ASSESSING THE IMPACT OF LAND USE LAND COVER CHANGE ON LAND SURFACE TEMPERATURE USING GEOSPATIAL TOOLS: A CASE STUDY OF ADDIS ABABA, ETHIOPIA

Bewketu Adinew Birhane

A Thesis Submitted to the Department of Architecture
College of Civil Engineering and Architecture

Presented in Partial Fulfillment of the Requirement for the Degree of Master of Science in
Geo-Informatics Engineering

Office of Graduate Studies
Adama Science and Technology University

May, 2025

Adama, Ethiopia

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APPROVAL SHEET

I the advisors of the thesis entitled “Assessing the impact of land use/cover change on Land surface temperature using Geospatial tools: a case study of Addis Ababa, Ethiopia “and developed by Bewketu Adinew, here by attesting that the board of examiners' recommendations and suggestions have been suitably included in the thesis's finalized version.

Getachew Birhanemeskel (PhD)	_______________	_______________
Major Advisor/Supervisor	Signature	Date

As members of the Board of Examiners for Bewketu Adinew's thesis, we, the undersigned, have read and assessed the thesis entitled “Assessing the Impact of Land Use/Cover Change on Land Surface Temperature Using Geospatial Tools” and conducted an open defense examination of the candidate. Therefore, this certifies that the thesis has been approved to partially complete the requirements for the Master of Science degree in Geo-informatics.

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Chairperson	Signature	Date
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Internal Examiner	Signature	Date
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External Examiner	Signature	Date

The final copy of the thesis must be submitted to the Office of Postgraduate Studies (OPGS) via the Department Graduate Council (DGC) and College Graduate Committee (CGC) in order for it to be approved and accepted.

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Department Head	Signature	Date
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College Dean	Signature	Date
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Office of Potgraduate Studies,Dean	Signature	Date

DECLARATION

I affirm that this thesis, which is named “Assessing the Impact of Land Use Land Cover Change on Land Surface Temperature Using Geospatial Tools: A Case Study of Addis Ababa, Ethiopia “is original to me and hasn't been submitted for a similar reason to any university. The references used in this proposal are duly recognized by proper citations.

Bewketu Adinew Birhane		
Name	Signature	Date

RECOMMENDATION

As the thesis's advisor, I hereby attest that we have read the updated thesis, which was prepared under my direction by Bewketu Adinew and is titled "Assessing the Impact of Land Use/Cover Change on Land Surface Temperature Using Geospatial Tools: A Case Study of Addis Ababa, Ethiopia." As a result, I advise submitting the updated thesis to the department in accordance with the relevant protocols.

Getachew Birhanemeskel (PhD)		
Advisor	Signature	Date

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ACRONYMS and ABBREVATIONS

DEM	Digital Elevation Model
DN	Digital Number
ETM+	Enhanced Thematic Mapper Plus
ERDAS	Earth Resources Data Analysis System
ESS	Ethiopian Statistical Services
FAO	Food and Agricultural Organization
GIS	Geographical Information System
LSE	Land Surface Emissivity
LST	Land Surface Temperature
LULC	Land Use Land Cover
NDVI	Normalized Difference Vegetation Index
NDBI	Normalized Difference Built-up Index
NIR	Near Infrared Radiation
MLC	Maximum Likelihood Classification
OLI	Operational Land Imager
RS	Remote Sensing
SUHI	Surface Urban Heat Island
TM	Thematic Mapper
TIRS	Thermal Infrared Sensor
TOA	Top of Atmospheric
UHI	Urban Heat Island
USGS	United States Geological Survey
UTM	Universal Transverse Mercator

ABSTRACT

This study investigates the geographical and temporal dynamics of vegetation cover and its influence on LST in Addis Ababa over a 21-year period (2003–2024), utilizing multi-temporal Landsat satellite imagery and geospatial analysis techniques. The Normalized Difference Vegetation Index (NDVI) was used in assessing shifts in vegetation cover quantitatively and their spatial distribution across the rapidly urbanizing city. Results demonstrate a significant and sustained decline in vegetation, particularly in urban expansion zones, with profound implications for the warm climate of the city and ecological sustainability. A highly significant inverse Connection among NDVI and LST was observed throughout the study period, utilizing the (R^2) coefficient of determination values of 0.9551 in 2003, 0.9012 in 2013, and 0.9557 in 2024, indicating that vegetation consistently exerted a strong moderating effect on surface temperature variations despite fluctuations possibly linked to land use changes. Vegetation density mitigates surface temperatures through shading, reduced solar radiation absorption, and enhanced evapotranspiration, thereby alleviating urban heat island effects. Furthermore, the study reveals differential impacts of land use and land cover (LULC) categories—such as urban settlements, farmland, and bare land—on LST patterns, with impervious and non-vegetated surfaces exhibiting notably higher temperatures. These outcomes demonstrate how urgently integrated, sustainable urban planning strategies that prioritize the conservation and expansion of green spaces, implementation of green infrastructure, and reforestation initiatives to enhance climate resilience. This research provides useful data for environmental managers, urban planners, and legislators seeking to strike a balance rapid urban development with ecological sustainability amid ongoing climate change challenges.

Keywords:

Land Surface Temperature (LST), Normalized Difference Vegetation Index (NDVI), Urban Heat Island (UHI), Remote Sensing, Land Use Land Cover (LULC), Vegetation Dynamics, Climate Resilience, Sustainable Urban Planning, Pearson's Correlation Coefficient

CHAPTER ONE

1. INTRODUCTION

1.1 Background of the Study

The notion of Land Use Land Cover (LULC) is essential to comprehending how the surface and atmosphere of the Earth interact. As the primary interface for material and energy exchange, LULC significantly influences various environmental processes, especially Land Surface Temperature (LST), a key indicator of surface energy balance and climate dynamics (Fu et al., 2000; Lambin et al., 2003). Numerous studies have highlighted the strong relationship LULC change and LST, particularly in rapidly urbanizing areas (Deng et al., 2023; Chen et al., 2023).

LULC refers to the classification of the exterior of the earth into groups adore forests, agricultural land, bodies of water, urban areas, and bare land. It directly affects surface energy balance through its impact on albedo, surface roughness, and evapotranspiration (Anderson et al., 2023). Monitoring LULC dynamics is essential for assessing environmental changes, especially in urban areas where natural landscapes are transformed into built-up zones (Gao et al., 2024).

Urbanization is a major driver of LULC change, replacing natural landscapes with built-up areas characterized by impervious surfaces like concrete and asphalt. This transition reduces vegetation cover, lowers evapotranspiration, and increases heat absorption, leading to elevated LST and the formation of Urban Heat Islands (UHIs) (Jiang et al., 2023). For instance, a study in New Town Kolkata, India, reported an increase in built-up areas from 21.91% to 45.63% between 1991 and 2021, causing a substantial rise in LST (Ghosh et al., 2024).

One popular remote sensing tool is the Normalized Difference Vegetation Index (NDVI) for assessing vegetation cover and health based on the difference between near-infrared (NIR) and red light reflectance. NDVI values range from -1 to +1, with higher values indicating dense, healthy vegetation and lower values representing bare soil, water, or urban surfaces (Rouse et al., 1973; Li et al., 2024). NDVI is crucial for analyzing vegetation dynamics and their relationship with LST (Zhang et al., 2023).

The temperature of the surface of the planet is known as the Land Surface Temperature (LST), and it is determined by thermal infrared sensors on satellites. It is a key parameter in climate studies, reflecting surface heat exchange processes. LST is influenced by surface characteristics such as LULC, vegetation cover, and surface moisture (Weng et al., 2004; Kumar et al., 2024). Globally, the relationship between LULC and LST is well-documented, with urbanization often leading to higher LST due to reduced vegetation and increased impervious surfaces (Peng et al., 2023).

Geospatial technologies, including RS and GIS, are essential for analyzing LULC, NDVI, and LST. These technologies enable spatial and temporal analysis of variations in land cover and how they affect the temperature at the surface. Such analyses are critical for urban heat studies, especially in rapidly urbanizing cities like Addis Ababa, where natural landscapes are being transformed (Yang et al., 2023).

Despite extensive global research on LULC, NDVI, and LST, studies focused on African cities, particularly Addis Ababa, remain limited. This study attempts to close this gap by assessing how LULC changes in Addis Ababa influence NDVI and LST using advanced geospatial technologies. The findings were providing data-driven insights to support policymakers in designing urban plans that mitigate the UHI effect, promote sustainable land management, and enhance climate resilience.

For example, in Addis Ababa, built-up areas expanded from 115.42 km² in 1990 to 483.2 km² in 2023, fragmenting agricultural land and significantly increasing surface temperatures (Mengesha et al., 2024). A study in Adama City, Ethiopia, using Landsat data from 2002 to 2022, reported a decline in vegetation cover from 17.47% to 13.15%, alongside an increase in average LST from 28.25°C to 31.78°C (Benti et al., 2024).

Similarly, in southwestern Ethiopian cities like Jimma, Bonga, Mattu, and Nekemte, LST rose by up to 3.96°C over 22 years due to urbanization and the loss of natural landscapes (Abera et al., 2024). In Jimma and Nekemte, LST increased by 1.9°C and 2.2°C, respectively, with a clear link between expanding built-up areas and rising temperatures (Tufa et al., 2024).

This study aims to bridge the research gap on LULC, NDVI, and LST in African cities, focusing on Addis Ababa. The findings was inform policymakers in developing sustainable urban plans that reduce the UHI effect, enhance green spaces, and promote urban resilience against climate change.

1.2 Research Gap

Rapid urbanization and associated LULC changes has become a defining feature of contemporary cities, with profound environmental implications, particularly concerning LST. Globally, numerous studies have documented the significant LULC dynamics' effects on urban thermal environments, illustrating how the replacement of vegetated surfaces with impervious materials elevates LST and intensifies the UHI effect. However, despite the global proliferation of such research, there remains a critical paucity of focused, high-resolution spatial and temporal studies assessing these interactions within the context of African cities, especially Addis Ababa.

Addis Ababa, characterized by its unique highland topography and complex climatic conditions, presents a distinctive urban environment where conventional models of LULC-LST interactions may not be entirely applicable or sufficient. Existing studies on Addis Ababa tend to be fragmented, often limited to generalized urbanization assessments without employing advanced geospatial technologies capable of delivering nuanced insights into the LST's dynamical variability in reaction to specific LULC transformations. Furthermore, these studies frequently overlook the synergistic influence of additional physical factors such as elevation gradients, slope variability, soil texture heterogeneity, and surface moisture conditions, all of which are known to modulate surface thermal dynamics.

The absence of comprehensive, integrative analyses that combine remote sensing-derived LULC classification, NDVI assessments, and detailed LST mapping restricts the ability to fully understand the extent and mechanisms through which urbanization influences local climate regimes in Addis Ababa. This knowledge gap impedes the formulation of precise, context-specific urban planning and climate adaptation policies that are crucial for mitigating adverse environmental and public health outcomes associated with rising urban temperatures. Therefore, there is an urgent need for research that systematically investigates the complex interactions among LULC changes, vegetation dynamics, topographical factors, and surface temperature variations using cutting-edge geospatial methodologies tailored to the city's unique landscape and climatic context.

1.3 Statement of the Problem

Addis Ababa is experiencing rapid urban expansion fueled by economic expansion and population growth. This urbanization has transformed natural and semi-natural landscapes—such as forests, agricultural lands, and grasslands—into built-up areas dominated by impervious surfaces like concrete and asphalt. These changes fundamentally alter the city's surface energy balance, resulting in measurable increases in LST and intensifying the occurrence of heat waves in cities.

Despite the acknowledged significance of these environmental changes, there is a significant lack of detailed empirical studies that rigorously quantify the temporal and location dynamics of LST in connection with specific LULC changes within Addis Ababa. Existing research often fails to disaggregate the thermal impacts of different land cover types and neglects critical environmental influences such as topography, soil characteristics, and moisture conditions. This narrow focus limits grasp of the intricate, multifactorial drivers of urban heat and reduces the reliability of models used for urban climate management.

Furthermore, previous studies rarely utilize the integrated GIS and remote sensing approaches necessary for high-resolution, longitudinal monitoring of LULC and LST dynamics. This limits the effectiveness of urban planning and policymaking efforts aimed at mitigating heat stress, reducing energy consumption, and promoting environmental sustainability.

This study addresses these critical gaps by employing advanced remote sensing and GIS techniques to provide a comprehensive spatiotemporal assessment of how LULC changes affect LST patterns in Addis Ababa. By incorporating NDVI and terrain variables, it offers a comprehensive comprehension of urban thermal dynamics unique to the scenery of the city and climatic context. Findings are intended to support evidence-based urban planning and climate resilience methods to lessen the influence of the urban heat island, conserve green spaces, and enhance Addis Ababa's ability to adapt to ongoing environmental and anthropogenic pressures.

1.4 Objective of the study

1.4.1 General objective

The overall goal of this research is to assess the impact of LULC changes on LST in Addis Ababa over a 21-year period (2003–2024) using geospatial tools, with the aim of understanding the connection among vegetation cover and urban temperature dynamics in the city.

1.4.2 Specific objective

1. To analyze the spatial and temporal structures of land use cover changes in Addis Ababa over a specified period.

2. To evaluate the spatial and temporal variations in land surface temperature.

3. To examine the relationship between land use cover changes and land surface temperature.

4. To produce maps of land-use land cover and LST of the study area.

1.5 Research Questions

1. What are the spatial and structures of land use/cover changes in study area over the study period?

2. What is the link between land use/cover changes and variations in land surface temperature?

3. Which areas of the study area are most affected by increased land surface temperatures as a result of shifting land cover and urbanization?

4. What strategies can be recommended to mitigate the effect of changes in land cover and use on the study area's land surface temperature?

1.6 Significance of the Study

This research is very valuable for both scientific research and practical applications in urban planning and environmental management. As Addis Ababa undergoes rapid urbanization, being aware of the impact of LULC changes on LST is essential for addressing urban surroundings challenges.

1. Scientific Contribution: - The study contributes to the expanding collection of knowledge on the connection with LULC changes and urban thermal behavior. By leveraging geospatial technology to assess spatial and temporal changes, it fills a critical research gap, particularly in sub- Saharan African cities like Addis Ababa, where such studies are limited. The outcomes can act as a reference for similar research in other developing regions.

2. Policy and Urban Planning: - The insight obtained from this investigation was aid policymakers and an urban planner in designing how decreases the urban heat island effect. Recommendations on preserving green spaces and managing urban development can support the creation of more climate- resilient and sustainable cities.

3. Climate Change Adaptation: - By identifying the link between LULC changes and LST, the study highlights the need for adaptive measures to address rising temperatures. These measures are particularly relevant in the context of global climate change, where urban areas are increasingly vulnerable to extreme heat events.

4. Improved Livability: - The study's outcomes can inform interventions to enhance urban livability in Addis Ababa. Addressing LST increases were benefit public health, reduce energy demands for cooling, and create a more comfortable urban environment.

5. Capacity Building and Awareness: - The application of geospatial technology in this research demonstrates its potential as a means of monitoring ecological conditions and making choices. The study can raise awareness among stakeholders about the significance of incorporating ecological factors into urban development plans.

6. Government policymakers and other relevant bodies may utilize it as a source of information when making decisions about how land use and LST develop over time. In addition, based on the study's findings, it could be a place to start or reference for future research. Generally, the study equips government policymakers, non-governmental organizations, and environmental experts with valuable insights for informed making judgments about allocation of resources, handling of land, and climate change adaptation.

1.7 Scope of the Study

This study focuses on assessing the impact of LULC changes on LST in Addis Ababa, Ethiopia, using geospatial technology.

The study area has different LULC patterns, and the LULC have been occasionally altering. Consequently, knowing the location of resources and how they interact spatially and temporally seems critical to those resources and human resources over time.

Evaluating these changes gives insight into how changes in land cover affect the local climate and helps pinpoint the regions most impacted by rising LST. Furthermore, the study is crucial to comprehending the socioeconomic effects of LULC dynamics, including how they affect housing demand, the strain on infrastructure, and differences in temperature exposure between areas. Additionally, peri-urban agricultural output, the availability of water resources, and susceptibility to climate-related risks may all be impacted by elevated LST.

From an environmental point of view, rising LST is linked to increased greenhouse gas emissions, biodiversity loss, and the deterioration of urban green spaces. These effects call for well-informed land management techniques, such as encouraging sustainable zoning, urban forestry, and green infrastructure. In order to enable environmental monitoring and make evidence-based decisions for urban resilience, climate adaption, and efficient land management systems in Addis Ababa, evaluation of the connection between LST and LULC changes is required.

1.8 Limitation of the Study

By gathering, analyzing, and interpreting primary and secondary data, the current study made a concerted attempt to gather the required inputs. Notwithstanding these endeavors, the study encountered various obstacles. The bureaucratic obstacles and delays in the process of obtaining necessary data from several institutions were a major drawback.

1.9 Structure of the thesis

This study is structured into six chapters. Chapter One outlines the introduction, problem statement, objectives, research questions, scope, significance, and limitations. Chapter

Two reviews relevant literature, focusing on LULC changes, LST, and NDVI. Chapter Three details the research methodology, data sources, and study area. Chapter Four presents the results, including LULC maps, LST and NDVI analyses, and spatiotemporal change assessments. Chapter Five discusses the findings in relation to the study objectives. Finally, Chapter Six provides conclusions and recommendations for policy and future research.

CHAPTER TWO

2.1 REVIEW LITERATURE

This section surveys in brief the conceptual detentions and theoretical background of LULC and its dynamics and instrumental factors, as well as the results of some empirical studies made at various spatial and temporal levels in different parts of the world, specifically Ethiopia. It also surveys the literature on the results of studies and how LST may be the impact of land use/cover.

2.2 Concepts and definition of related terms

LULC Change: The transformation of the earth's surface, including both natural and human-driven changes in the types of land cover (e.g., vegetation, water, urban, agricultural land) and the way land is utilized.

Land Use: How humans use the land for activities such as agriculture, urbanization, and industrialization.

Land Cover: Earth's surface material includes natural and built features such as bare soil, water, vegetation, and urban structures (Di Gregorio, 2005).

According to Kayet et al. (2016), urbanization has become an inevitable factor contributing to rising LST in urban areas. It is also a component of observations of climate characteristics, uncertainty surrounding climate change, temperature distribution, and energy budgets at local and global scales (Varade and Dikshit 2020). For monitoring how the Earth's climate system is impacted by biological, chemical, and physical processes. The lowest layer of the atmosphere's air temperature is significantly altered by LST, which fluctuates with the energy of the earth's surface (Hasanlou and Mostofi, 2015). Because the surrounding environment affects air temperature, LST obtained Compared to the air temperature measured by terrestrial meteorological stations, what is learned from satellite data are superior.

Land Use Change: Land shift from one use to another (e.g. Forest to urban, agricultural expansion).

Temperature is the measure of an object's heat or coldness (Martin & Kline, 2004).

Land and land resources: A measurable portion of the earth's surface is called "land and land resources" This area includes all characteristics of the biosphere that are immediately above or below this surface, such as the near-surface climate, the soil and terrain forms, surface hydrology (which includes marshes, shallow lakes, rivers, and swamps), the near-surface sedimentary layers and the associated groundwater and hydrological reserve, the populations of plants and animals, the pattern of human settlement and the physical traces of past and present human activities—such as terracing, water management systems, roads, and buildings—reflect how humans have shaped the landscape (Briassoulis, 2009).

Urban: An urban area, built-up area, or urban agglomeration is a human settlement with a high population density and infrastructure of the built environment (McMillen & Smith, 2003).

The previous few decades have seen significant human-induced changes to the earth's surface, including deforestation, agricultural practices, and urbanization. Land is the most superior resource in the biosphere, and the LULC concept has been combined in many studies.

Nonetheless, the definitions of these two phrases differ, and they clarify two distinct problems. The term "land cover" describes the biophysical cover that is now visible on the surface of the earth, comprising hard surfaces, vegetation, water bodies, and soil. According to Di Gregorio and Jansen (2000), land use refers to the exploitation or utilization of land by human activities for settlements, agriculture, forestry, and grazing, affecting land surface processes such as biogeochemistry, hydrology, and biodiversity. Given this, a change in the surface component of the landscape is only regarded as having happened if the surface appears differently when viewed at least twice in succession (Lemlem, 2007). FAO (1999) defined Land use as the configurations, actions, and resources that humans use make on a particular type of land cover to either preserve or produce change.

