Assessment of Urbanization and its Impact on Agricultural Land a case of Motta town, Ethiopia

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Declaration

I declare that this thesis which I submitted to the school of Civil and Environmental Engineering of Addis Ababa University Institute of Technology in partial fulfilment of Degree of Masters of Science in Geodesy and Geomatics is my own work. The thesis has not been submitted previously to qualify for any academic award .I was cared for the academic rights of others in the processes of thesis work.

Muhammed Belale ______________________

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This thesis has been presented for evaluation with my endorsement as an academic mentor at the university.

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Abstract

Urbanization poses significant challenges to the sustainability of agricultural land, which plays a crucial role in food security and local economies in rapidly urbanizing areas. The study assesses the impact of urbanization on agricultural land in Motta town using Geographic Information System (GIS) and remote sensing techniques. Land use and land cover (LULC) changes from 1992 to 2023 were analysed using Landsat satellite images from the United States Geological Survey (USGS). Both Supervised and unsupervised classification methods of classification were used to classify four land use classes namely built-up area, vegetation, bare land, and agricultural land. The study compared classification algorithms including Support Vector Machine (SVM), Maximum Likelihood Classification (MLC), and unsupervised classification based on their results and accuracy. Additionally, urbanization indices such as New Built-up Index (NBI), Urbanization intensity Index (UII), and Normalized Difference Built-up Index (NDBI) were employed to assess urbanization dynamics. Results indicate a consistent trend of agricultural land loss and built-up area increase. SVM classification shows built-up areas increasing from 323 hectares in 1992 to 607 hectares in 2023, with agricultural land decreasing from 944 hectares to 510 hectares. MLC classification similarly reveals an increase in built-up areas from 534 hectares to 757 hectares and a decrease in agricultural land from 791 hectares to 352 hectares by 2023. Unsupervised classification identifies an increase in built-up areas from 510 hectares to 910 hectares and a decrease in agricultural land from 695 hectares to 346 hectares over the studied period. Accuracy assessments confirm SVM as the most accurate method. The study concludes that urban expansion significantly diminishes agricultural land in Motta town and suggests implementing sustainable land use policies and employing satellite remote sensing for effective monitoring of urban sprawl to mitigate further agricultural land loss

***Keywords*:** Urbanization, Agricultural land, Remote Sensing, Motta town.

Table of Contents

List of Table

List of Figure

List of Abbreviations

- SVM: Support Vector Machine
- MLC: Maximum Likelihood Classification
- UTM: Universal Transverse Mercator
- GIS: Geographic Information System
- USGS: United States Geological Survey
- GPS: Global Positioning System
- LULC: Land Use Land Cover Change
- ERDAS: Earth Resources Data Analysis System
- HA: Hectare
- FAO: Food and Agriculture Organization
- ETM+: Enhanced Thematic Mapper
- EIA: Environmental Impact Assessment
- NBI: New Built-Up Index
- NDBI: Normalized Difference Built-up Index
- UII: Urbanization Intensity Index

Chapter One

1 Introduction

1.1 Background of the Study

Ethiopia's rate of urbanization is among the highest in Africa. From 1960 to 1991, the annual rate of urban development was 4.8 percent; from 1991 to 2000, it increased to 5.8 percent. The annual growth rate from 2000 to 2010 was 5.5 percent, while in 2017 it was 4.73 percent. This rapid urbanization places Ethiopia among the twenty-three countries that are urbanizing the fastest. The primary causes of the increase in urbanization and town growth include rural-urban migration, the geographical annexation of urban areas, and the conversion of rural villages into small urban settlements (Redman & Jones, 2004; Cohen, 2006).

Rapid urbanization poses a serious threat to population growth in emerging country cities. One of the numerous challenges is urban expansion, an inevitable by-product of the urbanization process. Numerous cities and towns in Ethiopia have rapidly expanded horizontally, presenting challenges in regulation due to poor planning interventions, insufficient implementation skills, limited institutional capacity, and a lack of effective city and town governance (Angel, 2012; UN-Habitat, 2014).

Unplanned, rapid horizontal growth of cities and towns into agricultural settlements has led to social, economic, environmental, and political issues (Eyasu, 2007; Demel, 2011; Firew, 2010; Mulu, 2016; Debela, 2016). Due to urban growth, Motta Town is currently experiencing issues with natural resources and the environment. The primary concerns are the conversion of agricultural and forest land to various urban land uses, including residential, commercial, and other activities. The town's settlement layout has a more linear structure. Different types of vegetation, including agricultural areas, marshes, and grasslands, are being converted into urban land uses due to residential and various investment activities in many towns (Ziena, 2017; Tigezew, 2014). Additionally, deforestation has been occurring at an alarming rate, with 4,850 hectares of agricultural land converted to urban uses from 1998 to 2017.

To evaluate the impact of urbanization on agricultural land, Geographic Information System (GIS) and Remote Sensing (RS) techniques are employed in this study. GIS is used for mapping and analysing land use changes, while RS provides satellite imagery to monitor and detect changes over time. These technologies allow for precise, comprehensive analysis of spatial data, facilitating the identification of trends and patterns in urban expansion and its effects on agricultural land (Campbell & Wynne, 2011; Lillesand, Kiefer, & Chipman, 2015).

The methodology of this study involves collecting and analysing spatial data using GIS and RS, conducting field surveys to validate the satellite imagery, and employing statistical techniques to quantify the extent of land use changes (Jensen, 2015). This integrated approach provides a robust framework for understanding the pattern of urbanization and its effect on agricultural land in Motta Town.

1.2 Statement of the Problem

Urban sprawl is a characteristic of urban landscape dynamics and is described as the growth of a city onto undeveloped land near a more or less populated city, which then has an impact on farmers' livelihoods and adjacent agricultural land (Fekadu, 2015)) .It affects more of the farmers in per urban territories and agrarian economy like Ethiopia (G/Hiwot, 2006)

Urbanization has a detrimental effect on the town's periphery, particularly the agricultural land. The primary reason for the loss of agricultural land is the reclassification of rural regions as part of the municipality as an administrative entity, as a result of the strong demand for residential dwellings among the occupants. Redman & Jones (2004) claim that a lot of cities are rapidly expanding in their peripheral, engulfing previous agricultural regions and villages and turning them into industrial zones, shanty towns, or less dense suburban expansions. A decrease in output and a shift in the number of family farmers to the surrounding urban areas are the results of urban centres growing by encroaching on productive farmland and uprooting farmers. Urbanization is happening faster in Ethiopia than in a number of other African nations, and in the peri-urban regions, there is growing rivalry for land between agricultural and non-agriculture (Achamyeleh, 2014). According to a closely related research, in Ethiopia, urbanization causes settlements to spread outside and alters land usage, with the government, local governments, and federal agencies taking agricultural property for public use (Solomon et al, 2006). Changes in property rights and food security are directly responsible for this phenomenon. Landlessness and the loss of farmland and grazing land have an effect on farm livelihoods in peri-urban areas, and the conversion of agricultural land into residential areas has been increasing, leading to the change.

While several studies have investigated urbanization trends in various Ethiopian cities (Redman & Jones, 2004; Cohen, 2006; Henok, 2014), there is a notable gap in research concerning the rate and extent of urbanization in Motta Town and its implications for agricultural land. Currently, there is a lack of understanding regarding the specific impact on productive agricultural land due to urbanization in this specific locality. This research aims to fill this gap by examining and evaluating Motta Town’s urban growth and its influence on agricultural land.

1.3 Objective of the Study

1.3.1 General Objective

The general objective of this study was assessing urbanization and its impact on the agricultural land of Motta town by using GIS and Remote Sensing techniques.

1.3.2 Specific Objectives

- Comparison of LULC result by different classifier
- Quantifying spatio-temporal land use land cover change of Motta town from1992 to 2023
- To investigate trends and rates of urbanization and its impact on agricultural land

1.4 Research Questions

The research answered the following basic research questions

- How to map and quantify spatio temporal urban dynamics of Motta town
- What are the tends urban land scape dynamics and analyses its impact on pre urban agriculture using GIS and remote sensing

1.5 Scope of the Study

The study focused on the examination of urbanization in Motta Town, Ethiopia, and its impact on agricultural land. Urbanization trends over the past decade are analysed from 1992 to 2023, utilizing Geographic Information System (GIS) and Remote Sensing (RS) techniques for spatial analysis. The study assessed the conversion of agricultural land to urban uses within Motta Town boundary.

1.6 Limitation of the Study

As usual like many studies this study had its own limitation. The study was limited to evaluate urban land scape dynamics using remote sensing, GIS, and uses land sat imagery with a resolution of 30m for LULC classification due to inaccessibility and expensiveness other finest resolution satellite imagery's like Quick Bird this intern may leads to misclassification of features and to coup up with this problem field data gathering was required to verify the actual land use land cover change and this had taken time and energy.

1.7 Significance of the Study

Understanding the dynamics of urbanization in Motta Town and its impact on agricultural land holds significant implications for sustainable development in Ethiopia. As urban areas expand into agricultural regions, there are profound socio-economic and environmental consequences, including loss of fertile land, disruptions to local economies reliant on agriculture, and increased pressure on natural resources. By examining these dynamics using Geographic Information System (GIS) and Remote Sensing (RS) technologies, this study aims to provide policymakers, urban planners, and local communities with valuable insights into effective land use planning and management strategies. The findings are expected to contribute to evidence-based decision-making processes aimed at mitigating the negative impacts of urbanization on agricultural sustainability while promoting balanced urban growth and rural development.

1.8 Organization of the Study

The study organized into six major chapters. The first chapter contains the introduction objective and significance of the study in which clear information to the readers has been provided. The second chapter the second chapter covers the work of previous researchers about the theoretical background of urban landscape dynamics studies, which have assisted the researcher to produce different arguments on the selected topic. The third chapter deals methodology and starts with the description of the study area followed by the methods employed including data types and sources, software and instruments utilized to carry out the research. The forth chapter is dedicated to the results and discussion of the thesis. The fifth and final chapter of the study provides a summary of conclusions drawn from the findings, along with the researcher's insights.

Chapter Two

2 Literature Review

2.1 The Concept of Urbanization

The term urbanization as traditionally measured by demographers is urban population divided by total population of a region (Glenn, 1984). Urbanization is also defined as the difference between the growth rate of urban population and that of total population and the annual rate of change of the percentage of people living in urban areas, Hope. Roland and Mogopodi (1999). Closely linked to this, Nsiah (2000) defined it as the shift from a rural population to an urban population and an incensement of the number of people in the urban areas. A common theme throughout these definitions is the concentration of population in a certain urban region. Thus, the population concentration at a certain location at a specific time would be considered urbanization for the purposes of this study. Urbanization has an impact on every economic sector. It is thought to be an interdisciplinary phenomenon encompassing every facet of human society and the economy.

In both urban and rural settings, urbanization has an impact on all facets of human existence. Urbanization is on the rise due to demographic factors like reclassification, natural population growth in towns and cities, and migration from rural areas to urban areas.

2.1.1 Urbanization indices

Urbanization indices such as the New Built-up Index (NBI), Normalized Difference Built-up Index (NDBI), and Urban Index of Inaccessibility (UII) are critical tools in remote sensing and urban studies. The NBI, developed by Jensen, Cowen, & Jensen (2005), utilizes spectral bands to distinguish newly developed urban areas from natural land cover, aiding in the monitoring of urban expansion. Similarly, the NDBI, proposed by Zha, Gao, & Ni (2003), measures spectral differences to identify built-up areas amidst vegetation and water bodies, facilitating assessments of urban growth and density. In contrast, the UII, as described by Wu, Murray, & Lo (2014), assesses urban fragmentation and accessibility by analysing the spatial distribution of urban land cover relative to infrastructure and amenities. These indices collectively contribute to understanding urbanization patterns, supporting effective urban planning and environmental management strategies.

2.2 Urban Landscape Dynamics causes

Urban sprawl in emerging nations is often attributed to population growth. From an economic perspective, as urban populations increase, it becomes increasingly challenging to accommodate the same proportion of residential and commercial activities within urban boundaries if those boundaries remain fixed. Moreover, higher-income individuals are more likely to reside on the outskirts of developed metropolitan areas since they require larger housing and more affordable land for construction (Ewing, 1997).

According to UN-Habitat (2010), additional factors contributing to urban sprawl include the failure to provide land for the urbanizing poor, inadequate attention to slums, and deficiencies in land, services, and transport provision. Furthermore, there is often a lack of ability to predict urban growth. A significant cause of urban sprawl in developing nations is the denial of land rights to the urban poor, which drives them to the outskirts of cities.

In developing countries, urbanization occurs for two main reasons: people migrate from rural areas to cities in search of employment opportunities, and fertility rates among existing urban residents are high. A critical difference between urban sprawl in developing and developed countries is that, in developed nations, people often choose to leave cities due to personal preferences. In contrast, in developing countries, people move out because there is insufficient space within the city to accommodate them (Haregewoin, 2005). This outward migration leads to the spread of development without adequate infrastructure, resulting in issues such as the loss of agricultural land and difficulties in providing essential services.

Currently, rapid population growth in urban areas exerts pressure and competition for land-related resources, driving up land values, particularly in suburban areas. Developing effective solutions to the challenges posed by urban growth in suburban regions and implementing sustainable land management practices are not receiving sufficient attention (UN-Habitat, 2010).

UN-Habitat (2010) also notes that in several African cities, the urban land market is biased against the poor. Various factors and rising urban land prices prevent poor and vulnerable groups from accessing suitable land. Another factor contributing to urban sprawl is the lack of clear regulatory mechanisms for recent suburban development. Zoning is the primary method for managing municipal land use, regulating the use and intensity of development, such as housing type and density. Although zoning regulations are technical in their implementation, they often reflect a community's unwritten social rules (Harris, 2002).

Urban zoning is a land-use planning tool used by local governments. Zoning regulations can limit the supply of land available for development, thereby increasing land prices. This is beneficial for maintaining environmental quality, open spaces, agricultural use, and commercial or industrial activities. However, the absence of strict zoning regulations allows wealthy individuals to buy land in suburban areas and build rental properties. While this provides affordable housing for low-income residents or migrants who cannot afford to build their own homes, unregulated development exacerbates scattered development.

2.3 Effects of Urbanization that are Detrimental

urbanization has also some negative effects to its surrounding peri-urban areas in different aspects particularly in regard to displacement of farmers from their farmland and to degradation of valuable agricultural land Efrem(2007)so, to accommodate more people and for different service provision, as the nation's population increase, cities must grow spatially to their peri-urban areas .

According to Webster (2005) in Ethiopia, in 1950 urbanization was increased from 5% to 16% on average 4.3% in 2000 per year. Furthermore, it is predicted that by 2025, the population rates of the world, Africa, and Ethiopia would be 58 percent, 52 percent, and 32 percent, respectively. The following negative impacts of urban expansion on their peri-urban areas are the basis for an optimistic prognosis regarding the rise of urbanization. Loss of farmland, solid waste disposal and land degradation, enclosed surrounding villages for urban territory, over exploitation of natural resources and urban expansion causes conflict. Loss of farmland as pointed out by Daylong (2004) uneven urban expansion will occupy considerable valuable farmland around urban centres, which causes to sensitive contradiction and conflicts with the farmers who are displaced from their farmland. Urbanization negatively affects the peri-urban areas in different ways. As urban centres, expand by occupying fertile farmland, and displacing farmers cause to reduce the amount of production and number of family farmers and move to the nearby urban centres.

Land grabbing by regional governments for the growth of cities and towns is increasing in Ethiopia. rapidly because urbanization causes cities to grow outward and changes the way that land is used and how the landscape looks, resulting in the expropriation of agricultural property for public use by federal, regional, and local governments. . In addition, the federal law on rural land expropriation and compensation, have been crafted by the agencies that are taking land seem to disfavour that are losing the land (Solomon, 2006).

As a result, because they depend on their agricultural output rather than being well educated and qualified, farmers with large family sizes would be subject to unemployment and poverty (food insecurity). It is acknowledged that those without a minimum level of education or talent are unable to compete for employment.

2.4 Impact of Urban Expansion on Agricultural Practices

According to Cooney (2008), urban sprawl on the outskirts of a certain area impacts neighbouring communities, either directly or indirectly. Rapid urban expansion in peri-urban areas brings dynamic labour and market conditions, loss of farmlands, and changes in social, cultural, and lifestyle aspects. Planning and development control become problematic when existing institutions, which span several administrative boundaries, are inadequately organized to manage urbanization's effects. This results in the neglect of land issues or, at worst, competing land use planning decisions (Thuo, 2013).

Rapid urbanization in emerging nations is typically associated with unplanned development on the periphery, necessitating high infrastructure costs. Even in planned developments, infrastructure development often fails to keep pace with the large tracts of land developed in a low-density pattern. Consequently, urban expansion leads to social, environmental, and economic problems (Abdissa, 2005). Agricultural fields are the first to suffer from urban sprawl due to their proximity to metropolitan centres. Urbanization threatens food supply as cities expand into surrounding agricultural areas, significantly affecting food production.

One immediate result of rapid urbanization is the crowding out of agricultural land and a reduction in agricultural capacity (Kim, 2003). Cohen and Garrett (2009) note that to meet the increased demand for processed agricultural products, employment within the food system has shifted, with fewer people working in agriculture and more in transport, wholesaling, retailing, food processing, and vending. Urban encroachment on farmland forces farmers to cultivate poorer quality land to meet the increased demand for agricultural goods (Statistics Canada, 2005). Once farmland is acquired for urban use, farmers cannot simply relocate their farms, which impact their livelihood (Cooney, 2008). Many metropolitan settlements have expanded over productive agricultural land due to its high fertility (Satterthwaite, 2010). This urbanization threatens food supply by reducing the availability of agricultural land, impacting food production and food security.

Urban sprawl generally affects food security because, as populations grow and urbanize, the demand for food rises. Rural and peri-urban areas are required to cater to this increasing demand. Matuschkle (2009) observes that sprawling cities hinder the ability to meet new demand patterns due to the encroachment of cities on prime agricultural land. Numerous peri-urban farms have been converted into residential, commercial, and industrial areas, which are crucial for supplying cities with perishable crops (FAO, 2008). Each developing city's food supply is jeopardized by this conversion. The increasing demand for food in expanding cities and towns puts additional pressure on rural infrastructure, transport, technologies, and food distribution, which are already insufficient, further threatening food supply stability (FAO, 2008).

2. 5 Rapid Urbanization

High rates of urbanization which is monumental increases in population have out grown the management capabilities of cities within developing world (Efrem, 2007). Urbanization is one of the most glaring realities of the 21st century. All over the world, people are moving towards the cities. The bright lights of the cities, the perception that cities give greater opportunities and the desire to be at the heart of a ‘fast life’ is drawing people to cities. Urbanization is a process of society’s transformation from a predominantly rural to a predominantly urban population. It contains an increase in the number of people living in urban settlements and an increase in the percentage of the population engaged in non-agricultural activities, living in such place. Urbanization leads to urban spatial expansion due to the demand for development and housing growth, as well as facilities areas to serve human life, the main factors for migration from rural to urban.

2.6 Urban Landscape Dynamics Trends

2.6.1 World Trends of Urban Landscape Dynamics

Urban sprawl is more pronounced than ever on a worldwide scale as the population grows. Increases in population frequently result in increases in development, which have a direct impact on the conversion of agricultural land. Based on Masser (2003) in 2014, 54 percent of the world's population lived in urban regions, which are home to more people than rural areas globally. Urbanization is expected to increase during the next 20 years, with the majority of this expansion expected to occur in less developed nations. In 1950, 30% of the world's population lived in cities; by 2050, that percentage is expected to rise to 66 percent.

North America, Latin America, and the United States are now the most urbanized regions, with 82 percent of residents living in urban areas in 2014. The Caribbean (80%), plus Europe (73 percent), In contrast, Africa and Asia still have a large rural population, with urbanization rates of 40 and 48 percent, respectively. Over the ensuing decades, more urbanization is anticipated in every region. By 2050, it is predicted that Africa and Asia would have urban populations of 56 and 64 percent, respectively, faster than any other continent.

Since 1950, the global rural population has increased gradually, and it is anticipated that it will peak in a few years. Africa and Asia are home to approximately 90% of the world's rural population, which is estimated to be close to 3.4 billion people now and drop to 3.2 billion by 2050 (UN World urbanization prospects 2014 revision). India, followed by China, has the most rural people (857 million) (635 million). Since 1950, the number of people living in cities worldwide has increased significantly, from 746 million to 3.9 billion in 2014. Despite having a lower rate of urbanization than Europe or Latin America and the Caribbean, Asia is home to 53% of the world's urban population (13 percent).

It is projected that the world’s urban population will increase by 2.5 billion people by 2050 due to rapid and ongoing population growth and urbanization, with almost 90 percent of this increase occurring in Asia and Africa (United Nations, 2018). However, some cities have seen a decline in population in recent years, particularly those in low-fertility countries in Asia and Europe, where overall population levels are either stagnant or decreasing (Smith & Johnson, 2020). Additionally, economic downturns and natural disasters have also led to population reductions in certain cities (Brown, 2019).

Rapid and unplanned urban growth poses a significant threat to sustainable development when infrastructure is inadequately developed or policies are not effectively implemented to ensure equitable distribution of the benefits of city life (World Bank, 2021). Urban areas today are more unequal compared to rural regions, despite the advantages cities offer, with hundreds of millions of urban poor living under poor conditions (UN-Habitat, 2019). Unmanaged or poorly managed urban expansion leads to unsustainable patterns of production and consumption, accelerated sprawl, pollution, and environmental degradation (Jones & Clark, 2020). The problems of sustainable development will concentrate in cities more and more as the globe continues to urbanize, especially in lower-middle-income nations where urbanization is occurring at the quickest rate. There is a need for integrated strategies to enhance the lives of both urban and rural residents.

2.6.2 Trends of Urban landscape Dynamics in Africa

In the upcoming decades, Asia and Africa, which are at the core of global urbanization, will see the fastest rate of urbanization. Only 31% of Africans lived in urban areas in 1990; by 2035, that percentage is expected to rise to 49%. A megatrend with significant effects on Africa's development and change is urbanization. Africa is now the least urbanized continent, yet it is urbanizing at the fastest rate in the world 3.5% annually.

The demographic landscape of Africa is not only changing, but so are the economic, environmental, and social implications due to the pace and scope of urbanization (African Development Bank, 2022). By 2035, approximately half of Africa's population is expected to live in urban areas, presenting challenges for infrastructure, services, and employment, while also offering opportunities for economic growth (World Bank, 2023). As the continent undergoes a demographic shift with a growing young population moving into cities, the urban transition is becoming increasingly evident. Rapid urbanization in Africa brings both opportunities and challenges. While the prevailing narrative has often focused on the negative aspects of urban growth, there is now a growing recognition of its potential to drive progress and transformation (UN-Habitat, 2021). African leaders are beginning to explore and harness these opportunities for sustainable development.

According to Habitat III, the necessity of leveraging urbanization for structural change was reaffirmed through the Common African Position at the Third United Nations Conference on Housing and Sustainable Urban Development in 2016 (UN-Habitat, 2016). Urbanization is crucial, as highlighted by the New Urban Agenda established at Habitat III and the specific Sustainable Development Goal focused on cities and human settlements adopted in 2015 (United Nations, 2015). Economic growth and the transition of economies towards productive sectors, especially industry and services, are closely linked to urbanization. However, evidence suggests a disparity between urban and industrial growth in Africa, leading to missed opportunities for job creation and improved well-being (African Development Bank, 2022). Many African cities struggle to provide sufficient employment opportunities to meet the increasing demand, particularly for the young population, due to significant infrastructural and service deficiencies. To ensure the sustainability of both cities and industries, it is crucial to implement deliberate policies, strategies, and investments that integrate urban and industrial growth in Africa (World Bank, 2023).

According to the United Nation Economic Commission for Africa's 2017 report, industrialization and urbanization confront similar problems since cities need better performing industrialization and vice versa. The report's main takeaway is that, in the framework of national development planning, intentional efforts are required to integrate urban and industrial growth. A massive unavoidable movement that is gaining momentum quickly, with cities playing a crucial role in structural change and industrialization in particular, it's also crucial to dispel common misconceptions about the urban trajectory, such as the notion that stopping rural-to-urban migration will slow down urban expansion and that the urban agenda is predominantly social in nature. In truth, urban expansion is mostly driven by natural growth, but economic development is cantered upon urbanization. The increase in agricultural production has not been the main driver of urbanization in many African nations. In spite of low agricultural productivity and falling or stagnant industrial production, most nations are increasingly urbanizing. "Consumption cities" appear to be the result of natural resource exports from resource-rich nations and associated expenditure, which is mostly on non-traded services. African cities face numerous challenges, including low productivity, slow job growth, high levels of informality, significant infrastructure and service deficits, poor connectivity to rural areas, increasing inequality, environmental degradation, vulnerability to climate change, and weak institutional capacities (African Development Bank, 2022). If these barriers are not addressed, Africa's urban potential for structural change will be undermined. The significant challenge for Africa is to accelerate structural transformation by harnessing rapid urbanization to promote economic diversification, with a particular focus on industrialization. This approach aims to boost employment, enhance access to essential services, and reduce inequality and poverty (UN-Habitat, 2016; World Bank, 2023).

2.6.3 Trends of Urban Landscape Dynamics in Ethiopia

Ethiopia is the second most populous country in Africa, after Nigeria. Its population distribution varies significantly by residence, with approximately 80% living in rural areas and the remaining 20% in urban areas (Central Statistical Agency, 2020). The urban population in Ethiopia is growing at a rate of 6%, which is considerably higher than in other African countries (World Bank, 2021). Despite this rapid urbanization, Ethiopia remains one of the least urbanized regions in the developing world, facing significant social challenges in its large cities. The country's economy is largely agricultural, but food production is hindered by adverse weather and outdated technology. Poverty limits the adoption of advanced and year-round production methods, with about 80% of the population depending solely on agriculture and animal husbandry for their livelihoods (United Nations Development Programme, 2019).

Urbanization in Ethiopia also exhibits considerable regional disparities. Rural-to-urban migration, driven by conflicts and tribal warfare, is common. Many people are forced to leave their rural homes and end up in expanding slums, particularly in the capital city, where such informal settlements often become the only option for impoverished residents (UN-Habitat, 2017).

