ANALYSIS OF URBAN GREEN SPACES AND THEIR DISTRIBUTION BY INTEGRATING SENTINEL 2 AND MACHINE LEARNING ALGORITHM IN ADAMA CITY, ETHIOPIA

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Thesis submitted to the Department of Architecture

College of Civil Engineering and Architecture (CoCEA),

Office of Graduate Studies
Adama Science and Technology University

June, 2025

Adama, Ethiopia

Analysis of Urban Green Spaces and Their Distribution by Integrating Sentinel 2 and Machine Learning Algorithm in Adama City, Ethiopia.

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Under the Supervision of

Dejene Tesema (PhD)

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DECLARATION

I hereby declare that this research thesis entitled "**Analysis of Urban Green Spaces and Their Distribution by Integrating Sentinel 2 and Machine Learning Algorithm in Adama City, Ethiopia.**" is my original work. That is, it has not been submitted to any other university. All materials used for this thesis have been duly acknowledged through citation.

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Name of student	Signature	Date

RECOMMENDATION

I, the advisor of this thesis, hereby certify that I have read this thesis entitled "**Analysis of Urban Green Spaces and Their Distribution by Integrating Sentinel 2 and Machine Learning Algorithm in Adama City, Ethiopia.**" prepared under my guidance by Gutama Garo. Therefore, I recommend the submission to the department following the applicable procedures.

Dejene Tesema (PhD)	_________________	________________
Name of Major Advisor	Signature	Date

ACKNOWLEDGMENT

First and foremost, I would like to express my deepest gratitude to the Almighty God for granting me the strength, health, and perseverance to successfully complete this research work.

I extend my sincere appreciation to my advisor, Dr. Dejene Tesema, for his continuous guidance, insightful feedback, and invaluable support throughout the entire process of this thesis. His expertise and encouragement were instrumental in shaping the direction and quality of this research.

I am also grateful to the Department of Architecture and the Office of Graduate Studies at Adama Science and Technology University for providing the academic environment and resources necessary for this work. Special thanks go to the faculty members and administrative staff for their cooperation and support.

My heartfelt thanks go to my family and friends, whose unwavering support, patience, and encouragement have been a great source of motivation throughout my academic journey.

Lastly, I acknowledge the providers of Sentinel-2 satellite imagery and the open-source communities for their contributions to the tools and data that enabled this research, as well as all individuals who directly or indirectly supported me during this study.

APPROVAL PAGE OF THE THESIS

I, the advisor of this thesis entitled "**Analysis of Urban Green Spaces and Their Distribution by Integrating Sentinel 2 and Machine Learning Algorithm in Adama City, Ethiopia."** and developed by Gutama Garo hereby certify that the recommendation and suggestions made by the board of examiners are appropriately incorporated into the final version of the thesis.

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Major Advisor Signature Date

We, the undersigned, members of the Board of Examiners of the thesis proposal by Gutama Garo have read and evaluated the thesis entitled "**Analysis of Urban Green Spaces and Their Distribution by Integrating Sentinel 2 and Machine Learning Algorithm in Adama City, Ethiopia."** and examined the candidate during open defense. This is, therefore, to certify that the thesis is accepted for future thesis work.

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

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ACRONYMS AND ABBREVIATIONS

Acronym/Abbreviation	Full Form
UGS	Urban Green Spaces
ESA	European Space Agency
SWIR	Shortwave Infrared
NIR	Near-Infrared
NDVI	Normalized Difference Vegetation Index
EVI	Enhanced Vegetation Index
GVI	Green Vegetation Index
SRVI	Simple Ratio Vegetation Index
UGSI	Urban Green Space Index
GEE	Google Earth Engine
GIS	Geographic Information System
RS	Remote Sensing
LULC	Land Use and Land Cover
RF	Random Forest
SVM	Support Vector Machine
CNN	Convolutional Neural Networks
ROI	Region of Interest
MSI	Multispectral Instrument
OSM	OpenStreetMap

Abstract

Urban green spaces (UGS) are essential to sustainable urbanization with ecological, recreational, and aesthetic functions. The present research integrates Sentinel-2 satellite image data with machine learning algorithms to map and examine the spatial distribution of UGS in Adama City. The research utilized high-resolution 13-band multispectral Sentinel-2 imagery from the Copernicus Open Access Hub. Data encompass NDVI, GCI, NDWI and SAVI vegetation indices used in quantification of vegetation cover and health. Points of validation were derived from google earth high resolution image to validate accuracy of classification. Cloud masking, Sentinel-2 image spatial resampling and atmospheric correction forms data preprocessing. Random Forest algorithm was used to classify machine learning where the UGS has been distinguished from the remaining land cover classes. According to research, Urban Green Space (UGS) in Adama City's central zone totals 2,840.94 hectares or 36.52% of the total area, built-up area taking up 3,790.65 hectares (48.72%), and urban agriculture taking up 1,148.41 hectares (14.76%). A zonal distribution indicated that UGS is rather uniformly distributed in the city's four structural zones, the highest percentage recorded in Zone 3 with 773.77 hectares (27.63%), followed by Zone 4 (26.27%), Zone 1 (26.22%), and the lowest in Zone 2 with 556.70 hectares (19.88%). Strong integration of UGS–LST relationship, confirming the cooling effect of green spaces; areas of dense vegetation cover (0.3–0.56 NDVI) were low in surface temperature (30.4°C–30.8°C), yet areas of sparse vegetation cover (NDVI < 0.1) were high in LST (>31.5°C), demonstrating the effect of vegetation in alleviating urban heat. The study reconfirmed UGS is highly homogeneously distributed over Adama City's four structural zones, with the highest rate occurring in Zone 3. The inverse relationship between UGS and Land Surface Temperature (LST) shows vegetated surfaces reduce temperatures. Because UGS is a major factor in managing urban temperatures, more development and upkeep of vegetation are recommended, particularly in Zone 2 where comparatively lesser cover of UGS is found.

Keywords: Urban Green Space (UGS), Sentinel 2, Random Forest (RF), Spectral Indices

CHAPTER ONE

1. INTRODUCTION

1.1.Background of the study

Urban green spaces (UGS) are now a normal component of sustainable urban design, referring to pieces of land with plants within the city that provide essential ecosystem services to urban residents (Biernacka et al., 2023; Liu & Russo, 2021). These areas are typologically varied, from public parks, urban gardens, and avenue trees to green corridors and spontaneous green areas integrated into the built-up environment (Kabisch et al., 2015). Urban green spaces are not necessarily about how they look because they have multiple uses that directly affect urban environmental quality and human health (F. Zhang & Qian, 2024). UGS has been demonstrated in recent research to be an effective agent in combating urban environmental problems, particularly regulating the urban heat island effect and promoting microclimatic conditions (Mexia et al., 2018). By evapotranspiration and shading, among others, urban green spaces help in city cooling as studies have shown that urban parks are always cooler than the surrounding city built-up areas (Bowler et al., 2010).

Urban green space pattern globally varies extensively by region and income. Recent trends point towards overall decline in per capita urban green cover in rapidly growing cities, particularly in developing countries (Fuller & Gaston, 2009). In the developed world, while most cities possess relatively high green cover, the pressures of urbanization and densification persist. Cities within Europe, for instance, possess a mean green cover of 18-40%, though divergent by significant degree across cities and countries (Kabisch et al., 2015). The African nations, and Africa as a whole, have a tougher time. The cities in Africa are facing rapid urbanization and an extensive loss of urban open spaces. Research shows that the coverage of urban green space in large African cities is normally less than 10% of the urban area, much lower than the World Health Organization's recommendation (du Toit et al., 2018). This is an alarming trend, especially in light of African cities' continued expansion at a high rate, typically as unplanned settlements with no planned green areas.

East Africa and thus Ethiopia is faced with the effects directly. Ethiopian cities have seen high urban expansion during the past decades, most often at the expense of green city areas and outer agricultural land (Girma et al., 2019). Even the Ethiopian capital, Addis Ababa, has experienced enormous changes in use of urban green space, with reports showing a decline from 32% in 1986 to approximately 7% in more recent years (Woldegebriel, 2023). This enormous decline is reflective of the broader issues that face rapidly expanding Ethiopian cities, where demands of urban expansion come to outweigh maintenance of green space. Ethiopia's secondary cities are not exempt from the same problems but with even fewer resources to create and sustain green spaces. It has been proven through science that such cities typically cover less than 5% green cover, and the available little green space is fragmented and in deplorable condition (Yeshitela, 2019). The trend is also fueled by poor urban planning policy and institutional capacity in green space management. But there are certain recent policy efforts in Ethiopia that demonstrate increasing appreciation for the value of urban green spaces. The national Urban Green Infrastructure Development Strategy is a bid to turn those negative trends around, although implementation issues are still large (Girma et al., 2019). Sentinel-2 satellite imagery is a rich asset in urban greenspace monitoring due to the strong synergy between spatial resolution (10m, 20m, and 60m), and revisit time (5 days) (Haas & Ban, 2018; Schug et al., 2020).

Sentinel-2's multispectral instrument (MSI) delivers 13 bands of which the red, green, blue, and near-infrared bands at 10m resolution are especially beneficial for analyzing urban vegetation (Dagne et al., 2023). The stability of a set of vegetation indices derived from Sentinel-2 data, the NDVI and Sentinel-2 specific Red-Edge Chlorophyll Index (CI), has been proven by research to reliably measure urban vegetation health (Ghayour et al., 2021). For creating maps of city greenspaces, Sentinel-2's 10m resolution is useful in identification and monitoring of quite small greenspaces within the city environment that are beneficial in monitoring the dynamic character of the city forest (Xu et al., 2022). Experiments have shown effective applications in urban park, street tree, and other green infrastructure feature mapping with various classification approaches (Degerickx et al., 2020). Random Forest and Support Vector Machine classifiers were greatly accurate for the classification of all types of urban vegetation using Sentinel-2 data (Shi et al., 2023). Traditionally employed techniques of monitoring urban green spaces were insufficient because they were very costly, spatiotemporal bounded, and had differences in collection protocols (Balram & Dragićević, 2005; Weng, 2012). These have made urban planning and environmental management ineffective, and evidence-based policy implementation for sustainable urban development has been difficult (Bibri, 2021; Carmichael et al., 2019).

Five-day repeat cycle of Sentinel-2 provides the opportunity to monitor vegetation seasonal cycles and provide early warning of green space decline (Cheng et al., 2020; Sallis et al., 2016). These very high temporal resolutions with advanced machine learning provide unmatched potential for studying urban vegetation dynamics and heat island effects (Kafy et al., 2024; F. Li et al., 2024). The combination of globally accessible Sentinel-2 data with machine learning algorithms offers lower operational costs than conventional surveys but scalable monitoring capacity and high-performance data processing capacity (Ghayour et al., 2021; Hunt et al., 2019; Praticò et al., 2021). Analysis by means of machine learning can be used to identify the best locations to create new green spaces, monitor compliance with urban planning, and analyze the impact of urban sprawl on vegetation (Rojek et al., 2024; Tékouabou et al., 2022).

In environmental management, Machine learning enables extensive assessment of urban ecosystem services, monitoring of urban biodiversity corridors, and climate change impact on urban vegetation (Maxwell et al., 2018). The rapid urbanization of Adama City has necessitated an urgency to embrace new approaches in the observation and management of urban green spaces. Being one of the fastest developing towns in Ethiopia, Adama is confronted with the grim challenge of sustaining its environmental viability amidst urbanization.

The increasing high population in the city has led to wide urban sprawl and slums that put undue pressure on accessible green areas and natural resources. Thus, this study will try to estimate the current Urban Green Space of Adama city using Sentinel 2 satellite data and Machine learning algorithms to offer quality environmental monitoring.

1.2.Statement of the problem

Urban green spaces (UGS) are at the heart of urban sustainability, providing such ecosystem services as climate moderation, air purification, and recreational space whose existence is itself increasingly threatened by urbanization (Kabisch et al., 2015). Short-interval (5-day revisit time) and high-resolution (10 m) spatial resolution Sentinel-2 satellite image data may be able to provide valuable information for UGS monitoring, where the urban planner can monitor vegetation health, density, and area expansion in a duration of time (Li et al., 2021). It has been possible in recent studies to utilize Sentinel-2 multispectral data in estimating vegetation indices like the Normalized Difference Vegetation Index (NDVI) to assess UGS health and cover, making it easier to monitor green space fragmentation as well as monitor the impact of urban expansion (Sun & Chen, 2017).

Besides, Sentinel-2 data integration with machine learning algorithms has improved the accuracy of green space type classification to facilitate evidence-based intervention towards enhanced sustainable urban development and resilience (Hu et al., 2021; Veloso et al., 2017; Wang et al., 2019).

Machine learning steps are becoming more and more utilized in classification processes and have become popular with the reality that they can be leaders when handling image classification. There are different algorithms being implemented but every single one of them is a leader in its own right to help bring about effectiveness and efficiency in image classification processes. Random Forest (RF) is used in every field since it is stable, very accurate, and appropriate for large and complex datasets but with the requirement of tuning parameters in an attempt to offset the computationally expensive nature (Del Río et al., 2014; Dudek, 2022). Support Vector Machine (SVM), whose height is constructed on handling high-dimensional data as well as small-sized data, turns out to be effective in discriminating between the UGS and non-UGS classes but is parameter-sensitive and computationally expensive (Ghaddar & Naoum-Sawaya, 2018; Hussain, 2019). Artificial Neural Networks (ANN) identify non-linear patterns of data and thus are best applied in complex cities but require enormous amounts of data, intensive computation, and are challenging to interpret (Hussain, 2019; Maldonado et al., 2014). Convolutional Neural Networks (CNN) learn spatial features automatically and are suitable to apply in UGS mapping using high-resolution data but require tremendous computational power and are susceptible to overfitting when dealing with small data (Chen et al., 2021). Lastly, "k-Nearest Neighbors" is simply easy to implement and works extremely well with small data but not as efficiently with noisy and large data, hence reducing its possible use with complicated satellite images (Tan et al., 2005). Random Forest will be employed within Adama City UGS mapping due to its efficacy, accuracy, and robustness in multispectral Sentinel-2 data processing in a complex urban environment and thus suitable to deal with subpixel as well as accurate urban green space identification to achieve sustainable planning.

All around the globe, experiments have demonstrated the ability of Sentinel-2 images to map UGS. The greatest strength of Sentinel-2 data is that it captures some spectral bands such as the near-infrared (NIR) and short-wave infrared (SWIR) bands, which are quite helpful in discriminating urban and vegetation. They enable the utilization of indices such as the Normalized Difference Vegetation Index (NDVI) to measure vegetation health and density, which is one of the most important parameters used in UGS discovery and monitoring (Nouri et al., 2017). Moreover, Sentinel-2 high revisit time (five-day revisits) underscores the importance of temporal UGS cover and quality change monitoring through time-series analysis, which is significantly crucial to urban planners and environment managers who would want to plan sustainable cities (Hunter et al., 2019)). The study further explored Sentinel-2 data fusion with ancillary data sources like OpenStreetMap (OSM) in order to augment UGS mapping. This integration is most effective in overlaying private and public green spaces and other accuracies of classifications. Further data regarding Sentinel-2 classifications on the borderlines and accessibilities of UGS that are hard to extract from satellite data have also been integrated on the basis of OSM data (Ludwig et al., 2021). Sentinel-2 data have also widely been used in Ethiopia to map land use in the urban parts of various cities, exhibiting its capability to map varied land uses.

Interestingly, (Dagne et al., 2023) used Sentinel-2 Multispectral Instrument (MSI) data to classify the urban land cover of Gondar city and demonstrated that Sentinel-2 performed extremely well in the discrimination of urban land cover classes, which is very significant in urban management and planning. Therefore, Kebede (2022) utilized Sentinel-2 imagery in Addis Ababa to map built-up by spectral indices with good results, confirming Sentinel-2 spectral capability for detecting infrastructure in an urban setting. (Kefale et al., 2024) furthered this work with the use of Sentinel-2 for temporal change detection of urban green covers of Debre Birhan and Debre Markos cities, confirming the capability of Sentinel-2 in detecting temporal change in urban green cover. Although past research provided insightful data for categorizing urban land cover and detecting changes, they handled large land cover categories or built-up areas in urban cities without fulfilling some of the requirements of UGS mapping. Addressing this research gap is an objective of this research using Sentinel-2 satellite imagery and the Random Forest (RF) machine learning algorithm to enhance UGS mapping in Adama City. Random Forest (RF) is among the most widely applied ensemble machine learning algorithms employed to conduct land use and land cover (LULC) mapping.

A few of the researches, like Talukdar et al. (2020) and Abdi (2020), have recorded successful application of Sentinel-2 satellite image data integrated with RF with highly accurate classification for various LULC classes. It is following richness of Sentinel-2 spectra and the capacity of RF to efficiently handle complex data structures that make it highly useful in LULC classification.

Nonetheless, there is an issue in applying remote sensing (RS) data in mapping urban green spaces (UGS) because of the heterogeneity of the cover vegetation and the mixed pixels. Such complications, researchers like Chen et al. (2021) take into consideration, but they think that RF's ability in dealing with heterogeneous data and reducing the classification error is highly advantageous in RS studies. RF has managed to reduce spectral heterogeneity, and it has managed to classify well LULC even in heterogeneous land cover and with varying vegetation sizes, as demonstrated in (Noi Phan et al., 2020). The model will proceed to explore the performance of model fusion between Sentinel-2 data and model fusion of the RF classification method in mapping urban green space within the study area. Random Forest (RF) will be employed within this study based on the fact that it has previously been demonstrated to provide high accuracy in classification, resistance to overfitting, and the ability to deal with complicated high-dimensional data such as Sentinel-2's multispectral data. RF also has the ability to deal with the non-linear interactions of the urban green cover that exhibit heterogeneous spatial and spectral patterns. Its ease of application, order of importance of features, and proven performance in similar studies also suggest its use. RF use on cloud-based platforms like Google Earth Engine also makes it more feasible to scale up to large-area green space mapping. The approach was able to capture both the uniform green patches in space, i.e., the forests, and the dispersed heterogeneous green cover, i.e., the gardens and small green patches, that contribute towards the observation of UGS distribution in various landscape sizes and classes.

1.3.Objective of the study

1.3.1. General Objective

The main objective of this research is to analyze and map the distribution of urban green spaces (UGS) in Adama City using Sentinel-2 imagery combined with a machine learning algorithm.