As per Lambin and Meyfroidt's (2010) findings, changes in socio- economic innovations and changes that result in a significant loss of ecosystem services can have negative socio-ecological feedback, leading to a shift in LULC.

Urbanization: The expansion of cities and towns often associated with increased impervious surfaces and heat island effects.

2.3 Land-use and land-cover change in Ethiopia

Ethiopia's changing land cover land usage and natural resource availability vary greatly throughout Ethiopia, and regional variations in management are common. Differences in terrain, climate, and biogeography are the causes of this variability. Human activity is speeding changes in land use and cover but is also having an impact on individuals (Agarwal et al., 2002).

The existence of many biophysical resources, such as water, vegetation, soil, animal feed, and others, is altered by the dynamics of LULC (Ali, 2009). According to earlier research, Ethiopia has experienced significant LULC variations in several regions, as well as the development of cultivated land at the expense of forestland and into undeveloped areas as a result of land scarcity. Agricultural methods and human habitation, particularly in Ethiopia's highlands, have a long history. More recently, highland population pressure has resulted in unsustainable practices and the degradation of natural resources (Miheretu and Yimer, 2017).

2.4 Causes of land-use and land-cover changes

It’s the transformation of natural landscapes due to human activities or natural processes. These changes can have profound environmental, social, and economic impacts.

Land-use changes can be seen as a window into the human past and even the future. Numerous factors are connected to the increase in the human population, including economic development, environmental shifts, and technology (Houghton, 1994). Changes in land use occur first when land managers are dealing with particular land parcels determine that a shift towards a different type of land utilization is desirable. The conversion of one land cover type to another and the alteration of conditions within a category are referred to as changes in land cover (Meyer and Turner, 1992). Growing populations are one of the main causes of the LULC shift. The most valuable natural resource is people, who depend on one another for their sustained growth (Santa, 2011). The majority of human activities, including forestry, agriculture, industry, energy generation, recreation, habitation, and water catchment and storage, depend on land, which is why land use is important as a limited resource (http://www.ciesin.org/docs/002-105/002-105b.html). In the last three centuries, the amount of land that has been farmed has increased by nearly 45%, from 2.65 million Km^2 to 15 million Km^2. Meanwhile, the growth of agricultural land has resulted in the shrinkage of other natural resources, such as forests. Poverty and population expansion are most frequently linked to the high rates of forest loss in many developing nations (Mather and Needle, 2000).

Global environmental changes are largely caused by shifts in terrain and land usage, which have grown to be serious issues for the entire world (FAO, 1999). Large-scale land-use changes brought about by urbanization, deforestation (tree clearing), and the growth in the area used for cultivation in rural areas and other natural occurrences, as well as human activity, are causing modifications to the world's systems and cycles. Nonetheless, historically, the global the growth of land for farming has been the primary alteration in land use (Houghton, 1994).

2.5 Land Surface Temperature

LST is a fundamental variable in both climate science and ecology, influencing ecosystems and species across local to global scales. LST records the thermal radiation emitted from exposed terrain or vegetation canopies as a result of absorbed solar energy. NASA and other international organizations recognize LST as an essential Earth System Data Record (King, 1999). Its responsiveness to changes in surface conditions makes it a trustworthy measure of energy exchange at the land–atmosphere interface (Nemani et al., 1996; Wan et al., 2004; Lambin & Ehrlich, 1995; Mildrexler et al., 2009).

Unlike standard air temperature, daytime LST more accurately represents biophysical controls such vegetation density, surface roughness, and evapotranspiration and is more strongly correlated with the radiative and thermodynamic characteristics of the surface (Mildrexler et al., 2011a; Oyler et al., 2016). As a result, LST has become increasingly valuable in ecological and biogeographic research. It has been integrated with vegetation indices to differentiate land cover types (Lambin & Ehrlich, 1995; Nemani & Running, 1997), monitor land cover changes and disturbances (Julien & Sobrino, 2009; Mildrexler et al., 2007, 2009; Coops et al., 2009), and assess drought and plant stress in agricultural and natural ecosystems (Anderson et al., 2007; Scherrer et al., 2011; Wan et al., 2004;

Mildrexler et al., 2016). Furthermore, LST has been used to evaluate surface moisture status (Nemani et al., 1993) and study climate impacts such as heatwaves, thermal anomalies, and melting ice sheets (Li et al., 2015; Mildrexler et al., 2018), as well as their effects on wildlife communities and habitat use (Albright et al., 2011; Briscoe et al., 2014).

Land Surface Temperature (LST) has become a key variable in understanding the impacts of land cover changes on climate and ecosystems. Studies have linked LST to climate phenomena such as heatwaves, ice sheet melting, and droughts in tropical forests (Li et al., 2015; Mildrexler et al., 2018). It has also been used to examine the effects of extreme heat on wildlife, including bird communities and koala habitats (Albright et al., 2011; Briscoe et al., 2014). In urban areas, LST is critical for analyzing the Urban Heat Island (UHI) effect, where cities experience higher temperatures than surrounding rural areas due to surface characteristics (Weng, 2009; Zhou et al., 2019).

Beyond urban climate studies, LST plays an important role in climate-resilient planning and public health by helping identify areas vulnerable to heat stress (Li & Zhou, 2018). Technological advancements—such as the launch of ECOSTRESS, Landsat 8, MODIS, and Sentinel-3—now allow for higher-resolution LST monitoring, supporting applications in hydrology, drought assessment, wildfire risk, and biodiversity conservation (Hulley et al., 2019; Sobrino et al., 2020; Hook et al., 2019). Moreover, integrating LST data with artificial intelligence and machine learning is enhancing climate risk prediction, land cover classification, and anomaly detection, making thermal datasets more valuable for environmental monitoring and informed decision-making (Zhu et al., 2017; Ma et al., 2019).

2.6 Land Surface Temperature Retrieval Algorithms

Remote sensing methods used include the split-window method, single-channel algorithm, temperature/emissivity separation method, and mono-window algorithm (Ayanlade et al., 2021). The most common approach for deriving LST from satellite data involves minimizing atmospheric effects by leveraging the difference in atmospheric absorption between two neighboring thermal infrared bands, typically centered around 11 µm and 12 µm (Mirsanjari et al., 2021)). Split window algorithm (SWA) is the most popular method for obtaining LST from satellite data. SWA uses different atmospheric absorption in two adjacent TIR channels to obtain the LST (Wang et al., 2019).

Remotely sensed thermal data are the best sources of land surface estimates over a wide area, of which only data from geostationary satellites can fully characterize the LST diurnal cycle (Trigo et al., 2012). Satellite-based TIR data are directly linked to LST via the radiative transfer equation. The search for LSTs from remotely sensed TIR data has received much attention and its history dates back to the 1970s (Li et al., 2013). Although many LST retrieval techniques and platform data have been employed recently, the investigation of urban LST variations over time has taken many different forms, utilizing both satellite and ground data. Because Landsat data has a great spatial resolution of thermal bands, it is often used to get LST in urban regions and examine the spatial fluctuation of LST in urban environments (Yin et al., 2020). In order to retrieve LST from satellite photos, many techniques have been devised.

2.7 Normalized Difference Vegetation Index

The NDVI is one of the earliest and most widely adopted spectral indices for quantifying vegetation vigor and biomass from multispectral satellite imagery. By comparing the contrast between the near-infrared (where healthy vegetation reflects strongly) and red (where vegetation absorbs strongly) bands, NDVI effectively highlights areas of dense, photosynthetically active vegetation (Huang et al., 2021). It is calculated as:

NDVI= (NIR-Red) / (NIR+Red)

Where **NIR** and **Red** represent the reflectance values in the near-infrared and red wavelengths, respectively.

Urban green spaces and vegetation cover play a critical role in mitigating urban heat through latent heat flux, whereby evapotranspiration transfers energy from the surface to the atmosphere. High NDVI values correspond to dense, healthy vegetation and are consistently associated with lower LST due to increased latent heat flow (Goward et al., 2002; Roza et al., 2017). Conversely, areas of sparse or stressed vegetation (low NDVI) exhibit elevated LST, contributing to UHI effects.

To complement NDVI, the Normalized Difference Moisture Index (NDMI) is often employed to assess moisture conditions within the landscape. NDMI contrasts the near-infrared and short-wave infrared bands to estimate vegetation water content, with values greater than 0.1 indicating higher moisture levels and values approaching –1 reflecting dry conditions (Mihai, 2012). Together, NDVI and NDMI provide a more nuanced understanding of the biophysical controls on urban thermal patterns, as moisture availability directly influences the magnitude of latent heat flux.

In the Ethiopian context, where vegetation cover has declined markedly, LST increases of 3–8 °C have been observed between 1985 and 2015, underscoring the thermal consequences of LULC change (Odindi et al., 2015; Sruthi & Aslam, 2015). Detailed analyses across Addis Ababa’s sub-cities reveal a strong negative correlation between NDVI and LST (Worku et al., 2021; Gebrekidan et al., 2021), confirming that neighborhoods with higher vegetation density experience significantly lower surface temperatures. Furthermore, studies demonstrate that LST positively correlates with the Normalized Difference Built-up Index (NDBI) and inversely with NDVI, reinforcing the critical cooling role of urban greenery (Balew & Korme, 2020; Chaithanya et al., 2017).

Between 2020 and 2024, significant advancements have enhanced the application of NDVI in environmental and urban studies. High-resolution data from UAVs and Cube Sates now enable detailed, daily vegetation monitoring, particularly useful in data-scarce regions like Ethiopia. NDVI and LST are increasingly integrated into AI and machine learning models to improve predictions of urban heat, vegetation health, and land degradation. Cloud platforms like Google Earth Engine support long-term NDVI time-series analysis, while NDVI anomaly indices help assess extreme weather impacts and post-disaster recovery. NDVI is also used to evaluate urban ecosystem services and inform nature-based climate solutions. Recent studies link NDVI and LST to public health, highlighting inequalities in green space access and heat stress vulnerability. By combining NDVI with indices like NDMI and NDBI and socio-economic data, researchers can better map Urban Heat Island effects and guide green infrastructure planning, supporting sustainable urban development in cities such as Addis Ababa.

By integrating NDVI, NDMI, and NDBI metrics with high-resolution thermal data, researchers can more accurately map UHI intensity and identify priority zones for green infrastructure interventions, there by informing sustainable urban planning and climate adaptation strategies.

2.8 The Role of Remote Sensing and GIS

Over the past several decades in Remote Sensing community, LST is found to be one of the most important parameters in the physical processes of surface energy and water balance at local through global scales(Anderson et al. 2008; Brunsell and Gillies 2003; Karnieli et al. 2010; Kustas andAnderson 2009; Zhang et al. 2008). The temperature of the Earth's surface as measured by RS satellites—which pick up anything visible through the atmosphere from a top-down perspective—is more generally referred to as LST. For a variety of environmental and climate-related applications, it is crucial to estimate LST in order to uncover temporal and geographical fluctuations in the thermal state of the surface.

RS is the art, science, and technology of observing objects, scenes, or phenomena through instrument-based techniques (Damen, 2022). The function of remote sensing is to provide data useful for the analysis of temporal and spatial variations in large-scale parameters of the environment. This data is used for crop yield estimation, growth regulation, environmental damage assessment, land use monitoring, calculations, perimeter reconnaissance, urban planning, radiation monitoring, and geographic mapping for civil and military purposes (Javed et al., 2021). The field of remote sensing known as "thermal remote sensing" is mainly concerned with the collection, analysis, and interpretation of data in the electromagnetic (EM+) spectrum's thermal infrared (TIR) region. LST estimate and measurement heavily rely on remote sensing and GIS techniques. Surface temperatures are derived from geometrically corrected Landsat TIR Band 6 and Landsat 8 TIR Bands 10 and 11 (Khin et al., 2012)

One type of system is a geographic information system designed to gather, preserve, work with, evaluate, organize, and display geographic or spatial data (Coppin and Bauer, 1996). The types of data in GIS can be divided into two main groups' spatial data and non-spatial data. Spatial data is location-valued data, and no spatial data is a more tabular description of spatial data. According to Burrough (1990), GIS data consists of three dimensions: geographic, temporal, and attribute. Monitoring land use/land cover and surface temperature changes using advanced GIS and remote sensing is increasingly vital in global research (Alemu, 2019).

2.9 The impact of land-use land-cover change on land surface temperature

Developing countries are experiencing a significant population growth, particularly in sub- Saharan Africa where the annual rate population growth exceeds 2 % (Dimnwobi et al., 2021; Ezeh et al., 2012). In metropolitan regions, rapid population expansion is especially noticeable. The main drivers of urban population growth are more work opportunities, industrial growth, and rising living standards. People move from rural to urban regions in significant quantities because of the better living circumstances in cities. The heightened need for rental accommodation due to this movement pushes many people into illegal settlements and unpermitted home construction. In order to satisfy the housing demand and other offerings, a city's borders inevitably grow as its urban population rises. The LULC dynamics have been significantly impacted by the city's periphery's rapid expansion. Rapid urbanization threatens the environment and has an impact on sustainable urban development, according to a study by Barman et al. (2024). Study conducted by Yang et al. (2024) in China reveals a significant decline in rural population and a swift shift towards urban areas, impacting vegetation due to the rural-urban development trend. The horn of Africa's Ethiopia has also seen tremendous urbanization in recent decades, which has increased demand for open spaces for residential, commercial, and industrial uses (Weldegebriel et al., 2023; Koroso et al., 2021; Vandercasteelen et al., 2018). Approximately 50% of people on Earth reside in urban regions (Su et al., 2023; Yu et al., 2015; Cohen, 2006), and according to UN estimates, the proportion of people living in urban areas is predicted to rise to 67% by 2050 (Kohlhase, 2013). Rapid urbanization and population growth in developing countries significantly increase impermeable surfaces, namely roads, pavements, buildings, and other parking lots, which reduces the amount of vegetation in urban areas (Shao et al., 2019). Impervious surfaces have become a major concern in urbanization and environmental evaluation over the past few decades (Lian et al., 2024; Kesikoglu et al., 2021).

Change in LULC driven by rapid population growth around urban areas plays a significant role in modifying the thermal characteristics of the city, ultimately leading to the formation of an UHI effect (Nurwanda and Honjo, 2020). As the amount of impermeable surfaces increases, this UHI effect gets worse (Wang et al., 2022). Increased LST, heat waves, and changes to the entire climatic systems can result from the combined effects of unregulated rapid urban growth and LULC variations on the surface about the earth hydrology and thermodynamics. Land use type is one of the local variables that affect changes in LST near metropolitan areas (Chen et al., 2022). By 2050, 68% of the world's population is predicted to be vulnerable to surface urban heat islands (SUHI) because to the rising trend in LST, according to United Nations (2018) forecasts. The negative environmental effects of urban growth, such as rising temperatures and altered landscapes that provide environmental risks, are the root cause of the UHI issue (Fahmy et al., 2023; Atasoy, 2020).

The urban microclimate is impacted by changes in LULC because they result in the production of UHI (Siqi and Yuhong, 2020). Investigating the Connection among LULC change and LST is crucial factor to mitigate the problem of climate change around urban areas (Bokaie et al., 2016). Growing LST and UHI effects are causing urban climatic discomfort, which has a detrimental impact on quality of life in quickly expanding cities. One important metric in research on urban climate is LST (Tran et al., 2017). Understanding how LULC changes impact LST is critical for urban residents and city planners in rapidly urbanizing emerging countries. The use of geospatial technologies enables us to understand the connection among LST and LULC change (Merga et al., 2022; Moisa et al., 2022; Saha et al., 2021; Pal and Ziaul, 2017). Landsat and MODIS datasets are widely utilized to evaluate the impact of LULC changes on LST and the UHI effect in urban environments (Fahmy et al., 2023; Chakraborty et al., 2021; Qiao et al., 2020; Mukherjee et al., 2017; Ayanlade, 2016).

Because the radiances measured by satellite radiometers are affected, it is difficult to estimate LST directly from the radiation released in the thermal infrared spectral area by both surface characteristics and atmospheric conditions, making it difficult to achieve high accuracy (Li et al., 2013; Prata et al., 1995). Relying on ground measurements to collect data over large areas is impractical due to the intricacy of LST across land. However, the development of satellite RS technologies has empowered us to compute LST over vast geographical areas instead of relying on individual data points (Li et al., 2013).

Over the past few decades, extensive research on LST has been carried out in various regions of Ethiopia (Getu and Bhat, 2024; Bekele et al., 2022; Moisa et al., 2022; Merga et al., 2022; Worku et al., 2021; Yeneneh et al., 2022). Even though earlier research on LST was carried out in several regions of Ethiopia, there is still a dearth of data, particularly in large cities like Nekemte, Mattu, and Bonga. Additionally, no comparative analysis has been carried out to investigate how LULC modification affects LST in the many main cities in southwest Ethiopia. LST changes significantly in both space and time as a result of the dynamic character of LULC modification (He and Tang, 2023). As a result, LST analysis is crucial since it can help policymakers create practical plans to reduce possible risks associated with LST. Knowing how LULC change affects LST in the study region emphasizes the need for better urban land management policies and practices.

LULC change's impact on LST in various urban settings has been studied before. But because they have concentrated on a single urban region, the majority of these studies have not been able to differentiate between the spatiotemporal changes in LULC dynamics and their effects on LST in different metropolitan locations. Previous studies did not take into consideration the newly new urban areas in different sections of Ethiopia; instead, they only looked at large cities. Four major Ethiopian cities—Jimma, Bonga, Mattu, and Nekemte—in the southwest are the subject of this study. These cities were chosen due to the fact that their populations have grown significantly and quickly. Furthermore, little information is available about the LULC alterations' effects on LST in southwest Ethiopia.

Elevated land surface temperatures (LST) present sustainability concerns for urban areas, thus planners must be aware of the factors influencing LST, including changes in LULC. In order to determine if LULC changes or other variables contribute to LST increases, this study examines the effects of LULC changes on LST in four metropolitan locations in southwest Ethiopia.

Recent developments in urban climate research (2020–2024) have a strong emphasis on using AI, machine learning, and GIS technologies to enhance LST monitoring and analysis. Real-time evaluation is improved and post-disaster recovery is supported by tools such as Google Earth Engine, UAVs, and NDVI anomaly detection.

Furthermore, the necessity of fair access to green spaces is highlighted by the increased awareness of the connections among LST, environmental justice, and public health. By encouraging green infrastructure to lessen heat exposure and improve urban climate resilience, the study's conclusions were help shape urban policy.

2.10 Conceptual Framework

A structure of thought is a visual representation it aids in demonstrating the anticipated causal relationship in study. It describes the relevant objectives of the study and demonstrates how they are integrated to yield rational conclusions. When evaluating changes in land use and cover and examining how they relate to LST, a conceptual framework can be developed to understand the relationship b/n different variables. In this case, the variables would include Types of LULC and how they affect LST. A variety of landscape types, including built-up areas, dry soil, rocks, metaled roads, concrete infrastructure, water bodies, wetlands, woods, grasslands, scrublands, and cultivated land, would be taken into account by the conceptual framework, the effects of these various terrain types on LST varies. For instance, whereas water bodies, marshes, forests, and farmed land tend to lower LST, built-up areas and concrete infrastructure tend to increase it.

The health and coverage of these landscape structures may vary in different seasons, which should also be taken into account in the conceptual framework. By understanding the connections among different types of land use and cover and LST, it becomes possible to analyze the impact of LULC on LST and identify any correlations.

Developing a conceptual framework for assessing land use/cover change and analyzing its correlation with LST involves conducting an investigation of the literature on current studies on the topic this review helps identify relevant variables and their relationships, which can then be incorporated into the conceptual framework.

All things considered, the conceptual framework offers an organized method for comprehending the intricate connection between LST and changes in land use and cover. It acts as a research guide, assisting in the formulation of research questions, the identification of variables, and the analysis of anticipated cause-and-effect linkages.

