ANALYSIS AND MODELING THE SPATIOTEMPORAL DYNAMICS OF URBAN EXPANSION: A CASE OF DUKEM TOWN, ETHIOPIA

Gemechu Mulatu Negasa

A Thesis Submitted to

The Department of Geomatics Engineering

School of Civil Engineering and Architecture

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

Office of Graduate Studies

Adama Science and Technology University

October, 2022

Adama, Ethiopia

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DECLARATION

I hereby declare that this Master Thesis entitled "Analysis and Modeling the Spatiotemporal Dynamics of Urban Expansion: a Case of Dukem Town, Ethiopia" is my original work and, it has not been submitted for the award of any academic degree, diploma or certificate in any other university. All sources of materials that are used for this thesis have been duly acknowledged through citation.

______________________________ ______________ ______________

Name of student Signature Date

RECOMMENDATION

I, the advisor of this thesis, hereby certify that I have read the revised version of the thesis entitled “Analysis and Modeling the Spatiotemporal Dynamics of Urban Expansion: a Case of Dukem Town, Ethiopia” prepared under my guidance by Gemechu Mulatu submitted in partial fulfillment of the requirements for the degree of Mater’s of Science in Geo-informatics Engineering Therefore, I recommend the submission of revised version of the thesis to the department following the applicable procedures.

Tilahun Erduno (PhD)	______________________	_____________
Advisor	Signature	Date

APPROVAL SHEET

I, the advisor of the thesis entitled “Analysis and Modeling the Spatiotemporal Dynamics of Urban Expansion: a Case of Dukem Town, Ethiopia” developed by Gemechu Mulatu, hereby certify that the recommendation and suggestions made by the board of examiners are appropriately incorporated into the final version of the thesis.

Tilahun Erduno (PhD)	______________________	_____________
Advisor	Signature	Date

We, the undersigned, members of the Board of Examiners of the thesis by Gemechu Mulatu have read and evaluated the thesis entitled “Analysis and Modeling the Spatiotemporal Dynamics of Urban Expansion: a Case of Dukem Town, Ethiopia” and examined the candidate during open defense. This is, therefore, to certify that the thesis is accepted for partial fulfillment of the requirement of the degree of Master of Science in Geo-informatics Engineering.

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ASTER	Advanced Space borne Thermal Emission and Reflection Radiometer
CA-ANN	Cellular Automata and Artificial Neural Network
CSA	Central Statistical Agency
DEM	Digital Elevation Model
GDP	Gross Domestic Product
GIS	Geographic Information System
GPS	Global Positioning System
IHDP	Integrated Housing Development Program
LPI	Largest Patch Index
LSI	Landscape Shape Index
LULC	Land Use and Land Cover
MOLUSCE	Modules for Land-Use Change Simulation
OUPI	Oromia Urban Planning Institute
RS	Remote Sensing
SHDI	Shannon's Diversity Index
SSA	Sub-Saharan Africa
SVM	Support Vector Machine
UN	United Nation
USGS	United States Geological Survey
UTM	Universal Transfer Mercator

ABSTRACT

Studies reveal that the rate of urbanization around the world is at an all-time high. By 2030, there will be approximately 5 billion people living in towns and cities, which currently account for more than half of the world's population. A significant portion of this urbanization will take place in Africa and Asia, resulting in profound social, economic, and environmental challenges. The main objectives of this study is that integrating spatial metrics, GIS, Remote sensing and Land use Land cover Modeling tools to Model Spatio temporal Urban Land use Changes of Dukem Town using Landsat of 2001,2011,2016 and 2021 year for the last two decades (2001-2021) and predict for future three decades (2031, 2041 and 2051). For this study using supervised classification method, support vector machine algorithm. The overall accuracy of Classified Dukem Town Land use for 2001, 2011, 2016 and 2021 is 89.51%, 96.77%, 93.63*% and 90.2% and respectively which is acceptable. Finding of this result show that urban land use land cover changes due to urban expansion of Dukem Town is highly increased from 426.174 Ha (4.4%) to 2352.671Ha (24.2%) in last two decades (2001-2021) and for future three decades 2674Ha (27.8%) in 2030, 2822Ha (29.00%) in 2040 and 3259Ha (33.49%) in 2050. Selected spatial metrics indices show that there is a fast Change of Urban Landscape Patterns in study period of time. Largest Patch Index (LPI) in percentage also shows a growing trend from 3.827% in 2001 to about 34.295% in 2021. This is a good indication that largest patch is growing more and more in size forming a continuous urban agglomeration towards the center of the town. During the entire study period (2001–2021), the urban area expanded mainly as edge expansion it increased from 54.20% in 2001-2011 to 74.56% in 2016-2021. As well as infilling types of growth was slightly increased and Outlying growth was decreased continuously.CA-ANN technique inside the MOLUSCE plug-in under QGIS Software was used for modeling using Factors and constraints and validating kappa statistic is moderate and acceptable to predict for future urban expansion. Therefore Analyzing Spatio temporal urban Land use Changes and predict for future is very important for Dukem Town and the town planners need to plan ahead and implement plans properly to handle up with the rapid and unparalleled growth of the town in coming years.*

KEY WORDS: Spatial metrics, urban expansion, Landscape expansion index.

CHAPTER I: INTRODUCTION

1.1. Background of the study

The rate of urbanization around the world is at an all-time high. By 2030, there will be approximately 5 billion people living in towns and cities, which currently account for more than half of the world's population. A significant portion of this urbanization will take place in Africa and Asia, resulting in profound social, economic, and environmental changes. The advent of urbanization holds the promise of a new era of prosperity, resource efficiency, and economic expansion (United Nations, 2018).

Today, around 56% of the world's population of 4.4 billion inhabitants lives in cities. This trend is expected to continue. By 2050, with the urban population more than doubling its current size, nearly 7 out of 10 people in the world will live in cities. With more than 80% of global GDP generated in cities, urbanization can contribute to sustainable growth if managed well by increasing productivity, allowing innovation and new ideas to emerge (United Nations, 2022). Urbanization is a sophisticated socioeconomic process that changes the built environment, turning once rural settlements into cities, and redistributing people's geographical distribution from rural to urban areas. It involves shifts in the predominant professions, way of life, culture, and behavior, which affects both urban and rural areas' demographics and social structures (Montgomery et al., 2013).

Urban expansion is among the most significant processes that extensively shape the earth's ecosystems (Zhou et al., 1987), especially in regions where rapid economic and population developments have reduced the amount and distribution of natural resources that are vital services to the society. Currently, there are many various ways to comprehend and interpret the idea of urban expansion. Urban expansion, according to William Robert, is the process of increasing a settlement's or group of settlements' built-up area (e.g. at the national level). This frequently occurs together with a rise in the urban population (i.e. urban growth). However, in situations when habitation density is rising, urban growth can occur without expansion; conversely, urban expansion can happen without urban growth in situations where de-densification occurs, such as sub-urbanization (*Urban Governance*, 2021).

There are numerous studies on the expansion of urban land in single metropolitan regions and relatively better studied worldwide such as: (Artmann et al., 2019; Magidi & Ahmed, 2019; Sun et al., 2014; Zhang et al., 2018). however, they are not well-documented for small and medium sized cites in developing countries, primarily attributed to lack of reliable and up-to-date demographic and spatial data (Cohen, 2006).

According to data from a global sample of cities, between 1990 and 2015, cities in developed nations increased their urban land area by 1.8 times while the urban population increased by 1.2 times, implying that the ratio of the growth of urban areas to the growth of the urban population increased by 1.5 times (World Cities Report, 2020). By encroaching on agricultural land, the built-up area increased from 3.7 percent in 1991 to 5.0 percent in 2001 and 6.2 percent in 2011, which represents a major change in land use. Urbanization process results in urban change. The process of urbanization also results in an expansion in the size of urban outskirts. Agricultural land is continuously being converted to urban uses in the process of urbanization all over the world (Shrestha et al., 2015). Urban areas account for 0.5% of the planet’s surface but accommodate more than half the global population. Most cities have seen sharp increases in population and quick urban area expansion during the past few decades. Urban areas desperately require effective monitoring to ensure their sustainable growth. Because it is essential to comprehending the relationship between physical and social structures inside urban regions, forecasting urban development is crucial for decision-makers (Marshall, 2007).

Rapid and unrestricted urban expansion is a characteristic of African urbanization. Numerous socioeconomic and environmental issues have resulted from this, including urban poverty, food insecurity, a lack of affordable housing and essential amenities, unemployment, racial tensions and violence, drug misuse, crime, and societal disintegration (World Urbanization Prospects, 2018). Over half of the world's population currently resides in cities, according to the 2017 Drivers of Migration and Urbanization in Africa report from the United Nations. At a rate of 65 million urban people annually, this percentage is predicted to rise to 75 percent by 2050. The world's fastest-urbanizing region is frequently thought to be Sub-Saharan Africa (SSA). Currently, there are 472 million people living in urban areas; within the next 25 years, this number will quadruple. Urban African populations are expected to increase from 11.3 percent in 2010 to 20.2 percent by 2050. The 143 cities in the SSA collectively generate $0.5 trillion, or 50% of the region's GDP. The contemporary urbanization process that is taking place in emerging nations shows that this process requires significant attention as a foundation for both sustainable development and the transformation of societies in these nations (Saghir & Santoro, 2018).

Ethiopia is among the least urbanized countries in Africa, which has a very low level of urbanization (21.2%) in 2019 (Tsegaye, 2010). Despite this low level of urbanization, however, the country has one of the highest rates of urbanization even by the standards of developing countries, which is estimated at 4.1percent. This is also much higher than the average growth rate of the total national population, which is estimated at 3 per cent per annum. The level of urbanization has been only 6 per cent in the 1960, which has increased to 11 per cent in 1984 and 14 per cent in 1994, which is estimated to have already reached 17.2 per cent by 2013 and projected to account for 30 per cent of the total population in the year 2025 (MUDHCo, 2014). The Oromia Special Zone surrounding Addis Ababa is one of the most rapidly growing towns in Ethiopia. There has been rapid urban growth in this zone in general and in the towns in particular. The settlements quickly became centers for both industry and habitation. Large scale migration from various rural areas and from Addis Ababa to the neighboring towns fueled the boom (Berhanu et al., 2019a).

Dukem Town is one of the special zones which growing rapidly. The town close proximity to Addis Ababa presents a significant opportunity for the growth of the manufacturing and industrial sectors as well as for the people's access to various social services. As a result, the town's expansion is becoming erratic, unmanaged, and frequently leads to the formation of fragmented development. Due to the significant increase in land use interests and industries expansion, Dukem town has expanded remarkably. Urban expansion has been studied widely with the help of remote sensing (RS) and geographic information system (GIS) (Martinuzzi et al., 2007). However, previous researchers does not use advanced model and techniques in remote sensing and GIS, such as, Cellular Automata (CA), Landscape expansion index (LEI), Markov Chain Model and other were used to identify urban changes and future urban forecasts that have occurred in Land Use and Land Cover (LULC) in this area. The Town is in desperate need of recent research that displays the LULC map of the study area for the previous years as well as future urban forecasting using the aforementioned cutting-edge model and approaches.

As a result, this study sought to close a research gap by analyzing the expansion of urban land use changes, magnitude and rate of urban expansion, spatial patterns of urban expansion and types of urban growth in Dukem Town over the last two decades using spatial metrics, LEI and satellite images: 2001, 2011, 2016, and 2021. In addition, projecting LULC map for next three decades by applying cellular automata and artificial neural network (CA-ANN) technique using QGIS software was conducted.

