A STUDY ON URBAN GROWTH AND MODELING USING GEOSPATIAL TECHNOLOGY: A CASE STUDY OF SEBETA SUB-CITY

Hunde Ayana Mosisa

A Thesis Submitted to

The Department of Architecture

School of Civil Engineering and Geo-informatics Engineering

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

Office of Graduate Studies

Adama Science and Technology University

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Adama, Ethiopia

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STUDENT DECLARATION

I Hunde Ayana hereby declare that this Master Thesis entitled “A study on urban growth and modeling using geospatial technology: A case study of Sebeta sub-city” is my original work. That is, it has not been summited for the award of any academic degree, diploma or sources certificate in any other university. All sources of materials that are used for this thesis have been dully acknowledged through citation.

Name of student	Signature	Date

RECOMMENDATION OF ADVISOR

I, the major advisor of this thesis, hereby certify that I have read the revised version of the thesis entitled "A study on urban growth and modeling using geospatial technology: A case study of Sebeta sub-city" prepared under our guidance by Hunde Ayena submitted in partial fulfillment of the requirements for the degree of Master's of Science in Geo-informatics.

Therefore I recommend the submission of the revised version of the thesis to the department following the applicable procedure.

Dejene Tesema (PhD	________________________	________________
Major Advisor	Signature	Date

APPROVAL SHEET

I, the major advisors of the thesis entitled "A study on urban growth and modeling using geospatial technology: A case study of Sebeta sub-city" by and developed by Hunde Ayena, hereby certify that the recommendation and suggestions made by the board of examiners are appropriately incorporated into the final version of the thesis.

Dejene Tesema (PhD)	______________________	_______________
Major Advisor	Signature	Date

We, the undersigned, members of the Board of Examiners of the thesis by Hunde Ayena have read and evaluated the thesis entitled "A study on urban growth and modeling using geospatial technology: A case study of Sebeta sub-city" and Examined the candidate during the open defense. This is, therefore, to certify that the thesis is accepted in partial fulfillment of the requirement of the degree of Master of Science in Geo-informatics.

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

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ACRONOMY

ANN:	Artificial Neural Network
CA:	Cellular Automata
CAD:	Computer Aided Design
CSA:	Central Statistical Agency
DEM:	Digital Elevation Model
ERDAS:	Earth Resource Data Analysis System
ETM:	Enhanced Thematic Mapper
GIS:	Geographic Information System
GPS:	Global Positioning System
GUI:	Graphical User Interface
LCM:	Land Change Modeler
LG:	Logistic Regression
LULC:	Land Use /Land Cover
MCE:	Multi Criteria Evaluation
MOLUSCE	Method of land use change evaluation
MUDHCo	Minister of urban dynamics and house cooperation
OLI:	Operational Land Imager
QGIS:	Quantum Geographical information System
RS:	Remote Sensing
SVM:	Support Vector Machine
TIFF:	Tagged Image File Format
USGS:	United states Geological Survey
UTM:	Universal transfer Mercator
WGS:	World Geological Survey

ABSTRACT

This study uses Land Use and Land Cover Change (LULCC) computed from Landsat, ETM, OLI and Sentinel datasets of 2003, 2013 and 2023 respectively. The study aimed to simulate future LULCC using Landsat images in the fastest-growing Sebeta sub-city. Supervised classification and support vector machine algorithm was applied to estimate the LULC for years 2003, 2013 and 2023. These were analyzed by using Arc GIS10.8.1, Erdas imagine 2015 QGIS 2.18 and IDRISI V.17 to make clear land use structure. The change detection of multiple Landsat images was conducted between 2003 and 2023. A simulation model were done by Cellular Automata in Qgis to model the future LULC for 2050.The historical LULC change data of 2003–2013, 2013-2023 and 2003–2023 were used as a baseline. Both transition rules and transition area matrix for the period 2003–2013, 2013-2023 and 2003–2023 were produced quantitatively using the Markov chain model. The model was validated using simulated and observed LULC 2023 by using kappa parameters; with the overall kappa index 0.97%; which indicates good kappa index values. The result shows that the proportion of built up area was 1.22% in 2003, this figure rose to just over 6.92% in 2023, indicates an expansion in built-up area was 270.051 ha, resulting in farmland, sparse, and dense forest were 13674.8 ha, 5194.8 ha, and 462951.04 ha, respectively. In 2023 built up was cover1529.02ha other land use/land cover result farmland, dense, and sparse forest indicated that 15447.8ha, 2295.32ha and 2818.06ha of the total area coverage2050 respectively. According to prediction at 2050, indicate that these patterns of bare land changing into built-up and farmland will continue over the next 27 years due to urban expansion and deforestation. It is predicted that the conversions of other land-use types into built-up areas will persist in the south-west, southern and western areas of the city, as northern growth trend of the city is hampered by the natural barriers of hilly ridges of subba forest, despite the city has almost a compact settlement shape. The output of the study provides useful information for land use planners and decision makers to make better decisions in improving future land use policies and formulating management strategies within the framework of sustainable land use planning.

Keywords: *Modelling, urbanization, Sebeta sub-city, simulation, Landsat, LULC, MOLUSCE.*

CHAPTER I. INTRODUCTION

1.1 Background of the Study

Land use land covers (LULC) are two different terms. Land use defines the human use of land, and land cover represents the physical properties of surface elements. Land-use and land-cover (LULC) change has become important and essential component in current strategies for monitoring environmental changes and managing natural resources (Rawat et al., 2013). Urban growth can be defined by the movement of people from primarily agricultural communities to other communities. In these new communities, activities are centered around government, trade, manufacturing, or allied interests (Hassan & Elhassan, 2020). Urbanization is a two-way process because it involves not only movement from village to cities and change from agricultural occupation to business, trade and service but it also involves change in the migrant's attitudes, beliefs, values and behavioral patterns. Rapidly growing urbanization of different cities and villages overpowers the meager resources by encroaching them which leads to unmanaged and unsustainable development situation. Urban Growth can be managed in a planned way by planning future scenarios for which land use /land cover area change dynamics is crucial to understand (Bengston et al., 2003).

Planning of sustainable growth of the cities would lead to the planning of natural resources and therefore society won't suffer in an adverse way. Population Growth is a major driving factor of urban growth. It is of two types, natural increase in population and migration of population to urban areas with aspiration of people for better living conditions, facilities, better infrastructure and services. Industrialization is another important driving factor of urban growth. There are many examples where urban areas have been developed and increased as a result of high industrial activities like Tata Nagar in India. Industries are developed in bulk on the outer areas of a city which results in conversion of agricultural land into built-up areas. Industrialization and aspiration of better facilities and amenities in urban areas lead to further migration of people which requires housing and other infrastructure to support such migrated population. Speculation of future growth also leads to urban growth. Speculation is sometimes blamed for urban sprawl because it produces withholding of land for development which is one of the important reasons for discontinuous development (ELbakry et al., 2018).

Developing countries are facing the problem of ever-increasing urban population due to migration of population from rural to urban areas in search of employment and better facilities. This migration of population in effect, is putting pressure on land, water and biological resources in urban area. Recently, African urbanization is also characterized by rapid and uncontrolled urban growth. This has brought various socio-economic and environmental problems. Urbanization causes not only the loss of agricultural farmlands but also displacement of farm households and challenges to the livelihood of the farming community in the rural urban fringes (Alemu, 2015).

Ethiopia has the second largest population in Africa having a total population of over 100 million. It has an average of 2.3% annual population growth and 4.6% of average annual urban growth rate(Haregeweyn et al., 2012). Despite its low urbanization rate compared to other African countries, however the impact of urban expansion on land use/land cover changes becoming a big challenge to the country. According to Central Statistical Agency (CSA, 2013) the growth of urban populations is attributed to three factors: natural growth, migration to existing urban centers and project sites and statistical growth of urban population due to the upgrading of rural villages to towns and formal expansion of existing urban areas.

Urban expansion is major challenges of sebeta Sub-city in the last decades. This urban expansion has great impact on land use and land cover such as: farm land, vegetation cover, open space, land management, environmental etc. but in this study area, no studies were conducted to solve those problems until now. Some researchers employ remote sensing and GIS to explore the analysis of changes in land use and land cover. They use satellite images from various years with a 30m resolution. In this study area to analysis urban growth and prediction use satellite image of the different years with 30m and 10m spatial resolution. Like; Landsat 7 and 8 have 30m spatial resolution and Sentinel-2A have 10m spatial resolution which is different from previous researcher data. Sentinel-2A has high accuracy than other satellites image for urban growth analysis and also for modeling. Resampling method is used for changing 10m to 30m spatial resolution.

1.2 Statement of the Problem

Despite witnessing infrastructural advancements, Ethiopia continues to be one of the least urbanized nations globally (UN-Habitat, 2017). While rural-urban migration has accelerated urbanization (Badasa et al., 2021), this growth is often unplanned and sprawling (Fenta et al., 2017). Towns like Sebeta prioritize horizontal expansion along transportation routes, often at the expense of agriculture and green spaces.

Sebeta sub-city exemplifies this challenge. Its rapid, unplanned growth mirrors a national trend. This expansion, though fostering financial activity, has come at a cost. The surrounding ecosystem faces threats like agricultural land loss, deforestation, and reduced open space due to road expansion. Additionally, a lack of accurate and timely data hinders sustainable urban development planning (Hassan & Elhassan, 2020).

This research seeks to address the pressing need for information on urban expansion in Sebeta. By raising awareness among stakeholders, analyzing current trends, and predicting future growth, the study aims to contribute to both scientific understanding and sustainable development efforts.

The research focused on changes in built-up areas, sparse forest, dense forest, and farmland. It employed spatial and temporal analysis to understand past trends and anticipate future ones. This information proved crucial for establishing a land-use and land-cover database, developing a reliable urban growth model, and formulating a robust monitoring strategy. Ultimately, these outcomes paved the way for informed policy interventions to guide the sustainable future of the Sebeta sub-city.

1.3 Objective of the Study

1.3.1 General Objective

The primary objective of this research is to analyze the trends of urban development in Sebeta sub-city within a defined timeframe, spanning from 2003 to 2023 and to employ geospatial technology to create a model that predicts its potential growth until the year 2050.

1.3.2 Specific Objective of the Study

The specific objectives of this study were to:-

- ✓ Assess the spatiotemporal dynamics of urban expansion in the study area between 2003 and 2023.
- ✓ Quantify the rates at which land use and land cover have changed within Sebeta sub-city from 2003 to 2023.
- ✓ Determine the rate of gain and loss that has transpired in the area throughout the chosen periods.
- ✓ Utilize the Cellular Automata technique in marko model to forecast future urban growth in the study area up to the year 2050.

1. 4 Research Question

To fulfill the specific objectives mentioned above, the following research questions will be formulated:

- ✓ How does the spatial and temporal variation of urban dynamics manifest within the chosen study periods?
- ✓ What are the discernible trends in the land use and land cover patterns of Sebeta sub-city during the specified years?
- ✓ How can the rate of gain and loss that has transpired in the region between 2003 and 2023 be computed?
- ✓ What can be projected as the future rate of urban growth for Sebeta sub-city from 2023 to 2050?

1.5 Significance of the Study

This study on urban growth in Sebeta sub-city, Ethiopia, offers valuable insights for future development. By analyzing urban sprawl and land-use changes, it equips planners and policymakers with the information needed to create effective strategies for sustainable development, land management, and urban planning. Additionally, the study showcases the practical application of geospatial technology for monitoring and managing urbanization, providing a valuable reference for other researchers and professionals.

Furthermore, the study goes beyond understanding growth patterns. It analyzes land consumption rates and quantifies land-use changes, allowing for the assessment of potential environmental challenges like deforestation and habitat loss. The predictions and models generated, including future urban growth rates, empower decision-makers to make informed choices regarding infrastructure development, resource allocation, and urban land use planning. Finally, this study fills a crucial knowledge gap by addressing the lack of accurate data for urban land-use planning in Sebeta. It contributes to the existing body of knowledge on urban growth and modeling in Ethiopia, paving the way for further research in the field.

1.6 Scope of the Study

This study explores urban growth patterns and models spanning from 2003 to 2023 and to employ geospatial technology to create a model that predicts its potential growth until the year 2050. The timeframe covered between selected years, with the goal of predicting urban area expansion up to 2050. To ensure manageable research, the study focuses on

Sebeta sub-city, the largest city within Shegar city with an area of approximately 22090.3hectares. By concentrating on Sebeta, the research aims to gain a deeper understanding of urban growth dynamics and associated challenges within this specific Ethiopian context.

1.7. Limitation of the study

The accuracy of predicted urban growth ultimately depend on the quality of historical data used for model calibration, particularly the spatial resolution of remote sensing imagery. As (Chaudhuri & Clarke, 2013) highlight, higher resolution data leads to better simulation results. While this study utilized 30-meter Landsat data (acquired from USGS Earth Explorer) and even 10-meter Copernicus data, these resolutions presented challenges in generating precise land-use/land-cover maps. The coarse resolution made it difficult to distinguish between various land-use classes. Ideally, high-resolution satellite imagery like Quickbird, IKONOS, GeoEye, Worldview, or SPOT would provide more detailed and accurate information for land-use/land-cover classification, potentially yielding significantly higher overall accuracy.

1.8. Organization of the thesis

This five-chapter thesis guides the reader through the research journey. Chapter 1 lays the groundwork with a general introduction, outlining the research problem, questions, objectives, scope, and limitations. Chapter 2 explores relevant scholarship through a literature review. Chapter 3 focuses on the chosen study area, detailing data layer map generation, methodology, and data sources. Chapter 4 dives into the research findings with a detailed discussion of the results. Finally, Chapter 5 concludes the thesis, summarizing the findings, offering recommendations, and outlining possibilities for future research.

CHAPTER II. LITERATURE REVIEW

2.1 Definition and concept of terms

Urbanization is universal phenomenon and the most powerful and visible anthropogenic force that a brought change in land use/land cover at global level and rapid urbanization is the manifestation of the developing world in the 21century (Hammad et al., 2019).

2.2 Types of Land Use and Land Cover

2.2.1 Urban Land

Urban or built-up land consists of areas of rigorous use with much of the land covered by structures. This category comprises of cities, towns, and villages, strip developments along highways, transportation, power, and communication facilities. These include areas occupied by mills, shopping centers, industrial and commercial complexes, and institutions that may, in some instances, be isolated from urban areas (Fenta et al., 2017). A village in KwaZulu-Natal (Adams Rural) possesses some of these characteristics such as villages and commercial complexes. As fantel assert that as development progresses in this KZN region, land having less intensive or non-conforming use may be located in the midst of urban or built-up areas and will generally be included in this category.

2.2.2 Agricultural Land

Land used primarily for production of food and fibre is defined or classified as agriculture or agricultural land. On high-altitude imagery, the main indications of agricultural activity are mostly the geometric field road patterns on the landscape and the traces produced by livestock or mechanized equipment. However, these characteristics do not always exist as in grassland and other lands. Where such equipment is used infrequently it may not show as well-defined shapes as in other areas. Thus site visits to Adams Rural to confirm land uses was very important before the classification scheme was developed. Urban activity indicators and the associated concentration of the population should make it possible to distinguish between agricultural and urban or built-up areas. In agricultural land, building complexes are smaller and the density of the road and highway network is much lower than in urban or built-up land (Dlamini, 2015).

parks, open spaces, undevelopable land and large cemeteries may be mistaken for agricultural land, especially when they occur on the periphery of the urban areas. The border of agricultural land with other classes of land use may sometimes be a transition zone in which there is an intermixture of land uses. In cases where farming is restricted by wetness, the precise boundary may also be difficult to pinpoint (Kindu et al., 2013).

2.2.3 Forest Land

Forest land usually can be identified on high-altitude imagery, although the boundary between it and other categories of land may be difficult to delineate precisely. Land from which trees have been removed for production is part of forest land because in the near future these will grow again. The forest land pattern can at times be identified by the presence of cutting operations. Areas of little forest growth are usually categorized as forest land classes. Basically, where the dominant activities are forest-related and there has been extensive forest land grazing, those areas should be included in the forest land class(Suryabhagavan, 2019).

2.2.4 Bare Land

Bare land usually consists of sites visually dominated by considerable areas of exposed gravel on the ground. Such conditions are common in desert regions where combinations of sandy areas, bare rock, surface extraction, and transitional activities could occur in close proximity and in extent too small for each to be included at mapping. There are cases where there existed forest land or agricultural land but those land types have been removed causing the exposure of bare land. These should be carefully studied for their later use, if there would be built-up land or agriculture (Yeshaneh et al., 2013).

2.3 Quantifying Changes in Land Use and Land Cover

According to (Biney & Boakye, 2021) on urban sprawl and its impact on land use land cover dynamics of Sekondi-Takoradi metropolitan assembly, Ghana. The result of the study indicates that Settlement increased by 25.93% whereas water, vegetation, and bare land reduced by 0.08%, 16.00%, and 9.86% respectively. This reveals the occurrence of an unguided expansion of built-up area in the metropolis. Also, results from entropy calculations showed high entropy values ranging from 2.42 to 2.50, though the entropy values did not significantly change throughout the study.

2.4 Extract LULC dynamics from urban expansion.

Timely and accurate information about the dynamics of urban expansion is vital to reveal the relationships between urban expansion and the ecosystem, to optimize land use patterns and to promote the effective development of cities in China (Qiu et al., 2011). The dynamics of urban expansion in China from 1992 to 2008 were extracted with an average overall accuracy of 82.74% and an average Kappa of 0.40. Bahir Dar is in a state of rapid horizontal expansion; it increased from 279 ha in 1957 to 4830 ha in 2009, at an average growth rate of about 31% (88 ha) (Haregeweyn, et al., 2012).