1.3.2. Specific Objectives

- To evaluate the capability of Sentinel-2 spectral bands in differentiating vegetation from built-up areas within Adama City.
- To quantify and map the spatial extent and patterns of urban green spaces, categorizing them into types such as parks, home gardens, institutional greenery, and natural vegetation.

- To analyze the spatial distribution of UGS across different urban zones and assess their accessibility and implications for urban sustainability.
- To examine the relationship between urban green spaces and Land Surface Temperature (LST), with the aim of understanding the cooling effects of green areas in urban microclimates.

1.4.Research questions

- How effectively can Sentinel-2 spectral bands differentiate between vegetation and built-up areas in Adama City?
- What is the spatial extent and distribution pattern of urban green spaces (UGS) in Adama City, and how can they be categorized into different types such as parks, home gardens, institutional green areas, and natural vegetation?
- How are urban green spaces distributed across different zones of Adama City, and what does this imply about accessibility and urban sustainability?
- What is the relationship between the distribution of urban green spaces and Land Surface Temperature (LST), and how do green spaces contribute to mitigating urban heat?

1.5.Significance of the study

This study analyzes the usability in the context that UGS of Adama City, Ethiopia, is blessed with usable data regarding magnitude and trend by utilizing Sentinel-2 satellite images. Measuring UGS types such as parks, gardens, and natural green spaces, this study will provide urban planning and environmental management interventions for enhancing the green infrastructure of the city. The study also considers the distribution of UGS in various urban cities to ensure that there is even access to green space, which is of utmost importance in urbanizing sustainability, biodiversity, and human health. Lastly, the study encourages sustainable urban development by ensuring a cost-efficient mechanism through which planners and policymakers can plan green space, advance social justice, and reduce the negative effects of urbanization.

1.6.Scope and delimitation of the study

The research topic is estimation and mapping of Urban Green Spaces (UGS) in Adama City, Ethiopia, from Sentinel-2 data for comparative spectral characteristics of different vegetation and urban features. The research categorizes and estimates different types of UGS, i.e., gardens, parks, and natural greenspaces, and computes their area coverage in urban space to identify accessibility and urban sustainability impact. Study period is 2016-2024 since that is when there are high-resolution Sentinel-2 data available and temporal change of UGS can be quantified. Deficit of the study is that it has been conducted only on Adama City and not on rural and peri-urban cities and on remotely sensed data rather than on large-scale field validation.

1.7.Operational terms of definition

Urban Green Spaces (UGS): Urban green spaces refer to vegetated or natural lands within the urban environment, i.e., parks, gardens, and forests, with ecological, recreational, and aesthetic purposes (Tzoulas et al., 2007).

Normalized Difference Vegetation Index (NDVI): Satellite image-based vegetation index, i.e., red and near-infrared bands, used in the measurement of vegetation cover and health. NDVI is widely used to identify urban green spaces in remote sensing (Rouse et al., 2014).

Urban Heat Island Effect: The process by which city regions tend to be hotter than countryside regions primarily due to human activities, land use change, and vegetation degradation. Concentration of urban parks can mitigate the effect (Oke, 2012).

Object-Based Image Analysis (OBIA): Satellite image classification method in which the image is divided into homogeneous objects based on spectral and spatial characteristics. OBIA may be used to map green space in cities with greater accuracy (Blaschke, 2010).

Urban Ecosystem Services: Useful services provided by urban green areas to urban society and the environment at large, including air and water purification, climate regulation, biodiversity preservation, and recreation (Barton & Pretty, 2010).

Spectral Bands: Different bands of wavelengths that are captured by satellite sensors for the investigation of different land features. Bands of Sentinel-2 (blue, green, red, and near-infrared) help to distinguish different land cover features, e.g., urban green area (Sentinel-2 Mission, 2015).

CHAPTER TWO

2. LITERATURE REVIEW

2.1.Theoretical Review

2.1.1. Urban Green Spaces (UGS) Theory

Urban green spaces (UGS) are intrinsic components of urban regions that offer various environmental, social, and health benefits. UGS support theoretically the quality of life in cities by mitigating urban heat islands, improving air quality, offering recreational areas, and improving biodiversity (Kuo, 2015). Environmental psychology, urban sustainability, and ecological urbanism are the pillars of UGS. Urban planning theories argue that green spaces are inherent elements of resilient cities, fostering ecological balance and enhanced living conditions for urban populations. Environmental justice theories also argue that equal access to green spaces should be the focus of urban planning, reducing the problem of socio-economic disparities (Cohen et al., 2016).

2.1.2. Remote Sensing and Satellite Imagery in UGS Monitoring

The application of remote sensing theoretically to investigate green space in the urban environment relies on the use of satellite images in monitoring, mapping, and analyzing the urban landscape at large spatial scales. Remote sensing technology, for instance, Sentinel-2 mission, offers a non-destructive means of obtaining high spatial resolution information across multiple spectral bands necessary in discriminating between other land cover types (Drusch et al., 2012). Theoretically, remote sensing enhances the capacity to monitor UGS over large regions, providing urban planners and scholars cost-effective, timely data for making decisions.

2.1.3. Machine Learning Theory in Remote Sensing

Theory of machine learning applies in urban land cover classification, i.e., discrimination of UGS from other urban land. Supervised learning algorithms like Random Forest (RF), Support Vector Machine (SVM), and Decision Trees (DT) apply tagged data to learn patterns and make predictions on land cover using spatial characteristics (Mather & Tso, 2016). Machine learning algorithms aid in the mapping and identification of green spaces in UGS based on locating complex patterns in satellite images. Theoretical theory in ML, particularly supervised and unsupervised learning, has immensely improved the precision and efficiency of UGS classification in cities.

2.1.4. The Role of Urban Green Spaces in Urban Sustainability

Urban sustainability is a broad theme in urban planning that aims at creating cities that are socially, economically, and environmentally sustainable. Urban sustainability theory assigns a central role of UGS as being among the primary pillars of the system. Urban greens are important for reducing urban ecological footprints, improving air quality, and improving urban resilience to climate change (McDonald et al., 2016). Urban heat island effect is reduced by greens, which produce a cooling effect within the city and, hence, improve the quality of life (Bowler et al., 2010). Theoretical underpinnings of urban sustainability highlight that their maintenance and augmentation is one of the methods of reducing the negative environmental consequences of high-rate urbanization.

2.1.5. Ecological Theories and Urban Green Spaces

Ecologically, UGS are indispensable to improving biodiversity and providing ecological services in towns (Tzoulas et al., 2007). Towns, even when fragmented, can harbor various species of animals and plants and therefore contribute to overall ecological health. Urban ecological models assume that greenization of even urban spaces is essential to preserving ecological processes such as filtering of water, pollination, and nutrient circulation (Elmqvist et al., 2015). The ecosystem approach to urban areas views UGS as integrated with the urban matrix as ecological corridors facilitating greater mobility of species and promoting urban biodiversity conservation.

2.1.6. Social Sustainability and Well-being

Social sustainability in cities is yet another conceptual framework that emphasizes the importance of UGS. Social sustainability concepts acknowledge the component that proximity to green spaces highly relates to individuals' well-being and quality of life within the city (Maas et al., 2006). The areas provide means for physical and mental recreation, stress relief, and social interaction that enables integration of city dwellers. The UGS theory in this case also converges with public health and well-being theories that argue exposure to green spaces enhances healthier living and psychological well-being (Kuo, 2015).

2.1.7. Environmental Justice Theory

Environmental justice theory is concerned with unequal distribution of environmental burdens and benefits, including access to UGS. This paradigm informs that the poor and marginalized groups do not get proper access to green space and hence are impacted by a plethora of social inequalities. Environmental justice theorists believe that the provision of UGS should be accorded fairly across socio-economic and demographic groups so that social justice and harmony can be attained (Heynen et al., 2006). UGS, in this sense, are viewed as a social good to be shared by every sector of urban society regardless of socio-economic standing or ethnicity.

2.1.8. Urban Heat Island Effect and UGS Theory

Urban heat island (UHI) theory explains the urban heat island effect where urban locations are warmer than rural locations due to human activities and land cover transformation. Green spaces, especially those with high canopy covers, are theorized to counteract the UHI effect through cooling of the area through mechanisms such as evapotranspiration and shading (Oke, 1987). The natural remedy concept of UGS theory to UHI theory underscores the knowledge of the urban climate, as well as the value of having green spaces for urban climate change resilience.

2.1.9. Green Infrastructure Theory

Green infrastructure (GI) theory is an advancement of UGS theory with a focus on the use of natural systems to enhance ecosystem services in urban areas. The GI approach suggests that the city should be planned incorporating green infrastructure as a cheaper alternative to traditional gray infrastructure (e.g., concrete roads, concrete drainage, etc.) for managing floods, water management, and climate control (Tzoulas et al., 2007). UGS, being green infrastructure, helps in stormwater management, preventing pollution, and fostering sustainable urban growth.

2.2.Conceptual Review

2.2.1. Concepts of Urban Green Spaces (UGS)

Urban green spaces are referred to as areas within a city covered entirely by vegetation, e.g., parks, gardens, forests, and nature reserves. Conceptually, UGS vary based on purpose (e.g., recreational, ecological, aesthetic) and accessibility to urban residents. The concept of urban sustainability is drawing attention to UGS contribution to making cities resilient to climate change, such as minimizing urban heat island effects and provision of ecosystem services (Cohen et al., 2016).

Environmental justice concept is also important in the determination of just access to UGS, with particular emphasis on ensuring that all citizens are able to gain benefits from such spaces (Zhao et al., 2019).

2.2.2. Remote Sensing and Sentinel-2 in UGS Mapping

Remote sensing technologies, particularly those enabled by Sentinel-2, are theoretically applicable for observing and mapping urban greenspace at extensive spatial scales. Sentinel-2's capacity to image data in 13 spectral bands facilitates the computation of vegetation indexes, i.e., NDVI and EVI, which are theoretical identification and classification methods of urban greenspaces (Tucker, 1979; Zhang et al., 2019). Satellite imaging principle of urban planning supports the necessity for data-driven management of UGS, an improved scaled-up alternative to traditional field surveys (Reed et al., 2019).

2.2.3. Concepts of Machine Learning in UGS Analysis

Machine learning methods of UGS analysis involve training algorithms on labeled data so that the algorithms can learn to recognize patterns in spectral data for different classes of land cover. Supervised methods like RF, SVM, and DT have been applied theoretically for remote-sensing UGS in the urban environment with the basis of classification on their spectral signature (Mather & Tso, 2016). Unsupervised methods like k-means clustering groups points of data into classes of similar features, allowing UGS mapping where there is no labeled data (Benediktsson et al., 2012). Most recently, deep learning algorithms and in particular Convolutional Neural Networks (CNNs) have been utilized, bringing a new generation of UGS analysis with the feature extraction done automatically from raw image data (Zhu et al., 2017).

2.2.4. Integration of Sentinel-2 and Machine Learning for UGS Mapping

In theory, Sentinel-2 integration and machine learning algorithms leverage both technologies' strengths towards more efficient mapping and monitoring of UGS. Sentinel-2 provides remote sensing images of high resolution, and the data is machine learning algorithm classified and processed. The concept is to improve the accuracy, efficiency, and scalability of UGS analysis to enable monitoring big cities in near real-time. The hybrid strategy provides more precise determination of green area distribution and coverage and plays a crucial role in urban planning and sustainable development (Ghosh et al., 2020).

2.2.5. Urban Green Space Conceptualization

Conceptualization of urban green spaces (UGS) has also evolved with the evolving agenda of urban planning and the environment with the passage of time. UGS are commonly defined as bunches of vegetation, parks, gardens, and natural habitats within the city that are planned to fulfill ecological, recreational, and aesthetic functions (Tzoulas et al., 2007). Conceptually, UGS are neither green pockets nor fragments but an integral part of a well-structured urban ecosystem. This connectivity is found under the umbrella of "green networks" or "green corridors," whereby green spaces are used as eco-connectors to facilitate the mobility of biodiversity and increase urban resilience (Hansen & Pauleit, 2014).

2.2.6. Types of Urban Green Spaces

UGS can be classified into various types based on their purpose and the urban context in which they are situated. Amongst the enumerated are open areas and public parks, private green areas, natural green areas, and green roofs and walls. Public parks are used by human beings, with leisure and social functions like sports, strolling, and social gatherings. Private green areas, like in residential estates, are not accessible by the general public. Natural green areas, like river banks, forests, and wetlands, are not altered from their form. In addition to green roofs and walls, common to modern urban landscape design, vegetative integration within the city's built-up area takes place (Dunnett & Kingsbury, 2004). The typological approach enlivens the sensibility among urban planners towards multi-functionality of UGS in the city, from recreational areas to ecological green oases and climatic managers.

2.2.7. Access and Equity in Urban Green Spaces

Access and equity form another central aspect of UGS conceptualization. Green cities, as beneficial to the environment and human health, in the majority of instances are not proportionately available across the urban spaces, with disadvantaged groups having limited access (García et al., 2018). The limited access is one of the central topics in the environmental justice and spatial justice literature concerning the equitable share of natural and green space. Theory of spatial justice posits that equal access UGS is necessary in its efforts to support social cohesion, health disparity reduction, and community welfare improvement (Soja, 2010).

2.2.8. Green Space as Ecosystem Services

UGS has been pushed even further into the ecosystem services paradigm. Ecosystem services are the benefits human beings derive from nature, and UGS provide numerous fundamental services, i.e., regulating services such as air and water cleansing, climatic regulation (in the form of carbon sequestration and cooling), and flood control. Provisioning services such as food production (urban agriculture, for instance) and raw materials, and cultural services such as recreational activities, aesthetic services, and mental health services are also fundamental (Millennium Ecosystem Assessment, 2005). This is promoted by green infrastructure theory, which posits that natural systems like UGS can potentially introduce positive services to urban resilience and sustainability (Ahern, 2011).

2.2.9. Sustainability and Resilience of Urban Green Spaces

In terms of sustainability, UGS are primarily a determinant to the long-term urban resilience. They are said to be defense mechanisms against natural disasters like floods and heatwaves, and also drivers of climate resilience. On these grounds, resilience theory is teaching cities to integrate green spaces in an effort to maximize their ability to absorb, recover from, and adapt to climate shocks (Folke et al., 2010). Cities that use UGS to help regulate their local climate, reduce flood risk, and enhance social resilience by providing safe grounds for socialization are resilient.

2.2.10. The Future of Urban Green Spaces: Smart Cities and Technology

There has been the evolution of the idea of the smart city in the modern urban environment, e.g., the integration of digital technology and data thinking into city planning. The role of UGS towards intelligent cities is also considered one of a green intelligent infrastructure, which, via sensors, geographic information systems (GIS), and satellite imagery (e.g., Sentinel-2), will be watching, controlling, and optimizing the utilization of green spaces (Neirotti et al., 2014). There can be a use of smart technologies for tracking the quality, accessibility, and availability of UGS in order to make urban planning more efficient and greener space management more efficient.

2.2.11. Urban Green Space and Social Inclusion

UGS are also referred to as spaces that promote social inclusion in urban areas. Green spaces can be employed as spaces for promoting social contact, cultural encounter, and citizen participation (Sullivan et al., 2004). Green spaces are areas where people from diverse social, economic, and cultural groups have a chance to come together, promoting unity as well as restraining social exclusion. Green spaces are "social equalizers," benefitting every urban population member regardless of socio-economic group or origin.

2.3.Recent Trends and Future Directions

Rising trends in Sentinel-2 and machine learning-based UGS analysis have revolved around increasing the spatial resolution and accuracy of classification. While the 10-meter resolution of Sentinel-2 is adequate to spatially delineate green spaces in most cities, there is greater interest in incorporating higher-resolution commercial satellite imagery from satellites such as Worldview or Planet Scope for mapping small and dispersed green spaces in extremely dense cities (Morisette et al., 2019). Both, in their capability to integrate high-resolution visual data with sophisticated machine learning algorithms, have the capability to better map UGS and provide more detailed information about the size, shape, and location of green space. Deeper models like CNNs are also being made more powerful in order to be able to process richer datasets and extract image features automatically from images with less human intervention (Zhu et al., 2017).

Besides that, even greater stress is laid on the improvement of the overall UGS analysis through greater exploitation of multi-source data. The merging of Sentinel-2 data with other data such as LiDAR and OpenStreetMap can lead to a higher knowledge of the urban system, such as the three-dimensional structure of green spaces and their spatial relationship with urban infrastructure (Morisette et al., 2019). Future research will consider the quality and accessibility of UGS instead of their quantity to make a contribution towards equity and environmental justice in urbanization (Li et al., 2020). This includes looking at to what extent green spaces are distributed among different socio-economic groups and ensuring that everyone has an equal chance of accessing these precious urban amenities.

2.4.Empirical Literature

The study by Zhou et al. (2020) with Sentinel-2 images to map Chinese cities' green urban space. The study focused on the impact of green urban space on climate distribution within a city and quality of life, in general. Even more so, green urban space is of greatest concern for temperature control, air quality, and human beings' health. Zhou et al. (2020) depicted how strategically located green spaces can mitigate urban heat island effects, reduce air pollution, and make recreational areas that promote the physical and psychological health of urban residents. With urbanization still increasing further and climate change threat looming big over our heads, it is paramount to understand the patterns and dynamics of green space through advanced means like Sentinel-2 imagery in sustainable city planning. This study takes the empirical contribution of Zhou et al. and attempts to gain more insight into how urban green spaces may be appropriately monitored and preserved in a bid to develop healthier and sustainable cities.

The Pereira et al. (2021) study that employed Sentinel-2 data for mapping the quantity of urban vegetation that occurs in European cities proved the vast potential of remote sensing for planning sustainable cities. Pereira et al. (2021) arrived at the conclusion that Sentinel-2 imagery offers a cost-effective yet effective means of accurate mapping and monitoring of green spaces for large urban areas, enabling urban area planners to ascertain the accessibility and availability of green spaces. This ability to monitor green space allocation supports quality sustainable urban planning choices by determining areas where the green space is lacking or in need of strengthening, informing equitable resource distribution, and allowing for easy decision-making towards urban sustainability and resilience improvement. With increased pressure on cities to preserve urbanization and the environment, data provided by remote sensing such as that available from Sentinel-2 can be beneficial in ensuring that vegetation is not broken and is strengthened, toward improving the lives of urban residents. This study is grounded in the work of Pereira et al. (2021) and seeks to explore further the possibility of utilizing new remote sensing techniques in providing efficient urban green space management and more sustainable and habitable cities.

