations in each cell (Xii), the total number of observations in each row (Xi+), and the total number of observations in each column (X+i-) are the factors used to compute K.

4.1.2 Analysis of Classified LULC of Bekoji Town

To analyze the Land Use and Land Cover (LULC) classification of Bekoji town for the years 1994, 2004, and 2024, based on the given categories (Built-up, Vegetation, Farmland, Grssland, and Bare Land), we would typically follow these steps. The technique used to classify LULC types from satellite data is supervised classification, which involves training the model using known LULC types (e.g., training areas for Built-up, Vegetation, Farmland, grassland, and Bare land). Analysis of the 1994, 2004, and 2024 Bekoji imagery reveals that Built and farmland were the predominantly changed LU/LC types in the study area. As revealed above Built up highly increasing from 9.4% in 1994 to 22.5% in 2024 and agriculture expansion from 36.4% in 1994 to 18.8 % in 2024.

Table 4.1 Magnitude of LULC change during 1994,2004,2014 and 2024

No	LULC types	1994		2004		2014		2024	
		Area(hect)	Area (%)	Area(Hect)	Area(%)	Area(hect)	Area(%)	Area(hect)	Area(%)
1	Built up	324.2	9.53	500	14.7	697	20.5	985.4	22.5
2	Farmland	1226	36.05	1039.745	30.58	1251.875	36.81	1134	34.1
3	Bareland	464.1	13.65	745.7	21.93	493.3	14.5	603.1	14.6
4	Vegetation	1253.3	36.86	1003.55	29.51	886.5	26.07	625.5	18.8
5	Grassland	132.4	3.9	111.005	3.26	71.325	2.09	52	1.9

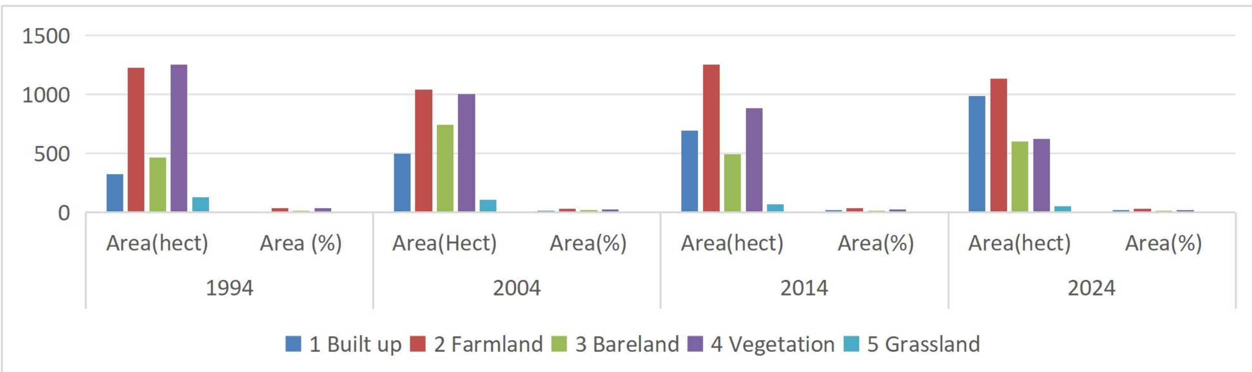
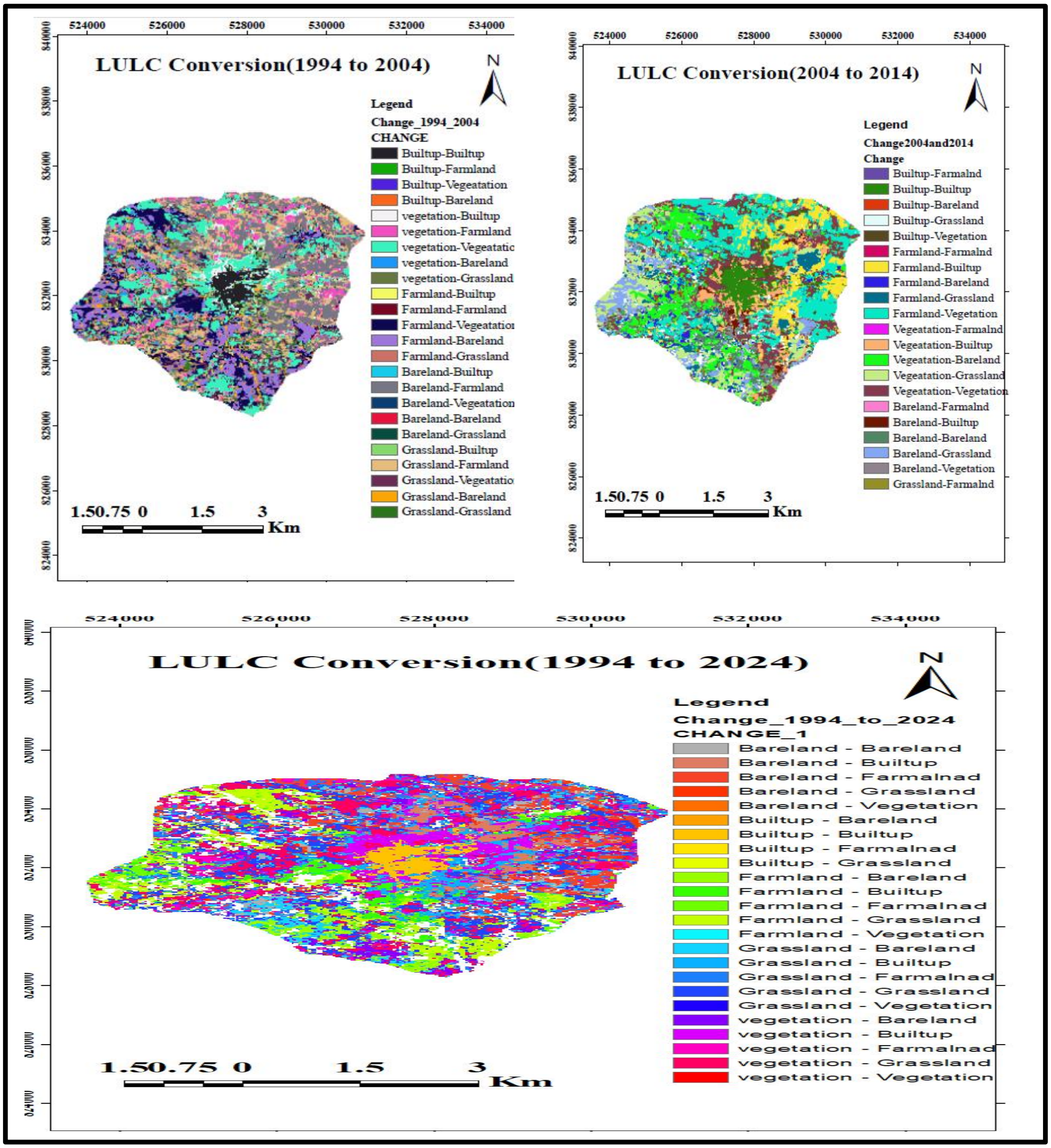


Figure 4.2 Magnitude of LULC change during 1994.2004,2014 and 2024

4.1.3 LULC change Detection analysis

Once the LULC maps for different years are generated, compare them to assess the changes in land cover of 1994, 2004,2014 and 2024. Post-classified change Detection involves a direct comparison of classified images to detect areas that have transitioned from one land use type to another of the following features: Built-up, vegetation, farmland, grassland, and bare land. Analysis of the 1994, 2004, and 2024 Bekoji imagery reveals that Built-up and vegetation were the predominantly changed LU/LC types in the study area. As revealed above Built up highly increasing from 9.4% in 1994 to 22.5% in 2024 and vegetation continuously decreasing from 36.4% in 1994 to 18.8 % in 2024. The assessment of LULC dynamics in Bekoji town over 30 years reveals substantial transformations primarily driven by urban expansion and changing land management practices. The data from the years 1994, 2004, and 2024 provide critical insights into the temporal and spatial alterations across five major land cover categories: built-up area, farmland, bare land, vegetation, and grassland. In 1994, the land cover was dominated by vegetation (36.4%) and farmland (35.7%), together comprising over 70% of the total land area. The extent of built-up land was relatively minor, occupying only 9.4%, indicating limited urban infrastructure at the time. Bare land and grassland accounted for 13.5% and 3.8%, respectively.By 2004, significant changes had occurred. The proportion of built-up areas increased to 14.5%, reflecting growing urban development. This expansion coincided with a decline in vegetation cover to 29.2% and a reduction in farmland to 31.1%. Notably, bare land expanded to 21.7%, suggesting increased land clearing and soil exposure associated with construction and agricultural pressures. In built-up land continued to grow, reaching 20.3%. Interestingly, farmland rebounded to 37.3%, possibly due to land reclamation or shifts in agricultural policy. Conversely, vegetation further declined to 25.8%, and bare land slightly decreased to 14.3%, hinting at a partial stabilization in exposed soil areas. Grassland continued its downward trend, shrinking to 2.0%. The most recent data from 2024 confirms ongoing urbanization, with built-up areas comprising 22.5% of the total land area. Farmland decreased again to 34.1%, and vegetation experienced a sharp decline to 18.8%, highlighting significant ecological degradation. Grassland reached its lowest point at 1.9%, nearly vanishing from the landscape. Bare land maintained a relatively stable share of 14.6%, indicating sustained anthropogenic pressure on land resources. From 1994 to 2024 is characterized by a marked increase in built-up land and a corresponding decrease in vegetative and grassland areas. These findings underscore the urgency for integrated land use planning and sustainable development strategies to mitigate environmental degradation and ensure balanced urban growth in Bekoji town. A detailed LULC analysis of Bekoji town would provide insights into how the town has evolved and how these changes are impacting the environment, economy, and community. Satellite imagery and GIS tools, combined with ground-truthing data, are essential for performing such an analysis. The findings would inform better planning for sustainable development, land conservation, and climate resilience. Because of their cost-effectiveness and high temporal resolution GIS-based change detection methods are frequently employed. Multi-temporal datasets can be used from different dates to discriminate against each other and detect the changes. To find areas of change, the post-classification comparison technique includes classifying images and comparing the relevant classes. The post-classification comparison approach obtained the greatest classification accuracy in a comparative analysis of diverse techniques. The post-classification comparison was conducted by converting the classified raster images into vector layers. The changes in LULC were calculated for each land cover type and represented in separate images in this investigation for better understanding. The result of LULC change detection analysis revealed that no changes in LULC and transitioned from one land use land cover type to another. Analysis of change detection shows that from 1994 to 2024 Bekoji imagery Built, farmland and vegetation were the mostly altered LULC types in the study area. Analyzing land use and land cover (LULC) changes in Bekoji Town, Ethiopia, involves examining shifts in categories such as farmland, grassland, bare land, built-up areas, and vegetation. While specific data for Bekoji is limited, insights from nearby regions offer valuable perspectives.