2.5 Urbanization

2.5.1 Urbanization and Urban Growth

Urbanization refers to the growth of towns and cities, often at the expense of rural areas, as people move in to urban centers in search of jobs with the expectation of a better life, enabling cities and towns to grow. It can also be termed as the progressive increase of the number of people living in towns and cities. It is highly influenced by the notion that cities and towns have achieved better economic, political, and social mileages compared to the rural areas (Batta, 2010). Urban growth is a spatial and demographic process as that refers to the increased importance of towns and cities as a concentration of people with in a particular economy and society (Batta, 2010). There are at least three different and widely studied concepts of urban growth in the urban and regional planning literature, related to population change, economic performance and the spatial expansion of urban areas (Reis, 2015). The socio-demographic dimension of urban growth focuses on demographic trends and migration. The first includes the natural population growth rate, depending mainly on fertility and mortality rates, while the second depends on the capacity of a city to attract residents from other cities or rural settlements (Rieniets, 2009).

2.5.2 Urban Expansion in World

The world is rapidly urbanizing and cities are experiencing the dynamic processes of urbanization and globalization (Kazemi, 2017). According to (Qiu et al., 2011), prior to 1950, global urbanization trends were calculated based on the transformations that took place in Organization for Economic Cooperation and Development (OECD) countries. The proportion of the world‛s population, which is urban, has been growing rapidly and currently a larger fraction of the total population lives within cities (UN-Habitat, 2007). According to United Nations world Urbanization Prospect (MUDHCo, 2014) the percentage of urban population in 1950 was 30% , which was increased to 54% in 2014, and estimated to be 66% by 2030. Urbanization is not merely a modern phenomenon, but a rapid and historic transformation of human social roots on a global scale, whereby predominantly rural culture is being rapidly replaced by urban culture (Pawan, 2016).

2.5.3 Urban Expansion in Africa

According to (Omoakin, 2012) Africa used to be, and perhaps is still, the least urbanized continent, with growth rates of cites close to, if not the fastest in the world. But, today, in virtually every part of the continent, new cities have been emerged, while the old ones have drastically expanded, some of which have become mega-cities. By 2030, for the first time in the history, more of the continent's people will be living in urban areas than in rural regions and by 2050 an estimated 1.23 billion people, or 60% of all Africans will be city dwellers. Currently, even if the level of urbanization in Africa is low, the rate of urbanization is high due to the population growth, which is one of the most important driving forces of changes in any urban system. If urban population swells, the city must expand upward or outward. Along with economic development and technologies (mainly transport and communication) revolution, rapid urban growth can be characterized by the development of suburban expansion and redevelopment in city centers (Rui, 2013).

2.5.4 Urban expansion in Ethiopia

Ethiopia is still predominantly a rural country, with only 20% of its population living in urban areas. But this is set to change dramatically. Figures from the Ethiopian Central Statistics Agency, project the urban population is will triple to 42.3 million by 2037, growing at 3.8% a year. According to the 2015 Ethiopia Urbanization Review, the rate of urbanization will be even faster, at about 5.4% a year. That would mean a tripling of the urban population even earlier by 2034, with 30% of the country's people in urban areas by 2028.

In parallel with rapid urbanization, Ethiopia is going through a demographic transition. The labor force has doubled in the past 20 years and is projected to rise to 82 million by 2030, up from 33 million in 2005. Creating job opportunities in urban areas will be essential if Ethiopia is to exploit its demographic dividend (Alemayu, 2019).

2.6 Factors Influencing Urban Expansion

There are several factors of urbanization, such as Economic development, innovation of technology, industrial revolution, emergence of large manufacturing factors, job opportunities, availability of infrastructures and migration. Generally, the causes of urbanization and urban expansion are group into three major classes.

2.6.1 Demographic Effects

It includes rural to urban migration and natural population growth in the city, the level of urbanization and the rank of the city/town in the country‘s urban hierarchy. Natural population growth is a major element in urban growth for all countries, and migration of rural to urban contributes fast growth of urban population in many developing countries (Fenta et al., 2017).

2.6.2 Economic Effects

It include the level of economic development, difference in household incomes, exposure to globalization, the level of foreign direct investment, the degree of employment, the level finance markets, the level and effectiveness of property taxation and the presence of high inflation and acute shortage of housing (Fenta et al., 2017).

2.6.3 Environment Effect

It includes those of climate, slope, mountain barriers, and the existence of drillable water aquifers. In addition the minor causes such as Redevelopment and rebuilt-up of inner cities again cause displacement of citizens (Sharma et al., 2012). Urban growth can be a double-edged sword for economies. Cities are hubs for innovation, attracting businesses and talent, which leads to increased productivity, job creation, and overall economic output. This concentration of people also fosters knowledge sharing and specialization, further boosting growth(Oğuz, 2004). However, this can also strain infrastructure, leading to congestion and rising costs for housing and services.

2.7 Impacts of Urban Expansion on Land Use/Land Cover Change

2.7.1 Impacts on Forest and Biodiversity

One obvious consequence of land-use and land-cover change, particularly of deforestation is the shortage of fuel-wood. As the population increases household energy consumption also increases. Of the total population of the world, 30 to 40 percent largely depends on fuel wood and charcoal. For the poor in rural areas, it is not only a source of energy but a means of income generation too. Globally, about 29 percent of the land surface was originally under forest cover. Presently, however, it is only a fifth of this original that remains undisturbed (Khawaldah, 2016). Land-use and land-cover change and changes in land cover due to land use are not necessarily land degradation (Planner et al., 2000). The impact of the change on the land is measured in terms of the productivity of the converted land(Ayele & Tarekegn, 2020). A major impact of land-use and land-cover is on soil and biotic resources. For example, the annual loss of plant species in tropical Africa is as high as 27,000. The loss of biodiversity due to land-use and land-cover changes takes place at multiple levels (landscape, ecosystem and species), and in multiple dimensions (structure and function)(Ayele & Tarekegn, 2020).

2.7.2 Impact on Farm Land

Due to the acceleration of the global urbanization in both intensity and area, there is a growing interest in understanding its implications with respect to a broad set of environmental factors including loss of farm land, habitat destruction, decline in natural vegetation cover and climate at local, regional, and global scales (Mohan et al., 2020). Rapid economic growth rates and urban land expansion have led to widespread LULC changes (Wu et al., 2016). The increase in the number of urban population and the need for housing among other urban needs have brought about a substantial growth in urban areas with inherent impact on agricultural land area mostly at the periphery (Khan & Himanchal, 2019). The expansion of condominium on agricultural on peripheral area of urban and expansion impervious surface on vegetation cover and grassland were the main parameters for expansion of built- up area as well as decline of agricultural and grassland in Addis Ababa City (Badasa et al., 2021). If the rate of decline in agricultural land remains unchecked, in the nearest future food production will be a serious challenge and rural livelihood will negatively be impacted (Khan & Himanchal, 2019).

2.8 Geo-spatial technologies useful for urban LULC Change Assessment

New tools for sophisticated ecosystem conservation are now available thanks to advances in remote sensing, GIS, IDRIS Selva and QGIS. With the advent in technology, data costs have decreased, and historic spatiotemporal data and high definition satellite imagery are now available for use in spatial design, mapping, earth science, traffic planning, environmental planning, emergency response, and study of urban expansion transition.

2.8.1 Application of Geographic Information System (GIS) for the study of Urban LULC Change

GIS is defined as a computerized system designed to store, retrieve, manipulate, analyze, and map geographical data. Remote sensing and geographical information systems are proven tools for assessing land use and land cover changes that help planners to advance sustainability (Waseem et al., 2015).

The use of a location referencing system is the key component of a GIS, allowing information about a single location to be examined in relation to other locations. This makes it possible to take data stored in one form and combine it with data entered and stored in some other form.

The GIS technology is employed to assist decision-makers by indicating various alternatives in development and conservation planning and by modeling the potential outcomes of a series of scenarios. It should be noted that any task begins and ends with the real world. Data are collected about the real world. After the data are analyzed, information is compiled for decision-makers. Based on this information, actions are taken and plans implemented in the real world (Gis et al., 2021).

Geographic information system has long been recognized as essential and powerful tools in determining LULC changes at different spatial scales (Twisa & Buchroithner, 2019). The evidence from remotely sensed data has been extracted using a variety of change detection approaches and image analysis. On the other hand, information acquired from RS has been integrated to create a clear knowledge of land use/land cover modeling (Hammad et al., 2019).

2.8.2 Application of Remote Sensing for the study of Urban LULC Change

Remote sensing data are applicable and valuable for land use and cover change detection Analysis (Tewabe & Fentahun, 2020)**.** One of the most crucial data sources for research of land cover spatial and temporal changes has been remote sensing data utilized as the basis for GIS. In reality, because of the processing and elaboration of multi-temporal remote sensing information, it is now possible to map and identify land escape changes, making it possible to manage and develop sustainable landscapes (Mekonnen, 2017). Through the analysis of data collected by a device that is not in contact with the object, location, or event being studied, remote sensing is the science and art of learning more about those things (Chipman et al., 2003). It describes the processes of capturing, viewing, and perceiving (sensing) things or occurrences in distant (remote) locations. The sensors used in distant sensing are not in close proximity to the objects or activities being monitored. The information must be physically transported from the objects or events to the sensors via a third-party media. In remote sensing, electromagnetic radiation is typically utilized as a data carrier.

In this broad sense, the human visual system serves as an illustration of a remote sensing system. Since the development of remote sensing and geographic information systems

(GIS) techniques, land use/cover mapping has been a practical and thorough means to enhance the choice of areas planned for agricultural, urban, and/or industrial sections of a region (Rawat et al., 2013). It was feasible to analyze the changes in land cover using remotely sensed data in less time, for less money, and with better result (Khawaldah, 2016) in association with GIS which provides a suitable platform for data analysis, update and retrieval (Cihlar, 2003) RS along with GIS tools used to gather, display, store, analyze and output data related to changes on environment, can provide researchers and planners with certain data sets in order to better understanding and management of a given area.(Sharma et al., 2012) stated as Remote Sensing data is very useful because of its synoptic view, repetitive coverage and real-time data acquisition. Therefore, the digital data in the form of satellite imagery makes it possible to precisely calculate different land use/land cover categories and aids in maintaining the spatial data infrastructure, both of which are crucial for studies that monitor urban expansion and change over time.

2.8.3 Application of Quantum Geographic Information System for Urban LULC Change

Quantum geographic information system (QGIS) is an open-source GIS product. As such the software is constantly developing and being improved upon by the world-wide GIS community. QGIS is free and the source code is openly available for those who want to improve or customize the interface/tools (QGIS Manual, 2015). The MOLUSCE plugin incorporates some well-known algorithms, such as artificial neural networks (ANNs) and cellular automata (CA) modeling to forecast future land use/land cover approaches (Abbas et al., 2021). To use the data for transition potential modeling and prediction, resampling techniques is used in ArcGIS to fix the spatial resolution differences between the LULC data and spatial variables (Khawaldah, 2016).

2.9 Image Classification

According to Weng (2012), image classification is the process of assigning or sorting pixels into a finite number of individual classes, or categories of data, based on their data file values. Typically, each pixel is regarded as a unique unit made up of data from several spectral bands. It is possible to arrange comparable pixels into classes that correspond to the informative categories of relevance to users of remotely sensed data by comparing them to one another and to pixels of known identity. Classification is one of the digital image processing that is very useful when multispectral imagery of the same geographical region is compared. Classification algorithms can be used that derive a value for each pixel in the image from its brightness values in each image. The analyst that is classifying an image must distinguish between spectral classes and information classes. Spectral classes are groups of pixels that have nearly uniform spectral characteristics. Information classes are the various themes or groups the analyst is attempting to identify in an image (Gidado et al., 2018). Unsupervised and supervised image classifications are the most frequently applied classification techniques in remote sensing.

2.9.1 Unsupervised Classification

Unsupervised classification is an approach that uses statistical clustering techniques to combine pixels into groups (classes) based on the degree of similarities of their brightness value in each spectral band. The analyst then combines spectral classes into real land cover type using maps and field-based knowledge. To effectively classify various clusters into a certain information class, the analyst must have a thorough understanding of the spectral properties of the terrain in the area of interest (land cover type). In this process many spectral classes can be assigned to a few land cover types (Hall, 2007).

2.9.2 Supervised Classification

As cited in (Akay et al., 2008) supervised classification is performed when some prior or acquired knowledge of the classes in a scene is used to identify representative samples of different cover types. This prior knowledge is used to select homogenous areas within the image that possess the thematic information to be extracted. In order to create a numerical description of the spectral attribute for each of the interest land cover types, the first step in the supervised classification is to identify representative areas. These areas are commonly referred to as training sites and must be selected for every image class that is to be identified. The determination of training sites is based on the analyst's knowledge of the geographical region and the surface cover types present in the image. After all training sites have been selected and the classifier algorithm examines the spectral characteristics of the training sites to determine statistical parameters related to each class. Next all the pixels, including the training sites, are spectrally evaluated and assigned to a class based on the highest likelihood of being a member of that class. The final product is a classification in which all pixels within the image have been assigned to one of the predefined classes (Morisette & Khorram, 2003).

2.10 Urban LULC Change Detection

Change detection can be defined as the process of identifying differences in the state of an object or phenomena by observing them at different times by using remote sensing techniques. Essentially, it also involves the ability to quantify temporal applications of remotely-sensed data obtained from Earth-orbiting satellites (Singh, 1989). Change detection has a wide range of applications in different disciplines such as land use change analysis, forest management, vegetation phenology, seasonal changes in pasture production, risk assessment and other environmental changes (Singh, 1989). The main objective of change detection is to compare the spatial representation of two points in time frame by controlling all the variances due to differences in non-target variables and to quantify the changes due to differences in the variables of interest (Lu et al., 2003).

2.11 Forecasting Urban Land Use/Land Cover

The Commonly used models are the modeling techniques embedded in Cellular Automata (CA), CA-Markov and CA-ANN. Since LUCC models can be radically different in a lot of ways, it's difficult to equate their results.

2.11.1 Cellular Automata (CA)

Cellular Automata (CA) is a spatial dynamic model which predicts transitions among any number of LULC categories (Li et al., 2015). In the CA model, the transition of a cell from one LULC to another depends on the state of the neighboring cells (Adhikari & Southworth, 2012), which is based on the idea that a cell with higher proximity to a cell will have a higher probability to change in the future. Hence, the CA model is very important to study complex geographic phenomena (Wang et al., 2020). Nevertheless, it pays attention merely to the local interactions of cells (Sang et al., 2011).

Mathematically, the CA model (Alderwish & Almatary, 2012) is expressed as:

$$S(t, t+1) = f(S(t), N) \quad \text{Equation (1)}$$

where, S is the states of discrete cellular, t is the time instant, t+1 is the coming future time instant, N is the cellular field and f is the transition rule of cellular states in local space.

2.11.2 CA-Markov Model

This short coming is mitigated by combining the Markov model with a more dynamic and empirical cellular automata (CA) model and commonly referred to as the CA–Markov model. Thus, the CA–Markov model has the advantage of predicting two-way transitions among the available land use types and is proven to have outperformed regression-based models in predicting land use change (Gidey et al., 2017). Hence, CA-Markov predicts not only the trend but also the spatial structure of different LULC categories (Wang et al., 2020) To predict future LULC conditions, the model requires a basis LULC image (time 2 image), transition probability matrix and suitability images as a group file(Chaudhuri & Clarke, 2013) The strength of CA-MARKOV is that it is simple to create data, that it adds spatial dimension to the model, and that it can simulate change across several categories. Its flaws are that socioeconomic considerations are ignored, and calibrating the model with MCE takes much too long relative to other approaches (Adhikari & Southworth, 2012)

2.12 Empirical Literature Review

Several study applied on evaluate the impact of urban expansion on land use/land cover change in deferent areas. According to (Biney & Boakye, 2021) Urban sprawl and its impact on land use land cover dynamics of Sekondi-Takoradi metropolitan assembly, Ghana by using Landsat imageries from 1991, 2002, 2008, and 2018 of Sekondi-Takoradi, together with geospatial and Shannon’s entropy techniques. Biney & Boakye, used supervised classification with maximum likelihood algorithm for image classification. Results of land use land cover change showed significant changes during the period of study. Settlement increased by 25.93% whereas water, vegetation, and bare land reduced by 0.08%, 16.00%, and 9.86% respectively. Another studies conducted on the Impact of Urban Expansion on Agricultural Land and Crop Output in Ankpa, Kogi State, Nigeria (Khan & Himanchal, 2019). Two methods used for data collection. The first was geospatial technology used to obtain Land use/Land cover and to check the rate of urban expansion. The land-sat image of Ankpa was acquired for three different years of 1987, 2001 and 2016 with the aid of Idrisi Andes land use change modeler and Arc GIS 9.3 used to generate the statistics to show change over the period of 29 years of study. The second data was on crop yield obtained from Kogi Agricultural Development Project. The obtained result where indicate that built-up areas had expanded significantly during the twenty-nine years period. Agricultural lands, vegetation and bare surface declined due to the growths in population and physical developments.

The previous study (Khan & Himanchal, 2019) depend on the impact of urban expansion on agricultural land only but current study is conduct the impact of urban expansion on farmland, open space, and vegetation. The land-sat image of Ankpa was acquired for three different years of 1987, 2001 and 2016 with the aid of Idrisi Andes land use change modeler and Arc GIS 9.3 used to generate the statistics to show change over the period of

23 years of study. In this study integration of Cellular Automata-Artificial Neural Network for predicting urban land use/land change analysis with the help of another geospatial tools and technologies. In this paper an integrate Cellular Automata-Artificial Neural Network in python for the purpose of predicting impact urban expansion on land use/land cover change in Sebeta sub-city. (Biney & Boakye, 2021) used supervised classification with maximum likelihood algorithm for image classification but in this study used supervised by using support vector machine algorithm.