1.2. Statement of the problem

Nowadays, rapid urbanization rate in most of the developing countries is on the priority of global problems, while this phenomenon has a significant impact on future environment and urban planning processes (Alkaradaghi et al., 2018). According to a number of studies, unplanned land use changes and uncontrolled urban expansion have become significant issues in many urban areas. It is also emphasized that urban expansion is mostly driven by unorganized growth, greater immigration, and rapidly growing populations in emerging countries where the rate of urbanization is quite fast (Alqurashi & Kumar, 2013).

Many African countries, including Ethiopia urban expansion is typically characterized by inadequate planning or poor implementation of plans, leaving cities with a dearth of essential infrastructure and services (Ayele Fenta et al., 2017). Migration from rural to urban areas and recent infrastructure growth has increased urbanization processes. However, this urbanization process is rarely well planned, and towns and cities face significant difficulties as a result of horizontal expansion.

In Ethiopia context, most of towns are expanding horizontally in the same directions as their transportation infrastructure (Tsegaye, 2010). Dukem is one of the towns that have experienced a similar pattern of unplanned expansion. Currently, vast area of Dukem Town and Farm lands are occupied by many Industries which consume more Land and Squatter settlements (Diriba et al., 2016). The expansion of those industries influences people to build their homes in the town and this leading the town spread to surround areas. Interestingly, the expansion of Dukem town was influenced by 'pulling' forces such as governmental institutions and policies and 'pushing' forces such as industrial investment, and access infrastructures, and market for the urban land, in which the price of land is lower at the outskirt. This resulted in the intensified trend of dispersed urban land expansion in a town (Berhanu; et al., 2020).

In Dukem Town no research similar to this title but, there are related papers that attempt to show the town's urban expansion in different ways, such as (Diriba et al., 2016 ; Berhanu; et al., 2020 ; Abebe A., 2012). In general the previous study has limitation regarding on address such as: Researcher does not apply currently update data and software, lack of the studies considering current Dukem town structural plan updated in 2020, urban growth type of Dukem town was not investigated in previous studies using landscape expansion indices methods, on Previous research prediction of future urban expansion of a town using QGIS has not been investigated and There is no particular research in this study area researched concerning on the dynamics of landscape structures, urban growth types, urban spatial patterns, process, and modeling in the town. This research was, therefore, initiated to provide information regarding on issues of Dukem town LULCC, extent of urban expansion, urban growth types and forecast future urban Expansion trend of the study.

1.3. Objectives of the study

1.3.1. General Objective

The general objective of this study is to Analysis and Modeling the Spatiotemporal Dynamics of Urban Expansion of Dukem town.

1.3.2. Specific Objectives

More specifically, the Specific objectives of the study are to:

- Detecting land use land cover changes and rate of urban Expansion of the Dukem town between 2001 and 2021 using remotely sensed images.
- Measure and examine spatial pattern of Dukem Town urban expansion by calculating selected spatial metrics indices.
- Quantify pattern of urban growth types of Dukem town using landscape expansion index (LEI).
- Predict future urban expansion of Dukem Town in 2031, 2041 & 2051 by using CA-ANN model in MOLUSCE plug-in underneath QGIS.

1.4. Research Questions

In order to achieve the stated objectives, the following research questions were designed:

1. What are the extents and rates of urban land use changes of Dukem Town from 2001 to 2021 year?
2. What was the pattern of development and rate of spatial expansion of Dukem Town?
3. How to quantify pattern of urban growth types of Dukem town?
4. What are the extents of Dukem Town Urban expansions in the next three decades?

1.5. Significance of the Study

Analyzing and future modeling with regard to anticipating where and how urban land use and land cover changes will occur is the most recent study, known as LULC, is an area of science that is expanding quickly. Models of urban land use and land cover changes are used to enhance and/or better comprehend the change in land use brought on by human activities (Brown et al., 2012). Analyzing accurate, timely and cost effective expansion of urban land use and land cover changes of the previous year (2001,2011,2016 and 2021) and predicting for future in 2031, 2041 & 2051 year using Remote Sensing and GIS is highly required to Dukem Town urban planners and development office, land administration and management office, environmental protection office, and policy makers, to make decision concerning land resource management and conflict resolution related to land, for better land use management and environmental development, for monitoring the negative consequences and increases the benefits, and for estimating rates of deforestation, loss of agricultural land, and urbanization of the Town. Additionally, the result of the study helped identify urban spatiotemporal pattern of Dukem town in order to make adequate future planning for proper provision land use land covers changes of study area.

1.6. Scope of the Study

The spatial scope of this study was limited to Oromia Regional State, Dukem Town Administration and the contextual scope was mainly focus on Analyzing spatiotemporal dynamics of urban Expansion of Dukem Town for the last two decades (2001-2021) by analyzing remote sensing data and using spatial metrics and LEI methods and predicting coming three decades (2031, 2041 & 2051) using CA-AN techniques in MOLUSCE plug-in underneath QGIS techniques.

1.7. Limitation of the Study

In order to map and categorize LULC maps of the study area with high accuracy and precision, it was challenging to get high resolution satellite images. For LULC analysis, Landsat and sentinel images were utilized. These images have a resolution of 30 m and 10m, which is not very high resolution, and they had some LULC classification errors, which were shown in error matrices of accuracy assessment. High resolution satellite images like those from SPOT, Quick Bird, and IKONOS were not accessible easily. Difficult to get Dukem town kebele boundaries shape file. In addition, reactance of the interviewers to give reliable information and town has poor documentation system farther more some officials and authorities are not willing to give the required information.

1.8. Organization of the Thesis

This thesis is organized into five chapters. The first chapter's introduction section provides the study's history, problem statement, objectives, and research questions, as well as its significance, scope, and limitations. The second chapter in this portion provides a theoretical framework, background information, Research knowledge and gaps, as well as empirical review of urban expansion and various analytical techniques applied to this study. Additionally, it highlights a review of the literature that includes both conceptual and research-related reviews of the literature. The third chapter provides a description of the research area, data and software packages, image processing methods, classification, several methods for: computing indices, accuracy assessment, urban growth analysis, and future prediction are given to address the issues mentioned in the problem statement. The fourth chapter discussed result of study analysis of the data, findings, and discussion. The conclusion and recommendations for further research are included in the thesis's final section.

CHAPTER II: LITERATURE REVIEW

With the intention of write this thesis of Assessment of urban expansion on land use land cover in Dukem town, it is important to review historical background and concepts and related works done literature focusing on GIS, Remote Sensing, spatial metrics, landscape expansion indices, land cover modeling tools and their applications for urban expansion studies.

2.1. Overview of Urbanization

A population that is urban is one in which vast numbers of people are clustered together in very small areas called towns and cities. “Urbanization is a process of population concentration. It proceeds in two ways: the multiplication of points of concentration and the increase in size of points of concentration.” (Bijimi, 2013) The physical growth of urban areas can be explained demographically and functionally. While demographic definition of urbanization is restricted to factors such as population size and density, the economic functional definition refers to the territorial concentration of productive activities (industries and service) rather than population. The physical expansion of urban areas as a result of global change is known as urbanization or urban drift. The United Nations defines urbanization as the migration of people from rural to urban regions as a result of population expansion. Large city growth, urban concentration, changes in land use, and the shift from a rural to a metropolitan style of organization and government are all results of social, economic, and political processes (World Urbanization Prospects, 2018).

Urbanization is a complex socio-economic process that transforms the built environment, converting formerly rural into urban settlements, while also shifting the spatial distribution of a population from rural to urban areas and it includes changes in dominant occupations, lifestyle, culture and behavior, and thus alters the demographic and social structure of both urban and rural areas (Montgomery et al., 2013). A major consequence of urbanization is a rise in the number, land area and population size of urban settlements and in the number and share of urban residents compared to rural dwellers. Urbanization is shaped by spatial and urban planning as well as by public and private investments in buildings and infrastructure. An increasing share of economic activity and innovation becomes concentrated in cities, and cities develop as hubs for the flow of transport, trade and information (World Urbanization Prospects, 2018).

2.2. Definition of urban Expansion and urban land use changes

The term "urban expansion" indicates the spatial or physical enlargement of built-up areas. (Heidarinejad, 2017) defined urban land expansion as one of the main indicators to measure the intensity of urbanization. He claimed that urban land expansion is the most easily identifiable characteristic of the process in the spatial dimension. (Ewing, 1994) defined that as the process of land conversion from non-built-up land use categories into built-up developed land over time. It is possible for a city to experience urban growth without expansion if this growth is absorbed within existing settlement boundaries.

The urbanization and urban growth have accelerated worldwide. Within two decades, the population of cities has doubled or even tripled. At the beginning of the nineteenth century, only about 3 percent of the world's population lived in urban places (Ojo et al., 2017) This continuous urban growth, particularly in developing country cities, is neither anticipated nor strategically planned for. Therefore, the cities face high risks and problems, which result in a conflict between their environmental resource base and development needs.

According to the World Urbanization Prospects,(World Urbanization Prospects, 2018), in 1950 the urban population was 0.4 billion and 0.3 billion in more developed regions (MDR) and less developed regions (LDR) respectively. However, in 2010, there were 0.9 billion urban residents in MDR and were 2.6 billion in LDR. Moreover, by 2050, it is predicted that the number of urban residents in MDR and LDR will increase to 1.1 billion and 5.1 billion (Figure 2.1), respectively.

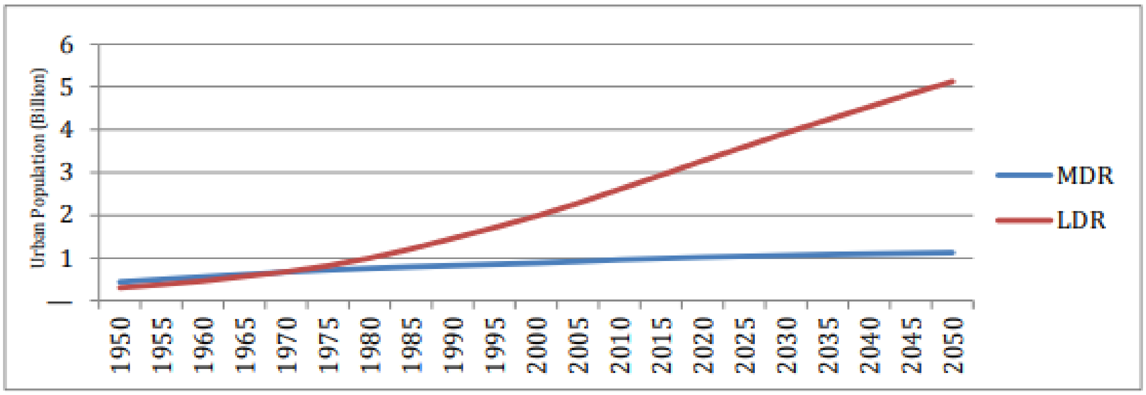

Figure 2.1: Urban Population Change in MDR and LDR from 1950 to 2050

Source: (World Urbanization Prospects, 2018)

The current rates of urbanization in Africa, exceeding 4 to 5 % per annum in most countries, are close to those of western cities at the end of the nineteenth century. In 2019, Gabon had the highest urbanization rate in Africa, with nearly 90 percent of its population living in urban areas. Libya and Djibouti followed at around 80 and 78 percent, respectively. On average, the African urbanization rate stood at approximately 46 percent in that year. Many countries in the continent indeed had the majority of the population residing in rural areas. In 2019, urbanization in South Sudan, Rwanda, Malawi, Niger, and Burundi was below 20 percent each (Güneralp et al., 2018).