In contrast, in wealthier countries, the demand for larger suburban properties is driven by higher population growth and increasing household incomes. From 1950 to 1980, much of the suburban expansion in the United States was attributed to rising wealth (Kahn, 2003). Suburban residents generally live in larger homes with bigger lots and use cars more frequently compared to urban dwellers. Developed countries like the USA invest heavily in road and transportation infrastructure, promoting car use. Rising incomes and car ownership are crucial for suburban growth, which often results from personal preference rather than necessity (Menno, 2001).

Conversely, sprawl in developing countries is largely driven by necessity, as people move to cities in search of better employment and opportunities. Factors such as adverse weather, poor crop yields, and financial constraints force people to abandon their farms and migrate to urban areas. This influx leads to the expansion of cities beyond their planned limits. When urban growth is insufficient, residents are pushed into informal settlements, resulting in increased congestion, higher household densities, and a lack of essential services (United Nations, 2018).

2.7 Empirical Studies

Land is fundamental to all life forms and other production factors. Verheye and Paul (1997) observed that most households, particularly in developing nations, rely on land and natural resources to meet their immediate needs and achieve their long-term goals. For many rural families, land is the primary resource available to build their livelihoods.

American economist and philosopher Henry George (1839-1897) underscored the critical role of land, stating that humans not only use land for its materials and forces but also depend on it for survival. He highlighted that land is essential for human life, serving as our home and storehouse for necessities. Without land and its products, humans cannot benefit from the sea, sunlight, or other natural forces. We are intrinsically connected to the earth, akin to grass or flowers, as we are born on this land, live on it, and return to it. George emphasized that without land, humans lose their tangible connection to nature (George, 1879).

The land is man's home, his storehouse from which he must obtain all of his necessities, and the material from which he must apply his labour to satisfy all of his desires. Without the land and its products, it is impossible to take advantage of the sea's bounty, enjoy the sun's light, or harness any other force of nature. We are as much children of the earth as a blade of grass or a field flower; we are born on this land, live there, and return there. Man becomes a disembodied spirit if everything that pertains to the land is taken away from him. It was evident to George that no production could occur without land. Numerous studies on urban growth have been conducted globally. These studies, which utilized similar methods to this study and were conducted in countries with comparable demographic trends and structures, have been closely monitored.

The reports examined urban growth in various locations: Los Angeles (Ewing et al., 1997), China (Chen et al., 2000), Ouagadougou, Burkina Faso (de Jong et al., 1997), along the Islamabad highway, Pakistan (Naseem et al., 2000), and Alexandria, Egypt (Azaz, 2001). The findings from all these case studies indicated rapid urban growth in all investigated areas, characterized by the expansion of the main urban area and urban sprawl. The primary cause of urban growth in these cases was a high natural population increase due to high birth rates and rural-urban migration. Urbanization rates tended to rise when the regional and national economies were flourishing (Masek, 1996). This was notably evident in Oman when oil was discovered, offering new employment opportunities in the cities (Al-Awadhi et al., 2003).

A common trend observed was the rapid, unplanned urban growth, leading to extensive informal housing areas (Azaz, 2001; Naseem et al., 2000). These case studies concluded that significant changes were detected in various land classes, demonstrating the impact of urban expansion on other land use categories. However, this study specifically focuses on urban landscape dynamics and their effect on agricultural land.

2.8Conceptual Framework

Urbanization has significantly transformed urban areas in Ethiopia. The primary drivers of this urbanization are natural population growth and rural-urban migration as people seek better opportunities in urban centres. Consequently, numerous issues arise, prompting the population to move to urban fringes. This movement leads to the sprawling of urban land uses into these fringes, which are predominantly agricultural areas. The encroachment of urban land uses into these fringes results in the displacement of agricultural lands, directly and indirectly affecting both residents and migrants. The impacts on land use include the loss of farmlands, a reduction in agricultural labour, and the creation of jobs in non-agricultural sectors. As a result, there is a decline in agricultural productivity, leading to food insecurity-related issues, as illustrated in Figure 2 below.

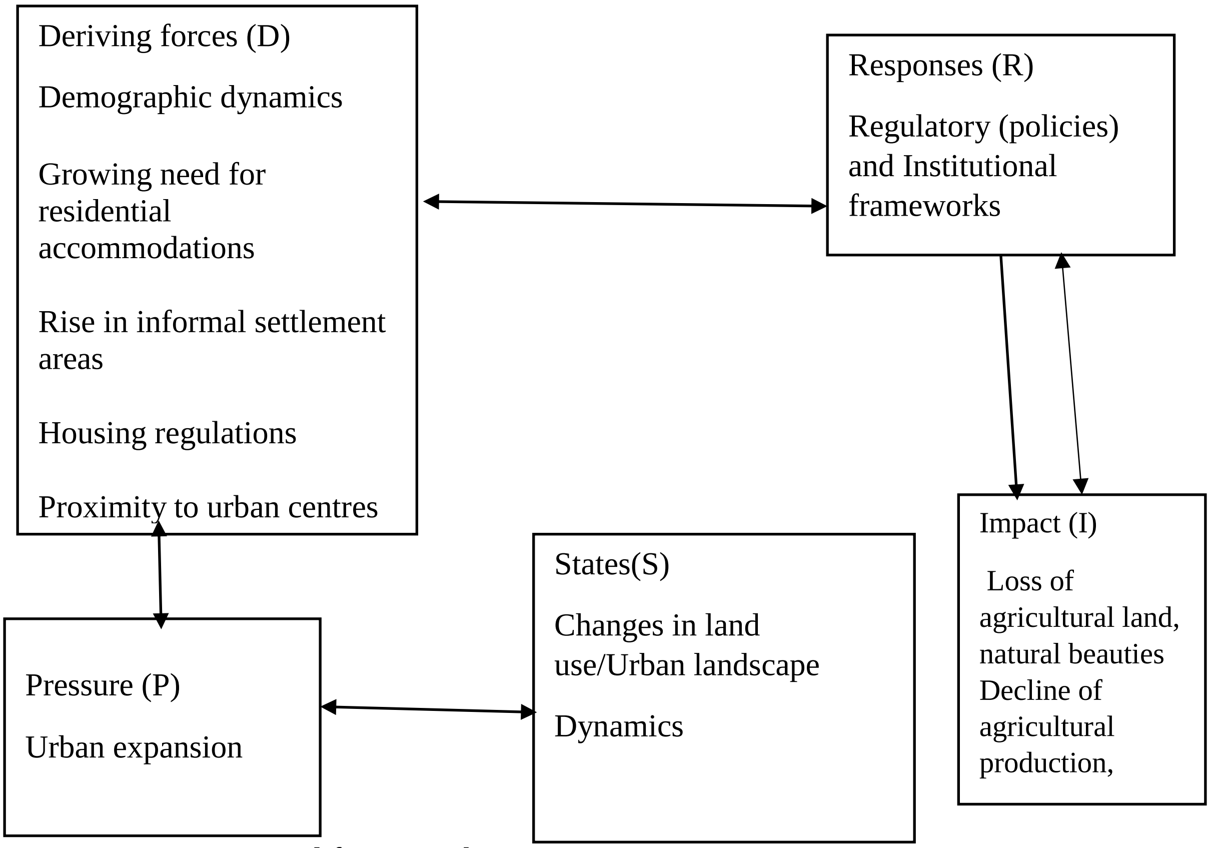

Figure 2.0 conceptual frame work

Source: Developed by author from different literature concepts and legal legislations.

The urban expansion in the Amhara regional state is driven by public sector initiatives, the need for residential spaces, private investments, and economic policy changes (Abdella and Nuredin. 2020). Population dynamics, including mortality, fertility, and migration, are key factors influencing changes in population size and composition (UNFPA 2014). These dynamics result in urban growth, leading to horizontal expansion, particularly in the east and south, facilitated by gravel roads and central government policies (Jong Kory, 2009).

2.9 Integration of Remote Sensing and GIS

Remote sensing and GIS technologies are crucial for detecting changes in land use and land cover. Remote sensing involves using space-borne sensors to monitor changes on the earth's surface, aiding planners in analysing agricultural patterns, urban sprawl, and disaster impacts (Ramachandra and Kumar 2004). GIS combines data from multiple sources to create detailed maps and change detection systems, enhancing the accuracy and comprehensiveness of environmental monitoring (Rogan and Chen 2004).

2.10 Land Use Land Cover (LULC)

Land use refers to human activities on land, such as agriculture or urban development, while land cover describes the physical surface, like forests or grasslands, observable via remote sensors. Understanding these terms is essential for effective planning and management of natural resources, ensuring sustainable use and conservation (Sankhala et al. 2014).

2.11 Purpose of Land use Land Cover

Remote sensing data provide critical information on land cover, from which land use can be inferred, particularly when combined with ancillary data or prior knowledge. This information is crucial for baseline mapping, monitoring changes, and developing strategies to balance conservation, conflicting uses, and developmental pressures. Effective land use planning is vital for maintaining harmony with the environment, which is essential for the survival and well-being of human civilizations (Kavitha et al. 2012).

2.12 Land Use Land Cover Change

Human activities have significantly modified the earth's surface, leading to land use land cover change (LULCC). These changes impact local, regional, and global ecosystems, necessitating careful management and planning. Monitoring LULCC is essential for understanding population dynamics, urban expansion, and protecting environmentally sensitive areas. Remote sensing methods efficiently detect and classify land use changes over large areas, providing valuable data for urban planning and environmental protection (Zahra et al. 2014).

2.13 Land Use Land Cover Mapping

Mapping land use and land cover, from local to global scales, is crucial for planning, managing activities, and understanding the earth as a system. Remote sensing techniques, including image classification, provide detailed and timely information for creating accurate land cover maps. These maps support socioeconomic planning, hydrologic studies, and environmental monitoring (Basudeb 2004).

2.14 Urban Land use Changes

Urban expansion shapes regional economic viability and affects ecosystems. As cities grow, they often encroach on agricultural and forest lands, leading to significant environmental changes. Monitoring urban land cover and land use changes is essential for policymakers and local communities to manage the dynamic processes of urbanization and its impacts. Enhanced multi-spatial-temporal data and analytical techniques enable cost-effective and accurate monitoring of urban sprawl, supporting regional planning and urban ecology (Nations 2001).

Chapter Three

3 Research Materials and Method

3.1 Over View of the Study Area

The town of Motta is the site of the research. Located in the Amhara region of Ethiopia, it is the second biggest town in the East Gojjam zone after DebreMarkos. It was founded during the Ate susynyos era in the 17th century. Astronomically speaking, it is located at 11°04' N latitude and 37°52' E longitude. It is located 370 kilometers from Addis Abeba, 120 kilometers from the regional seat of Bahir Dar, and 196 kilometers from DebreMarkos (the zonal capital). Geographically, the town is bordered to the north by MeklitLaymariyam, to the south by YerezeAtetanate, to the west by Beru Georges, and to the east by HebereSelam.

The town is organized into six urban Kebeles and serves as the hub for two governmental administration offices, namely the HuleteEijuEnesseworeda administration office and the Motta town administration office. The settlement occupies 19995.35 hectares of land. The village of Motta is located in the WoinaDegaagroclimatic zone, which has moderate annual precipitation and average monthly minimum and maximum temperatures of 9.70°C and 22.10°C, respectively. The social groups residing in the town are all native speakers of the Amharic common language, having come from the same communities.

The main town of HuletEjjuEneseworeda, Motta town is blessed with extremely productive and rich agricultural areas that are ideal for raising cattle, high-value crops, and other agricultural pursuits. The most common kind of agricultural production system is a mixed farming system, which includes both crop production and animal husbandry. Teff (Eragrostistef), maize (Zea mays), wheat (Triticumaestivum), barley (Hordeumvolgare), finger millet (Eleusinecoracana), and potatoes from the region's vegetables make up the majority of the district's agricultural production. Next to agriculture production, raising livestock is the main source of income. Various animal products, including cattle, goats, sheep, horses, and chickens, are significant livestock species raised by farmers in the research region.

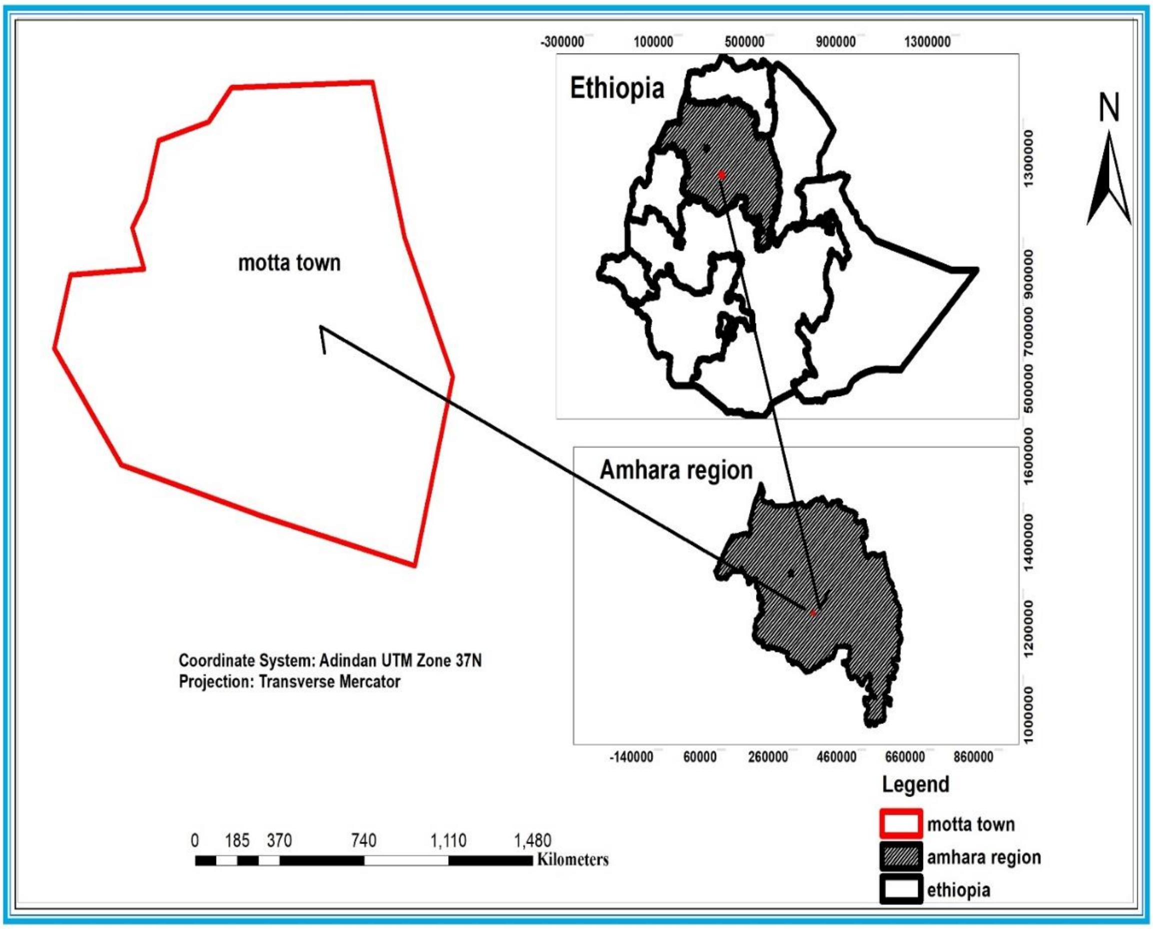

Figure 3.1 Motta town map

3.2 Research Design

The study utilized a descriptive observational research design to conduct a detailed examination of the effects of urban expansion on agricultural land. To ensure comprehensive findings, the design incorporated both qualitative and quantitative research elements. Quantitative methods included the use of Geographic Information Systems (GIS) and remote sensing data to create maps for the years 1992 and 2023, and to measure urban expansion within the study area using Landsat classified images. The ARCGIS software facilitated the reclassification of land cover data into categories relevant to examining urban landscape dynamics and their impact on agricultural land. The qualitative approach was employed to evaluate the socio-economic factors contributing to urban expansion in the Motta town area and its surroundings.

3.3 Data Sources and types

For this study, both primary and secondary data were considered, depending on their significance.

3.3.1 The primary Data

Primary data that will be collected in this study includes filed observation and reconnaissance, GPS measurements topographic data, and urban trends will be noted interview and two satellite images will be obtained from USGS databases' online resources The satellite images taken by land sat between 1992 and 2023

3.3.2 Secondary Data

To add supportive concepts and findings from the primary data, secondary data were obtained and collected from review of related literature, peer journals, research reports, and existing maps

3.4 Software and Instrument

ERDAS IMAGINE 2015, was used for image enhancement ARC GIS 10.5, for map preparation, and Ms office were used In order to achieve the desired objective of the study qualitative data and quantitative data which includes GIS and remote sensing data to produce a map of 1992 and 2023 showing urban land scape obtained from land sat .ARCGIS pro were used for reclassification of land cover data into categories appropriate for the purposes of this study. A thematic change analysis of individual land use/land cover will also be conducted using ArcGIS Pro software.

3.5 Data Collection

In order to assess the impacts of urbanization on agricultural land in Motta town Landsat images of 1992, and 2023 were used. For this research purpose, Landsat satellite images have been chosen that could be available in free public-domain (https://www.usgs.gov/.) The images were acquired in February, as this was a clear sky season in the region. Only images with high quality standard and less cloud cover with good cloud qualities were considered. The Landsat images were taken at visible and infrared wavelength with 30mx30m spatial resolution.

3.5.1 Types of Satellite Image

Table 3.1 types of satellite image

Year	Date of Image Acquisition (dd/mm/yyyy)	Sensor	Cloud cover (%)	Spatial resolution	Path/Row	Source
1992	29/01/1992	Landsat5 Thematic Mapper	0	30	170/052	USGS
2023	18/01/2023	Landsat 8 Operational Land	0	30	170/052	USGS

3.6 Methods of Data Processing

3.6.1 Image Enhancement and Visual Interpretation

Image improvement is necessary, according to Lillesand and Kiefer (1994), to improve the overall visual interpretability by differentiating between features and the clarity of images for human viewing by reducing blurriness and noise, boosting contrast, and revealing detail

Visual interpretation utilized in conjunction with software-based image interpretation since the mind is adept at analysing spatial properties of an image and is capable of finding obscure or subtle elements.

3.6.2 Sub setting/Clipping of Area of interest

The study conducted in Motta town therefore by having the towns boundary shape file land sat data sub stetted/clipped into the specific area of interest by using ArcGIS pro software's.

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3.6.3 Development of Classification Scheme

Based on the prior knowledge of the study area, a brief reconnaissance survey was carried out using Subset image (based on the shape of the study area) and a classification scheme was developed land are used to produce the final land use/land cover map of the study area. Accordingly four classes were identified namely agricultural land, built up area, vegetation and bare land (in Table 3.2)

Table 3.2classes of land use land cover change

Land use class	Description
Built up area	All residential, commercial and industrial areas, villages, settlements and transportation infrastructures.
Agricultural land	Including crop fields and fallow land
Vegetation	In this study the vegetation includes planted of trees around compounds, eucalyptus wood lots and road side tree plants and parks.
Bare land	All vacant spaces, sands, rocky areas, cleared land

The type and number of land use classes are determined by a number of factors. The contribution of the land use type on the recorded change is the primary determinant reason. This is directly related to the area the land use shares in the town the other is land use types that its change easily recognizable and identifiable. Again, typical land features of the area are taken as a class. In order to make sample collection and classification easy, land use/land cover nomenclatures are required to create and define the possible land use/land cover classes first. The land use/land cover classes applied in this paper are adopted from Anderson land use/land cover classification scheme which is widely applied in East African Countries (1976). For the sake of simplicity, the researcher modified the descriptions of some of the land use/land cover classes considering the land use/land cover diversity of the study area. Therefore, four major land use/land cover classifications: agricultural land, vegetation, built up area and bare land.

3.6.4 Image Classification

Land use/land cover change analysis the classified images were compared in two periods i.e. 1992- 2023 Change detections was computed by comparing values of area of one data set with the corresponding value of the second data set in each period. The values were presented in terms of hectare and percentage. Quantification of the rate of change has been applied to generate information about the land use/land cover dynamics of the study area.

In this study, both supervised classification and unsupervised approach was used and passed through the steps such as: select training samples which were typical representative for the land cover classes; perform classification using maximum likelihood algorithm (MLC) support vector machine (SVM) and pixel based unsupervised classification algorithm were used

3.7 Training and Test point Collection

Training areas/sample objects which are typical representatives of the classes were collected using personal experiences and local knowledge of the physiographical nature of the area. In addition, image enhancement and composition were applied for better discriminating the land cover classes. Test samples for 1992and 2023 from Google Earth map (created random point in ArcGIS pro and convert to kml format then takes a value of each random points) and 2023 using hand held GPS for each classes were collected randomly.

Table 3.3 Random test points

Land use class	1992	2023
Built up area	74	95
Agriculture land	93	71
Vegetation	71	65
Bare land	58	90
Total	296	321

3.7.1 Random Test Points

As the above table3.3 shown 617 points were collected and used, to test the accuracy of the classified images of the 1992, and 2023. This study accuracy assessment was done by using these points to find out those errors so as to make the produced land cover maps become reliable and easily interpretable by users. Once the classified image is incorporated into a GIS, to become an information source for urban planners and researchers, accuracy assessment is supposed to process as it limits the classification results of a remotely sensed imagery data (Landsat image). To do so, the accuracy of a classified map has to be assessed and compared with a referenced data using an error matrix.

3.8 Accuracy Assessment

Accuracy assessment is a general term for comparing a classification to geographical data that are assumed to be true, in order to determine the accuracy of the classification process. The results of the land cover classifications derived from remotely sensed data are compared by an accuracy assessment. An accuracy assessment analysis was performed by producing an error matrix that compared the interpreted land cover map and a map contains the result of ground truth investigation. To perform accuracy assessment Google earth map and handheld GPS was used for random testing point's collection. Ground truth would be performed by going into the field at the location of each randomly collected point. The classification result would then be compared to actual land cover at each point's location. In this study the following error assessment steps was implementing. These were, determine the total number of samples to be collected for each category, design an appropriate sampling scheme, obtain ground reference information at sample locations, produce error matrix and evaluate the error matrices, producer accuracy, user accuracy, commission and omission. The error matrix allows us to be able to calculate a variety or accuracy metrics from our data. The columns normally represent the reference data, while the rows indicate the classified image. It also provides an excellent summary of the two types of thematic error that can occur, namely, omission and commission. Errors of omission occur when a feature is left out of the category being evaluated and errors of commission occur when a feature is incorrectly included in the category being evaluated. An error of omission in one category will be counted as an error in commission in another category. Most of the classification accuracy measurements are derived from confusion matrix. However, the most popular one is the correctly allocated cases in a percentage. This is the basis for computing the user accuracy (CA), which is determined by dividing the total number of pixels allocated to a given category by the number of correctly identified pixels. By informing the customer that a specific percentage of all regions classified as category X are truly correct, it accounts for errors of commission (schuckman, 2018). The image analyst can determine the proportion of pixels correctly classified in a specific category (less than or equal to) in the image by calculating the producer's accuracy (PA). The correctness of the producer quantifies omission errors**.**

3.8.1 User Accuracy

sometimes consumer accuracy refers to the number of appropriately classified pixels in each class grouping divided by the total number of pixels that were classified in that category of the classified image (row total).It represents the probability that a pixel classified into a given category actually represents that category on the ground.

3.8.2 Producer's Accuracy

It Refers to the number of correctly classified pixels in each class (category) divided by the total number of pixels in the reference data to be of that category (column total are classified. Overall accuracy is computed by dividing the total number of correctly classified pixels (i.e., the sum of the elements along the major diagonal) by the total number of reference pixels. It shows overall results of the tabular error matrix it is computed by dividing the total number of correctly classified pixels (i.e., the sum of the elements along the major diagonal) by the total number of reference pixels.

3.8.3 Overall Accuracy

It is computed by dividing the total number of correctly classified pixels (i.e., the sum of the elements along the major diagonal) by the total number of reference pixels. It shows overall results of the tabular error matrix it is computed by dividing the total number of correctly classified pixels (i.e., the sum of the elements along the major diagonal) by the total number of reference pixels. It shows overall results of the tabular error matrix as mentioned by Anderson et.al, (1976) for a reliable land cover classification, the minimum overall accuracy value computed from an error matrix should be 85%. However, Foody, (2002) showed that this baseline makes no meaning to be internationally acceptable standard for accuracy. This is because a universal standard is not precisely related to any specific study area. Foody, (2002) also, illustrious that Anderson et.al, (1976) do not explain in detail about the criteria of map evaluation for universal applications. Moreover, (Lud,2007) noted that the accuracies of change detection results highly depend on many factors, such as: availability and quality of ground truth data, the complexity of landscape of the study area, the change detection methods or algorithms used as well as classification and change detection schemes. So, the overall accuracies for both maps were above 85% based on Anderson's criteria. The first step or tasks were collection of test points for each LULC classes using Google earth and handheld GPS and then calculating the accuracy of classified and reference points.

3.9 Methods of Data Analysis

3.9.1 Spatial data Analysis

Supervised maximum likelihood, supervised support vector machine and unsupervised classification were used. Ground truth GPS data was used for Accuracy assessment of classified images LULC map of 1992 and 2023 were produced to Assess the impacts of urbanization on agricultural land Using Landsat 5and Landsat 8 detected agricultural land, built up area, vegetation and bare land, land use type in the study area. For accuracy assessment used Google earth map for 1992 and 2023 and Garmin handheld GPS for 2023 by created a set of random points from the ground truth data and compare that to the classified data in a confusion matrix. The numbers of this testing points was depends on how the interpretation difficulty. Accuracy assessment compares the classified image to another data source that is considered to be accurate or ground truth data. Satellite images permit accurate mapping of land cover and make landscape features understandable on the study area about temporary phenomena, such as agricultural lands, built-up areas, vegetation and bare lands could be studied by comparing images acquired at 1992, and 2023. For the purposes of this study, two periods of freely available Landsat images would be use. Quantitative data collected were expressed in detail the form of maps, charts, simple tables and graphs .