Built-up areas urban expansion has been a significant driver of land cover change and built-up areas grew notably, often at the expense of croplands and grasslands, driven by population growth and infrastructure development. Vegetation natural vegetation has generally declined due to agricultural and urban development.In western Ethiopia, areas covered by woody savannas and mixed forests expanded by approximately 119.7% and 21.3%, respectively, between 2001 and 2020. This suggests a complex interplay of factors affecting vegetation dynamics, including land management practices and climatic conditions. Agricultural Expansion Farmland expansion has led to the conversion of natural vegetation and wetlands into croplands. For instance, between 2001 and 2020, croplands in western Ethiopia decreased by about 90.1%, indicating significant agricultural development and land use change. Water Bodies Some regions have experienced an increase in water bodies due to changes in land use and climate factors(Abate, A., & Tadesse, T. (2023).. In the Bilate catchment area, water bodies expanded from 0.16% to 0.35% between 1986 and 2018, highlighting variations in hydrological features and the impact of land use changes on water resources(Haile, G. G., Tang, Q., Leng, G., Kebede, A., & Mechal, T. (2021). IWA Publishing Bare Land The transformation of forests and shrublands into bare lands has been observed in various Ethiopian highlands. Between 1979 and 2017, bare land in the Huluka watershed increased by 41.9%, primarily due to deforestation and unsustainable agricultural practices. These patterns underscore the dynamic nature of land use and land cover changes in Ethiopia, influenced by factors such as population growth, agricultural expansion, and urban development. To obtain precise data on Bekoji Town, conducting localized remote sensing analyses and field surveys would be essential. These patterns underscore the dynamic nature of land use and land cover changes in Ethiopia, influenced by factors such as population growth, agricultural expansion, and urban development(Fenta, A. A., Yasuda, H., & Haregeweyn, N. (2021). To obtain precise data on Bekoji Town, conducting localized remote sensing analyses and field surveys would be essential.



4.3 LULC conversion 1994 up to 2024

4.1.4 The spatial Temporal distribution of NDVI and NDBI

4.1.4.1 The spatial Temporal distribution of NDVI

NDVI is a popular remote sensing index used to monitor vegetation health, cover, and changes over time. It's calculated using the reflectance values in the red and near-infrared bands of satellite or aerial imagery. NDVI is widely used in agriculture, environmental monitoring, and land use studies. NDVI= NIR+RED/NIR−RED (Where: NIR = Near-Infrared reflectance value RED = Red reflectance value). NDVI Value Range: +1 to 0: Healthy, dense vegetation (higher values indicate healthier vegetation) 0 to -0.1:Bare land, rocks, or urban areas-0.2 to -1. As a results indicate NDVI of Bekoji town: in 1994 the average NDVI was 0.32, indicating relatively healthy vegetation cover.2004: A decline to 0.26 suggests a reduction in vegetation health, possibly due to factors like urban expansion or agricultural intensification.2014: A slight increase to 0.27 may indicate some recovery or stabilization in vegetation cover.2024: A further decrease to 0.24 points to continued vegetation stress, which could be attributed to ongoing land use changes or climatic factors.

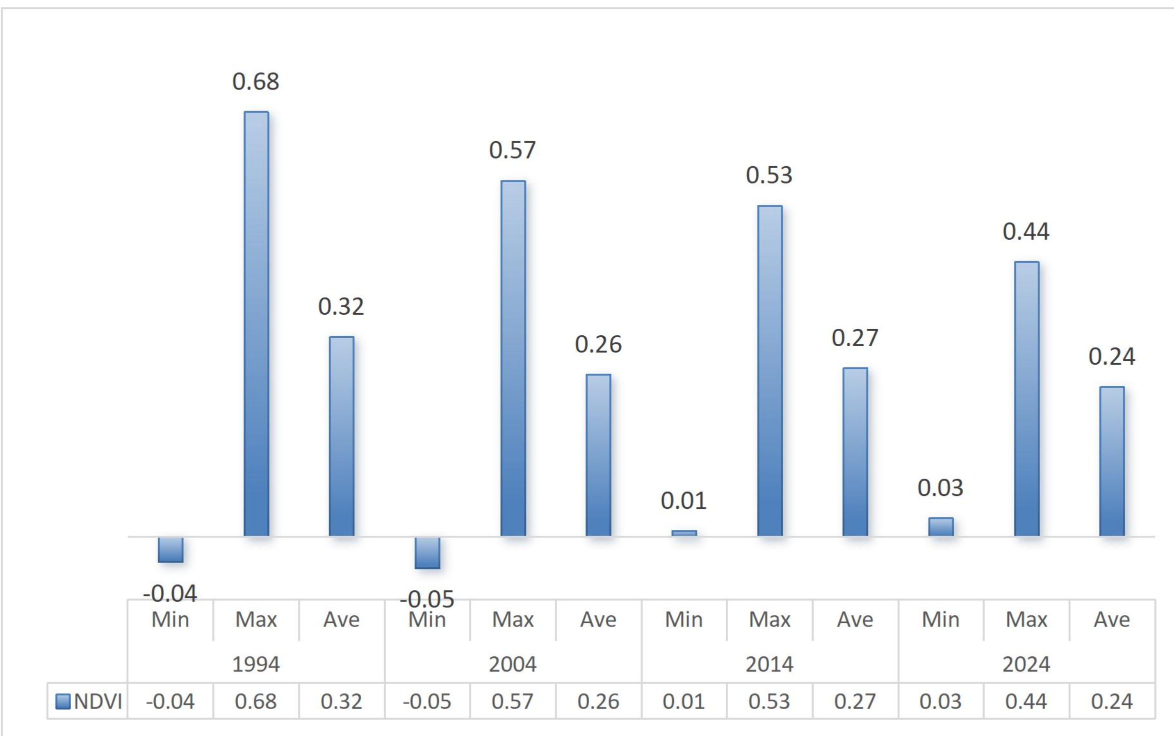
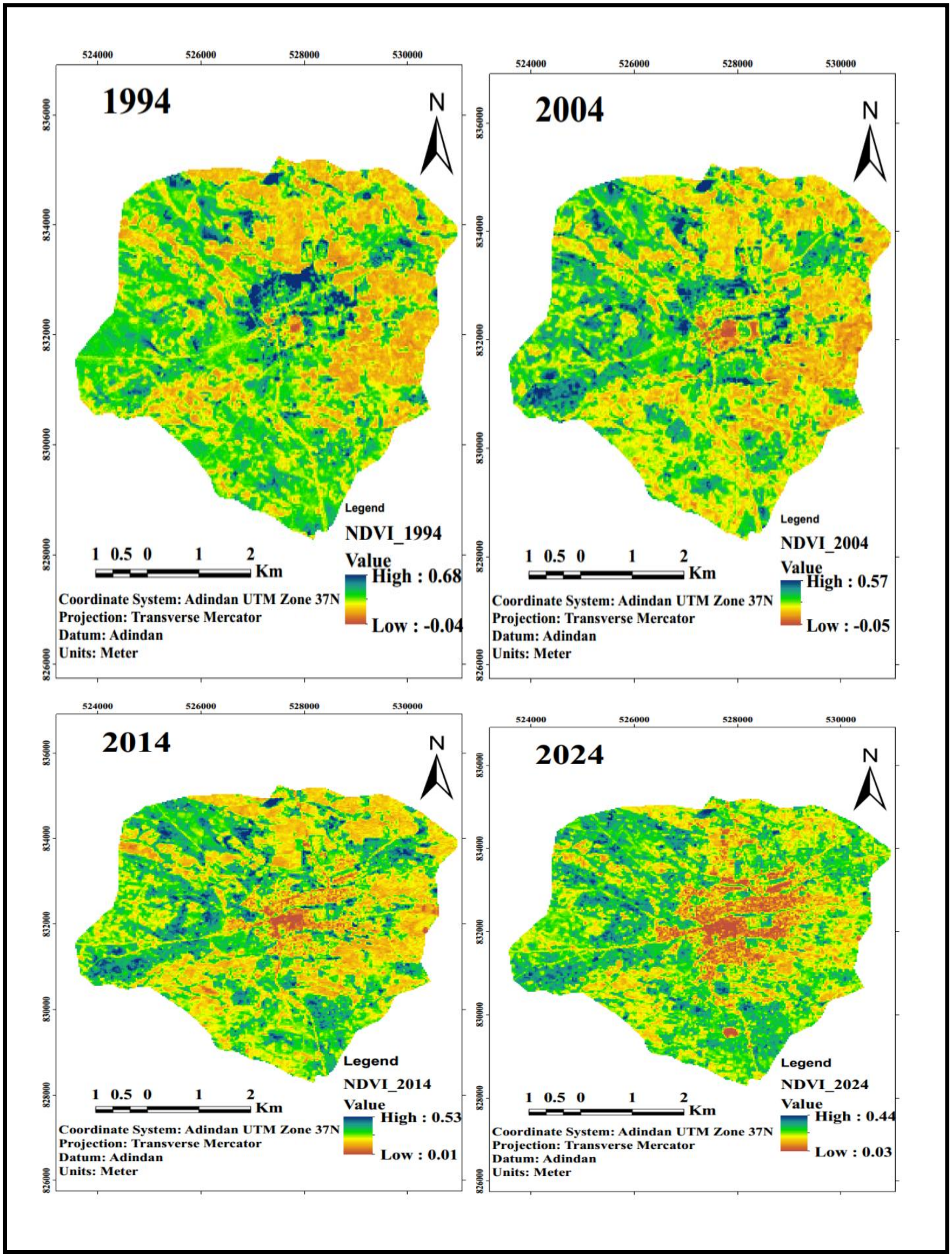