CHAPTER III. STUDY AREA, METHODS AND MATERIALS

3.1 Study Area

Shegar City was established in 2022 and comprises 12 sub-cities. Sebeta is included among the sub-cities that make up Shegar City. It is located in the region of Oromia. The distance from Sebeta to Ethiopia's capital Addis Ababa (Addis Ababa) is approximately 21 km and the total area is 22090.3hectare.

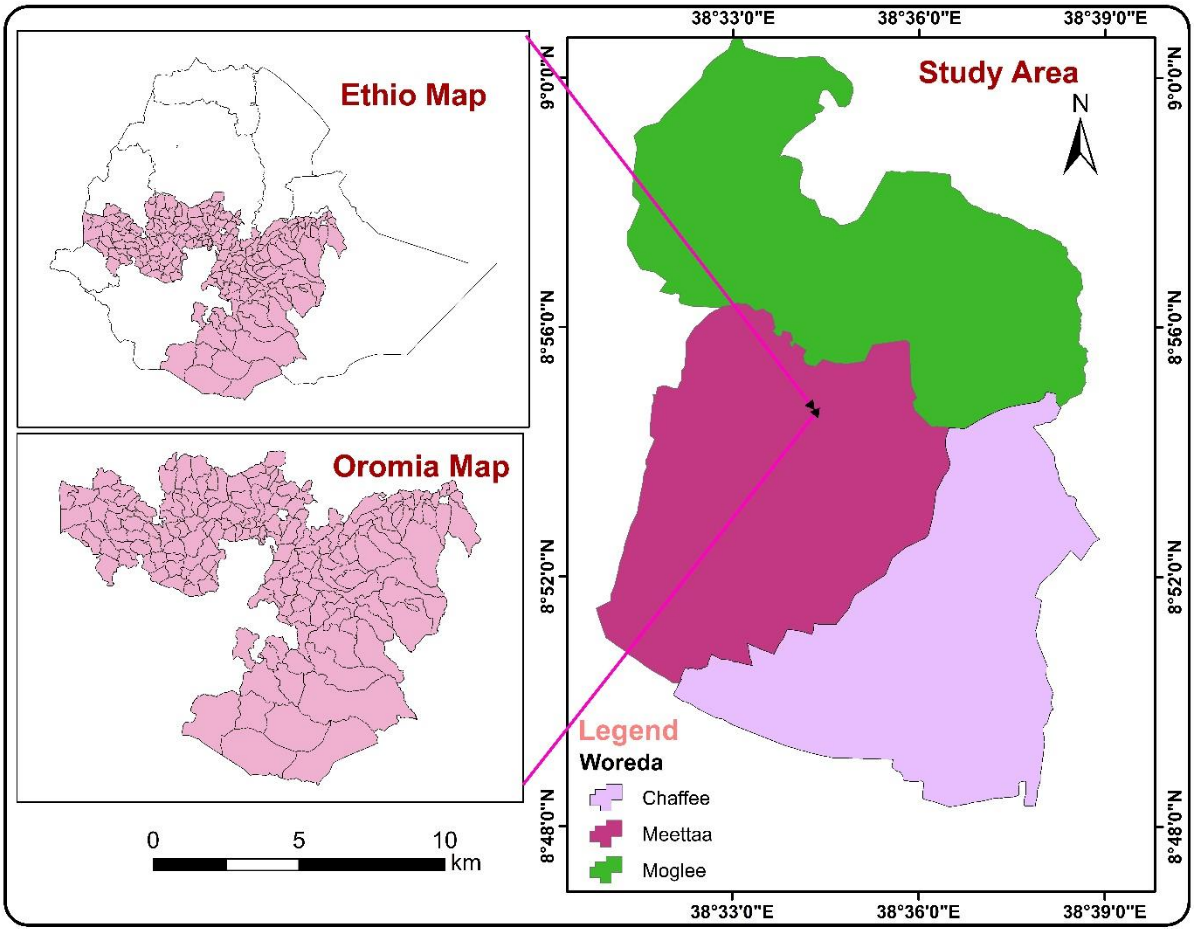

Figure 3.1 location map of Sebeta sub-city

3.2 Software

In this research various software‘s and materials were used for different purposes in order to achieve the proposed objective. There are a number of different kinds of methods, strategies and techniques to process input data to generate the required output with desired quality. The methodology integrates remote sensing and GIS tools as well as LULC prediction using CA and python Integration QGIS software.

To conduct the study on urban growth analysis and modeling using geospatial technology, the following software, materials, and data sources may be required:

Table 3.1 Materials and software required to conduct the study

Software and Material	Purpose
Geographic Information System (GIS) Software	GIS software such as ArcGIS, QGIS, or any other suitable GIS software will be essential for processing, analyzing, and visualizing geospatial data.
Remote Sensing Software	Remote sensing software like ENVI, ERDAS Imagine, or similar tools will be necessary for processing satellite imagery and extracting relevant information.
Google Earth Pro	Visualization and verification of classification and point data collection for accuracy assessment of 2003, 2013 & 2023 maps.
QGIS, Python Programming Language	Python, along with relevant libraries such as GDAL, NumPy, and Pandas, can be used for data manipulation, scripting, and developing models and algorithms.
Field Data using Handheld GPS	Field data collection tools, such as GPS devices, notebooks, and measuring instruments, may be required to collect ground truth data, validate remote sensing analysis, and gather additional information about the study area

3.3 Data Types and Sources

The study's data came from various sources, including websites, associations, and stakeholders. Landsat 7 ETM+, Landsat 8 OLI and Sentinel 2A (L1TP product of path 168, row 54) was used for mapping LULC of the study area for the year 2003, 2013, and 2023 respectively. Despite its medium spatial resolution and mixed pixel challenge the Landsat image is commonly used for urban LULC mapping (Lu & Weng, 2007). It is available for several dates at no cost. The United States Geological Survey included all images from each year with less than 10% cloud pollution (USGS). Since the accuracy of Landsat image recognition during the dry season is better than during the rainy season, all of the Satellite image were taken during that period (Liu et al., 2015). The National Aeronautics and Space Administration (NASA) use Landsat Level 1 (L1T) 26 photographs that have been geometrically corrected and ortho rectified (Gutman et al. 2013).

The atmospheric effects were minimized by converting raw digital number (DN) values to surface reflectance, which was done in the ERDAS software's radiometric calibration module. A variety of ancillary data was also gathered for this study. Global Digital

Elevation Model was downloaded from free ASTER. Administrative boundaries and population data were also obtained from sebeta land administration office. All of the datasets used in the study were geometrically calibrated using WGS 1984_UTM zone 37 North projections.

Table 3.2 Characteristics and properties of the Remote sensing data used

Remote sensed data	Band	Path/Row	Acquisition Date	Spatial Resolution (m)
Landsat 7 ETM 2003	8	169/054	27/03/2003	30*30
Landsat 8 OLI 2013	11	169/054	28/03/2013	30*30
Sentinel 2A,2023	12	169/054	05/03/2023	10*10

Table 3.3 Data Types and Data Sources of the study

Data	Source	Purpose	Format
Landsat 7 ETM2003	USGS earth explorer	For classification of LULC	Raster
Landsat 8 OLI 2013			Raster
Sentinel 2A,2023			Raster
Sebeta sub-city master plan & boundary	Sebeta sub-city land administration	To prepare boundary line	CAD
Handled GPS	Field Observation	Reference and ground truth data	Point
DEM	Free ASTER	used as a-Variables to predict	Raster
Road	From Sebeta sub-city structural plan	the future urban growth	Raster
Slope	From DEM		Raster

3.4 Land Covers Classification scheme

In almost any classification process, it is rare to find clearly defined classes that one would like. Before collecting training samples, the land cover classes should be known so as to make the classification easier (Bekalo, 2009). Accordingly, four major land cover classes were identified in the study area.

Table 3.4 Land use land cover classes of the study area

Land Cover Classes	Description
Built up	Comprises area with all types of artificial surface, including buildings and transportation infrastructure (asphalt, gravel, coble stone. Areas under construction are also included.
Farm land/agricultural land	Farm land is land area that is either arable, under permanent farm, or permanent pastures.
Vegetation	In a wider sense cover around and include any kinds of woodsy plant vegetation growing in and around human settlements.
Bare land	Includes areas with no or little vegetation, bare land, exposed soil, rocks and sand.

3.5 Methods of Data Analysis

3.5.1 Pre-Processing Image

Pre-processing is the preliminary processing with the intention of dealing with correcting radiometric distortions, atmospheric distortion, and geometric distortions there in the raw image data. Radiometric corrections include those that can be contributed through sight enlightenment, atmospheric factors, viewing geometry, and instrument response characteristics. Geometric corrections include those related to the variation of the flight altitude, attitude, earth curvature, velocity of the platform, and the like (Kousalya et al., 2012). Preprocessing functions engage those procedures that exist usually required before the main data analysis and extraction of information and are generally grouped as radiometric corrections. Atmospheric belongings can cause imagery to contain a partial dynamic variety, appearing as haziness or reduced contrast. For this study, haze reduction was complete to sharpen the representation and a nonlinear contrast stretch (histogram equalization) that redistributes pixel values to make approximately the same number of pixels with each value within a range. Combining multiple (usually single band) images as bands/layers into a single output multi-band image (layer stacking), and reducing the size of the image file to include only the area of interest (sub-setting) was performed. Before sub-setting, the images of the digital map (shapefile of the study area) are re-projecting to UTM/WGS84 zone 37 to make s similarities to satellite images. Composite bands 2 (blue), band 3 (green), band 4 (red), and band 5 (Near Infrared) are stacked and subsetted by the boundary shapefile of the study area using ERDAS Imagine 2015.

3.5.2 Layer Staking

The method of merging several images into a single image is known as layer stacking. To do this, the images must have the same degree (number of rows and columns), which necessitates resampling other bands of different spatial resolutions than the desired resolution. To put it another way, all images/bands must have the same spatial resolution in order to perform layer stacking. Combining images/bands, on the other hand, would increase the final stacked image scale, and therefore the processing time as you perform the research. If you know you won't need any of the images/bands in your study, stacking all of the images into a single image isn't necessary; instead, choose only the images that attract you.

3.5.3 Image Enhancement

The conversion of image quality to a higher and more understandable standard for feature extraction or image analysis is known as image enhancement (Bhatta, 2011). Image enhancement is a common technique for providing a clear display for image perception. Therefore, in this study, multispectral images were enhanced by using ERDAS software.

3.5.4 Sub-setting of Study area.

Image extraction is the first step of image pre-processing. Any of the image's non-essential elements can be omitted, and the image's emphasis can be narrowed. To minimize the size of the image file and include only the region of interest, it is necessary to remove the project field from the entire image (AOI). This not only removes the unnecessary data from the picture. However, since there is less data to handle, it speeds up the process. When using multiband data, such as Landsat ETM+ imagery, this is critical. Sub setting is the term for this data reduction. ERDAS IMAGINE and Arc GIS Software were critical at this stage. Each Landsat scene was clipped through by the project area during this process (Sebeta shape file). It must be done after layer stacking or a composite image has been formed.

3.5.5 Training Sample Selection

Each picture yielded a set of training samples for each level. Consistency in sample collection was maintained to eliminate sampling biases by choosing pixels that appeared constant at various times to train the classifier. First, samples were chosen from a 2003 Landsat image (first image). Following that, these samples were used as training samples for the first image and as a foundation for the next image (2013). Second, the base samples were superimposed on the second picture to see if there was a change in class. If some variations were discovered, a new sample from the surrounding area was substituted. Similarly, the same procedures were followed for the rest of the images.

3.6 LULC Classification

Images from different periods are used for the classification of land-use and land-cover dynamics of the study area. This multi-temporal raw satellite data were imported to Erdas Imagine 2015 image processing software. After this, land use/land covers dynamic maps, and land cover statistics were generated to compare the temporal dynamic of the study area for the past three decades using Arc GIS 10.8 software. The flow chart for the general methodology to classify LULC types is shown in Figure 3.2. Finally, land-cover maps of Sebeta Sub-city were produced based on Landsat 2003 ETM+, Landsat 2013 OLI and 2023 Sentinel 2A data using support vector machine algorism. However, after that, some classes were combined and the final land-cover map of Sebeta Sub-city was sketched. The step-by-step approach (methodology) taken to achieve the stated objectives of this thesis are the following; the satellite image of the study area was classified using Arc GIS 10.8. The existing analog boundary map was converted into digital format through digitizing using Arc GIS 10.8 application software.

3.6.1 Supervised Classification

The method of employing samples of known identity (i.e., pixels already allocated to informational classes) to classify pixels of unknown identity is known as supervised classification. It can be used to cluster pixels in a dataset into classes that match to user-defined training classes. The researcher must choose training areas to use as the classification's foundation in order to apply this classification type. The status of a specific pixel is then determined by using a number of comparisons. Paralleled and Support Vector Machine are two examples of supervised classification techniques.

3.6.2 Train Support Vector Machine Classifier.

A potent supervised classification technique is the SVM classifier. It can handle both common images and segmented raster input efficiently. It's a classification technique that's widely used in the scientific world. The tool accepts multiple-band images with any bit depth as conventional picture inputs, and it will perform SVM classification on a pixel-by-pixel basis using the supplied training feature file. The utility computes the index image and related segment properties from the RGB segmented raster for segmented raster whose key property is set to Segmented. To create the classifier definition file for usage in a different classification tool, the attributes are computed. Any picture supported by Esri can be used to compute the properties for each segment. There are several advantages to the SVM classifier tool, as opposed to the maximum likelihood classification method:

- The SVM classifier needs much fewer samples and does not require the samples to be normally distributed.
- It is less prone to noise, correlated bands, and imbalanced distribution of training sites within a class in terms of size or quantity.

Sebeta Sub-city classified land use land cover change using supervised classification method, train SVM algorithm, finally making accuracy assessment for each year classified land use land cover maps.

3.7 Accuracy Assessment

3.7.1 Producer's Accuracy

Producer's accuracy 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). This value represents how well reference pixels of the ground cover type are classified.

$$A = \frac{\sum TCS_{ij}}{TCsi} \qquad \text{Equation (1)}$$

Where; TCSij is the total number of the correctly classified pixels in rows i and column j, TCsi is the total number of the correctly classified pixels in row i.

3.7.2 User's Accuracy

Users accuracy refers to the number of correctly classified pixels in each class (category) 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.

$$UA = \frac{TCS_{ij}}{TSri} \qquad \text{Equation (2)}$$

Where; TCSij is the total number of the correctly classified pixels in rows i and column j, Tsri is the total number of pixels in row i.

3.7.3 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.

$$OA = \frac{TCS_{ij}}{TS}$$ Equation (3)

Where; TCSij is the total number of the correctly classified pixels in rows i and column j, TS is the total reference sample.

3.7.4 Kappa Coefficient

The Kappa Coefficient is used to equate the precision of a grouping to that of simply assigning values at random. The Kappa Coefficient can be somewhere between -1 and 1. The classification is no different than a random classification if the value is 0. The classification is significantly worse than random if the number is negative. A value close to 1 indicates that the classification is significantly better than random (Jensen, 2005)

$$K = \frac{TS*TCS-\sum TScj*TSri}{TS2-\sum(TScj-TSri)*(7)}$$ Equation (4)

Where; TCSij is the total number of the correctly classified pixels in rows i and column j, TS is the total reference sample, TScj is the total number of pixels in column j and TSri is the total number of pixels in row i.

3.8 LULC Change Analysis

After the classification of land use and covers, remote sensing data were converted into thematic maps. To assess temporal and spatial land dynamics in the study area Land-use and Land-cover were consecutively analyzed using datasets of remotely sensed Landsat imageries. Next, area change between two consecutive study periods was computed using the classified imageries. Then, the post-classification comparison dynamic technique was applied in 2003, 2013, and 2023 using Open source (QGIS) software. Change matrix for LULC change map for 2003, 2013. and 2023 was done by using arc GIS 10.8.1. The percentages of changes were computed using Eq. 1. In this case, the positive and negative values suggest a gain and loss in spatial extent, respectively. Percentage change LULC

$$\Delta \text{ LULC} = \frac{A2 - A1}{A1} * 100$$ Equation (5)

Where, A1 and A2 are areas of a LULC class in the consecutive years

3.9. Image classification and change Analysis

The methods in this study are composed of two methodologies those are:-Image Classification &Change analysis and predicting future urban growth.