. To calculate the rate of change for each land use and land cover, the formula used was: Rate of Change (hectares per year) = (A - B) / C. In this formula, A represents the current area of land use or cover in hectares, B denotes the previous area in hectares, and C is the number of years between A and B. The percentage change, or trend, was determined using: Percentage Change (Trend) = (Observed Change / Total Change) × 100. Additionally, thematic change analysis for each land use and land cover was performed using ARCGIS Pro, and the results were compared to a relative change detection matrix, which displays the changes from one class to another.

3.10 Overview of Methodological Procedures in a Flow Chart

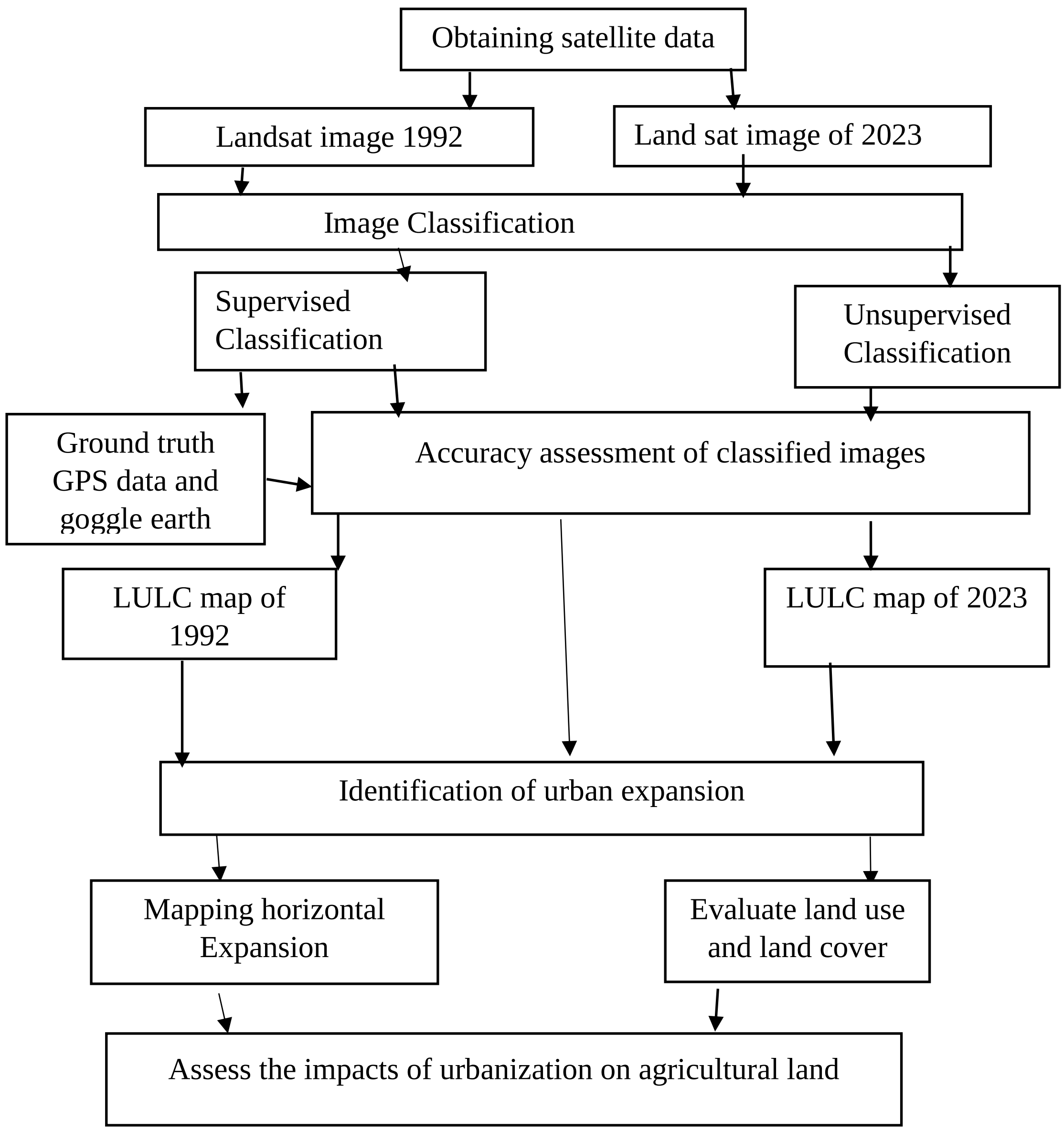

Figure 3.2 Workflow Chart

Chapter Four

4 Results and Discussion

4.0 land use land Cover Class Distribution and Change Detection

This chapter presents and analyses the results from the classification of Landsat images of Motta town and its surrounding rural areas using ArcGIS Pro. The analysis involved both supervised and unsupervised classification methods. The chapter discusses changes in land use and land cover, focusing on their impact on agricultural land. To meet the study's objectives, the research examined the expansion of built-up areas and its effects on farmland. Four land use/land cover classes were identified and mapped across a study area of 2,129 hectares, which represents the municipal boundary. These classes include built-up areas, agricultural land, bare land/open spaces, and vegetation cover (see Figure 4.1).

4.1 Supervised Land use land cover classification

4.1.1 Accuracy assessment of MLC Classification Algorism

4.1.1.1 Confusion matrix for Land Cover Map of 1992

Producer's accuracy of agricultural land 87.2%, built up area 91.2%, vegetation 83.6% and bare land 82% and user's accuracy agricultural land 88.2%, built up area 83.8%, vegetation 85.9% and bare 86.2%. The overall accuracies in the study period 1992 is 86.1%. As shown this result the highest user's and producer's accuracies were observed in built up area and agriculture respectively the lowest user's and producer's accuracy were built up and bare land .respectively The lowest values of class accuracies were misclassified due to spectral property similarities among other land cover classes. The results are shown in table4.1below

Table 4.1 Confusion matrix of 1992 land cover map

Classified data	Built up land	Agriculture	Vegetation	Bare land	Total	User accuracy (100%)
Built up area	62	4	3	5	74	83.8
Agriculture land	3	82	6	2	93	88.2
Vegetation	1	5	61	4	71	85.9
Bare land	2	4	2	50	58	86.2
Total	68	94	73	61	296	
	91.2	87.2	83.6	82.0		
	Producer accuracy (100%)					
	Over all accuracy		86.1			

Source accuracy assessment randomly generated points using ArcGIS pro

4.1.1.2 Confusion matrix for land cover map of 2023

the percentage of correctly classified pixels in each class (category) divided by the total number of pixels in the reference data that were assigned to that category (column total are classified) is known as the producer's accuracy .Producer's accuracy of agricultural land 82.9%, built up area 89.5%, vegetation 81.8% and bare land 90.5% whereas user's accuracy of agricultural land 88.7%, built up area 89.5%, vegetation 83.1% and bare land84.4%. The overall accuracies in the study period 2023 is 86.6%. The highest user's and producer's accuracies were built up and bare land area and the lowest users and spectral producer's accuracies were observed in vegetation land The lowest values of class accuracies were misclassified due to property similarities among other land cover classes the result is shown in the table 4.2 below

Table 4.2 Confusion matrix of 2023 land cover map

Classified data	Built up land	Agriculture	Vegetation	Bare land	Total	User accuracy (100%)
Built up area	85	3	3	4	95	89.5
Agricultural land	3	63	3	2	71	88.7
Vegetation	2	7	54	2	65	83.1
Bare land	5	3	6	76	90	84.4
Total	94	78	65	84	321	
	89.5	82.9	81.8	90.5		
	Producer accuracy (100%)					
	Over all accuracy		86.6%			

Source accuracy assessment ground truth points using ArcGIS pro

Overall accuracy is computed by dividing the total number of correctly classified pixels (i.e., the sum of the elements along the major diagonal) by the total number of reference pixels. It shows overall results of the tabular error matrix it is computed by dividing the total number of correctly classified pixels (i.e., the sum of the elements along the major diagonal) by the total number of reference pixels. It shows overall results of the tabular error matrix. Therefore the overall accuracy for 1992 and 2023 were 86.1% and 86.6respectively.

4.1.2 Maximum Likelihood Algorism Land use land Cover Distribution

Table 4.3 Land use land cover classification

Class name	1992		2023	
	Area in (ha)	Area (%)	Area in (ha)	Area (%)
Built up area	534	25	757	36
Agricultural land	791	37	352	17
Vegetation	502	24	653	30
Bare land	302	14	367	17
Total	2129	100	2129	100

Table 4.3 Source extracted from land sat map using ArcGIS pro 1992 to 2023

As above table 4.3 shown, the study area has a total of 2129 ha. Indeed, the area has four land-use types with different proportions, these are agricultural land, built-up area, vegetation, and bare land which has a land-use value of 791 (37%), 534 (25%), 502 (24%), and 302(14%) respectively in 1992. From this result, larger parts of the study area were covered by Agricultural land use 37 %. So, the study area was dominated by agricultural land and the minimum was bare land 18%. In 2023 agricultural land, built-up area, vegetation, and bare land were with a value of 17%, 36%, 30% and 17% respectively. This result shown the majority of the study area was covered by built up and the minimum were bare land and agricultural land. The coverage of agricultural land decreased 20% from 1992to 2023 due to transformations of other land use. From 1992to 2023 Built up area increased by 11% due to the towns rapid urbanization so the result revealed that the loss of fertile and very productive agricultural land in the effect of uncontrolled horizontal expansion in Motta town peripheral rural Kebeles

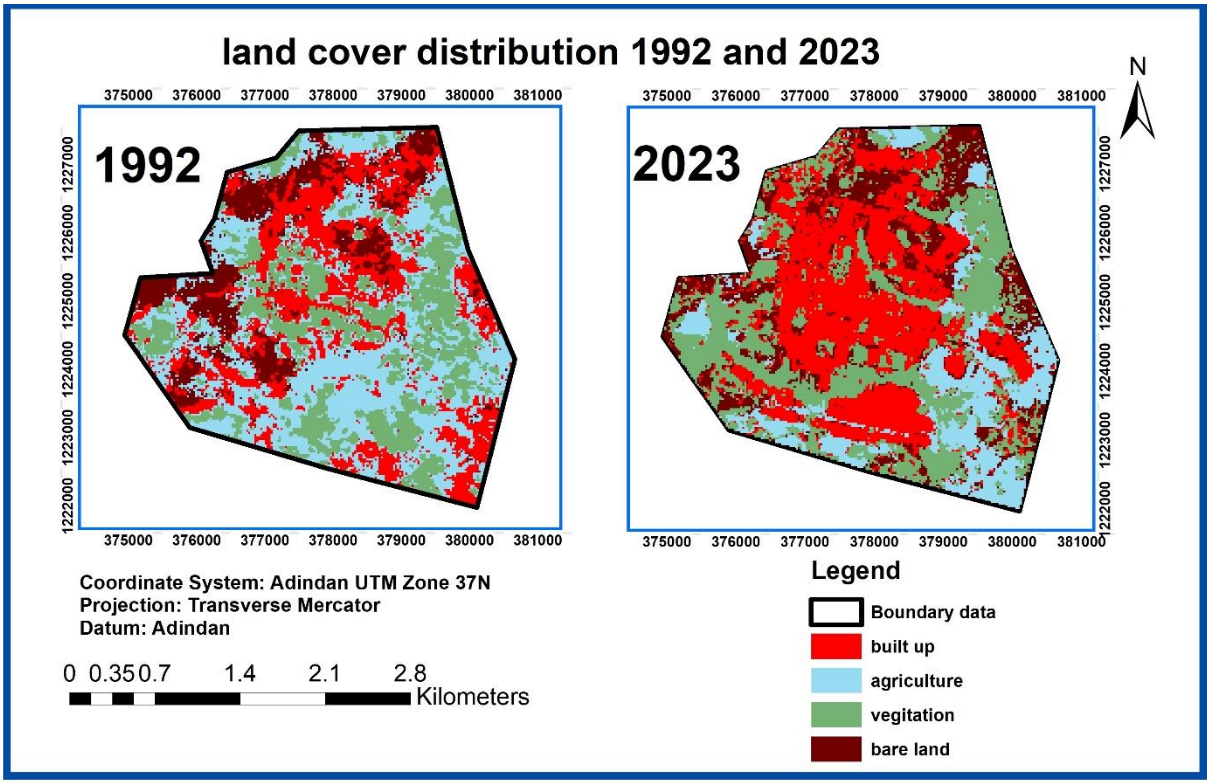

Figure 4.1 Distribution Map of Land Use and Land Cover

4.1.2.1 Change Detection Analysis

. The trends and rates of urban landscape dynamics in the town, presented for each land use class in both hectares and percentages, are detailed in Table 4.4 below.

Table 4.4 Change detection

Class name	1992	2023	Change 1992 to 2023	
			Change in (ha)	Change in percent (%)
Built up area	534	757	+223	+42
Vegetation	502	653	+151	+30
Agricultural land	791	352	-439	-56
Bare land	302	367	+65	22

Source: Extracted from analysis of Landsat images of 1992 and 2023

The positive (+) sign denotes an increase in the area covered, while the negative (-) sign signifies a decrease. As illustrated in Tables 4.4 and 4.5, the extent of change from 1992 to 2023 has been substantial. All land use classes, except built-up areas, have shown both increases and decreases. Specifically, over the 31-year period from 1992 to 2023, the area of agricultural land diminished by 56% (439 hectares), indicating a declining trend. Conversely, built-up land expanded by 223 hectares (42%), reflecting a significant increase.

Table 4.5 Rates and Trends of Land Use/Land Cover Dynamics for 1992 and 2023

Class name	1992	2023	Change 1992 to 2023		
			Change in (ha)	Annual rate Of change in (ha)	Change in percent (%)
Built up area	534	757	+223	+7.19	+42
Vegetation	502	653	+151	-+4.87	+30
Agricultural land	791	352	-439	-14.16	-56
Bare land	302	367	+65	+2.09	22

Source: Extracted from analysis of Landsat images of 1992 and 2023

As shown in the table 4.5 the annual rate of change in (ha) of built area shows an increase of 7.19(ha) and a decrease of 14.16(ha) of agricultural land and bare land increases by 2.09(ha) and vegetation increase by 4.87(ha)

Table 4.6 Land use/Land cover transition matrix (ha) from 1992to 2023

2023						
1992	Class name	Built up	Vegetation	agriculture	Bare land	Grand total
	Built up area	**204.912**	147.351	**39.9594**	**137.297**	529.519
	Vegetation	201.15	**156.91**	**115.71**	**23.0793**	496.8493
	Agricultural land	**236.057**	**268.81**	184.565	**93.4926**	782.922
	bare land	**102.19**	**75.6057**	**8.32639**	**116.523**	302.64496
	Grand total	744.309	648.6767	348.56079	370.3919	2111.935
	Total change	+214.79	+151.8274	-434.3612	+67.74694	

Source land sat map using ArcGIS pro1992 to 2023

As shown in table 4.6 the yellow coloured cells in the transition matric indicates the land use class that are unchanged from 1992 to 2023, 204.912 (ha),156.91(ha) ,184.565(ha) ,116.523(ha),built up , vegetation ,agriculture and bare land areas respectively remains unchanged. Built up areas changed into 147.351(ha), 39.9594(ha).137.297(ha), vegetation .agriculture and bare land respectively since the study primary concern is of agricultural land 268.81(ha), 184.565(ha), 93.4926(ha) of it is converted into built up, vegetation, and bare land respectively the change detection is also shown on figure 4.1.1

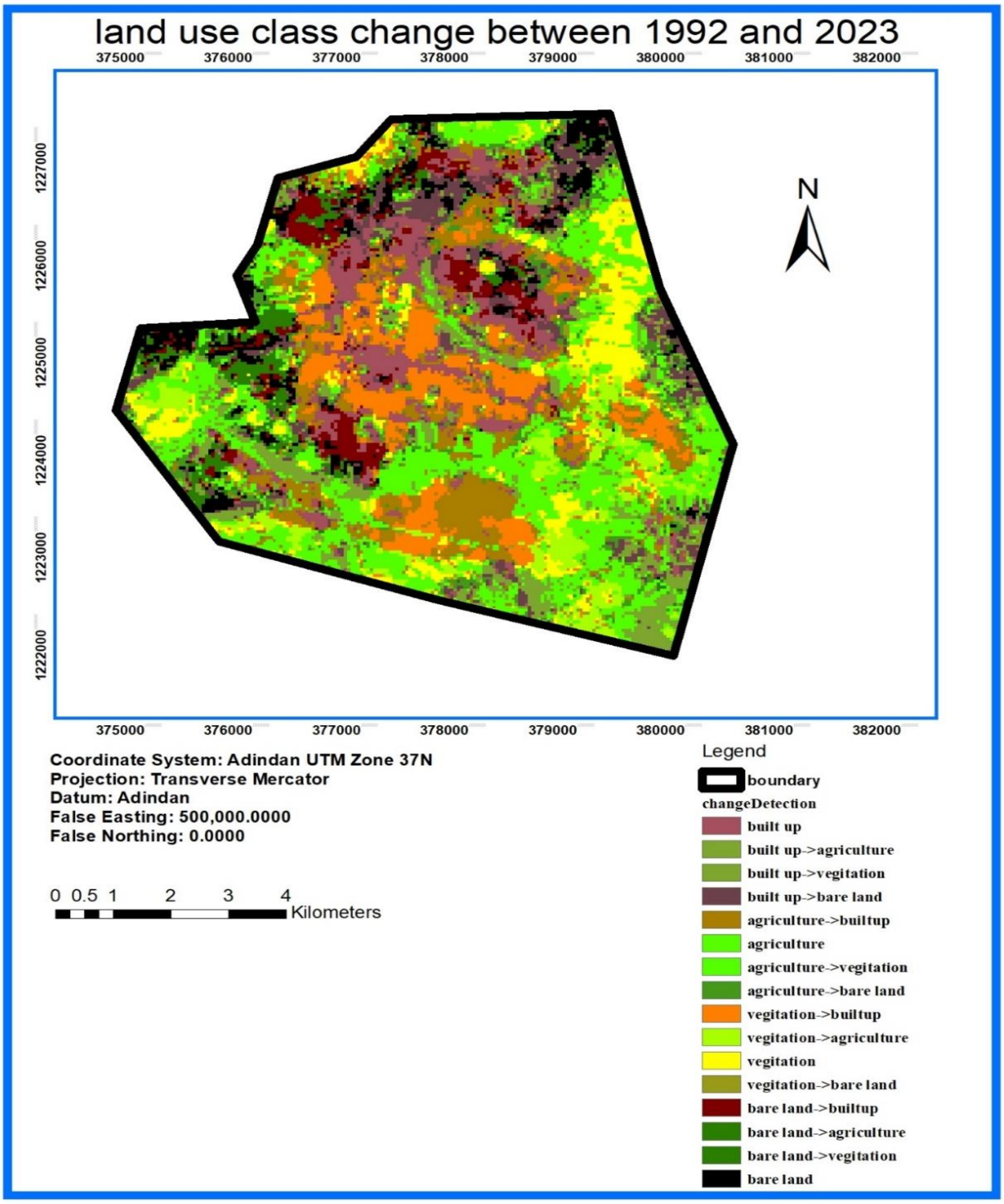

Figure 4.1.1 land use class change between 1992 and 2023

Source land sat image classification ArcGIS pro

4.1.2.2 LULC Class Conversion to Built-up Area

The LULC conversion to build up area as table 4.3and figure 4.3 revealed that agricultural land converted into 206 ha of built up between the time periods of 1992 to 2023, this result shown that the conversion of agricultural land to build up area is extremely increased. The vegetation converted into 143 ha of built up between the time periods of 1992 to 2023. This indicates vegetation to build up conversion is increased time to time. Bare land to built-up converted into 140 ha, between the time periods of 1992 to 2023 .it is less converted relatively from others the remaining 240 ha of built-up remains unchanged

Table 4.7 Conversion of Land Use/Land Cover (LULC) Classes to Built-Up Area in Hectares

Land use/land cover	1992-2023	
	Area(ha)	Percent (%)
agriculture to built-up area	236.01	31.71
bare land to built-up area	102.19	13.73
vegetation to built-up area	201.15	27.02
Built-up to built-up area	204.91	27.54
Total	744.31	100

Source land sat image change detection by ArcGIS pro

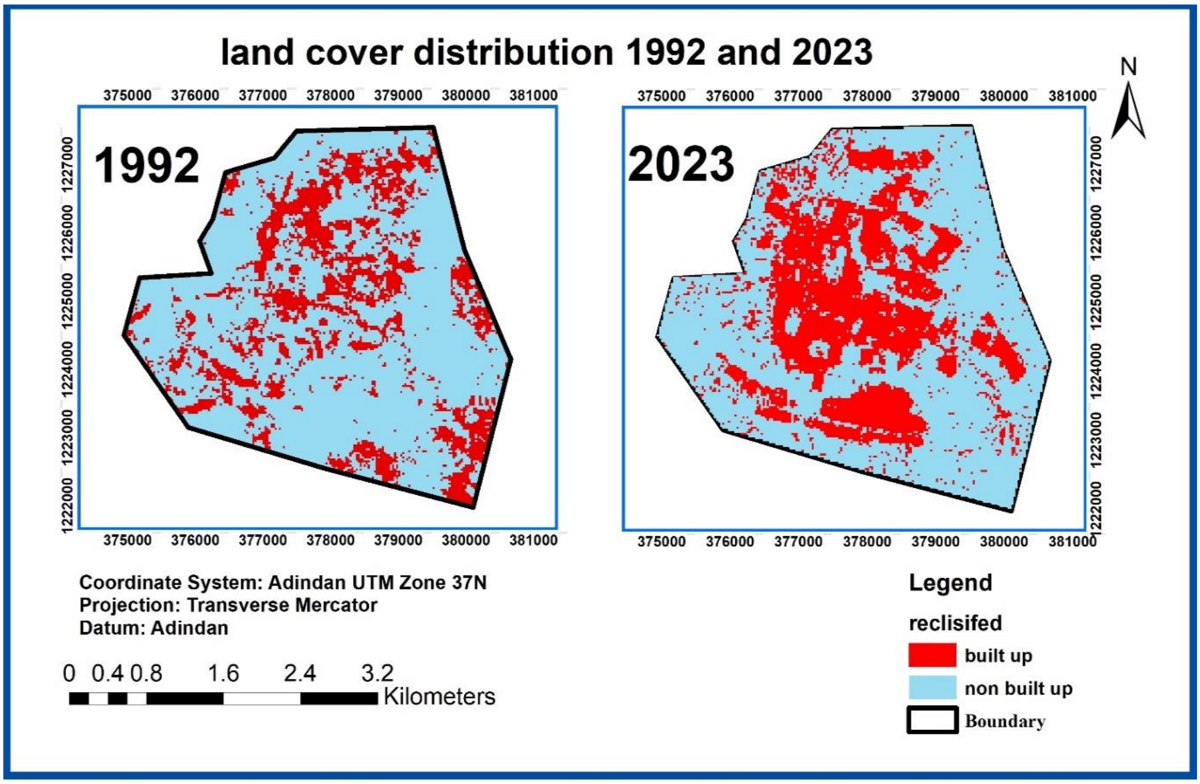

Figure 4.2 reclisifed image 1992-2023

Source land sat image classification ArcGIS pro

The reclassified land cover of Motta town the agricultural extent and loss is also shown in the map bellow as it can be shown the agricultural land is lost in 2023 as compared to 1992

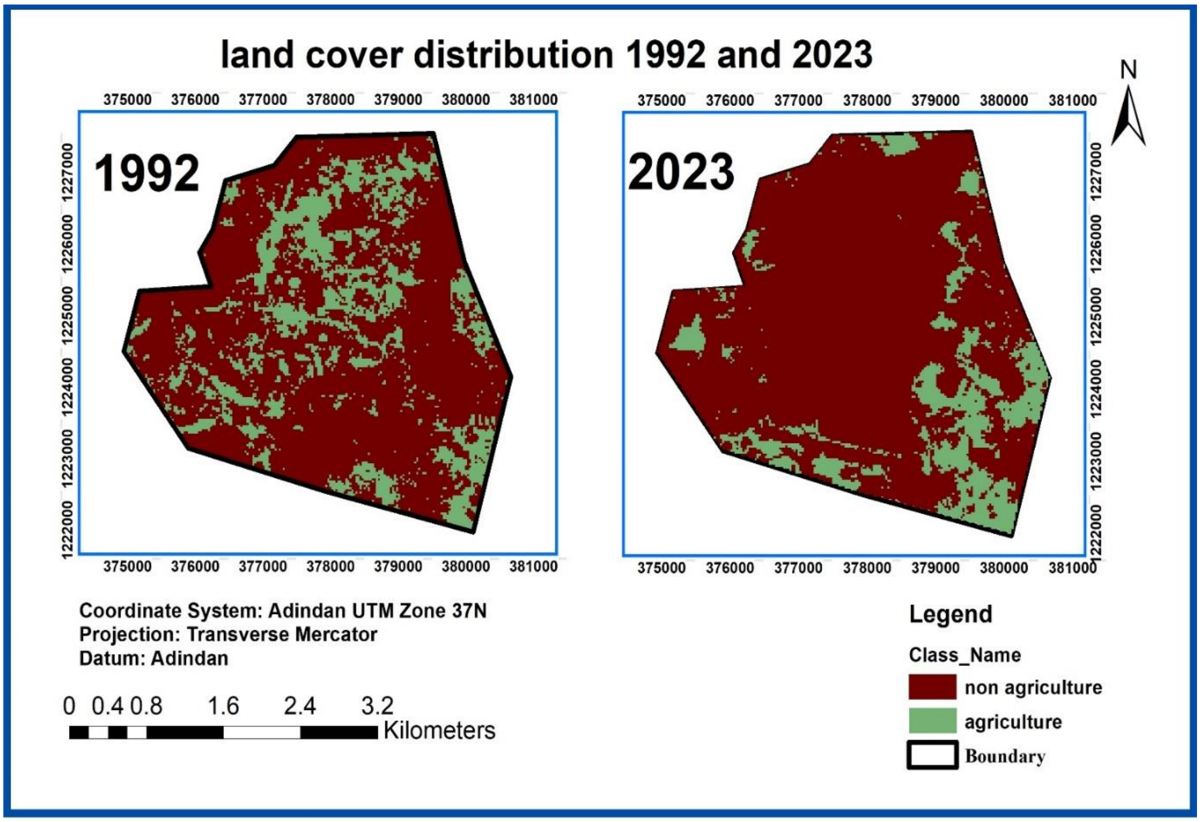

Figure 4.3 reclassified nonagricultural and agricultural

Source land sat image classification ArcGIS pro

4.1.2.3 Conversion from Agricultural to others

As it can be shown in the table below 306 ha is changed into bare land 206 ha changed into built-up and 109ha changed into vegetation the remaining 171 unchanged this shows that the towns horizontal growth significantly affects the agricultural land