2.3. The rate of urbanization

According to World urbanization prospect (2018) the rate at which the percentage urban grows or declines is called the urbanization rate. It is a function of the respective rates of change and relative sizes of the urban and rural populations in a country. Consequently, multiple scenarios of urban and rural population change are capable of producing rapid urbanization. Perhaps the most intuitive path to urbanization combines urban population growth with rural population decline.

This urban growth-rural decline scenario is typical of what is underway in many countries of Europe and Northern America, as well as parts of Asia and Latin America and the Caribbean. But urban population growth that is concurrent with rural population growth will also lead to the urbanization of a population if the absolute increase in the urban population exceeds the absolute increase in the rural population. This scenario is underway in most of Africa and Asia (Turok & McGranahan, 2013).

Table 2.1: urban percentage & rate of urbanization of the world by development group

Development group region	Percentage Urban						Rate of Urbanization (%)			
	1950	1970	1990	2018	2030	2050	1950-1970	1970-1990	1990-2018	2018-2030
World	29.6	36.6	43.0	55.3	60.4	68.4	1.06	0.80	0.90	0.74
More Developed	54.8	66.8	72.4	78.7	81.4	86.6	0.99	0.40	0.30	0.28
Less Developed	17.7	25.3	34.9	50.6	56.7	65.6	1.78	1.61	1.33	0.94

Source: (World Urbanization Prospects, 2018)

In rare instances like those observed in parts of Eastern Europe, urban population decline accompanies a positive rate of urbanization because the absolute decline in the urban population is less than a concurrent absolute decline in the rural population. Figure 2.2 illustrates the associations between the urban and rural population growth rates and the rate of urbanization for the period 1990-2018, for 201 countries or areas with at least 90,000 inhabitants in 2018. The dashed diagonal line passing through the origin marks the points at which the urban and rural population rates of change are equal (World Urbanization Prospects, 2018).

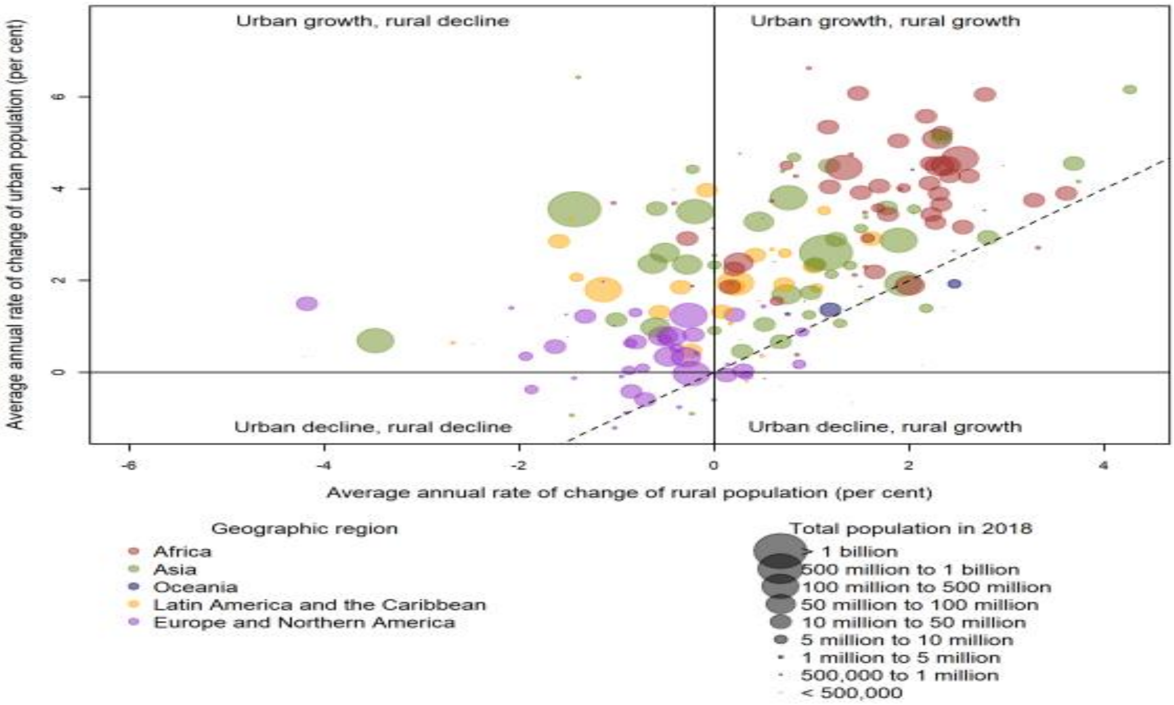

Figure 2.2: Average annual rates of populations in countries by geographic region

Source: (World Urbanization Prospects, 2018)

2.4. Forces Shaping Urban Expansion

In the arguments of urban land use and land expansion, different driving forces underlying the urban land expansion are identified. These include (i) demography or demands for space by people and employment (ii) the changing industrial landscape, with the growth of manufacturing and production facilities and associated working-class housing, services, and commerce to cater to those facilities (iii) improvements in transportation networks (roads, public transport, etc.), changes in mobility patterns and transit-oriented development and (iv) institutional factors, such as fragmentation in municipal jurisdictions and planning, and variations in tax structures (Gao et al., 2015).

The expansion of urban areas is determined by the interaction of the three broad types of phenomena. These are the physical or geographic factors, the demand for land by the households or firms who inhabit the city and the policy constraints that govern land use and spatial interactions in the city (Dennis Wei & Ye, 2014). More specifically, aspects of the natural environment that may affect urban expansion include those of climate, slope, mountain barriers, and the existence of drillable water aquifers. Demographic effects may include rural migration and natural population growth in the city, the level of urbanization and the rank of the city in the country's urban hierarchy (Bank, 2021). Aspects of the economy that can affect the urban expansion include the level of economic development, difference in household incomes, exposure to globalization, the level of foreign direct investment, the degree of employment decentralization, the level of real estate finance markets, the level and effectiveness of property taxation and the presence of high inflation and acute shortage of housing (Angel et al., 2011).

Natural population growth is a major element in urban growth for all countries, but rural urban migration contributes more in many developing countries (Ayata, 2008). Migration contributes fast growth of urban population due to the relative economic development that attracts people to urban nuclei for commerce, employment, and education. Many believe that cities are expanding very rapidly and are growing for non productive reasons specifically; some scholars believe that new policies and regulations on land acquisitions and illegal land markets might have encouraged the extensive shifts of cultivated area in to built up area (RASHID, 2009). A number of observers also suggest that housing price have risen unreasonably high in many cities of the developing countries and are inducing developers and investors to invest in more housing stock than would be rational in a purely market driven economy (Korkmaz, 2020). In short, scholars believe that there are economic and non-economic factors that are encouraging the expansion of urban to non urban areas.

2.5. Effect of Urban Expansion

Urban expansion takes place in different forms. The two major forms of urban expansion effects are:

I. Positive effects (orderly): form of urban expansion properly laid such as center of market area, center for production and distribution of goods and services, an opportunity for access to employment, economic development, full facilities, and technology development.

II. Negative effects (disorderly): of urban expansion are loss of prime agricultural farmland, displacement of farm communities, solid waste disposal and land degradation, enclosing surrounding rural land to urban territory, over exploitation of natural resources and conflict (Samat et al., 2014).

2.6. Consequences of the negative effects of Urban Expansion

As the World Bank Transport and Urban Development Department (2018) indicated, even though, the available evidences are spotty, controversial and not necessarily applicable to developing country cities, suggest that the above mentioned differences in the growth and expansion of cities are associated with both positive and adverse outcomes that affect the welfare and well being of the citizens. The available literature concerning urban expansion is rife with blame for its inappropriate and unnecessarily costly for developing world cities. Most blame is directed at expensive leapfrogging green filed development. It is claimed that such development reduces both access and view of open space (Doig & Adow, 2011). It encroaches on sensitive environments and on scarce farmlands. It also requires longer and more costly extensions of public infrastructure networks and it imposes additional costs on residents of new expansion sites. It also diverts construction away from the central parts of the cities that needs to be redeveloped. As a result of urban expansion highly increase the land use and land cover changes and becomes many problems such as uncontrolled development, deteriorating environmental quality, loss of prime agricultural land, displacement of farm communities, solid waste disposal and land degradation, over exploitation of natural resources and conflict (Samat et al., 2014).

2.7. Urbanization in Africa

Urbanization and urban expansion are accelerating at an alarming rate in developing countries, especially in Africa, as a result of a growing population flow towards urban areas. The share of urban growth for developing countries from 2000–2025 is estimated to be 90% which was 57% from 1975–2000 (Stecklov, 2020). According to (Mundia & Murayama, 2010) Africa will have 11 mega cities with a population of more than 10 million and about 3, 000 towns with population of more than 20, 000 by 2020. Africa is urbanizing rapidly and expected to triple in the coming 50 years. Eastern Africa will experience higher than African average urban growth (Adam-Bradford et al., 2010). Africa is changing the trend of urbanization happened before in other part of the world for two reasons first it is urbanizing fast, second urbanization in Africa is not producing the economic growth and capital investment it is expected to generate. (Gedefaw et al., 2015) indicated that Africa’s urbanization faces four major challenges: i) Rapid population growth with low level of economic activity based on inadequate capital, ii) Low density, sprawl and informality in peri-urban fringe, iii) Poor coverage of infrastructure services such as water, energy and sanitation that makes difficult to improve welfare in both in urban and rural, iv) Weakness in administration, institutions and overall planning capacity.

2.8. Population Growth and Urbanization Trend in Ethiopia

Table: 2 shows population growth rates for the two most recent five year periods, presented at the national and regional levels. Population growth is the change in a population over time**,** and can be quantified as the change in the number of individuals of any species in a population using "per unit time" for measurement. Growth rates are shown for rural and urban populations in addition to overall growth rates. For both periods, the growth rates for rural and urban population were not similar. The urban population growth rate was above 4%, while the growth rate for rural areas was around 2.6%. While growth rates are similar in many places, they are especially high in SNNP, for both rural and urban populations and for both periods (Tsegaye, 2010).

Table 2.2: Urban & rural population growth in Ethiopia at regional levels, 1995-2005

Geographical Area	**1995-2000**			**2001-2005**		
	Rural	Urban	Total	Rural	Urban	Total
National	2,74	4,38	2,92	2,57	4,10	2,73
Tigray	2,5	4,9	2,85	2,3	4,5	2,67
Afar	2,2	3,8	2,39	2,0	4,1	2,20
Amhara	2,6	4,9	2,86	2,5	4,4	2,67
Oromia	2,8	5,1	3,09	2,6	4,7	2,87
Somalia	2,3	4,5	2,58	2,3	4,5	2,63
Benishangul Gumuz	2,5	4,7	2,57	2,4	4,4	2,54
SNNP	3,1	5,3	3,26	2,8	4,8	2,92
Gambela	2,2	4,7	2,62	2,2	4,4	2,57
Harari	2,5	4,2	3,50	2,6	3,8	3.49
Addis Ababa	--	2,9	2,90	--	2,8	2,8
Dire Dawa	2,2	4,8	4,00	2,3	4,3	3,8

Source: CSA (2004), Projection based on 1994 Ethiopian Population and Housing Census.