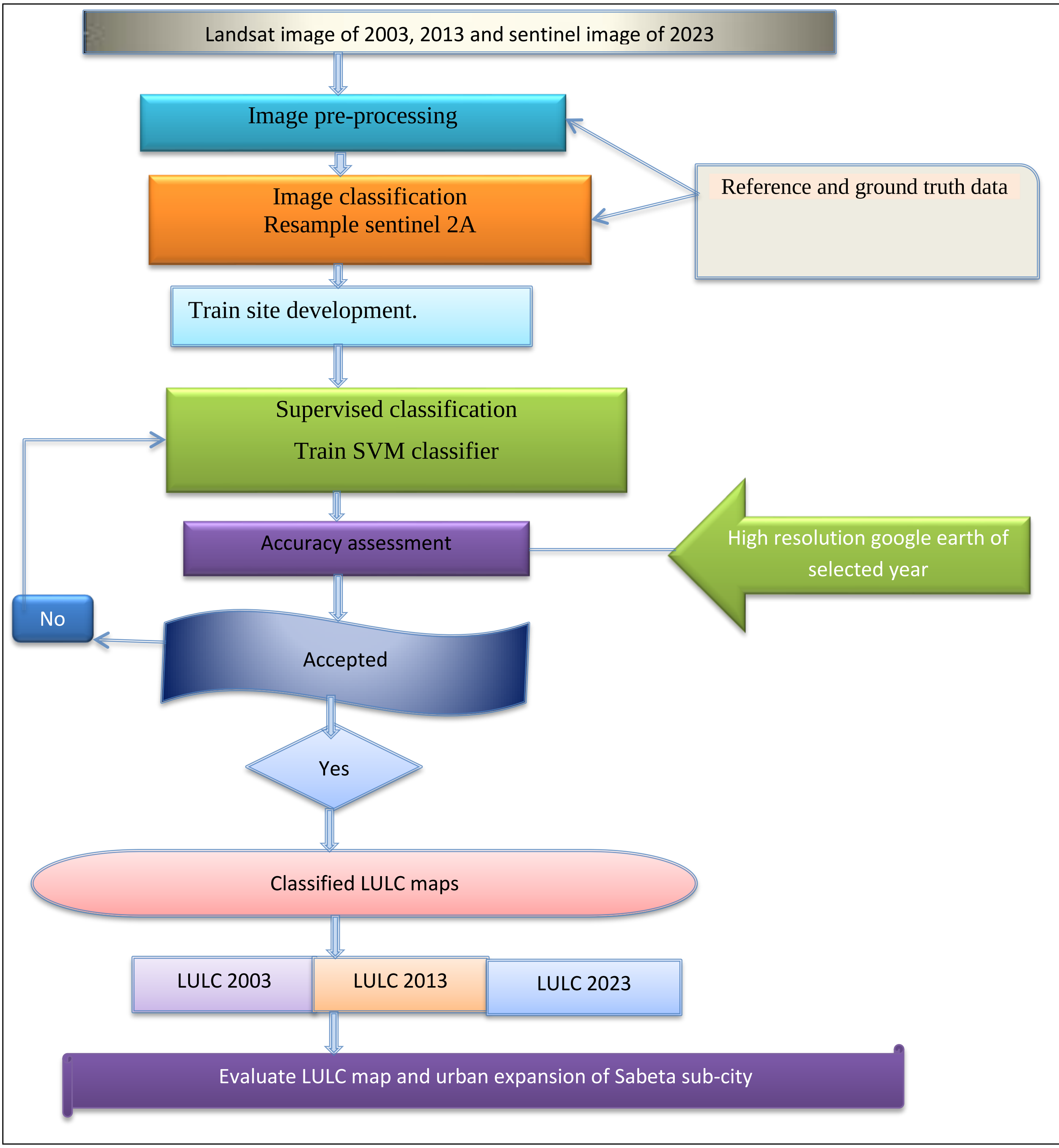

Figure 3.2 Technological Scheme of the Study of LULC and Urban Expansion

3.9.1 Urban growth modeling from 2023 to 2050

In order to forecast future urban growth of sebeta sub-city the following methodologies will be taken by using CA modelling integrating with QGIS and Python.

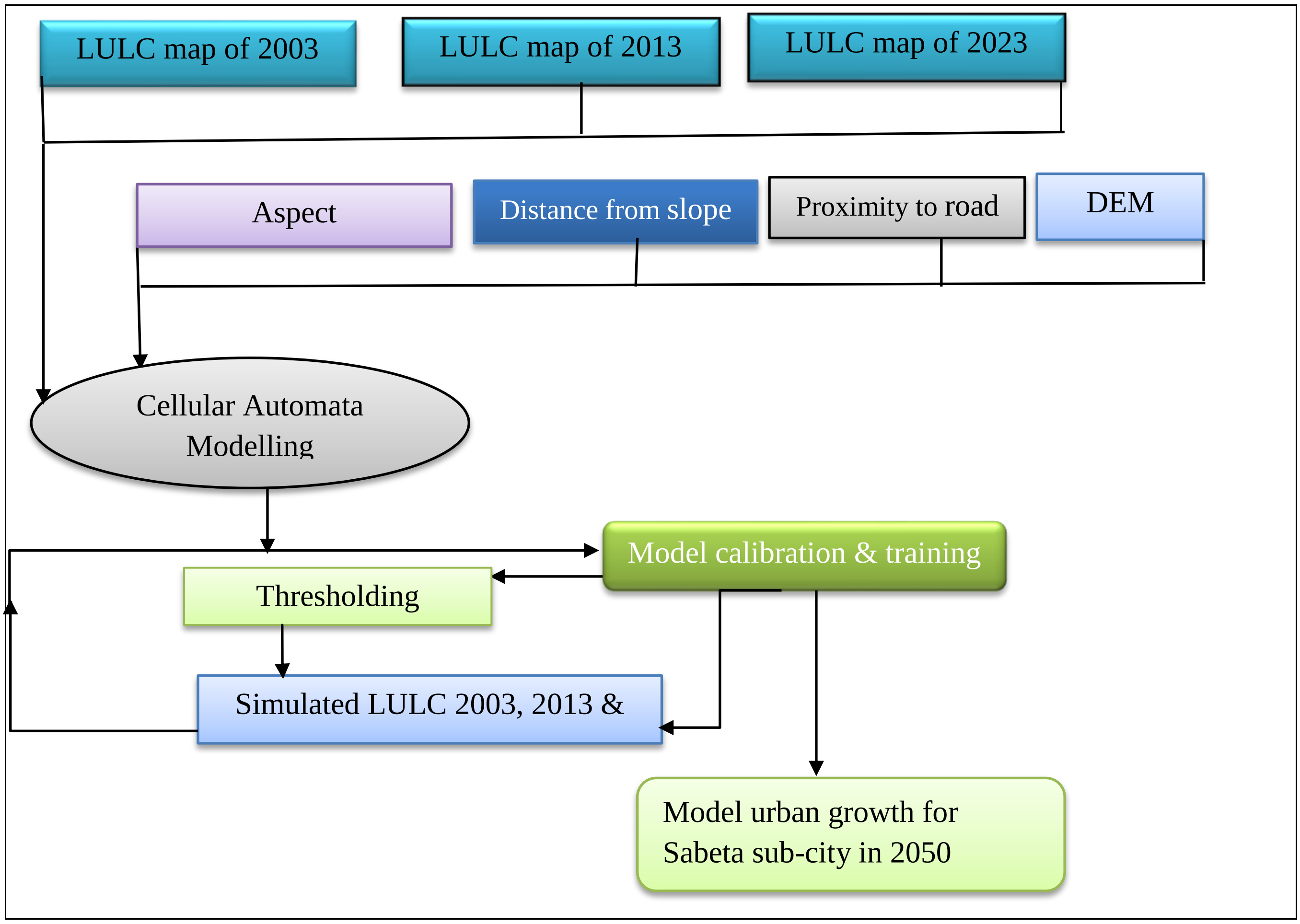

Figure 3.3 Technological Scheme of the Study for urban growth modelling

CHAPTER IV RESULT AND DISCUSSION

4.1 Introduction

This part includes the overall methods, techniques and materials used to achieve the research objectives. This includes image acquisition, classification, and accuracy assessment using classified images and ground truth data. It also encompasses change detection analysis like area calculation, field data collection, and image processing like preprocessing of data, remote sensing image classification, analysis, change detection and prediction for future urban growth.

4.2 Accuracy assessment of the images.

Classification accuracy was assessed quantitatively using an error matrix which is the commonly used method in LULC classification accuracy assessment (Adane, 2018). In this regard, sample pixels were selected from each of classified images through a stratified sampling scheme in ArcGIS software. The samples were overlaid with Google earth (for 2003, 2013 and 2023). Supported the error matrix generated for every classified map overall accuracy, user's accuracy, producer's accuracy and overall kappa were calculated. The accuracy requirements for change detection analysis were determined and supported by the suggestion of (Congalton, 2005).

Table 4.1 land use land covers accuracy assessment from 2003 to 2023

Year	2003		2013		2023	
LULC classes	PA(%)	UA(%)	PA(%)	UA(%)	PA(%)	UA(%)
Dense forest	85.7	85.7	92.86	98.18	84	100
Built-up	89.4	84	100	84.21	96	100
Farm Land	82.9	85.1	89.71	100	114	86.42
Sparse forest	77.7	73.6	87.5	90	19	100
Overall Accuracy (%)	85.3		93.95		94.8	
Overall kappa (%)	81		90.42		92.58	

Note: PA and AU indicate producer accuracy, and Users accuracy respectively.

4.3. Spatio-temporal dynamics of urban expansion in the Sebeta city between 2003 and 2023

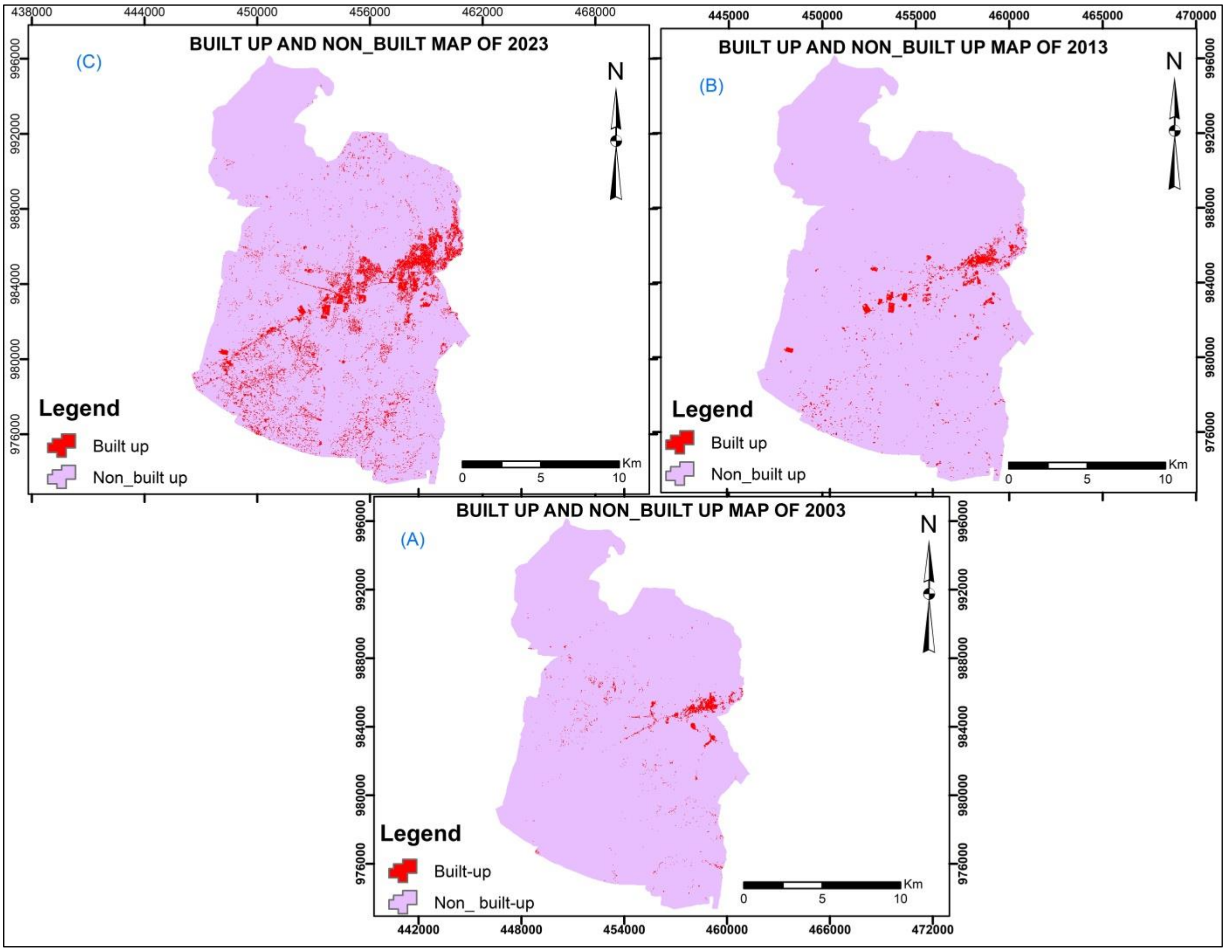

Figure 4.1 Built up and non-built up map of Sabete sub-city (2003-2023)

An analysis of Land Use Land Cover (LULC) maps (Figure 4.1) reclassified into built-up and non-built-up areas reveals a clear trend of urban sprawl. These maps illustrate the spatiotemporal pattern of urban growth, with expansion extending outwards from the city center along transportation corridors towards adjoining undeveloped areas. As evident in Table 4.2, the built-up area proportion within the study area grew significantly, increasing from 1.22% in 2003 to 1.88% in 2013 and reaching 6.69% by 2023.

Table 4.2 Built and non-built-up areas (2003- 2023)

No	LULC	Study period					
		2003		2013		2023	
		ha	%	ha	%	ha	%
1	Built-up	270.1	1.22	415.02	1.88	1529.02	6.92
2	Non_built-up	21,820.1	98.88	21,675.18	98.22	20,561.18	93.8
3	Total	22090.2	100	22090.2	100	22090.2	100

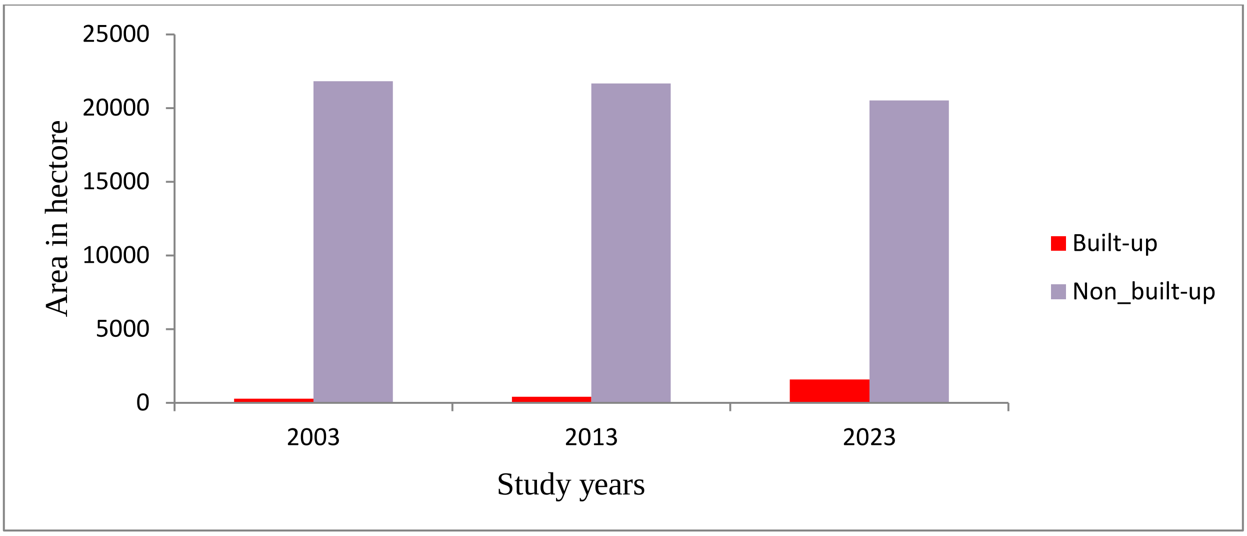

Figure 4.2 Change Trend of built-up area expansion between 2003 and 2023

Figure 4.2 illustrates a spatial increase in various land use and land cover classes across the study area. This includes built-up areas, which have grown due to both horizontal expansion and conversion of other land cover types during the study periods. Figure 4.1 further emphasizes this point, with the reclassified images revealing a rapid shift from non-built-up areas towards built-up ones.

4.4 Land use/land cover classification of Sebeta city

Land use and land cover maps of the study area were categorized into four major types: built-up, dense forest, farmland, and sparse forest. Therefore, the result of the three-period land use/land cover classification map of the study area is described in figures 4.3, 4.4, and 4.5 below.

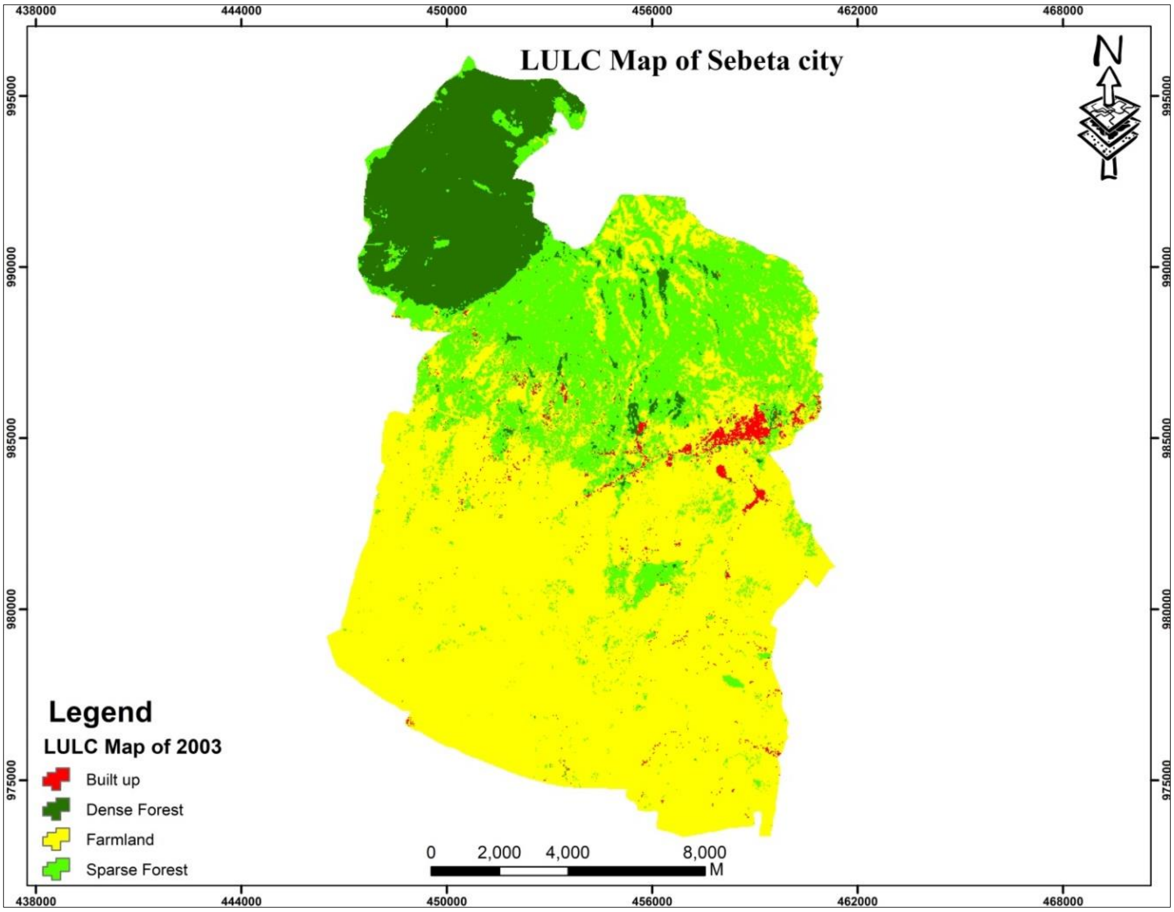

Figure4.3 Land use/land cover map of Sebeta city in 2003

Based on the land-use/land-cover data for Sebeta sub-city in 2003 (Figure 4.3), the area was dominated by farmland, covering a significant 61.9% of the total area. Forests were also prevalent, with dense and sparse forests accounting for 13.36% and 23.51% respectively. Built-up areas were much less extensive at that time, occupying only 1.22% of the total area.