Figure 4.4 NDVI of Bekoji town 1994,2004,2014 and 2024

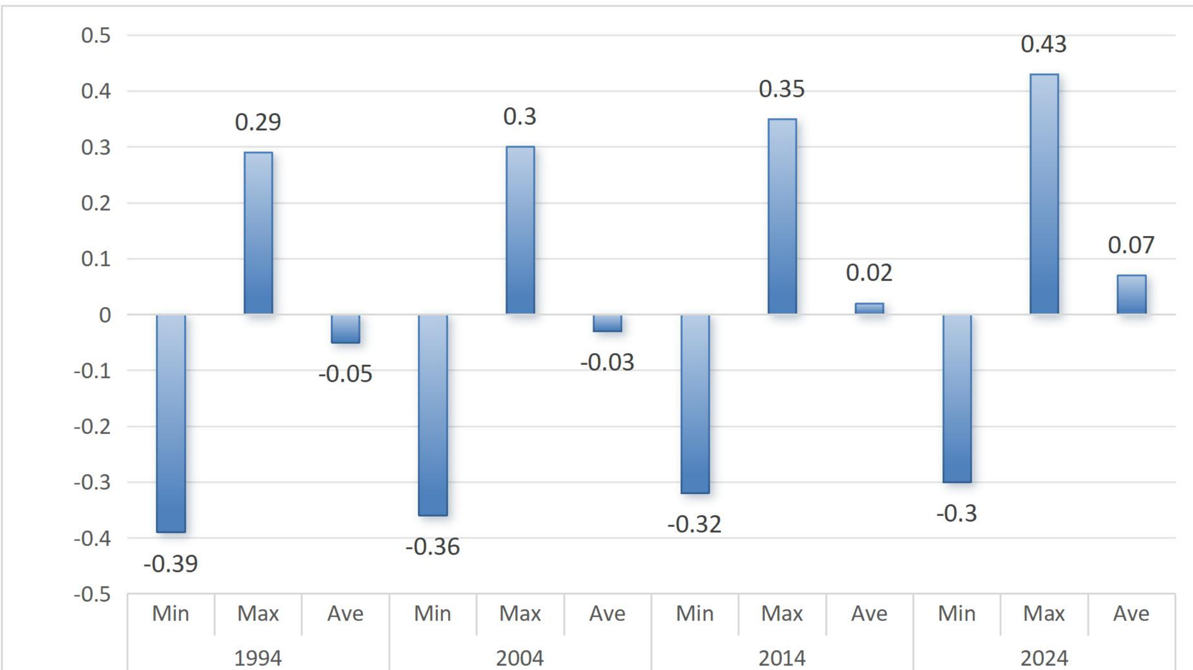


4.5 NDVI map of Bekoji town 1994.2004.2014 and 2024

4.1.4.2 The spatial Temporal distribution of NDBI

NDBI (Normalized Difference Built-up Index) is a remote sensing index used to monitor urban areas and built-up regions, such as town, roads, and infrastructure. It is designed to distinguish between built-up land and non-built-up land.

The formula for NDBI=SWIR−NIR/SWIR+NIRNDBI (Where: SWIR = Short-Wave Infrared reflectance value, NIR = Near-Infrared reflectance value).NDBI Interpretation: Positive values (closer to +1): Indicate built-up areas (urban areas, buildings, roads, etc.)Negative values (closer to -1): Indicate non-built-up areas such as vegetation, water, and bare land Values near 0: Usually represent transitional areas between built-up and non-built-up land.



	1994			2004			2014			2024		
	Min	Max	Ave	Min	Max	Ave	Min	Max	Ave	Min	Max	Ave
NDBI	-0.39	0.29	-0.05	-0.36	0.3	-0.03	-0.32	0.35	0.02	-0.3	0.43	0.07

Figure 4.6 NDBI Map of Bekoji town 1994,2004,2014 and 2024

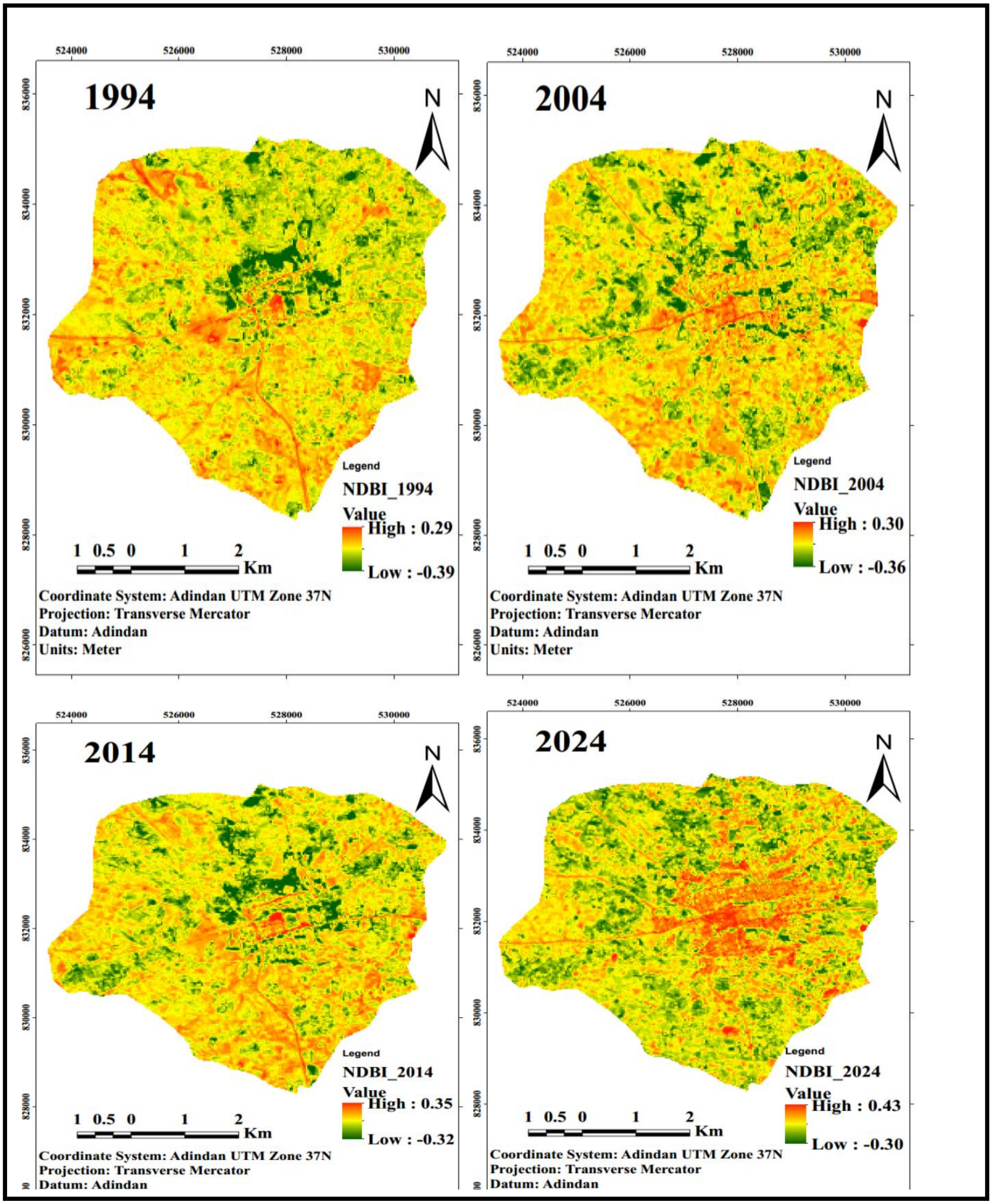


Figure 4.7 NDBI Map 1994.2004,2014 and 2024

4.2 Temporal changes in LST of Bekoji town

To analyze the changes in surface temperature of Bekoji town over time, we can apply remote sensing techniques that use satellite data to track variations in Land Surface Temperature (LST). This can help understand how land use and land cover changes (LULC) and urbanization have impacted the local climate, particularly in terms of temperature. Bekoji, as a town in Ethiopia, is likely to have changed surface temperature due to various factors such as urbanization, deforestation, agricultural activities, and changing land cover patterns. Monitoring these changes in surface temperature is important for: understanding the impact of urbanization (Urban Heat Island effect), assessing the impacts of deforestation and agricultural expansion, and informing local climate adaptation strategies. Surface temperature can be extracted from thermal infrared bands. The calculation generally follows these steps: Emissivity Correction; emissivity is a measure of how efficiently the surface emits thermal radiation. Different land cover types (e.g., water, vegetation, urban areas) have different emissive values. Thermal Band Analysis: Using the thermal infrared band, the surface temperature is calculated using algorithms like the Single-Channel Method or Split-Window Method to retrieve temperature values.