Table 4.8 conversation from agriculture to others

Class changed	Year between 1992-2023
	Area in (ha)
agriculture - agriculture	171
agriculture - bare land	306
agriculture - built up	206
agriculture - vegetation	109

Source land sat image classification ArcGIS pro

4.1.3 Accuracy Assessment of SVM Classification Algorithm

By selecting the same number of samples for classification done by ArcGIS pro an accuracy assessment was done and the result is shown below

4.1.3.1 Confusion Matrix for Land cover Map of 1992

The percentage of correctly classified pixels in each class (category) divided by the total number of pixels in the reference data that were assigned to that category (column total are classified) is known as the producer's accuracy

Producer’s accuracy of agricultural land 90.4%, built up area 93.2%, vegetation 90.1% and bare land 91.2% and user’s accuracy agricultural land 91.4%, built up area 93.2%, vegetation 90.1% and bare land 89.7%. The overall accuracies in the study period 1992 is 91.2%. As shown in the result the highest user’s and producer’s accuracies is shown in built up area and the lowest users and producer’s accuracy is shown in bare land and vegetation. The lowest values of class accuracies were misclassified due to spectral property similarities among other land cover classes. The result is shown in table 4.7

Table 4.9confusion matrix for land cover 1992

<table>
<tr><td>Classified data</td><td>Built up land</td><td>Agriculture</td><td>Vegetation</td><td>Bare land</td><td>Total</td><td>User accuracy (100%)</td></tr>
<tr><td>Built up</td><td>69</td><td>2</td><td>2</td><td>1</td><td>74</td><td>93.2</td></tr>
<tr><td>Agriculture</td><td>3</td><td>85</td><td>3</td><td>2</td><td>93</td><td>91.4</td></tr>
<tr><td>Vegetation</td><td>1</td><td>4</td><td>64</td><td>2</td><td>71</td><td>90.1</td></tr>
<tr><td>Bare land</td><td>1</td><td>3</td><td>2</td><td>52</td><td>58</td><td>89.7</td></tr>
<tr><td>Total</td><td>74</td><td>94</td><td>71</td><td>57</td><td>296</td><td></td></tr>
<tr><td rowspan="3"></td><td>93.2</td><td>90.4</td><td>90.1</td><td>91.2</td><td rowspan="3" colspan="2"></td></tr>
<tr><td colspan="4">Producer accuracy (100%)</td></tr>
<tr><td colspan="2">Over all accuracy</td><td colspan="2">91.2</td></tr>
</table>

Source accuracy assessment randomly generated points using ArcGIS pro

4.1.3.2 Confusion, Matrix for Land Cover Map of 2023

Producer's accuracy of agricultural land 93.1%, built up area 93.7%, vegetation 88.2% and bare land 93.0% whereas user's accuracy of agricultural land 94.4%, built up area 94.7%, vegetation 93.8% and bare land 93.3%. The overall accuracies in the study period 2023 was 94.1%. The highest user's and producer's accuracies is built up areas and the lowest users and spectral producer's accuracies were vegetation land and agricultural land. The lowest values of class accuracies were misclassified due to property similarities among other land cover classes the result is shown in table 4.10

Table 4.10 Confusion matrix for land cover 2023

Classified data	Built up land	Agriculture	Vegetation	Bare land	Total	User accuracy (100%)
Built up	90	1	3	1	95	94.7
Agriculture	1	67	2	1	71	94.4
Vegetation	1	1	61	2	65	93.8
Bare land	1	3	2	84	90	93.3
Total	93	72	68	88	321	
	93.7	93.1	88.2	93.0		
	Producer accuracy (100%)					
	Over all accuracy		94.1			

Source accuracy assessment ground truth points using ArcGIS pro

4.1.3.3Overall Accuracy

Overall accuracy is computed by dividing the total number of correctly classified pixels (i.e., the sum of the elements along the major diagonal) by the total number of reference pixels. It shows overall results of the tabular error matrix it is computed by dividing the total number of correctly classified pixels (i.e., the sum of the elements along the major diagonal) `22 by the total number of reference pixels. It shows overall results of the tabular error matrix. Therefore the overall accuracy for the year 1992 and 2023 is 91.2 and 94.1respectively

4.1.4 Land use Land Cover Classification using Support vector machine Algorism

In this section SVM classifier is discussed with same method of supervised image classification

Table 4.11 land use land cover distribution between 1992 and 2023

Class name	1992		2023	
	Area(ha)	Percent (%)	Area(ha)	Percent (%)
Built up area	323	15.17	607	28.52
Vegetation	471	22.12	720	33.82
Bare land	391	18.37	292	13.71
Agricultural land	944	44.34	510	23.95
Total	2129	100	2129	2129

Source land sat image classification from 1992 to 2023

As it is shown in the table 4.9 the built-up area is 1.17% in 1992 and 28.52% in 2023 showing a slight increase in area and vegetation, bare land and agricultural land are 33.82%, 13.71% and 23.95% of the total area respectively the maximum land cover in1992 is agriculture and the minimum is built up, vegetation and bare land are the maximum and the minimum land covers in 2023 respectively

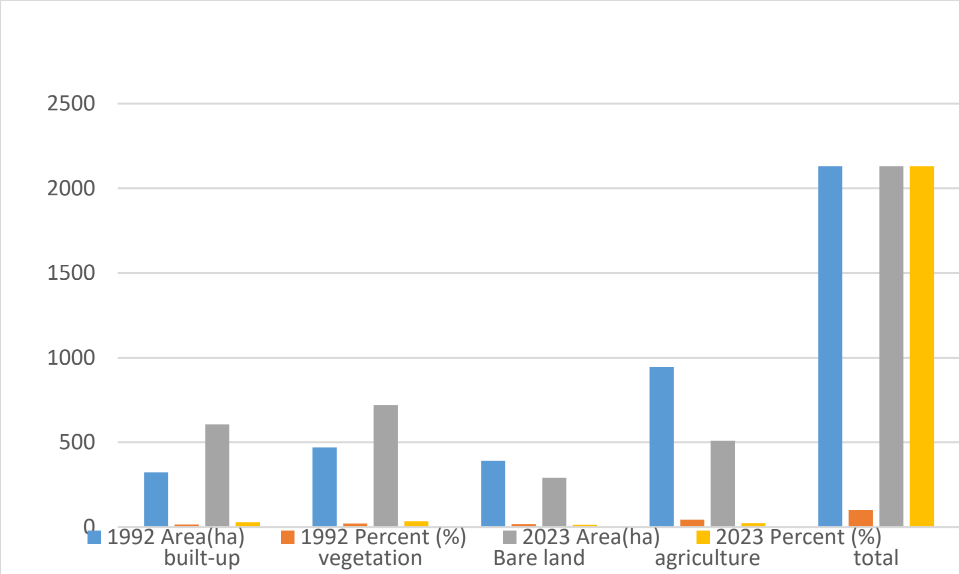

Figure 4.4 land cover distribution graph

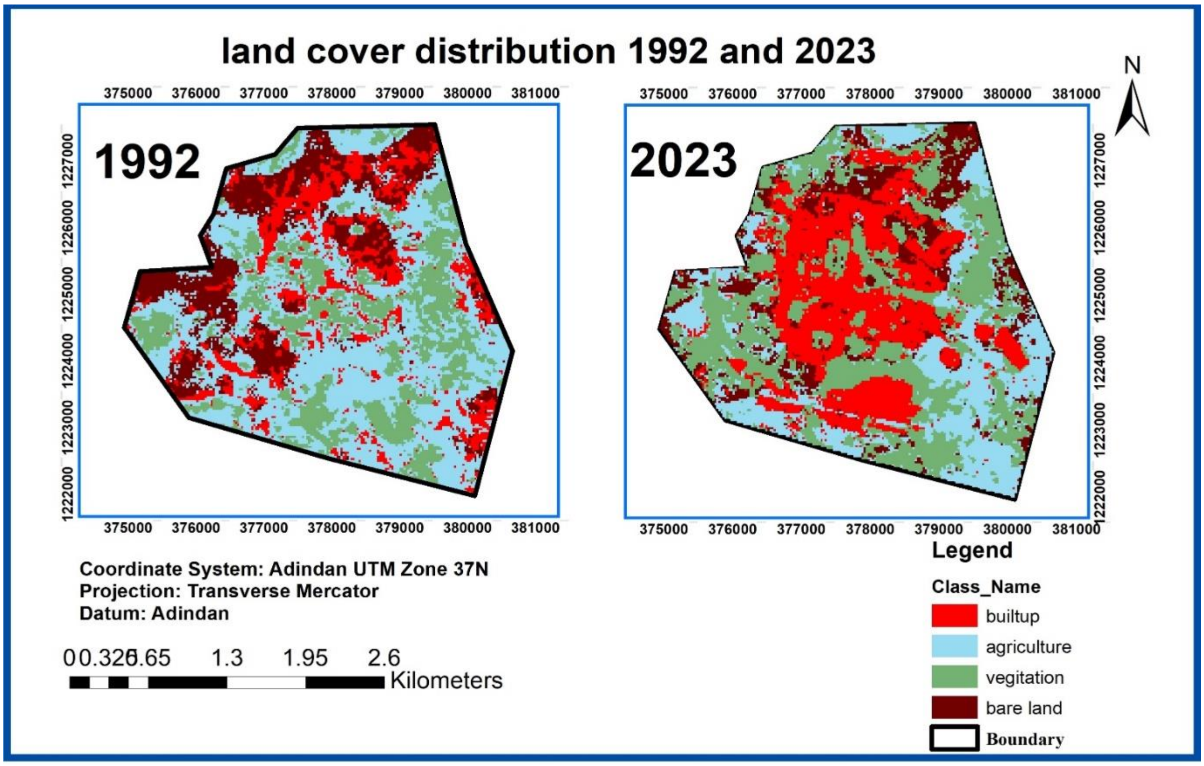

Figure 4.5 land cover distribution

4.1.4.1 Change Detection Analysis

As shown in the table 4.10 below The area of built up from 1992 to 2023 shows dramatic increase of 87.62 % which is 283ha and vegetation also relatively maximum increases by 52.86%which is 249ha whereas the land cover of agricultural land show a decrease of 45.97% which is 434ha and bare land shows a decrease by 25.32 % which is 99ha

Table 4.12 change in hectare and percentage of changes

Class name	1992	2023	Change (1992-2023)	
	Area(ha)	Area(ha)	Area(ha)	%
Built up area	323	607	+283	+87.62
Vegetation	471	720	+249	+52.86
Agricultural land	944	510	-434	-45.97
bare land	391	292	-99	-25.32
Total	2129	2129		

Note the negative sign in the table means decrease in area while the positive sign means increase in area

As shown in table 4.13 the yellow coloured cells in the transition matric indicates the land use class that are unchanged from 1992 to 2023, 179 (ha),52(ha) ,264(ha) ,153(ha),built up , vegetation ,agriculture and bare land areas respectively remains unchanged. Built up areas changed into 60(ha), 55(ha).242(ha), vegetation .agriculture and bare land respectively since the study primary concern is of agricultural land 182(ha), 108(ha), 223(ha) of it is converted into built up, vegetation, and bare land respectively

Table 4.13 Land use/Land cover transition matrix (ha) from 1992to 2023

2023						
1992	Class name	Built up	Vegetation	Agriculture	Bare land	Grand total
	Built up area	103.468	93.4127	**35.18693**	**90.4508**	322.51843
	vegetation	**154.1332**	**161.2713**	136.2226	**15.00528**	466.63238
	Agricultural	231.3784	**340.4861**	**285.4852**	**74.00555**	931.35525
	bare land	102.3327	**119.5355**	**53.16505**	116.3021	391.33535
	Grand total	591.3123	714.7056	510.05978	295.76373	2111.84141
	Total change	+268.79387	+248.07322	-421.29547	-95.57162	

Source Landsat image 1992 -2023

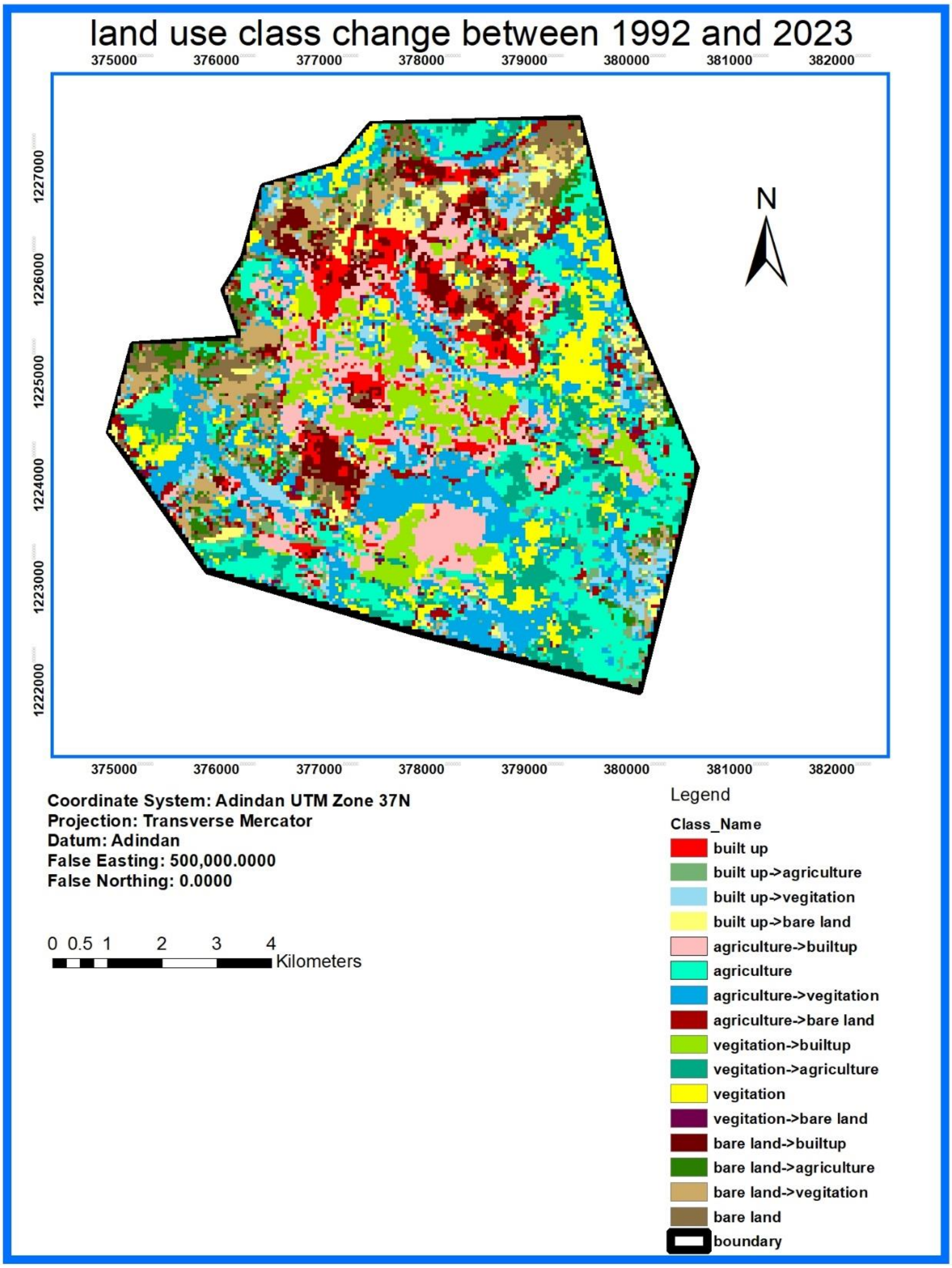

Figure 4.5.1 change detection

Source land sat image classification

Table 4.14: Dynamics of Land Use/Land Cover Classes, Rates and Trends for the Periods of 1992 and 2023

Class name	1992	2023	Change (1992-2023)		
	Area(ha)	Area(ha)	Area(ha)	Area%	Annual rate Of change in(ha)
Built up area	323	607	+283	+87.62	+9.13
Vegetation	471	720	+249	+52.86	+8.03
Agricultural land	944	510	-434	-45.97	-14
bare land	391	292	-99	-25.32	-3.19
Total	2129	2129			

As table 4.14shows agricultural land shows a maximum decrease of 14(ha) from 1992 to 2023 annually whereas built up areas show a maximum increase of 9.13(ha)

4.1.4.2 Conversion of Land Use/Land Cover (LULC) Classes to Built-Up Area (hectares)

By using ArcGIS pro the study tried to analyses the changes occurred during the period of 1992 to 2023 shows that the area of agricultural change into built up area is the maximum which is 231.39ha (39.13%) whereas bare land show a minimum change into built up area which is 102.33ha (17.30%)

Table 4.15 Conversion of Land Use/Land Cover (LULC) Classes to Built-Up Area (hectares)

Change in class	Change(1992-2023)	
	Area(ha)	Area (%)
Built up to Built-up	103.47	17.51
Agriculture to built-up	231.39	39.13
Bare land to built	102.33	17.30
Vegetation to built-up	154.13	26.06
Total	591.32	100

Source Landsat image 1992 to 2023

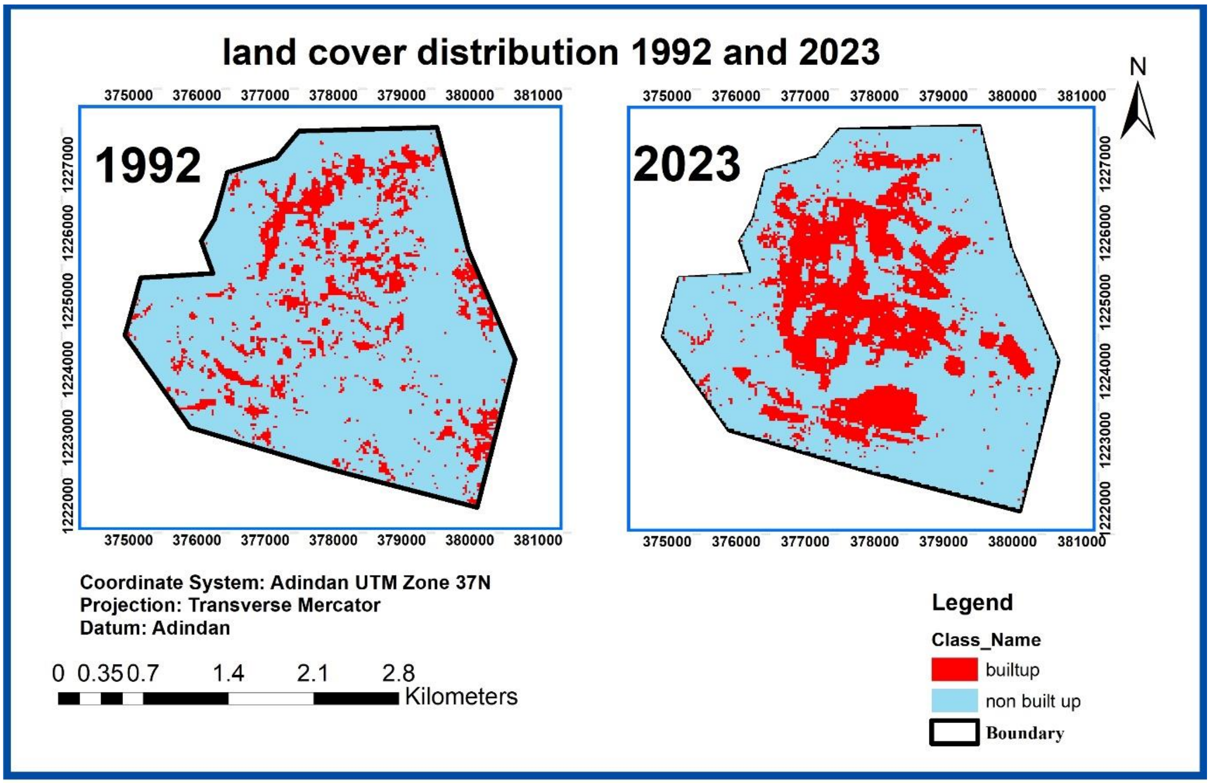

Figure 4.6 Reclassified image of built up and non-built up image

Source land sat image classification ArcGIS pro

Table 4.15 shows that 74.00555(ha), 231.3784(ha), 340.4861(ha) area is changed into bare land, built-up, and vegetation respectively from 1992 to 2023

Table 4.16 Conversion of Land Use/Land Cover (LULC) Classes to Agricultural Land Area (hectares)

Class changed	Area (ha)	Area (%)
Agricultural to agricultural	285.4852	30.65
Agricultural to bare land	74.00555	7.94
Agricultural to built-up	231.3784	24.84
Agricultural to vegetation	340.4861	36.56
Total	931.35525	100

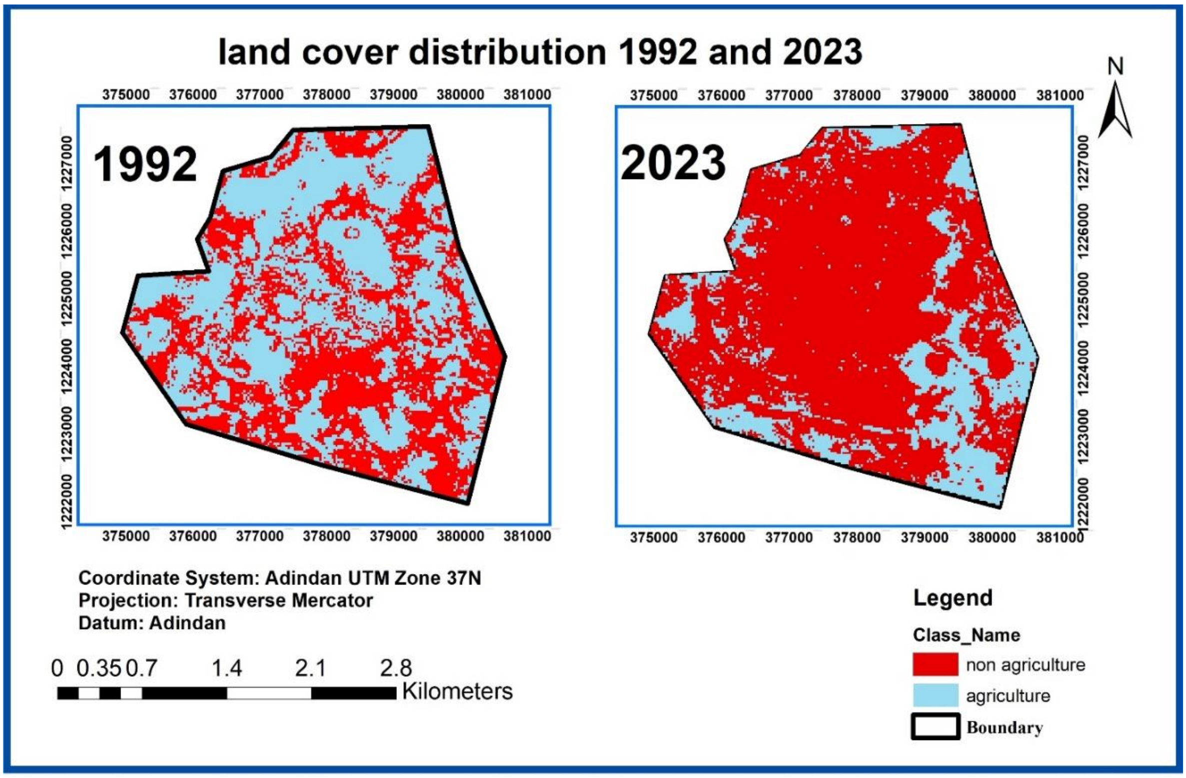

Figure 4.7 Reclassification of agricultural areas

Source land sat image classification ArcGIS pro

4.2 Unsupervised Land use Land cover Classification

4.2.1 Accuracy Assessment of Unsupervised Classification

By selecting the same number of samples for classification done by supervised classification by ArcGIS pro an accuracy assessment was done and the result is shown below

4.2.1.1 Confusion Matrix for Land cover Map of 1992

The percentage of correctly classified pixels in each class (category) divided by the total number of pixels in the reference data that were assigned to that category (column total are classified) is known as the producer's accuracy

Producer’s accuracy of agricultural land 85.7%, built up area 84.3%, vegetation 81.9% and bare land 77.8% and user’s accuracy agricultural land 83.9%, built up area 79.7%, vegetation

83.1% and bare land 84.5%. The overall accuracies in the study period 1992 was 82.8%. As shown this result the highest user's and producer's accuracies is bare land and agricultural area s and the lowest user's and producer's accuracy were built up and bare land. The lowest values of class accuracies were misclassified due to spectral property similarities among other land cover classes. The result is shown in table 4.17

Table 4.17 confusion matrix for land cover 1992

Classified data	Built up land	Agriculture	Vegetation	Bare land	Total	User accuracy (100%)
Built up area	59	5	7	3	74	79.7
Agricultural land	5	78	3	7	93	83.9
Vegetation	3	5	59	4	71	83.1
Bare land	3	3	3	62	58	84.5
Total	70	91	72	63	296	
	84.3	85.7	81.9	77.8		
	Producer accuracy (100%)					
	Over all accuracy		82.8			

Source accuracy assessment randomly generated points using ArcGIS pro

4.3.3.2 Confusion Matrix for Land Cover Map of 2023

Producer's accuracy of agricultural land 82.2%, built up area 90.2%, vegetation 81.8% and bare land 85.6% whereas user's accuracy of agricultural land 84.5%, built up area 87.4%, vegetation 83.1% and bare land 85.6%. The overall accuracies in the study period 2023 was 85.4%. The highest user's and producer's accuracies is built up area and the lowest users and spectral producer's accuracies is vegetation land. The lowest values of class accuracies were misclassified due to property similarities among other land cover classes

Table 4.18 confusion matrix for land cover 2023

Classified data	Built up land	Agriculture	Vegetation	Bare land	Total	User accuracy (100%)
Built up area	83	5	4	3	95	87.4
Agricultural land	3	60	1	7	71	84.5
Vegetation	2	6	54	3	65	83.1
Bare land	4	2	7	77	90	85.6
Total	95	72	68	86	321	
	90.2	98.2	81.8	85.6		
	Producer accuracy (100%)					
	Over all accuracy		85.4			

Source accuracy assessment ground truth points using ArcGIS pro

4.2.1.2Overall Accuracy

Overall accuracy is computed by dividing the total number of correctly classified pixels (i.e., the sum of the elements along the major diagonal) by the total number of reference pixels. It shows overall results of the tabular error matrix it is computed by dividing the total number of correctly classified pixels (i.e., the sum of the elements along the major diagonal) `22 by the total number of reference pixels. It shows overall results of the tabular error matrix.