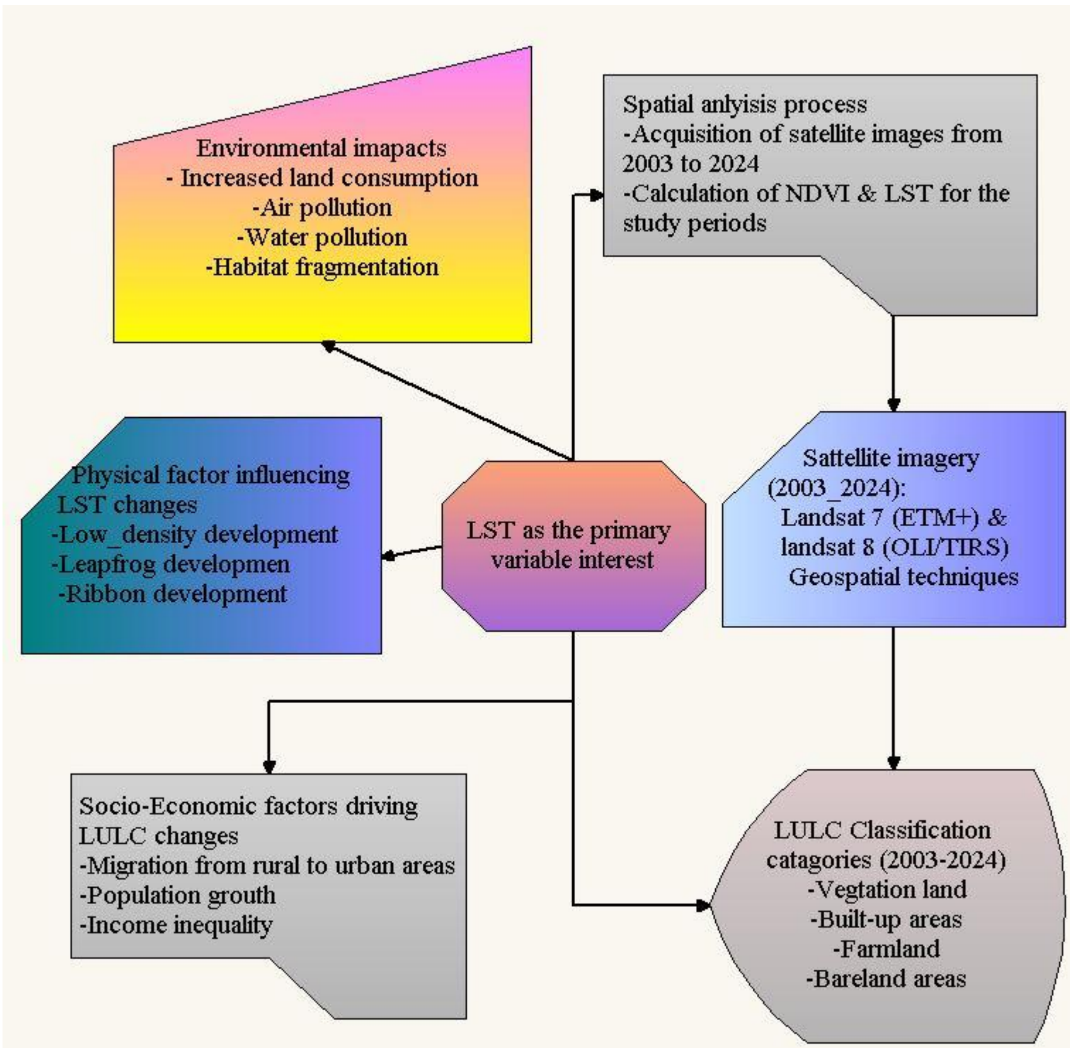


Figure 2.1: Conceptual Framework

CHAPTER THREE

3. MATERIALS AND METHODS

3.1 Description of the study area

3.1.1 Location

The African Union's headquarters and Ethiopia's capital, Addis Ababa, is frequently referred to as the "African Capital" because of its significant political, diplomatic, and economic role on the continent. It is well located close to the East African Rift, a magnificent continental rift that splits Ethiopia in two parts, at the length: 38°45'48.9996" E; a latitude: 9°0'19.4436" N.

Addis Ababa is a thriving city that is a significant center for trade, logistics, and transportation. The city is a desirable location for investment, company development, and the formation of a variety of projects because it is home to many multinational businesses and firms. Business and commerce are the main drivers of its economy, with tourism coming in second but steadily increasing. The National Museum of Ethiopia, which has the well-known fossil of "Lucy" (Australopithecus afarensis), the Gulele Botanical Garden, Meskel Square, Unity Park, Sheger Park, Friendship Park, Edna Mall, and Zoma Museum are just a few of the city's many notable attractions. With the renowned Addis Ababa University, Addis Ababa is also a hub for higher education.

The subtropical highland climate of Addis Ababa is distinguished by consistently mild temperatures. The city experiences a hot, dry summer and a distinct period of precipitation in the winter. Its attractiveness as a business and cultural destination is increased by its distinctive landscape and pleasant temperature. Significant political and economic changes have occurred in Addis Ababa in recent years. In order to direct urban and regional growth, the government has reorganized the city's administrative structure and implemented long-term development plans. In addition to changing the city's urban landscape, these reforms have strengthened the city's position as a vital hub for international cooperation, trade, and diplomacy.

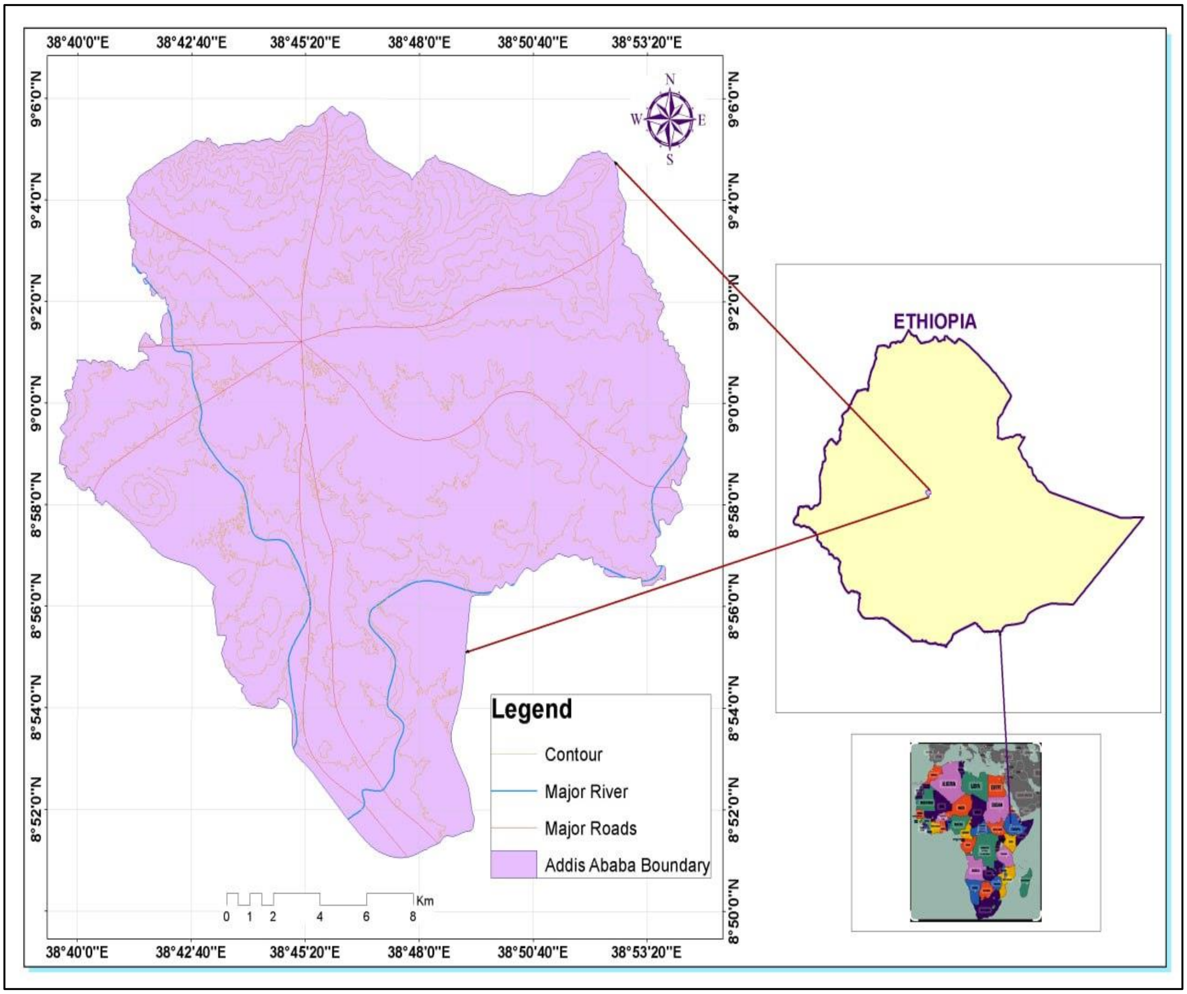


Figure 3.1: Location map of the study Area map.

3.1.2 Topography

Topography is a branch of geographical science that examines the natural features of the surface of the Earth, emphasizing the analysis of landforms, elevation, spatial characteristics, and associated natural phenomena. It encompasses the study of landforms, including hills, valleys, and other surface features, along with their spatial distribution, which is commonly represented through topographic maps. These maps utilize geographic coordinates to accurately depict the location and elevation of surface features, providing a detailed representation of terrain.

In the context of Addis Ababa, the elevation varies significantly, ranging from approximately 2,043 meters in the southern regions to around 3,022 meters in the northern areas. Understanding topography is fundamental in various disciplines, including geography, geology, environmental science, and engineering, as it provides important information about the physical characteristics and spatial distribution of landscapes.

Situated at the foot of Mount Entoto, the city is a component of the Awash watershed. From its lowest point at Bole International Airport in the southern outskirts, at 2,326 meters above sea level, Addis Ababa rises to a height of over 3,043 meters in the Entoto Mountains to the north.

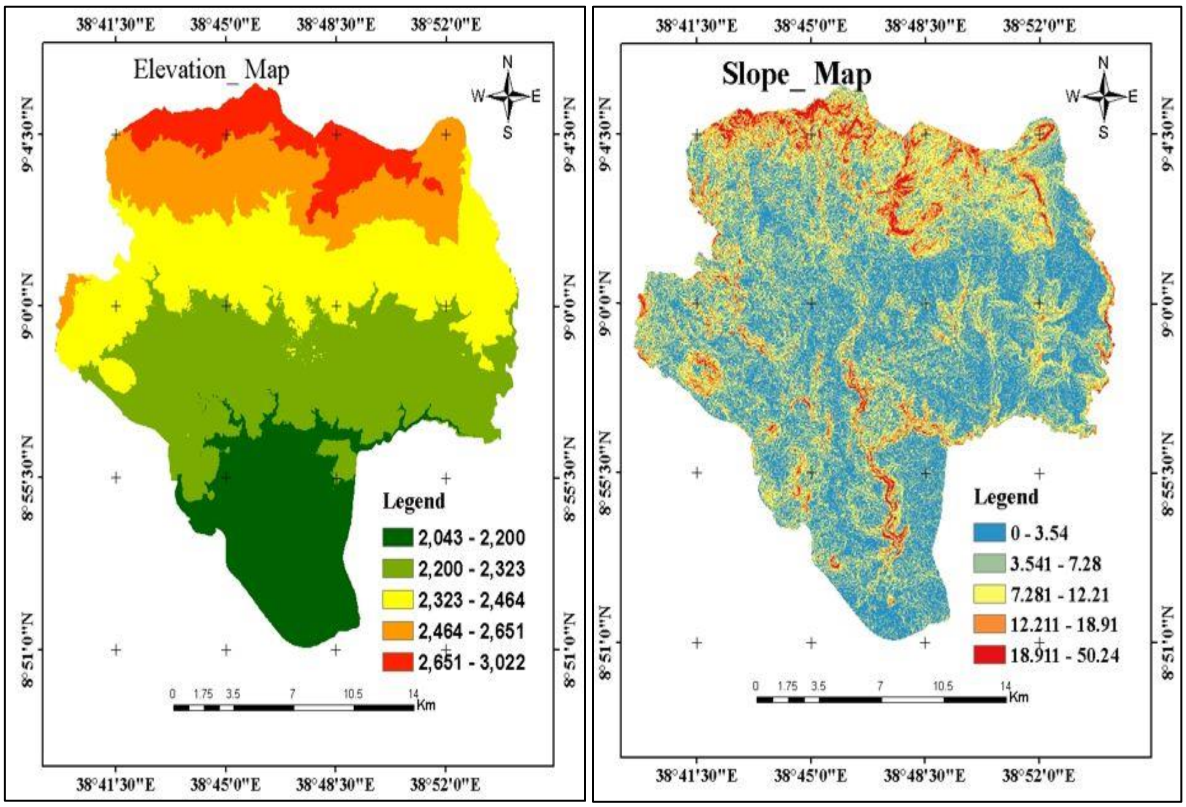


Figure 3.2: Slope Map and Elevation Map of the Study Area

3.1.3 Land use Land cover

The land cover in Addis Ababa can be categorized into several major types, each with distinct impacts on the local climate and temperature:

1. **Urban Areas**: As the city grows the proportion of built-up areas (e.g., residential, commercial, industrial) increases. These areas are characterized by concrete, asphalt, and other materials that absorb and retain heat,

contributing to higher LST. Urban heat islands (UHIs) are most pronounced in densely populated and industrial zones.

2. **Vegetation (Forests and Green Spaces)**: Vegetation in Addis Ababa is primarily located in parks, residential green spaces, and in the surrounding highland forests (e.g., Entoto Forest). Vegetation plays a cooling role through evapotranspiration and shading,helping to regulate local temperatures. However, the rapid loss of these vegetated areas due to urban sprawl and deforestation has exacerbated the UHI effect.
3. **Agricultural Land**: Agriculture has been an important land use in Addis Ababa's outskirts, where farming activities are widespread. Agricultural areas tend to have lower temperatures than urbanized zones but higher temperatures than forests or water bodies due to reduced canopy cover and evapotranspiration.
4. **Barren or Bare Land**: Unused or sparsely vegetated areas in the city, such as rocky terrains and construction sites, contribute to higher surface temperatures due to the lack of vegetation and the heat retention properties of exposed soil and rock.

3.1.4 Climate

A. Rainfall

The long-term rainfall data from 2003 to 2024 at Addis Ababa shows patterns of wet and dry seasons, meteorological station shows an average amount of rainfall each year during the main rainy seasons (belg and kiremt) being around 600-800mm, with some years having more rain and others less, likely due to climate change. There are fluctuations in rainfall that can affect farming and water supplies, and the data also suggests changes in when the rainy seasons start and end. Sometimes, there are more extreme weather events like heavy rains or droughts, which highlight the need for better planning and adaptation to protect communities and resources.

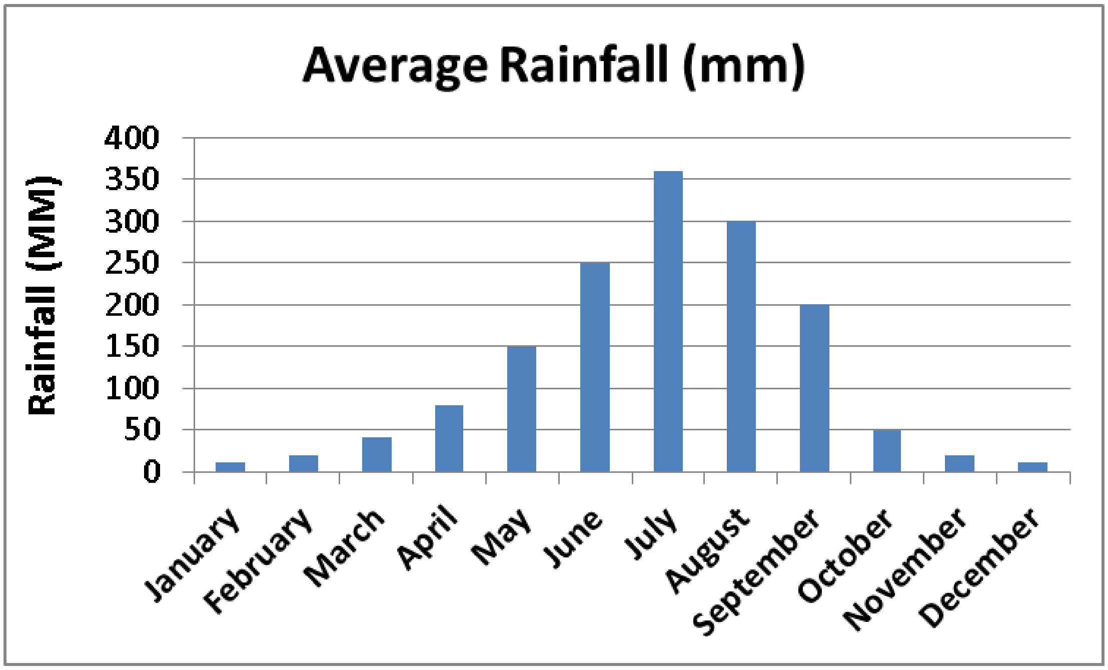


Figure 3.3: The study area's monthly average rainfall distribution.

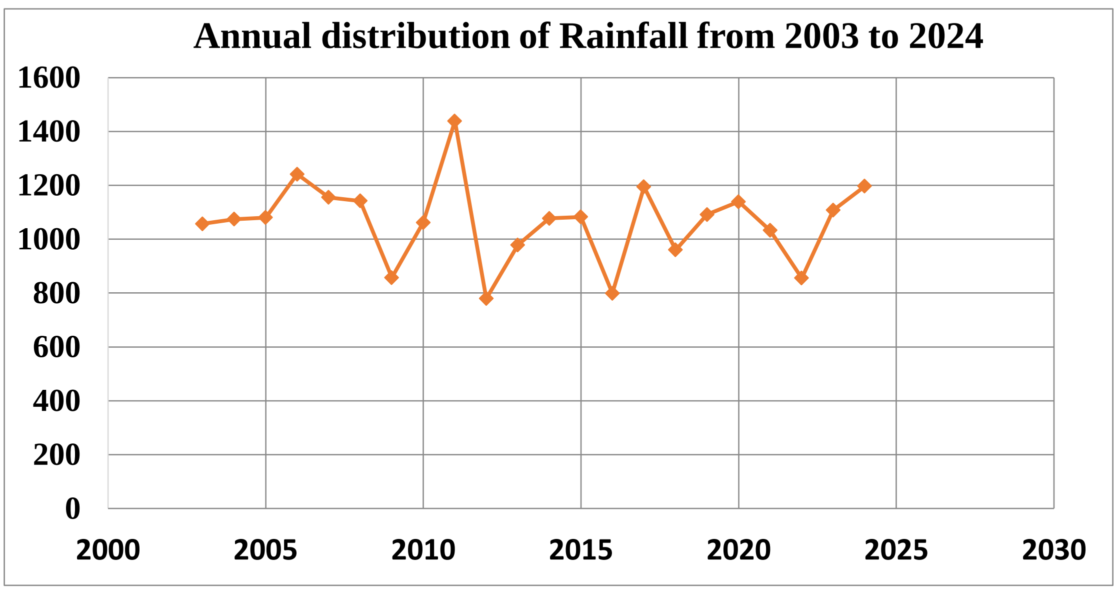


Figure 3.4: Annual distribution of rainfall from 2003 to 2024.

B. Temperature

Addis Ababa experiences its maximum precipitation during the summer months of June to August, and the minimum during the winter season from December to February, with a distinct dry season from December to April as noted by Abo et al. (2018). The climate near the city features a mean annual temperature ranging from about 12°C to 24°C, with daily temperatures fluctuating between 10°C and 15°C at night and 20°C to 24°C during the day; the lowest temperatures occur in December, while the highest are recorded in May. Over the period from 1998 to 2017, the average temperature was approximately 18.4°C (Wubneh 2013), illustrating the city's moderate climate with seasonal variations that influence both weather patterns and living conditions the detailed information presented Figure 3.4.