Table 4.3 Quantitative Distribution of LULC in 2003

Year		2003
LULC Classes	Area	Percent
Built up	270.051	1.22
Farmland	13674.8	61.90
Dense Forest	2951.04	13.36
Sparse Forest	5194.28	23.51
Total	22090.2	100.00

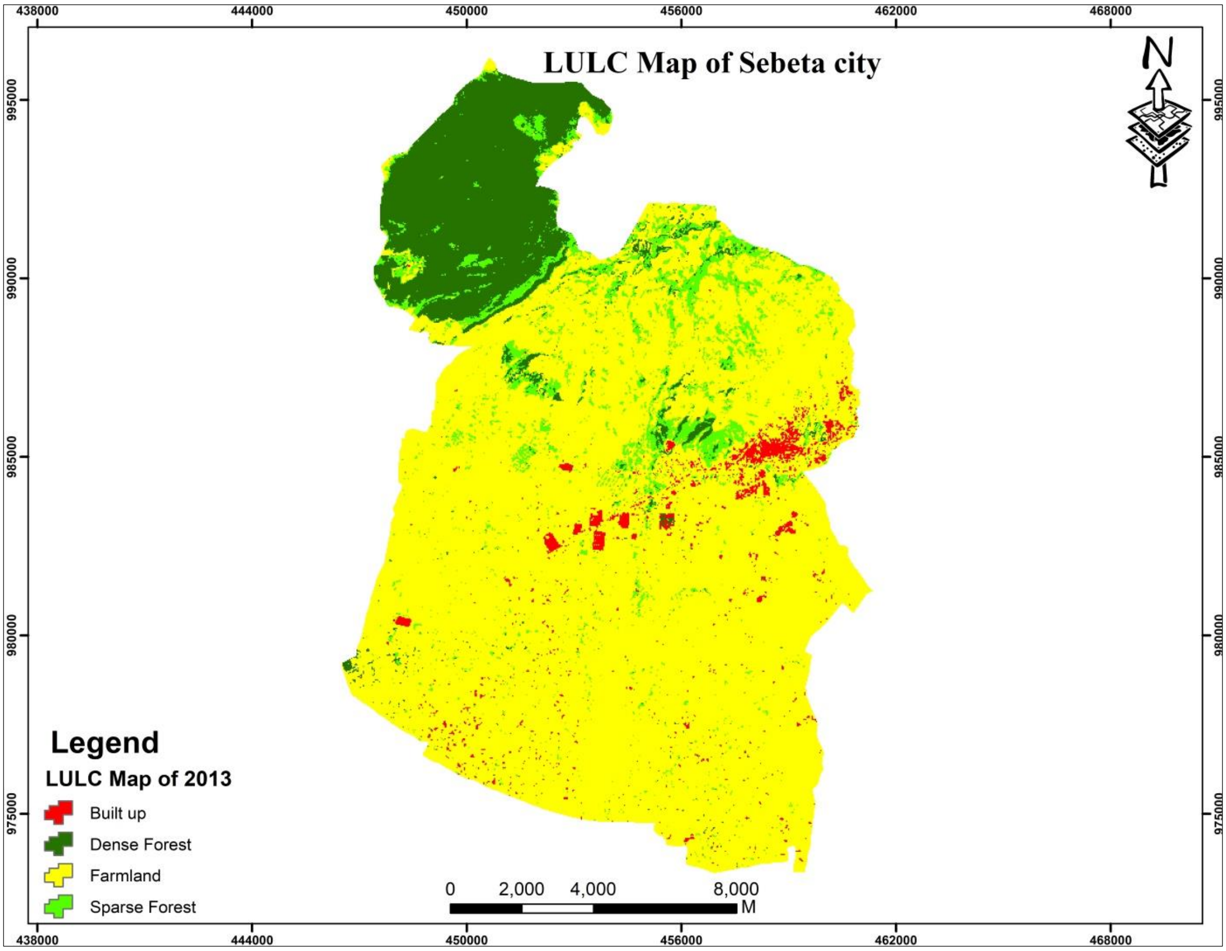

Figure4.4 Land use/land cover map of Sebeta city in 2013

The land use/land cover data for Sebeta sub-city in 2013 suggests a landscape primarily dedicated to agriculture (78.63% farmland). This is accompanied by a presence of forest cover, with dense forest (13.25%) and sparse forest (6.24%) occupying a notable area. Interestingly, built-up areas appear to be quite limited, covering only 1.88% of the total area.

Table 4.4 Quantitative Distribution of LULC in 2013

year		2013
LULC_Class	Area in ha	Percent
Built up	415.02	1.88
Dense forest	2927.11	13.25
Farmland	17369	78.63
Sparse Forest	1379.1	6.24
Total	22090.2	100.00

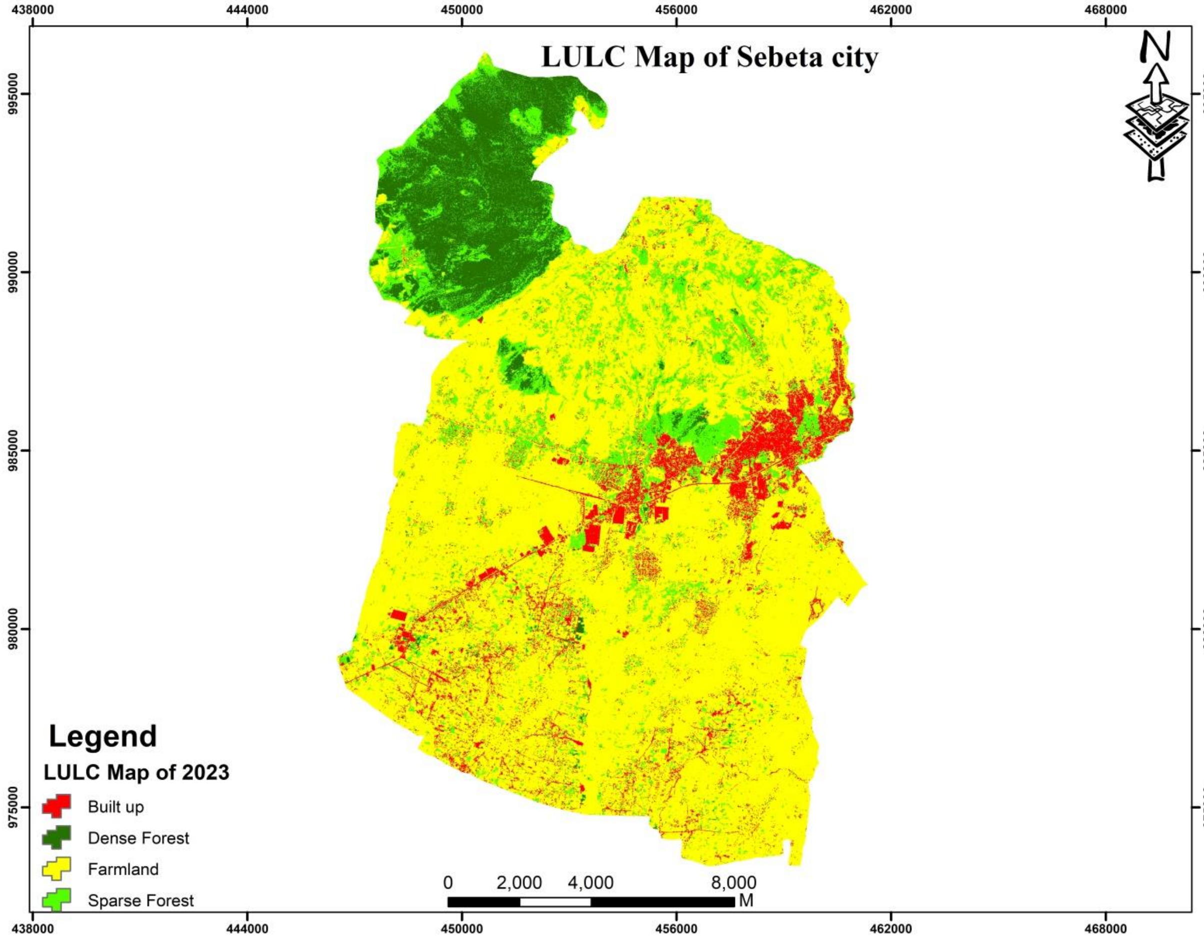

Figure 4.5 Land use/land cover map of Sebeta city in 2023

Table 4.5 Quantitative Distribution of LULC in 2023

YEAR		2023
LULC classes	Area in hector	Percent
Built up	1529.02	6.92
Dense Forest	15447.8	69.93
Farmland	2295.32	10.39
Sparse Forest	2818.06	12.76
	22090.2	100.00

The 2023 land use/land cover data for Sebeta sub-city reveals a landscape balancing agriculture (69.93% farmland) with development (6.92% built-up area), but raises concerns about forest cover. Compared to a possible range in 2013 (1.88% built-up area), 6.92% in 2023, warranting investigation into potential causes. While data verification and spatial variability within Sebeta require consideration, further information like source details and land cover distribution maps for both 2013 and 2023 would be crucial to understand the drivers behind these changes, such as population growth, development projects, or environmental factors impacting forests. This comprehensive analysis is essential to inform future decisions about Sebeta's land-use trajectory.

Table 4.6 Quantitative Distribution of LULC in 2003, 2013 and 2023

Year	**2003**		**2013**		**2023**	
LULC_Classes	Area	Percent	Area in ha	Percent	Area in ha	Percent
Built up	270.051	1.22	415.02	1.88	1529.02	6.92
Farmland	13674.8	61.90	17369	78.63	15447.8	69.93
Dense Forest	2951.04	13.36	2927.11	13.25	2295.32	10.39
Sparse Forest	5194.28	23.51	1379.1	6.24	2818.06	12.76
Total	22090.2	100.00	22090.2	100.00	22090.2	100.00

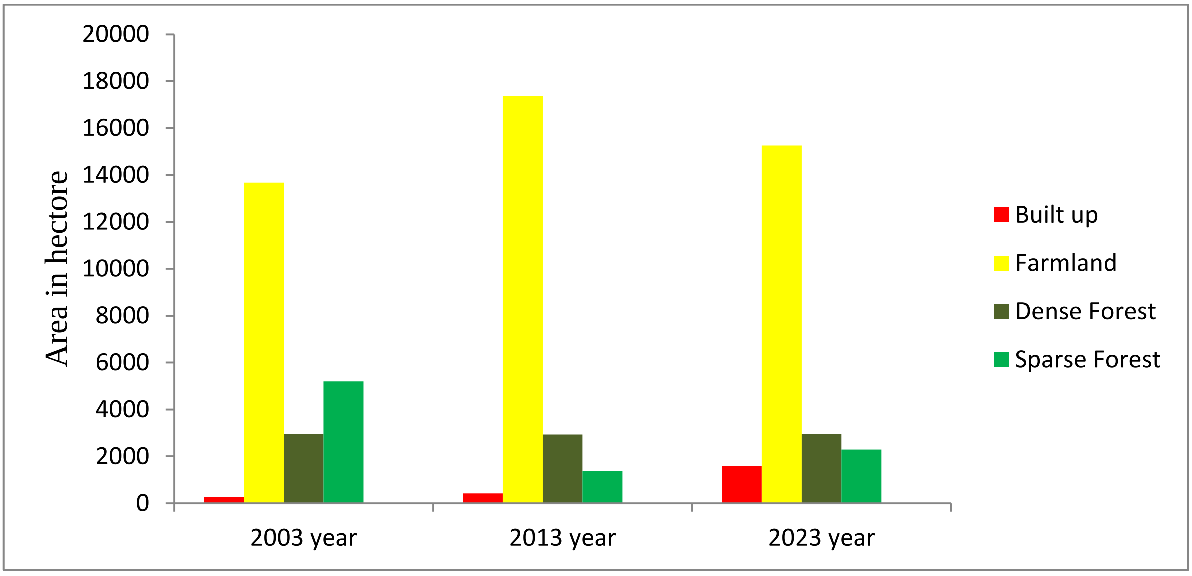

Figure 4.6 historical land use/land cover results in 2003, 2013, and 2023

4.5. LULC Change Analysis

Three visualizations are available in the Change Analysis panel to examine changes in land cover between two user-defined maps (as given in the Project Parameters). The first graph shows the gains and losses for each category of land cover, giving a brief summary. By adding gains to the starting area and deducting losses, the second option, "net change by category," determines the final area for each category. Lastly, a more in-depth option called "contributors to net change" looks at which forms of land cover were most responsible for the changes that a certain category underwent. The significance of these analysis tools was highlighted by the noteworthy cross-tabulation comparison of land use/land cover maps for 2003, 2013, and 2023, which showed notable changes across all land cover classes.

4.5.1. LULCC between 2003 and 2013

During the first period between 2003 and 2013, the built-up/urban area gained 349ha (1.03%) and lost 185ha (0.54%), witnessing a net gain of 165ha (0.48%). Farmland cover gained 4324ha (12.71%) and lost 757ha (2.23%), having a net gain of (3567)ha (10.49%). Sparse forest cover gained 623ha (1.83%) and lost 4335ha (12.74%), having a net loss of (3712)ha (10.91%). Dense forest gained 317ha (0.93%), and lost 337ha (0.99%) and witnessing a net gain of 20ha (0.06%)(table 4.7). The different LULC classes that added to the Contribution to net change in built-up areas during the period between 2003 and 2013 include the change of 137 ha (0.40%) of farmland to built-up areas and the conversion of 27 ha (0.08%) of sparse forest to the built-up area. Sparse forest experienced the most significant loss during this period. This decline can be mainly due to the factors contributing to the reduction in sparse forest between 2003 and 2013 include inadequate legislation, institutional weakness, unaccountability, and uncontrolled human activities.

Table 4.7 Losses, gains, and net changes of LULC classes between 2003 and 2013 (in ha)

			Gain, losses and net change between2003 &2013					
LULC Types	GAIN		LOSS		Net change		contribution to net change in built-up	
	ha	%	ha	%	ha	%	ha	%
Built up	349	1.03	-185	-0.54	165	0.48	0	0
Farmland	4324	12.71	-757	-2.23	3567	10.49	137	0.40
Sparse forest	623	1.83	-4335	-12.74	-3712	-10.91	27	0.08
Dense forest	317	0.93	-337	-0.99	-20	-0.06	0	0

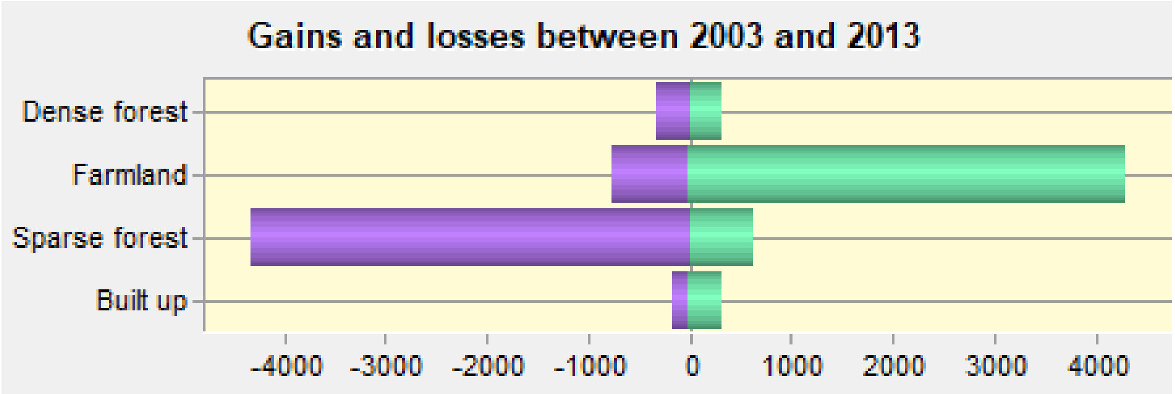

Figure 4.7 Gain and loss between 2003 and 2013

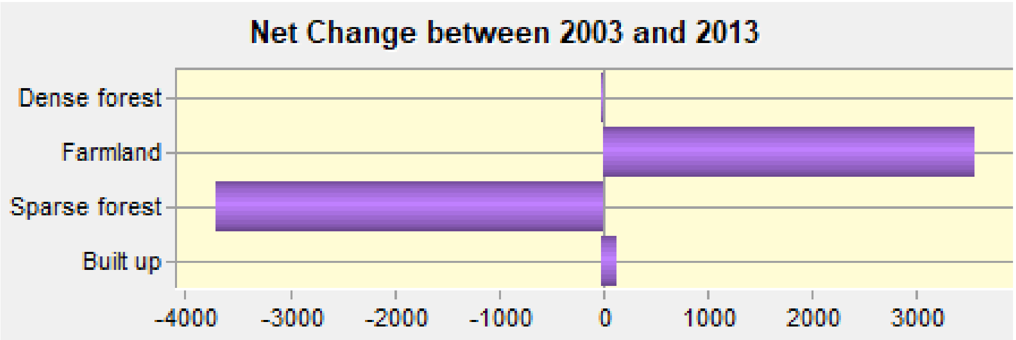

Figure 4. 8 Net change between 2003 and 2013

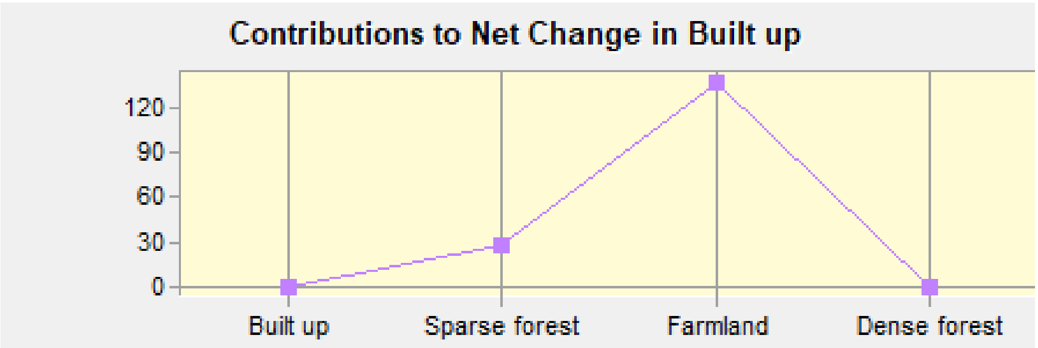

Figure 4.9 contribution to net change in built-up area between 2003 and 2013 in ha