4.2.1.3 Land use Land Cover Classification Using pixel Based Unsupervised classification

As it is shown in the figure built up area is increased from 506(ha) to 910(ha) and agricultural land decrease from 695(ha) to 346(ha), since 1992 to 2023 and vegetation shows an increase from 465(ha) to 506(ha), bare land decrease from 460(ha) to 367(ha) since 1992 to 2023

Table 4.19 Distribution of Land Use/Land Cover Classes from 1992 to 2023

Class name	1992		2023	
	Area(ha)	Percent (%)	Area(ha)	Percent (%)
Built up area	509	23.90	910	42.74
Vegetation	465	21.84	506	23.77
Bare land	460	21.60	367	17.24
Agricultural land	695	32.64	346	16.25
Total	2129	100	2129	100

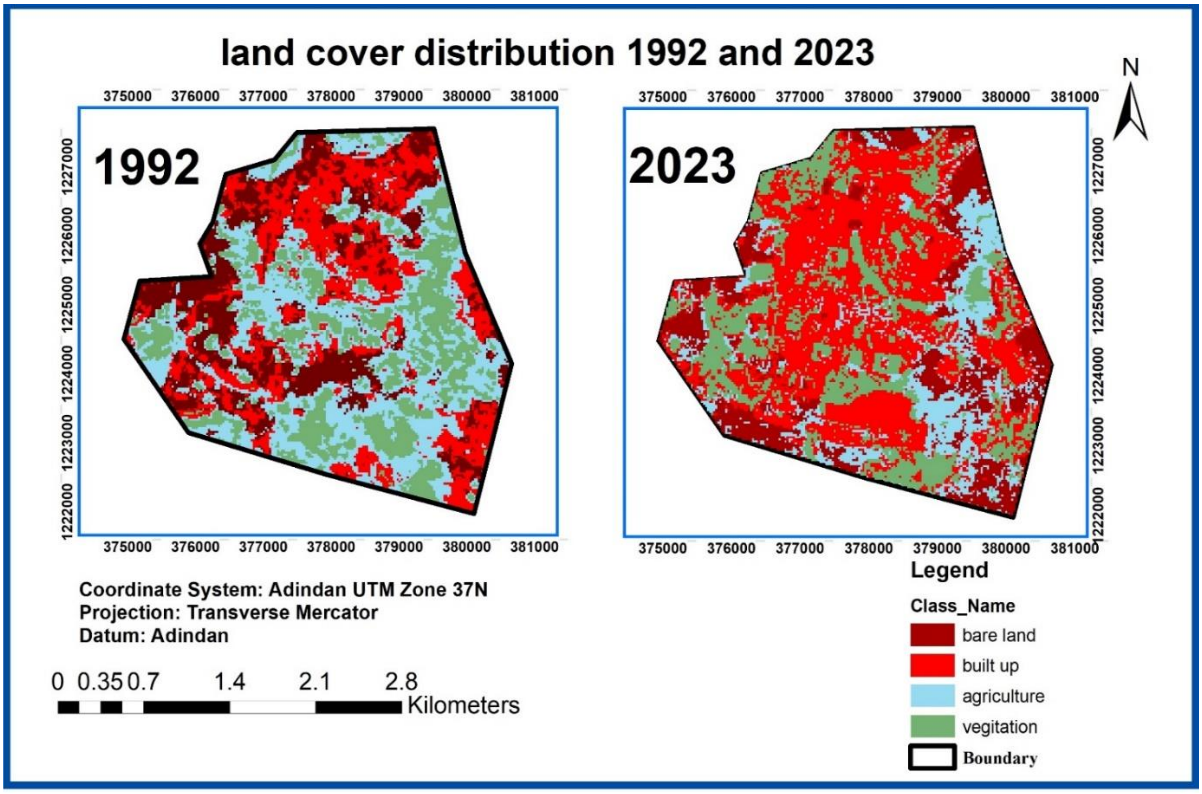

Figure 4.8 land use land cover distribution unsupervised clasification

Source land sat image classification ArcGIS pro

4.2.2 Change Detection Analysis

As shown in the table below since 1992 to 2020, built up area shows a maximum increase of 401(ha) which 78.78% increase of the total area and agricultural land has shown a maximum decrease of area of 349(ha) which is 50.21 % of the total area which shows that the loss of agricultural land

Table 4.20 Change detection unsupervised classification

Class name	1992	2023	Change (1992-2023)	
	Area(ha)	Area(ha)	Area(ha)	%
Built up area	509	910	+401	+78.78
Vegetation	465	506	+41	+8.82
Agricultural land	695	346	-349	-50.21
bare land	460	367	-93	-20.21
Total	2129	2129		

Source land sat 1992 and 2023 image

Note the negative sign in the table shows an increase in land cover whereas the negative sign shows decrease in land use

Table4.21 Land use/Land cover transition matrix (ha) from 1992to 2023

2023						
1992	Class name	Built up	Vegetation	Agriculture	Bare land	Grand total
	Built up	270.030	139.845	**29.422**	**67.094**	506.391
	Vegetation	**165.853**	**78.049**	**130.880**	**86.690**	461.472
	Agriculture	270.251	**163.568**	**126.581**	**128.100**	688.5
	bare land	197.344	**122.988**	**57.429**	81.560	459.321
	Grand total	903.478	504.45	344.312	363.444	2115.684
	Total change	+397.087	+42.978	-344.188	-95.877	

Source land sat 1992 to 2023

As table 4.21 shows the yellow coloured cells in the transition matric indicates the land use class that are unchanged from 1992 to 2023, 270.030 (ha),78.049(ha) ,126.581(ha) ,81.560(ha),built up , vegetation ,agriculture and bare land areas respectively remains unchanged. Built up areas changed into 60(ha), 55(ha).242(ha), vegetation .agriculture and bare land respectively since the study primary concern is of agricultural land 163.568(ha), 126.581(ha), 128.100(ha) of it is converted into built up, vegetation, and bare land respectively

4.2.2.1: Conversion of Land Use/Land Cover (LULC) Classes to Built-Up Area (hectares)

By using ArcGIS pro using pixel based unsupervised classification the study tried to analyses the changes occurred during the period of 1992 to 2023 shows that the area of agricultural change into built up area is the maximum which is 230.25ha (26.66%) whereas vegetation show a minimum change into built up area which is 165.85ha (19.21%)

Table 4.22 Conversion of Land Use/Land Cover (LULC) Classes to Built-Up Area (hectares)

Change in class	Change(1992-2023)	
	Area(ha)	Area (%)
Built up to Built-up	270.03	31.28
Agriculture to built-up	230.25	26.66
Bare land to built	197.34	22.85
Vegetation to built-up	165.85	19.21
Total	863.47	

Source Landsat image 1992 to 2023

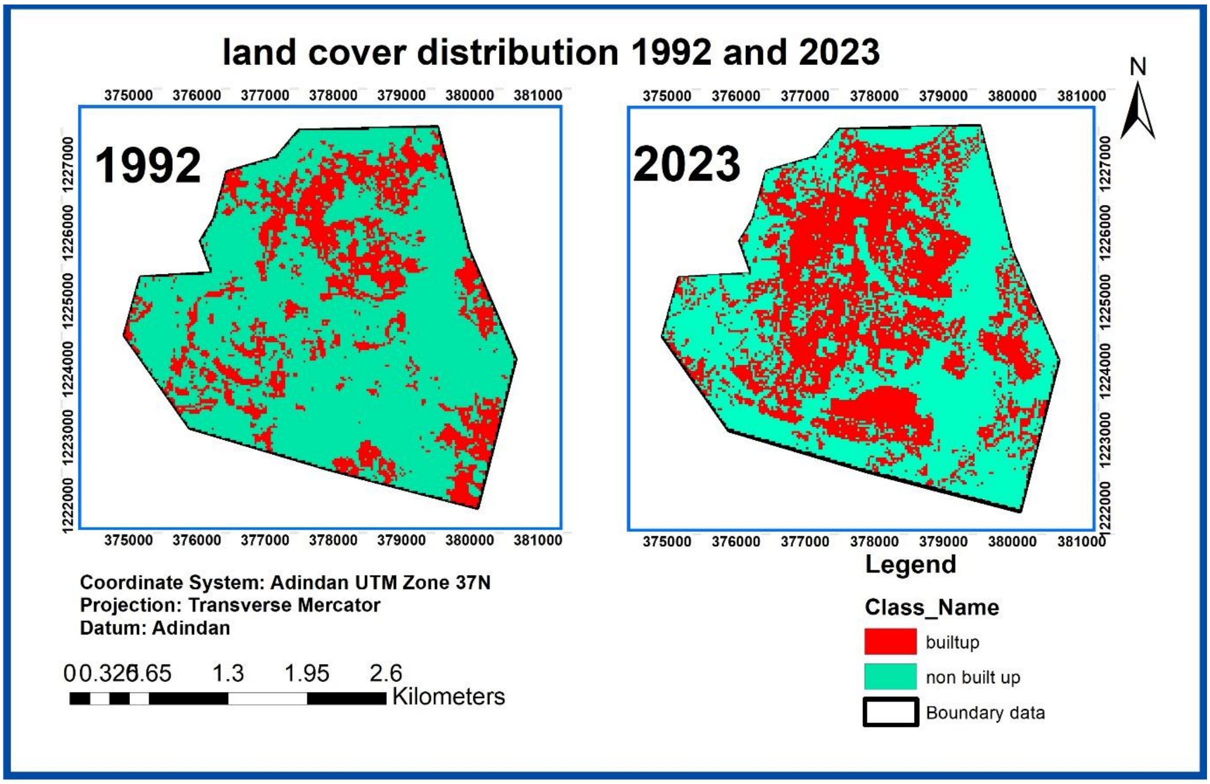

Figure 4.9 Reclassified image of built up and non-built up image

Source land sat image 1992 and 2023

Table 4.23 Conversion of Land Use/Land Cover (LULC) Classes to Agricultural Land Area (hectares)

Class changed	Area (ha)	Area (%)
Agricultural to agricultural	126.581068	18.38
Agricultural to bare land	128.10011	18.60
Agricultural to built-up	270.249947	39.25
Agricultural to vegetation	163.568427	23.77
Total	688.499552	100

The figure below 4.10 shows the land cover distribution after reclassified into agricultural and non-agricultural land

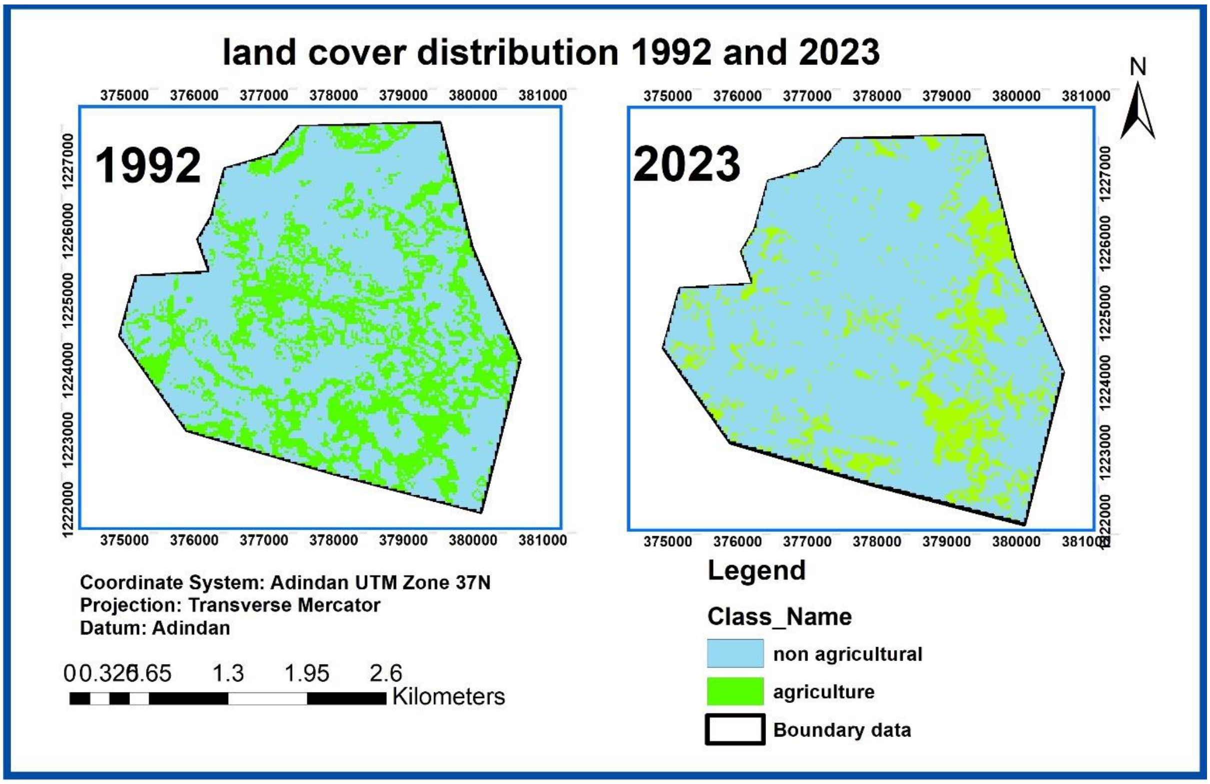

Figure 4.10 Reclassification of agricultural areas

Source land sat image 1992 and 2023

4.3 Comparison of Result between LULC between Supervised and Unsupervised Classification using Arc GIs pro

As i shown in the table below supervised classification methods include SVM , MLC in order to Compare the results of classification the study using unsupervised method and as it is shown in the table below based on the classification done by SVM 323(ha),471(ha),391(ha),944(ha), is covered by built-up, vegetation bare land ,and agriculture in 1992 respectively and 607(ha),720(ha),292(ha),510(ha) is covered by built-up, vegetation, bare land and agriculture in 2023 respectively . Based on the classification done by MLC 534(Ha), 502(ha), 302(ha), 791(Ha) is covered by built-up, vegetation, bare land and agriculture respectively in 1992 and 757(ha) 653(ha), 367(ha), 352 (ha) is covered by built-up, vegetation, bare land and agriculture respectively in 2023 based on the result of unsupervised classification 509(ha),465(ha),460(ha),695(ha) is covered by built-up, vegetation, bare land and agriculture respectively in 1992 and 910(ha),506(ha),367(ha),346(ha)) is covered by built-up, vegetation, bare land and agriculture respectively in 2023

Table 4.24comparison of LULC supervised and unsupervised

Land use class	Supervised				Unsupervised	
	SVM		MLC			
	1992	2023	1992	2023	1992	2023
	Area(ha)	Area(ha)	Area(ha)	Area(ha)	Area(ha)	Area(ha)
Built up area	323	607	534	757	509	910
Vegetation	471	720	502	653	465	506
Bare land	391	292	302	367	460	367
Agricultural land	944	510	791	352	695	346
Total	2129	2129	2129	2129	2129	2129

The figure 4.14 shows classification map of supervised and unsupervised classifications of the year 1992

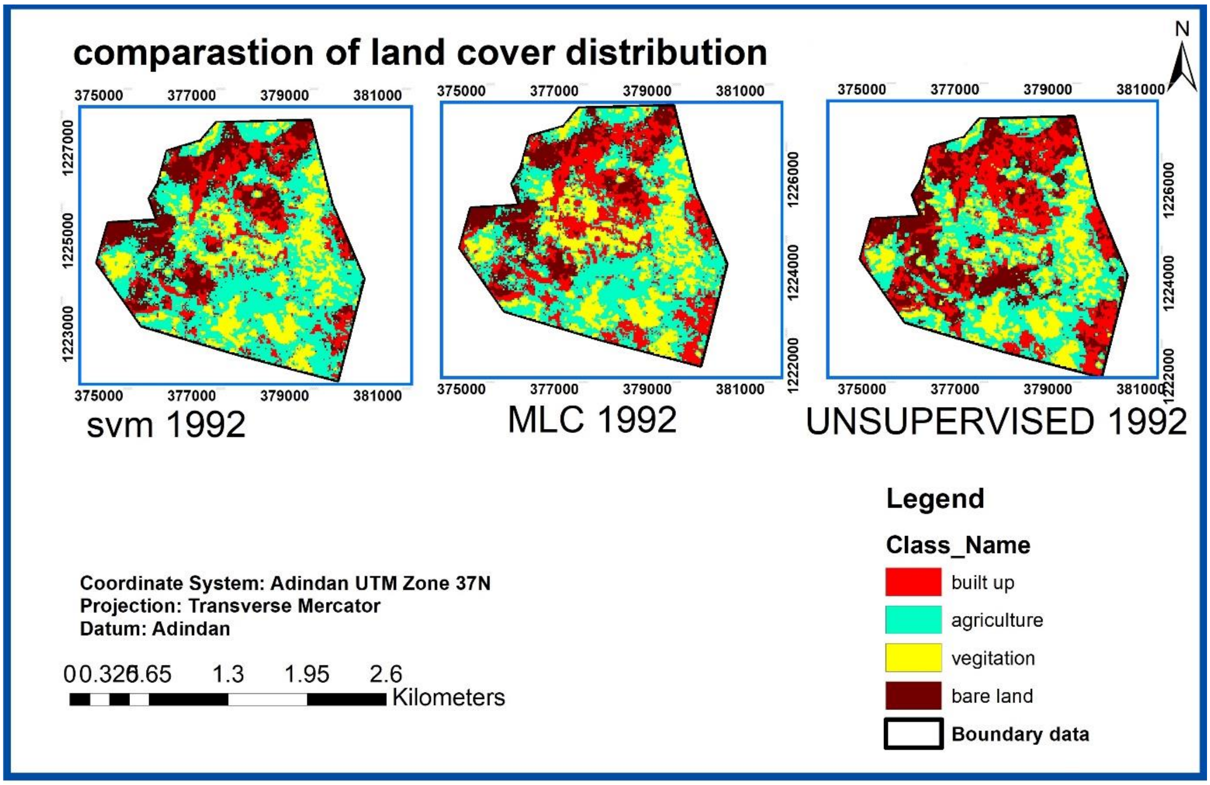

Figure 4.11 LULC supervised and unsupersiped 1992

Source land Sat image 1992 and 2023

Figure 4.12 shows a map of supervised and unsupervised classification of the year 2023

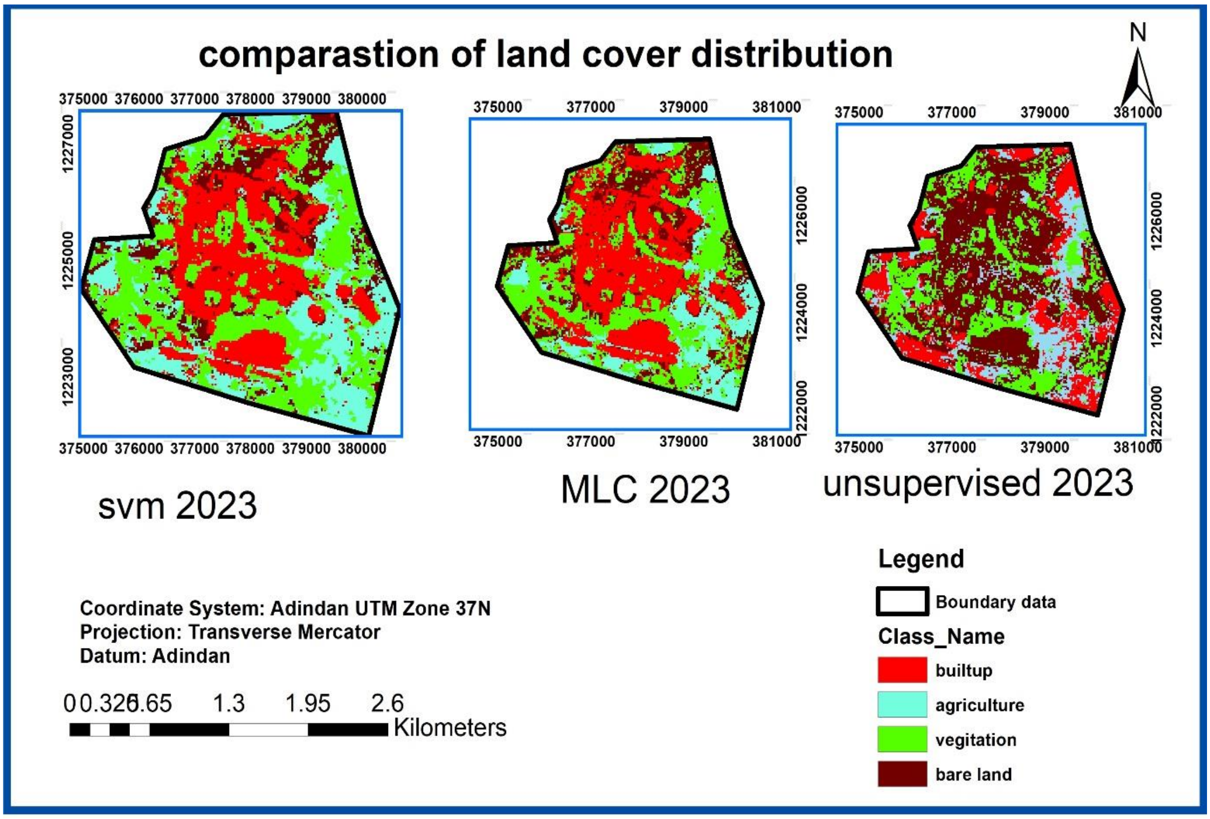

Figure 4.12 LULC supervised and unsupersiped 2023

Source land sat image 1992 and 2023

4.3.1 Comparison Accuracy Assessment results of Supervised and Unsupervised Classification

As shown in the table 4.25 below the user accuracy of different years of classification by supervised and unsupervised classification is summarized and accordingly the user and producer accuracy result are mentioned Generally the overall accuracy of supervised classification is 91.2%, and 86.1% for SVM and MLC respectively in the year 1992 and 94.1% and 86.6 % for SVM and MLC respectively for the year.

Table 4.25 a comparison of accuracy assessment

Accuracy result	Class	Supervised				Unsupervised	
		SVM		MLC			
		1992	2023	1992	2023	1992	2023
User accuracy	Built up area	93.2	94.7	83.8	89.5	79.7	87.4
	Agricultural land	91.4	94.4	88.2	88.7	83.9	84.5
	Vegetation	90.1	93.8	85.9	83.1	83.1	83.1
	Bare land	89.7	93.3	86.2	84.4	84.5	85.6
Producer accuracy	Built up	93.2	96.8	91.2	89.5	84.3	90.2
	Agriculture	90.4	93.1	87.2	82.9	85.7	82.2
	Vegetation	90.1	89.7	83.6	81.8	81.9	81.8
	Bare land	91.2	95.5	82.0	90.5	77.8	85.6
Over all accuracy		91.2	94.1	86.1	86.6	82.8	85.4

4.4 Urbanization Indices

4.4.1 Urbanization Intensity Index (UII)

Based on the classification SVM urban and non-urban areas are classified and that’s used for UII calculation

$$UII = (urban/T - non\text{-}urban/T) \times 100$$

Where T is the total area.

Table 4.26 UII of the 1992 to 2023

CLASS	1992	2023
	Area(ha)	Area(ha)
Urban areas	312	594
Non-urban areas	1817	1535
Total area	2129	2129
UII	−70.68	−44.20

Table shows the increase in the proportion of urbanized land in Motta Town from 1992 to 2023 the negative values indicate that non-urban areas were more dominant in both years. The less negative UII in 2023 compared to 1992 suggests an increase in urban areas over the period, reflecting urbanization.

4.4.2Normalized Difference Built-up Index (NDBI)

Since land sat 5 was used for the year 1992 NDBI= (Band 5-Band 4)/ (Band 5+Band 4)and

Land sat 8 was used for the year 2023 NDBI= (Band 6-Band 5)/ (Band 6+Band 5) the result is described in table 4.29

Table 4.27 NDBI range

Year	NDBI Range	Interpretation
1992	-0.57377 to0.370079	Significant non-urban features (vegetation, agricultural land s, bare land). Moderate urbanization present, but not highly dense.
2023	-0.282369 to0.271416	Presence of non-urban features possibly reduced dense non-urban areas. More uniform urbanization with fewer high-density built-up areas. Expansion of less dense urban development.

4.4.3 New built up index (NBI)

NBI is calculated for the year 1992 using landsat5 and land sat8 for the year 2023

Using formula NBI= Band 4− (Band 3+Band 2)/ Band 4+ (Band 3+Band 2) for 1992 and

NBI=) Band 5− (Band 4+Band 3)/ Band 5+ (Band 4+Band 3 for 2023 the result is discussed in tables 4.3

Table 4.28 NBI range

Year	NBI Range	Interpretation
1992	-0.390728 to 0.413793	- The range indicates a mix of non-urban and built-up areas. - Negative lower end (-0.390728) suggests non-urban features like vegetation, bare soil. - Positive upper end (0.413793) indicates areas with significant built-up structures and urban development. - A balanced landscape with both natural and developed areas.
2023	-0.359025 to 0.0788606	- The lower end (-0.359025) still indicates non-urban areas but less negative compared to 1992, suggesting some reduction in non-urban land. - Positive upper end (0.0788606) is significantly lower than 1992, indicating some urban development but at a lower intensity. - A mixed-use landscape with more urban spread but less concentrated development.

From table 4.24 the shift in NBI range from 1992 to 2023 indicates urban spread into previously non-urban areas. The lower end becoming less negative suggests a reduction in purely non-urban areas. The drop in the upper end value from 0.413793 in 1992 to 0.0788606 in 2023 suggests that while urban areas have spread, the intensity or concentration of development has decreased. This could reflect urban sprawl, where built-up areas are more spread out. The broader and lower upper end of the NBI range in 2023 indicates a more heterogeneous and mixed-use landscape, with a blend of urban and non-urban features.