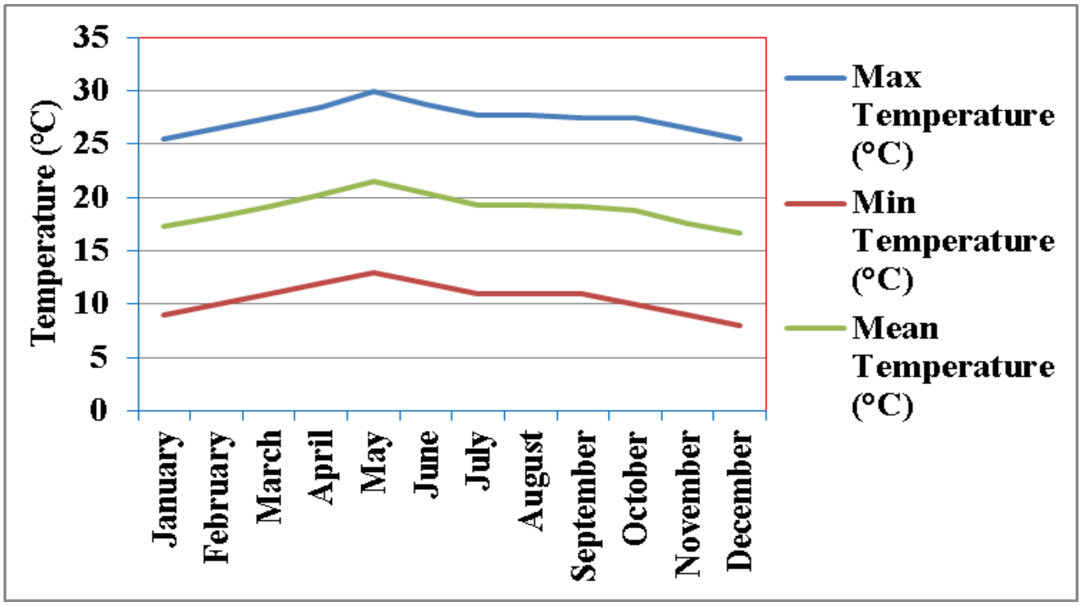


Figure 3.5: Monthly indicate, most, and greatest temperatures from 2003 to 2024.

3.1.5 Population

Like other cities in emerging nations, Addis Ababa's population is occasionally growing. The city's population grew from 2,112,737 in the 1994 national population census to 2,738,248 in 2007, Population projection values of 2017 at Addis Ababa city in all sex is 3,433,999 [Ethiopian Statistical Services (ESS), 2007].

Forecasts for the metro region of Addis Ababa's population are also provided for the year: 5,704,000 people live in the metro area of Addis Ababa as of 2024, a 4.45% rise from 2023.

- The Addis Ababa metro area had 5,461,000 residents in 2023, an increase of 4.46% from 2022.
- There were there are 5,228,000 residents in the Addis Ababa metropolitan area in 2022, up 4.43% from 2021.
- In 2021, there were 5,006,000 residents in the metro area of Addis Ababa, a

4.42% increase over 2020.

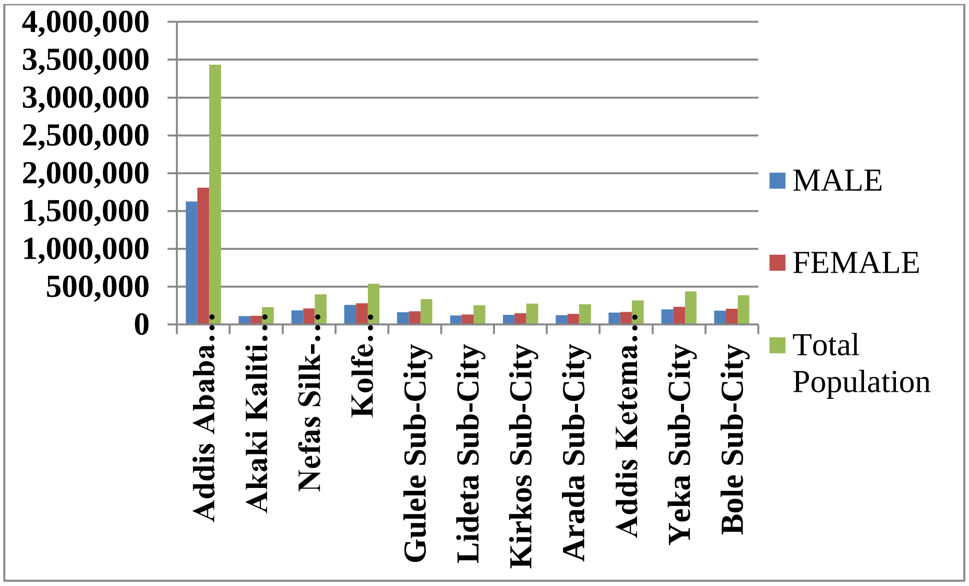


Figure 3.6 projection Population values of 2017

3.2 Research Approach

This study adopts a mixed-methods research design, integrating both qualitative and quantitative approaches to comprehensively investigate the relationship LULC changes and LST. His rationale for employing this design lies in the complex and multifaceted nature of urban environmental transformations, which require both empirical measurement and contextual understanding. Recent research emphasizes the importance of mixed approaches to better capture the dynamic interplay between human activities and environmental change, especially in rapidly urbanizing regions (Fisher & Reynolds, 2022).

Qualitative methods are utilized to explore the underlying drivers, processes, and socio-economic dynamics that influence LULC change. Techniques such as semi-structured interviews, focus group discussions (FGDs), and case studies enable the collection of nuanced insights from stakeholders, including local residents, municipal officials, and urban planners. These methods help uncover perceptions, motivations, land use decision-making processes, and institutional or policy-related factors that are not easily captured through quantitative data alone. This in-depth contextual understanding is essential for interpreting the human-environment interactions that drive urban expansion and land transformation.

In contrast, quantitative methods are employed to objectively measure and analyze spatial and temporal patterns of LULC change and its effects on LST. Remote sensing techniques and satellite imagery (e.g., Landsat, Sentinel) are used to perform land cover classification and to derive LST values. Geospatial and statistical analyses, including correlation and regression techniques, are then applied to quantify the relationship between LULC types and variations in surface temperature. This allows for the detection of trends, patterns, and significant associations across different time periods and urban zones.

The integration of qualitative and quantitative data strengthens the validity and depth of the research. While quantitative analysis provides measurable evidence of LULC-LST interactions, qualitative insights enrich the interpretation of those patterns by revealing the socio-political and economic contexts in which they occur. Such a mixed-methods approach enables a more holistic understanding of the environmental impacts of urbanization and supports the development of evidence-based, context-sensitive urban planning and land management strategies.

3.3 Data Collection and Sources

3.3.1. Primary Data

Satellite imagery from the Landsat program constitutes the principal dataset for this study, enabling detailed monitoring of surface dynamics over time. Imagery was acquired for three key epochs—2003, 2013, and 2024 using Enhanced Thematic Mapper Plus (ETM+) for Landsat 7 in 2003, the ETM+ in 2013, and a Landsat 8 OLI/TIRS in 2024. These sensors collectively provide multispectral observations across visible, near-infrared, and thermal infrared bands, supporting comprehensive analyses of land cover transitions, vegetation distribution, and LST variations. The higher spatial and spectral resolution of the ETM+ (2003) and OLI/TIRS (2024) sensors allows for more precise delineation of landscape features and improved change-detection capabilities.

In addition to optical and thermal data, a Digital Elevation Model (DEM) measuring 10 m by 10 m was incorporated for getting elevation and slope attributes, facilitating topographic mapping and slope analysis. Field campaigns provided ground-truth reference data: precise GPS coordinates were recorded at representative sites, and photographic documentation captured key land cover types—agricultural fields, bare land, settlements, and places with vegetation. These field observations were essential for validating satellite-derived classifications and enhancing thematic accuracy. The integration of Landsat imagery, DEM data, and field measurements thus establishes a robust framework for assessing spatial and temporal LULC trends in the research area.

3.3.2. Remote Sensing Data Acquisition

Remote sensing-derived indices and classifications were produced for every academic year (2003, 2013, and 2024) to quantify LST, the NDVI, and land cover categories—namely Agriculture, Bare Land, Settlement, and Vegetation. LST was retrieved from thermal infrared bands using split-window algorithms calibrated to each sensor's spectral characteristics. The red and near-infrared bands were used to calculate the NDVI evaluate vegetation vigor and spatial distribution. Supervised classification techniques implemented in GIS software were then applied to multispectral imagery to delineate the four simplified LULC classes, with signature training and validation informed by field-collected GPS points and photographs. This consistent methodology across the three epochs facilitates a rigorous comparison regarding variations in surface temperature throughout time, vegetation cover, and land use patterns throughout the study area.

Table 3. 1: Features and origin of satellite imagery

No	Data Sets	Acquisitions Date	Source	Resolution	Purpose of the data
1	Landsat 7ETM +	2003	USGS/ Copernicus Open Access Hub	30m/10m	For LULC, LST and NDVI
2	Landsat 7ETM +/ Sentinel Data	2013		30m/10m	For LULC, LST and NDVI
3	Landsat8 OLI/TIRS/ Sentinel Data	2023		30m/10m	For LULC, LST and NDVI
4	Ground truth	2023	GPS	2 m	For LULC Validation
5	Google Earth pro	5 cm			For Validation

A. Enhanced Thematic Mapper Plus (ETM+) for Landsat 7

Launched in July 1999, the Landsat 7 satellite's ETM+ sensor has provided near-continuous Earth imagery on a 16-day revisit cycle, delivering consistent, and high-quality data for over two decades. Its eight spectral bands capture diverse surface characteristics: Bands 1–5 and 7 record visible, both shortwave and near-infrared reflectance at 30 m resolution—ideal for monitoring vegetation health, geological formations, and land-cover classification.

In addition, ETM+ includes a thermal infrared band (Band 6) at 60 m resolution for detecting surface temperature variations, such as urban heat islands or volcanic activity, and a panchromatic band (Band 8) at 15 m resolution, which enhances visual detail for urban planning, infrastructure mapping, and disaster response. The combination of multispectral, thermal, and high-resolution panchromatic data has made Landsat 7 ETM+ an indispensable resource for environmental monitoring, resource management and change-detection studies worldwide.

A. Landsat 8 Thermal Infrared Sensor (TIRS) and Operational Land Imager (OLI)

The launch date of Landsat 8 was February 11, 2013, carries two complementary instruments—OLI and TIRS—that together extend and refine Earth surface observations. OLI captures nine spectral bands: a "ultra-blue" coastal/aerosol band (Band 1), visible blue, green, red, near-infrared, two shortwave-infrared bands (Bands 6), a cirrus detection band (Band 9), and a 15 m panchromatic band (Band 8). All OLI reflective bands (except the panchromatic) have a 30 m spatial resolution, enabling detailed monitoring of land cover, coastal dynamics, and atmospheric aerosols.

TIRS adds two thermal infrared bands (Bands 10 and 11) at a 100 m resolution, improving surface temperature retrievals and facilitating studies of thermal anomalies, urban heat islands, and energy fluxes. The dual-band TIRS design reduces atmospheric absorption errors via split-window algorithms, yielding more accurate LST measurements. Together, OLI and TIRS provide unparalleled multispectral and thermal datasets that support many different applications from vegetation and hydrological monitoring to climate-change research and urban environmental assessments.

3.3.3 Software packages used

ArcGIS 10.8 was the main platform for geospatial analysis, used for managing spatial data, conducting overlay and zonal statistics, and generating LULC and LST maps. Its advanced tools supported accurate spatial correlation and trend analysis.

ERDAS IMAGINE 2015 was essential for remote sensing data preprocessing, including geometric correction, radiometric calibration, atmospheric correction, and supervised classification. These steps ensured data accuracy before spatial analysis in ArcGIS.

Together, these tools provided a reliable workflow—ERDAS IMAGINE for image preparation and ArcGIS for detailed spatial analysis and visualization.

Table 3. 2: Characteristics of Software

S. No	Materials	Function
1	Computer	Data analysis and report writing etc.
2	ArcGIS 10.8	Used for Data presentation, data analysis map compilation (preparation), etc.
3	ERDAS 2015 IMAGINE	Used for image classification, accuracy evaluation, satellite image processing, etc.
4	Earth Pro by Google	Utilized to visualize the study area, compare and verify the results with the ground truth LULC validation, etc.
6	Quantum (QGIS)	A free source program, which also features map algebra and neighborhood analysis, was utilized for raster manipulation.
7	ENVI	Used for LULC classification, change detection, and temperature analysis
8	Microsoft Office	Utilized for managing spreadsheets, producing Word documents, and database presentation and data management and other software may be used as needed.

3.4 Methods

The approaches employed in this proposal to accomplish the research's aims was commence with the acquisition of Landsat 8 from https://libra.developmentseed.org and Landsat imagery for 2003, 2013, and 2023 from the USGS website. The selection of over the years was based on the data's accessibility and the shifting nature of land use. The photo was taken during the dry season and downloaded without any clouds. The following Figure 3.7 Methodological flow chart was depicting the general methodological flow chart project.

3.5 Research Design

The research design uses a mixed-methods strategy, combining quantitative and qualitative methods to comprehensively assess LULC and its correlation with LST. Statistical analysis examines the LST and LULC's relationship variables like NDVI and land cover classifications.

3.6 Methodological flow chart

The flow chart approach is a visual means to present the step-by-step progression of my research methodology. Each step in the flow chart represents a distinct research activity or analysis phase, and lines connecting the steps indicate the sequential or parallel relationships between these activities.

By visually representing the methodology in a flow chart, I can effectively communicate the research plan and process for assessing changes in land cover and use and how they relate to LST. This can aid in both comprehending the methodology and explaining it to others.

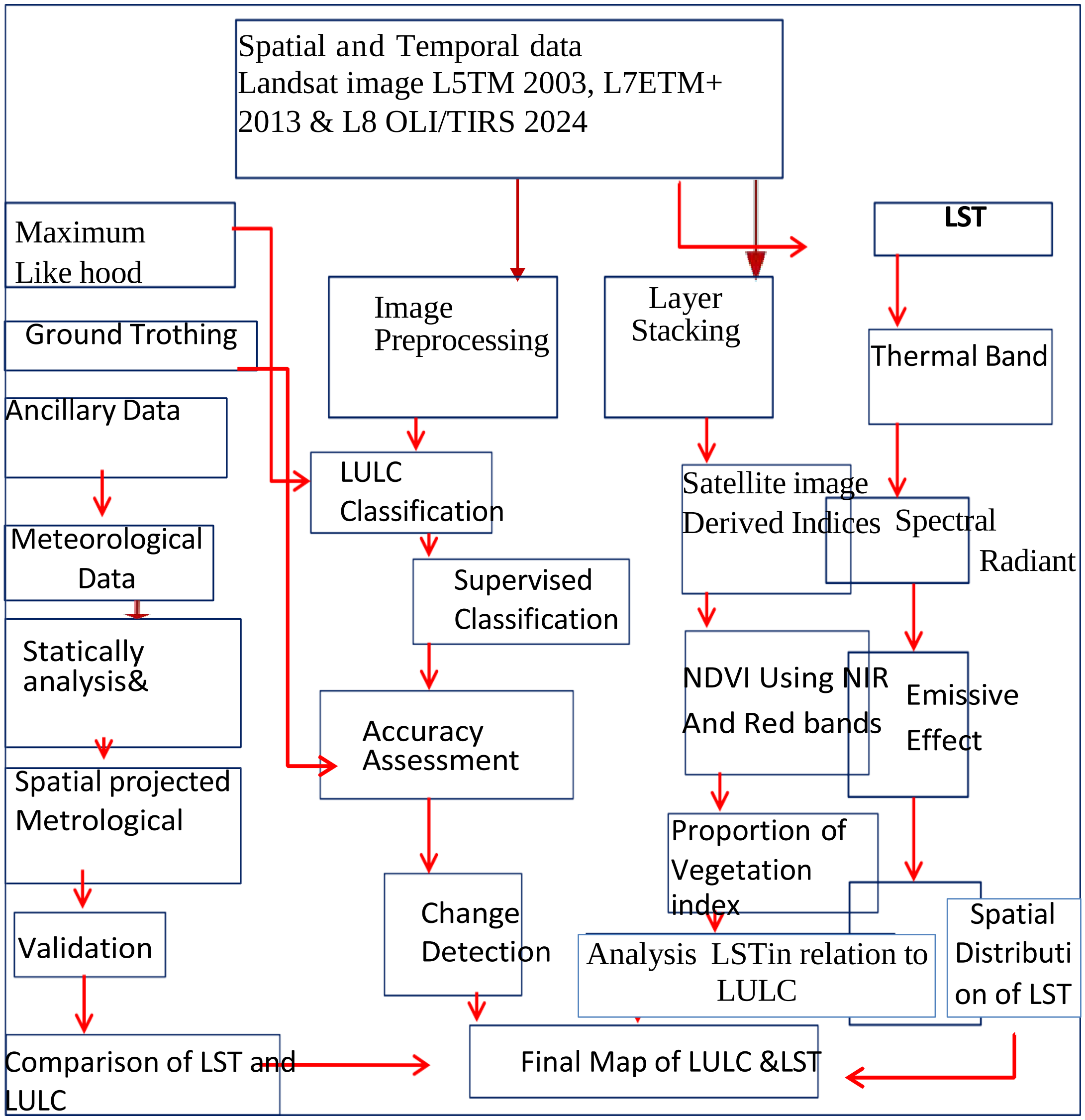


Figure 3.7: Methodological flow chart

3.7 Data Analysis

3.7.1 Digital Image Preprocessing

These methods aim to correct distorted or damaged picture data to create a more realistic representation of the original scene and to make an image more valuable for further processing. To do this, raw image data typically needs to be processed first in order to eliminate noise, adjust radiometric correction for geometric distortions, and use mosaicking or sub-setting to increase or decrease an image's extent.

3.7.2 Image Classification

The classification process involves assigning every pixel in a digital image to a specific land cover class or category. These classified data can then be used to create thematic maps showing the distribution of land cover types and to generate summary statistics of the area covered by each class. In this study, the LULC of the area was derived using GIS and ERDAS Imagine software with a supervised classification approach based on the maximum likelihood algorithm. Supervised classification method with a MLC algorithm, is mostly accepted classification method used in RS data (Foody, 2002).

In this study, supervised classification techniques are employed.

I. Supervised classification

Supervised classification is a widely used method in remote sensing; based on the principle that different surface features exhibit unique spectral signatures due to their distinct reflectance characteristics. These spectral signatures serve as identifiers, enabling the differentiation of various land cover types. In this study, supervised classification was performed for the years 2003, 2013, and 2024, focusing on key LULC categories such as bare land, farmland, vegetation, and settlement,. Field verification ensured the accuracy of these classifications.

The classification process began with the collection of training samples, which are representative areas of each LULC class, capturing their spectral variability. Remote sensing software tools facilitated the selection of these training sites directly on the image. These samples were then used to train a classification algorithm, such as MLC, which categorized each pixel based on its spectral similarity to the training samples—a process known as pixel-based classification.

For this study, bands 1 to 7 of preprocessed images were used to classify LULC patterns for the years 2003, 2013, and 2024. The classification process was completed using ERDAS Imagine 2015's Maximum Likelihood Classification method, with accuracy assessment performed in ArcGIS. The study was divided into four primary LULC classes: farmland, bare land, settlement, and vegetation. Supervised classification enabled the creation of information classes that aligned with user-defined categories, providing detailed LULC maps for each study year.

Despite its advantages, supervised classification may encounter challenges, such as discrepancies between information classes and spectral classes, as well as variability in class signatures. To address these issues, preprocessing techniques, including atmospheric correction and radiometric calibration, were applied. Additionally, Amplification of spectral methods, Principal Component Analysis, for instance and spectral unmaking, were used to improve the reparability of classes. Noise reduction techniques were also employed to enhance the clarity of spectral data, ensuring more accurate LULC classification.