Once surface temperatures are extracted from the satellite imagery, the changes in temperature over time can be analyzed. You can perform the following steps; time Series Analysis and compare surface temperature data from different years to identify trends. Urbanization Impact: Higher surface temperatures in urbanized areas compared to rural/agricultural areas. The increase in impervious surfaces (roads, buildings, etc.) generally leads to higher LST. Deforestation: forested areas typically have lower surface temperatures due to the cooling effect of vegetation and evapotranspiration. The loss of forest cover for agriculture or urbanization can lead to higher surface temperatures. Agricultural Changes: Areas with agricultural land may have different temperature dynamics depending on crop types, irrigation methods, and seasonality. Bekoji has experienced urban growth, the urban areas (e.g., newly developed residential, commercial, or industrial zones) may exhibit a rise in surface temperature due to the UHI effect. These areas would have higher temperatures compared to surrounding rural or agricultural areas due to the high thermal inertia of built surfaces.

If significant deforestation has occurred around Bekoji, there may be an increase in surface temperature in these regions as forests are replaced by crops or urban settlements. This effect is particularly strong in tropical and subtropical regions where forests play a key role in regulating temperature. Surface temperature could show seasonal patterns, with higher temperatures in the dry season due to the reduced cooling effect of evapotranspiration from vegetation.

The Land Surface Temperature (LST) analysis conducted over 30 years from 1994 to 2024 for Bekoji town shows a clear upward trend in minimum, maximum, and mean LST values.

Table 4.2 LST 1994,2004,2014 and 2024 Bekoji town

	Year				LST change(1994-2024)
	1994	2004	2014	2024	
Minimum LST(oc)	6.87	7.89	8.35	9.71	2.84
Maximum LST (0c)	19.44	20.11	21.65	22.41	2.97
Mean LST (0c)	13.15	14	15	16.06	2.91

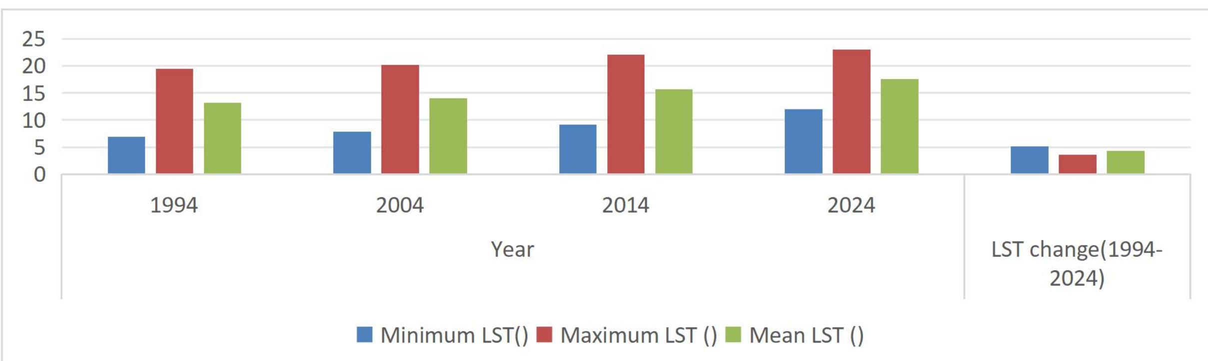
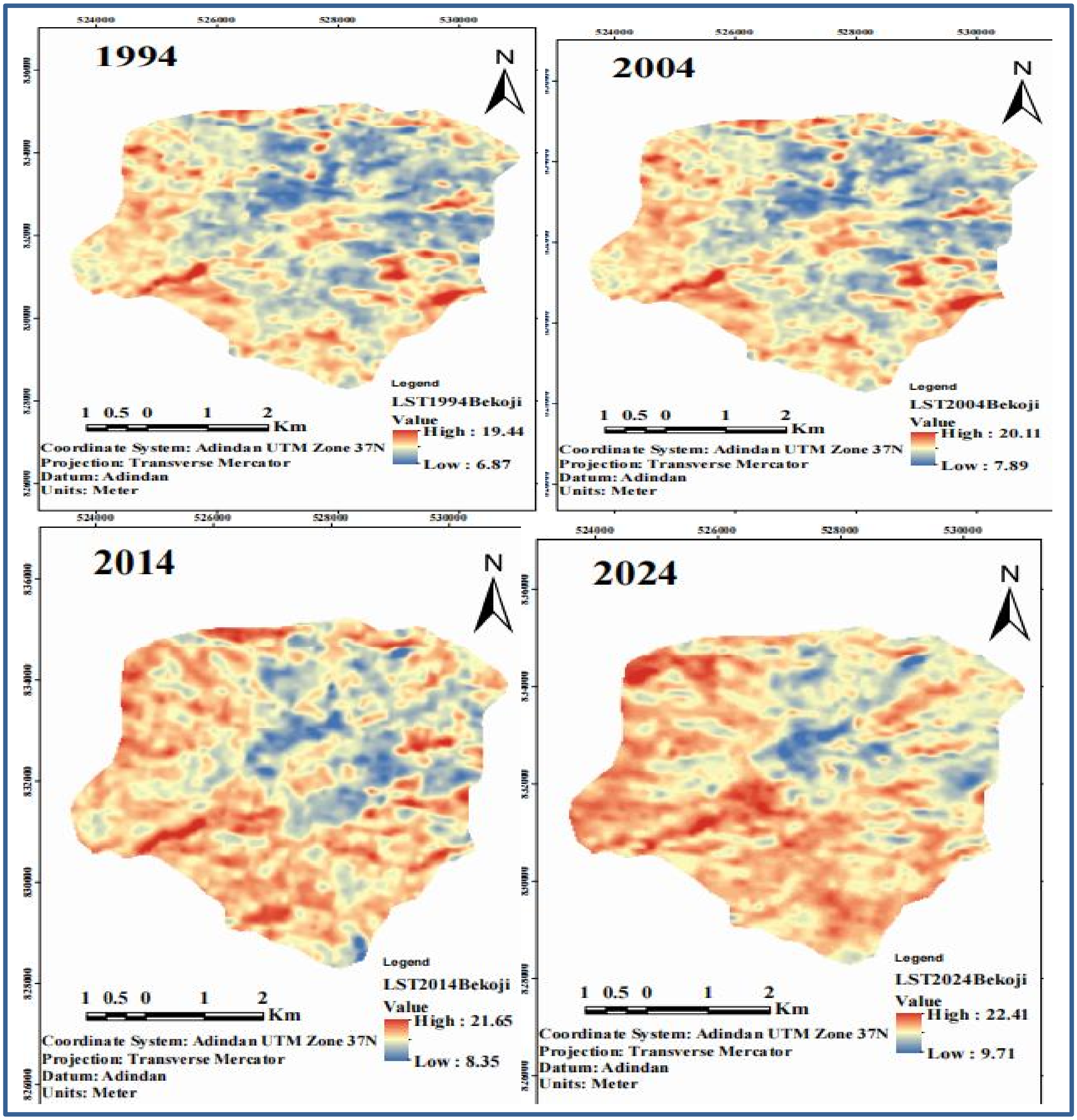


Figure 4.8 LST 1994.2004,2014 and 2024

The consistent rise in LST values over Bekoji town is likely linked to urbanization, reduction in vegetative cover, and expansion of built-up areas. Several studies have established that such land use transitions contribute to the urban heat island (UHI) effect, which leads to increased LST values, especially in rapidly urbanizing towns (Voogt & Oke, 2003). Increased surface temperatures can have wide-ranging implications, including elevated energy demands, increased public health risks (especially heat-related illnesses), and changes in local microclimates and hydrological cycles. In agricultural towns such as Bekoji, rising LST may also influence soil moisture content and evapotranspiration rates, with direct consequences for crop productivity and land degradation.

To further illustrate the trend, Figure 4.9 presents a graph showing the progression of minimum, maximum, and mean LST values over the study period. By comparing LST values from different periods you can detect areas where the temperature has increased significantly and correlate this with specific land use/land cover changes.



4.9 LST map of Bekoji town 1994,2004,2014 and 2024

By using statistical methods (e.g., correlation analysis, regression analysis) to quantify the relationship between LULC changes (urbanization, deforestation, agriculture) and changes in surface temperature. Spatial analysis techniques to overlay the LST data with land use data to determine if certain land cover types (e.g., built-up areas) are associated with higher surface temperatures used. Analyzing the changes in surface temperature in Bekoji provides valuable insights into how local environmental changes, such as urbanization, deforestation, and agriculture, have impacted the climate. By using remote sensing data and GIS tools, it's possible to track temperature trends over time and understand the causes and consequences of surface temperature changes. This information can guide future urban planning and climate mitigation strategies to ensure that Bekoji remains resilient to the challenges posed by rising temperatures.