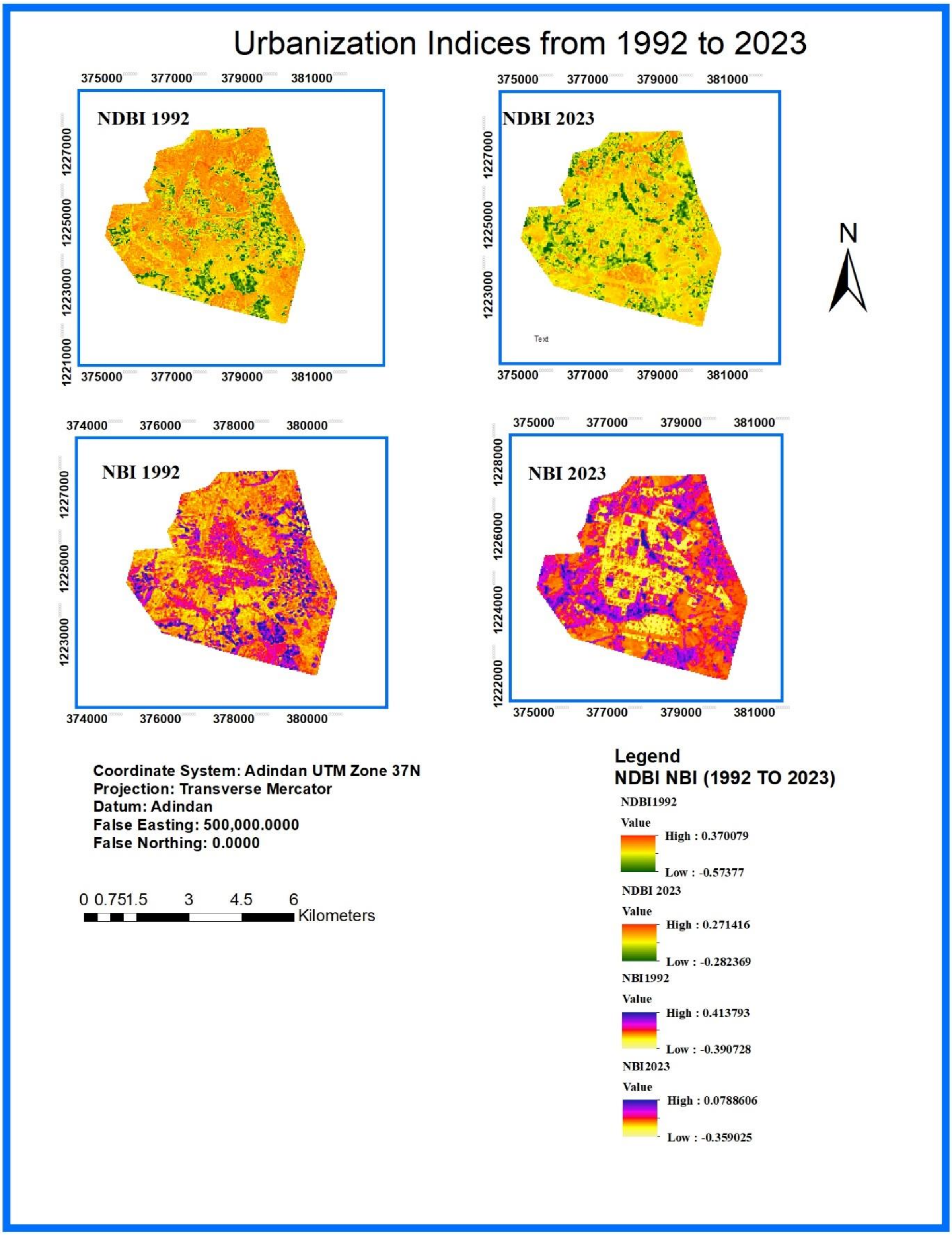

Figure 4.13 Urbanization indices

4.5 Assessment of Crop Production Losses

Based on supervised SVM classification 231.3784(ha) of land is converted from agricultural land to build up from 1992 to 2023 that means 7.47(ha) of land is converted into built up Annually which in turn contribute to the loss of crop production in Motta town pre urban areas table 4.28 overview of the average yield of each crop in tons per hectare, allowing for easy comparison between different crops in terms of their productivity. And table 4.25 shows calculated Annual Crop Production Losses due to Conversion to Built-up Areas.

Table 4.29average yield of crop production

Crop	Average Yield (tons/ha)
Teff	1.5
Wheat	2
Barley	1.5
Maize	3
Sorghum	1.5
Beans	1
Chickpeas	1
Potatoes	15

For the period from 1992 to 2023 assuming the total area converted to built-up areas over this period is 231.3784 hectares, we can divide this by the number of years (31 years) to get the annual conversion rate.

Annual Conversion Rate = Total Area Converted / Number of Years = 231.3784 hectares / 31 years ≈ 7.47 hectares/year

The study used this annual conversion rate to estimate the crop production loss per year for each crop.in table 4.26

Table 4.30 Annual Crop Production Losses due to Conversion to Built-up Areas

Crop	Area Converted per Year (ha**)**	Average Yield (tons/ha	Estimated Crop Production Loss per Year (tons
Teff	7.47	1.5	11.20
Wheat	7.47	2	14.94
Barley	7.47	1.5	11.20
Maize	7.47	3	22.41
Sorghum	7.47	1.5	11.20
Chickpeas	7.47	1	7.47
Beans	7.47	1	7.47
Potatoes	7.47	1.5	112.05

The table presents the estimated annual crop production losses (in tons) for Teff, Wheat, Barley, Maize, Sorghum, Chickpeas, Beans, and Potatoes due to agricultural land conversion to built-up areas in the Amhara Region. The estimated crop production loss per year for each crop is calculated by multiplying the annual area converted to built-up areas (in hectares) by the average yield of each crop (in tons per hectare). These estimates provide insights into the annual impact of urbanization on crop production in the region, highlighting the challenges faced by agriculture amidst urban expansion. It reveals the annual crop production losses for various crops in the Motta town due to agricultural land conversion to built-up areas. These losses signify the ongoing challenges posed by urbanization on agricultural sustainability and food security.

4.6 Discussion

The findings presented in Chapter Four reveal significant land use and land cover (LULC) changes in Motta town between 1992 and 2023, illustrating the profound impact of urbanization on agricultural lands.

The results indicate a substantial transformation in land use patterns over the study period. In 1992, agricultural land accounted for 44.4% of the total area, but by 2023, this had decreased to 24.0%. Conversely, built-up areas expanded from 15.2% in 1992 to 42.8% in 2023, highlighting the rapid urbanization driven by population growth and economic development. This trend is consistent with global patterns observed in rapidly developing regions (Redman & Jones, 2004; Cohen, 2006).

The conversion of agricultural land to urban areas has significant implications for local food security and agricultural productivity. For example, the study estimates that maize, with an average yield of 3 tons per hectare, experiences an estimated annual loss of 22.41 tons due to land conversion. This reduction in agricultural land directly impacts local food production, potentially leading to increased dependency on external food sources and higher food prices. Similar findings are reported in studies focusing on the global impact of urban expansion on agricultural land (Seto et al., 2011).

In addition to classification algorithms, urbanization indices such as Normalized Difference Built-up Index (NDBI), Built-up Index (NBI), and Urbanization Intensity Index (UII) were utilized to quantify and analyse urbanization trends in Motta town. NDBI measures the density and distribution of built-up areas, providing insights into urban expansion (Zha et al., 2003). NBI, on the other hand, focuses on the spatial extent of built-up areas, complementing NDBI by evaluating the intensity of urban development (Zhang et al., 2010). UII integrates multiple indicators, including population density and land use changes, to assess the overall urbanization intensity and its socio-economic implications (Imhoff et al., 2010).

These indices collectively contribute to a comprehensive understanding of how urbanization has reshaped the landscape of Motta town over time. They reveal not only the extent of built-up area expansion but also the intensity and socio-economic impacts of urban growth on agricultural lands and local communities.

The study employed both supervised (Support Vector Machine - SVM, Maximum Likelihood Classification - MLC) and unsupervised classifications to analyse LULC changes. SVM emerged as the preferred choice in this study due to its high accuracy in classifying land cover types, particularly in datasets with complex patterns and limited training data (Pal & Mather, 2005).

The high overall accuracy of SVM in this study, exceeding 85%, underscores its reliability in interpreting land cover changes due to urbanization. However, the study acknowledges limitations such as the quality of ground truth data and landscape complexity, which may have influenced the precision of change detection, as discussed in similar research (Lu & Weng, 2007).

Future studies could enhance accuracy by incorporating higher-resolution satellite imagery and enhancing ground truthing efforts. Additionally, further exploration of socio-economic drivers behind urban expansion, as suggested by Angel et al. (2011), could provide deeper insights into managing urban growth sustainably.

Chapter Five

Conclusion and Recommendations

This study was conducted to evaluate urbanization and its impact on agricultural land within the study area. The research focused on employing remote sensing and Geographic Information Systems (GIS) techniques to analyse urbanization and its effects on agricultural land, particularly by detecting changes in urban land use and land cover through Landsat satellite images. Landsat imagery from 1992 and 2023 was utilized to track urban landscape dynamics in the study area, with changes in Land Use/Land Cover (LULC) analysed using ArcGIS Pro through both supervised and unsupervised methods.

The study revealed a consistent decline in agricultural land and an increase in built-up areas. According to the supervised classification results using Support Vector Machine (SVM) techniques, agricultural land covered 44.34% of the study area in 1992 but decreased to 23.95% by 2023. Conversely, built-up areas grew from 15.17% to 28.52% of the total area. Additionally, Multi-Layer Classification (MLC) results showed that 25% of the land was built-up in 1992, rising to 36% in 2023. The unsupervised classification indicated an increase in built-up areas from 23.90% in 1992 to 42.74% in 2023, while agricultural land decreased from 32.64% to 16.25%.

Despite observing significant changes in LULC between 1992 and 2023, the SVM classification highlighted the highest rate of change in agricultural lands, which declined by 14 hectares annually, while built-up areas increased by 9.13 hectares per year. Since 1992, 24.4% of agricultural land has been converted into built-up areas. This increase in urbanization has primarily come at the expense of other land uses, posing a potential threat to sustainable development. Identifying and analysing sprawl patterns are crucial for effective land use planning and environmental management in urban areas.

The study effectively demonstrates the application of geoinformatics in analysing urban sprawl dynamics. The expansion of residential areas, in particular, threatens future natural resources, highlighting the urgent need for alternative solutions or more prudent utilization of land. Among the classification methods used, the SVM approach yielded the highest accuracy, with an overall accuracy of 91.2% for 1992 and 94.1% for 2023.

5.2 Recommendations

There is a pressing need to plan for balanced physical urban growth and population expansion in our cities and towns. This can only be achieved through a comprehensive understanding of urban growth dynamics, demographic pressures, available service levels, and the resources required for future urban development. Urban planning authorities and town planners must anticipate future growth and recognize the consequences of unbalanced urban expansion on public services and infrastructure. Utilizing a spatial database and information system is essential for managing urban development sustainably, ensuring that public services and infrastructure can adequately support future growth.

Satellite remote sensing, with its capabilities for repetitive and synoptic viewing and multispectral imaging, serves as a valuable tool for mapping and monitoring ecological changes in urban areas and surrounding land uses. Integrating remote sensing into urban planning processes can assist in monitoring developer activities and mitigating unplanned urban sprawl, which often leads to the loss of agricultural lands. Given the current rate of population dynamics, increases in land-use and land-cover changes are anticipated. Therefore, several management strategies are recommended prioritizing the renewal and infill development of existing buildings, rather than expanding new housing onto agricultural land, can help accommodate a growing population. Constructing condominium houses, a strategy already being implemented by the government, should continue as a viable solution for addressing housing needs. Additionally, Environmental Impact Assessments (EIA) and public participation in decision-making are crucial for assessing the impacts of urban development on surrounding ecosystems. To manage rapid population growth, it is important to create favourable conditions in rural areas to reduce migration to urban centres. Moreover, sustainable land use practices must be adopted to prevent the loss of agricultural land due to uncontrolled horizontal urban expansion. For improved accuracy, it is advisable to use high-resolution satellite images, such as those from QuickBird and Sentinel, to compare land-use and land-cover data within the same year, thereby yielding more reliable results and enhancing the accuracy of urban growth assessments.

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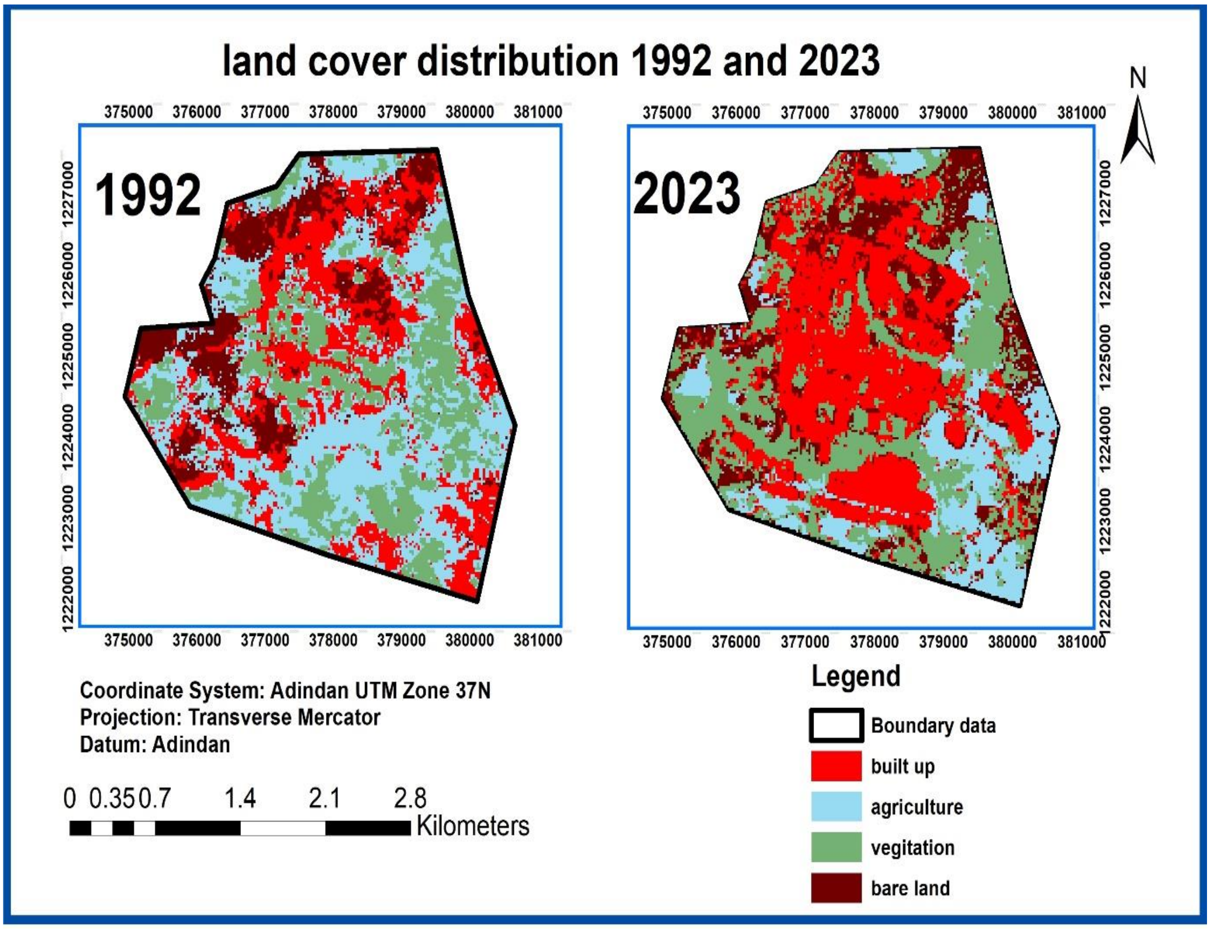
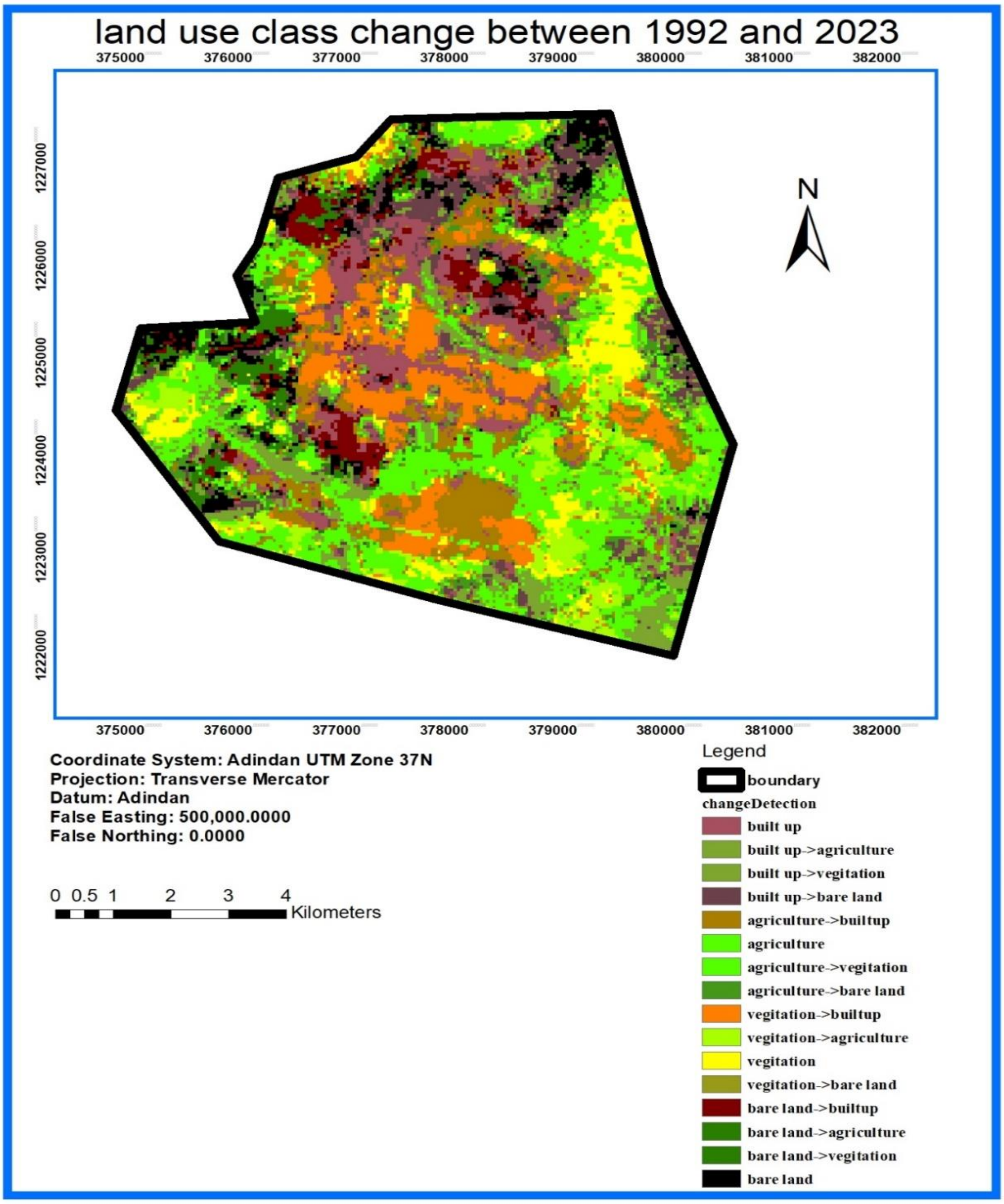
Appendices

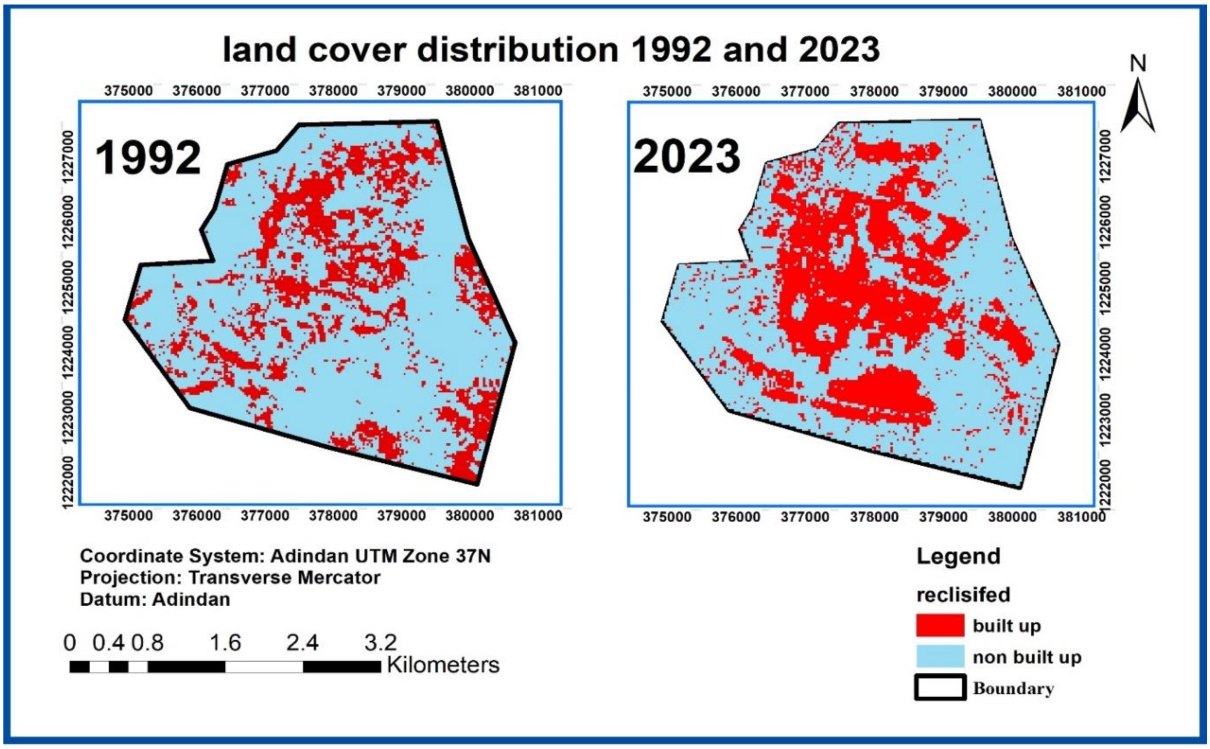
Appendix A: land use land cover distribution map of 1992 to the left and map 2023 to the right, prepared using ArcGIS pro software by supervised MLC classifier.



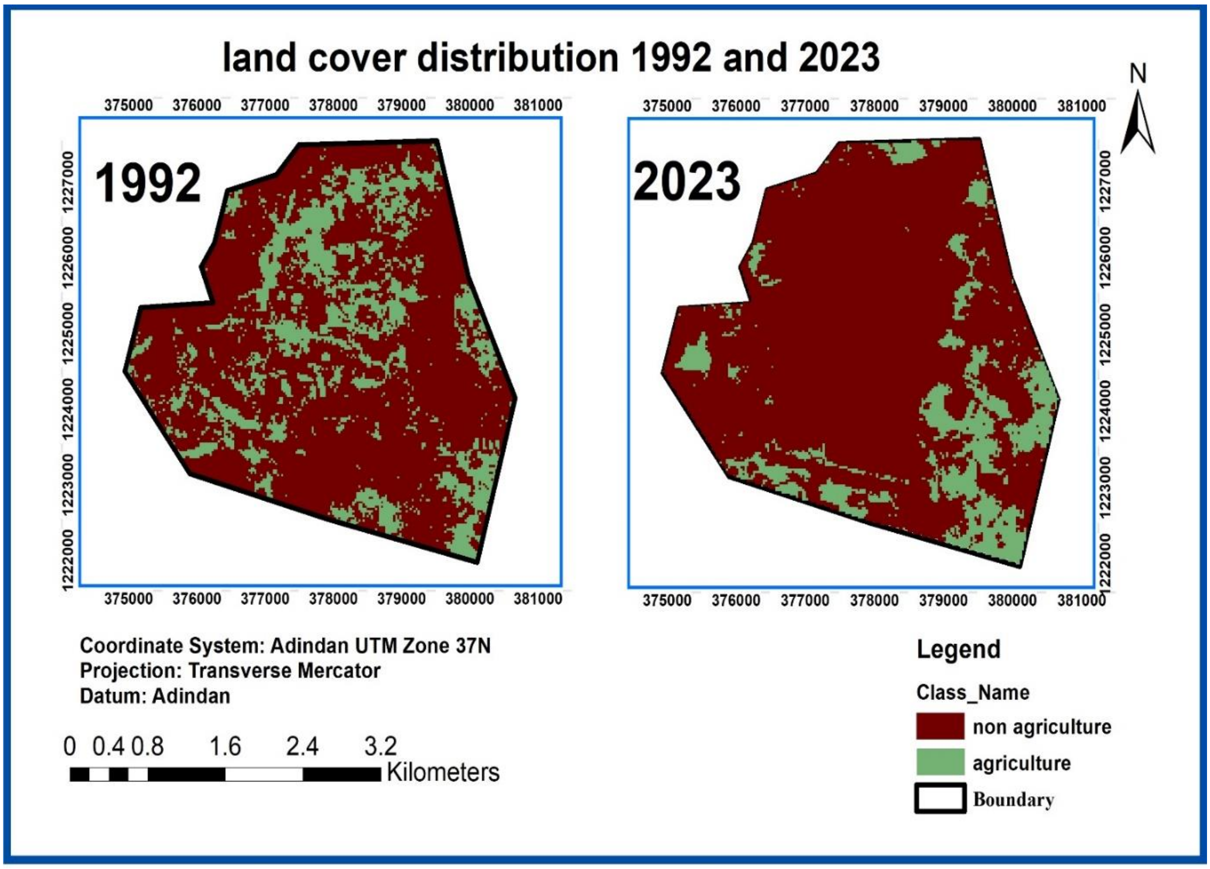
Appendix B: land use land cover change map since 1992 prepared using ArcGIS pro software by supervised MLC classifier



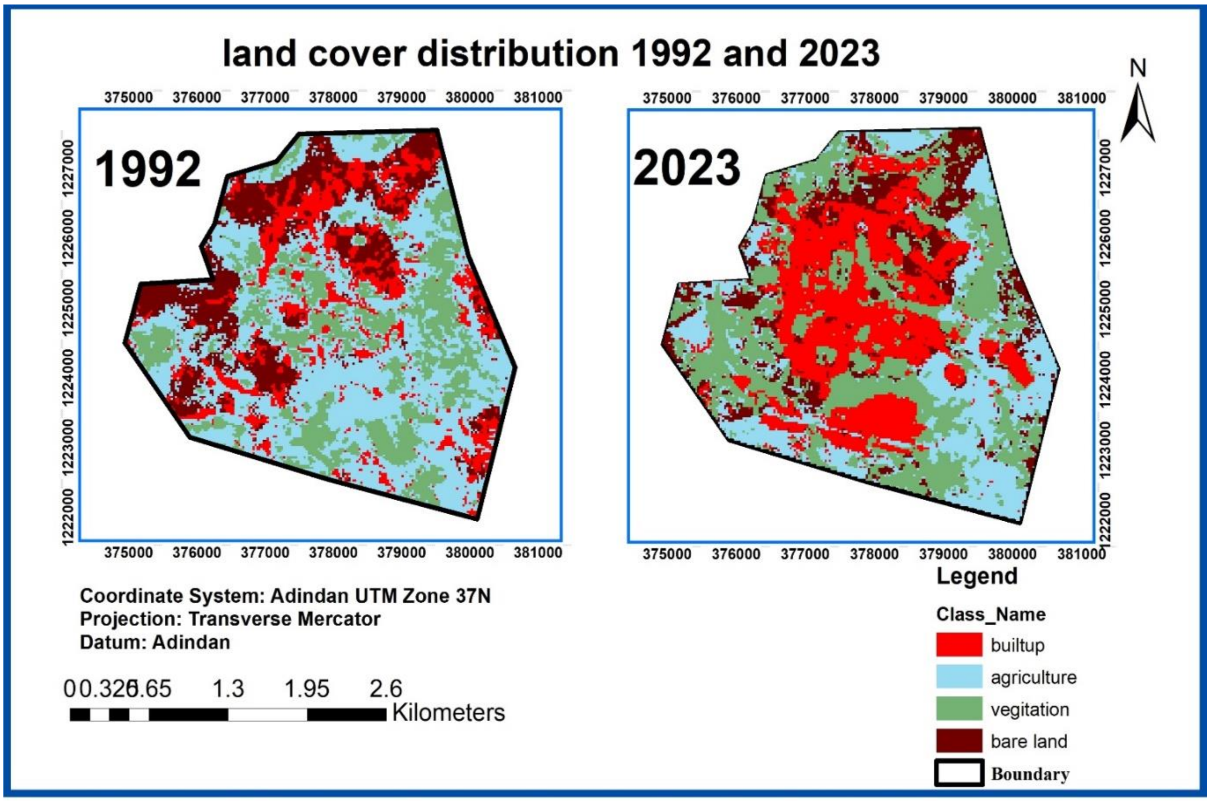
Appendix C: reclassified built and non-built up land use land cover distribution map of 1992 to the left and map 2023 to the right, prepared using ArcGIS pro software by supervised MLC classifier.