II. Maximum likelihood classification

MLC is a widely used remote sensing method that divides pixels into groups according to the types of land cover. By analyzing the spectral characteristics of each class, it uses statistical decision theory to assign each pixel to the class to which it most likely belongs. Unlike simpler methods, such as parallelepiped classification, MLC provides greater accuracy, particularly when dealing with overlapping spectral signatures among different land cover types.

MLC determines the likelihood that a pixel belongs to each class using the distribution of pixel values (mean and covariance) in the training data. Next, each pixel is assigned to the class with the greatest likelihood, ensuring a more precise classification. However, the primary drawback of MLC is its relatively high computational demand, making it slower than some other classification methods.

In practice, the MLC tool considers the unique spectral characteristics of each class listed in the signature file, ensuring that even classes with similar spectral properties can be accurately distinguished. This capability makes MLC an effective method for detailed and accurate land cover classification in remote sensing applications.

III. Ground truth

A ground trothing exercise took place in the research space to validate various LULC class. The LULC classes observed included farmland, Vegetation, bare land, and built-up areas. These categories were instrumental in developing the map legends. Assisted by GPS, training datasets necessary for image classification were collected. Additionally, during these ground trothing efforts, photographs and coordinates of specific scenes representing the sampled LULC classes were recorded.

Table 3. 3: LULC Classes and Descriptions

LULC Classes and Descriptions	
LULC Class	Description
Farmland	Areas dedicated to the cultivation of annual and perennial crops, including both small-scale rural farms and extensive agricultural fields.
Settlement/Built-up Area	Urban and semi-urban regions comprising residential, commercial, industrial structures, roads, and other infrastructure.
Bare Land	Non-vegetated areas including beaches, dunes, exposed rocks, salt flats, degraded landscapes, quarries, and sites with eroded soil.
Vegetation	Refer to regions of land covered by plant life, including forests, grasslands, shrub lands, wetlands, and agricultural fields. These areas are characterized by the presence of plant species that naturally grow in the environment or are cultivated by humans. Vegetation is essential for ecological balance, climate regulation, soil protection, and wildlife habitat.

3.7.3 Data Preparation and Analysis

Satellite images often contain various imperfections, such as distortion, noise, haze, and striping, which can affect their quality and accuracy. Therefore, a series of pre-processing steps were undertaken before data analysis to guarantee the accuracy of the findings. Initially, the satellite image bands were imported and stacked to create a multispectral image suitable for analysis. The image was then clipped to fit the boundaries of Addis Ababa city, defining the study area.

Geometric correction was applied to rectify positional distortions, ensuring spatial accuracy. Radiometric correction followed, where atmospheric noise was removed to enhance the representation of ground truth conditions, improving the accuracy of pixel values. Any visible stripes or line artifacts were corrected, maintaining the visual integrity of the image. Additionally, pan sharpening techniques were employed, which involved merging higher-resolution panchromatic bands with lower-resolution multispectral bands to enhance spatial detail.

Further methods for improving images were applied to optimize the contrast and clarity of the images, making them more suitable for interpretation and analysis. To maintain consistency, all geospatial data were geo-referenced using the Adindan coordinate system, Zone 37N, which is the local datum for Ethiopia. This consistent spatial referencing, applied across vector and raster data, ensured accurate alignment and reliable analysis throughout the study.

3.7.4 Land Use Land Cover Change Detection

The process of detecting change in particular locations is known as change detection. To ascertain the degree and type of changes over time, many remote sensing programs analyze two or more photos taken at various times. One of the most commonly used techniques for detecting changes is post-classification comparison. In this study, LULC changes were analyzed using satellite images from the years 2003, 2013, and 2024. The change detection process involved technical integration procedures carried out with ArcGIS software. The initial step was to create a table showing the area coverage in square kilometers and the percentage change for each LULC class across the three years. To quantify the percentage of LULC change, a specific calculation formula was applied.

3.7.5 Image Enhancement

In digital image processing, image enhancement is an essential phase that aims to improve the visual quality of images for improved interpretation, display, and more accurate analysis. It involves applying various techniques to increase the contrast and distinction of features within an image, making them easier to identify. As noted by Billah and Rahman (2004), this process focuses on enhancing the visibility of scene elements, which is essential for both manual examination and automated image processing.

The main goal of image enhancement is to make images more understandable to human viewers or to optimize them for further automated analysis. This can be achieved through several techniques, including contrast stretching, which adjusts pixel values to enhance visibility; histogram equalization, which redistributes pixel intensities for improved contrast; and spatial filtering, which sharpens or smooth the image to highlight critical features.

Enhanced images not only facilitate better visual interpretation but also provide more accurate input for automated analysis. By reducing noise, emphasizing subtle details, and improving overall image quality, image enhancement ensures that subsequent interpretation and analysis are more precise and reliable.

3.7.6 Classification and Accuracy Assessment

Image classification is a process that involves assigning each pixel in a digital image to a specific land cover category or theme. This process enables the creation of summary statistics for the area covered by each land cover type and the production of thematic maps that illustrate the spatial distribution of LULC within the study area. In this study, image classification was performed using the supervised classification method in GIS and ERDAS Imagine software, specifically employing the MLC technique. The MLC algorithm, widely recognized as one of the most reliable classification methods for remote sensing data (Kamusoko, 2022), operates by evaluating the reflectance values of individual pixels.

During the classification process, pixels were grouped into clusters based on their reflectance properties, which were derived from the chosen spectral bands. The user specified both the number of clusters and the particular bands to be used, and the classification software generated the clusters accordingly. This study employed supervised classification because it enables the researcher to directly select training areas representing specific land cover types, thereby ensuring that the classification accurately captures the unique features of the study area.

Following the completion of the land cover classification, it was essential to assess the accuracy of the classification results. A classification is not considered complete without an evaluation of its accuracy. One of the most commonly used methods for assessing classification accuracy is the preparation of an error matrix (also known as a confusion matrix or contingency table). This matrix compares the classification results with evidence of reference that is known (ground truth) on a category-by-category basis, providing a clear assessment of classification performance. A confusion matrix was employed in this investigation to evaluate classification accuracy, with representative points selected from each land cover type to ensure a reliable assessment.

3.7.7 Land Surface Temperature Retrieval

The thermal bands of Landsat images (Landsat 7 and Landsat 8) were used to generate LST values for the study periods (2003, 2013, and 2024). Thermal was used for Landsat 7 and Landsat 8, with Landsat 7 using was band 6 and Landsat 8 using was band 10 and 11, respectively. The same mono-window algorithm was used as the following steps are included in the reinvestigating method for producing LST from thermal bands that was reported by Imran et al. (2021) and Kafy et al. (2020).

A. DN to Spectral Radiance Conversion

Using the image processing program ArcGIS 10.8, the digital numbers (DN) of the thermal infrared (TIR) bands were transformed into spectral radiance. The Radioactive Transfer Equation (RTE), which is described in Equations (1) and (2), was used to carry out this conversion. For data from Landsat TM:

$$L_{\lambda} = L_{Min} + (L_{Max} - L_{Min}) \times DN/255 \quad \text{.......................................Eq. (1)}$$

Equation (1) is used to convert digital integers to spectral radiance, following the methodology's instructions.

$$L_\lambda = \frac{L_{Max_\lambda} - L_{Max_\lambda}}{Q_{Cal_{Max}} - Q_{Cal_{Max}}} * Q_{Cal_{Max}l} - Q_{Cal_{Min}} + L_{Min_\lambda} \text{...Eq.(2)}$$

Where L_λ is the value of spectral radiance; Q_{CAL} represents the DN value of the quantized calibrated pixel; $L_{MAX\lambda}$ represents the value of spectral radiance in ($Wm^{-2}sr^{-1}\mu m^{-1}$) scaled to Q_{CALMAX}; $L_{MIN\lambda}$ represents the value of spectral radiance in ($Wm^{-2}sr^{-1}\mu m^{-1}$) scaled to Q_{CALMIN}; Q_{CALMIN} and Q_{CALMAX} are the min and max DN values of the quantized calibrated pixels that correspond to $L_{MIN\lambda}$ and $L_{MAX\lambda}$, respectively. For Landsat OLI/TIRS:

$L_\lambda = M_L \times Q_{Cal+A_l}$ .... Eq. (3)

The top-of-atmosphere spectral radiance, expressed in watts per square meter per steradian per micrometer ($W \cdot m^{-2} \cdot sr^{-1} \cdot \mu m^{-1}$), is represented by Lλ. The band's radiance multiplicative scaling factor, ML, is derived from the metadata (e.g., Radiance Mult Band 10 & 11); the digital number (DN) value of the calibrated and quantized pixel is represented by QCAL; and the radiance additive scaling factor, AL, is derived from the metadata (e.g., Radiance Add Band 10 & 11).

B, Conversion of Spectral Radiance to TOA Brightness Temperature (BT)

The TOA brightness temperature (BT), commonly known as the satellite-derived temperature was determined in Kelvin using the spectral radiance values that were obtained by converting the pixel digital numbers. Equation (4) was used to calculate the brightness temperature under the assumption of a homogeneous surface emissivity.

$$BT = \frac{K_2}{\ln(\frac{K_1}{L_\lambda} + 1)} \text{.. Eq. (4)}$$

Where BT is brightness temperature at the top of the atmosphere (TOA) expressed in ◦K; L_λ is the spectral radiance at TOA expressed in ($Wm^{-2}sr^{-1}\mu m^{-1}$); K1 and K2 are the retrieved metadata's thermal conversion constants.

(C) Using Brightness Temperature (BT) to Calculate Land Surface Temperature

In this stage, the at-satellite brightness temperature (BT) was corrected to determine the land surface temperature (LST) in Kelvin. Equation (5), which corrects the BT values to more precisely reflect surface temperature conditions while taking air influences and surface emissivity into consideration, was used to do this.

$$\mathbf{LST(^{\circ}K)} = \frac{\mathbf{B_T}}{[\mathbf{1} + \boldsymbol{\lambda}\left(\frac{\mathbf{B_T}}{\mathbf{E}}\right)\mathbf{ln}(\boldsymbol{\varepsilon})]} \text{ .... } \textbf{Eq. (5)}$$

where E is a constant derived from Planck's law, calculated as (h × v)/s, with a value of 1.4388×10^{-2} mK; BT is the at-satellite brightness temperature as measured by the sensor; and λ is the wavelength of emitted radiance, which is roughly 11.5 µm for Band 6 in Landsat 4/5/7 and 10.8 µm for Band 10 in Landsat 8. Here, v is the speed of light (2.998×10^{8} m/s), s is the Boltzmann constant (1.38×10^{-23} J/K), and h is Planck's constant (6.626×10^{-34} J·s). Equation (6) was used in this investigation to calculate the land surface emissivity, denoted by the term ε.

(ε) =N (Pv) + n .... Eq. (6)

Where N is 0.004; n is 0.986; and Pv is the vegetation proportion expressed in Equation (7).

$$\mathbf{P_v} = \left(\frac{\mathbf{NDVI - NDVI_{min}}}{\mathbf{NDVI_{max} - NDVI_{min}}}\right)^{\mathbf{2}} \text{ ....} \textbf{Eq. (7)}$$

With NDVImax and NDVImin denoting the highest and lowest DN values recorded, NDVI stands for the digital number (DN) values obtained from the NDVI image. Lastly, the proper conversion formula (Equation 8) was used to convert the estimated LST, which had been initially computed in Kelvin, to degrees Celsius (°C). This stage guarantees that the temperature readings are easier to understand and appropriate for real-world uses.

LST (◦C) = LST (◦K) − 273.15 ....Eq. (8)

Where:

◦C is the Land Surface Temperature in Celsius.

◦K is the Land Surface Temperature in Kelvin.

Verification of the Approximated LST

To evaluate the precision and dependability of the estimated LST data for the planned analysis, validation is necessary. Google Earth was used to choose random sample sites for this study's validation process. Using zonal statistics, the matching LST values were derived from the Landsat 8 Thermal TIRS data. The accuracy and consistency of the calculated LST were then assessed by comparing the mean LST values for each sample polygon.

3.7.8 Normalized Difference Vegetation Index (NDVI) Estimation

The NDVI, a reliable index for deriving vegetation conditions from remotely sensed data, is one of the most widely used indicators of the urban climate in environmental research. Since NDVI is directly utilized to calculate land surface emissivity, it plays a crucial role in estimating LST (Guha & Govil, 2020). Non-vegetated areas are indicated by negative NDVI values, while vegetated areas are represented by positive NDVI values, which range from -1 to +1. Equation (9), was used to extract the research area's NDVI.

$$\mathbf{NDVI} = \frac{\mathbf{NIR(Band\ 4{,}5) - RED\ (Band\ 3{,}4)}}{\mathbf{NIR(Band\ 4{,}5) + RED\ (Band\ 3{,}4)}} \quad \textbf{Eq. (9)}$$

Where NIR (Band 4) is for Landsat 4–5 TM and NIR (Band 5) is for Landsat 8 OLI. RED (Band 3) is for Landsat 4–5 TM and RED (Band 4) is for Landsat 8 OLI.

Statistical Analysis

Statistical analysis is very significant to analyze different variables both dependent and independent variables. This study used statistical techniques to investigate the connection between variations in LST and LULC. The connection among LST and the NDVI was also investigated using a linear regression analysis. This entailed turning the research area's raster pixels into point data, from which sample points from the produced maps for each distinct time period under analysis were used to extract parametric values.

3.8 Validation of Estimated LST

Validating the estimated LST is a crucial step to ensure the accuracy, reliability, and suitability of the derived data for subsequent analysis and decision-making processes.

This validation process assesses the degree of agreement between the estimated LST values and actual surface conditions, thereby providing confidence in the data's representativeness.

In this study, the validation procedure commenced by selecting random sample locations across diverse land covers types and environmental settings using Google Earth as a reference platform. LST values were extracted from Landsat 8 TIRS data corresponding to these locations through the application of zonal statistics. By calculating the mean LST values within defined polygons representing different land cover classes, a comprehensive comparative assessment was performed. This method enabled the identification of potential spatial inconsistencies and systematic errors in the LST estimation.

The integration of random sampling, zonal statistics, and comparative analysis in the validation framework enhances the robustness of the LST data. Ensuring the precision and consistency of the estimated LST across heterogeneous spatial contexts improves the data's credibility, rendering it more appropriate for environmental studies, urban planning, and climate-related decision-making. Ultimately, this validation step serves as an essential quality assurance measure, confirming that the estimated LST data are accurate and fit for their intended applications.

3.9 Zonal Analysis

Zonal analysis aggregates raster data values based on spatial zones defined by an input dataset, which can be either vector or raster, by summarizing cell statistics within each zone boundary. In this study, zones were delineated according to LULC classes, and the Zonal Statistics tool in ArcGIS 10.8 was utilized to overlay LULC maps, NDVI raster's, and LST raster's for the years 2003, 2013, and 2024.

For each LULC category—including Agriculture, Bare Land, Settlement, and Vegetation—zonal statistics computed key summary metrics such as mean and standard deviation of NDVI and LST values within each zone. This produced detailed tabular summary describing variations in vegetation vigor and surface temperature by land cover type.

In order to investigate the connection among vegetation health and surface temperature, the mean LST and mean NDVI values for each zone were exported to Microsoft Excel and subjected to correlation analysis. By converting pixel-level reflectance and temperature data into aggregated zone-level statistics, this approach elucidated the spatial dynamics between LULC and thermal characteristics. For example, vegetated zones consistently demonstrated lower mean LST and higher mean NDVI values, whereas built-up areas exhibited higher surface temperatures and lower vegetation indices.

Thus, zonal analysis provided a robust statistical framework to quantify the spatial interactions between land cover changes and surface temperature dynamics over the study period, contributing critical insights into urban environmental processes.

CHAPTER FOUR

4. RESULT AND DISCOSSION

Using sophisticated geospatial technologies, the study's findings were methodically examined to determine how changes in LULC affected LST in Addis Ababa, Ethiopia. The analysis's main goal was to investigate the territorial patterns of LST and the NDVI, looking at both the effects of each measure alone and in combination. Important new information on the complex connections among LULC, LST, and spectral markers like NDVI was discovered after a thorough investigation. Comprehensive historical LULC trend exploration provided crucial background information for the investigation. The analysis offered a sophisticated knowledge of the changes in the environment and its utilization affect surface temperature in the study area by identifying and quantifying the interactions among LST, LULC, and NDVI using extensive statistical approaches.

4.1 Spatiotemporal Distribution of Land Use Land Cover (LULC)

Analysis of Addis Ababa's LULC from 2003 to 2024 shows notable shifts in a number of land cover categories. Table 4.1 illustrates how settlement areas have grown while vegetation cover has drastically decreased. Decreases in farmland and bare terrain were also significant. These modifications are a reflection of the city's continuous land transformation and development.

Table 4. 1 : LULC Distribution (Hectares and Percentages) in Addis Ababa City (2003–2024)

LULC	2003 (ha)	2003%	2013 (ha)	2013%	2024 (ha)	2024%
Vegetation	7,712.92	20.30%	6,710.56	17.70%	5,144.73	13.60%
Settlement	11,925.07	31.30%	16,783.56	44.20%	23,272.35	61.70%
Farmland	15,547.06	40.70%	12,561.23	33.10%	10,136.67	26.90%
Bare land	8,100.63	21.20%	7,230.33	19.00%	4,731.93	12.50%
Total	**43,285.68**	**100%**	**43,285.68**	**100%**	**43,285.68**	**100%**

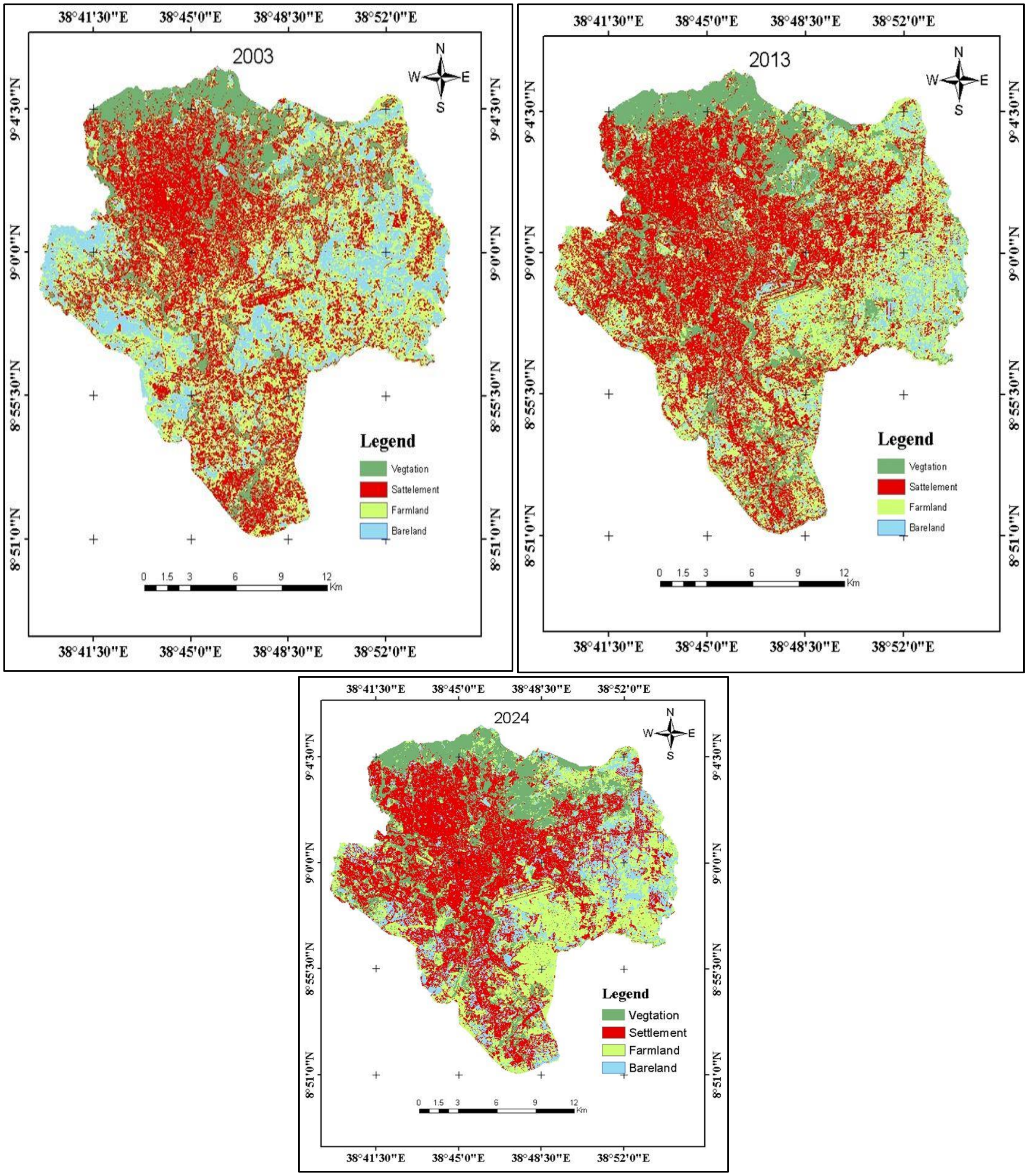


Figure 4.1: Maps of land cover and land use in the Addis Ababa city from 2003 to 2024

4.2 LULC Distribution Net Change in Addis Ababa City (2003–2024)

An examination of Addis Ababa's net changes in LULC between 2003 and 2024 shows notable changes, mostly due to the city's explosive urban growth. Over the course of the study, a notable reduction in the amount of vegetation cover, falling by 2,568.19 hectares, or 33.3%. Due in large part to the continuous conversion of vegetated areas into urban settlements, this reduction emphasizes the significant loss of green spaces and natural habitats. The settlement class had the most rises, growing by 11,347.28 hectares, or a remarkable 95.2% expansion, which almost doubled the built-up area in just 20 years. The encroachment of once rural or natural lands is the outcome of the city's rapid development of cities that is a reflection of population expansion and development demands. Similarly, as agricultural lands were turned into residential, commercial, and infrastructure complexes, agriculture lost 5,410.39 hectares, or 34.8%. Food security and rural livelihoods in the surrounding areas are seriously threatened by this change. Additionally, bare land decreased by 3,368.70 hectares (41.6%), mostly as a result of urban sprawl turning it into built-up regions. The total study area size stayed at 43,285.68 hectares in spite of these significant internal changes, suggesting that the observed changes are due to land conversion rather than an expansion of the city boundaries. These significant LULC shifts highlight the urgent planning and environmental issues Addis Ababa faces, especially the predominance of urbanization at the price of farming, bare ground, and vegetation. Figure 4.2, which graphically represents the trends and magnitudes of land cover alteration in the study area, shows the precise spatial distribution and percentage changes of different LULC classes throughout time.