4.5.2. LULCC between 2013 and 2023

During this period between 2013 and 2023, the built-up/urban area gained 1371ha (4.03%) and lost 187ha (0.55%), witnessing a net gain of 1185ha (3.48%). Farmland cover gained 838ha (2.46%) and lost 2930ha (8.61%), having a net loss of (2092)ha (6.15%). Sparse forest cover gained 2300ha (6.76%) and lost 708ha (2.08%), having a net gain of (1592)ha (4.68%). Dense forest gained 212ha (0.62%), and lost 896ha (2.63%) and witnessing a net loss of 685ha (2.01%)(table 4.8). The different LULC classes that added to the Contribution to net change in built-up areas during the period between 2013 and 2023 include the change of 1141 ha (3.35%) of farmland to built-up areas and the conversion of

26 ha (0.08%) of sparse forest to the built-up area while 18ha (0.05%) of dense forest converted to built-up during this time. Between 2013 and 2023, the amount of farmland decreased, while sparse increased dramatically.

Table 4. 8 Losses, gains, and net changes of LULC classes between 2013 and 2023 (in ha)

	Gain, losses and net change between2013 &2023							
LULC Types	GAIN		LOSS		Net change		contribution to net change in built-up	
	ha	%	ha	%	ha	%	ha	%
Built up	1371	4.03	-187	-0.55	1185	3.48	0	0
Farmland	838	2.46	-2930	-8.61	-2092	-6.15	1141	3.35
Sparse forest	2300	6.76	-708	-2.08	1592	4.68	26	0.08
Dense forest	212	0.62	-896	-2.63	-685	-2.01	18	0.05

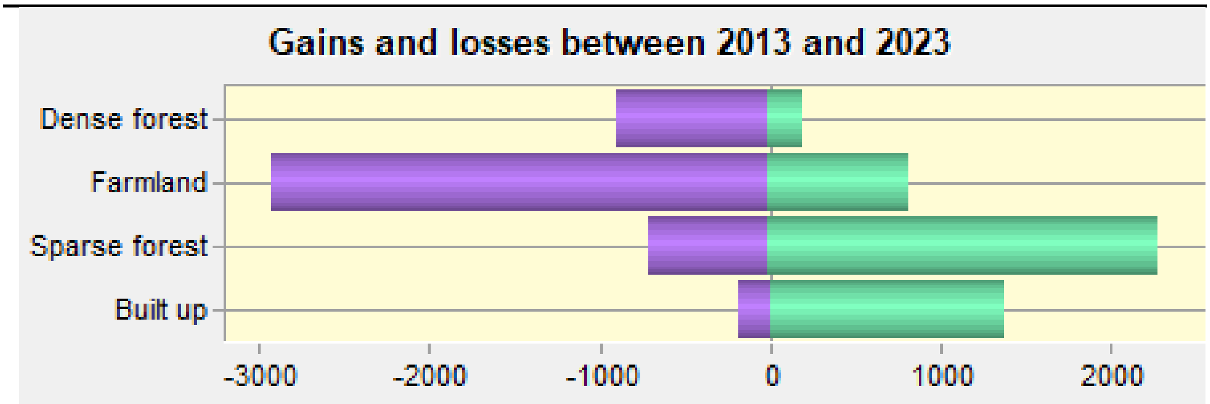

Figure 4.10 Gain and loss between 2013 and 2023

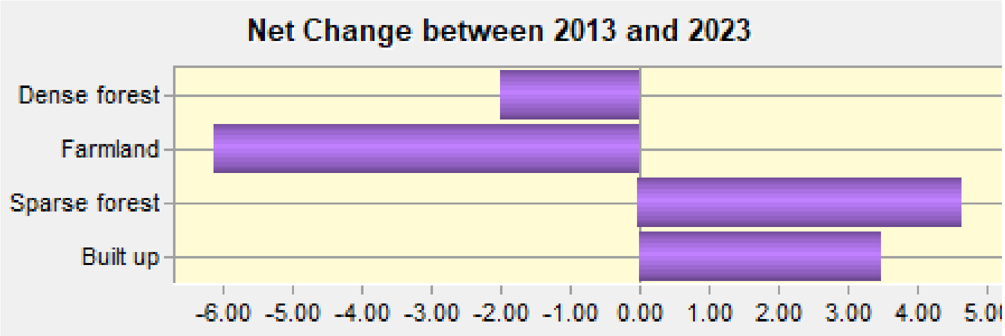

Figure 4.11 Net change between 2013 and 2023

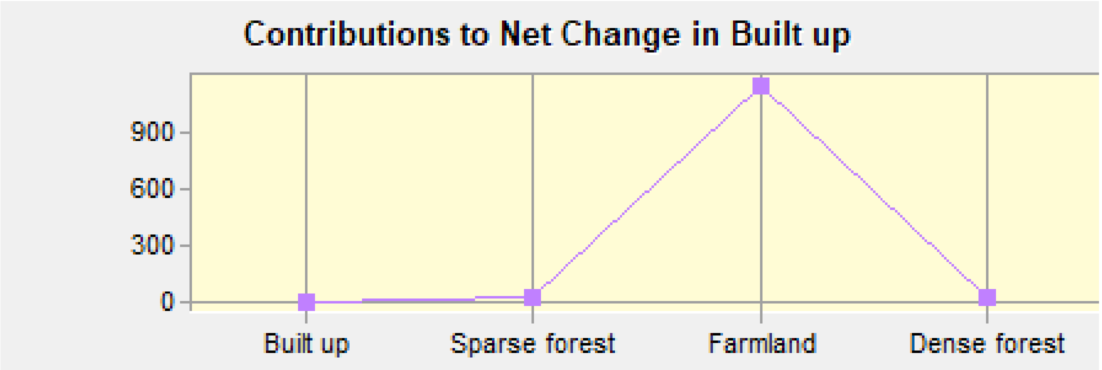

Figure 4.12 contribution to net change in built-up area between2013 and 2023 in ha

4.5.3. LULCC between 2003 and 2023

During this period between 2003 and 2023, the built-up/urban area gained 2644ha (47.77%) and lost 104ha (0.30%), witnessing a net gain of 2540ha (7.47%). Farmland cover gained 3285ha (9.66%) and lost 2816ha (8.28%), having a net loss of (469)ha (1.38%). Sparse forest cover gained 1334ha (3.92%) and lost 3829ha (11.26%), having a net loss of (2495)ha (7.33%). Dense forest gained 123ha (0.36%), and lost 637ha (1.87%) and witnessing a net loss of 514ha (1.51%)(table 4.9). The different LULC classes that added to the Contribution to net change in built-up areas during the period between 2003 and 2023 include the change of 1966 ha (5.78%) of farmland to built-up areas and the conversion of 564ha (1.66%) of sparse forest to the built-up area while 11ha (0.03%) of dense forest converted to built-up during this time. It implies that between 2003 and 2023, the built-up area has seen the most significant development in the previous 20 years. This study reveal that the different gains and losses in each land use/land type (in hectares) and the net change in additions to built-up areas (in hectares) during study periods

Table 4. 9 contribution to net change in built-up area between 2003 and 2023 in ha

	Gain, losses and net change between2003 &2013							
LULC Types	GAIN		LOSS		Net change		contribution to net change in built-up	
	ha	%	ha	%	ha	%	ha	%
Built up	2644	7.77	-104	-0.30	2540	7.47	0	0
Farmland	3285	9.66	-2816	-8.28	469	1.38	1966	5.78
Sparse forest	1334	3.92	-3829	-11.26	-2495	-7.33	564	1.66
Dense forest	123	0.36	-637	-1.87	-514	-1.51	11	0.03

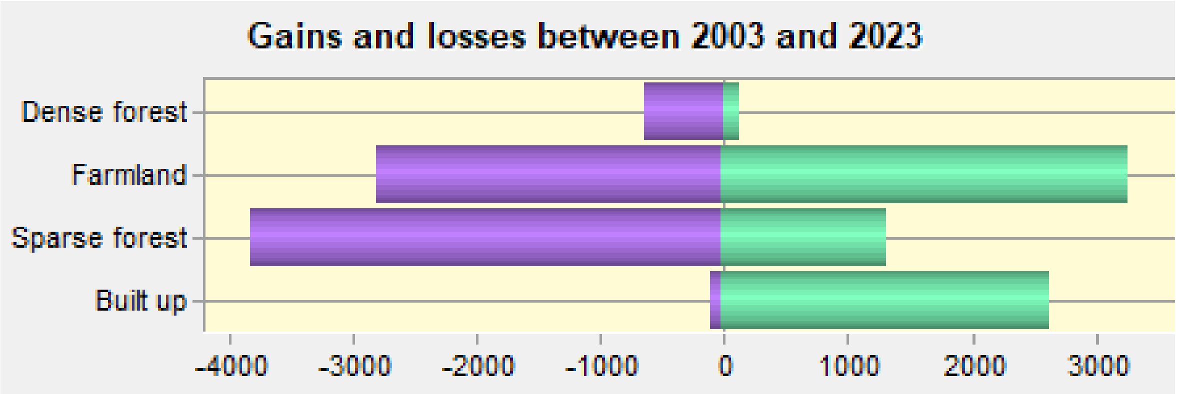

Figure4. 13 Gain and loss between 2003 and 2023

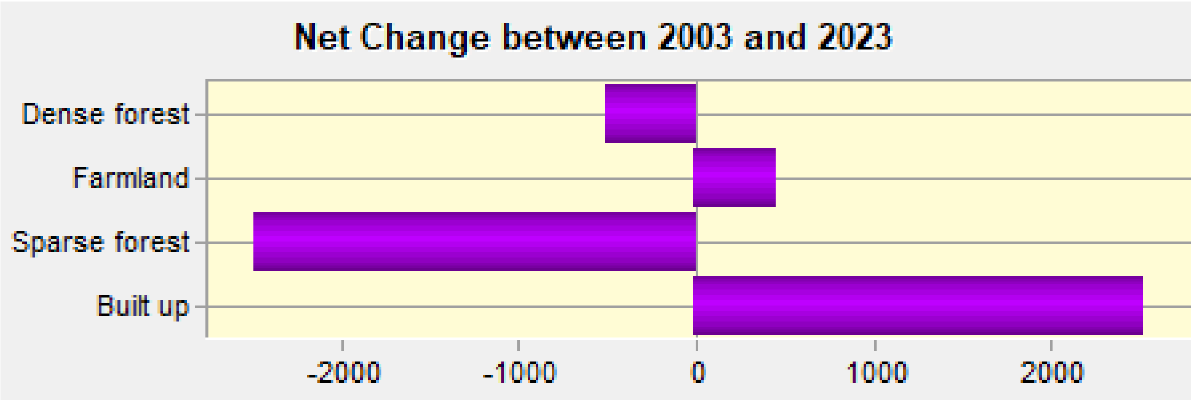

Figure4. 14 Net change between 2003 and 2023

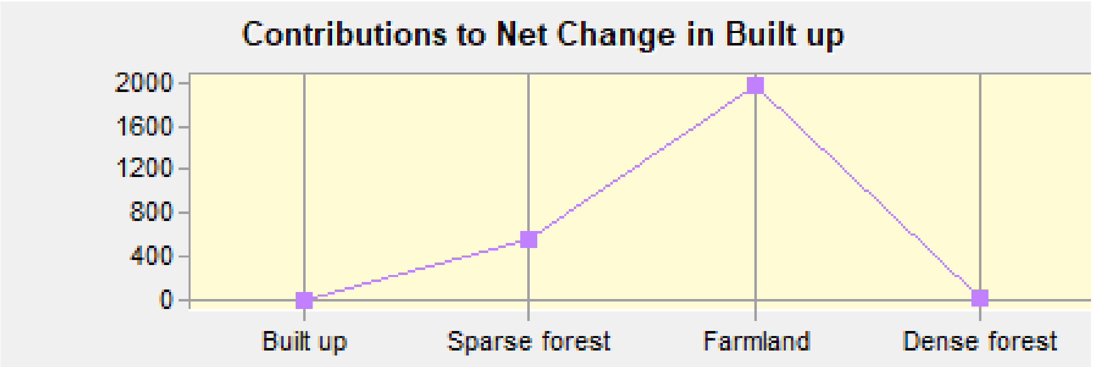

Figure 4.15 contribution to net change in built-up area between 2003 and 2023 in ha.

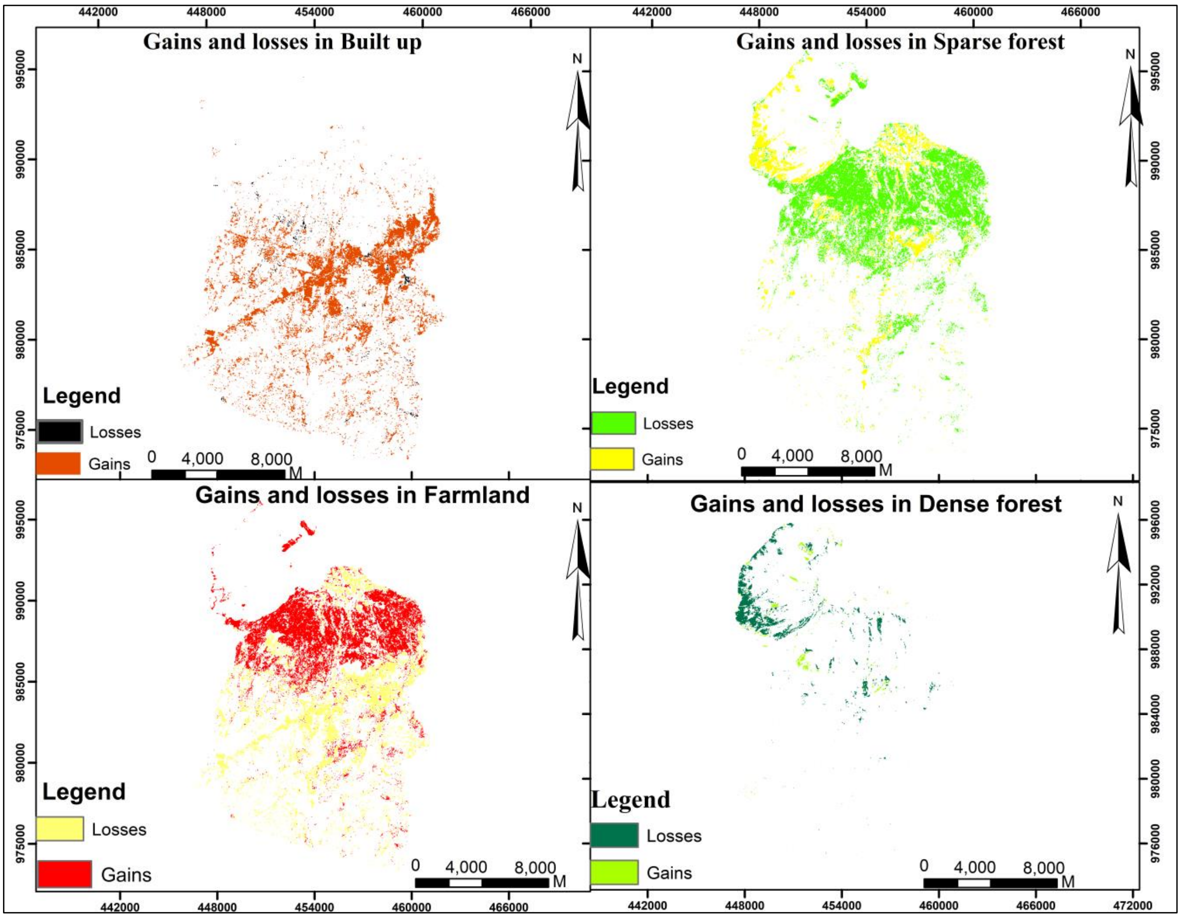

Figure 4.16 Losses and gains in the different LULC classes from 2003 and 2023

4.6. Transition potential modeling.

Transition Potential modeling, is probability that determine the potential of land to transition from one state to other state see table below. In order to observe the transformation from all land cover to Built-up figure 4.17 and table 4.10 prepared. The result indicated that 2059.2 hectare of farmland, 573.57 hectare of sparse forest, and 11.16 hactares of dense forest were converted to built-up class respectively (Table 4.10.).