4.3 Correlation of LULC and LST of Bekoji Town

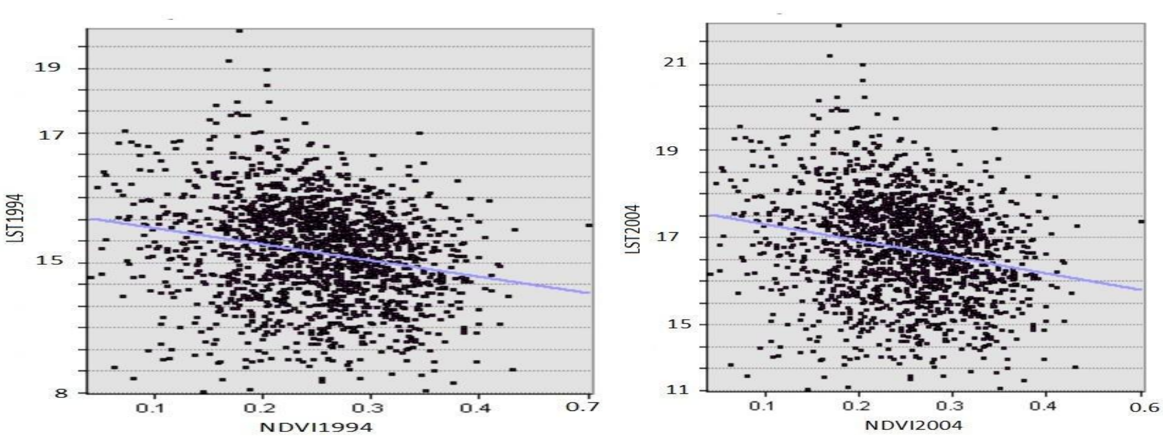
To analyze the correlation between Land Use/Land Cover (LULC) and Land Surface Temperature (LST) in Bekoji Town, we would need to explore how changes in land use impact the surface temperature over time. This type of analysis helps identify the relationship between different types of land cover (e.g., urban, forest, agricultural land) and their corresponding effects on the local surface temperature. Below is a step-by-step guide to carrying out such an analysis. The goal is to examine whether certain land cover types (urban, agricultural, Vegetation, bareland, and grassland) have a statistically significant impact on the surface temperature in Bekoji. Quantitative analysis correlation between LULC and LST. Correlation analysis helps determine the strength and nature of the relationship between LULC and LST. Extract LST Values for Each LULC Class: For each land cover class (e.g., urban, agricultural, vegetation), extract the corresponding surface temperature values for the relevant periods. Average LST for Each LULC Class: For each class (e.g., urban, agricultural.), calculate the average LST over time to analyze the trend. Pearson Correlation Coefficient: this coefficient quantifies the linear relationship between LULC types and surface temperature. It ranges from -1 (negative correlation) to +1 (positive correlation), where 0 indicates no linear correlation.

Positive Correlation: if urban areas show higher temperatures than agricultural or forest areas, there is a positive correlation between urban land cover and higher surface temperature. Negative Correlation: if forests or wetlands tend to have lower temperatures compared to urban areas, the correlation between forest land cover and lower surface temperature was negative. Spearman's Rank Correlation; if the relationship between land cover types and surface temperature is not linear, a Spearman's rank correlation can be used to assess monotonic relationships (i.e., whether the relationship is consistently increasing or decreasing, even if not linearly).Multiple Linear regressions; if you want to model the effect of different land cover types on surface temperature, you can run a multiple regression analysis. This allows you to quantify the impact of urban, agricultural, forest, and other land uses on surface temperature, considering multiple factors at once. Urban Areas and Temperature: Urban areas typically show a positive correlation with surface temperature due to the UHI effect. This means that as urbanization increases in Bekoji, the surface temperature will likely increase. Forested Areas and Temperature; forested areas tend to show a negative correlation with surface temperature due to the cooling effects of vegetation and evapotranspiration. Higher proportions of forest cover may reduce local surface temperature. Agricultural land may have an intermediate relationship with temperature. Typically, non-irrigated agricultural land can increase LST.

Heat maps to visualize the areas with higher and lower temperatures overlaid with land use types. This helped identify the specific areas where temperature variation is most pronounced due to land cover changes. Scatter Plots; create scatter plots to visually inspect the relationship between LST and each LULC class. For example, plot the LST values for urban areas against agricultural areas and forests to visually identify any patterns. In correlation analysis, R and R^2 are statistical measures used to quantify the strength and direction of the relationship between two variables. R, also known as the Pearson correlation coefficient, measures the strength and direction of the linear relationship between two continuous variables. It ranges from -1 to 1, where 1 indicates a perfect positive linear relationship, -1 indicates a perfect negative linear relationship, and 0 indicates no linear relationship. Positive values (0 to 1) mean that as one variable increases, the other variable tends to increase. Negative values (0 to -1) mean that as one variable increases, the other variable tends to decrease. The closer R is to 1 or -1, the stronger the linear relationship between the variables. R 2 is the square of the correlation coefficient R. It represents the proportion of the variance in the dependent variable that is predictable from the independent variable(s) and ranges from 0 to 1. A value of 0 indicates that the independent variable explains none of the variance in the dependent variable.

4.3.1 Correlation between LST and NDVI

The Analyzed Landsat images from 1994, 2004, and 2024 revealed that NDVI and LST share an inverse relationship. Areas with low NDVI values exhibited high LST, while regions with high NDVI values displayed low LST. In contrast, for water bodies, NDVI and LST showed a direct or positive correlation, as both NDVI and LST values were lower for these areas. Land Surface Temperature (LST) and Normalized Difference Vegetation Index (NDVI) have a generally negative correlation, meaning that as NDVI increases, LST tends to decrease, and vice versa. This relationship is stronger in vegetated areas and can be influenced by factors like vegetation type, density, and moisture. This study demonstrates that a higher NDVI (indicating more vegetation and healthy plant life) is associated with lower LST, and conversely, lower NDVI (indicating less vegetation or stressed plants) is associated with higher LST. Vegetation type and density; different plant types and densities can affect how vegetation absorbs and reflects solar radiation, influencing both NDVI and LST. Moisture; vegetation with good moisture content tends to have a lower LST due to evaporative cooling. Land Use/Cover (LULC): The type of land cover (e.g., forest, urban, bare land) also plays a role, with vegetation generally having a lower LST compared to impervious surfaces. Atmospheric factors like cloud cover and humidity can also influence the relationship between LST and NDVI. In this research typically NDVI and LST have a negative correlation and NDVI for LST generally ranges between -0.3 and -0.8: Higher NDVI lower LST. Vegetation provides shade and promotes evapotranspiration, which cools surface temperature. Stronger negative correlation in dense green areas (e.g., forests, parks) and weaker in urbanized.



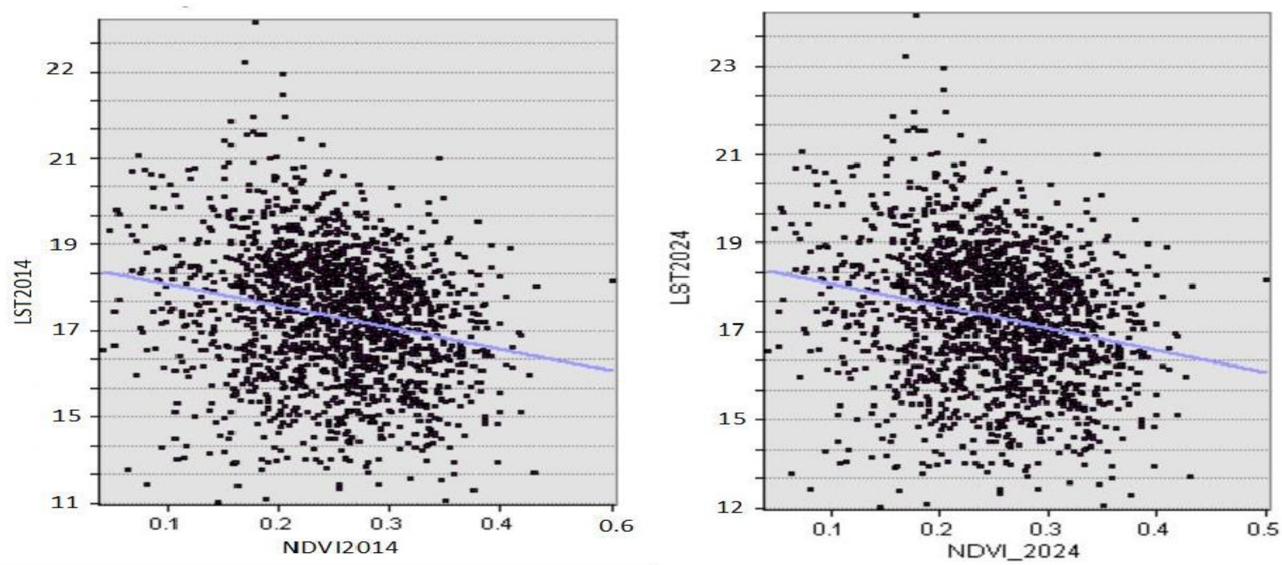


Figure 4.10 Correlation between NDVI and LST Bekoji town,1994,2004,2014 and 20224

4.3.2 Correlation between LST and NDBI

The correlation between Land Surface Temperature (LST) and Normalized Difference Built-up Index (NDBI) is a commonly studied topic in urban climate and remote sensing. Here's a breakdown to help understand the relationship: The Analyzed Landsat images from the years 1994, 2004, and 2024 revealed a direct correlation between NDBI and LST, where higher NDBI values are associated with higher LST. Studies often show a positive correlation between LST and NDBI. As NDBI increases (i.e., more built-up/urban surfaces), LST also tends to increase. Urban materials (concrete, asphalt) retain heat, leading to higher surface temperatures known as the Urban Heat Island effect. Land Surface Temperature (LST) and the Normalized Difference Built-up Index (NDBI) exhibit a positive correlation, meaning that as built-up areas increase, LST tends to increase as well. This relationship is primarily due to the higher albedo and thermal inertia of built-up surfaces compared to natural surfaces like vegetation. Built-up surfaces (roads, buildings, etc.) have lower albedo (reflectivity) and higher thermal inertia compared to vegetation and water bodies. This means they absorb more solar radiation and retain heat longer, leading to higher surface temperatures, which are calculated using NIR and SWIR bands, effectively highlighting built-up areas, and allowing researchers to analyze the relationship between urban expansion and temperature changes. Seasonality: Studies have shown that the LST-NDBI correlation can vary depending on the season, with stronger correlations observed in certain seasons like post-monsoon. Vegetation

Coverage: the presence of vegetation can mitigate the warming effect of built-up surfaces, potentially reducing the strength of the LST-NDBI correlation. Surface Characteristics: factors like soil type, rock exposure, and the presence of water bodies can also influence the LST-NDBI relationship. In this research correlation coefficients between LST and NDBI typically range from 0.4 to 0.8, depending on city size and structure, vegetation cover, time of year climate zone, and sensor resolution. A high positive correlation supports the notion that urban areas significantly contribute to surface heating. If the correlation is low or negative, it could mean the presence of vegetation in built-up areas, and seasonal variation.