Table 4. 2: LULC Distribution Net Change in Addis Ababa City (2003–2024)

LULC Class	2003 (ha)	- 2003%	2013 (ha)	- 2013%	2024 (ha)	- 2024%	Net Change (ha)	Net Change (%)
Vegetation	7,712.92	20.30 %	6,710.56	17.70 %	5,144.73	13.60 %	-2,568.19	-33.30%
Settlement	11,925.07	31.30 %	16,783.56	44.20 %	23,272.35	61.70 %	11,347.28	95.20%
Farmland	15,547.06	40.70 %	12,561.23	33.10 %	10,136.67	26.90 %	-5,410.39	-34.80%
Bare land	8,100.63	21.20 %	7,230.33	19.00 %	4,731.93	12.50 %	-3,368.70	-41.60%
Total	43,285.68	100%	43,285.68	100%	43,285.68	100%	-1,000.00	-2.60%

Table 4.2 presents the precise numerical distribution and net changes in LULC classes between 2003 and 2024, providing exact figures in hectares and percentages for detailed quantitative analysis. Complementing this, Figure 4.2 graphically illustrates the spatial and temporal patterns of these changes, allowing for immediate visual identification of trends and magnitudes across the study area. Together, the table and figure offer a comprehensive understanding of the dynamics of land cover transformations in Addis Ababa, addressing the needs of both technical scrutiny and accessible communication.

4.3 Accuracy assessment

4.3.1 Accuracy Assessment of LULC Classification for 2003

Table 4.3 presents the validation of results of the LULC categorization for the year 2003, detailing accuracy metrics for every class of LULC. Details overall classification accuracy for this period was determined to be 90%, with an 82% Kappa coefficient. A high degree of agreement between the 2003 LULC categorization and reference data suggests accurate and dependable findings. This attests to the categorization technique' accuracy and appropriateness for additional spatial and temporal investigation.

Table 4. 3: Accuracy Assessment for LULC of 2003

Class Name	Vegetation	Farmland	Settlement	Bare Land	Total	User's Accuracy	Kappa
Vegetation	4	1	0	0	5	0.8	
Farmland	2	27	1	1	32	0.84	
Settlement	0	0	8	2	10	0.8	
Bare Land	0	1	1	29	31	0.85	
Total	6	35	10	32	83	0	
Producer Accuracy	0.67	0.77	0.8	0.91	0	0.9	
Kappa							**0.82**

4.3.2 Accuracy Assessment of LULC Classification for 2013

Results from the 2003 LULC classification are accurate and dependable because of its high degree of agreement with reference data. This demonstrates the accuracy of the categorization procedure and its applicability for additional temporal and spatial research.

Both commission and omission mistakes, mostly as a result of vegetation types' spectral similarity, which made precise classification difficult. Despite these challenges, the overall classification obtained a precision of 90% with a Kappa coefficient of 0.81, reflecting strong agreement with reference information. Users and producer's precision for every LULC class are also provided in the table, highlighting the reliability of the classification. Further improvements, such as refining classification algorithms and incorporating advanced machine learning techniques with multi-spectral imagery, could enhance the accuracy of future LULC assessments.

Table 4. 4: Accuracy Assessment for LULC of 2013

Class Name	Vegetation	Farmland	Settlement	Bare Land	Total	User's Accuracy	Kappa
Vegetation	8	1	1	0	10	0.8	
Farmland	1	29	1	1	33	0.88	
Settlement	1	3	172	3	179	0.96	
Bare Land	1	0	2	7	10	0.7	
Total	11	33	176	11	231	0	
Producer Accuracy	0.73	0.88	0.98	0.64	0	0.9	
Kappa							**0.81**

4.3.3 Accuracy Assessment of LULC Classification for 2024

The evaluation of the 2024 LULC classification, illustrated in Table 4.5's confusion matrix, indicates the presence of commission and omission errors, predominantly including misclassified pixels among vegetation groups owing to spectral similarities. The classification achieved a precision of 89% and a 0.85 is the kappa coefficient, signifying a robust concordance between the categorized image and the reference data. The table also presents the accuracy on the user and producer for each LULC class, further illustrating the trustworthiness of the 2024 categorization results.

Table 4. 5: Accuracy Assessment for LULC of 2024

Class Name	Vegetation	Farmland	Settlement	Bare Land	Total	User's Accuracy	Kappa
Vegetation	6	0	1	1	8	0.75	
Farmland	1	41	2	2	46	0.89	
Settlement	1	2	31	0	34	0.91	
Bare Land	2	0	1	60	63	0.95	
Total	10	43	35	63	151	0	
Producer Accuracy	0.6	0.95	0.89	0.95	0	0.89	
Kappa							**0.85**

4.4 Normalized Difference Vegetation Index Analysis in Addis Ababa City (2003–2024)

One popular measure of the density, distribution, and health of vegetation is the NDVI. This study evaluated changes in plant cover and their possible effects on LST by analyzing the NDVI for Addis Ababa City over a 21-year period (2003–2024). In particular, as Table 4.5 illustrates, the NDVI values declined with respect to their minimum, maximum, and average values.

Table 4. 6: NDVI Values (Min, Max, and Average) in Addis Ababa City (2003–2024)

Year	Min NDVI	Max NDVI	Average NDVI
2003	-0.2	0.61	0.205
2013	-0.14	0.58	0.22
2024	-0.26	0.42	0.08

4.5 Spatial Distribution of NDVI

High NDVI values were concentrated in vegetated and forested zones, while low values were associated with urban and dry areas. Over time, high-NDVI regions declined, especially in rapidly urbanizing outskirts.

4.6 Implications of NDVI Changes

The steady decline in NDVI values in Addis Ababa reflects a loss of vegetation cover, leading to reduced biodiversity, weakened ecosystem services, and rising land surface temperatures. These changes negatively impact residents by worsening air quality and increasing heat exposure, highlighting the need for urgent actions like reforestation, green infrastructure, and sustainable urban planning.

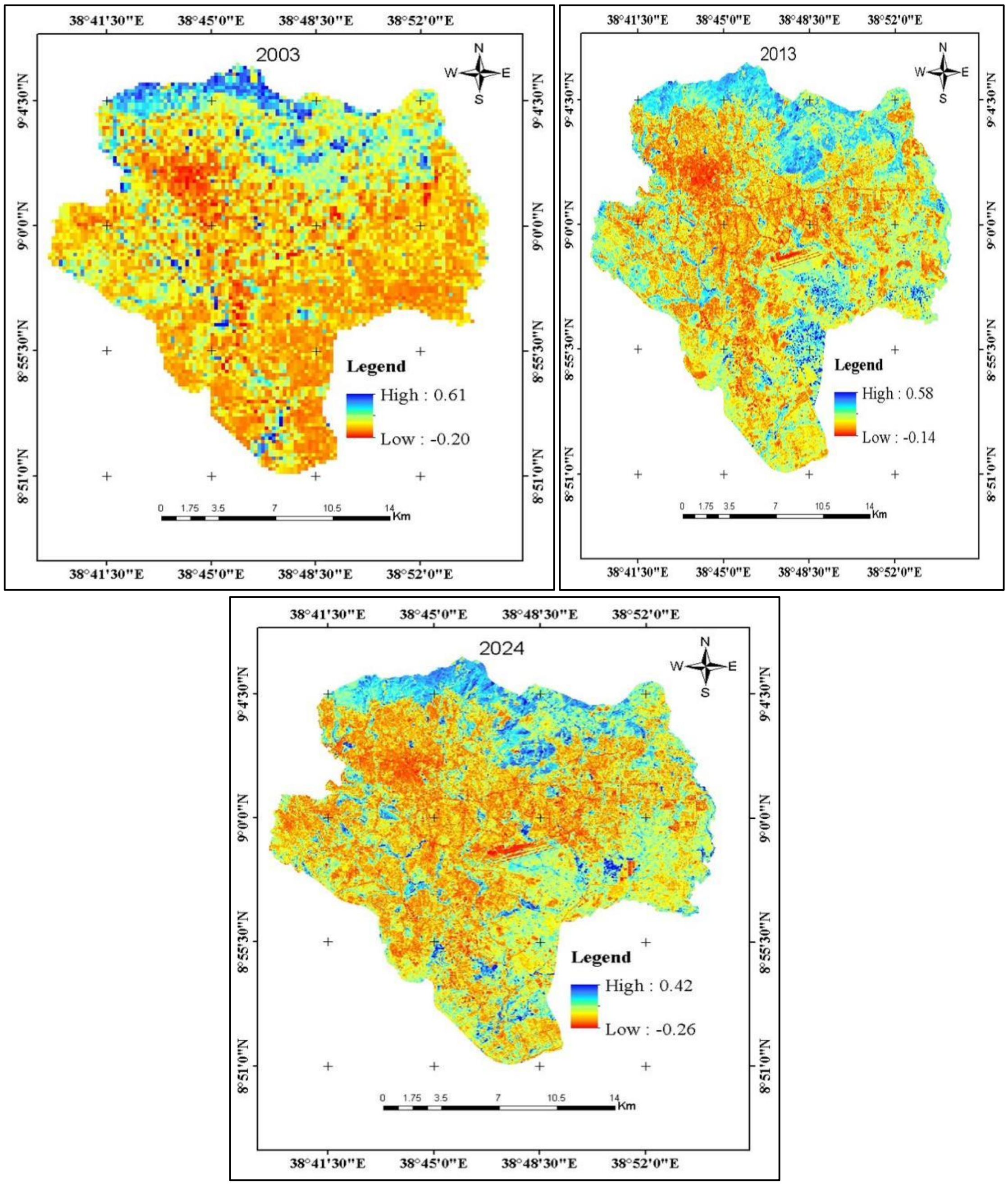


Figure 4.4: Spatial Distribution of LST in Addis Ababa City (2003–2024)

4.7 Relationship between LULC and Normalized difference vegetation index

According to the study, the NDVI values of various LULC types vary, reflecting variations in the density and health of the vegetation. The highest NDVI is found in plantation and shrub land, scores because of their dense vegetation cover, while other classes have lower values. This link demonstrates how useful NDVI is as a vegetation status indicator for a variety of land types, allowing for more focused monitoring and management of land resources according to vegetation vigor. Assuming that NDVI values correspond to land cover types, figure 4.6 is based on the area coverage and normal NDVI ranges for the land use/land cover classes for 2003, 2013, and 2024.

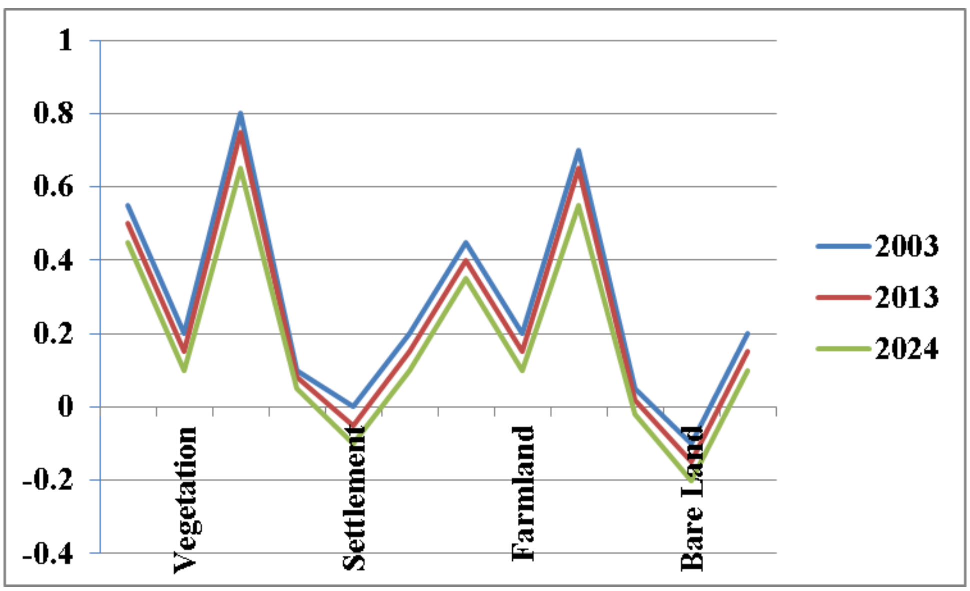
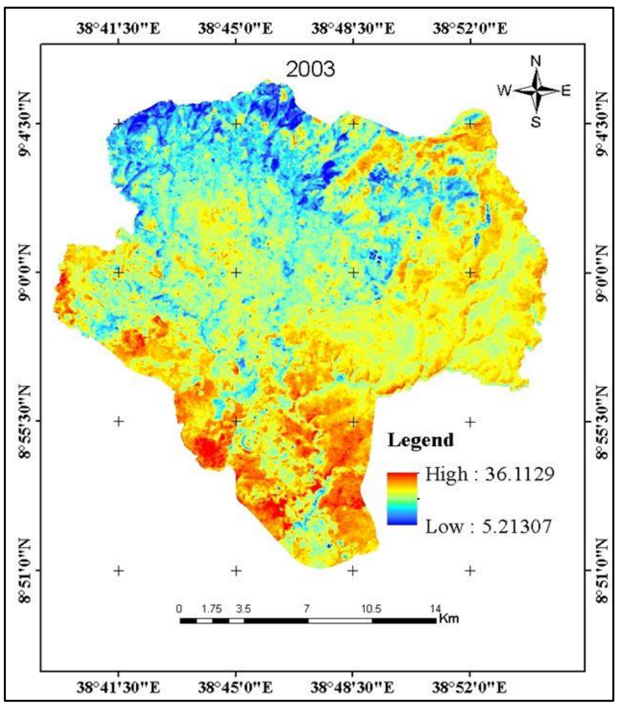
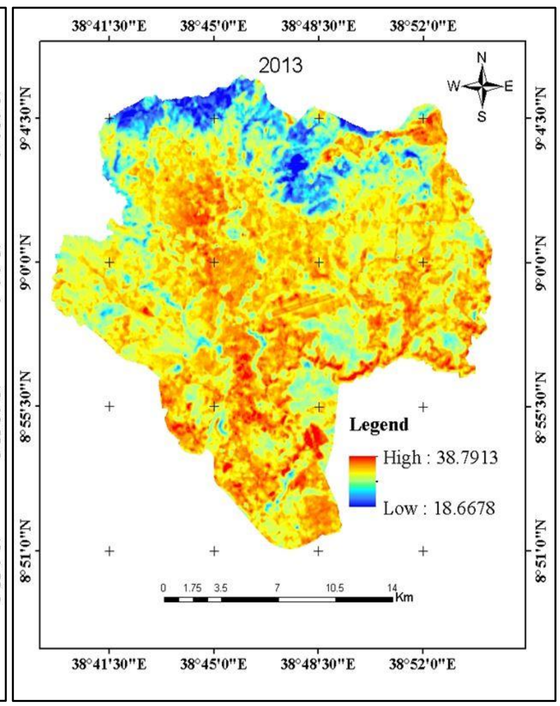


Figure 4.5: Zonal statistical summary of NDVI values across various LULC categories in the study area for the years 2003, 2013, and 2024.

4.8 Spatiotemporal Distribution of Land Surface Temperature.

Within the research area, the spatial distribution of LST was derived and analyzed utilizing Landsat imagery from 2003, ETM+ data from 2013, and OLI/TIRS thermal bands from 2024. The analysis showed that land surface temperature (LST) values varied from 5.21°C to 42.3°Cover the study period. Thermal image processing revealed that elevated temperatures were mainly concentrated in the eastern, northeastern, and southeastern parts of the study area. A detailed spatiotemporal evaluation of LST in Addis Ababa between 2003 and 2024 indicates a clear upward trend in surface temperatures over time. In 2003, LST values ranged from 5.21°C to 36.11°C, representing a moderate thermal environment. By 2013, this range had increased to between 18.66°C and 38.79°C, reflecting significant warming. The highest temperatures were recorded in 2024, with LST values spanning 19.99°C to 42.30°C. This gradual rise in surface temperatures highlights the impacts of urbanization, vegetation degradation, and other environmental changes. Densely developed urban areas experienced higher LSTs, while vegetated zones exhibited comparatively cooler temperatures, illustrating the urban heat island phenomenon and emphasizing the importance of green spaces in regulating urban thermal conditions.





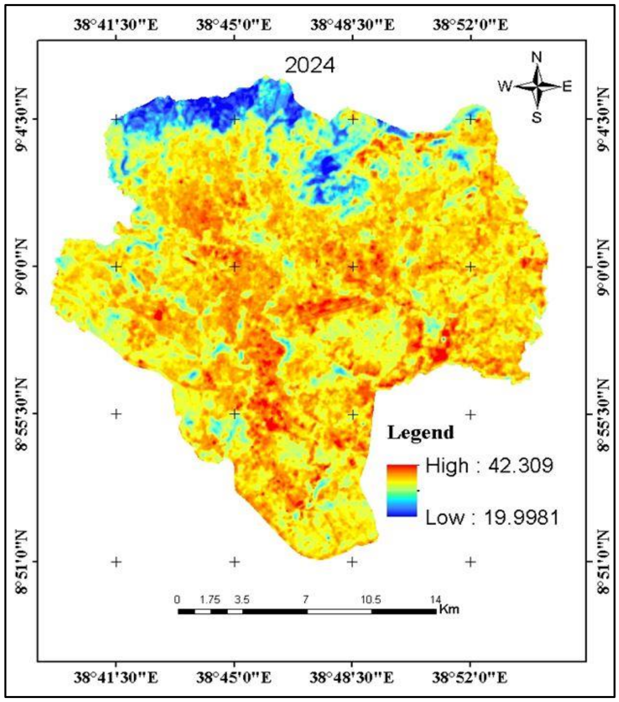


Fig 4.6: Spatial Distribution of LST in in Addis Ababa (2003–2024)

Between 2003 and 2024, the mean temperature increased from 20.66°C to 31.15°C, indicating a notable increase overall temperature a total change of 10.49°C. Notably, the mean temperature in 2013 already increased by 8.07°C compared to 2003, reaching 28.73°C, and further rose by 2.42°C by 2024. Minimum temperatures have also increased substantially from 5.21°C in 2003 to 19.99°C in 2024, indicating a warming trend that reduces the occurrence of cold conditions. Conversely, maximum temperatures have shown a marked escalation from 36.11°C to 42.3°C, suggesting an intensification of heat extremes. This upward trend in temperatures over the two decades reflects ongoing climate warming, possibly driven by urbanization, land cover changes, and reduced vegetation cover, emphasizing the need for mitigation strategies to address rising thermal stress and its impacts on the environment and urban populations.