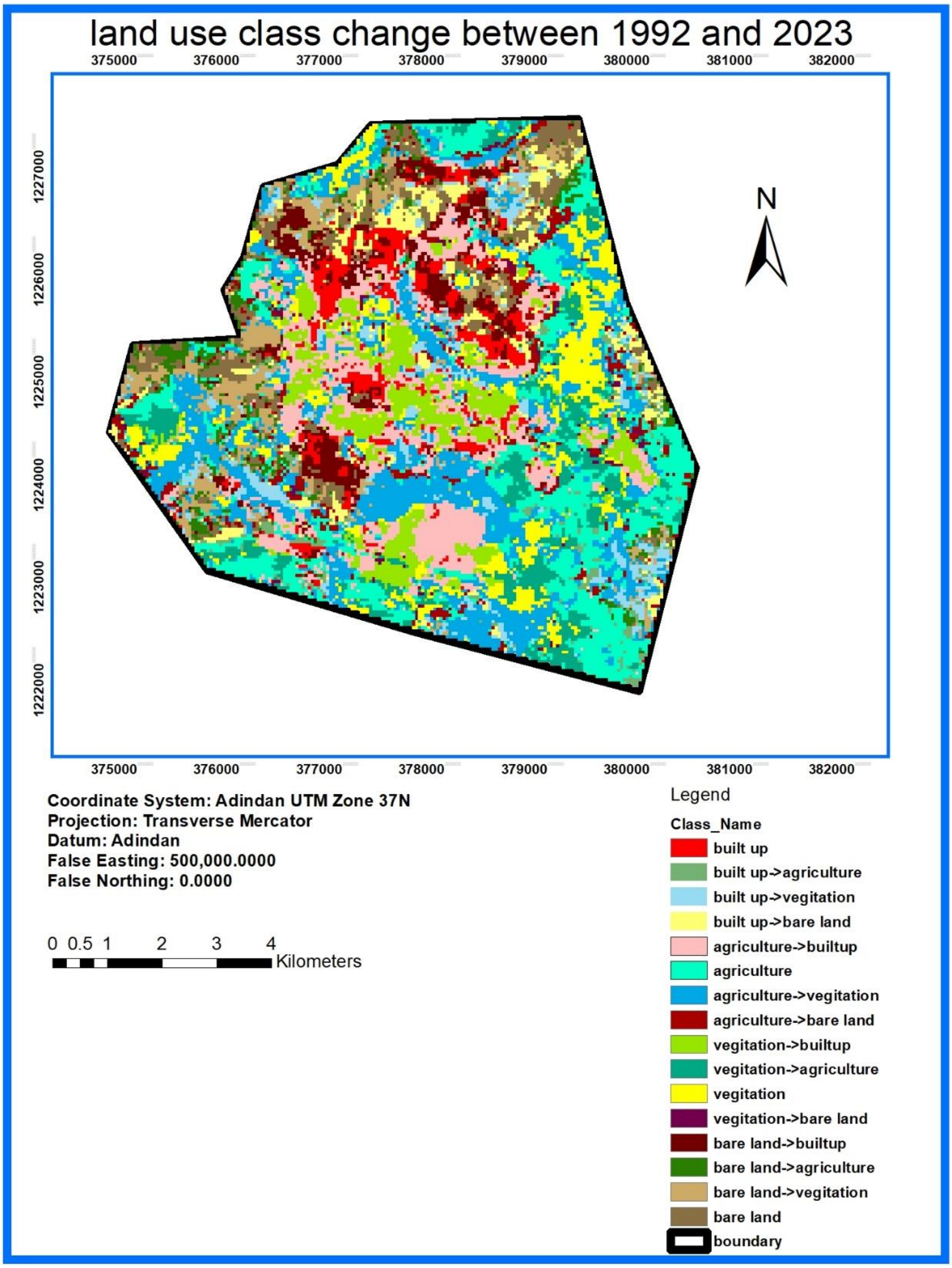
Appendix D: reclassified agriculture and non-agriculture land use land cover distribution map of 1992 to the left and map 2023 to the right, prepared using ArcGIS pro software by supervised MLC classifier.



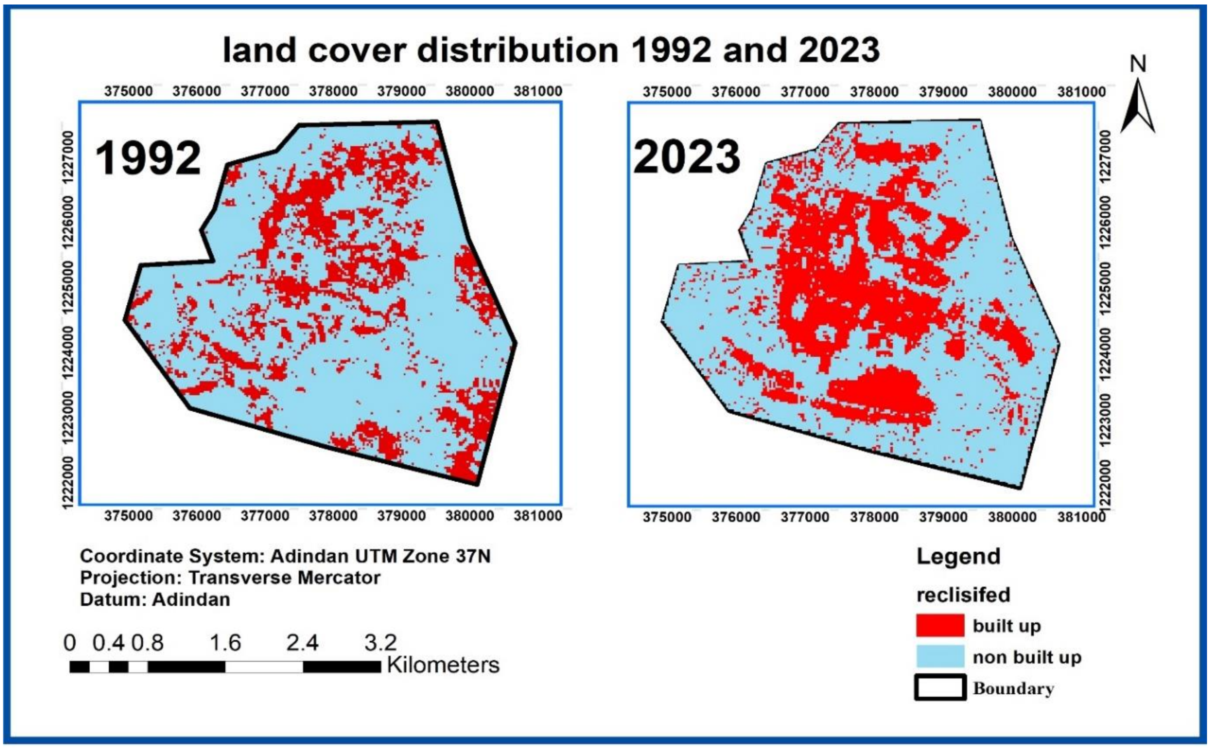
Appendix E: land use land cover distribution map of 1992 to the left and map 2023 to the right, prepared using ArcGIS pro software by supervised SVM classifier.



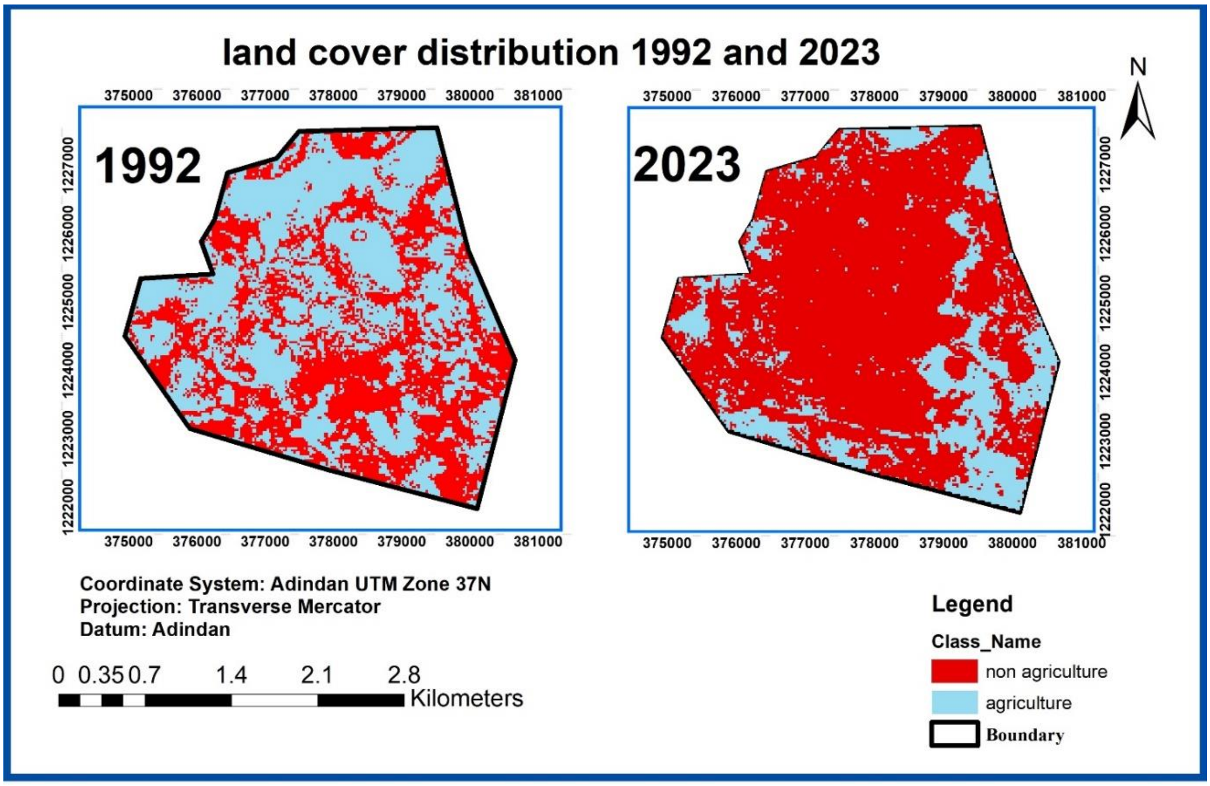
Appendix F: land use land cover change map since 1992 prepared using ArcGIS pro software by supervised SVM classifier



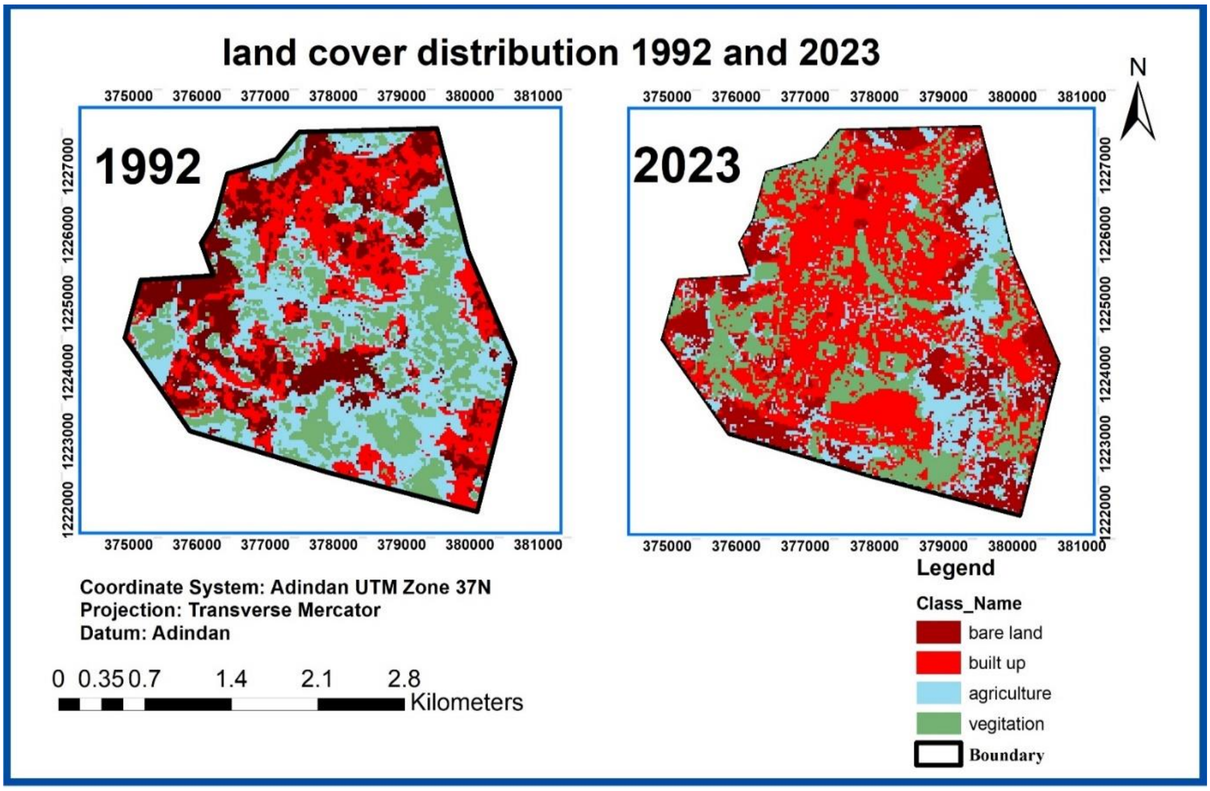
Appendix G: reclassified built and non-built up land use land cover distribution map of 1992 to the left and map 2023 to the right, prepared using ArcGIS pro software by supervised SVM classifier.



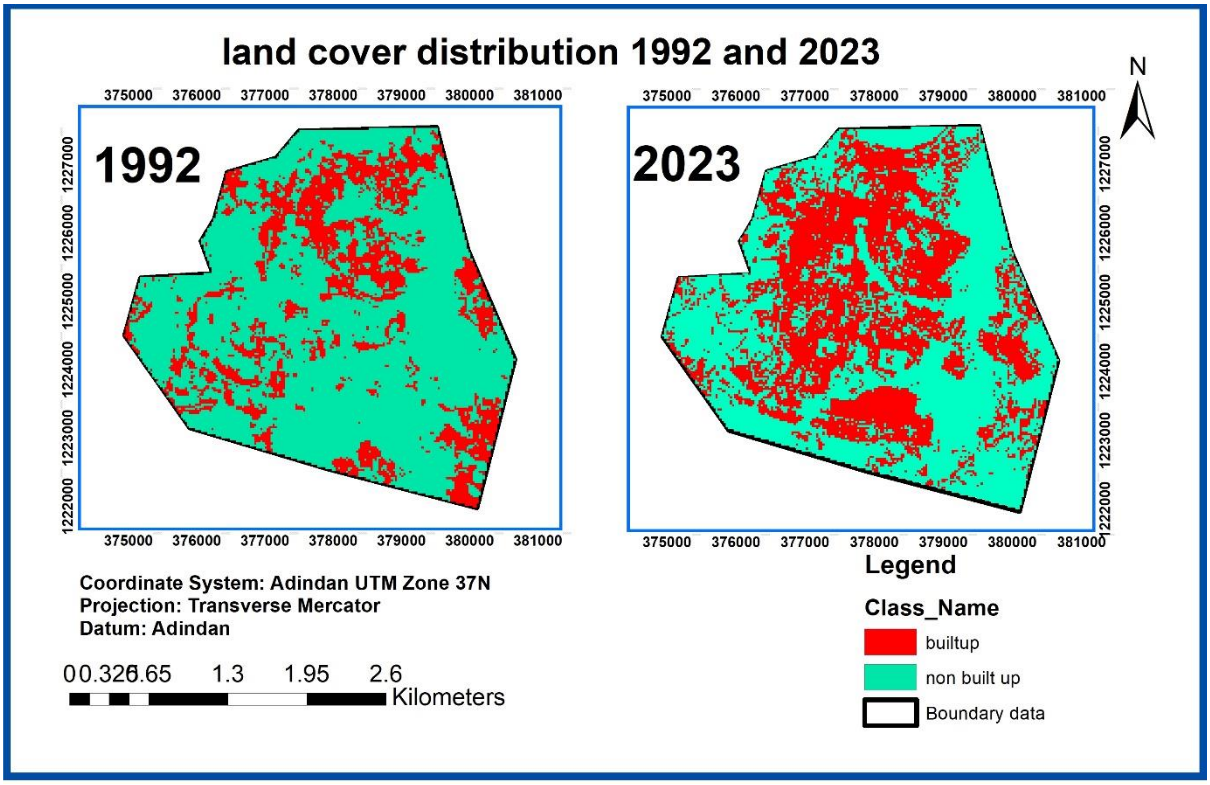
Appendix H: reclassified agriculture and non-agriculture land use land cover distribution map of 1992 to the left and map 2023 to the right, prepared using ArcGIS pro software by supervised SVM classifier



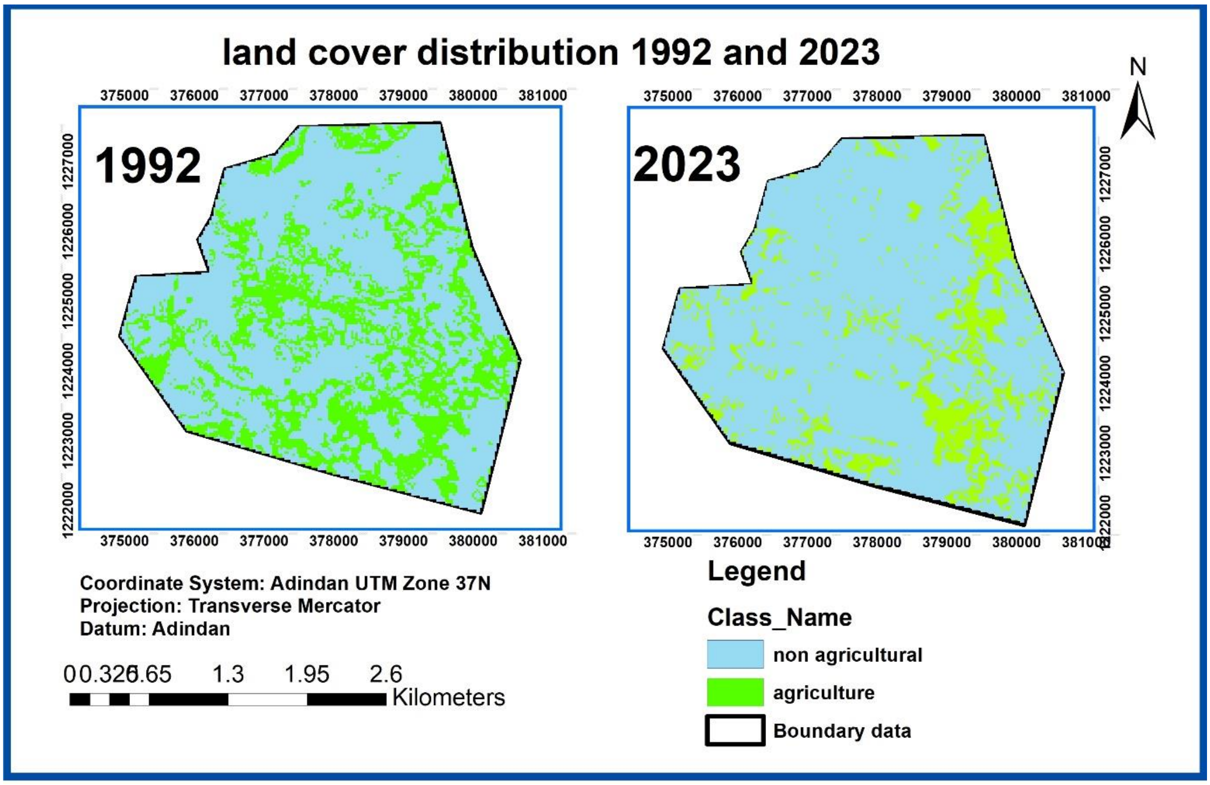
Appendix I: land use land cover distribution map of 1992 to the left and map 2023 to the right, prepared using ArcGIS pro software by unsupervised classification



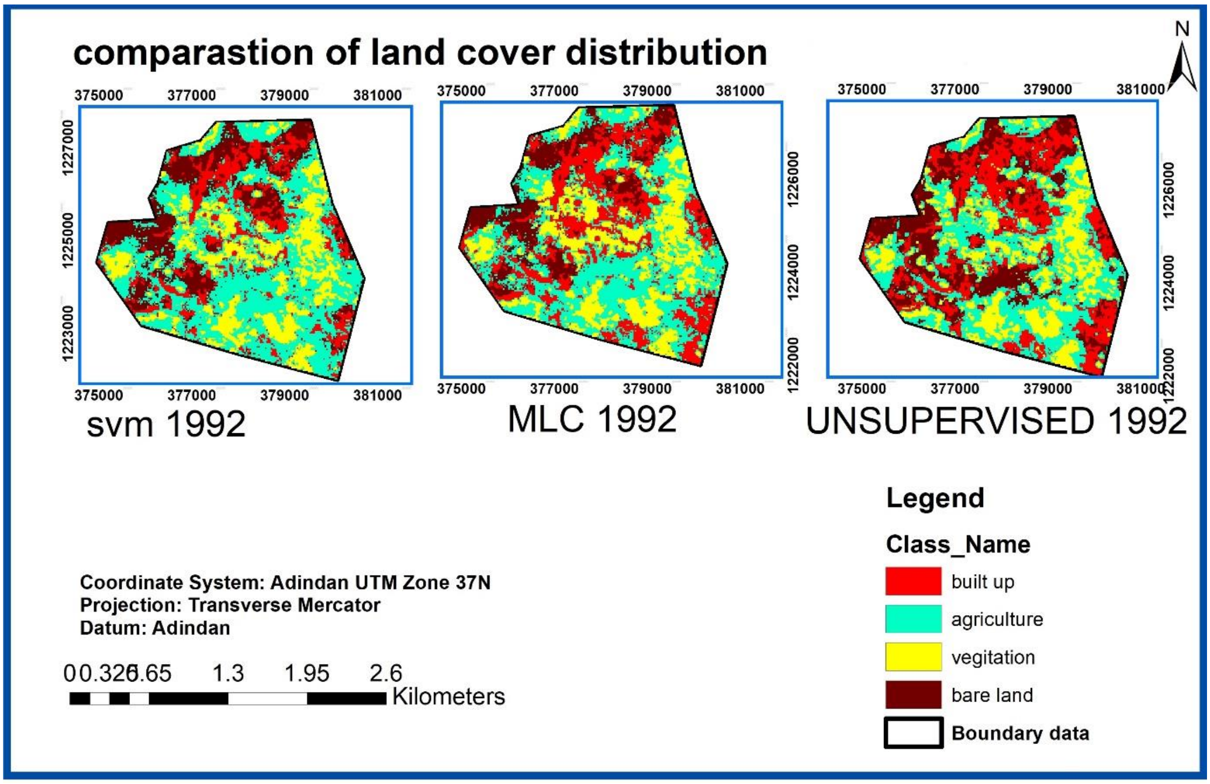
Appendix J: reclassified built and non-built up land use land cover distribution map of 1992 to the left and map 2023 to the right, prepared using ArcGIS pro software by unsupervised classification