2.9. Trends of Urban Expansion in Dukem Town

The settlement of Dukem town was influenced by the railroad, the main high way and the feeder roads that connected the rural areas with the town. The first is the southern portion of the hill slope facing the market place. Then, to the south following the railroad and the main right way, settlement pattern were regulated. This continued until 1980‟s. Later on, because of the change of market place the direction of expansion was also changed following the bank of Dukem River. Some quarter names such as "Yerer Bar," and cuqqala Bar were created. Expansion to south ward direction is also resulted in the formation of a neighborhood (Abebe A., 2012).

According to OUPI (Oromia Urban Planning Institute) team report the location opportunities that contribute for the growth of Dukem town includes: I) Proximity to Addis Ababa II) Transport facility and the highway to Southern and eastern part of the country pass through Dukem town III) Surrounded by Agricultural productive districts. IV) Poor policy implementation which results in squatter settlements Constructions of houses require land. The methods of urban land acquisition have its own impact on horizontal expansion of the town towards the periphery. Reclassification of land from rural to urban area have significant role in the population growth and expansion of the town. For example recently a number of farming villages and farm land surrounding the town has been reclassified in to urban area and put under the administration of the town (OUPI, 2008).

2.10. Machine Learning Algorithms

Machine learning algorithms are programs (math and logic) that adjust themselves to perform better as they are exposed to more data. The "learning" part of machine learning means that those programs change how they process data over time, much as humans change how they process data by learning. It is an advanced technology in improving the extraction of impervious surfaces by overcoming subjective factors and improves the concrete algorithm automatically in the process of learning (Okolie & Smit, 2022)The Artificial Neural Network (ANN), Support Vector Machine (SVM), Random Forest (RF), and Logistic Regression are the most widely used in machine learning algorithms. Most machine learning algorithms are categorized in a non-parametric approach, which able to handle continuous and nominal data, interpretable classification rules, and swift application (Gewali et al., 2018).

I. Artificial Neural Network (ANN): it is a non-parametric supervised classification approach and it can estimate the property of data based on training samples. ANN works in the input used to train the neural network is the spectral data of the period of change. A back propagation algorism is often used to train the multi-layer perceptron neural network model (Hu & Weng, 2009).

Nonetheless, this algorism is time-consuming, sensitive to the amount of training data used, and the hidden layers are poorly known(Jensen & Lulla, 1987) Estimate the percentage of impervious surfaces by creating activation level maps from high spatial resolution imagery (i.e., IKONOS) using a three-layer feed-forward back propagation neural network. However, this approach has difficulty in determining the initial weight (Hu & Weng, 2009).

II. Support Vector Machines: SVMs use the concept of mathematical planes (maximum-margin hyperplanes) to distinguish between multiple classes based on a decision boundary, or hyperplane, intending to minimize misclassification (Gewali et al., 2018) SVM draws a plane between two classes and maximizes the distance of this plane from both classes to classify accurately in the case of linear classification, this margin is drawn directly. But, when it comes to nonlinear classifications, SVMs use the kernel to convert nonlinear to linear and then find the hyperplane (Singh, 2019) SVM minimizes error on unseen data without prior assumptions on the distribution and avoids over fitting (Zhang et al., 2018). From all machine learning methodology of global optimization, the SVM algorithm is prior as the classifier because of its improved performance compared to other approaches (Guo et al., 2013).

III. Random Forest (RF**):** it is an integrated machine learning algorithm based on decision trees. It is non-parametric depending on whether training samples can be represented by a Gaussian probability density function (Gewali et al., 2018). A decision tree relies on a certain statistical threshold; it can determine whether a particular thing belongs to one class or the other (Liao et al., 2021). More recently the application of random forest has been increased to medium spatial resolution data to more accurately represent the complexity of land covers within a pixel.

IV. Logistic Regression**:** logistic regression is one of the most famous algorithms in machine learning. This concept is a modified form of linear regression in which logistics are used to determine the probability of an element belonging to a particular class. It gives us an output between zero and one. If the output is greater than 0.5, the element is said to belong to one class; otherwise, it belongs to the other (Singh, 2019).

V. Cellular Automata (CA): are increasingly being used to simulate spatiotemporal urban expansion and to address many environmental problems. For understanding the complexity of urban systems, CA, that can provide a powerful simulation tool to predict and understand urban transformation over space and time, is one of the most prevalent urban modeling methods in recent year. CA also advances our fundamental understanding of urban dynamics and the complex relationships among urban changes, socio-economic development, and sustainable systems (Yeh et al., 2021).

2.11. Remote Sensing and Spatial metrics

the main strength of remote sensing technique lays on its capability to deliver spatially consistent data set that cover a wide range of spatial extent with both high and detailed spatio-temporal resolution, including historical time series data (Clarke et al., 2005). Yet, it cannot provide full description of the underlying processes that are responsible for the changing patterns of urban landscape. To bridge this gap spatial metrics are used. The thematic land cover maps obtained from the analysis of Landsat TM and ETM+ images will used to further quantify and describe urban landscape pattern, (Gustafson, 2006). Spatial metrics are expedient tools for quantifying spatial heterogeneity and to have better insight on how spatial structures impact the system interaction in a heterogeneous landscape. Spatial metrics can provide rich numerical description of the landscape structure at patch, patch class or the whole landscape level (Herold et al., 2003).

Spatial metrics can be categorized into three broad classes: patch, class, and spatial metrics (Bhatta, 2010). Patch is a relatively homogeneous area that differs from its surroundings (Mcgarigal, 2015). Patch metrics are computed for every patch in the landscape, class metrics are computed for every class in the landscape, and spatial metrics are computed for the entire landscape (Bhatta, 2010). However, most spatial metrics are scale dependent and they are determined by the extent of spatial domain, the spatial resolution and the thematic definition of the map categories. It is up to the user to define the landscape, including its thematic content and resolution, spatial grain and extent, and the boundary of the study area, based on the phenomenon under consideration before conducting any kind of metrics computation (Mcgarigal et al., 2009).

2.12. Analyzing Urban Growth Pattern Using Remote Sensing & Spatial metrics

Patterns are distinguished by spatial relationships among component parts in landscape metrics. A landscape pattern can be characterized by both its composition and configuration of its component parts (McGarigal & Marks, 1995). These two characteristics of a landscape can individually or in combination affect ecological processes. A variety of metrics have been developed to quantify categorical map patterns in the past studies (Mcgarigal et al., 2009). Despite the availability of plenty of metrics, offered by different literature, to describe landscape structure, they are still categorized under the two major components, namely, composition and configuration of a landscape (Gustafson, 2006). Composition metrics is easy to quantify and can be defined as features related to the presence, proportion and the variety and richness of patch types within the landscape mosaic. Nevertheless, composition metrics does not consider the spatial character, arrangement, or location of patches within the mosaic. A variety of quantitative descriptors of landscape composition are available, but the principal measure of composition includes; the proportional abundance of each class in the entire landscape, patches richness, patches evenness, and patch diversity (Mcgarigal, 2015). Shannon's diversity index (SHDI), Shannon's evenness index (SHEI), dominance (DOM) and patch richness density (PRD) are some of the examples of commonly used composition metrics. Conversely, configuration metrics is relatively more challenging to quantify. It refers to the spatial arrangement, character and position of patches within the class of patches or entire landscape (McGarigal & Marks, 1995).The principal aspects of configuration metrics includes: patch area and edge, patch shape complexity, core area, contrast, aggregation, subdivision, and isolation. Some of the most frequently used configuration metrics includes: number of patches (NP), percentage of landscape (PLAND), edge density (ED), landscape shape index (LSI), mean patch size (MPS) and number of patches (NP), largest patch index (LPI), total edge (TE), mean shape index (MSI), area-weighted mean fractal dimension (AWMFD), total core area (TCA), mean Euclidean nearest neighbor index (MENNI), contagion (CONTAG), effective mesh size (MESH), aggregation index (AI). Urban growth and land cover change has been the major topic concerning remote sensing applications (Masser, 2001). The spatial and temporal dimensions are major concerns of remote sensing in urban studies. To better understand the complexity of urban systems and its spatial and temporal dimensions, urban growth analysis need to be linked with land cover change model. Currently, there has been an increasing interest in applying remote sensing and spatial metrics techniques (Mcgarigal, 2015) to analyze urban environment. There are several methods to analyze and quantify the dynamics of urban growth patterns and processes. However the selection of method depends on the objectives of the problem on hand and the clear understanding of the different tools and techniques used for analyzing urban environment. Several studies reviewed in this section indicate the value of medium resolution remote sensed satellite images and spatial metrics for the analysis of urban change.

2.13. Landscape expansion Index and Spatial modes of urban growth

There are obvious limitations with conventional landscape indices for analyzing urban expansion in many fast growing regions. An essential one is that they can only quantitatively reflect the landscape patterns and their distribution for one single time point. Thus, the purpose of the proposed landscape expansion index (LEI) is to give a deeper insight of landscape patterns and temporal dynamics. In addition to identifying the types of landscape expansion, LEI can also be used to describe the process of landscape pattern changes within two or more time points. LEI are defined by using the buffer analysis, which is one of the most important spatial analysis functions of GIS. The buffers are the zones with specified distances around a target geographical feature. The analysis can be used in queries to determine which entities occur either within or outside the defined buffer zone.

Pattern-process analysis is one of the main threads in landscape ecological research, which aims at understanding the complex relationships between landscape patterns and landscape change processes (Schröder & Seppelt, 2006). Resulting from interactions among different ecological processes and natural environments, landscape patterns can affect ecological processes in multiple ways, while ecological processes can facilitate the evolution of landscape patterns. One of such important ecological processes is landscape expansion (including urban growth, species spreading, desertification, soil erosion, etc.). It involves mainly three types of spatial pattern: infilling, edge-expansion, and outlying, while other patterns can be regarded as variants or hybrids of these three basic forms. An infilling type refers to the one that the gap (or hole) between old patches is filled up with the newly grown patch. While edge-expansion type, defined as a newly grown patch spreading unidirectional in more or less parallel strips from an edge. If the newly grown patch is found isolated from the old, then it would be defined as an outlying type (X. Liu et al., 2010).

2.14. Land use and land cover change (LULCC)

Land-use and land-cover change (LULCC) is an integral component of global environmental change. Land cover refers to the physical characteristics of Earth's surface. Land use refers to how the land is utilized by humans for various purposes. There is a large body of both theoretically and empirically grounded work on LULCC that falls under the umbrella of the relatively new discipline of land-change science. The biophysical processes and human activities interact in changing land use and land cover (Güneralp, 2020).

In general LULCC term indicate for the human modification of Earth's terrestrial surface. Though humans have been modifying land to obtain food and other essentials for thousands of years, current rates, extents and intensities of LULCC are far greater than ever in history, driving unprecedented changes in ecosystems and environmental processes at local, regional and global scales. These changes encompass the greatest environmental concerns of human populations today, including climate change and the pollution of water, soils and air. Monitoring and mediating the negative consequences of LULCC while sustaining the production of essential resources has therefore become a major priority of researchers and policymakers around the world (Liping et al., 2018).

Land change studies attempt to explain (1) where change is occurring, (2) what land cover types are changing, (3) the types of transformation occurring, (4) the rates or amounts of land change, and (5) the driving forces and proximate causes of change. The ultimate reasons for studying these change characteristics are to understand land change trends, evaluate and manage the consequences of change, and define future scenarios of change. Challenging issues are associated with measuring, gathering, and documenting the characteristics of land change. Understanding urban dynamics is one of the most complex tasks in planning sustainable urban development while also conserving natural resources. Despite these difficulties, urban growth and urbanization are major environmental concerns that need consideration and careful assessment and monitoring (Angel et al., 2005).