Table 4. 7: Mean Temperature and Changes in Temperature (2003–2024)

Year	The lowest temperature (°C)	The highest temperature (°C)	Temperature Average (°C)	Variation in Average Temperature (°C)
2003	5.21	36.11	20.66	-
2013	18.66	38.79	28.73	8.07
2024	19.99	42.3	31.15	2.42

4.9 Changes in LULC and Their Effects on LST

The analysis of LULC changes and their effects on LST in Addis Ababa from 2003 to 2024 reveals a marked warming trend closely linked to shifts in land cover patterns. Vegetation cover—crucial for its natural cooling effect—declined substantially from 7,712.92 ha in 2003 to 5,144.73 ha in 2024, significantly contributing to increased land surface temperatures. In contrast, settlement areas expanded dramatically, nearly doubling from 11,925.07 ha to 23,272.35 ha over the same period. This rapid urban expansion has intensified the urban heat island (UHI) effect, particularly in densely built-up zones with limited vegetation.

Additionally, reductions in farmland and bare land—converted into impervious surfaces—further exacerbated temperature rises due to their lower albedo and higher heat absorption characteristics. The spatial analysis confirmed a strong negative correlation between vegetation cover and LST, reinforcing the vital role of green spaces in mitigating urban heat. Moreover, temporal patterns revealed that peripheral areas undergoing rapid urbanization exhibited the greatest increases in LST, emphasizing the spatially uneven impact of urban growth.

These findings highlight the critical need for integrated and climate-sensitive urban planning strategies. Key recommendations include prioritizing reforestation and urban greening, implementing green infrastructure (e.g., green roofs, urban parks), enforcing land use zoning regulations that protect existing vegetation, and promoting compact, climate-resilient urban development. Such measures are essential not only for mitigating

LST but also for enhancing urban livability, biodiversity, and public health in the face of rapid urbanization and climate change.

Table 4. 8: Changes in LULC and Their Effects on LST (2003–2024)

LU/LC Class	Area (ha) in 2003	Area (ha) in 2024	Net Change (ha)	% Change	Mean LST (2003) (°C)	Mean LST (2024) (°C)	Change in LST (°C)
Vegetation	7,712.92	5,144.73	-2,568.19	-33.30%	18.5	26.1	7.6
Settlement	11,925.07	23,272.35	11,347.28	95.20%	29.3	35.4	6.1
Farmland	15,547.06	10,136.67	-5,410.39	-34.80%	21.4	28.8	7.4
Bare land	8,100.63	4,731.93	-3,368.70	-41.60%	25.2	32	6.8

4.10 The relationship between LULC and LST

LST is typically characterized by distinct temperature variations across different land categories; urban areas with dense impervious surfaces prone to have increased LSTs as a result of heat retention and reduced evapotranspiration, contributing to urban heat island effects. Conversely, vegetated and forested areas generally show lower LSTs owing to transpiration and shading, which help cool the surface. Increased LSTs are frequently the result of changes in land cover, such as deforestation, urbanization, or the conversion of natural landscapes into built-up regions. Exacerbating heat stress and impacting local climate conditions. Therefore, understanding LULC patterns is crucial for managing urban heat and implementing sustainable land management practices that mitigate temperature rise, promote ecological balance, and improve urban resilience to climate change.

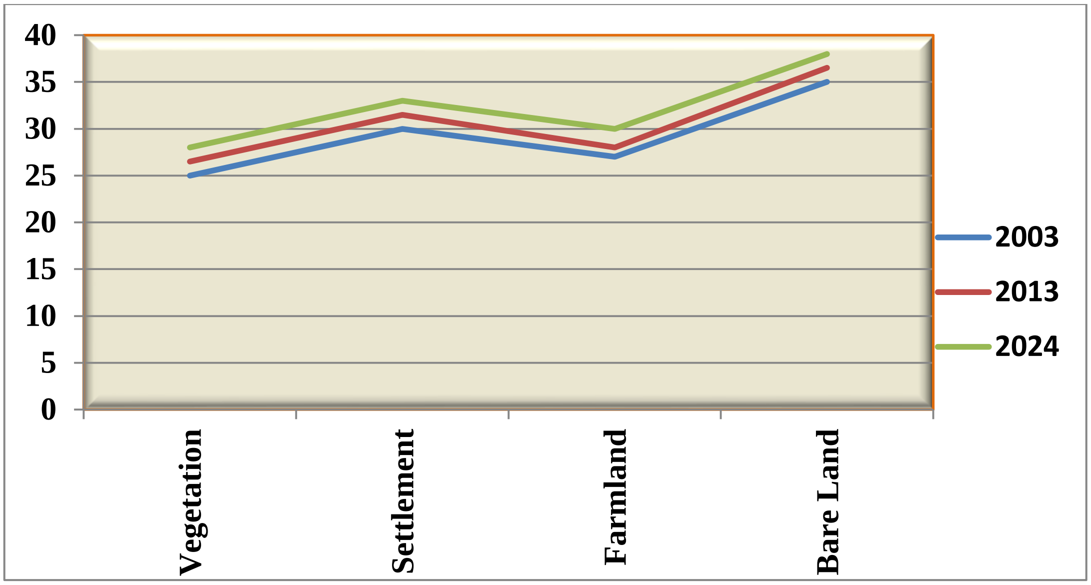


Figure 4.7: Comparisons of mean LST in different LULC classes during the study period

Table 4. 9: Mean temperature and changes in temperature during 2003−2024 in the study area

LULC Class	2003 Mean (°C)	2013 Mean (°C)	2024 Mean (°C)	Change 2003–2013 (°C)	Change 2003–2024 (°C)
Urban	27	28.5	29.5	1.5	2.5
Forest	23	23.5	24	0.5	1
Agricultural	24	24.8	25.5	0.8	1.5
Bare Land	22	22.2	22.5	0.2	0.5

4.11 Correlation between LST and NDVI

The correlation between LST and the NDVI is of great interest in remote sensing studies, particularly for understanding the dynamics between vegetation, climate, and land cover. In this study, the Landsat data from 2003, 2013, and 2024 have been analyzed to evaluate this relationship in the context of a specific study area. The findings reveal an indirect inverse correlation between LST and NDVI, as well as a nuanced relationship for water bodies within the region.

1. Correlation and R^2 Values:

The statistical measure of correlation, represented by the R^2 values, was consistent over the three years of study, with values of 0.9551 in 2003, 0.9012 in 2013, and 0.9557 in 2024. The elevated R^2 values reflect a robust association between NDVI and LST throughout the three study years. In particular, the 2003 result ($R^2 = 0.9551$) demonstrates a highly significant correlation, indicating that vegetation cover played a major role in influencing temperature variations during that year.

2013 ($R^2 = 0.9012$): While the correlation is slightly weaker than in 2003, it still indicates a robust association. This slight decrease may reflect changes in vegetation cover or land use practices during this period.

2024 ($R^2 = 0.9557$): The correlation once again increases to nearly the same level as 2003, possibly suggesting a return to vegetation conditions similar to those seen in the earlier years.

2. Inverse Correlation between NDVI and LST:

The analysis reveals that NDVI and LST generally exhibit an inverse relationship. In areas with high NDVI, which typically corresponds to dense vegetation, LST values are lower. This is because dense vegetation provides more shade, reduces direct solar absorption, and facilitates increased evapotranspiration, all of which contribute to cooling the land surface.

Conversely, in areas with low NDVI, indicating sparse vegetation or bare land, LST values tend to be higher. The absence of vegetation cover is the cause of this, which allows for greater solar energy absorption and less evapotranspiration. As a result, bare surfaces heat up more rapidly, leading to higher LST values.

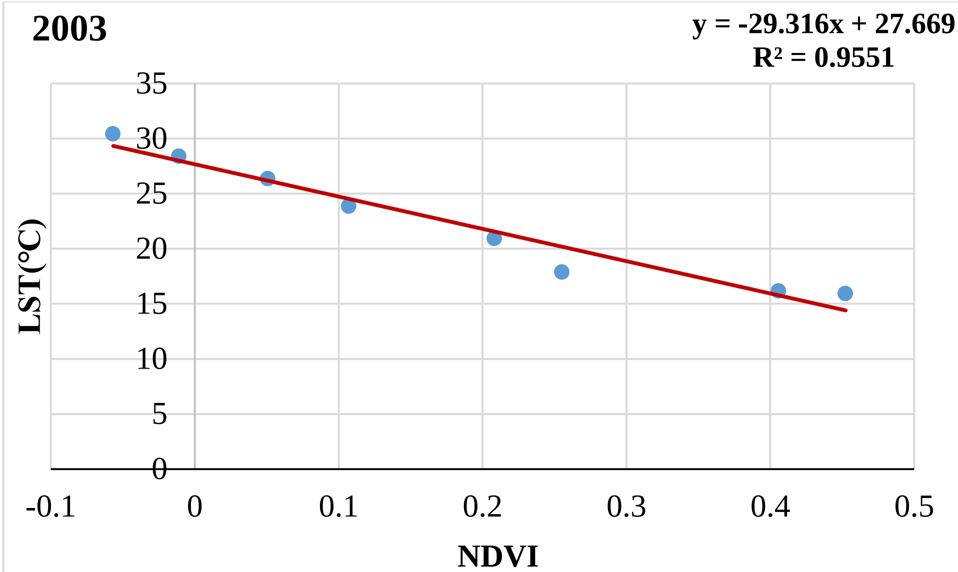


Figure 4.8: LST–NDVI Relationship in 2003.

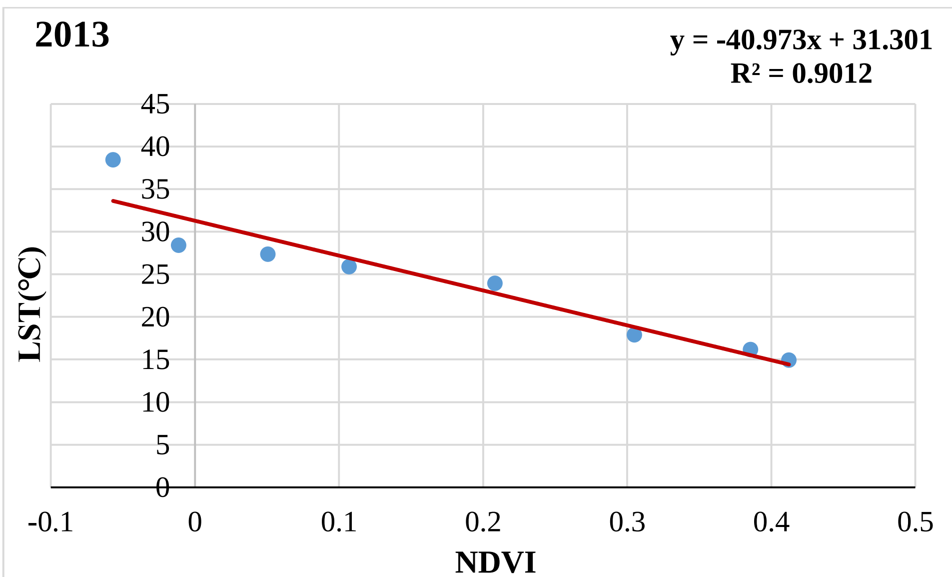


Figure 4.9: LST–NDVI Relationship in 2013.

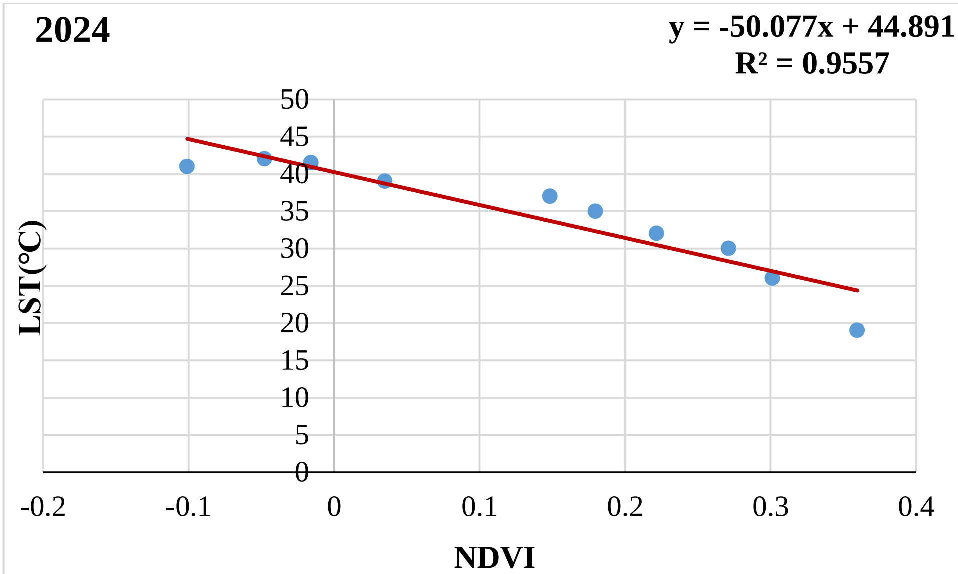


Figure 4.10: LST–NDVI Relationship in 2024.

Table 4. 10: Zonal LST Summary by LULC Class for 2003, 2013, and 2024

Year	LU/LC Class	Min LST (°C)	Max LST (°C)	Mean LST (°C)	Std Dev (°C)
2003	Vegetation	5.21	36.11	18.5	6.2
	Settlement	10.4	35.7	22.3	4.8
	Farmland	7.8	34.2	20.1	5
	Bare Land	8.5	33.8	21	4.5
2013	Vegetation	18.66	38.79	22.7	5.9
	Settlement	20.1	39.2	24.5	4.7
	Farmland	17.9	37.5	22	5.2
	Bare Land	19	37.8	23.1	4.6
2024	Vegetation	19.99	42.3	25.4	6.1
	Settlement	21.4	41.8	27.3	5.3
	Farmland	20.5	40.2	24.8	5.5
	Bare Land	21.8	40.7	26.1	5

4.12 Implications of the LST-NDVI Relationship

The findings highlight the complex relationship between vegetation, land surface temperature, and other land cover types, such as water bodies. It is commonly known that there is a negative link between NDVI and LST, which is mostly caused by biological processes like plant transpiration. and shading. The slight fluctuation in the strength of the correlation over the study period (from 2003 to 2024) may reflect long-term changes in land cover or climate conditions, such as shifts in vegetation density, urbanization, or climate warming. The year 2013, with its slightly lower R^2 value, may indicate a transitional period with altered land surface characteristics.

The correlation coefficient (r) quantifies the degree and direction of a linear association between two variables. In this context, it indicates how NDVI (vegetation) and LST (temperature) are related

Table 4. 11: Correlation between NDVI and LST (2003–2024)

Year	Correlation Coefficient (r)
2003	-0.68
2013	-0.71
2024	-0.73

The strong negative conversation of LST and NDVI highlights the critical role of vegetation in regulating urban temperatures. As vegetation cover decreases in Addis Ababa, surface temperatures have consistently increased, leading to a more pronounced urban heat island effect. These results highlight the necessity of preserving and growing green areas as part of sustainable strategies for the city's urban planning and climate resilience.

4.13 Verification of LST Results

The LST extracted from the research area's Landsat thermal bands showed a clear correlation with the interpolated air temperature. This study utilized Landsat imagery acquired during the dry season and the harvest period, ensuring a consistent assessment of LST under stable weather conditions.

To validate the geographical dispersion of LST, the results were cross- confirmed using the research area's LULC classes and weather data, with further validation using Google Earth. The atmospheric temperature was interpolated using meteorological data from five stations within and around the study area: Kotebe, Kotebe TTC, Bole, Addis Ababa Observatory (OBS), and Entoto.

A strong relationship was identified between the remotely sensed LST and the interpolated atmospheric temperature based on these 5 stations. This relationship underscores the value of remotely sensed LST in making it a trustworthy indicator of atmospheric conditions by describing and forecasting the temporal and spatial patterns of atmospheric temperature. The interpolated atmospheric temperature map is presented in Figure 4.11.

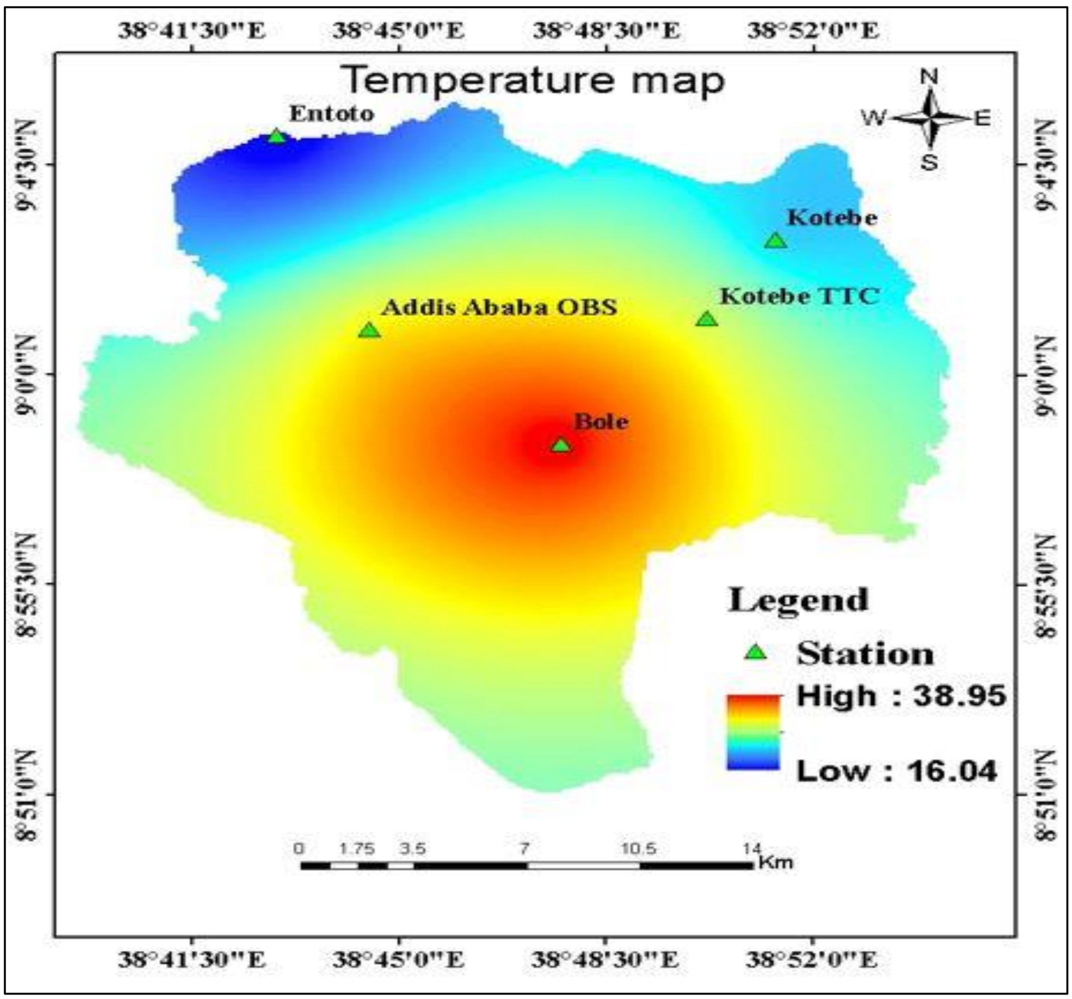


Figure 4.11: Temperature interpolation map of Addis Ababa.