Application of Sentinel-2 data and machine learning has also been a powerful instrument in enhanced accuracy and coverage of urban green space analysis, as cited in García et al. (2022) and Li et al. (2021) et al., making great contributions towards environmental management and urban planning. Machine learning methods such as Random Forest (RF), Support Vector Machine (SVM), and Convolutional Neural Networks (CNN) have become progressively prominent in improving the spatial analysis and precision of cities, particularly when combined with satellite data. They are of broad application in three of the primary major green area urban analysis topics: change detection, land cover mapping, and spatial pattern analysis. Machine learning techniques used for land cover classification are employed in mapping and classifying various land covers in an urban space, including green, impervious surface, and water bodies, from satellite images like Sentinel-2. Machine learning algorithms can differentiate between various land covers based on the spectral information of these satellites and can do the job more efficiently than traditional classification techniques. For example, García et al. (2022) used Random Forest to classify urban green spaces in different American cities. Based on their research, they were able to make more accurate classification than with the common technique, for the sake of more accurate mapping of the green space, which comes in handy in city planning and monitoring of the environment.

Apart from classification, machine learning is also most appropriate for the detection of temporal change in urban greenspaces and offers information on how urban greenspaces change over time. Change detection from satellite images facilitates change detection and quantification of the impact of urbanization on the quality and quantity of green spaces. Urban growth, ecosystem degradation, and green loss can be used to inform policy intervention with change detection from satellite imagery. For instance, Li et al. (2021) integrated Sentinel-2 imagery with deep learning techniques for improved city vegetation boundary delineation in the case of intricate land covers such as mixed land use with urban structure and greenspace dominance. The study revealed the ability of deep learning algorithms to address such complexity since they enabled improved greenspaces delineation in mixed land use.

Urban green space spatial structure is the main driving force towards sustainability, environmental health, and urban resilience. Urban green space spatial patterns have been used in numerous studies to depict their effects on the environment as well as on social health. One of the Jiang et al. (2020) studies employed the topological structure of green space to explore the impacts of urban heat islands in mega-cities in China. The authors applied machine learning and Sentinel-2 data to map and study green space spatial distribution and its association with UHI effects. According to their analysis, the more densely covered green spaces had reduced UHI intensity, and the influence of green spaces as an urban heat island barrier and climate resilience increase. The study emphasized the role of green spaces in improving the urban microclimate and air quality and, as a result, the urban sustainability of life.

Like Zhang et al. (2023), presented the issue of distributional justice of green space with concern for how some areas, especially in urban cities, are lacking in such green space. Their study demonstrated the environmental injustices that occur due to uneven distribution of green space, where poor and inner-city communities have limited access to recreational areas, thus resulting in rising health inequities. Through the use of advanced spatial analysis, the authors showed how socio-economic characteristics influenced the accessibility and supply of green space. This study also puts major importance on the consideration of equity in urban design in terms of green space provision so that all citizens, regardless of the socio-economic class, can access it and enhance their quality of life as well as environmental justice.

The spatial distribution of the availability of green spaces and the spatial analysis of provision is a critical component of urban studies with a capacity to affect the accessibility of the aforementioned spaces to city dwellers in very densely populated urban cities. In addition, study of the impact of green spaces towards reducing the urban heat island effect is also critical in assessing their contribution to environmental quality and urban resilience. Jiang et al. (2020) and Zhang et al. (2023) confirm the complex inter-link between urban heat islands, green spaces, and socio-economic inequalities has been established in their work, which again adds to the way the green spaces may be utilized strategically by the urban planners for urban sustainability and equity increase.

The combination of Sentinel-2 data and machine learning models has significantly improved the accuracy and scale of urban green space analysis, enabling extensive area monitoring and land cover classification. Some research has demonstrated the applicability of the approach for improving the accuracy of land classification and enabling multitemporal analysis. For instance, Yang et al. (2019) used Sentinel-2 satellite imagery and deep learning models together to detect and classify greenspaces in urban environments of different cities. Using the application of deep learning techniques, the research achieved greater classification accuracy compared to traditional methods, especially in high-density urban areas where it may be challenging to estimate a large number of land cover classes. The research demonstrated that deep learning models could successfully recognize intricate patterns in the data, thereby improving the mapping of urban green space.

Furthermore, Shao et al. (2021) integrated temporal Sentinel-2 imagery with machine learning to examine green space transformation across China's rapidly expanding cities. This article focused on employing overlaying multitemporal imagery in tracing the temporal development of green space cover, particularly in densely urbanized areas. By analyzing Sentinel-2 images captured across different intervals of time, authors were able to ascertain the trends in the expansion or reduction of green cover area, which were used as evidence of the effects of urbanization on green infrastructure. The ability to monitor these changes over time is vital to urban planning as it will specify the regions losing green cover or undercovered with green, enabling interventions to be made in a specific fashion towards sustainable urbanization.

These papers demonstrate how integration of Sentinel-2 high-resolution spectral data with latest machine learning algorithms has not only improved the precision of land mapping but also made it possible to track the dynamics of urban greens. Through the integration of Sentinel-2's temporal and spatial resolutions with machine learning, it is possible to end up with a more detailed and accurate record of urban greens, making valuable inputs for urban planners and policymakers eager to make cities greener and resilient.

2.5.Research and Knowledge Gap

The discrepancy between knowledge of analysis of urban city green space from Sentinel-2 images and machine learning is nearing effective, large-scale, and equitable monitoring of green spaces, especially for rapidly expanding cities. While studies like those of Zhou et al. (2020) and Pereira et al. (2021) have proven the potential of Sentinel-2 data in application to green space mapping, there is still more to be explored in the exploitation of such a tool in addressing urban challenges like heat islands, air quality, and socio-economic disparities in access to green space.

Zhou et al. (2020) also declared the importance of green spaces being put in place to mitigate urban heat island effects, but much remains to be done in further maximizing green space distribution through machine learning and real-time information. Similarly, while Pereira et al. (2021) demonstrated Sentinel-2's effectiveness for urban planning, employing multi-temporal images and machine learning to track long-term changes in green spaces remains an untapped potential. Apart from this, although machine learning models like RF, SVM, and CNN have improved land classification as well as land change detection, they have yet to be applied in complex urban areas with mixed socio-economic levels and land covers.

CHAPTER THREE

3. MATERIALS AND METHODS

3.1.Study area description

Adama City, located in the mid-Ethiopia Oromia Region, lies between latitudes 8°26'N to 8°34'N and longitudes 39°13'E to 39°19'E, approximately 100 km south of Addis Ababa. The city is located at an altitude of 1,600–1,700 m in the semi-arid Great Rift Valley with a mean rainfall of 600-800 mm per year and mean temperatures of 20°C to 30°C. As a rapidly growing city, Adama is strategically located for transportation and trade, connecting Addis Ababa with the Port of Djibouti through road and railway. Urbanization has resulted in the city being a combination of residential, commercial, and industrial sites, yet the development at expense is land use conflict and environmental degradation.

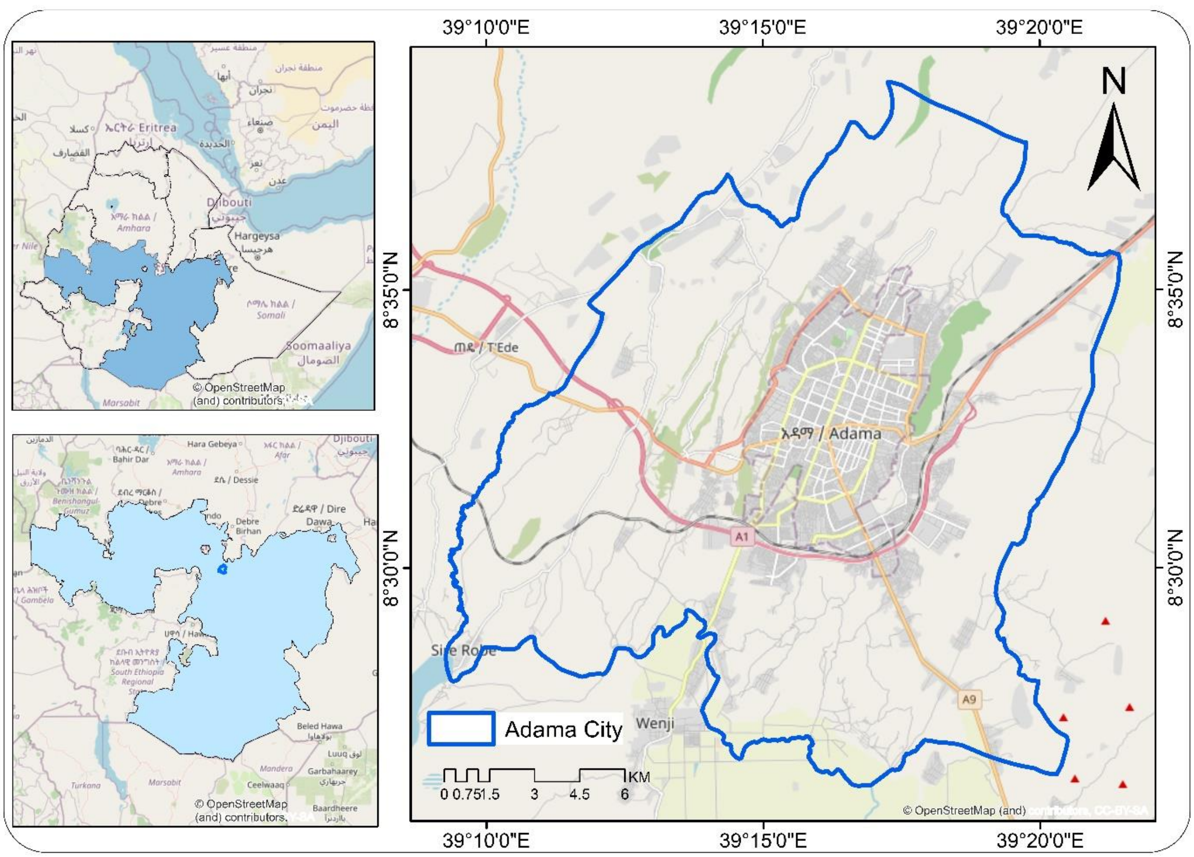

Figure 3-1: Location map of the study area

3.2.Data source and type

3.2.1. Sentinel-2A

Sentinel-2A data, obtained from the Copernicus Open Access Hub, served as the primary data source for this study. Sentinel-2A is part of the Copernicus Earth Observation Programme and is operated by the European Space Agency (ESA). Equipped with the advanced Multi-Spectral Instrument (MSI), Sentinel-2A captures information in 13 spectral bands spanning the visible to shortwave infrared (SWIR) regions of the electromagnetic spectrum (Aryal et al., 2022; Kopecká et al., 2017). These bands are provided at three spatial resolutions: 10 meters, 20 meters, and 60 meters, catering to different analytical requirements. Bands at 10-meter resolution, including Red (Band 4) and Near-Infrared (NIR, Band 8), are especially suited for detecting and analyzing urban vegetation. The 20-meter bands, such as Red Edge and SWIR, assist in identifying stressed vegetation and estimating material properties, while the 60-meter bands, primarily used for atmospheric correction, offer higher radiometric accuracy. Detailed information about Sentinel-2 spectral bands is presented in Table 3-1. Although the research scope mentions the period from 2016 to 2024, this study employs a time series analysis using Sentinel-2A imagery acquired on November 12, 2016 and November 21, 2024.

Table 3-1: Description of Sentinel-2A satellite image providing band details, corresponding wavelength, and spatial resolution

Band	Wavelength (CW) (nm)	Spatial Resolution (m)
Band 1 — Coastal aerosol	443	60
Band 2 — Blue	490	10
Band 3 — Green	560	10
Band 4 — Red	665	10
Band 5 — Vegetation red edge	705	20
Band 6 — Vegetation red edge	740	20
Band 7 — Vegetation red edge	783	20
Band 8 — Near-infrared (NIR)	842	10
Band 8A — Narrow near-infrared (NIR)	865	20
Band 9 — Water vapour	945	60
Band 10 — Shortwave infrared (SWIR) - Cirrus	1375	60
Band 11 — Shortwave infrared (SWIR)	1610	20
Band 12 — Shortwave infrared (SWIR)	2190	20

3.2.2. Field data for validation

In this study, field data collection was conducted to validate the land cover classification map generated from Sentinel-2 MSI imagery, with a particular focus on urban green space (UGS) categories. A total of 260 sample points were systematically digitized and geo-referenced using high-resolution Google Earth imagery, which has been widely accepted in remote sensing studies for visual interpretation and reference data extraction (Potapov et al., 2020). These points were categorized into five land cover classes: urban vegetation, grassland, shrubland, urban agriculture, and built-up areas. Each point was carefully labeled based on visual interpretation of spectral and spatial patterns and supported by known ground features.

To ensure spatial representativeness across Adama City, the study area was divided into four distinct urban zones: Zone 1 (central city), Zone 2 (intermediate urban area), Zone 3 (sub-urban), and Zone 4 (peri-urban). A stratified random sampling approach was applied, with strata defined based on these urban zones to reflect their varying land use intensities and green space distributions. Stratified sampling has been proven effective in improving classification accuracy by ensuring adequate representation of heterogeneous landscapes (Foody, 2002; Congalton & Green, 2019). Within each stratum, sampling locations were randomly selected and distributed proportionally to cover all five land cover classes. This approach ensured the inclusion of diverse vegetation structures, from compact city parks and scattered street trees to extensive peri-urban agricultural plots.

The collected GPS-located points were used for two primary purposes. First, a portion of the dataset was used as training data for supervised classification using a machine learning algorithm—Random Forest—which has demonstrated high accuracy in land cover mapping using multispectral satellite imagery (Belgiu & Drăguţ, 2016). Second, the remaining portion was reserved for accuracy assessment. The classified output was evaluated against the validation dataset using standard accuracy metrics such as Overall Accuracy, Producer's Accuracy, User's Accuracy, and the Kappa Coefficient, following the methodological guidelines of remote sensing classification validation (Congalton & Green, 2019).

This field data collection strategy and its integration into the classification workflow not only ensured high-quality model training but also provided reliable means for quantitative validation. The use of high-resolution imagery as a ground truth source has become increasingly common in urban studies where field access is limited, as it allows precise identification of fine-scale features such as home gardens and narrow vegetated strips (Phiri & Morgenroth, 2017). In the context of rapidly urbanizing environments like Adama City, such a hybrid validation approach combining remote visual annotation with stratified sampling ensures robustness and spatial balance in the classification output.

3.3.Software/tools

A variety of software and tools were employed to map and analyze urban green spaces in an effective manner. Google Earth Engine (GEE) served as a cloud-based preprocessing environment for Sentinel-2A imagery, performing spectral analysis, and calculating vegetation indices such as NDVI and EVI. Spatial analysis, cartographic visualization, and ancillary data integration such as administrative boundaries and road networks were performed using ArcGIS to produce high-resolution urban green cover maps. Statistical analysis, data visualization, and satellite-derived metric verification using spatial packages such as raster and sf were performed by R Studio. Copernicus Open Access Hub permitted access to Sentinel-2A imagery so that high-resolution data acquisition was guaranteed for the research. Microsoft Excel also helped in tabular data organization and analysis such as accuracy assessment and statistical summarization.

Table 3-2: Software and tools to be used in this research

Software/Tool	Purpose
Google Earth Engine (GEE)	Cloud-based geospatial analysis platform for preprocessing, spectral analysis, and vegetation index computation.
ArcGIS	GIS software for spatial analysis, cartographic visualization, and integrating ancillary data.
R Studio	Statistical analysis, data visualization, and validation of green space metrics using spatial packages.
Copernicus Open Access Hub	Portal for downloading Sentinel-2A imagery and accessing raw/pre-processed datasets.
Microsoft Excel	Organizing and analyzing tabular data, including accuracy assessments and statistical summaries.

3.4.Data processing and analysis

3.4.1. Preprocessing

Preprocessing of Sentinel-2A imagery was undertaken to ensure data quality and suitability for urban green space (UGS) mapping in Adama City. The selected image was acquired on November

12, 2016 and November 21, 2024, a date chosen to capture vegetation during the early dry season, which helps in reducing seasonal variability and cloud contamination (Huete et al., 2002). This period also aligns with minimal rainfall, providing clearer atmospheric conditions for analysis.

The raw Sentinel-2 Level-1C data were processed using the Sen2Cor atmospheric correction algorithm to convert top-of-atmosphere (TOA) reflectance to surface reflectance, thereby correcting atmospheric effects such as aerosol scattering and water vapor absorption (Louis et al., 2016). Additionally, cloud and shadow masking were applied using Sen2Cor outputs and supplementary cloud detection tools within Google Earth Engine to exclude pixels affected by clouds and shadows.

To maintain consistency in spatial resolution across spectral bands originally at 10m, 20m, and 60m resolutions, all bands were resampled to 10 meters using nearest neighbor interpolation. This step is essential for accurate pixel-based classification, especially in heterogeneous urban environments where fine spatial details are important (Drusch et al., 2012). Lastly, the imagery was clipped to the administrative boundaries of Adama City to focus the analysis exclusively on the study area.

These preprocessing steps ensured that the input imagery was atmospherically corrected, cloud-free, and spatially consistent, laying a strong foundation for subsequent urban green space classification and analysis.

3.4.2. Spectral Indices for Urban Green Space Mapping

Normalized Difference Vegetation Index (NDVI)

NDVI is among the most used vegetation indices due to the fact that it is easy and effective in delineating vegetation from non-vegetative cover. The index exploits the property of vegetation to reflect highly in infrared (NIR) but to absorb visible (Red) light. NDVI provides clear discrimination between healthy vegetation (high NIR reflectance and low Red reflectance) and non-vegetation features like bare ground, water bodies, or urban structures in urban green space mapping. NDVI varies from -1 to +1, and denser and healthier vegetation has high values. This index is extensively utilized for the detection of urban vegetation, where vegetation cover in towns is frequently fragmented, so NDVI values of > 0.2 to > 0.5 are useful in classifying urban vegetation cover (Martinez & Labib, 2023). The NDVI formula is as follows;

$$NDVI = \frac{NIR - Red}{NIR + Red}$$

Enhanced Vegetation Index (EVI)

EVI was created to be a better version of NDVI by limiting the impact of atmospheric conditions, soil background, and canopy structure in the estimation of vegetation. This index is especially useful in dense vegetation or urban heat island areas where atmospheric perturbation would distort NDVI values. EVI is less sensitive to canopy background and more suitable to areas of large non-vegetated surface fraction, hence more accurate for discriminating vegetation in urban areas with a mixture of developed and green surfaces. EVI values ranging from 0.2 to 0.3 are generally considered healthy vegetation and is informative in the identification of urban green spaces (Karnieli et al., 2013).

$$EVI = G * \frac{(NIR - Red)}{(NIR + C_1 * Red - C_2 * Blue + L}$$

Where:

- G is the gain factor (usually 2.5),
- $C1$ and $C2$ are coefficients for the red and blue bands,
- L is a canopy background adjustment value (usually 10000).