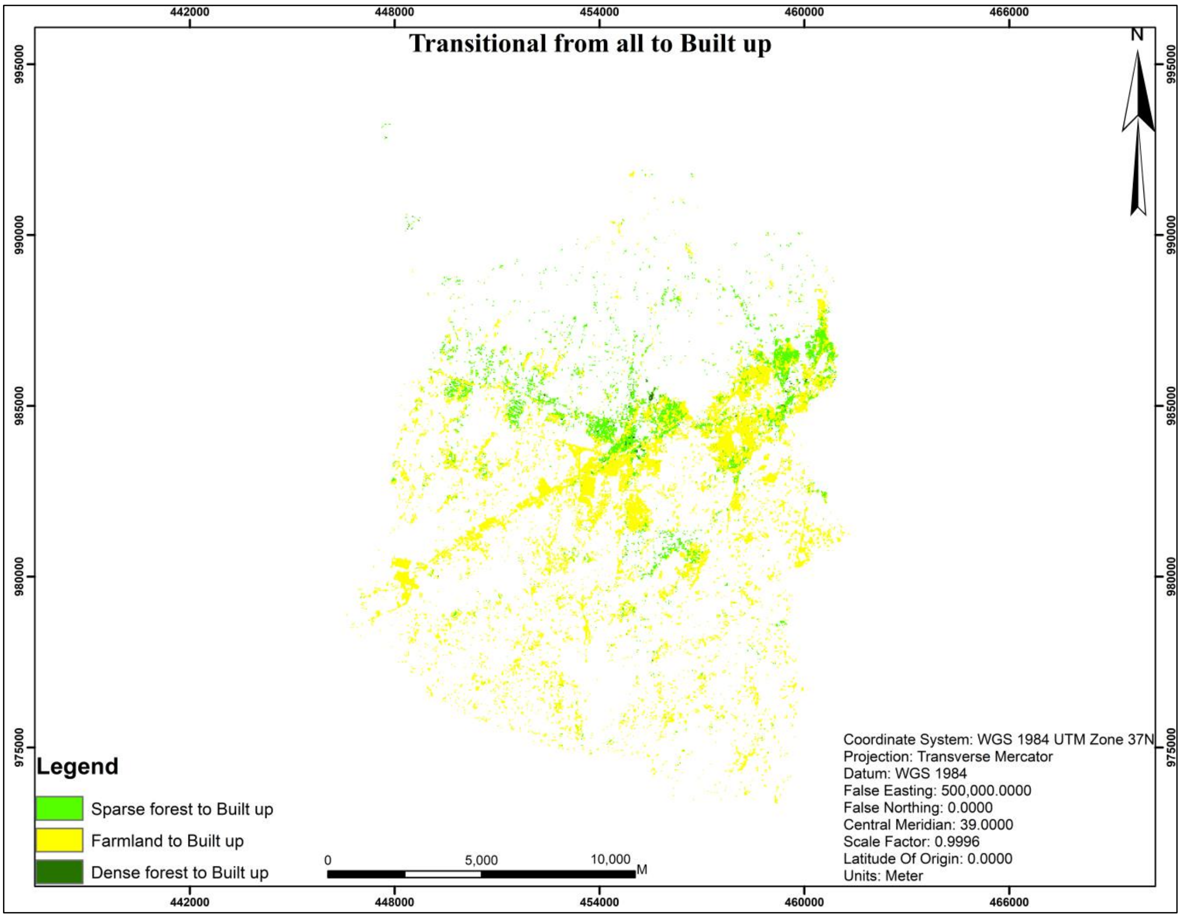

Figure 4.17 Transition from All to Built up class from 2003 to 2023

Table 4. 10 transition from all to built-up (2003 to 2023)

Transition	Area (ha)
Sparse forest to Built up	573.57
Farmland to Built up	2059.2
Dense forest to Built up	11.16

4.7. Spatial Trend of Change

The spatial trend analysis tool in LCM was used to compute maps of transition trends from all land cover categories to build up areas between 2003 and 2023. 3rd order of polynomial, which is best fit to the pattern of change, in LCM was used. The numeric values produced don't have any special significance (Eastman, 2012). Thus, the result is interpreted as: the lower the value, indicate less changes and the higher the value indicates more changes. The resulting map is presented in figure 4.17 below which provides a means of generalizing transition trends of built up areas for easy interpreting complex land change patterns. From figure 4.18 it is evident that the transition intensity of built up areas was more intense in the center of the study area, with the highly changed value (0.0073) and less change at the value of (-0.0014). The trend has shown a growing (sprawling) of built up areas towards the North West and towards south West relative to other directions. Thus, the trend and extent of changes in built up areas are likely to continue with the rapid development of infrastructure, economy and increasing of population.

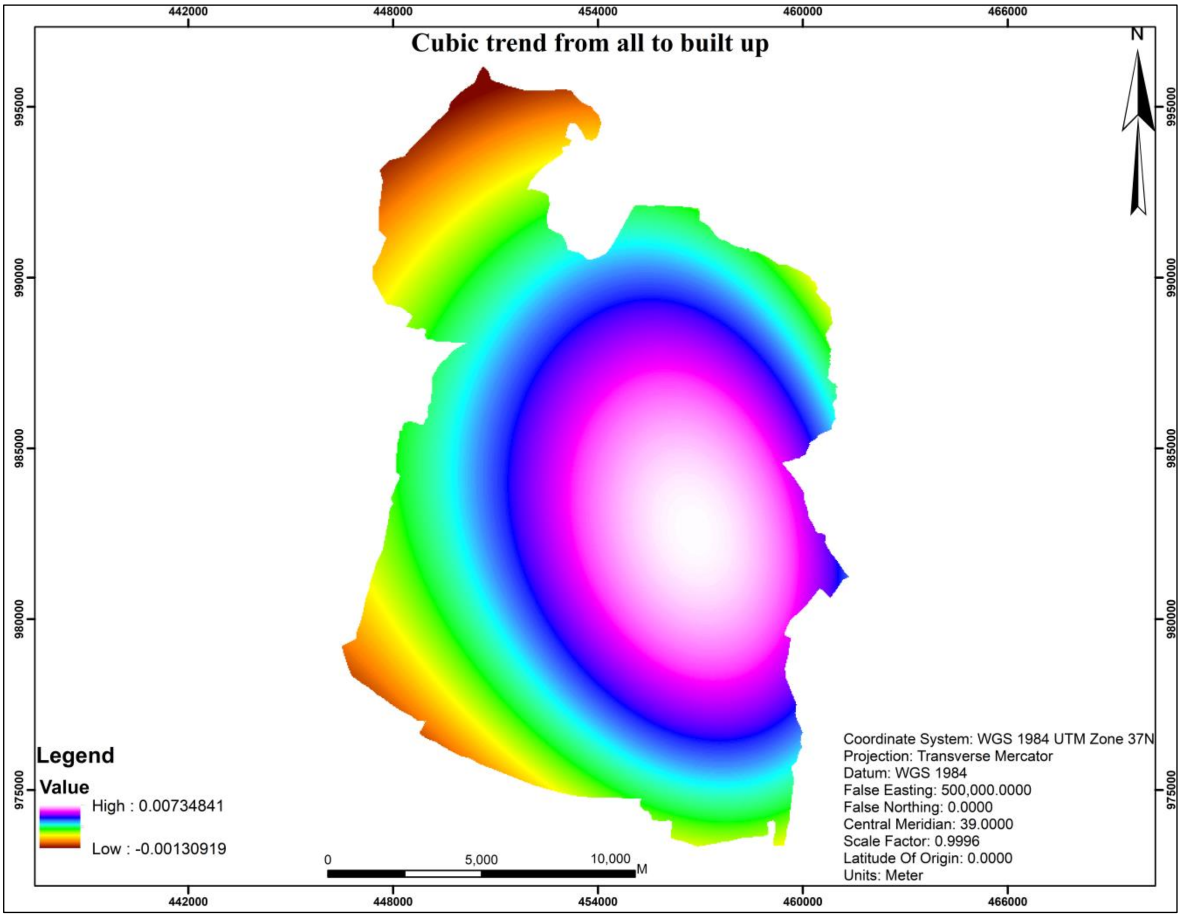

Figure 4.18 Map of spatial trend of changes All to Built-up between 2003 and 2023

4.8. Modeling possible expansion of sebeta sub-city up to 2050.

4.8.1 LULC Map of sebeta sub-city in 2050

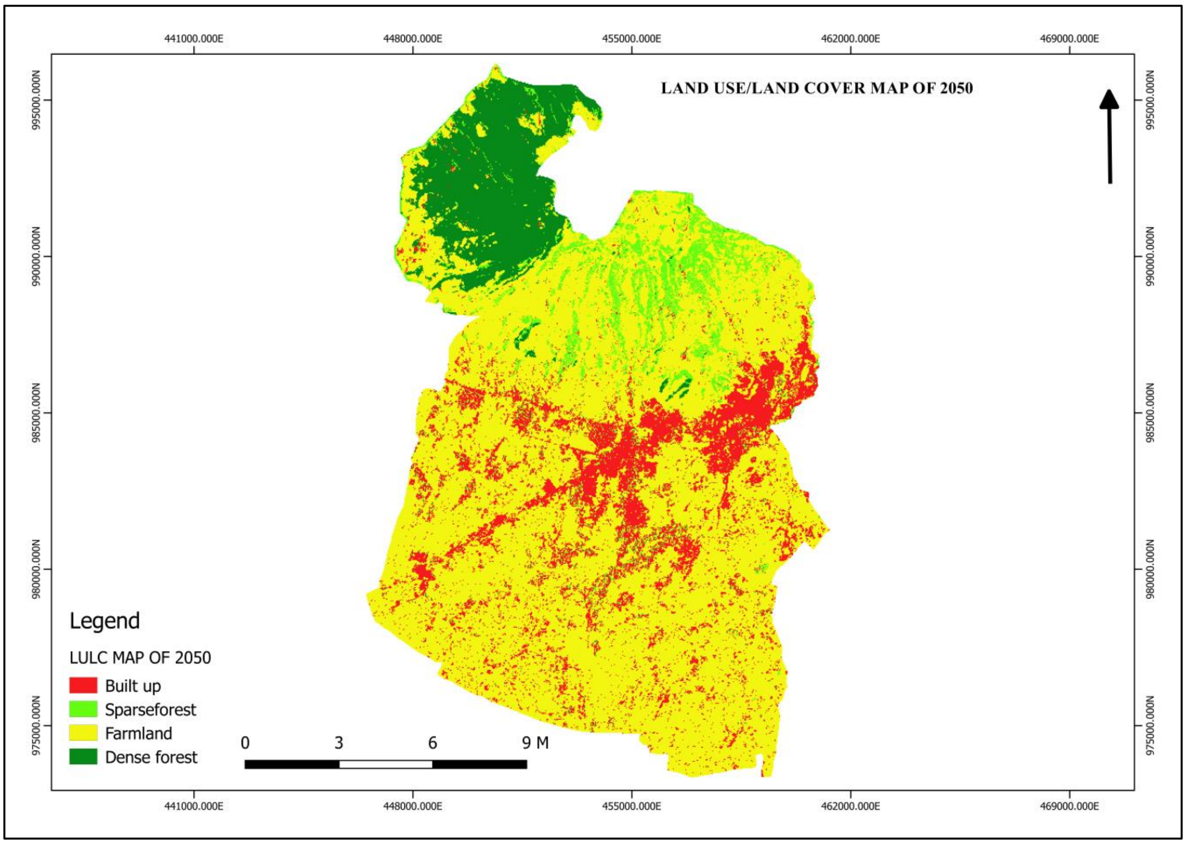

Figure 4.19 Land use land cover map of Sebeta sub-city in 2050

Table 4. 11 Land use /land cover changes of 2023-2050

LULCC	2023	2050	Δ	2023%	2050%	Δ %
Built up	2830.86 ha	3195.63 ha	364.77 ha	12.81321	14.46426	1.651044
Sparse forest	2683.80 ha	1389.78 ha	-1294.02 ha	12.14758	6.290507	-5.85707
Farmland	14133.69 ha	15259.68 ha	1125.99 ha	63.97277	69.0693	5.096525
Dense forest	2444.94 ha	2248.20 ha	-196.74 ha	11.06644	10.17594	-0.8905

The provided data suggests a land use landscape in 2050 dominated by farmland, accounting for nearly 69% of the total area. This is followed by built-up areas at 14.46%, indicating a significant expansion of human settlements. Dense forest cover is projected to be around 10%, while sparse forest occupies a little over 6%. These figures imply a potential trade-off between agricultural lands and natural ecosystems. While the increase in built-up areas is expected, it's crucial to monitor how much agricultural land expands at the expense of forests. Sustainable practices and land management strategies will be essential to balance these competing demands.

4.8.2 land use/land cover change detection between 2023-2050

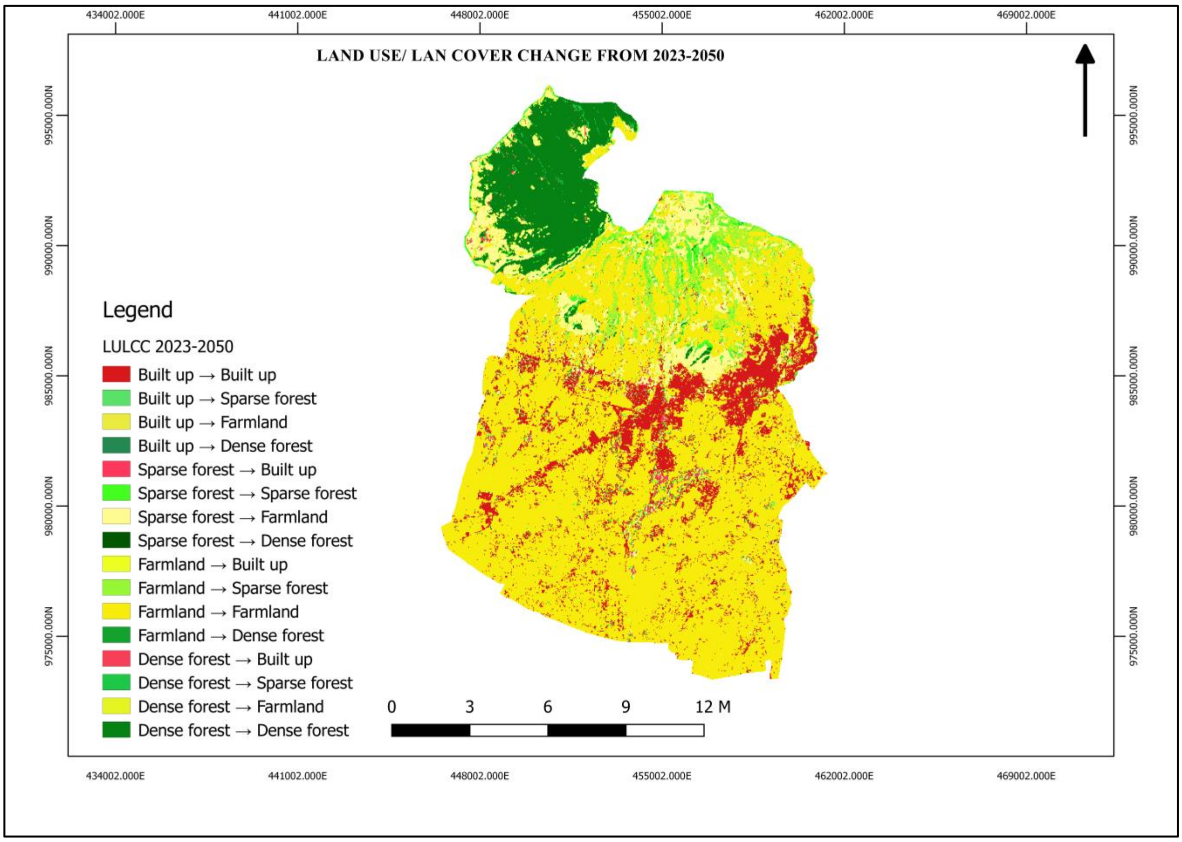

Figure4.20 Land use/ land over change detection

Table 4.12 Land use/ land cover change matrix's from 2023-2050

LULC	Built up	Sparse forest	Farmland	Dense forest
Built up	0.88577	0.011859	0.101831	0.00054
Sparse forest	0.072133	0.283635	0.643561	0.000671
Farmland	0.034017	0.039066	0.926809	0.000108
Dense forest	0.005632	0.017522	0.059302	0.917544

The land use change matrix for 2023-2050 reveals a surprising level of stability across all four categories: built-up, sparse forest, farmland, and dense forest. For built-up areas, a significant 89% of land classified in 2023 remains so in 2050. Similarly, a high proportion of land remained classified as farmland (92%) and dense forest (92%) throughout the projection period. This suggests minimal conversion between these land uses over the next 27 years. However, the data also highlights a potential concern for sparse forests. Only 28% of the area classified as sparse forest in 2023 is projected to remain unchanged by

2050. This indicates a higher likelihood of conversion to other land uses compared to the other categories. Further investigation into the drivers of this change and potential mitigation strategies would be crucial for sustainable land management.

4.9 Discussion on LULC, urban expansion and future prediction for urban growth.

As the results shows that, the total area covered by each land use/land cover classes' area 22090.2ha. Based on the land-use/land-cover data for Sebeta sub-city in 2003, the area was dominated by farmland, covering a significant 61.9% of the total area. Forests were also prevalent, with dense and sparse forests accounting for 13.36% and 23.51% respectively. Built-up areas were much less extensive at that time, occupying only 1.22% of the total area. In 2013 and 2023 built-up, farmland, sparse and Dense forest are covered by (1.88, 6.92),(78.63, 69.93), (6.24, 12.76) and (13.25,10.39) in percent respectively. The covered by built-up in first year are high as compare with the second selected years as well as it is also increased in the last year. This show that the built-up are highly increased as compared with others LULC classes. As information shown on built-up and none built-up map, built-up area proportion within the study area grew significantly, increasing from 1.22% in 2003 to 1.88% in 2013 and reaching 6.69% by 2023. However in none built up cover 98.88% in 2003, 98.22% in 2013 and 93.8% in 2023 as compared built-up and none built up area for selected three years.