4.14 DISCUSSION

4.14.1 Land-Use/Land-Cover Status of Addis Ababa

The main causes of Addis Ababa's notable LULC changes between 2003 and 2024 were the city's fast urbanization, population expansion, and infrastructure development. Settlement areas increased significantly during this time, growing from 11,925.07 hectares (27.55%) in 2003 to 23,272.35 hectares (53.75%) in 2024. Vegetation, which fell from 15,547.06 hectares (35.91%) and 7,712.92 hectares (17.82%) in 2003 to 10,136.67 hectares (23.42%) and 5,144.73 hectares (11.88%) in 2024, respectively, was the main victims of this expansion. In the same time frame, the amount of bare land decreased from 8,100.63 hectares (18.72%) to 4,731.93 hectares (10.92%).

These tendencies are consistent with more general trends seen in the Upper Awash Basin, where major as a result of gentrification, agricultural and vegetative fields have been transformed into built-up areas in cities like Addis Ababa. These modifications are a reflection of the city's explosive urban growth, which has been fueled by rising demand for commercial, industrial, and residential real estate (Hirpa et al., 2023). Population expansion, infrastructure improvements, and economic activity that raise the demand for land are some of the factors causing these shifts.

Those LULC shifts have significant ramifications for biodiversity, food security, and the sustainability of natural resources. Reduced agricultural output and ecosystem services may result from the loss of farmland and vegetation cover. According to studies, Addis Ababa's declining plant cover has a direct effect on ecological processes as soil fertility and carbon sequestration (Ayenachew & Abebe, 2024). Additionally, food insecurity may worsen in light of the loss of agricultural land, particularly for low-income urban residents who depend on urban agriculture for a living.

Strategies for sustainable development and coordinated land-use planning are crucial to overcoming these obstacles. Initiatives like Ethiopia's initiative to improve food security and rehabilitate degraded lands highlight how crucial it is to work together to mitigate the negative effects of LULC changes. The long-term viability of Addis Ababa is depend on encouraging effective land use, safeguarding agricultural areas, and repairing damaged ecosystems (Tadesse et al., 2024).

In the final analysis, Addis Ababa's LULC modifications during the previous 21 years emphasize the need for sustainable land management strategies that balance the needs of development with environmental protection. Restoring degraded ecosystems, protecting agricultural areas, and encouraging effective land use was all essential to the region's long-term viability.

4.14.2 Normalized Difference Vegetation Index (NDVI)

One of the most important metrics for measuring the vegetation's health and how it affects LST is the NDVI. Across a range of habitats, recent research has consistently shown a substantial inverse link between NDVI and LST. For example, a global investigation from 2000 to 2024 by Rahimi et al. (2024) showed that almost 80.4% of significant associations between NDVI and LST were negative, suggesting that lower surface temperatures are frequently associated with increased vegetation density. Similarly, Ullah et al. (2023) highlighted the cooling effect of vegetation cover by finding a negative association between NDVI and LST in the lower Himalayan region.

NDVI values in Addis Ababa have been trending downward over time, which is indicative of shifting vegetation cover. With NDVI values ranging from -0.2 to 0.61 in 2003, some regions had rather good vegetation. The range decreased to -0.26 to 0.42 by 2024 after somewhat narrowing to -0.14 to 0.58 by 2013. This negative trend points to a decrease in vegetation density, most likely brought on by changes in land use and urbanization. The observed rise in built-up areas and the associated decline in vegetative and agricultural fields in Addis Ababa during this time period are consistent with the decline in NDVI values. Because NDVI and LST have an inverse connection, it is crucial to preserve and improve urban green spaces. Because it offers shade and promotes evapotranspiration, which cools the surrounding area, vegetation is essential for reducing the effects of urban heat islands. In order to combat rising surface temperatures and encourage sustainable urban life, Addis Ababa's urban planning initiatives should place a high priority on the expansion and protection of green spaces.

4.14.3. Land surface temperature

LST is a critical environmental parameter that plays a significant role in understanding the thermal dynamics of a landscape, especially in relation to land cover, urbanization, and climate change. The relationship b/n LST and the NDVI, a widely used vegetation index, is essential for measuring the outcome of vegetation cover and LULC on surface temperature. This section discusses the key findings of the inquiry of the temporal and spatial dispersion of LST across different LULC categories, and how these patterns reflect broader environmental changes. Furthermore, the results are contextualized within the framework of existing research, drawing on studies that highlight the factors influencing LST and NDVI in similar environments.

4.14.4. Temporal Trends in LST

The analysis of LST from Landsat satellite imagery spanning 2003, 2013, and 2024 reveals a clear upward trend in surface temperatures over time. In 2003, LST values ranged from 5.21°C to 36.11°C, indicating moderate thermal conditions across the study area. However, by 2013, the LST range increased to 18.66°C to 38.79°C, signaling a notable warming trend. This increase became more pronounced in 2024, with LST values ranging from 19.99°C to 42.30°C. The upward trend in LST corresponds with a broader pattern of climate change and urban expansion, particularly in urban areas such as Addis Ababa, where surface temperatures have risen significantly due to UHI effects (Kikegawa et al., 2006). This progressive increase in LST is largely attributed to urbanization, vegetation loss, and the replacement of natural land surfaces with impervious materials like concrete and asphalt, which absorb and retain heat (Zhou et al., 2011).

The findings align with other studies that have reported similar warming trends in urban environments over time. For example, Yang et al. (2005) observed an increase in LST in China's fast-urbanizing regions,driven by the growth of populated places and a decrease in vegetated surfaces. Similarly, Jin and Wei (2015) found that LST increases in cities are often linked to urban sprawl and land use changes that reduce natural cooling processes such as evapotranspiration from vegetation.

4.14.5. LULC Influence on LST

The study revealed distinct patterns of LST across different LU/LC categories, with significant variations in temperature based on land cover types. Farmland, settlement, and bare land exhibited higher LST values, especially during the dry season (November, December, and January), when satellite images were acquired. During this period, agricultural land becomes dry following crop harvesting, leading to high surface reflectance and increased heat absorption. These findings are consistent with the observations of Gebrekidan Worku (2016), who noted that non-vegetated areas such as bare land and settlements typically exhibit higher LST due to their limited capacity for cooling through vegetation cover and evapotranspiration.

The negative correlation among NDVI and LST in vegetated areas was confirmed by the higher NDVI and lower LST values found in woods and shrubs. Vegetation contributes to cooling through shading, the absorption of solar radiation, and evapotranspiration processes, all of which help regulate surface temperature (Zhou et al., 2011). These patterns are consistent with studies by Gao et al. (2018) and Jin et al. (2015), who observed similar inverse correlations b/n LST and NDVI in vegetated areas and confirmed that green cover plays a crucial role in moderating surface temperatures.

Water bodies, while showing low NDVI due to their lack of vegetation, exhibited a direct positive correlation b/n LST and NDVI, as observed in the study. Water bodies tend to maintain relatively lower temperatures compared to land surfaces because to feel so high particular Cooling by evaporation and heat capacity. This phenomenon is not typical of land-based surfaces and underscores the unique thermal properties of water bodies. Burgan and Bartlett (1993) highlighted Water bodies' function in reflecting less near-infrared light, leading to lower NDVI values but relatively lower temperatures compared to other land types. This relationship demonstrates the importance of considering specific land cover types when analyzing LST patterns.

Factors Affecting LST Variability

Several additional factors beyond vegetation cover influence LST patterns. These include local soil types, altitude, geological context, and geothermal activity. In regions with specific soil compositions, such as clay-rich or rocky surfaces, surface reflectance and thermal properties may differ significantly, leading to higher LST values even in areas with some vegetation cover. Gao et al. (2018) emphasized that geothermal activity can also contribute to elevated LST, particularly in areas with volcanic activity or significant subsurface heat sources. These localized factors contribute significantly to the formation of the LST dispersion, especially in areas where geological features or geothermal influences are pronounced.

For instance, in parts of the study area with specific geological formations or elevated geothermal activity, LST may be higher than expected based on vegetation cover alone. The influence of geothermal energy on LST should be considered in further studies to more comprehensively assess the thermal dynamics of diverse landscapes (Parker et al., 2012). Harlan et al. (2006) also suggested that soil moisture and moisture availability in the atmosphere contribute significantly to LST variability, especially during seasonal dry periods.

Urban Heat Island Effect

The study highlights the significant impact of the Urban Heat Island (UHI) effect in densely built-up areas, where rising land surface temperatures result from the replacement of natural vegetation with heat-retaining surfaces. This intensification of UHI, driven by rapid urbanization and limited green cover, contributes to increased energy demand, air pollution, and climate stress. To mitigate these effects, the findings support the integration of green infrastructure and climate-responsive urban planning, as recommended by Bong et al. (2020), emphasizing vegetation's role in cooling urban environments.

CHAPTER FIVE

5. CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

Geospatial tools have proven to be highly effective for researchers in analyzing land use and land cover LULC trends and LST, identifying vulnerable areas, understanding their underlying causes, and formulating appropriate strategies. These tools offer a time-efficient, cost-effective, and straightforward approach for environmental management, particularly in monitoring LULC changes. In this study, Landsat imagery, including data from Landsat ETM+7 and Landsat OLI/TIRS, was utilized to assess LULC changes and their relationship with LST. The calculated LST and LULC data provide essential insights for tracking environmental changes and human activities.

The findings revealed that the LST's spatial dispersion is closely associated by LULC dynamics. Specifically, areas with the LST levels that greatest were found in settlements, bare ground, and agricultural land, but lower LST readings were recorded in vegetation areas. This pattern indicates that changes in LULC directly influence LST variations over time. The study further demonstrated that the calculated LST values from satellite data showed strong agreement with temperature measurements obtained from local weather stations, validating the accuracy of the satellite-based LST estimates.

Additionally, the NDVI values derived from satellite imagery served as a reliable indicative of the study area's vegetation condition, which lends additional credence to the examination of LST fluctuations. The integration of GIS and remote sensing techniques enabled a comprehensive assessment of LULC and LST dynamics, providing a rapid, cost-effective, and spatially extensive method for environmental analysis.

The temporal analysis covering the years 2003, 2013, and 2024 highlights the ongoing changes in LULC, which have directly impacted LST values. As the lowest and highest LST values have shown an increasing trend over the years, it is evident that LULC dynamics significantly influence the local climate and environmental conditions. The investigation emphasizes how important GIS and remote sensing technologies are to efficient environmental monitoring and well-informed decision-making.

5.2 Recommendations

Based on the study findings, the following recommendations are proposed:

- Integrated Land-Use Management and Policy Development: Develop comprehensive land-use policies that prioritize sustainable practices, integrating economic, social, and environmental aspects. Regularly update these policies to adapt to changing conditions.

- Enhancement of Green Spaces: Promote the planting of native and climate-adaptive tree species while expanding urban and rural green spaces, especially in areas with high LST values. Conservation efforts should focus on maintaining vegetation cover.

- Sustainable Urban Planning and Green Infrastructure: Urban planners should adopt climate-sensitive design principles, including the development of green roofs, urban parks, and vegetative buffers to reduce urban heat.

- Regular Monitoring and Use of Geospatial Tools: Expand the use of GIS and remote sensing technology to monitor LULC and LST trends in a methodical and ongoing manner. This was provided accurate, real-time data for decision-making and urban planning, enabling proactive interventions to address urban heat challenges.

- Consideration of Additional Factors Influencing LST: Promote more studies to assess the impact of other variables, such as surface albedo, moisture content, and soil quality, on LST, elevation, slope, surface moisture, and the geological context of Addis Ababa, which is located near the East African Rift Valley. The region's tectonic and geothermal activities may influence LST dynamics. Understanding these factors was enabling a more accurate assessment of LST dynamics and informs more effective climate resilience strategies.

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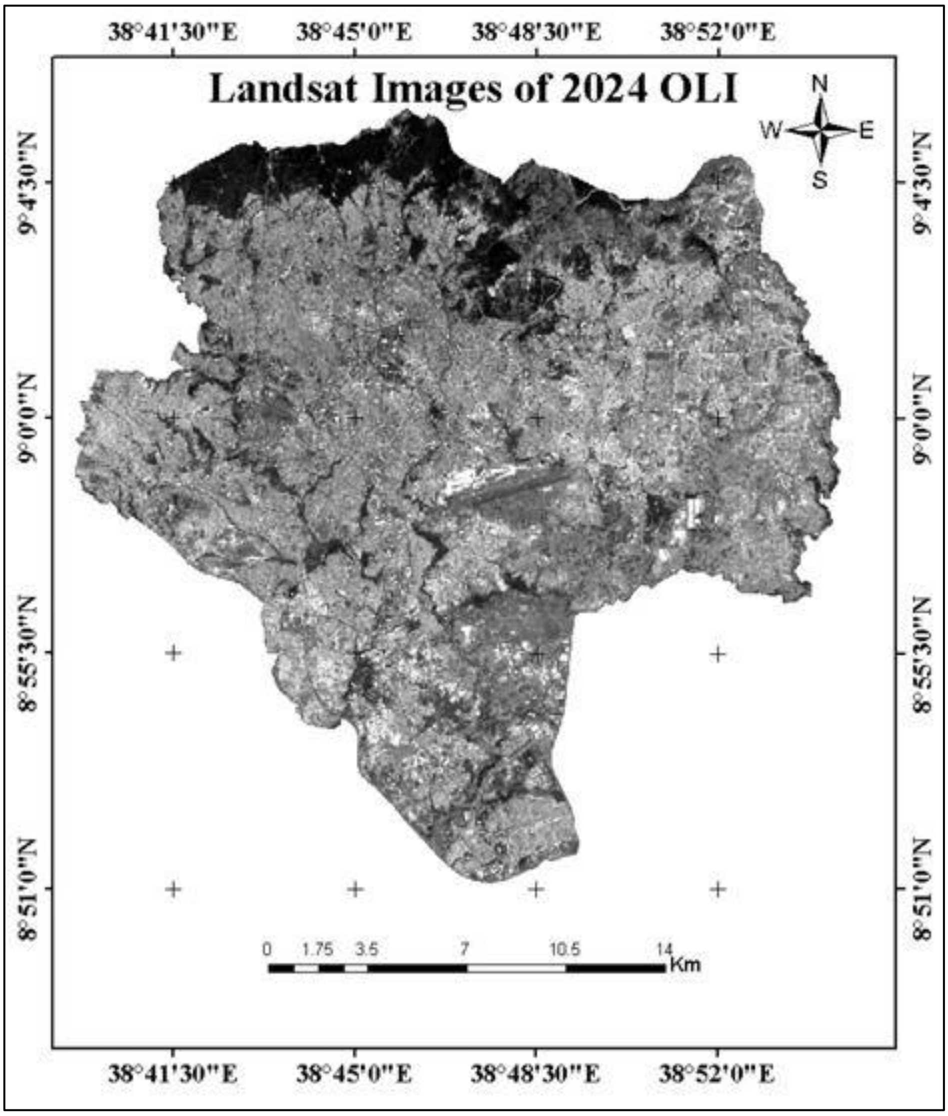
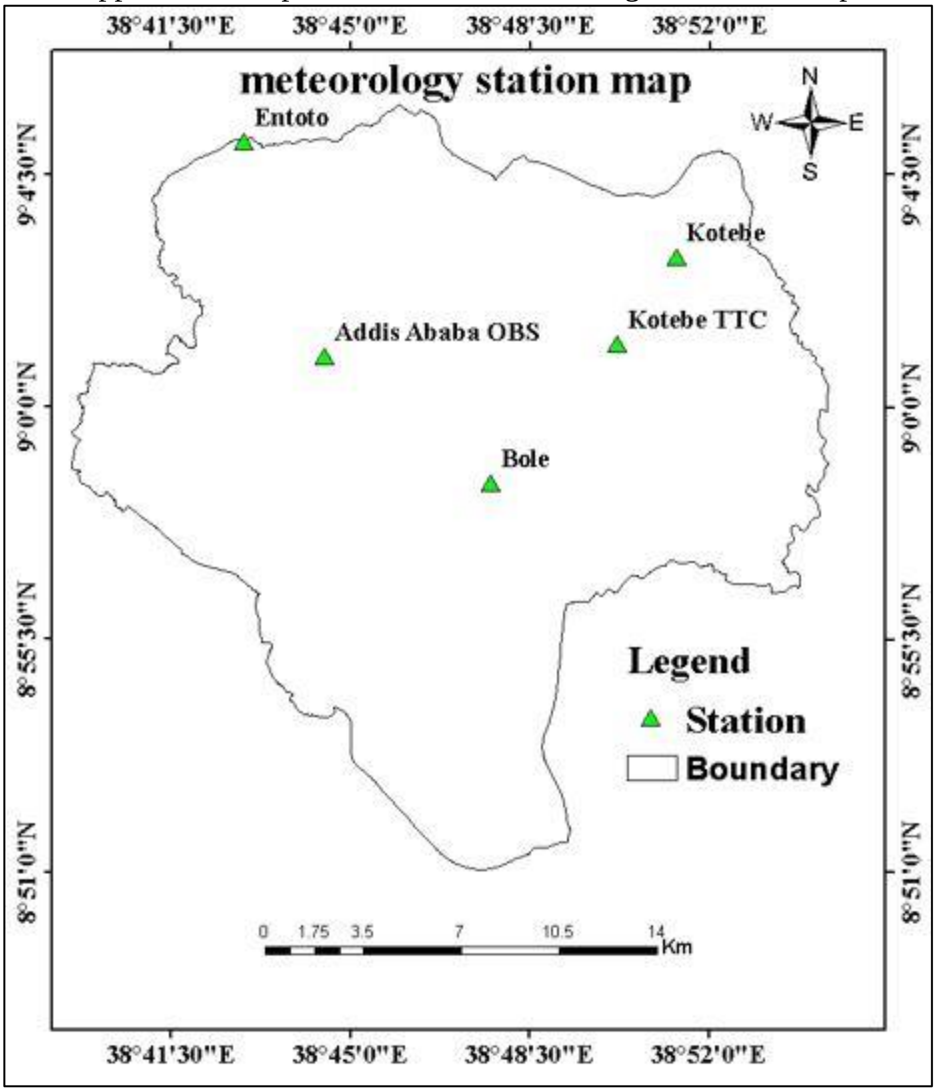
APPENDICES

Appendex1. Map 1: TIRS and OLI of Landsat Image.



Appendex2. Map 1: Location of meteorological stations map.



Appendex3.Table1: Lists the bands and descriptions for the Landsat 8 OLI/TIRS

Satellite/Sensor	Band	Description	Wavelength Range (µm)	Spatial Resolution (m)	Repeating Time	Source
Landsat 8 OLI/TIRS	Band 1	Coastal/Aerosol (Ultra-Blue)	0.433 - 0.453	30	16 days	USGS
	Band 2	Blue	0.450 - 0.515	30		
	Band 3	Green	0.525 - 0.600	30		
	Band 4	Red	0.630 - 0.680	30		

	Band 5	Near Infrared (NIR)	0.845 - 0.885	30		
	Band 6	Shortwave Infrared 1 (SWIR1)	1.560 - 1.660	60		
	Band 7	Shortwave Infrared 2 (SWIR2)	2.100 - 2.300	30		
	Band 8	Panchromatic	0.500 - 0.680	15		
	Band 9	Cirrus	1.360 - 1.390	-		
	Band 10	Thermal Infrared 1 (TIRS1)	10.60 - 11.19	100		
	Band 11	Thermal Infrared 2 (TIRS2)	11.50 - 12.51	10		

Appendex4. Table2: Thermal band calibration constant of Landsat 8.

Satellite & Sensor	Categories	Band 10	Band 11
Landsat 8 OLI/TIRS	K1	777.88530000000	480.88830000000
	K2	1321.07890000000	1202.14420000000
	Radiance MULT_BAND	0.00033420000	0.00033420000
	Radiance ADD_BAND	0.01000000000	0.01000000000
Landsat 7	ETM+	K1	666.1
		K2	1282.7

Appendex4. Figure 2: Comparative Analysis of LST in the Study Area for 2024