Green Vegetation Index (GVI)

The GVI is based on the green portion of the spectrum, which is very responsive to the concentration of chlorophyll within vegetation. This index is beneficial for the identification of green patches in urban areas as it emphasizes the green spectral band. It is strongly correlated with green vegetation. GVI is a simple index employed to distinguish between various surfaces like vegetation and non-vegetation in urban areas. Its superiority is due to its higher sensitivity to green plants, and hence it is suitable for the estimation of the area covered by the green portion in urban areas. Values greater than 0.3 are typically indicative of healthy vegetation, and values close to 0 reflect bare or urbanized land (Zhang et al., 2023).

$$GVI = \frac{Green}{NIR}$$

Simple Ratio Vegetation Index (SRVI)

SRVI is an uncomplicated yet effective index for vegetative vs. non-vegetative distinction based on the NIR/Red band ratio. Vegetation significantly reflects a large amount of NIR radiation and absorbs Red light, making the SRVI ideal for mapping urban greens. SRVI is ideally applied where vegetation is fragmented or sparse because it is less affected by background non-vegetated cover and soil. SRVI values above 1.0 are typically applied to map green land in the urban area, whereas values near 0 indicate barren or urbanized ground. This index can be applied to cities with multi-bio-cover and land use in their vegetation covers (Bajocco et al., 2012).

$$SRVI = \frac{NIR}{Red}$$

3.5. Urban Green Space Index (UGSI)

Urban green space index (UGSI) refers to a significant environmental indicator and urban planning metric that approximates the proportion of green in urban areas. Urban green areas (UGS) such as forests, parks, gardens, and other open grounds contribute meaningfully towards the health, environmental sustainability, and overall wellbeing of urban residents. They provide multi-functional ecosystem services like air cleaning, temperature moderation, biodiversity preservation, and social meeting and recreation space (Tzoulas et al., 2007; Wolch et al., 2014).

The use of UGSI provides a systematic approach of green space allotment and accessibility analysis in urban areas. Satellite remote sensing is inexpensive and provides an integrative approach of tracking large cities. Satellite imagery at higher spatial resolution, particularly from the likes of Sentinel-2 and Landsat, provides identification and mapping of urban vegetation. These data are particularly useful in urban studies in the context that they track land cover change in near-real time, for instance, urban sprawl and urbanization of green space (Yu & Fang, 2023).

UGSI can be used to significantly enhance urban sustainability. With the quantification of the proportion of urban land covered by vegetation, policymakers and urban planners have a data-informed decision to make in planning and designing green spaces in fast-growing urban cities (Chatzimentor et al., 2020). Urban parks play an extremely significant role in combating the urban heat island effect, reducing air pollution, and overall climate resilience of urban metropolitan areas

(Bowler et al., 2010). Additionally, studies have confirmed that green space exposure has a beneficial impact on human health in the form of mitigating stress, inducing exercise, and improving mental health (Maas et al., 2006).

The UGSI may also be employed in the prioritization of opportunities for green space development for those communities that do not have access to green spaces by all residents of a city, a growing key issue in managing social inequalities in access to nature (Kardan et al., 2015). In addition, by combining satellite-based vegetation indices such as NDVI (Normalized Difference Vegetation Index) and EVI (Enhanced Vegetation Index), UGSI also offers a comparable and reproducible method in tracking the growth of green space over time, allowing for the evaluation of the effectiveness of urban green space policy (Neyns & Canters, 2022).

The formula for the Urban Green Space Index (UGSI) is:

$$UGSI = \frac{Area\ of\ Green\ Space\ (NDVI > 0.3)}{Total\ Urban\ Area} * 100$$

3.6.Accuracy assessments

Accuracy assessment is the most crucial step in remote sensing and GIS-based mapping studies, especially when determining the type of land cover like Urban Green Spaces (UGS). Accuracy assessment is done for the purpose of confirming the validity of the performance of the classifiers and how far the result attained from the satellite imagery reflects the ground truth. Accuracy assessment renders the output of the classification reliable for decision-making, particularly urban development and environmental management.

Overall Accuracy: Overall accuracy is the most common and easiest measure that is used to determine how accurate the classified maps are. It is the ratio of correctly classified pixels to the total number of pixels. It can be calculated as:

$$Overall\ accuracy = \frac{Number\ of\ Correctly\ classified\ pixel}{Total\ Number\ of\ pixels} * 100$$

Producer's Accuracy: Producer accuracy or recall/sensitivity is a measure of quality on how well the classifier classifies instances of a specific land cover class correctly. It can be stated as the proportion of correctly classified pixels in the class to the total number of pixels in the reference data of the class:

$$Producer\ accuracy = \frac{Number\ of\ Correctly\ classified\ pixel\ in\ Class}{Total\ Number\ of\ pixels\ in\ class} * 100$$

User's Accuracy: User's accuracy or precision refers to the number of the pixels that are correctly classified into a single class and are correct. It is approximated by dividing correctly classified pixel of the class by the total number of pixels that were assigned as the class:

$$User\ accuracy = \frac{Number\ of\ Correctly\ classified\ pixel\ in\ Class}{Total\ Number\ of\ pixels\ as\ class} * 100$$

Kappa Coefficient: Kappa coefficient is a more sophisticated measure which adjusts for agreement by chance. The Kappa coefficient measures the degree of agreement between reference data and classified data, adjusted for random chance. The Kappa coefficient is given as:

$$k = \frac{p_o - p_e}{1 - p_e}$$

where:

- p_o is the observed agreement (overall accuracy),
- p_e is the expected agreement (the probability of chance agreement).

A Kappa value close to 1 indicates almost perfect agreement, while a value close to 0 indicates no agreement beyond chance.

3.7.Data analysis procedure

The flow chart is the overall process to detect Urban Green Spaces (UGS) using Sentinel-2 data and machine learning algorithms. The process starts with the acquisition of required data: Sentinel-2 Multispectral Instrument (MSI) data and GPS data. Sentinel-2 data provide multispectral high-resolution data, important in grass and other urban plant class differentiation and other land cover classes. Ground-truth points or hidden locations to validate accuracy come with remote sensing data in the form of GPS data and allow validation of the classification result.

Preprocessing of MSI data from Sentinel-2 is the first step. Preprocessing is one of the major determinants of the final product quality and accuracy delivery. Preprocessing operations include clipping, whereby the image is clipped to the area of interest (AOI) to remove unwanted data.

Mosaicking is the integration of multiple images in an attempt to cover the study area, especially where the Sentinel-2 images are of different time periods. Radiometric correction is then performed to remove sensor-induced variability or atmospheric interference to produce imagery accurately representing the Earth's surface. Geometric correction stretches the image to some coordinate system in such a way that it matches the real world. Meanwhile, the GPS data are processed such that they are in good condition and well aligned with the Sentinel-2 data. Preprocessing needs to be performed for effective comparison and validation of the remotely sensed data with the ground points.

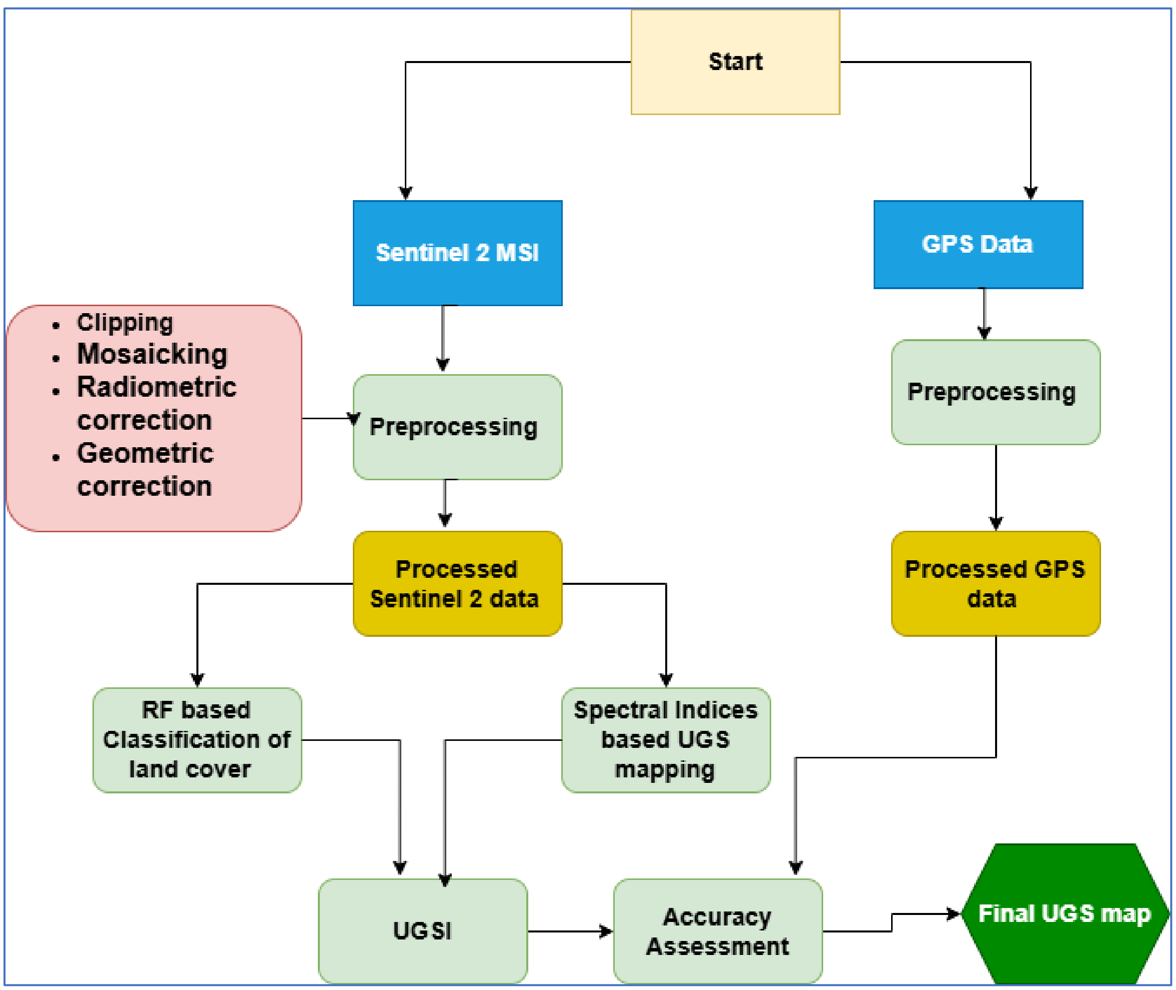

Figure 3-2: Methodological flowchart

Processed Sentinel-2 data are under consideration for machine learning classification where Random Forest (RF) algorithm is utilized for the same. Random Forest is a robust machine learning classification technique that classifies land cover using a number of spectral features of the images.

The classification separates different land covers from each other and between urban, green, water, and others. Urban Green Spaces, as gardens, parks, and other green ground in cities, can be rightfully classified under this classification. Finally, Sentinel-2 data spectral indices are utilized to further enhance the detectability of UGS. Spectral indices like the Normalized Difference Vegetation Index (NDVI) can be optimally utilized in the separation of vegetation from the rest of the land cover. Calculation and analysis of such indices can be used to identify areas of high vegetation density as UGS. This enhances the utilization of the specific reflectance properties of the vegetation in different spectral bands towards making the green areas more visible.

Accuracy checking is performed once UGS mapping is finished. The process verifies whether the green patches identified represent real conditions or not. Pre-accrued GPS observations are used in ground-truthing, which verifies the accuracy of the mapped UGS. There must be adjustment in the process to quantify the performance of classification as well as the validity of the resulting map.

The ultimate output of the process is a UGS map graphically showing identified urban green spaces. The map is the result of a vast data-driven process from Sentinel-2 imagery, machine learning models, and ground truthing. It is worth the urban planner, policymaker, and environmentalist who would like to manage and preserve green spaces in cities.

CHAPTER FOUR

4. RESULT AND DISCUSSION

4.1.Introduction

This study addresses the evaluation of Urban Green Spaces (UGS) in Adama City using innovative remote sensing and machine learning techniques. The methodology to be used relies on Sentinel-2 satellite imagery, which offers high-resolution, multispectral data required for accurate land cover research. The analysis is limited to the urban area of Adama City in a way that only the urban-associated green spaces are considered. This approach enhances the validity of results by eliminating the influence of non-urban spaces, such as rural or woodland areas outside of city administrative boundaries. The focus is to provide a better and appropriate description of UGS distribution, condition, and planning significance in the urbanization process.

4.2.Extent of urban green space at Adama city scale

A high-resolution analysis of Adama City land use of the urban area shows a heterogeneous and rich urban land cover condition with diverse land cover types. From Table 4-1, 14,216.38 hectares of area is under urban vegetation corresponding to 26.35%, grassland occupies 1,951.01 hectares (3.62%), and shrubland occupies 7,364.40 hectares (13.65%). These three land use classes together account for 43.62% of the city area and are termed as the urban green space of the city as a whole. They account for a high percentage of cover by vegetation, which indicates that it is a parameter of comparatively high frequency of natural or semi-natural environments in the city.

Table 4-1: Area and percentage share of classified urban land cover at the city scale

SN	Class	Area	Percentage
1	Urban Vegetation	14216.38	26.35
2	Grassland	1951.01	3.62
3	Shrubland	7364.40	13.65
4	Urban Agriculture	24949.66	46.24
5	Built-up	5478.14	10.15
6	Total	53959.59	100.00

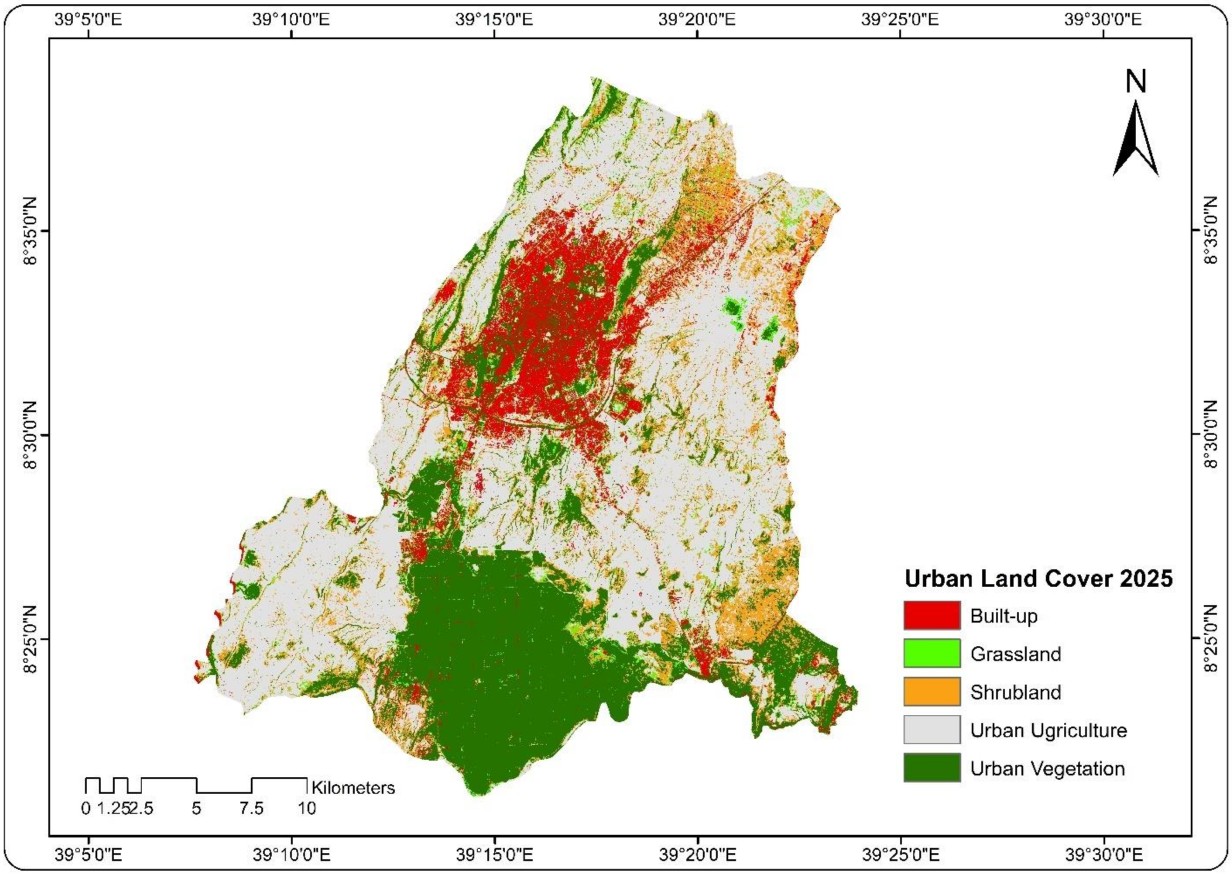

Figure 4-1: Existing urban land cover for the year 2025 at the Adama city scale

Urban agriculture, however, is the most common land use, occupying an area of 24,949.66 hectares or 46.24% of the city area. This dominance also represents the dominance of cultivated green spaces, meaning that agriculture remains a top activity even in the peri-urban and urban regions of Adama. Urbanized land occupies a small 5,478.14 hectares, a paltry 10.15% of the total area. This is a low percentage showing either low overall density or an urban setting still dominated by rural space characteristics and farm uses. Vegetative and agrarian land uses' prevalence is an urban-rural hybrid character, wherein the natural and cultivated green cover forms a part of the ecological make-up as well as contributes significantly to local livelihoods, food security, and microclimate in the city.

4.3.Spectral indices at the city scale

4.3.1. NDVI (Normalized Difference Vegetation Index

Normalized Difference Vegetation Index (NDVI) is a robust and robust index used for vegetation distribution, health, and density estimation landscape wide. NDVI is derived from the ratio of near-infrared and red bands of satellite imagery; here in this study Sentinel-2 data. Vegetated plants strongly absorb most visible red light for photosynthesis and reflect a significant percentage of near-infrared light, whereas non-vegetation cover like exposed ground, urban, or stressed vegetation reflect both wavelengths differently. NDVI exploits the difference to estimate vegetation cover and vigor on a -1 to +1 scale, with large values indicating dense, healthy vegetation and small values indicating bare, developed, or degraded land.