2.15 Predicting Future Urban Expansion

Spatiotemporal modeling, simulation and change transition potential techniques have evolved rapidly to study the LULC mechanism. Simulation models of LULC transition and prediction are effective and replicable techniques for evaluating both the causes and the significance of past, present and future scenarios under possible situations (Abbas et al., 2021). Many spatially explicit models have been proposed by researchers to analyze and project the LULC, such as FLUS, SLEUTH, Artificial Neural Network Markov Chain, CA-ANN, CLUE-S and SERGoM. Every model has its own specialty for addressing the composite issues of LULC. Among these models, cellular automata are common approaches to simulate LULC and can effectively represent nonlinear spatially stochastic land-use change processes. Cellular Automata are powerful approaches for understanding land-use systems and their integral dynamics, especially when integrated with other tools, such as ANNs. The Cellular Automata-Artificial Neural Network works on what-if scenarios; therefore, it can be useful for planning and land-use change simulation studies (Pahlavani[1] et al., 2017).

2.16. The role of remote sensing and GIS in urban planning

Researchers have developed an urban expansion measuring model by combining geospatial indices with socio-economic indices indicate that the causes, the evolution, and the consequence of this landscape pattern change should be discussed with geospatial indices. (Huang et al., 2009).The ability of GIS to store, manage and manipulate large amounts of spatial data provides urban managers with a powerful tool. GIS's ability to link tabular, non-spatial data to location information is likewise a powerful analytic capability.GIS also provides ways of viewing and analyzing data that was previously impossible or impractical. Remote sensing (RS) and Geographic Information system (GIS) is a novel technology widely used to survey the land use problem. The GIS adopts the numerical methods and spatial analysis tools to delineate the land use. The methods can yield the same results after repeatedly applying the same procedures. Moreover, they reduce the manpower and time consumption for the delineation of land use. In contrast with the manual methods, the GIS is the most economic and objective methods. They can be used separately or in combination for application in studies of urban expansion.

The applications of Remote Sensing and GIS in urban studies at present is giving more weight on the acquisition of urban land use information and the comparison on the urban sprawl spanning most recent several decades, giving an image that remote sensing and GIS applications are located in the dynamic monitoring of urban growth only, therefore only in a few cases, we see GIS technology are applied in empirical analysis on the urban spatial structure. Urban growth remains a major topic concerning GIS and remote sensing applications. Remote sensing and GIS have proved to be effective means for extracting and processing varied resolutions of spatial information for monitoring urban growth (Cabral et al., 2005).

2.17. Review of Empirical Studies

Internationally there are many researches are conducted regarding on urban expansion and related topic. Nowadays, in Ethiopia level also many scholars are addressed different research regarding on mentioned field of study. So, in this section I tried to discuss some of research done in international, Ethiopia as well as in my study area that have more proximity to my research title.

According to (Meng-jie, 2018),the focus of the recent studies related to urban expansion mainly categorized in to four: i) on the characteristics and models of urban expansion ii) on the mechanism and driving factors of expansion iii) on the benefits of expansion and iv) on the influences of expansion and counter-measures to control over-expansion, analyzes the characteristics and deficiencies of the related studies, and discusses the fields for further study. The urbanization expansion and landscape pattern change were influenced by many factors, such as geographical location, population, economic policy, resources, and transportation (Yin et al., 2011). Several studies have investigated the effects of urban expansion on the landscape composition and configuration (Cao et al., 2019; Su & Zhang, 2021; Yin et al., 2011), investigating the existing and projected urban land dynamics (Yin et al., 2011), and exploring the patterns and possible drivers (Berhanu et al., 2019b; Yin et al., 2011). The majority of these investigations, however, have focused on major metropolitan areas because of their substantial influences on socioeconomic and environmental conditions (Yin et al., 2011). In contrast, the smaller cities and towns, where scattered urban growth is more prominent, have been given little attention (Yin et al., 2011).

Landscape metrics can be useful to reveal the general circumstances of the urban landscape pattern , triggers of urban land use, and change analysis (Berhanu et al., 2019b) as well as assessing the projected future urban spatial form (Akbar et al., 2019). As a result, studies on urban land use dynamics have provided evidence to address serious ecological and environmental challenges affecting urban ecosystems in addition to presenting temporal and spatial aspects of urban development (D. Liu & Chen, 2017; Yin et al., 2011). Policymakers and urban planners can frequently find solutions to reduce negative impacts related to urban growth by making reference to land use maps and changes. As a result, research in large cities has had a significant impact on conceptual concepts about urbanization. It is crucial to study smaller cities because they are expected to dominate future urbanization globally.

In the context of Ethiopia, several researches are conducted and some of them are discussed as the following: (Busho et al., 2021) this study used GIS and remote sensing to identify different urban growth types in Addis Ababa. Multi-series remote sensing data and spatial metrics were used to investigate the dynamic pattern and change trend of urban growth types. The researchers' main intent was to access the urban growth pattern and growth type of Addis Ababa in different directions through eight landscape matrices over three decades. Eventually, the study aimed to test the urban growth theory. (Terfa et al., 2019) this study provides a comprehensive comparative analysis of the growth and spatial patterns of urban development in the three major cities of Ethiopia (Addis Ababa, Adama, and Hawassa) from 1987 to 2017. Also, the applicability of diffusion and coalescence theory on the evolution of these cities has been tested. Remote sensing and GIS technologies were combined with spatial metrics and morphological analysis was employed to undertake this study. (Ayele Fenta et al., 2017) this study evaluated the dynamics and spatial pattern of Mekelle City's expansion in the past three decades (1984–2014). Multi-temporal Landsat images and Maximum Likelihood Classifier were used to produce decadal land use/land cover (LULC) maps.

Some studies have been tried to attempt to analyze urban expansion and related topics in Dukem town. among those studies the following are discussed:- (Berhanu; et al., 2020) Accordingly this study focused on six towns of the Oromia Special Zone Surrounding Finfinnee, Ethiopia, which is broadly known to be experiencing dramatic growth. Dukem town is one of them that included in this spatial zone. Authors used time-series Landsat images from 1987 to 2019 with an integrated method, landscape metrics, and built-up density analysis were employed to characterize and compare the dynamics of landscape structures, urban expansion patterns, process, and overall growth status in the towns. Another research was studied by (Diriba et al., 2016), The study revealed that significant investments for the industrial and residential expansions remained major drivers of agricultural land conversion based on the overall hectares of lands allocated for the LUPs and the size of the lands actually distributed. For this research they applied GIS software used to create status and location maps of industries out of the GPS data and qualitative data obtained from interviews and focus group discussions. (Abebe A., 2012), also study about Assessment of urban expansion in Dukem town. It applies GIS and Remote Sensing techniques were used in this work to locate and estimate the expansion of urban areas in Dukem town.

2.18. Research and Knowledge Gaps

The above mentioned scholars conducted their research in Dukem town was more of focused on urban expansion and its impacts on agricultural land, dynamics of landscape structures. When I was review those research papers I observe the following gaps:

i) Researcher does not apply currently update data and software such as: sentinel-2 satellite images and software like: QGIS.

ii) Lack of the studies considering current Dukem town structural plan updated in 2020.

iii) In addition There is no particular research in this study area published regarding on the dynamics of landscape structures, urban expansion patterns, process, and overall growth status in the towns but, (Berhanu; et al., 2020) was done by taking generally six Oromia Special Zone Surrounding Finfinnee.

iv) Inadequacy of previous studies investigated urban growth type of town by applying current most effective analysis methods like landscape expansion indices.

v) On Previous research prediction of future urban expansion of a town using QGIS has not been investigated.

This study, therefore, was devoted to analyses urban expansion by examining urban change patterns and amounts in the town, over the past three epochs (i.e., 2001-2011, 2011-2016, and 2016–2021), based on time-series built-up area data developed from satellite images. An integrated framework was used to undertake this study. Specifically, this investigation attempted to characterize the magnitude, rate, forms, and dynamics of urban expansion, progress of urban growth and finally future urban expansion of the town. This research creates good understanding on urban expansion, spatial pattern of urbanization and future view of urban expansion in the town for urban planning, management, and sustainable urban development. Furthermore, the study provides an integrated approach incorporating remote sensing, GIS, spatial metrics and CA-NN model to analyze and predict urban expansion of Dukem town.

2.19. Conceptual Framework

Urbanization has greatly contributed to the modification of urban areas in Ethiopia. The major contributor to urbanization is natural population increase intertwined with rural-urban migration in search for better opportunities in the urban areas. As a result, a host of problems occur in these areas resulting to movement of population to the urban fringes leading to the expansion of urban land uses in the urban fringes which are majorly agricultural areas. The encroachment of urban land uses in urban fringes results to crowding out of agricultural lands impacting directly or indirectly on the inhabitants and the immigrants in these areas. The impacts of urban expansion on land uses include loss of farmlands, loss of labor in the agricultural sector and creation of jobs in other sectors mainly non-agricultural sectors among others. Consequently, a decline in agricultural productivity resulting to food insecurity related problems as vividly illustrated in Fig.2.3.

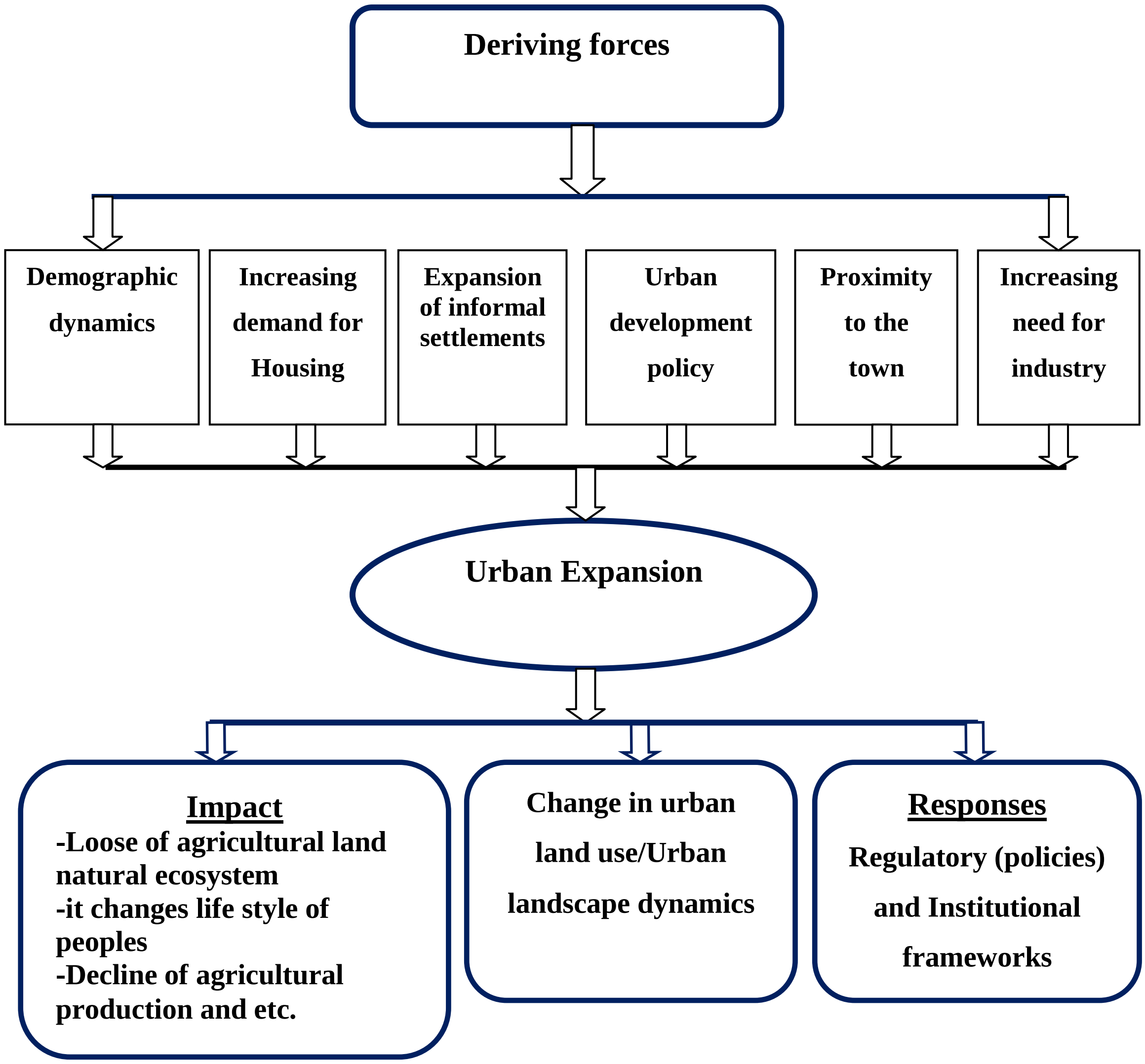

Figure 2.3: Conceptual Framework

Source: developed by the Author

CHAPTER III: MATERIALS AND METHODS

3.1. Introduction

In general, this chapter describes the study area of the research, data source, and method of data collection; main components and software needed for this study; methods of data analysis; and methodological work flow used to achieve objective sets in the chapter one section.