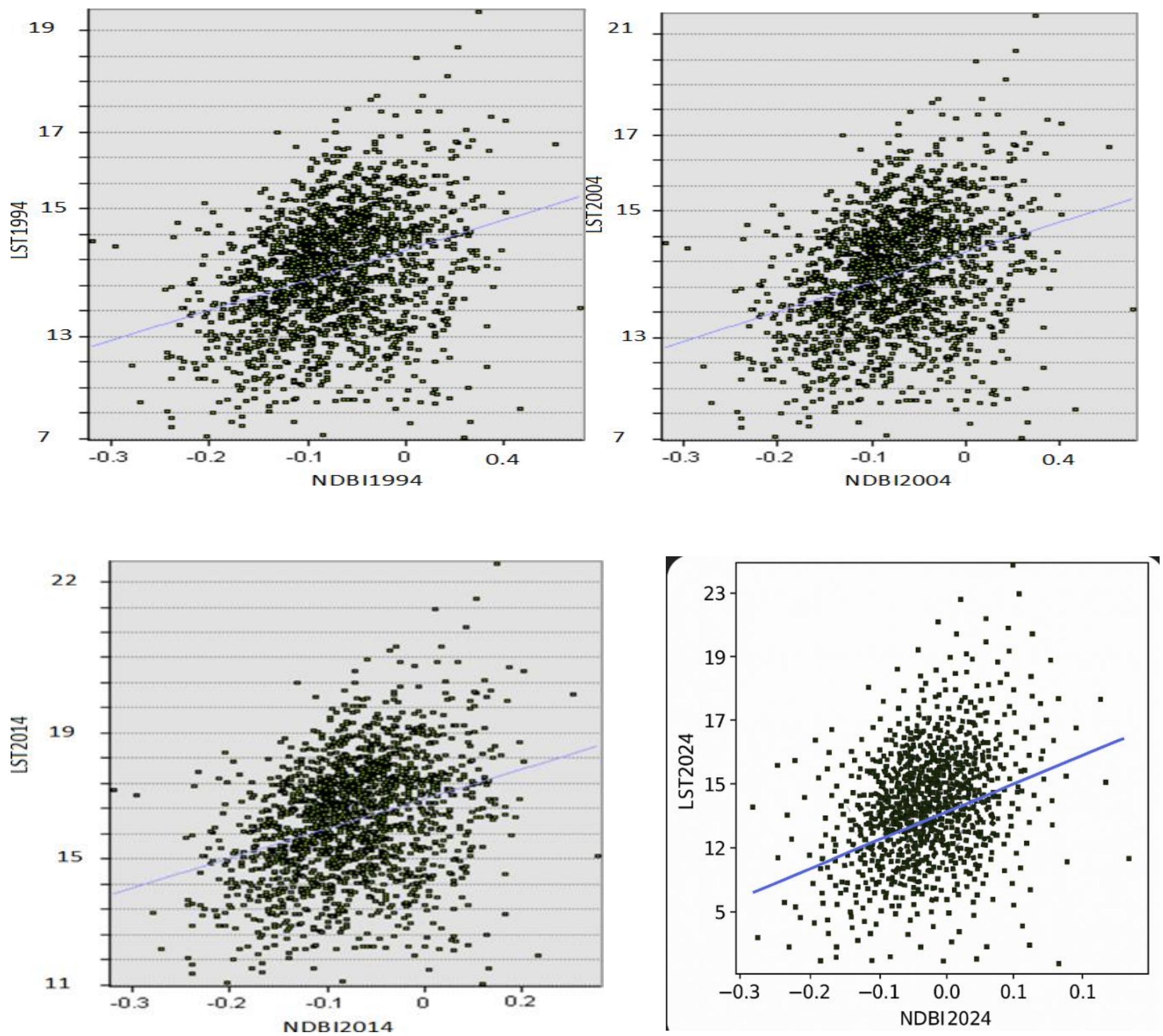


Figure 4.11 Correaltion between NDBI and LST of Bekoji town 1994,2004,2014 and 2024

4.4 Factors influencing changes in LULC and its impact on LST of Bekoji town

The observed LULC changes in Bekoji town from 1994 to 2024 are the result of a combination of anthropogenic and natural drivers. The primary influencing factors include Urbanization the most significant factor driving land cover change is urban expansion. The growth of the built-up area from 9.4% to 22.5% over three decades reflects increased h-ousing demand, infrastructure development, and population growth. This trend has led to the conversion of vegetation, farmland, and grassland into residential and commercial zones. As Bekoji town's population has grown, so has the demand for housing, services, and employment opportunities. These demographic shifts have encouraged land development and increased land conversion pressures. Changes in agricultural practices, land tenure, and policies have influenced fluctuations in farmland extent. Although there was a brief recovery in farmland areas the overall trend indicates increasing competition for land between agriculture and urban uses. Similar patterns have been noted in other developing urban centers where economic development and demographic growth place pressure on available land (Lambin et al., 2003; Turner et al., 2007).

Land Use and Land Cover (LULC) changes represent the transformation of natural environments due to both anthropogenic activities and natural processes. Remote sensing technologies, such as satellite imagery and vegetation indices like NDVI, are key tools for monitoring these changes. Indicators such as deforestation, urbanization, agricultural expansion, and changes in water bodies or soil quality are critical for understanding environmental and climatic impacts, including shifts in Land Surface Temperature (LST) (Weng, 2001; Jensen, 2007; Lambin et al., 2003).

Rapid population growth often leads to urban sprawl, deforestation, and the conversion of agricultural land into residential or commercial zones. Agricultural Expansion, the expansion or contraction of agricultural fields can be monitored using historical land cover maps or remote sensing data. The establishment of irrigation systems can convert non-arable land into cultivated fields, which can be observed through changes in land cover. Deforestation loss of forest cover is often linked to logging, agricultural expansion, and urban development, whereas afforestation or reforestation efforts may show a change in land cover. Changes in tree canopy cover, which can be tracked using remote sensing data, indicate deforestation or reforestation trends. Soil Erosion and Degradation in areas where land is heavily farmed or overgrazed, soil erosion can cause land degradation. This can be measured through field observations or remote sensing data showing reduced vegetation cover. The transformation of fertile land into the desert, often due to poor land management practices, is another indicator of LULC change.

Urbanized areas have more compact and less rough surfaces, which can disrupt wind patterns and reduce the natural cooling process. Forested or natural areas have a more varied topography, which promotes better wind circulation and cooling.Higher LST in urban areas leads to greater demand for cooling, increasing energy consumption and contributing to further urban heat. Higher LST can lead to increased evaporation, impacting water resources and intensifying drought conditions. The increasing urbanization and deforestation contribute to higher surface temperatures, with various environmental, social, and health implications. Understanding these impacts is essential for better urban planning and environmental management.

The study revealed a clear pattern of urban expansion in Bekoji town over the last three decades, resulting in the transformation of vegetated and agricultural lands into built-up areas. This has led to a noticeable increase in land surface temperatures, particularly in densely populated zones. Rising temperatures may reduce the overall quality of life, discouraging outdoor social interaction and increasing demand for cooling infrastructure, which is often lacking in small towns like Bekoji.The conversion of agricultural and vegetated land into urban infrastructure has both positive and negative economic implications:Loss of Agricultural Productivity: The reduction in farmland directly affects local food security and the income of families dependent on agriculture.Increased Energy Demand: Higher LST leads to greater use of cooling systems, increasing household energy expenses and straining local energy infrastructure. While urban expansion may spur construction and job creation, unplanned growth contributes to inefficient land use and higher costs for future infrastructure improvements.Geospatial analysis of LULC and LST trends indicates a strong environmental degradation pattern associated with the reduction of natural vegetation cover.

Decline in Vegetation and Biodiversity: The loss of green spaces not only elevates surface temperature but also disrupts habitats, affecting local biodiversity.With the rise in bareland and decrease in vegetative cover, soil becomes more exposed to erosion, reducing land fertility and increasing sediment runoff into nearby water bodies.The local climate in Bekoji is gradually shifting, with hotter days and reduced moisture retention due to LULC changes, threatening ecological balance and sustainability.

The study's findings reveal a strong correlation between urban expansion and increased land surface temperatures (LST), with built-up areas showing the highest thermal intensities. This has direct implications for urban policy and planning in Bekoji town.The rapid loss of vegetated and agricultural areas calls for urban policies that prioritize the inclusion of green spaces (e.g., urban forests, parks, and green roofs) to mitigate urban heat island effects.The unplanned conversion of land into residential and commercial zones highlights the urgency for revising local zoning regulations to protect ecologically sensitive areas and manage urban sprawlThe conversion of natural vegetation and agricultural lands into impervious surfaces has accelerated land degradation in Bekoji.The increase in bare land and reduction of vegetation cover enhance soil vulnerability to erosion, diminishing land productivity. Built-up areas reduce natural infiltration, increasing surface runoff, which can lead to flash floods and further degrade the land.The rise in LST in areas of land cover change is a critical indicator of environmental stress and land degradation, signaling the need for immediate land restoration efforts.The study highlights a significant reduction in ecosystem services due to LULC changes.