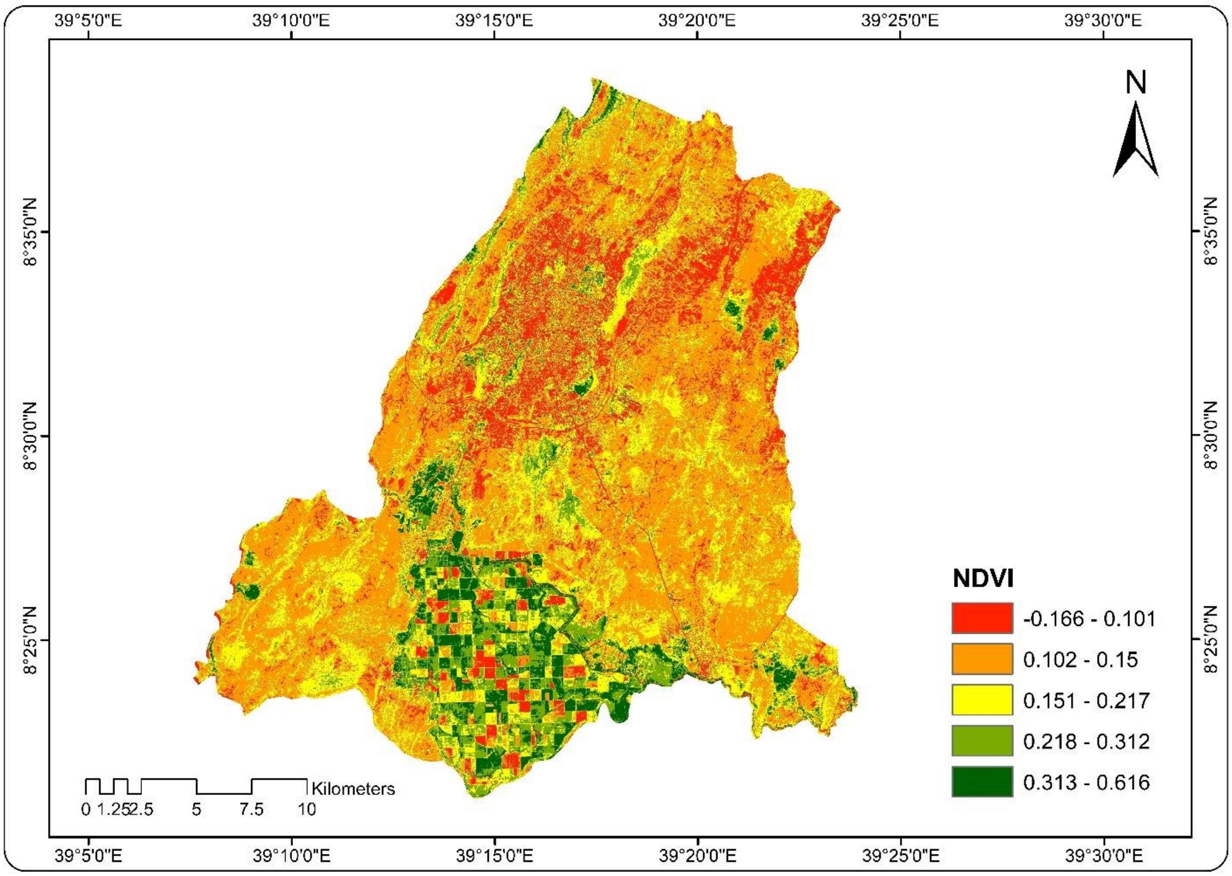

Figure 4-2:NDVI

For Adama City, NDVI is extremely useful in the discrimination of non-vegetated from green urban features. Dense and healthy urban vegetation is known to exhibit high NDVI in vegetation-dominant land covers: e.g., urban green parks, treed roadsides, and intensively used productive urban agriculture. Such areas are also indicative of the ecological viability and environmental quality potential of the city like cleaning air, heating/cooling, and recreation. Conversely, low NDVI values mark stressed or thin vegetation, impervious surface, or urban land use and reflect either ecological decline or urban area expansion. In this context, NDVI is a useful tool for mapping, monitoring, and analyzing the dynamics of urban green space. It makes it possible to spatialize vegetation cover, identify priority areas for greening, and analyze the impact of urbanization on ecological health over time.

4.3.2. NDWI (Normalized Difference Water Index)

The Normalized Difference Water Index (NDWI) is one of the most important spectral indices that are used to assess water content in vegetation and also to delineate surface water bodies such as reservoirs, rivers, or ponds. It is calculated from the difference between near-infrared (NIR) and short-wave infrared (SWIR) satellite image bands, Sentinel-2 data in this case, utilizing the high absorption of SWIR by water and high reflectance of NIR by vegetation. This contrast allows NDWI to measure very well the water content in vegetation or surface water bodies.

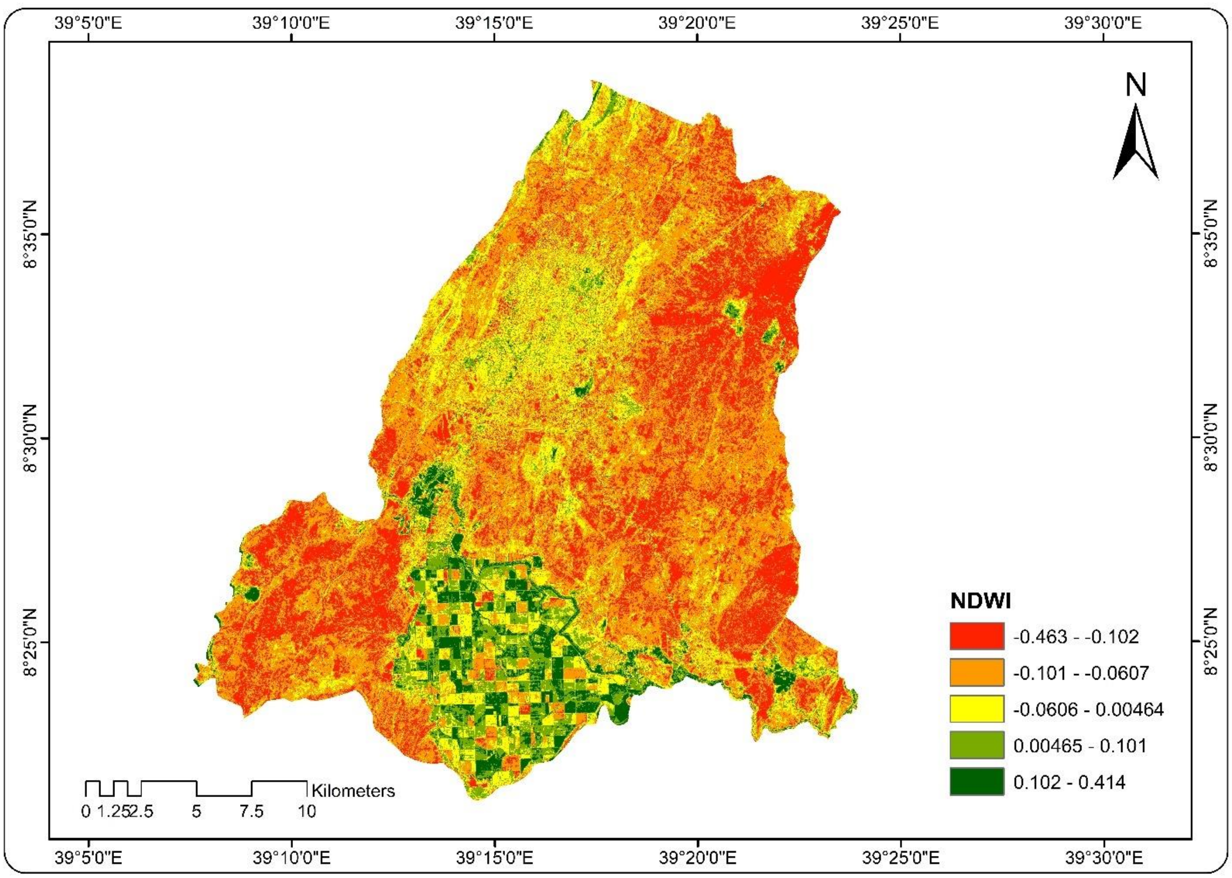

Figure 4-3: NDWI

For Adama City, NDWI plays a key role in urban and peri-urban green space water dynamics analysis. NDWI is particularly valuable for monitoring the fields' moisture content, which is a big portion of land utilization in the city. The NDWI higher values usually symbolize adequately irrigated fields or places with a considerable amount of soil and canopy wetness, indicative of lush and productive plants or crops. These values often correspond to areas of good irrigation practice or those privileged by nature with water bodies. Low NDWI values, on the other hand, may signify moisture stress, poor irrigation, or drought-like conditions, which generally produce low plant vigor and productivity.

By mapping the spatial pattern of NDWI within the city, urban planners and agricultural stakeholders can identify the areas facing hydrological stress and prioritize them for special interventions such as improved irrigation facilities, water conservation, or sowing drought-tolerant varieties. NDWI therefore serves as a diagnostic tool that enables sustainable urban and agricultural water management, enhances the resilience of green spaces to climatic variation, and promotes efficient allocation of water resources in a rapidly urbanizing city like Adama.

4.3.3. SAVI (Soil-Adjusted Vegetation Index)

Soil-Adjusted Vegetation Index (SAVI) is a modification of NDVI that has been developed to minimize the influence of soil brightness in areas of sparse vegetation cover. Bare or open soil, especially bright dry soils common in arid and semi-arid areas, can create biased outputs in normal NDVI calculations, and it is difficult to ascertain the presence and health of vegetation accurately. SAVI overcomes this by incorporating a soil brightness correction factor into the equation for the index, which significantly enhances the validity of vegetation measurement for regions of low canopy cover.

The correction renders SAVI highly suitable for a semi-arid city like Adama, where high sunlight and low rainfall will make patches of bare or degraded land likely. In such a situation, the soil background visibility can interfere with the normal vegetation indices by creating an underestimate or misinterpretation of the vegetative status. SAVI avoids such a limitation by inhibiting the soil noise and thus giving a better indication of vegetation status even in regions where the plant growth is sparse or spotty.

At the urban level, SAVI is a useful tool to map areas where vegetation cannot grow or is declining as a result of unproductive soil, compaction, erosion, or other processes of land degradation. These can be recently constructed building plots, neglected parks, or bare and unused parcels of land. SAVI highlights these areas and enables targeted urban greening efforts, soil remediation campaigns, and land use management. Lastly, it’s worth is in guiding intervention in situations where vegetation is limited not by lack of space, but by inherent soil and environmental conditions.

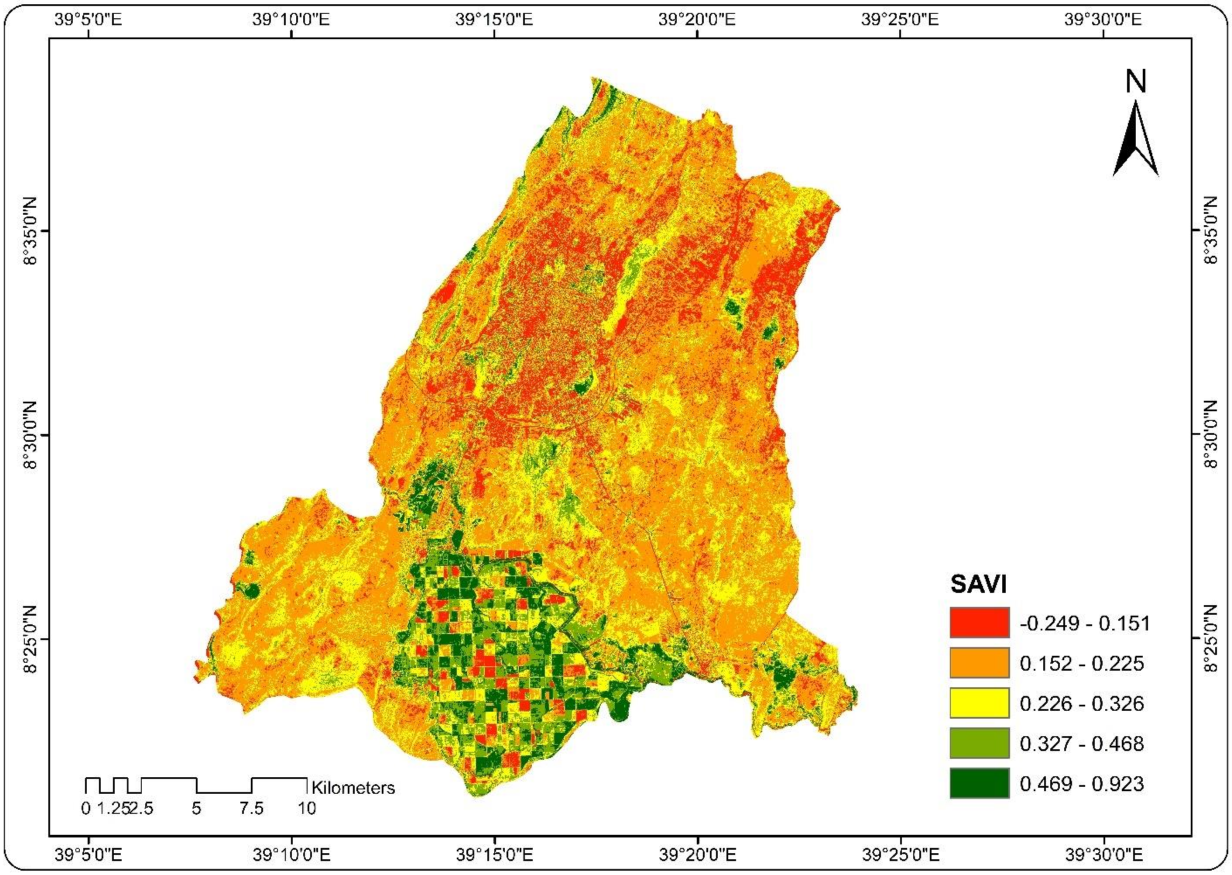

Figure 4-4:SAVI

4.3.4. GCI (Green Chlorophyll Index)

The Green Chlorophyll Index, or GCI, is a plant index that is used specifically to measure the quantity of chlorophyll in plant leaf tissue and thus is an extremely valuable tool to use in identifying the health, vitality, and photosynthetic ability of plants. Vegetation indices collectively give only a sense of the presence or quantity of the green cover, while GCI also gives an estimate of greenness vigor and is directly proportional to the physiological well-being of the vegetation. This is particularly beneficial where there can be some vegetation but not necessarily living due to pollution, soil erosion, water stress, or abandonment.

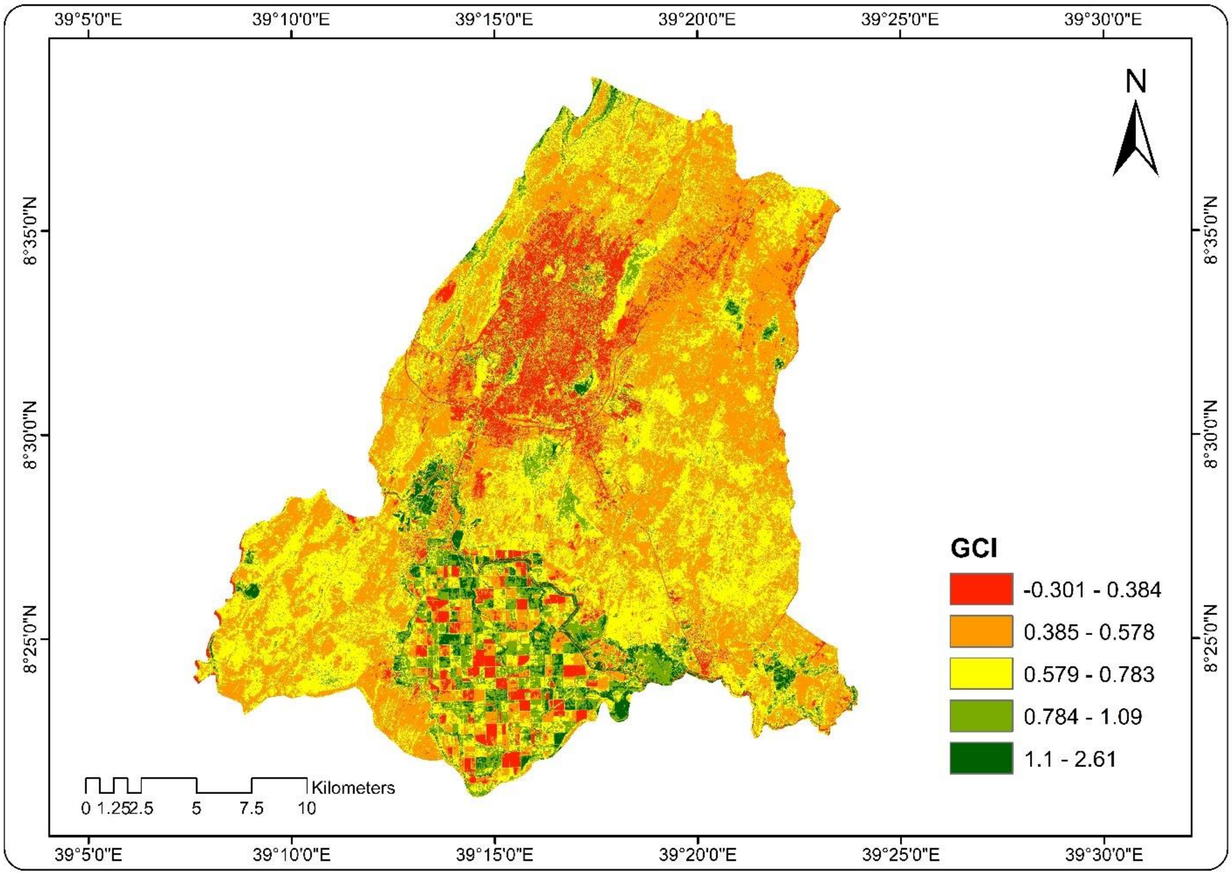

Figure 4-5: GCI

For Adama City, GCI is important to distinguish between current and increasing and photosynthetically active vegetation. Dense and high chlorophyll concentration vegetation is represented by high GCI; green and healthy vegetation usually linked with irrigated agriculture crops, landscaped urban parks, or urban parks. Such greens not only enhance urban looks but also offer important ecosystem services like carbon sequestration, air purification, and urban cooling.