3.2. Description of the study area

3.2.1. Geographic location

Dukem is a town in central Ethiopia. It is named after the Dukem River; it is located at 37 kilometers South East of Addis Ababa and 10 kilometers northwest of Bishoftu along the main road to Adama. Dukem is one of the reform towns of the region. Nowadays the town has increased into eight kebeles by including vast area of rural kebeles those are: Melka Dukem, Teddeche, kotiche, Gogecha, Oda Nabe, Yatu, Wejitu and Gimashe. It is the administrative center of Akaki woreda that is defined by the third-level administrative division of Ethiopia and is composed of a number of kebeles. Geographically, the study area located by latitude $8^{o}45'30''$N-$8^{o}50'30''$N and longitude 38^{o} $51'30''$E - $38^{o}56'00''$ E and an elevation of 1950 meters above sea level (Figure 3.1). It Progresses have been seen in the town since a number of houses, manufacturing, service sector and institutions have been constructed. The population is also rapidly growing because of its nearness to Addis Ababa and economic importance. The development plan has not been implemented properly. Population growth, coupled with industrial and commercial expansion has resulted in intense competition for land.

Dukem is home to Ethiopia’s first industrial park, the Chinese-owned Eastern Industrial Zone (EIZ), and some of the country’s most fertile land. Literally, the area of these industry parks is named "China" because many Chinese industries are constructed there. The town is situated along the Addis Ababa–Adama Expressway and is a station on the Ethio-Djibouti Railway. It is also the location of an industrial park covering 40 hectares owned and developed by East African Group (Ethiopia), Ltd.

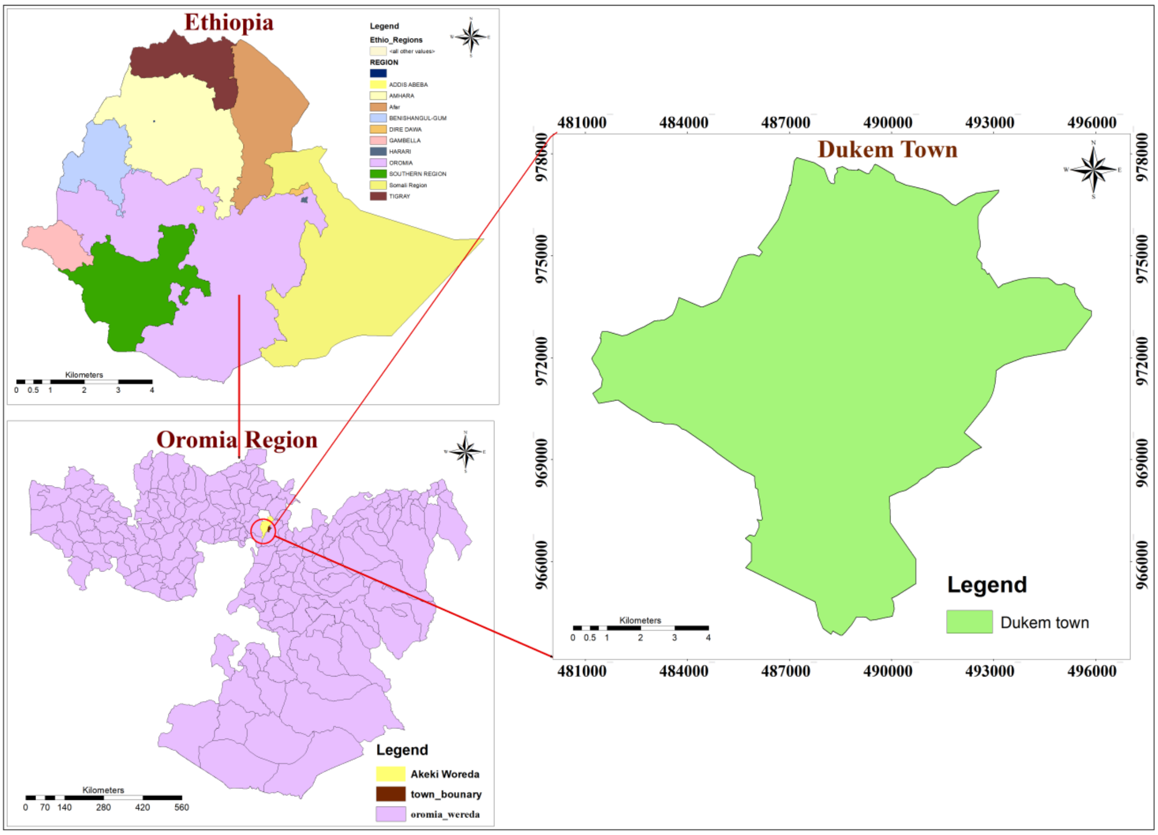

Figure 3.1: Location map of the study area

3.2.2. Demography

According to the last three consecutive censuses conducted in the country, Dukem Town showed a large increase in population. In the first Ethiopian population and housing census, which was held in May 1984, Dukem town had a population of 3,495 of whom 1,592 were males and 1,903 were females. The second population and housing census conducted in 1994 reported that Dukem had a total population of 4,876 of whom 2,506 were males and 2370 were females. According to the third Ethiopian population and housing census which was conducted in 2007, the town had 24,024 people of whom 12,185 males and 11,839 females were inhabited in Dukem. The population is increased to 162,233 whom 82,400 were males and 79,843 were females in 2021/22 (2014 E.C) (Socio-economic profile of Dukem, 2022).

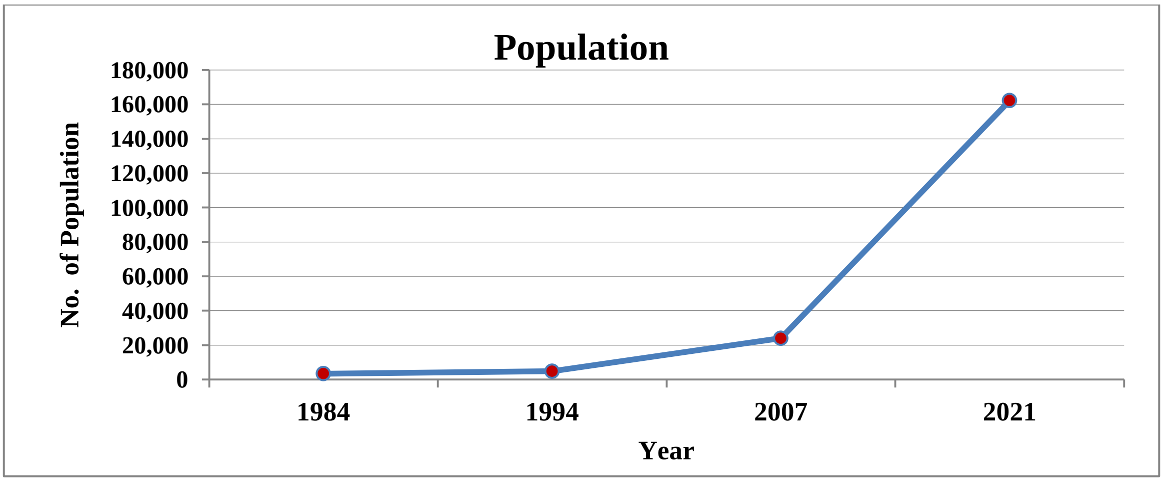

Figure 3.2: Population of Dukem Town from 1984 to 2021

Source: Socio-economic profile of Dukem, 2022

3.2.3. Climate and Vegetation

Dukem town is located near the western border and experiences temperate climate of the central Rift valley of Ethiopia. The mean annual rainfall of the area according to 1996 to 2013 year's meteorological data at Bishoftu station is 606.13 mm, and the mean maximum and mean minimum annual temperature of the area are 25.83^{o}C and 11.9^{o}C respectively.

Table 3.1: Temperature Data of Dukem Town (2010-2020)

Year	JA	FE	MAR	APR	MAY	JUN	JUL	AUG	SEP	OC	NO	DE	ANN
2010	0	79.1	68.5	131.8	94.9	179.3	290.0	221.4	200.3	0	15.8	5.2	1286.72
2011	0	10.5	58.0	47.46	84.3	131.8	142.3	137.1	79.1	5.27	15.8	0	711.91
2012	0	0	5.2	105.4	21.0	89.6	332.2	363.8	168.7	0	0	5.2	1091.6
2013	21.	0	73.8	179.3	79.1	163.4	326.9	247.8	137.1	73.8	26.3	0	1328.91
2014	0	15.8	47.4	58.0	121.2	89.6	237.3	205.6	163.4	84.3	15.8	15.	1054.69
2015	0	5.27	10.5	5.2	131.8	147.6	226.7	290.0	68.55	5.27	5.27	15.	912.3
2016	21.	15.8	31.6	94.9	158.2	100.2	221.4	305.8	189.8	31.6	5.27	0	1175.98
2017	0	94.9	52.73	21.09	142.3	68.55	311.1	290.0	268.9	31.6	5.27	0	1286.72
2018	0	47.4	5.27	116.0	63.28	158.2	221.4	332.2	52.73	26.3	15.8	0	1038.87
2019	0	0	47.46	137.1	21.09	147.6	210.9	305.8	358.5	21.0	31.6	5.2	1286.7
2020	0	0	31.64	195.1	121.2	174.0	421.8	442.9	226.7	42.1	0	0	1655.8

Source: https://en.climate-data.org/africa/ethiopia/dukem/dukem-532/)

Except planted trees, particularly eucalyptus trees found in the village and some sporadically scattered Acacia, existing in the farmland, the area is totally devoid of natural vegetation. The study area has flat topography generally possesses east and southeast and south west of Dukem Town extends to Bishoftu Town and the known Chukala mountain. The existing landscape of the area is formed by the formation of the great east African rift formation and subsequent volcanism, erosion and deposition. A ridge extends northeast and southwest to Yerer Mountain in the north east and to Guji and Bilbilo Mountain in the southwest (Dereje et al., 2020).