The built-up area was increased between selected years by 1.22%, 1.88%, and 6.69% respectively from 2003, 2013 and 2023 years. According to (Mekonnen, 2017b) conducted on monitoring urban growth and land use land cover change using remote sensing and geospatial technologies. Results shows that during the last thirty years, urban area has increased by 31.73% (i.e., 42.66 km2), while agriculture area have decreased by 24.53% (i.e., 32.98 km2). Further, it is observed that during this period, population in the area has increasing at an average rate of 5%. Correlating population and urban growth, it is found that by the year 2030 the whole area would be fully converted into urban area. In agreement with this result (Mohamed & El-raey, 2018), in Alexandria city, Egypt results showed that urbanized areas increased from 1999 to 2014 gradually, while the agricultural areas have been continued to decrease.

From the findings shown in table 4.16, the change between the previous (2023) and predicted (2050) land classes indicates that built-up increased by 12.8%. However farmland, Sparse and Dense forest were decreased by 63.97%, 12.14%, and 11.06%, respectively. 5.9% of none built up areas was converted to built-up area as indicated by the transition matrix built up area was increased between 2023 and 2050. In agreement with this finding, as discussed by (Abbas et al., 2021) it is predicted that forest areas are projected to continue to decline at alarming rates in some regions. According to (Mohamed & El-raey, 2018) the result of simulation from 2014 to 2050 years, it is expected that; the urban area would increase 263.38 km2 in total and about 330.76 km2 losses in agricultural lands and about 100.44 km2 would be transformed to the urban area if the existing trend continued.

CHAPTER FIVE

CONCLUSION AND RECOMMANDATION

5.1. Conclusion

The study used geospatial techniques to detect and predict land use and land cover change in Sebeta sub-city over a 20-years. Multi-temporal satellite data and GIS techniques were employed to monitor the city's historical land use/land cover pattern using the land cover maps of 2003, 2013 and 2023. The overall accuracy assessment for 2003, 2013, and 2023 were 85.3%, 93.95%, and 94.8% respectively. At the same time, the kappa coefficient of 2003, 2013, and 2023, were 0.81, 0.9 and 0.93 percent respectively. The results of this study give away the existence of significant land use/land cover and urban growth changes in the last 20 years. Particularly the expansion of built-up area increased while other LULC Classes where declined during the study periods.

The land-use/land cover transition from 2003 to 2023 has shown a dramatic change in several LULC categories. The built-up area increased by 270.05 ha (1.88%) and 1529.02ha. On the other hand, Farmland, sparse and Dense forest showed 13674.8 ha (61.9%) and 15447.7ha (69.93%), 5194.28 ha (23.51%) and 2818.06 ha (12.76%), 2951.04ha (13.36%),and 2295.32ha (10.39)respectively. Accordingly, more land was converted in to built-up area so; increase urban expansion there is impact on another land uses/land cover of the study area. To simulate the spatiotemporal change transition potential, variables (DEM, slope, and distance from roads) and an integrated CA-ANN in paython methodology within the MOLUSCE plugin of QGIS were utilized. In predicted urban expansion of the year 2050 indicate the same trends that built-up areas will increase by 14.46% whereas Sparse, farmland and dense forest areas will be d 12.14%, 63.97% and 11.06% respectively. Kappa statistic in 2050 is 0.97.The degree to which the data gathered for the study are accurate representations of the variables measured is what gives rater reliability its significance.

The study results revealed that besides to urban growth has an impact on the land use/land cover of Sebeta sub-city. Moreover, government policies for encouraging minimizing illegal expansion can be reduced.

5.2. Recommendations.

On the basis of this research following future prospects and recommendation can be made:

- ✓ From the research, urbanization of Sebeta sub-city from 2003 to 2050 is expected to causing severe impact on socio economic, environmental aspects and other land covers. It is high time for planner and policy makers to develop urbanization not only in horizontal dimension but in vertical dimension as well. Furthermore, implementation of building by laws and land use plans is highly recommended.
- ✓ The use of high resolution imageries such as IKONOS and Quick Bird are important in generating good quality of land cover maps. Because urban areas have complex and heterogonous features, high resolution imagery provides better information by mapping these areas. Moreover, the use of ancillary data as ground truth helps for better accuracy of an image classification.
- ✓ Consistent multi-temporal Landsat data for each year provides detail comparison of images, change analysis and modeling. Especially for Markov chain method and CA method in Qgis, it is a requirement of equal interval of images acquisition although there have been uneven temporal availability of data.
- ✓ Political factor, technology, land policy, biophysical and social factor could improve the performance of the models for future predictions. Hence, it is important to the urban planners and decision makers.

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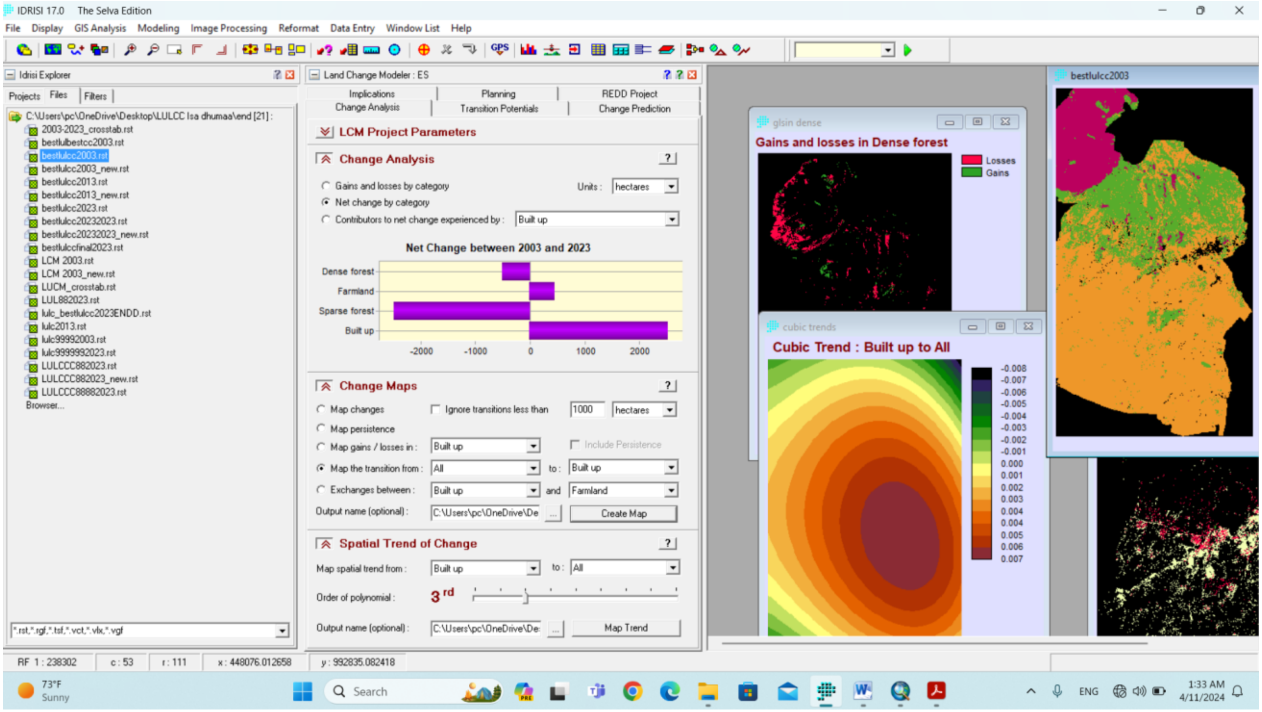
APPINDEX A:-Gain and losse, Net-change and contribution to change



Cross-tabulation of bestlulbestcc2003 (columns) against Endd2023_new (rows)

	0	1	2	3	4	Total
0	132471	0	0	0	0	132471
1	0	2077	6373	22880	124	31454
2	0	108	14999	8212	6501	29820
3	0	1036	35003	120544	458	157041
4	0	6	1167	194	25799	27166
Total	132471	3227	57542	151830	32882	377952

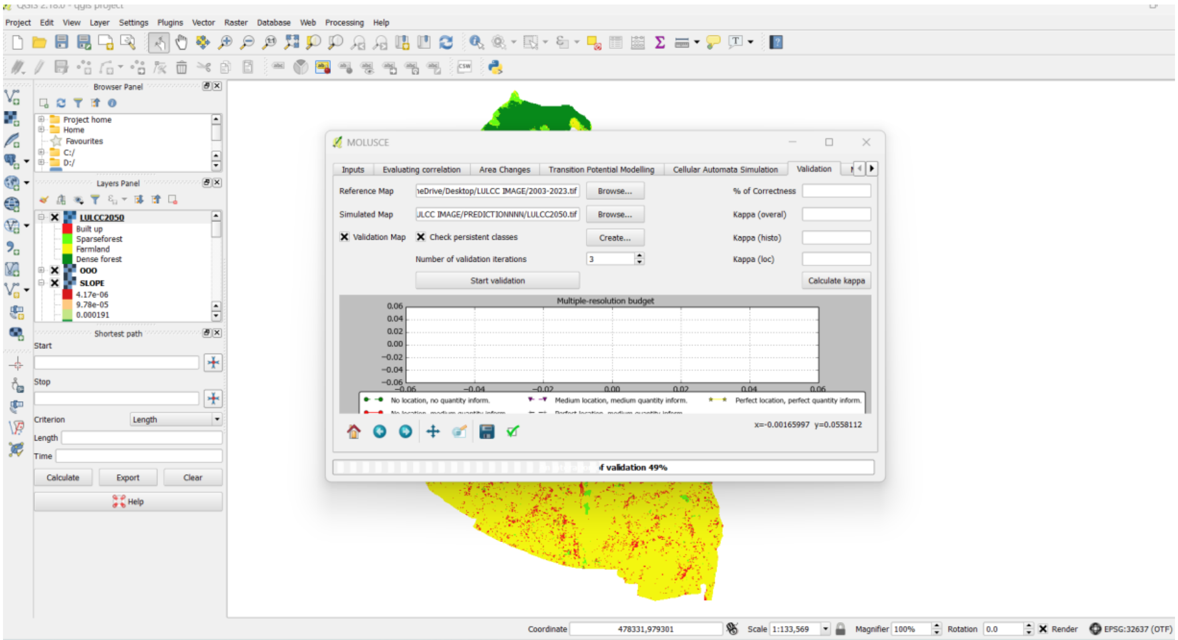
Chi Square = 701842.43750
df = 16
P-Level = 0.0000
Cramer's V = 0.6814

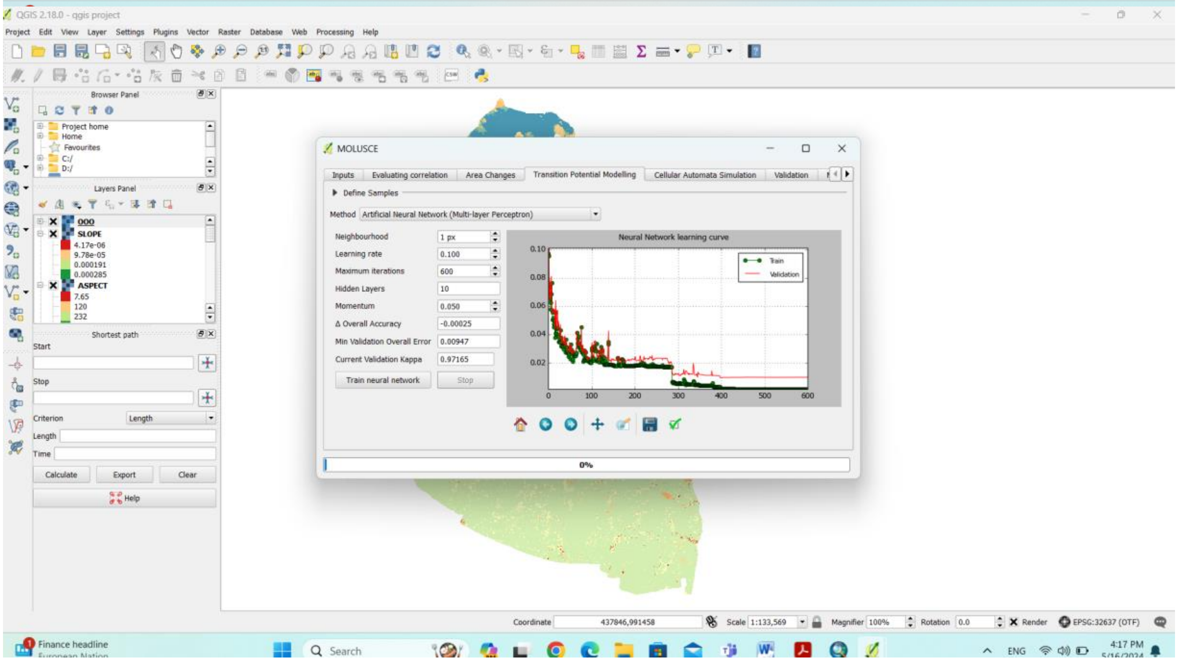
Proportional Crosstabulation

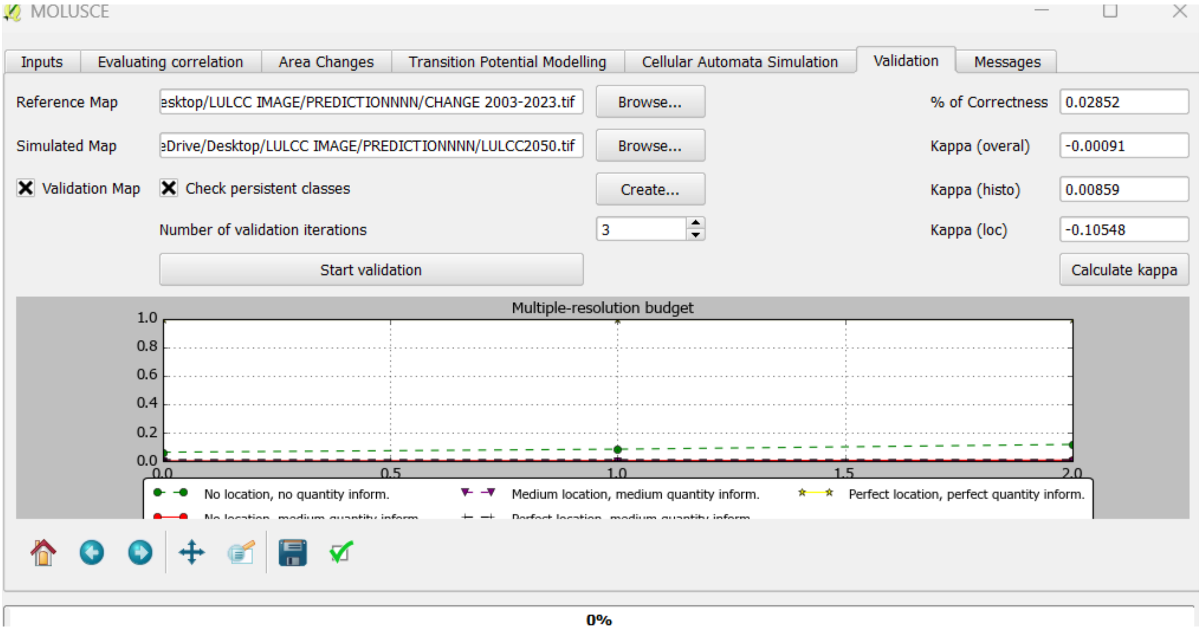
	0	1	2	3	4	Total
0	0.3505	0.0000	0.0000	0.0000	0.0000	0.3505
1	0.0000	0.0055	0.0169	0.0605	0.0003	0.0832
2	0.0000	0.0003	0.0397	0.0217	0.0172	0.0789
3	0.0000	0.0027	0.0926	0.3189	0.0012	0.4155
4	0.0000	0.0000	0.0031	0.0005	0.0683	0.0719
Total	0.3505	0.0085	0.1522	0.4017	0.0870	1.0000

Overall Kappa 0.3028

APPINDEX B:-multi-layer perception






MOLUSCE
Inputs
Evaluating correlation
Area Changes
Transition Potential Modelling
Cellular Automata Simulation
Validation
Messages
Reference Map
esktop/LULCC IMAGE/PREDICTIONNNN/CHANGE 2003-2023.tif
Browse...
% of Correctness
0.02852
Simulated Map
eDrive/Desktop/LULCC IMAGE/PREDICTIONNNN/LULCC2050.tif
Browse...
Kappa (overal)
-0.00091
Validation Map
Check persistent classes
Create...
Kappa (histo)
0.00859
Number of validation iterations
3
Kappa (loc)
-0.10548
Start validation
Calculate kappa
Multiple-resolution budget
No location, no quantity inform.
Medium location, medium quantity inform.
Perfect location, perfect quantity inform.
0%

Appendix C:- Sample point for ground verification

Easting	Northing	Description
458966	985059	Built-up
457799	985016	Built-up
458801	986008	Built-up
457707	985165	Built-up
457752	983843	Built-up
455622	984717	Built-up
456640	982590	Farmland
455857	981695	Farmland
452607	983494	Farmland
452949	985613	Farmland
451078	986071	Farmland
451117	980831	Farmland
457300	985706	Sparse forest
455581	987431	Sparse forest
385807	944783	Sparse forest
451488	987803	Sparse forest
448002	989484	Sparse forest
448648	990189	Sparse forest
451172	990546	Dense forest
449532	990824	Dense forest
456706	985373	Dense forest
450201	989208	Dense forest