Conversely, low values of GCI can be an indicator of stressed or deteriorating vegetation such as drought irrigated ornamental landscape, senescing city street trees, or neglected ornamental plantings. Therefore, variation in measurements of GCI offers invaluable information regarding the quality of the urban green space; not merely their size or quantity. To urban planners, landscape managers, and environmental decision-makers in Adama, GCI is offering a science-based method to evaluate the performance of greening programs, placing highest priority ecological restoration areas, and keeping urban vegetation rich and biologically productive.

4.3.5. Urban green space quantification at the urban zone

As a means of providing a more location-based and accurate definition of Urban Green Space (UGS) distribution, the study is carried out on the urban core of Adama City, which is segregated into four structural zones according to the master plan of the city. With the application of the zonal method, study can carry out localized land use analyses and present information regarding how spaces of various forms: green space, built-up space, and agricultural space—are distributed in the most developed sector of the city.

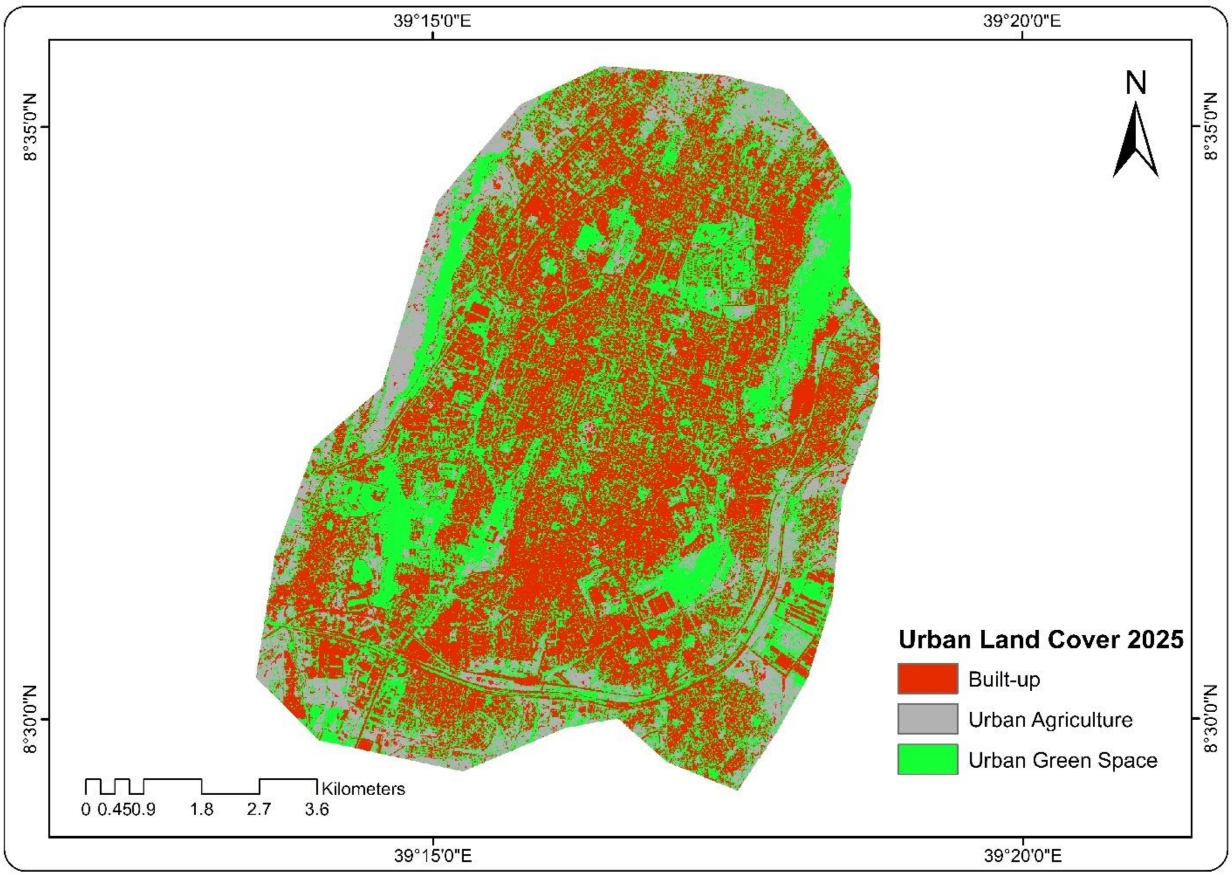

Figure 4-6: Urban zone land cover in the year of 2025

City greens in the central city, as indicated in Table 4-2, are 2,840.94 hectares and account for 36.52% of the total area. While it is a secondary area by size to the developed land, which occupies the majority of the 3,790.65 hectares or 48.72%, it is nevertheless an enormous portion of the city landscape. Urban agriculture occupies the other 1,148.41 hectares and represents 14.76% of the ground cover. These figures all show a urbane urban scene of intensive development with vast green coverage.

The balance of over one-third green cover to central positions is crucial, especially in an urban environment where pressure to build limits open area availability. The implication that the percentage in question carries the conscious addition of green infrastructure within the areas of high density is pivotal towards maintaining ecological balance, urban resilience, and overall city dwellers' quality of life. Urban agriculture's resilience in the inner city, embraced in activities such as home garden farming, back-yard farming or mini-garden lots, is also proof that food production is culture and adaptation against food security issues in the area. It reiterates the multivalence of green space not only as public space for recreational or beautification purposes but as productive space in the fabric of the urban landscape.

Table 4-2: Area and percentage share of UGS in Urban Zones

SN	Class	Area	Percentage
1	Urban Green Space	2840.94	36.52
2	Built-up	3790.65	48.72
3	Urban Agriculture	1148.41	14.76

These impacts align with green infrastructure policy planning initiatives that aim to facilitate a symbiotic relationship between built infrastructure and ecologically functioning green space. Consuming green space, promoting its equitable allocation, and preserving urban agriculture patches can enhance environmental quality, mitigate urban heat effects, and promote the social and economic well-being of urban residents. As Adama expands, these outcomes can guide future urban policy in the sense of attempting to sustain this fragile balance.

4.4.Distribution of UGS in different zone of the city

Adama City's green area allocation across the four urban development zones is very even, suggesting the effort of equal urban development. From Table 4-3, Zone 3 has the greatest proportion of green area at 773.77 hectares (27.63%), followed by Zone 4 at 735.84 hectares (26.27%) and Zone 1 at 734.25 hectares (26.22%). Zone 2 with the smallest green space area of 556.70 hectares, however, accounts for a substantial 19.88% of the total. This fairly uniform distribution; with none considerably ahead or behind the others in contributing green spaces; shows a high level of spatial equity in the distribution of city greens.

Table 4-3: Zonal distribution of UGS in the city

Zone	AREA	Percetage
Zone 1	734.25	26.22
Zone 2	556.70	19.88
Zone 3	773.77	27.63
Zone 4	735.84	26.27
Total	2800.56	100.00

This even distribution is proof of a thoughtful and deliberate process of urban planning that more than likely weighed the importance of environmental equity. The provision of all zones, both economic and population based, with access to parks shows dedication to environmental justice. Green spaces have a benefit beyond visual beauty; they are crucial to the enhancement of urban microclimates through air purification, stormwater management, temperature reduction, and habitat provision for biodiversity. Besides, access to green spaces, street trees, and natural amenities has an unequivocal effect on physical and mental health, active living promotion, as well as social cohesion in society.

The limited extent of coverage of Zone 2 might be a target for intervention or projects of green infrastructure with the aim to introduce it to compensate for when the city is on the growth path. The disposition here is that there is a low level of forwardness and sensitivity in planning for the aim of developing conditions favorable to sustainable development of the city. The ecologically resilient method of delivering UGS simultaneously creates ecological resilience and extends all; wherever they may reside; are capable of accessing the social, health, and environmental advantages of green space.

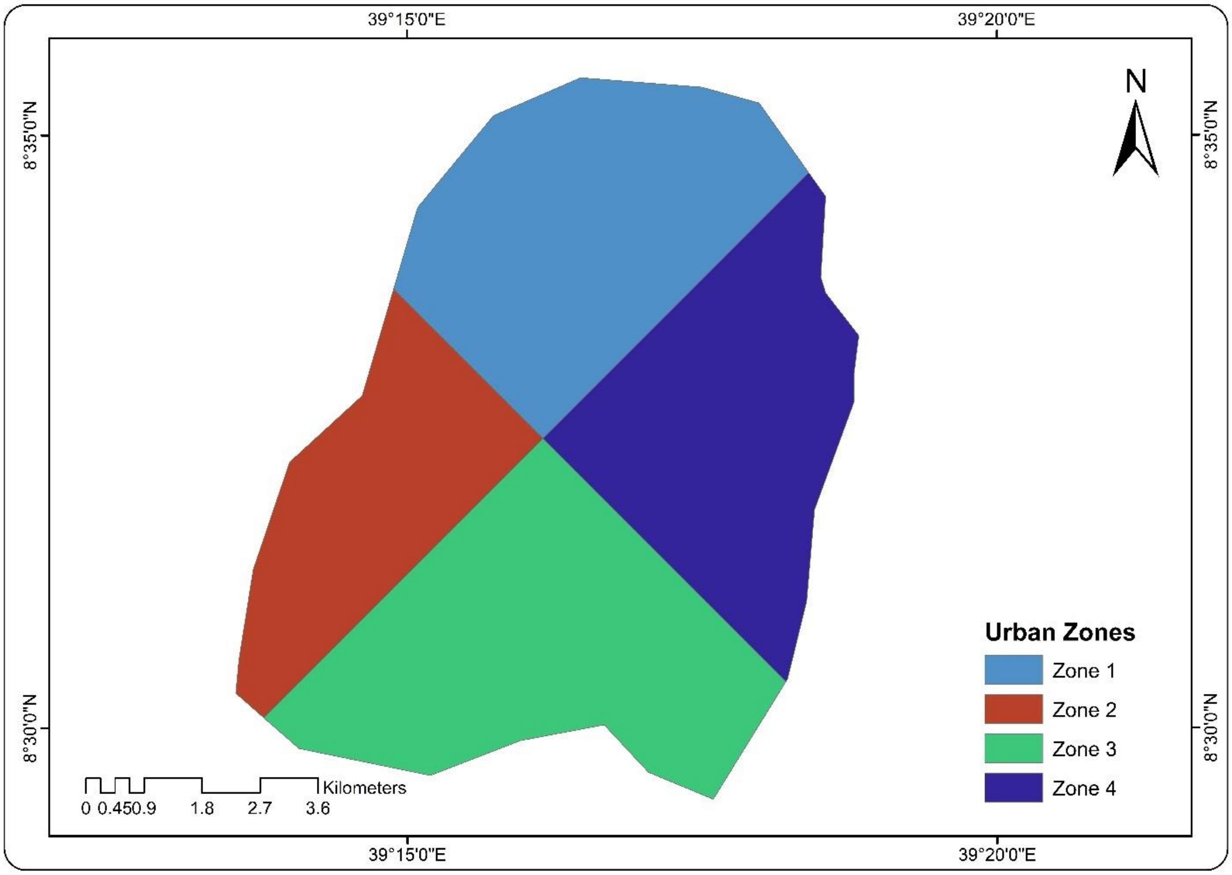

Figure 4-7: Classified urban Zones for the distribution of UGS in the entire city

4.5.Spectral indices at the urban zones

4.5.1. GCI (Green Chlorophyll Index)

In terms of urban area, the Green Chlorophyll Index (GCI) provides critical information about vegetation vigor, health, and photosynthetic vegetation productivity for parts of the city. GCI is a state-of-the-art diagnostic capable of doing more than providing proof of vegetation; its physiological state is characterized by estimating the quantity of chlorophyll in leaves of vegetation. Therefore, GCI allows for better comprehension of the efficacy of green spaces in the attainment of ecological and aesthetic benefits.

Areas with high GCI scores can be understood to have vegetation not only present but thriving. They could be irrigated home gardens, city parks well-maintained, greenways, or productive urban plots for farming. These high-performing greens are urban ecosystem values; regulating urban temperatures, sequestering carbon dioxide, filtering pollutants, and increasing biodiversity. From a planning perspective, such places are superb examples of urban greening that are preserved by policy or otherwise replicated within other parts of the city. They also provide enormous recreational and mental health advantages to their inhabitants, for overall livability in the city.

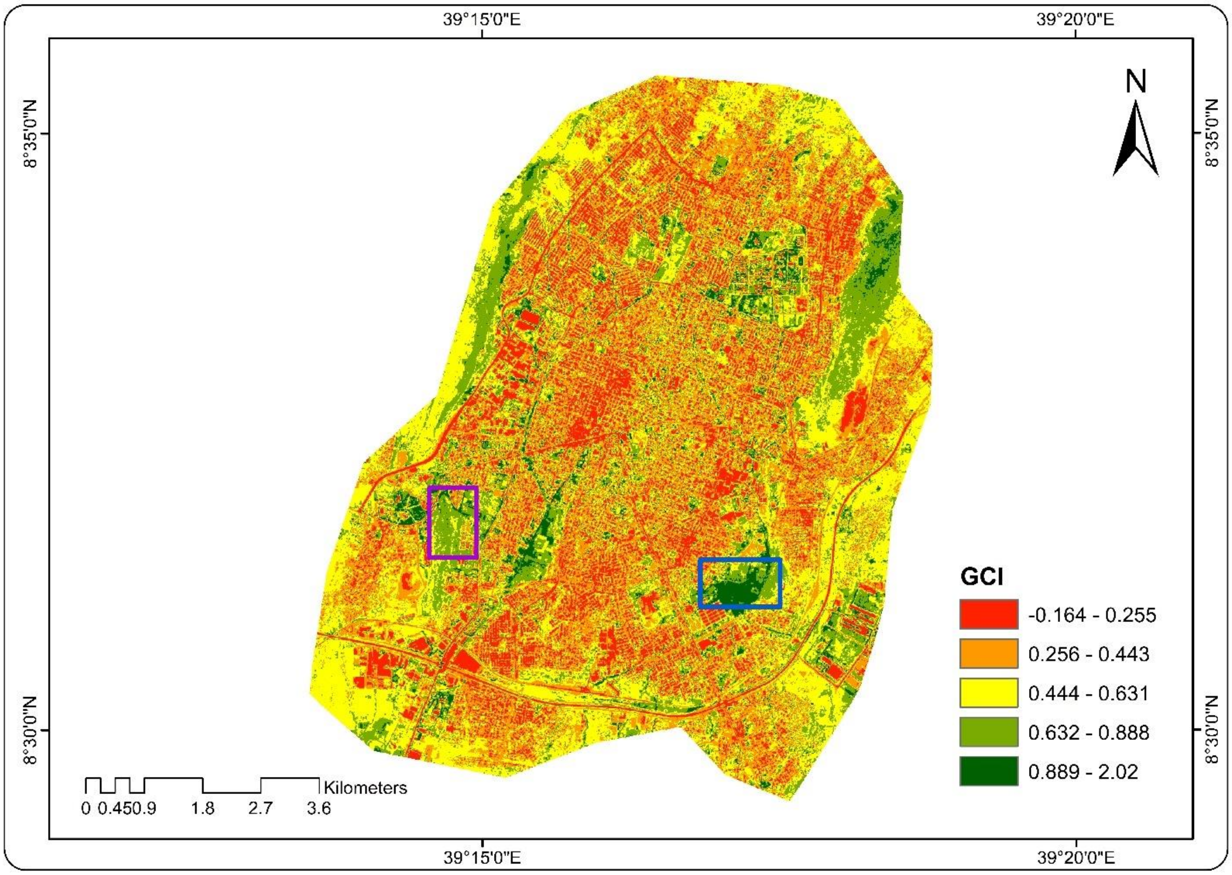

Figure 4-8: Urban Zone GCI

Conversely, areas with relatively low values of GCI can be under stress or deteriorated by, for example, water shortage, soil problems, pollution, or abandonment. Here, the GCI serves as an early alert to inform decision-makers where green infrastructure is compromised and where measures, such as improved irrigation, replanting, or replenishment of the soil, can be implemented.

Lastly, GCI allows the quality of vegetation to be analyzed zone by zone, encouraging targeted interventions making the urban vegetation well distributed as well as biologically effective and sustainable. Therefore, it's a handy planning tool toward a greener, healthier, and more resilient urban environment.

4.5.2. NDVI (Normalized Difference Vegetation Index)

Zone-level NDVI analysis is finer and more detailed in its estimation of vegetation health and cover in the different zones of Adama City's urban core. NDVI is expressly stated to capture differences in green cover and, by extension, varying vegetation status among zones that are otherwise unreported in city-level research. Zone-by-zone NDVI analysis enables environmental managers and city planners to identify healthy, resilient vegetation and areas of stress, degradation, or green space deficiency.