3.2.4. Topography

According to the extracted elevation of the study area from DEM, the study area is located along an elevation range from 1888m -2196m (Figure 3.3). The elevation map of the study area is extracted from ALOS 12m resolution which is downloaded from the Alaska Satellite website (https://asf.alaska.edu/).

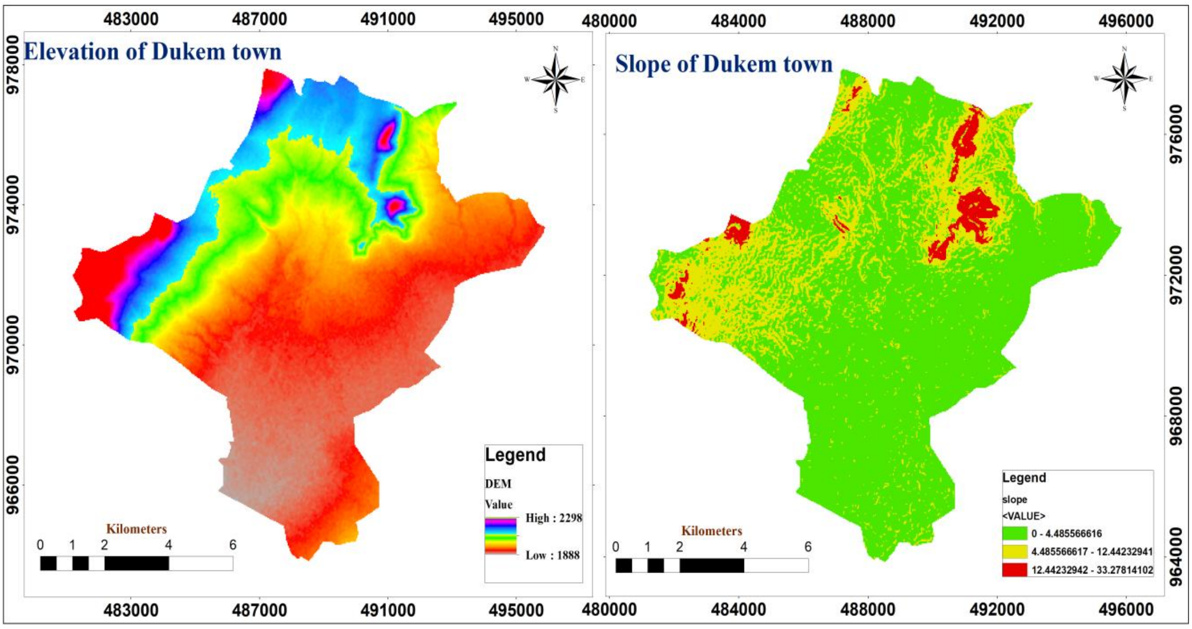

Figure 3.3: Elevation and Slope map of Dukem Town
Source: ASTER GDEM

3.2.5. Soil

According to Dukem town development plan team report the soil of the town is vertisol. This type of soil forms deep cracks during the dry season but logs water during the rainy season. The cracking of the soil during the dry season facilitates soil erosion. As a result, there are deep gorges in different parts of the town, especially along the courses of seasonal streams and Dukem river valley because of the very nature of the soil. Activities like quarrying and extraction of soil and also sand from the valleys of streams and river play their contribution for the formation of deep river gorges in different parts of the town. People dig out soil and also stones from the banks of Dukem River to provide soil for the construction of mud houses. The prevailing wind direction is from East to West. The principal natural constraints for the physical expansion of the town are flooding while manmade constraint is existence of unplanned urban expansion (MUDC, 2022).

3.2.6. Geology

Dukem is found in the main Ethiopian rift valley near the western escarpment. Volcanic rock materials of various compositions cover the area. Due to weathering of the rock, and subsequent erosion and deposition, thick residual clay and silt clay soil covered most part of the plain topographic landforms. The volcanic rocks found exposed along Dukem stream, Mandalo stream, Gogecha stream, rigs and slopes. According to the litho logical log of existing borehole, near Dukem stream ,(488800mE, 972368mN), that was drilled in December 2002 the area can be depicted by alternating layers of ignimbrite, scoraceous Basalt, aphanitic Basalt, scoria and clay . Litho logical log of the newly drilled borehole in September 2005 for Bishoftu town, in the plain land of Garbi Ballo, at the distance of 5km from Dukem, located at the geographic grid coordinate 969255mN and 492816mE, shows from top to bottom, the area formed from thick clay deposit, scoriacious basalt flow (14meters), and reworked pyroclastic deposits of different size, fine to medium grained sand of different composition, and medium to fine gravel of different rock type.

Due to the location of the study area in the main Ethiopian rift valley near the western escarpment parallel faults and step faults are prevalent in the area, which are governing ground water flow directions at depth and the flow of drainage pattern. A ridge extends northeast and southwest to Yerer Mountain in the north east and to Guji and Bilbilo Mountain in the southwest demarcated the western escarpment of the rift (Abebe A., 2012).

3.3. Data Collection and Data Source

Reliable data is necessary to realize the designed objectives and hence the study is based on both primary and secondary data. In this study the primary and secondary Data sources included both spatial and non-spatial data from fieldwork and different secondary data sources. The following table describes data required, data source, types of data used in the study, formats and where the data were gathered from.

Table 3.2: Data Source

No.	Data Required	Data Source	Data Type	Data Use
1.	Landsat (5,7,8 sensor) images Sentinel-2 image	USGS earth explorer	Secondary data	-For classification of LULC types.
2.	DEM	ASTER GDEM	Secondary data	-For knowing terrain types and slope of study area.
3.	Temperature	World climate	Secondary data	-For extracting climate data
4.	Structural plan of the town	Dukem town municipality office	Secondary data	-To Digitize Dukem Town Boundary. -To digitize Road network of the town.
5.	Population	CSA	Secondary data	-To know Dukem town population growth
6.	Ground truth	Researcher	Primary data	-For accuracy validation.

3.4. Software Used

To achieve the objective of these study different types of software was used. Software and materials for this study were chosen based on their potential to solve current issues and help achieve predetermined goals. Software is programs which are used for collection, organization, analysis, interpretation and presentation of data. The following table describes types of software’s to be used in the study, version of software’s and their purposes.

Table 3.3: Software Used

No.	Software Name	Version	Purpose
1	ArcGIS	10.8	For storing, managing, processing, and analyzing spatial information and thematic map preparation
2	ENVI	5.3	For processing and analyzing satellite images
3	Microsoft Word and Excel	2010	Integrating attribute data and compositing final thesis
4	Fragstats	4.2.1	To calculate spatial metrics
5	QGIS	2.18	Land change modeling and time series analysis compare and predict for the future
7	Google Earth pro		For Visualization and verification of classification
8	Global Mapper	20	For Downloading DEM

3.5. Methods of Data Analysis

In this section, mainly described the most important methods used for this study. After the data is collected from various sources, to monitor the changes, advanced techniques in remote sensing and GIS were used to identify the spatial and temporal changes that have occurred in LULC in Dukem Town. This thesis work is composed of three phases. The first phase is Examine land use land cover changes and rate of urban Expansion of the Dukem town between 2001 and 2021 through Classification of LULC and Accuracy assessment using remotely sensed images. The second phase is analysis of urban Expansion on Land Use Land Cover of Dukem town using spatial metrics analysis. The third one is landscape expansion indices analysis and the last phase was to prospect urban expansion for 2031, 2041 and 2051 presented in figure 3.5.

For this study in all Maps the following coordinate system information was applied projection =Transverse Mercator, Projection units = "meters", Datum and Ellipsoid= modified Clarke1880, Adindan, Ethiopia" and UTM zone = 37 Northern Hemisphere, scale factor=0.9996.

3.5.1. Analysis of LULC changes and rate of urban Expansion of the Dukem town

I. Pre-Processing Remote Sensing Image: Cloud-free, Landsat Thematic Mapper (TM), Landsat 7 ETM+, Landsat 8 (OLI) and Sentinel-2 images were used in this assessment. Sentinel-2 image were acquired on 24/03/2021 whereas, Landsat images were acquired on the 03, 10, 24 and 21 of February 2001, 2011, and 2016, respectively. The criterion I was used to select study period is depending on Dukem town high urban expansion rate. According to (Berhanu et al., 2019a) study shows urban expansion of Dukem town before 2010 was very slight rate however, after 2010 high urban expansion rate was exhibit. Depending on this fact, for this study 2001, 2011, 2016 & 2021 years are selected. All satellite images (path 168, row 54) were obtained from the United States Geological Survey and Global Land Cover Facility websites. The satellite image was processed using ENVI version 5.3. The coordinate system, layer stacking and layer extraction took place. Then Landsat images were corrected for the atmospheric, sensor and an illumination variance through radiometric calibration procedures. Image classification was also done using ENVI version 5.3, with accuracy assessments using ArcGIS version 10.8 to perform the image data processing which includes projection correction and producing maps.

For this study the land cover types were classified into four categories: (1) built-up area; (2) agricultural land; (3) Shrub and Bushes; and (4) Barren Land. They were classified based on knowledge of the areas, the spectral responses of features on the Landsat images, and visual analysis of different remote sensing products. Descriptions of these four categories are summarized in Table 6. Supervised image classification was done using the Support Vector Machine (SVM) Classifier algorithm which is widely applied for the urban area analysis (D. Liu & Chen, 2017).

Furthermore, Google Earth Pro® (GE) was applied to verify the accuracy of the classified satellite images. The Google Earth images acquired in each study period were used to verify the accuracy of the classified results. Due to the lack of high-resolution historical satellite images in the study site, the classification accuracy results of 2001 and 2021 were validated by generating random points for each land use/cover (LULC) class from the areas where the land cover remained unchanged.

Table 3.4: Land use/cover (LULC) classes and descriptions

LULC Classes Description	LULC Classes Description
Built-up Areas	Land covered by buildings and other man-made structures such as residential, commercial, industrial area, parking lots, railways, and road networks
Agricultural areas:	Cropland, horticultural farms, irrigation farms, and other agronomic regions
Shrub and Bushes;	Land covered by forest patches, woodland, shrubs, scattered trees mixed with grass, and perennial crops.
Barren Land	surface with no or little vegetation, open land, exposed soil, rocks and sand (eroded gullies)

Source: (D. Liu & Chen, 2017).

II.Image classification: Land use/land cover mapping Considering the importance of short-term changes in urban areas due to rapid urbanization and climate changes(Zhang et al., 2018), LULC maps of the study area were prepared in a various years' interval (2001, 2011, 2016, and 2021) using satellite images through supervised classification Support Vector Machine (SVM) method. It involves defining classification scheme, selecting training samples, running an algorithm to assign each pixel into a class and accuracy assessment (Dejene & Abebe, 2020). For classifying and processing satellite images the following procedural steps are applied:-

A. Defining classification scheme**:** The analysis focused on spectral resolution because the spectral dimension is the most important source of cover type information in coarse resolution images. The success of LULC usually, measured by the ability to match the spectral classes in the data to the information classes of interest (Weng, 2010) Information classes are those categories of interest that the analyst is actually trying to identify in the imagery, whereas spectral classes are groups of pixels that are uniform (or near similar) with respect to their brightness values in the different spectral channels of the data. In a complex urban landscape, a particular land use class may have diverse spectral characteristics (e.g., roof cover of old and new buildings). By contrast, different classes (objects) can have the same spectral characteristics (e.g., rock and concrete or bright building roofs).