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CHAPTER FIVE

5. CONCLUSION AND RECOMMENDATION

5.1 Conclusion

Generally, this MSC provides a thorough analysis that focuses insight into the complex relationship between environmental elements, land surface temperature dynamics, and changes in land use/cover (LULC) in Bekoji town, Ethiopia. The study investigated historical changes in LULC patterns and their consequences for local climate dynamics by analyzing multi-temporal Landsat satellite images from 1994 to 2024 using geospatial techniques. Notable changes in land use and land cover (LULC) patterns have resulted from the rapid expansion of urban areas where built-up areas have displaced agricultural land and vegetation cover. The creation of urban heat islands (UHIs) and variations in Bekoji town temperature patterns are two effects of these changes that have a significant impact on the local climate dynamics. Strong correlations between LST and LULC classes were found via correlation studies, showing that vegetated parts are cooler than built-up areas.The impact of water bodies on LST was also noted, with regions devoid of water features showing higher surface temperatures. The impact of topography features, especially elevation, on LST dynamics was also investigated in this study. Higher elevations were found to have lower temperatures, indicating that topography modifies local thermal dynamics. Consistent negative connections between altitude and temperature were detected. The study advances our knowledge of the complex connections that exist between LULC alterations and LST dynamics in Bekoji town. With areas urbanizing quickly, the findings offer important new information for activities related to climate resilience, environmental preservation, and sustainable urban development. This study guides evidence-based decision-making for reducing the negative consequences of urbanization on regional climates by clarifying the effects of land use changes on surface temperature.The findings from Bekoji town stress the urgent need to integrate urban environmental management into local governance frameworks. Urban policy must address the spatial patterns of development to prevent further land degradation and ensure the continued provision of critical ecosystem services. Geospatial techniques provide valuable tools for monitoring and managing these changes, offering data-driven insights to inform adaptive and sustainable urban development strategies

5.2 Recommendation

Integration of findings into urban planning the results of this study offer important light on how urbanization affects regional climate dynamics. It recommends that these findings be incorporated into the decision-making processes of urban planners. To mitigate the negative effects of urban heat islands (UHIs), strategies for sustainable urban development should place a high priority on the protection of green spaces, the promotion of vegetation cover, and the installation of heat mitigation techniques. Implementation of green infrastructure Considering the study's findings about the cooling effects of dense vegetation, it is advised that local governments fund green infrastructure projects. Urban surroundings can be made more livable by introducing green walls and roofs, planting trees, and establishing parks. These actions can also assist in reducing the impact of the heat island effect. Climate-responsive urban design new development projects should take climate-responsive design concepts into account, according to urban experts. This involves minimizing energy use, maximizing natural ventilation, and minimizing heat absorption in buildings and streetscapes. Urban comfort can be improved, and surface temperatures can be lowered by implementing techniques like permeable pavements and cool roofing materials. Community engagement and education a sense of responsibility as well as ownership can be promoted by involving local populations in environmental conservation initiatives and educating them about how urbanization affects the climate. Residents can be empowered to help mitigate environmental deterioration and promote resilience by participating in educational programs on sustainable land management techniques, water conservation, and disposal of waste. Monitoring and Evaluation of progress and new trends can only be tracked and identified by ongoing assessment and monitoring of changes in surface temperature, land use/cover, and environmental indicators. Policy Support:
- Environmental conservation should be given priority by local, regional, and national policymakers who implement laws and policies that encourage sustainable land management techniques. Green construction laws, incentives for investing in green infrastructure, and land-use zoning regulations are a few examples of this. Although the present study offers significant contributions, additional investigation is necessary to enhance our understanding of the intricate relationships between urbanization and climate dynamics. Additional factors impacting surface temperature changes, such as air pollution levels, anthropogenic heat outputs, and socioeconomic issues, should be investigated in future research.

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Appendix

Appendix 1: LULC Change 1994 to 2024 of Bekoji Town.

OBJECTID	change1994	change2024	Change_1	ChangeArea(hect)
1	Builtup	Vegetation	Builtup -Vegetation	0.000399
2	Builtup	Builtup	Builtup - Builtup	104.098934
3	Builtup	Farmalnad	Builtup - Farmalnad	0.806299
4	Builtup	Grassland	Builtup - Grassland	4.109272
5	Builtup	Bareland	Builtup - Bareland	1.239286
6	vegetation	Vegetation	vegetation - Vegetation	2.253037
7	vegetation	Builtup	vegetation - Builtup	215.463787
8	vegetation	Farmalnad	vegetation - Farmalnad	149.456174
9	vegetation	Grassland	vegetation - Grassland	422.635487
10	vegetation	Bareland	vegetation - Bareland	140.810191
11	Farmland	Vegetation	Farmland - Vegetation	1.976855
12	Farmland	Builtup	Farmland - Builtup	138.135584
13	Farmland	Farmalnad	Farmland - Farmalnad	100.032445
14	Farmland	Grassland	Farmland - Grassland	281.87374
15	Farmland	Bareland	Farmland - Bareland	95.258696
16	Bareland	Vegetation	Bareland - Vegetation	1.163421
17	Bareland	Builtup	Bareland - Builtup	115.648457
18	Bareland	Farmalnad	Bareland - Farmalnad	196.967182
19	Bareland	Grassland	Bareland - Grassland	74.492007
20	Bareland	Bareland	Bareland - Bareland	86.170703
21	Grasslannd	Vegetation	Grassland - Vegetation	3.068708
22	Grasslannd	Builtup	Grassland - Builtup	201.422849

23	Grasslannd	Farmalnad	Grassland - Farmalnad	194.311545
24	Grasslannd	Grassland	Grassland - Grassland	386.790949
25	Grasslannd	Bareland	Grassland - Bareland	175.90071

Appendix 2 LULC Change beween 2014 and 2024

OBJECTID *	Change2014	change2024	Change	ChangeArea
1	Farmalnd	Vegetation	Farmalnd-Vegetation	16.32
2	Farmalnd	Builtup	Farmalnd-Builtup	132
3	Farmalnd	Farmalnad	Farmalnd-Farmalnad	480
4	Farmalnd	Grassland	Farmalnd-Grassland	3
5	Farmalnd	Bareland	Farmalnd-Bareland	3
6	Builtup	Vegetation	Builtup-Vegetation	0.5
7	Builtup	Builtup	Builtup-Builtup	571
8	Builtup	Farmalnad	Builtup-Farmalnad	16
9	Builtup	Grassland	Builtup-Grassland	131
10	Builtup	Bareland	Builtup-Bareland	78
11	Bareland	Vegetation	Bareland-Vegetation	10
12	Bareland	Builtup	Bareland-Builtup	74
13	Bareland	Farmalnad	Bareland-Farmalnad	540
14	Bareland	Grassland	Bareland-Grassland	337
15	Bareland	Bareland	Bareland-Bareland	86
16	Grassland	Vegetation	Grassland-Vegetation	2

17	Grassland	Builtup	Grassland-Builtup	55
18	Grassland	Farmalnad	Grassland-Farmalnad	145
19	Grassland	Grassland	Grassland-Grassland	178
20	Grassland	Bareland	Grassland-Bareland	124
21	Grassland	Builtup	Grassland-Builtup	26
22	Grassland	Farmalnad	Grassland-Farmalnad	20
23	Grassland	Grassland	Grassland-Grassland	27
24	Grassland	Bareland	Grassland-Bareland	10
25	Vegetation	Vegetation	Vegetation-Vegetation	3

Appendix 3 LULC Change between 2004 and 2014

OBJECTID *	Change2004	Change2014	Change	ChangeArea
1	Builtup	Farmalnd	Builtup-Farmalnd	0
2	Builtup	Builtup	Builtup-Builtup	173
3	Builtup	Bareland	Builtup-Bareland	19
4	Builtup	Grassland	Builtup-Grassland	10
5	Builtup	Grassland	Builtup-Grassland	4
6	Builtup	Vegetation	Builtup-Vegetation	119
7	Farmland	Farmalnd	Farmland-Farmalnd	2
8	Farmland	Builtup	Farmland-Builtup	321
9	Farmland	Bareland	Farmland-Bareland	85
10	Farmland	Grassland	Farmland-Grassland	100
11	Farmland	Grassland	Farmland-Grassland	48

12	Farmland	Vegetation	Farmland-Vegetation	702
13	Vegeatation	Farmalnd	Vegeatation-Farmalnd	2
14	Vegeatation	Builtup	Vegeatation-Builtup	175
15	Vegeatation	Bareland	Vegeatation-Bareland	372
16	Vegeatation	Grassland	Vegeatation-Grassland	265
17	Vegeatation	Grassland	Vegeatation-Grassland	30
18	Vegeatation	Vegetation	Vegeatation-Vegetation	409
19	Bareland	Farmalnd	Bareland-Farmalnd	1
20	Bareland	Builtup	Bareland-Builtup	49
21	Bareland	Bareland	Bareland-Bareland	137
22	Bareland	Grassland	Bareland-Grassland	192
23	Bareland	Grassland	Bareland-Grassland	4
24	Bareland	Vegetation	Bareland-Vegetation	82
25	Grassland	Farmalnd	Grassland-Farmalnd	0

Appendix 4 LULC Change beteween 1994 and 2004

OBJECT ID *	change1994	Change2004	Change	ChangeArea
1	Builtup	Builtup	Builtup-Builtup	104
2	Builtup	Farmland	Builtup-Farmland	1
3	Builtup	Vegeatation	Builtup-Vegeatation	6
4	Builtup	Bareland	Builtup-Bareland	1
5	Builtup	Grassland	Builtup-Grassland	0
6	vegetation	Builtup	vegetation-Builtup	107