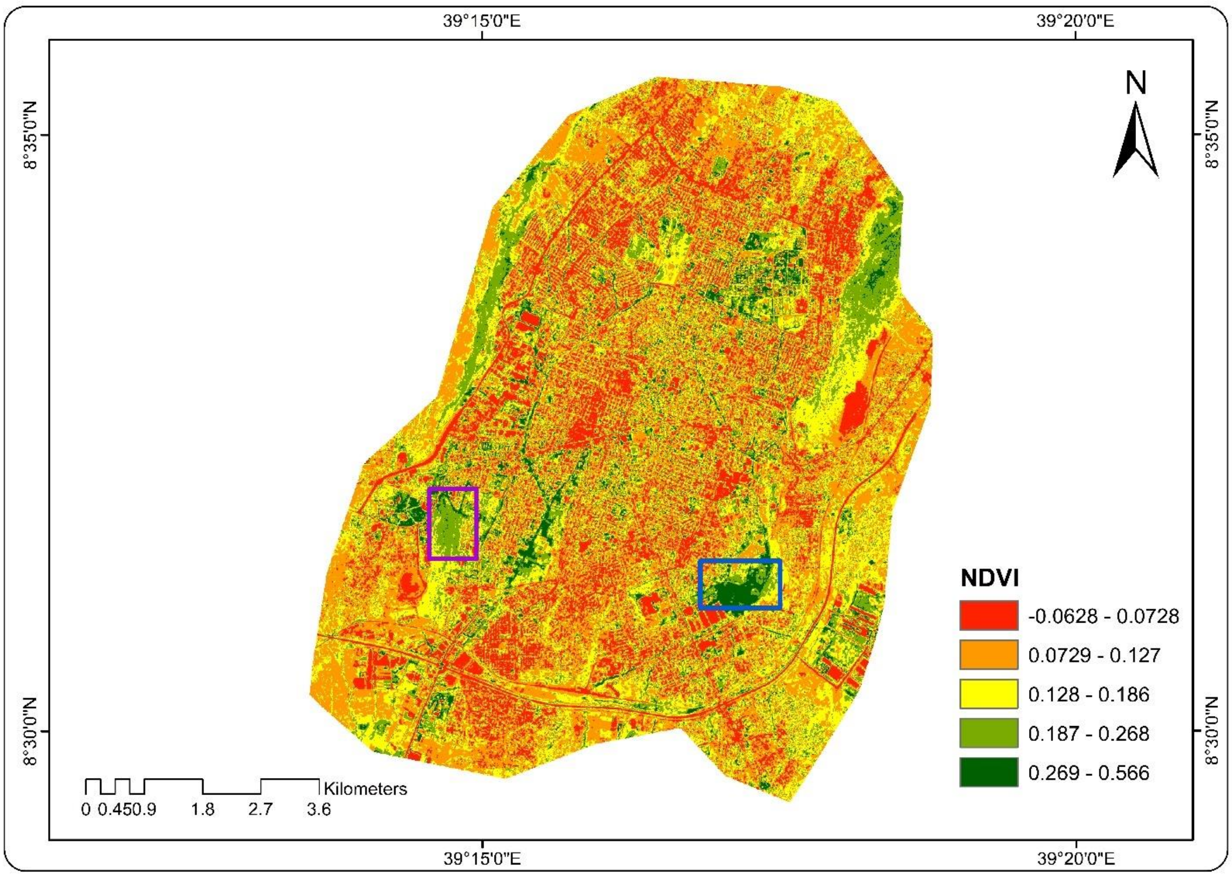

Figure 4-9: NDVI at urban zone scale

High NDVI areas likely contain dense, healthy vegetation: e.g., mature forest cover, well-planned parks, or productive urban agriculture; showing good land use planning and potentially higher ecological resilience. Such areas are ideal examples and models of good green space planning and are sustainable. On the contrary, not optimally optimized NDVI regions can be utilized for detecting thin, ill, or dead plants due to the effects of many factors such as soil erosion, improper irrigation, pollution, or excessive development with inferior inclusion of greens.

Real-world strategic planning can be useful for zonal analysis through the application of NDVI. It can help city planners and cities to see where intervention like additional tree planting, park building, reforestation measures, or additional landscaping is necessary most. NDVI is also a long-term observation index and can be utilized for determining the effect of such intervention. By repeated NDVI monitoring over a temporal interval, improvements in vegetation cover and health can be quantified, climatic or season effects can be monitored, and evidence-based improvement interventions to green can be achieved in urban greening interventions.

4.5.3. SAVI (Soil-Adjusted Vegetation Index)

Soil-Adjusted Vegetation Index (SAVI) is a very effective vegetation monitoring tool in urban environments, whose landscape is typically made up of a mixture of urban development, scattered vegetation, and extensive patches of exposed soil. Although traditional vegetation indices are affected by the reflectance of bare soil, SAVI includes a soil brightness correction factor, thus making it more accurate and effective in semi-arid or heterogeneous urban environments like Adama City.

At the urban zone level, SAVI works better in discrimination between actually vegetated land cover and places where scattered vegetation is mingled with soil, construction material, or degraded land. In development-prone or fragmented green area zones, this matters especially because mean indices such as NDVI might record spuriously low values from interference by reflectance from soils. By minimizing the effect of soil background, SAVI provides a clearer picture of actual vegetation presence and condition, even in marginal or transitional urban areas.

Urban planners and environmental managers can utilize SAVI as an effective tool to determine where vegetation is stressed by ongoing development, erosion, or poor soils. Places with persistent low SAVI readings might represent areas in which green areas are declining, plant cover is not establishing itself, or exposed land is coming under the invasiveness of development. All these helps develop more responsive city planning, i.e., upgrading poor areas in order of preference to restore the soil, or carry out planting projects or defense zones.

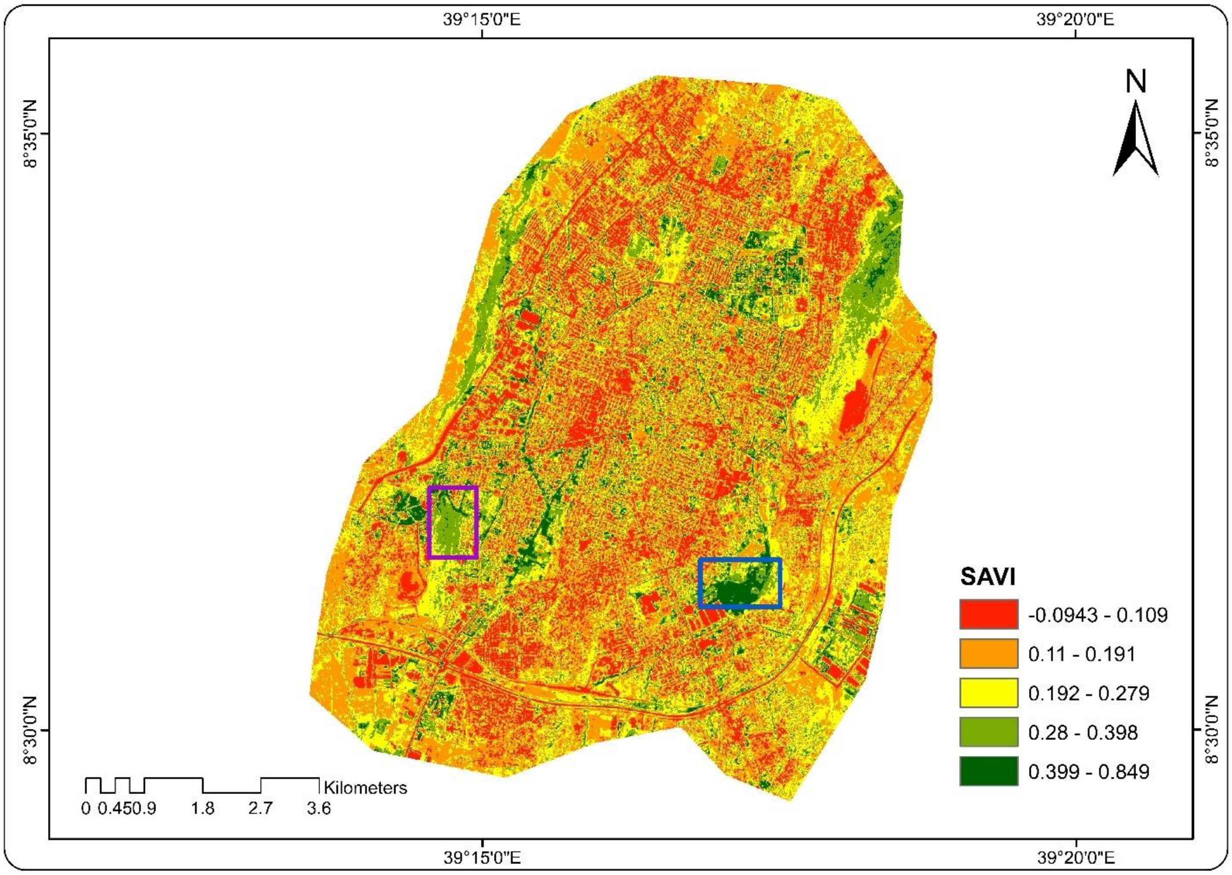

Figure 4-10: SAVI at the urban zone scale

Apart from that, SAVI fortifies the resiliency of green space value to errors initiated by confused land covers, pervasive in growing metropolises. It allows baseline mapping of the green infrastructure in more accurate conditions and enhanced observing of change a long time, mainly in regions wherein vegetation is diluted but still eco- and social-important.

Subsequently, SAVI improves on capacity to survey and preserve vegetation within cities with an onslaught of urban development so ecological function as well as open-space access aren't lost along the way in terms of city development.

4.5.4. NDWI (Normalized Difference Water Index)

Urban extent scale Normalized Difference Water Index (NDWI) is a useful analysis tool which can be employed in the estimation of spatial variability of moisture availability in vegetation, such as green cover and urban agriculture. NDWI makes use of differential shortwave infrared and near-infrared band reflection from Sentinel-2 satellite data to estimate plant canopy water content. Within the Adama City, NDWI provides localized information on to what extent the green zones of a zone are supported by adequate amounts of moisture; by rain, irrigation system, or aquifer supply.

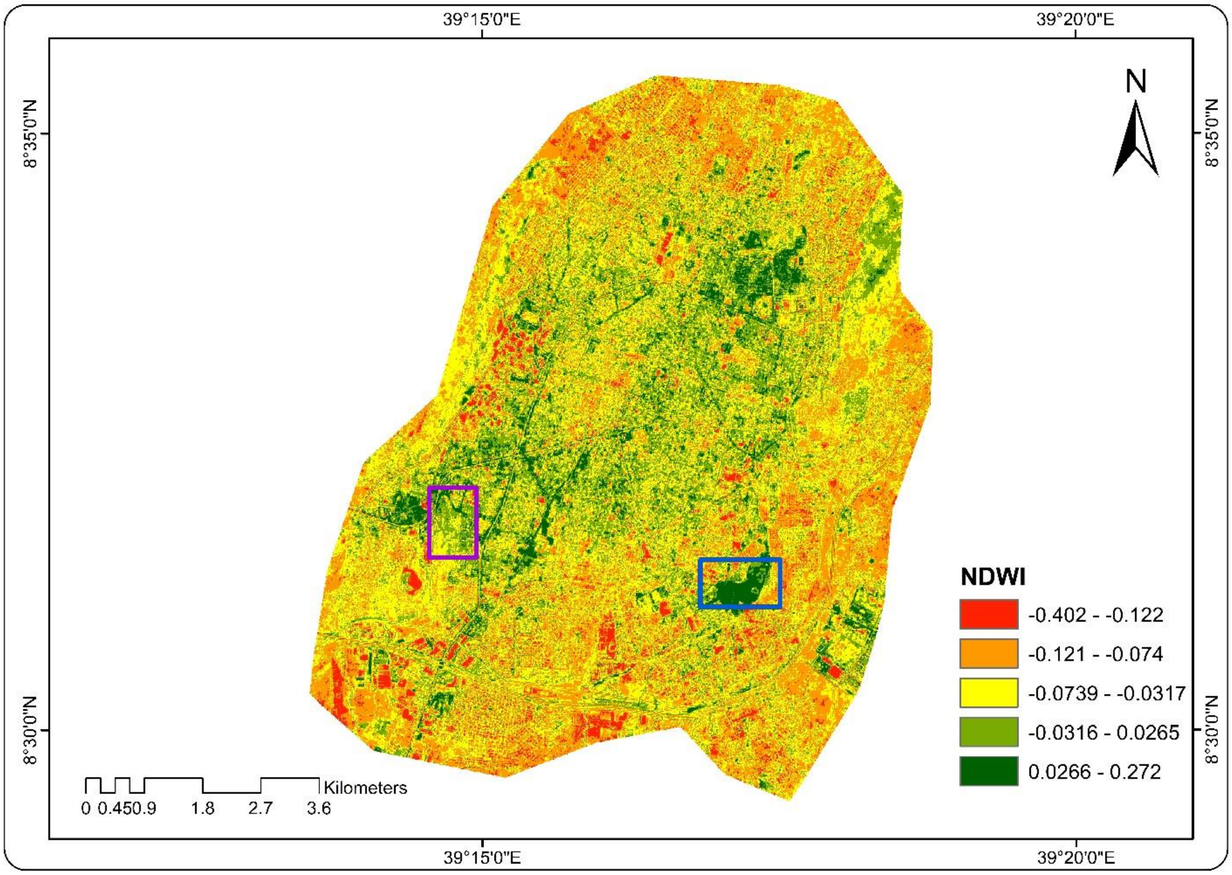

Figure 4-11: NDWI at urban zone

In each city zone, NDWI enables the identification, by researchers and planners, of the zones that are adequately irrigated and which suffer from water stress. High NDWI values are typically indicative of healthy vegetation and sufficient water content, which would typically manifest as well-manicured parks, irrigated urban agriculture plots, or water-sufficient natural environments. These lots are typically heat-tolerant and would likely contribute to ecological stability and human comfort through evapotranspiration and cooling.

Low NDWI values, on the other hand, show potential issues such as inadequate irrigation, water-stressed soils, or early signs of drought stress. This would be particularly significant in semi-arid areas such as Adama, where lack of water would easily compromise the health of plants. Locations with consistently low NDWI values could be fighting to accommodate urban agriculture, tree cover, or other forms of green infrastructure.

At the strategic policy and planning-level, NDWI spatial data can guide the creation and execution of specific water management measures. These may be investing in irrigation infrastructure upgrades, new drought-tolerant crop planting varieties, or rainwater harvesting and storage systems. In semi-arid and arid areas, these actions are crucial for supporting urban green covers, supplying populations through agriculture in urban areas, and mitigating impacts of urban heat islands.

In brief, zone-level NDWI analysis allows for better, wiser, and more reactive urban planning through the assurance that water resources are allocated and administered in a way that fosters healthy and dynamic green spaces within each nook and cranny of the city.

4.6.Accuracy assessment

The accuracy assessment presented in Table 4.4 evaluates the performance of the urban land cover classification conducted for Adama City, focusing on five land cover categories: Built-up, Shrubland, Grassland, Urban-agriculture, and Urban vegetation. The classification's overall accuracy (OA) is 81%, meaning that 81% of the reference (ground truth) data was correctly classified. This is considered a good level of accuracy for urban land cover classification, especially in heterogeneous urban environments like Adama, where class boundaries are often mixed or gradual.

The producer's accuracy (PA) and user's accuracy (UA) for each land cover class provide deeper insight into classification performance. Producer's accuracy reflects how well real-world land cover types were classified, indicating omission errors (i.e., how much of the class was missed). The PA values range from 73.53% for Shrubland to 87.5% for Grassland, suggesting that most classes were reliably detected, though Shrubland had a relatively higher omission rate.

User's accuracy, on the other hand, measures the reliability of the classification from the user's perspective by indicating commission errors (i.e., how much of the classified class actually belongs to it). The UA ranges from 73.33% for Urban-agriculture to 87.5% for Urban vegetation. High UA for Urban vegetation and Grassland suggests strong classification precision, whereas lower UA for Urban-agriculture indicates a higher rate of misclassification, likely due to its spectral similarity with other vegetative classes and built-up areas.

The Kappa coefficient of 0.76 further supports the robustness of the classification. This statistic accounts for agreement occurring by chance and values between 0.6 and 0.8 are considered substantial. A Kappa of 0.76 suggests a substantial agreement between the classified map and reference data, reinforcing the validity of the classification results.

Table 4-4: Accuracy assessment for urban landcover classification at the Adama city scale

	Built-up	Shrubland	Grassland	Urban-agriculture	Urban vegetation	Total	PA
Built-up	25	2	1	2	0	30	83.33
Shrubland	3	25	2	3	1	34	73.53
Grassland	2	1	28	1	0	32	87.50
Urban-agriculture	1	0	3	22	2	28	78.57
Urban vegetation	0	2	1	2	21	26	80.77
Total	31	30	35	30	24	150	
UA	80.65	83.33	80.00	73.33	87.50		
OA	0.81						
Kappa	0.76						

4.7.The relationship between UGS and LST

4.7.1. LST of the Urban Zone

The spatial distribution of Land Surface Temperature (LST) in Adama City, as shown in Figure 4-12, reveals distinct thermal variations across the urban landscape. The LST values range from 30.4°C to 32.2°C, with cooler areas depicted in dark green and warmer areas in red. The central and northeastern parts of the city exhibit relatively lower temperatures (30.4°C–31.2°C), likely corresponding to areas with higher vegetation density or open green spaces. In contrast, the southern, southeastern, and peripheral zones display higher LST values (31.7°C–32.2°C), indicating regions dominated by built-up surfaces or sparse vegetation cover. The map shows a gradient pattern, where LST increases outward from green cores, suggesting a possible urban heat island effect caused by dense infrastructure and reduced green coverage in certain parts of the city.

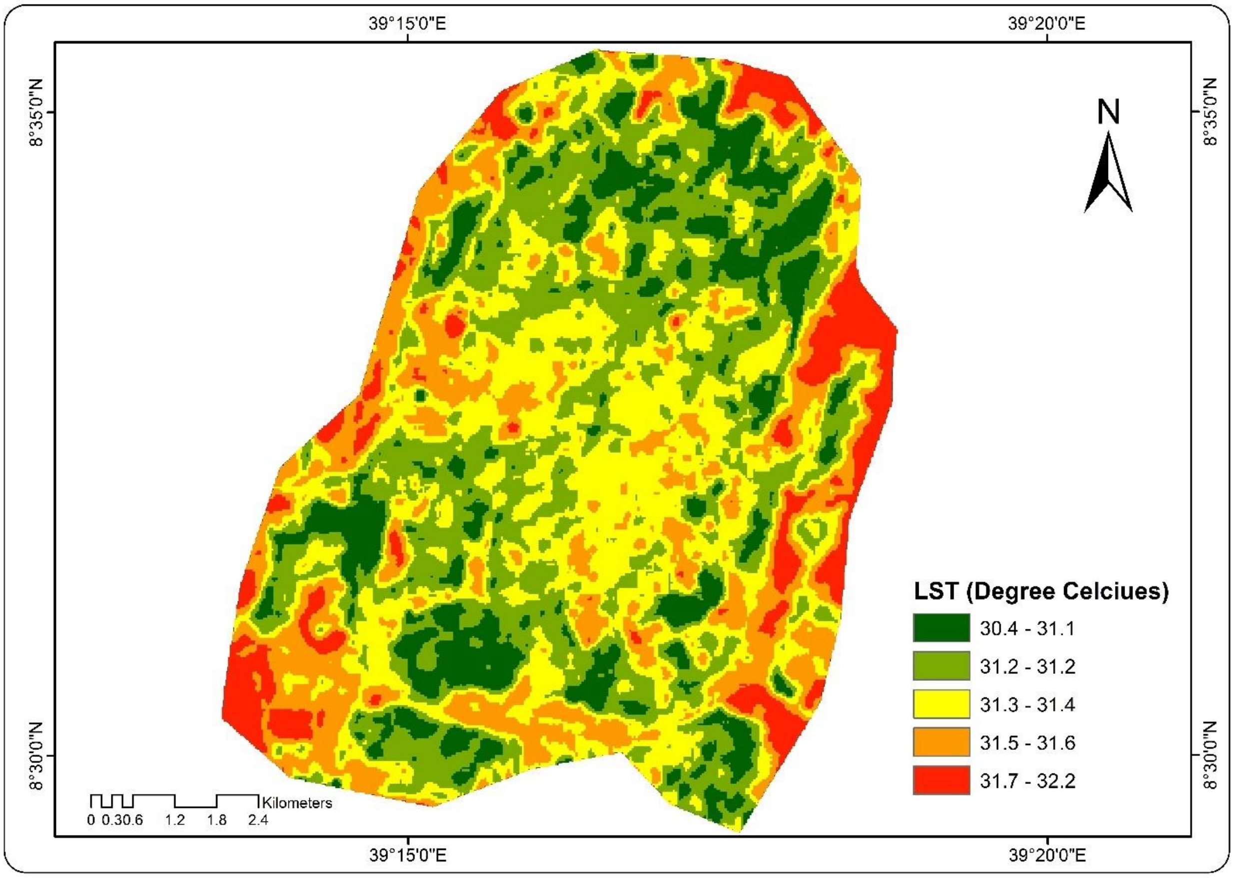

Figure 4-12: LST of Adama City

4.7.2. Comparison of LST and UGS

The comparison between Land Surface Temperature (LST) and Urban Green Spaces (UGS), as illustrated in the figure, clearly demonstrates an inverse relationship between vegetation cover and surface temperature in Adama City. Panel (a) shows the spatial distribution of LST, ranging from 30.42°C to 32.23°C, while panel (b) presents the NDVI map, with values from -0.06 to 0.56, representing vegetation density.