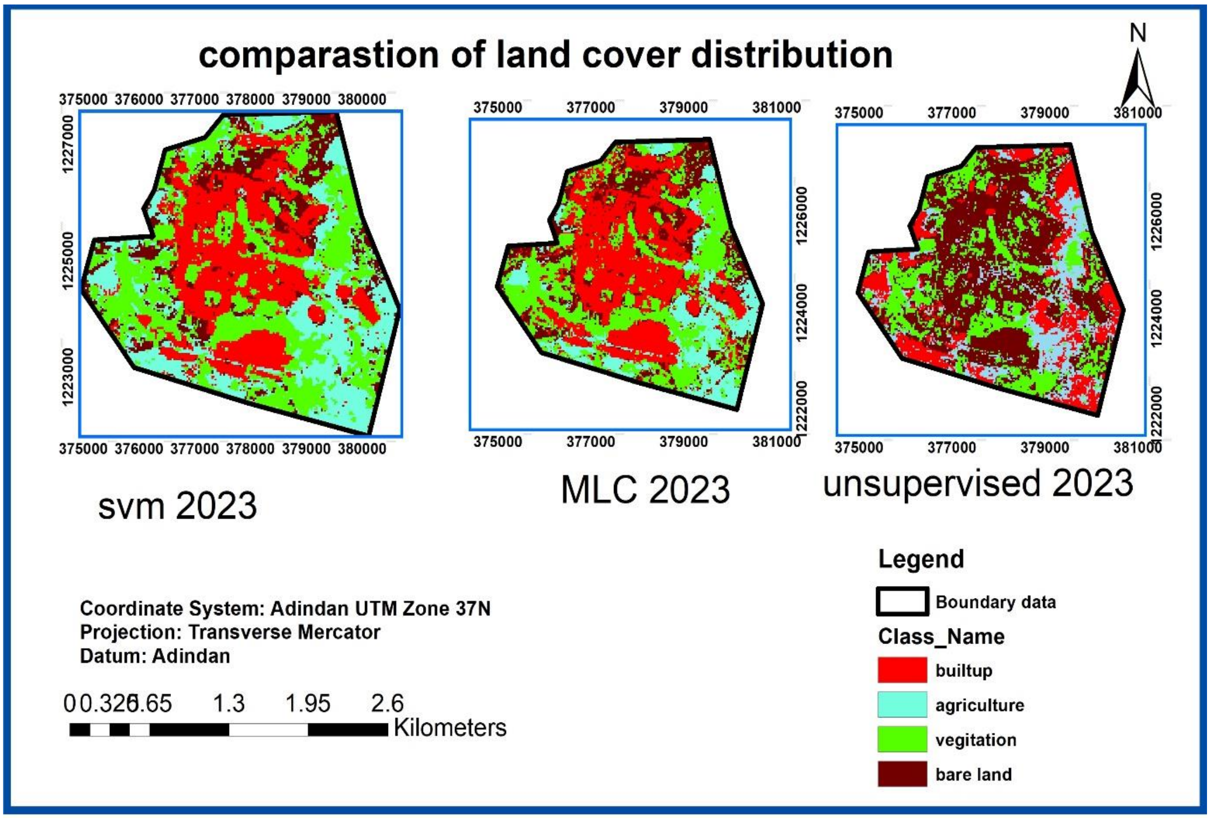
Appendix K: reclassified agriculture and non-agriculture land use land cover distribution map of 1992 to the left and map 2023 to the right, prepared using ArcGIS pro software by unsupervised classification**.**



Appendix L: map showing comparison of LULC distribution of supervised and unsupervised classification, land use land cover distribution map of 1992 by SVM to the left and 1992 by MLC in the middle and map 1992 by unsupervised calcification to the right, prepared using ArcGIS pro software



Appendix M: map showing comparison of LULC distribution of supervised and unsupervised classification, land use land cover distribution map of 2023 by SVM to the left and 2023 by MLC in the middle and map 2023 by unsupervised calcification to the right, prepared using ArcGIS pro software



Appendix N Ground truth points collected by handheld GPS in 2023

No	**x**	**y**
1	**380534.7**	**1224147**
2	**380524.8**	**1224099**
3	**380514.6**	**1224016**
4	**380505**	**1224119**
5	**380477.4**	**1223822**
6	**380444.9**	**1224328**
7	**380383.8**	**1224119**
8	**380358.7**	**1223479**
9	**380356.3**	**1224759**
10	**380356.3**	**1223403**
11	**380328.7**	**1224803**
12	**380326.5**	**1223599**
13	**380326.5**	**1223242**
14	**380325.9**	**1223763**
15	**380321**	**1224116**
16	**380311.7**	**1223377**
17	**380296.8**	**1224385**
18	**380296.2**	**1223852**
19	**380296.2**	**1223287**
20	**380281.9**	**1224863**
21	**380269.2**	**1223108**
22	**380267.1**	**1224982**
23	**380265.1**	**1224043**
24	**380263.2**	**1223305**
25	**380260.4**	**1223581**
26	**380253.7**	**1224775**
27	**380252.2**	**1223524**
43	**380177.8**	**1223257**
44	**380175.6**	**1224694**
45	**380175.5**	**1224483**
46	**380167.4**	**1224200**
47	**380163.3**	**1223474**
48	**380148.1**	**1223348**
49	**380143.4**	**1222528**
50	**380133.2**	**1224327**
51	**380130.7**	**1223040**
52	**380119.4**	**1224816**
53	**380119**	**1224951**
54	**380118.3**	**1225130**
55	**380118.3**	**1222842**
56	**380117.7**	**1224685**
57	**380116.2**	**1222662**
58	**380113.4**	**1223098**
59	**380108**	**1223312**
60	**380107.4**	**1223416**
61	**380101.5**	**1223161**
62	**380088.6**	**1223019**
63	**380088**	**1224982**
64	**380080.2**	**1224376**
65	**380073.7**	**1224476**
66	**380067.8**	**1225101**
67	**380059.5**	**1225250**
68	**380058.3**	**1224804**
69	**380049.6**	**1223194**
70	**380044**	**1224625**

28	380237.3	1225041
29	380237.3	1225011
30	380237.3	1224863
31	380237.3	1223376
32	380237.3	1223019
33	380236.8	1223088
34	380236.7	1224923
35	380222.4	1223227
36	380209.7	1224863
37	380207.6	1223376
38	380205.4	1224268
39	380196	1225092
40	380187.3	1222919
41	380180	1222692
42	380180	1222632

71	380031.3	1222870
72	380029.1	1224449
73	380028.5	1223763
74	380026.9	1224922
75	380021.8	1223889
76	380017.2	1222949
77	380002.7	1225223
78	380000	1225458
79	379999.4	1222486
80	379998.8	1224953
81	379997.9	1222940
82	379997.4	1223597
83	379995.5	1224513
84	379984.5	1224564
85	379971.8	1224625

86	379969.6	1223318
87	379967.5	1225101
88	379962.2	1224710
89	379954.8	1225309
90	379939.9	1225740
91	379939.9	1224952
92	379939.9	1223883
93	379939.3	1223763
94	379939	1225360
95	379938.7	1225674
96	379937.7	1223970
97	379937.7	1223019
98	379931.1	1225079
99	379923.1	1224834

128	379792.6	1224628
129	379791.2	1223049
130	379789	1223554
131	379776.3	1224267
132	379767.6	1224521
133	379765.9	1222303
134	379761.4	1223182
135	379760.8	1225100
136	379760.8	1222990
137	379760.4	1223755
138	379756.6	1223449
139	379750.6	1224927
140	379743.8	1222686
141	379738.5	1223869

100	379910.6	1225462
101	379910.2	1224805
102	379908.6	1223114
103	379906.6	1223430
104	379901.9	1224617
105	379900.5	1225389
106	379899.2	1223974
107	379882.6	1225755
108	379880.4	1223316
109	379880.1	1224315
110	379873.6	1225054
111	379860.8	1222811
112	379860.6	1223296
113	379858.1	1222892
114	379850.7	1225696
115	379850.7	1223762
116	379850.7	1222840
117	379850.1	1225280
118	379840.8	1225467
119	379838.7	1223145
120	379835.8	1222929
121	379829.8	1222585
122	379824.5	1223668
123	379820.3	1223912
124	379818.8	1222305
125	379804.1	1224220
126	379794.4	1224897
127	379794.2	1225501

142	379733.9	1226499
143	379731.8	1224446
144	379731.7	1222364
145	379731.6	1222418
146	379729.5	1223970
147	379721.4	1224783
148	379716.8	1225458
149	379716.8	1222900
150	379704.1	1222840
151	379702.6	1225606
152	379702	1223197
153	379700.9	1223041
154	379685.2	1224668
155	379674.4	1225487
156	379672.8	1224328
157	379672.2	1223956
158	379670.2	1224965
159	379670.1	1223376
160	379650.7	1223718
161	379648.7	1223995
162	379642.5	1222602
163	379638.4	1223104
164	379634.3	1223376
165	379629.2	1225667
166	379627.6	1226736
167	379627.6	1224774
168	379627.6	1224283
169	379627.6	1224030

170	379622.6	1226851
171	379620.9	1223167
172	379619.4	1222557
173	379618.7	1226778
174	379611.3	1224690
175	379605.3	1226714
176	379593.3	1226561
177	379592.9	1226890
178	379585	1226039
179	379583	1224060
180	379582.4	1226499
181	379581.3	1224225
182	379580.8	1225963
183	379555.4	1226766
184	379555.4	1224714
185	379553.3	1225950
186	379553.3	1223004
187	379553.3	1224032
188	379552.6	1223702
189	379543.3	1224070
190	379533.8	1227225
191	379523.5	1224089
192	379522.9	1223882
193	379514.2	1223155
194	379496.6	1226116
195	379493.8	1222379
196	379492.6	1222434

212	379440.9	1226891
213	379434.3	1227272
214	379434.3	1226052
215	379434.3	1224491
216	379434.3	1222957
217	379433.9	1222412
218	379433.7	1227153
219	379433.7	1223674
220	379431	1222618
221	379419.8	1222895
222	379419.4	1225844
223	379410.8	1225813
224	379409.7	1224076
225	379406.7	1222335
226	379406.2	1223315
227	379404.6	1225785
228	379403.9	1227241
229	379403.9	1223406
230	379391.2	1227363
231	379389.7	1224476
232	379389.7	1222870
233	379388.1	1222781
234	379384.6	1227499
235	379375.4	1224386
236	379374.8	1225785
237	379374.8	1225547
238	379374.8	1224506

197	**379492.2**	**1224364**
198	**379466.2**	**1224892**
199	**379466.2**	**1223286**
200	**379465.9**	**1224602**
201	**379464.6**	**1227302**
202	**379464.6**	**1225752**
203	**379464**	**1222930**
204	**379464**	**1222670**
205	**379463.4**	**1227391**
206	**379462**	**1226482**
207	**379457.7**	**1224150**
208	**379455.8**	**1223067**
209	**379452.5**	**1222373**
210	**379449.2**	**1224372**
211	**379445.1**	**1223309**

239	**379374.8**	**1224298**
240	**379374.8**	**1224268**
241	**379374.8**	**1224060**
242	**379374.8**	**1222840**
243	**379374.8**	**1222811**
244	**379374.8**	**1225755**
245	**379372.6**	**1223970**
246	**379359.9**	**1225606**
247	**379347.2**	**1223970**
248	**379345.7**	**1222306**
249	**379345.1**	**1225755**
250	**379345.1**	**1224863**
251	**379345.1**	**1224417**
252	**379345.1**	**1224327**
253	**379345.1**	**1223450**

254	**379345.1**	**1222840**
255	**379345.1**	**1222811**
256	**379345.1**	**1225664**
257	**379345.1**	**1224206**
258	**379345.1**	**1223522**
259	**379345.1**	**1222392**
260	**379345.1**	**1222367**
261	**379344.4**	**1224519**
262	**379344**	**1224729**
263	**379330.2**	**1225785**
264	**379316.3**	**1224251**
265	**379315.3**	**1222275**

296	**379181.5**	**1224476**
297	**379172.4**	**1223955**
298	**379168.8**	**1223227**
299	**379167.7**	**1225324**
300	**379167.2**	**1223317**
301	**379166.6**	**1227034**
302	**379164.3**	**1225675**
303	**379152**	**1227058**
304	**379150.2**	**1222900**
305	**379145.1**	**1224298**
306	**379136.9**	**1225014**
307	**379136.9**	**1224892**

266	379314.7	1227153
267	379309.4	1222858
268	379300.5	1224179
269	379293.2	1227310
270	379285.6	1224134
271	379255.8	1223286
272	379255.2	1227064
273	379253.7	1222751
274	379245.2	1224427
275	379241	1222454
276	379238.7	1225530
277	379226.1	1226377
278	379226.1	1227212
279	379225.5	1226766
280	379224.1	1226095
281	379223.9	1227361
282	379223.9	1222811
283	379210.1	1222685
284	379206.1	1226485
285	379204.5	1225736
286	379198.5	1226231

308	379136.9	1223792
309	379136.3	1224744
310	379123.5	1222416
311	379117	1224187
312	379109.3	1224298
313	379107.7	1226856
314	379107.1	1223733
315	379094	1224531
316	379093.8	1226917
317	379087.2	1227113
318	379079.2	1224463
319	379077.4	1222424
320	379076.8	1224655
321	379065.5	1222489

Appendix O Details of accuracy assessment

Ground truth

Information gathered on the research area's location is known as ground truth. It is particularly crucial for connecting image data to actual ground-based elements. Ground truth data gathering facilitates the calibration of remote sensing data and supports the understanding and analysis of the detected information. It is also used for the accuracy assessment of the year 2023

Overall accuracy

It shows the proportion of accurately categorized pixels at the Canada Centre for Remote Sensing (2010). The process involves dividing the total number of observations by the number of accurate observations. The National Oceanic and Atmospheric Administration (NOAA), (2008) has represented it using the following equation:

$$O= \frac{\sum A}{\sum B} * 100$$

Where, O = Overall Accuracy

A = the number of pixels assigned to the correct class

B = the number of pixels that actually belong to the class

Producer’s accuracy

. It is a gauge of the analyst's classification accuracy for the picture data. It displays the proportion of a certain ground class that has been successfully classified. It is computed by taking a class's total number of reference/ground truth pixels and dividing it by the class's accurate number of pixels. The precision of the map as seen by the map maker is known as the producer's accuracy (the producer). This is the likelihood that a certain area's land cover is classified, or how frequently actual features on the ground are accurately depicted on the classified map. The Omission Error is complemented by the Producer's Accuracy, which is equal to 100% - the Omission Error.

User’s accuracy

The User's Accuracy is the accuracy from the point of view of a map user, not the map maker. The User's accuracy essentially tells us how often the class on the map will actually be present on the ground. This is referred to as reliability. The User's Accuracy is complement of the Commission Error, User's Accuracy = 100%-Commission Error. The User's Accuracy is calculating by taking the total number of correct classifications for a particular class and dividing it by the row total.

Errors of Omission

According to Smith, J., & Doe, A. (2020) Omission error represents the percentage of actual instances of a specific class that were not correctly classified as that class. It indicates how much of the actual land cover type was "omitted" in the classification.

Calculation: Omission Error is calculated as 1−User's Accuracy.

Errors of Commission

According to Smith, J., & Doe, A. (2020) Commission error represents the percentage of pixels that were incorrectly classified as a certain land cover type when they actually belong to another type. It indicates the extent to which the classification has "committed" errors by including pixels that should not belong to a certain class.

The details of calculations of overall accuracy, user's accuracy and producer's accuracy of 1992 and 2023 by supervised MLC, SVM and supervised classification have been described as follows

Calculation: Commission Error is calculated as 1−Producer's Accuracy1

Accuracy assessment of classification done by ARCGIS pro maximum likelihood of the year 1992

Classified data	Built up land	Agriculture	Vegetation	Bare land	Total	User accuracy (100%)
Built up area	62	4	3	5	74	83.8
Agriculture land	3	82	6	2	93	88.2
Vegetation	1	5	61	4	71	85.9
Bare land	2	4	2	50	58	86.2
Total	68	94	73	61	296	
	91.2	87.2	83.6	82.0		
	Producer accuracy (100%)					
	Over all accuracy		86.1			

User Accuracy (UA)

Built up area: (62 / 74) * 100 = 83.8%

Agriculture land: (82 / 93) * 100 = 88.2%

Vegetation: (61 / 71) * 100 = 85.9%

Bare land: (50 / 58) * 100 = 86.2%

Producer Accuracy (PA)

Built up area: (62 / 68) * 100 = 91.2%

Agriculture land: (82 / 94) * 100 = 87.2%

Vegetation: (61 / 73) * 100 = 83.6%

Bare land: (50 / 61) * 100 = 82.0%

Overall Accuracy (OA)

OA = (62 + 82 + 61 + 50) / 296 * 100 = 86.1%

Omission Error

Built up area: 1 - 91.2% = 8.8%

Agriculture land: 1 - 87.2% = 12.8%

Vegetation: 1 - 83.6% = 16.4%

Bare land: 1 - 82.0% = 18.0%

Commission Error

Built up area: 1 - 83.8% = 16.2%

Agriculture land: 1 - 88.2% = 11.8%

Vegetation: 1 - 85.9% = 14.1%

Bare land: 1 - 86.2% = 13.8%

Accuracy assessment of classification done by ARCGIS pro maximum likelihood of the year 2023

Classified data	Built up land	Agriculture	Vegetation	Bare land	Total	User accuracy (100%)
Built up area	85	3	3	4	95	89.5
Agricultural land	3	63	3	2	71	88.7
Vegetation	2	7	54	2	65	83.1
Bare land	5	3	6	76	90	84.4
Total	94	78	65	84	321	
	89.5	82.9	81.8	90.5		
	Producer accuracy (100%)					
	Over all accuracy		86.6%			

User Accuracy (UA):

Built up area: UA = (85 / 95) * 100 = 89.5%

Agriculture land: UA = (63 / 71) * 100 = 88.7%

Vegetation: UA = (54 / 65) * 100 = 83.1%

Bare land: UA = (76 / 90) * 100 = 84.4%

Producer Accuracy (PA):

Built up area: PA = (85 / 94) * 100 = 90.4%

Agriculture land: PA = (63 / 78) * 100 = 80.8%

Vegetation: PA = (54 / 65) * 100 = 83.1%

Bare land: PA = (76 / 84) * 100 = 90.5%

Overall Accuracy (OA):

OA = (85 + 63 + 54 + 76) / 321 * 100 = 86.6%

Omission Error:

Built up area: Omission Error = 1 - 90.4% = 9.6%

Agriculture land: Omission Error = 1 - 80.8% = 19.2%

Vegetation: Omission Error = 1 - 83.1% = 16.9%

Bare land: Omission Error = 1 - 90.5% = 9.5%

Commission Error:

Built up area: Commission Error = 1 - 89.5% = 10.5%

Agriculture land: Commission Error = 1 - 82.9% = 17.1%

Vegetation: Commission Error = 1 - 81.8% = 18.2%

Bare land: Commission Error = 1 - 90.5% = 9.5%

Accuracy assessment of classification done by Arc GIS pro SVM classifier of the year 1992

Classified data	Built up land	Agriculture	Vegetation	Bare land	Total	User accuracy (100%)
Built up	69	2	2	1	74	93.2
Agriculture	3	85	3	2	93	91.4
Vegetation	1	4	64	2	71	90.1
Bare land	1	3	2	52	58	89.7
Total	74	94	71	57	296	
	93.2	90.4	90.1	91.2		
	Producer accuracy (100%)					
	Over all accuracy		91.2			

User Accuracy (UA):

Built up land: UA = (69 / 74) * 100 = 93.2%

Agriculture: UA = (85 / 93) * 100 = 91.4%

Vegetation: UA = (64 / 71) * 100 = 90.1%

Bare land: UA = (52 / 58) * 100 = 89.7%

Producer Accuracy (PA):

Built up land: PA = (69 / 74) * 100 = 93.2%

Agriculture: PA = (85 / 94) * 100 = 90.4%

Vegetation: PA = (64 / 71) * 100 = 90.1%

Bare land: PA = (52 / 57) * 100 = 91.2%

Overall Accuracy (OA):

OA = (69 + 85 + 64 + 52) / 296 * 100 = 90.5%

Omission Error:

Built up land: Omission Error = 1 - 93.2% = 6.8%

Agriculture: Omission Error = 1 - 91.4% = 8.6%

Vegetation: Omission Error = 1 - 90.1% = 9.9%

Bare land: Omission Error = 1 - 89.7% = 10.3%

Commission Error:

Built up land: Commission Error = 1 - 93.2% = 6.8%

Agriculture: Commission Error = 1 - 90.4% = 9.6%

Vegetation: Commission Error = 1 - 90.1% = 9.9%

Bare land: Commission Error = 1 - 91.2% = 8.8%

Accuracy assessment of classification done by Arc GIS pro SVM classifier of the year 2023

Classified data	Built up land	Agriculture	Vegetation	Bare land	Total	User accuracy (100%)
Built up	90	1	3	1	95	94.7
Agriculture	1	67	2	1	71	94.4
Vegetation	1	1	61	2	65	93.8
Bare land	1	3	2	84	90	93.3
Total	93	72	68	88	321	
	93.7	93.1	88.2	93.0		
	Producer accuracy (100%)					
	Over all accuracy		94.1			

User Accuracy (UA):

Built up land: UA = (90 / 95) * 100 = 94.7%

Agriculture: UA = (67 / 71) * 100 = 94.4%

Vegetation: UA = (61 / 65) * 100 = 93.8%

Bare land: UA = (84 / 90) * 100 = 93.3%

Producer Accuracy (PA):

Built up land: PA = (90 / 93) * 100 = 96.8%

Agriculture: PA = (67 / 72) * 100 = 93.1%

Vegetation: PA = (61 / 68) * 100 = 89.7%

Bare land: PA = (84 / 88) * 100 = 95.5%

Overall Accuracy (OA):

OA = (90 + 67 + 61 + 84) / 321 * 100 = 93.1%

Omission Error:

Built up land: Omission Error = 1 - 96.8% = 3.2%

Agriculture: Omission Error = 1 - 93.1% = 6.9%

Vegetation: Omission Error = 1 - 89.7% = 10.3%

Bare land: Omission Error = 1 - 95.5% = 4.5%

Commission Error:

Built up land: Commission Error = 1 - 94.7% = 5.3%

Agriculture: Commission Error = 1 - 94.4% = 5.6%

Vegetation: Commission Error = 1 - 93.8% = 6.2%

Bare land: Commission Error = 1 - 93.3% = 6.7%

Accuracy assessment of classification done by Arc GIS pro unsupervised classification of the year 1992

Classified data	Built up land	Agriculture	Vegetation	Bare land	Total	User accuracy (100%)
Built up area	59	5	7	3	74	79.7
Agricultural land	5	78	3	7	93	83.9
Vegetation	3	5	59	4	71	83.1
Bare land	3	3	3	62	58	84.5
Total	70	91	72	63	296	
	84.3	85.7	81.9	77.8		
	Producer accuracy (100%)					
	Over all accuracy		82.8			

User Accuracy (UA):

Built up land: UA = (59 / 74) * 100 = 79.7%

Agriculture: UA = (78 / 93) * 100 = 83.9%

Vegetation: UA = (59 / 71) * 100 = 83.1%

Bare land: UA = (62 / 58) * 100 = 84.5%

Producer Accuracy (PA):

Built up land: PA = (59 / 70) * 100 = 84.3%

Agriculture: PA = (78 / 91) * 100 = 85.7%

Vegetation: PA = (59 / 72) * 100 = 81.9%

Bare land: PA = (62 / 63) * 100 = 98.4%

Overall Accuracy (OA):

OA = (59 + 78 + 59 + 62) / 296 * 100 = 82.1%

Omission Error:

Built up land: Omission Error = 1 - 84.3% = 15.7%

Agriculture: Omission Error = 1 - 85.7% = 14.3%

Vegetation: Omission Error = 1 - 81.9% = 18.1%

Bare land: Omission Error = 1 - 77.8% = 22.2%

Commission Error:

Built up land: Commission Error = 1 - 79.7% = 20.3%

Agriculture: Commission Error = 1 - 83.9% = 16.1%

Vegetation: Commission Error = 1 - 83.1% = 16.9%

Bare land: Commission Error = 1 - 84.5% = 15.5%

Accuracy assessment of classification done by Arc GIS pro unsupervised classification of the year 2023

Classified data	Built up land	Agriculture	Vegetation	Bare land	Total	User accuracy (100%)
Built up area	83	5	4	3	95	87.4
Agricultural land	3	60	1	7	71	84.5
Vegetation	2	6	54	3	65	83.1
Bare land	4	2	7	77	90	85.6
Total	95	72	68	86	321	
	90.2	98.2	81.8	85.6		
	Producer accuracy (100%)					
	Over all accuracy		85.4			

User Accuracy (UA):

Built up land: UA = (83 / 95) * 100 = 87.4%

Agriculture: UA = (60 / 71) * 100 = 84.5%

Vegetation: UA = (54 / 65) * 100 = 83.1%

Bare land: UA = (77 / 90) * 100 = 85.6%

Producer Accuracy (PA):

Built up land: PA = (83 / 95) * 100 = 87.4%

Agriculture: PA = (60 / 72) * 100 = 83.3%

Vegetation: PA = (54 / 68) * 100 = 79.4%

Bare land: PA = (77 / 86) * 100 = 89.5%

Overall Accuracy (OA):

OA = (83 + 60 + 54 + 77) / 321 * 100 = 85.7%

Omission Error:

Built up land: Omission Error = 1 - 87.4% = 12.6%

Agriculture: Omission Error = 1 - 84.5% = 15.5%

Vegetation: Omission Error = 1 - 83.1% = 16.9%

Bare land: Omission Error = 1 - 85.6% = 14.4%

Commission Error:

Built up land: Commission Error = 1 - 90.2% = 9.8%

Agriculture: Commission Error = 1 - 98.2% = 1.8%

Vegetation: Commission Error = 1 - 81.8% = 18.2%

Bare land: Commission Error = 1 - 85.6% = 14.4%