7	vegetation	Farmland	vegetation-Farmland	250
8	vegetation	Vegeatation	vegetation-Vegeatation	579
9	vegetation	Bareland	vegetation-Bareland	49
10	vegetation	Grassland	vegetation-Grassland	17
11	Farmland	Builtup	Farmland-Builtup	4
12	Farmland	Farmland	Farmland-Farmland	22
13	Farmland	Vegeatation	Farmland-Vegeatation	364
14	Farmland	Bareland	Farmland-Bareland	335
15	Farmland	Grassland	Farmland-Grassland	21
16	Bareland	Builtup	Bareland-Builtup	1
17	Bareland	Farmland	Bareland-Farmland	489
18	Bareland	Vegeatation	Bareland-Vegeatation	1
19	Bareland	Bareland	Bareland-Bareland	0
20	Bareland	Grassland	Bareland-Grassland	7
21	Grasslannd	Builtup	Grassland-Builtup	108
22	Grasslannd	Farmland	Grassland-Farmland	496
23	Grasslannd	Vegeatation	Grassland-Vegeatation	301
24	Grasslannd	Bareland	Grassland-Bareland	80
25	Grasslannd	Grassland	Grassland-Grassland	86

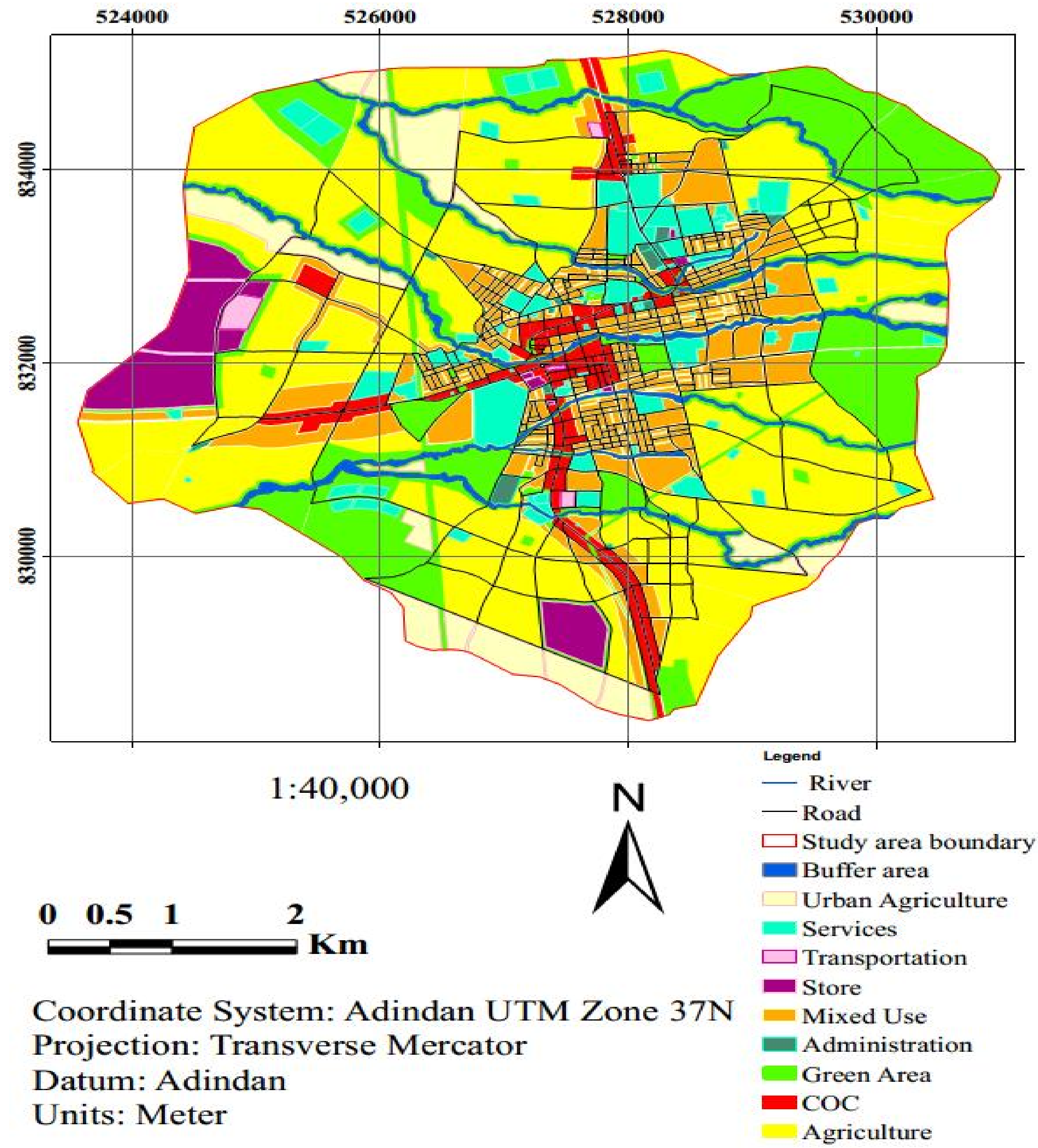
Appendix 5 : Mean Temperature, Rainfall, and Relative Humidity of Two Seasons at Bekoji Experimental Site.

Season	**Months**	**Mean Monthly Rainfall (mm)**	**Mean Air Temperature (°C)**	**Relative Humidity (%)**
			Minimum	Maximum
2020	May	83.9	6.3	20.6
	June	155.2	3.8	20.1
	July	296.3	3.9	18.9
	August	190.9	4.0	18.7
	September	109.0	4.2	19.0
2021	October	87.2	3.2	20.3
	May	74.2	5.3	21.0
	June	82.6	3.1	23.0
	July	213.0	3.1	23.8
	August	193.3	3.5	22.0
	September	100.1	3.3	19.4
	October	57.5	3.1	20.3

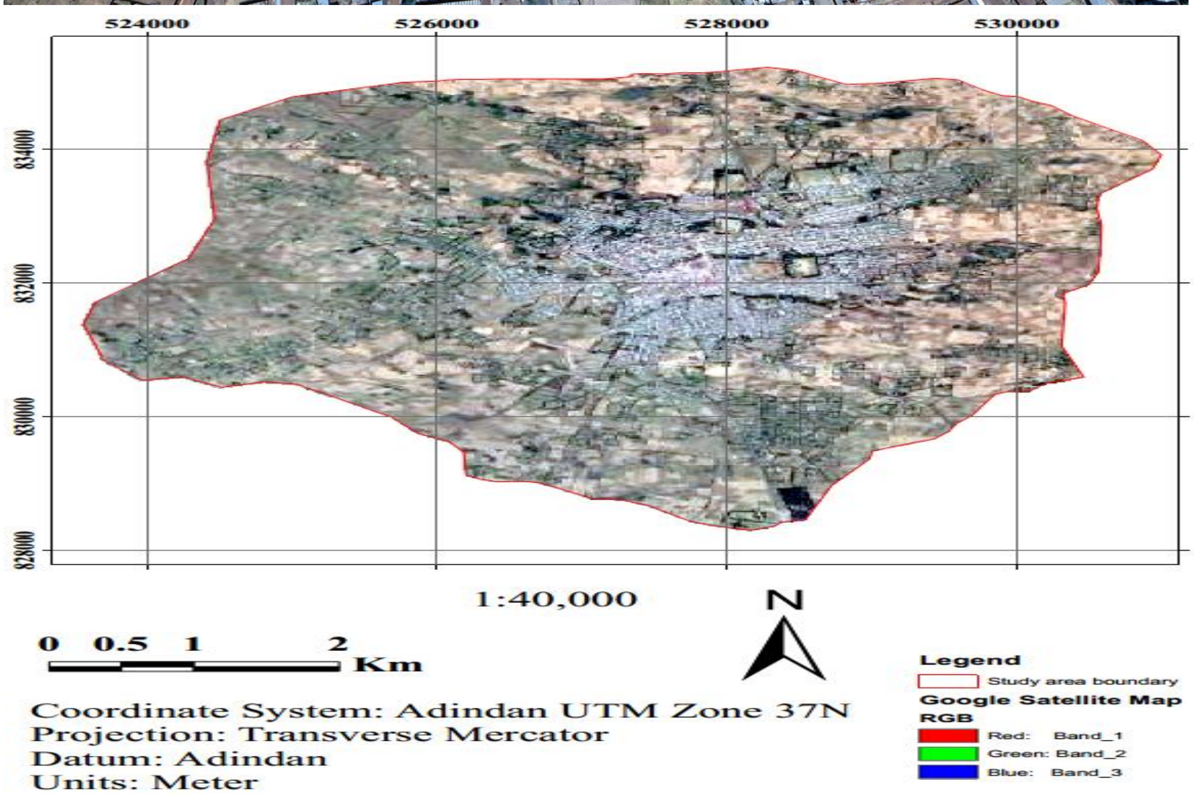
Table 6 Mean Temp, Rainfall and Relative Humidity of Bekoji Town

Source: Kulumsa Agricultural Research Center, Bekoji Meteorology Station, 2020 & 2021.

Appendix 6.B**ekoji Structural Plan**



Appendix 7. **Google Earth Map of Bekoji town.**



Adama Science and Technology University

College of Civil Engineering and Architecture

Department of Geoinformatics Engineering

Appendix 5. Format For Thesis Originality Declaration Report

Name of Student	Muhammed Kedir
ID.No.	PGE/28488/1
Department	Geoinformatics Engineering
College	College of Civil Engineering and Architecture
Course Title	Thesis
Tittle of work	Assessment of Land Use Land Cover Change Impact on land surface temperature using Geospatial techniques: a case of Bekoji town, Oromia Region, Ethiopia.
Date of Submission	May 2025

No	Particulars	Test		Averages	Remark
		Originality(%)	Plagiarism(%)	(%)	
1	Overall Thesis				

	Name	Signature	
Student	Muhammed Kedir		
Advisor	Getachew B/Meskel (Ph.D.)		

Getachew Brhanemeskel Mohammed

Mohammed
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