The blue-highlighted region across the panels marks a prominent green space within the city. In this region, NDVI values are relatively high (0.3–0.56), indicating dense vegetation, which corresponds to lower LST values (around 30.4°C–30.8°C) in the same area. Conversely, areas with sparse or no vegetation—reflected by low NDVI values (< 0.1)—exhibit higher LST values (>31.5°C), especially toward the southern and peripheral built-up zones.

Panels (c) and (d) further support this observation by zooming in on the highlighted UGS. Panel (c) (NDVI zoom-in) shows concentrated green coverage, while panel (d) (LST zoom-in) shows noticeably cooler temperatures in the same location. This indicates that UGS significantly contribute to urban cooling, mitigating the urban heat island effect by reducing surface temperatures through evapotranspiration and shade.

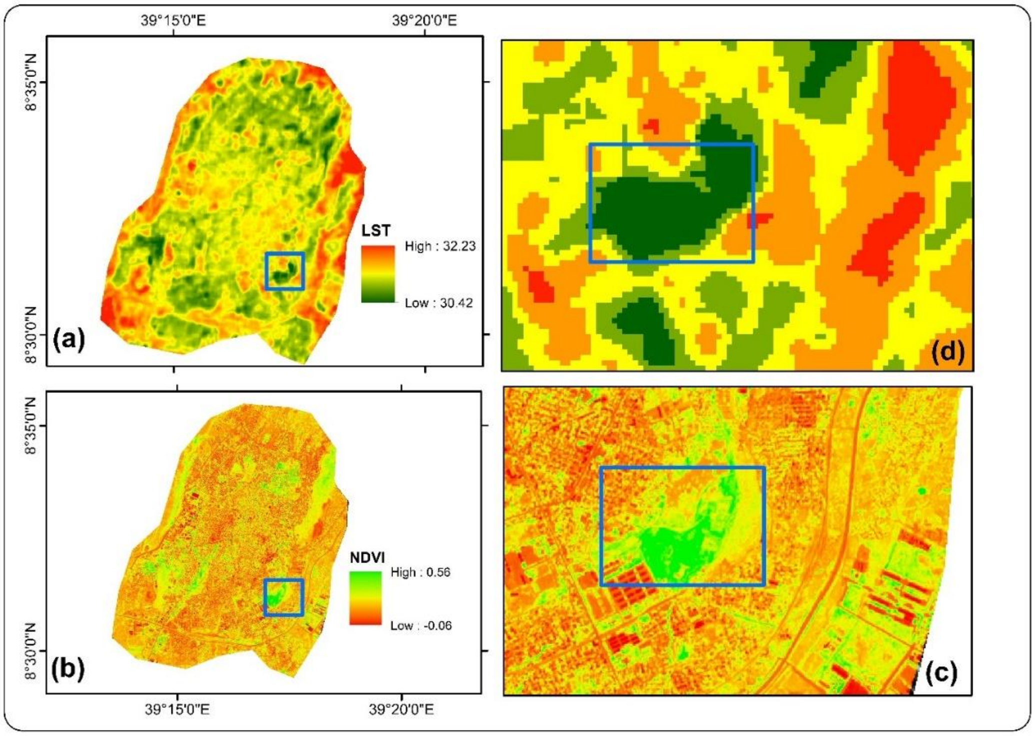

Figure 4-13: Pixel based comparison between LST and NDVI; (c) NDVI at pixel level; (d) LST at pixel level

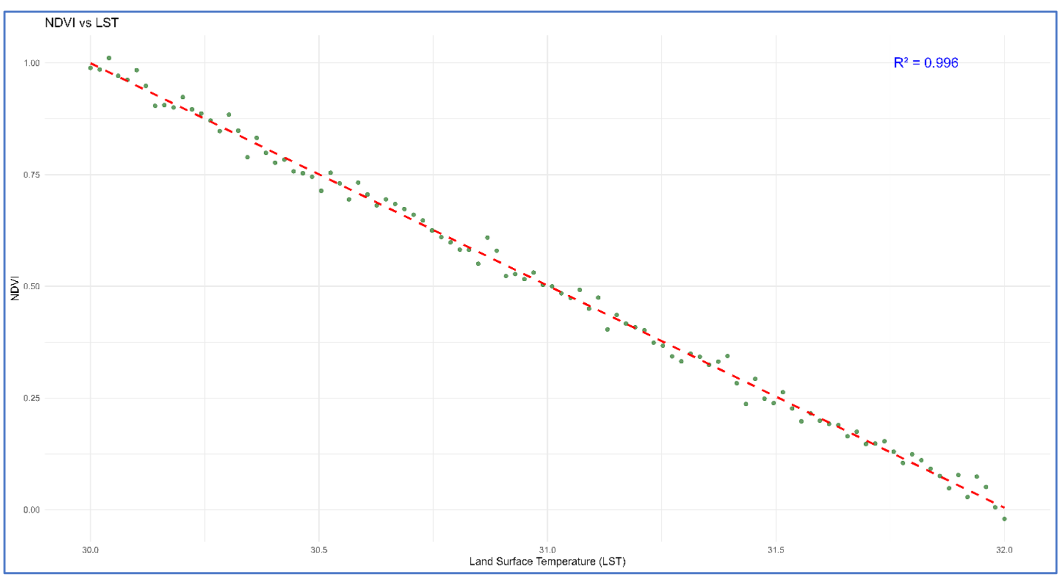

Figure 4-14: The relationship between LST and NDVI

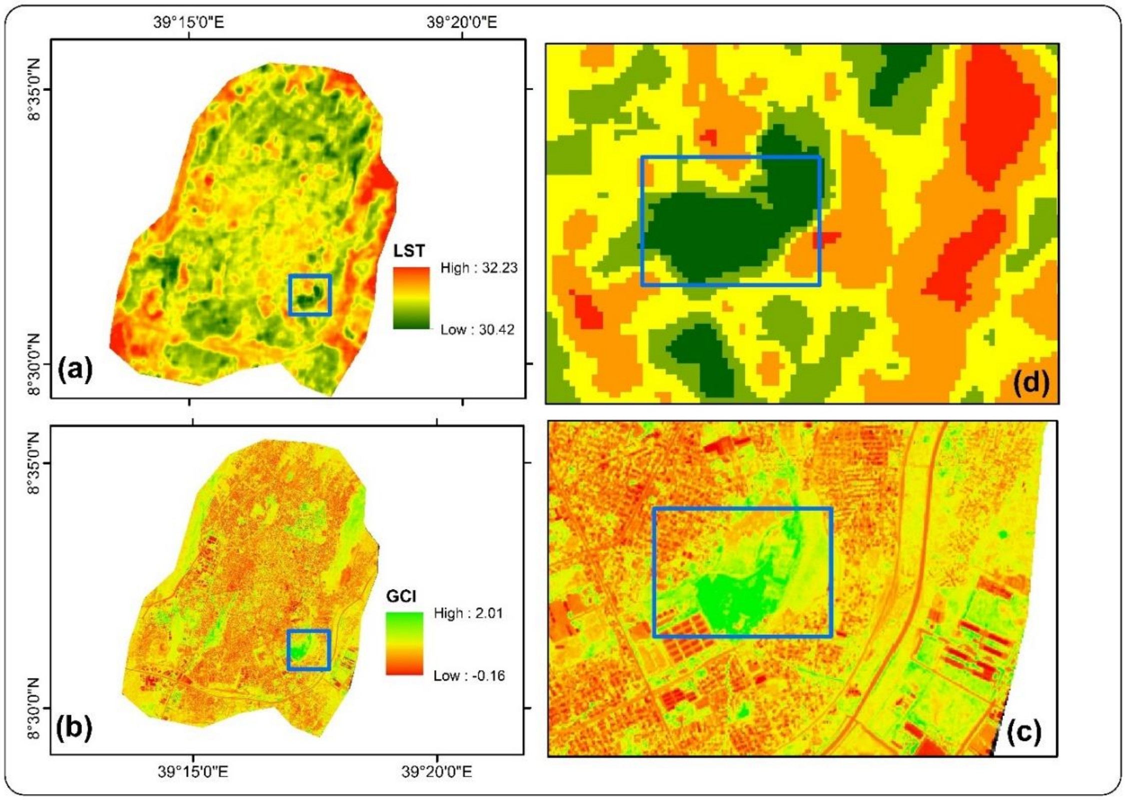

Figure 4-15: Pixel based comparison between LST and GCI; (c) GCI at pixel level; (d) LST at pixel level

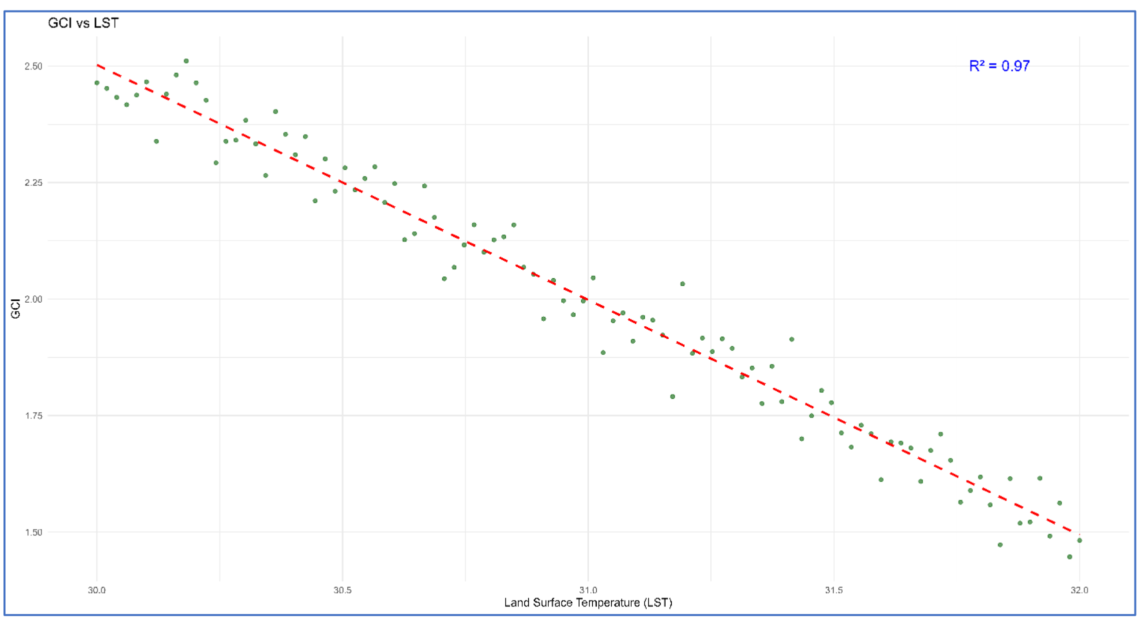

Figure 4-16: The relationship between LST and GCI

4.8.Discussion

The findings of this research on UGS measurement and spatial analysis in Adama City are typical of the overall world trends and also consistent with new scientific publications on sustainable city planning, green infrastructure, and environmental justice. The emphasis of the research on the UGS spatial pattern, use of spectral indices (GCI, NDVI, SAVI, NDWI), and urban agriculture is a collaborative approach to viewing urban ecology and land use planning.

The study finds a relatively balanced distribution of green space across the four city areas, reflecting environmental justice planning and nature accessibility. This concurs with spatial equity literature on urban green infrastructure. According to Kabisch & Haase (2014), equitable distribution of UGS ensures social inclusion, reduces environmental disparities, and grants all urban residents access to ecosystem services. Secondly, Wolch, Byrne, and Newell (2014) promote "just green enough" planning whereby green spaces and parks are made accessible to marginalised groups, and this seems to be reflected in the Adama City study.

The findings also highlight not only the leisure but also productive use of urban green spaces (e.g., urban agriculture), which is in line with the theorization by authors like McClintock (2010) who advance the socio-economic and cultural value of urban agriculture. Urban agriculture ensures food security, livelihood, and resilience overarching themes replicated in the case study of Adama. Application of spectral indices NDVI, SAVI, GCI, and NDWI in this study to estimate vegetation health and water content follows remote sensing literature. SAVI was proposed by Huete (1988) to remove soil background noise, which is extremely useful for semi-arid urban environment cities like Adama. Similarly, NDVI has been in use in urban ecology for long to estimate green cover (Weier & Herring, 2000). The use of GCI and NDWI indicates that there is a developing trend in the literature to use more advanced indices in plant health and water stress diagnosis related to green infrastructure in the urban setting (Gao, 1996; Jensen, 2007).

The study reinforces the extensive list of benefits of green space air purification, temperature regulation, stormwater management, and ecosystem upkeep. These results are further well-supported by researchers like Tzoulas et al. (2007), who seek to incorporate the role of urban green networks in the provision of ecosystem services and promotion of public health. Furthermore, the connection of UGS to the control of the microclimate is well-supported, especially in reducing the urban heat island effect, as evident from Gill et al. (2007). Due to this, such kinds of relationships are generalizable to climate-stressed and rapidly growing cities like Adama as well. The complementary relationship of Land Surface Temperature (LST) and Urban Green Spaces (UGS) in Adama City, as found in this study, is also consistent with what is established in urban climate literature.

The research strongly suggests that high-density vegetated surfaces in terms of indicators like NDVI and GCI are characterized by low LST values, while urban or low-vegetation cover surfaces exhibit high surface temperatures. The negative correlation offers a firm basis for the very well-documented fact that UGS is extremely effective at reducing the urban heat island (UHI) effect. Most of the studies indicated the same trend; that is, for example, Zhou et al. (2011) and Shashua-Bar and Hoffman (2000) both witnessed that urban parks and forested areas can reduce local temperature by a few degrees. In Adama, the cooler areas delineated in the central and northeast parts of the city coincide with areas of high NDVI and GCI values, once more pointing to the same mechanism. Moreover, the use of both the NDVI and the GCI in ascertaining the impact of vegetation on LST is methodologically beneficial to urban environmental science. NDVI is applied extensively in the determination of the density of vegetation, whereas GCI represents the chlorophyll content, thereby providing a better measure of the plants' vigour and health.

Use of both these indices enables broader assessment of the impact of various vegetative characteristics on thermal conditions. This methodological variation conforms to research guidelines like Weng et al. (2004) and Li et al. (2011), which encourage the application of composite vegetation index to capture the entire spectrum of complexity of urban vegetation and its climatic benefit. The pixel-level analysis of the research, which is on specific green spaces to see temperature and vegetation indices at a finer scale, brings nuance to the results and confirms the causal link between the presence of green space and local cooling. The second handy thing about the study is that it starts to broach the discussion of the problem of spatial distribution and fairness in UGS. The findings show that Adama has improved somewhat in green space balance between its administrative zones, and Zone 2 lags behind both in coverage of UGS and condition of vegetation. Such a spatial issue is relevant in urban planning literature that foregrounds access to green space equity.

CHAPTER FIVE

5. CONCLUSION AND RECOMMENDATION

5.1. Conclusion

The city has a relatively even spread of green cover over the zones, with the highest percentage in Zone 3 and the lowest in Zone 2. Although there are differences, overall balance here points towards planned urban development with environmental justice. This decreased proportion of green cover in Zone 2 brings it to our attention as a priority zone where green infrastructure intervention needs to be made available to all citizens so that everyone enjoys an equitable share of access to health and environmental benefits. This research has predominantly investigated the interaction of Land Surface Temperature (LST) with Urban Green Spaces (UGS) in Adama City using spatial analysis techniques and vegetation indices such as the Normalized Difference Vegetation Index (NDVI) and the Green Chlorophyll Index (GCI). The findings identify a significant negative relationship between vegetation cover and surface temperature whose higher vegetation areas have lower LST values in all cases. This is an indication of the higher significance of UGS in mitigating the urban heat island (UHI) effect by shading and evapotranspiration and enhancing urban thermal comfort. LST spatial distribution in Adama City showed high thermal gradients with the minimum temperatures aggregated in places having high vegetation cover, which are found in the central and northeast part of the city. In contrast, peripheral and southern areas with high built-up and low green cover held surplus temperatures.

5.2. Recommendations

According to the findings of urban green space (UGS) quantification and Adama City's spatial-spectral analysis, the following recommendations are offered to enhance the planning, sustainability, and fair distribution of the city's green infrastructure:

- Green space development needs to be made institutionalized by enacting new policies requiring the integration of UGS in every new urban development and redevelopment plan. The policies must ensure a minimum percentage of the urban space to be allocated to parks, community gardens, and green corridors.
- Since Zone 2 is behind in green space coverage, there must be specialized green infrastructure programs including pocket parks, green roofs, and vertical gardens that are

launched to attain ecological balance in regards to accessibility. Investment must also go into the rejuvenation of accessible green spaces through the optimization of vegetation health and public amenities.

- Urban farming has emerged as a significant potential not only in green cover growth but also food security and mass mobilization in the regions. The encouragement of rooftop farming, backyard cultivation, and communalizing food crops in the use of public parks can optimize the effectiveness and utilization of UGS.

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