Hence, it is rare that there is a simple one-to-one match between these two types of classes. Many times it is found that 2 to 3 spectral classes merge to form one informational class. Given the importance of the appropriate classification scheme, in this study, initially, by visually analyzing the color composite Landsat images with different band combinations, different classes were identified, and aggregated into four: built-up, barren land, agriculture and shrub and bushes.

B. Training sample section: The selection of training samples for each land cover is a pre requisite for supervised classification which is performed through visual interpretation and on-screen digitization of satellite images. All the images were displayed in natural color composite RGB (red, green, blue) format for digitization which created features called Region of Interest (ROI). Each land cover was marked with more than one ROI and each ROI was identified following Google Earth imagery and Landsat false-color composite images in which different bands combination highlights different land covers for ROI selection. Specific colors are assigned to each land cover (Ullah et al., 2020).

Training samples for each class were collected from each image. In order to reduce the sampling biases, consistency in sample selection was kept by selecting pixels that remained unchanged at different times to train the classifier. First, samples were selected from Landsat image of 2001 (first image). Subsequently, these samples were treated as training samples for the first image and used as a base for the adjacent image (2021). Second, the base samples were overlaid with the second image to check if change in class occurred. If changes were observed, new sample with more confidence was substituted from the surrounding area. Similarly, the same procedures were followed by selection of training samples for the rest of the images (Dejene & Abebe, 2020).

C. Classification algorithm: most of the classifiers under pixel-based classification are grouped into two groups: parametric and non-parametric classifiers. Parametric classifiers assume that the data is representative and normally distributed (Phiri & Morgenroth, 2017). Although parametric classifiers such as maximum likelihood have proved to be useful, these classifiers have two major drawbacks in land cover classification: data of high heterogeneous land covers are usually not normally distributed, and a lot of uncertainty is associated with distribution of land cover surfaces which cannot be described based on data distribution (Weng, 2010).

In this study each image was classified into a set of spectral classes using Support Vector Machine (SVM) algorithm in ENVI 5.3 software. Non-parametric classifiers such as SVM and ANN have proved to be more useful because they do not base classification on a normality assumption or statistical parameters explained that non-parametric classifiers are suitable when using non-spectral data in classification and that these classifiers provide better results than parametric classifiers in complex landscapes (Rodriguez-Galiano et al., 2012).

III. Accuracy Assessment: Post classification accuracy assessment is important because it quantitatively measures errors in the location of boundaries and sampled pixels in each classified land cover class. The accuracy of classification results was assessed by comparing classified ROIs and ground truth ROIs. Classified ROIs were created during the classification of satellite images. While ground truth ROIs were created through the generation of reference random points using ArcGIS 10.8 where 100 reference points were generated to cover the entire spatial extent of the study region. The location and coordinates of each reference point represent a classified land cover class. Each reference point was compared with ground truth data. In this study, high-resolution Google Earth imagery was used for ground truth data which offers clear identification of different land covers (Ullah et al., 2020).

Accordingly, error matrix was produced for all images in this study. An error matrix is a square array of rows and columns and presents the relationship between the classes in the classified and reference data. The increased usage of remote sensing data and techniques has made geospatial analysis faster and more powerful; however, the increased complexity also creates increased possibilities for errors (Dağıstanlı et al., 2018). Therefore, the assessment of the accuracy of mapping generated from remote sensing data is a critical and essential step in the classification process.

Error matrix is the most common tool in terms of determining the accuracy of the classification results (Fan et al., 2007). User accuracy, producer accuracy, overall accuracy and Kappa statistics were then derived from the error matrices for LULC classes. According to (Rwanga & Ndambuki, 2017) Kappa analysis is a discrete multivariate technique used in accuracy assessments. In other words, Kappa analysis is a standard component of accuracy assessment and is considered as a required component of most image analyses (Dağıstanlı et al., 2018).

Producer's Accuracy (Errors of omission): Producer's Accuracy measures the percentage of correctly classified pixels from a sample data or indirectly indicates errors of omission for a particular class. Producer's accuracy was calculated from dividing the number of correctly classified pixels in each category (on the major diagonal) by the number of training set pixels used for that category (the column total). It is calculated as:

Producer's Accuracy = $\frac{\mathbf{Ci}}{\mathbf{Ct}}*\mathbf{100}$……………………………………………….Equation (1)

Where, Ci = correctly classified sample locations of the reference data or column and

Ct = total number of sample locations of the column.

User's Accuracy (Commission error): user's accuracies are computed by dividing the number of correctly classified pixels in each category by the total number of pixels that were classified in that category (the row total). This result is a measure of commission error. It is calculated as:

User's Accuracy = $\frac{\mathbf{Ri}}{\mathbf{Rt}} * \mathbf{100}$ ……………………………………………….Equation (2)

Where, Ri = correctly classified samples in the row and Rt = total number of samples in the row.

Overall Accuracy: Overall accuracy was computed by dividing the total diagonal (i.e., the sum of the correctly classified sample units) by the total number of sample units in the error matrix. This value is the most commonly stated accuracy assessment statistic.

Overall Accuracy = $\mathbf{(S_d\ n) * 100}$…………………..…………………………..Equation (3)

Where, S_d = sum of values along diagonal and, n = total number of samples.

Kappa Coefficient: Kappa coefficient can be used as another measure of agreement or accuracy. Kappa was used to measure the agreement or accuracy between the remote sensing derived classification map and the reference data as indicated by the major diagonals and the chance agreement. This was indicated by the row and column totals. Kappa values can range from +1 to –1. But, as there should be a positive correlation between the remotely sensed classification and the reference data, positive values were expected and taken the possible ranges for kappa into three groups: a value greater than 0.80 (i.e., 80% and above) represent strong agreement; a value between 0.40 and 0.80 (i.e., 40%–80%) represents moderate agreement; and a value 0.40 (i.e., 40% and below) represents poor agreement (Landis & Koch, 1977),

$$\mathbf{K'} = \frac{\mathbf{n}\sum_{\mathbf{i=1}}^{\mathbf{r}}\mathbf{Xii} - \sum_{\mathbf{i=1}}^{\mathbf{r}}(\mathbf{Xi+}\cdots\mathbf{X+i})}{\mathbf{N2} - \sum_{\mathbf{i=1}}^{\mathbf{r}}(\mathbf{Xi+}\cdots\mathbf{X+i})} \text{.........Equation (4)}$$

Where r = number of rows in the error matrix; Xii = number of observations in row i and column i (on the major diagonal); Xi+ = total of observations in row i (shown as marginal total to right of the matrix); X+i = total of observations in column i (shown as marginal total at bottom of the matrix) and N = total number of observations included in matrix.

IV. Land use/land covers change detection: The change in LULC for the periods 2001-2011, 2011-2016, 2016-2021 was analyzed by using post-classification change detection technique in a GIS environment (Fenta, 2017). Post-classification change detection was selected as it reduces the possible effects of spectral resolution and sensor differences between the multi-temporal images (Lu, 2004.). This method enables to assess the temporal changes of the LULC types and to compute the extent of LULC conversion induced by the urban expansion.

LULC change statistics were computed in two different ways:

1) Total LULC change in hectare were calculated using the following equation:

Total LULC change = $\mathbf{Area}_{\mathbf{final\ year}} - \mathbf{Area}_{\mathbf{initial\ year}}$.................................Equation (5)

Where, area is extent of each LULC type. Positive values suggest an increase whereas negative values imply a decrease in extent.

2) Percentage LULC change were calculated using the following equation:

% LULC change = $\frac{\mathbf{Area\ final\ year - Area\ initial\ year}}{\mathbf{Area\ initial\ year}} * \mathbf{100}$ ....Equation (6)

Where, area is extent of each LULC type. Positive values suggest an increase whereas negative values imply a decrease in extent.

V. Analysis of Land Use/Cover and Urban Expansion: Expansion percentage of change (PC), annual increase (AI), and annual expansion rate (AER) indicators were employed to analyze the LULC changes and calculate the area and rate of annual urban expansion. The PC indicator is used to calculate the proportion of LULC changes, while the AI is employed to reflect the speed of urban areas growth across the study periods. The AER index is applied to show the rate of urban land expansion within each study period, as shown in Equations (7, 8 and9), which follows (Berhanu et al., 2019a) with some modification.

$$\mathbf{PC} = \mathbf{100}\% \times \frac{\mathbf{Ae-Ai}}{\mathbf{Ai}} \text{ ....Equation (7)}$$

$$\mathbf{Ai} = \frac{\mathbf{Ue-Ui}}{\mathbf{T}} \text{..........Equation (8)}$$

$$\mathbf{AER} = \mathbf{100}\% \times \left[\left(\frac{\mathbf{Ue}}{\mathbf{Ui}}\right)^{\frac{1}{\mathbf{T}}} - 1\right] \text{..........Equation (9)}$$

Where, Ai and Ae represent the area coverage of each land-use land-cover type at the initial and end of the monitoring period, respectively. Positive percentage values suggest an increase whereas negative values imply a decrease in area coverage. The Ui and Ue represent the same type of built-up area at the initial and end of the monitoring period, respectively, and T is the period from the time i to e. When T is 1 year, the AER is the annual built-up expansion rate.

3.5.2. Analysis of spatial pattern of Dukem Town urban expansion

Urban expansion is an ecological process that has an impact on ecology and the environment. Spatio-temporal characterization of urban expansion is important to understand its processes and driving mechanisms. Spatial information about urban landscape development can be accessed through the landscape indices which quantitatively measure the intensity; rate, direction, and pattern of urban expansion (Li et al., 2011). Landscape indices are factors of urbanization which represent patterns of urban sprawl and quantitatively measures the magnitude of change occurs in land cover.

Quantitative changes in the urban landscape are represented by changes in landscape indices. According to (Gui et al., 2019), the FRAGSTATS software (designed by Forest College Science of Oregon State University) is convenient for quantification of landscape indices. The software can work out three levels of metrics which are patch metrics, class metrics, and landscape metrics. Patch metrics calculate indices for a single patch of land cover and class metrics calculate indices for all the patches in a single land cover class while landscape metrics calculate indices for all the patches in a landscape (Ullah et al., 2020). In this study, I used Fragstats v4.2.1 to calculate 5 class metrics and 2 landscape metrics. The description for calculated metrics is given in Table 3.5.

These metrics were selected by considering: (i) relevance to the study objectives; (ii) significance in terms of theory and practice; (iii) minimal redundancy; and (iv) easy in calculating and interpreting the results (Wu et al., 2011) to characterize landscape dynamics due to the effects of urbanization. The UA landscape metrics quantify the spatial composition while the last four metrics calculate urban spatial configuration.

Table 3.5: selected landscape metrics used for the quantification of urban expansion

Metrics Name	Metric level	Category	Metric Unit	Description
Contagion (CONTAG)	Landscape	Aggregation	%	The aggregation and distribution of patches in the corresponding class in a landscape.
Shannon's diversity index (SHDI)	Landscape	Diversity	Information	Differentiation in patch types depends on the number and the proportion of different patch types.
Patch cohesion index (COHESION)	Class and landscape	Aggregation	N/A	It measures the physical connectedness of the corresponding patch type.
Largest Patch Index (LPI)	Class and landscape	Area and Edge	%	It measures the largest patch of a landscape.
Landscape shape index (LSI)	Class and landscape	Aggregation	N/A	It provides a standardized ratio of edge length to area.
Percentage of Landscape (PLAND)	Class	Area and Edge	%	The measurement of components of corresponding class in landscape.
Landscape division Index (DIVISION)	Class and landscape	Aggregation	Proportion	It interprets cumulative patch area distribution in a landscape.

Source: (Ullah et al., 2020)

3.5.3. Quantifying pattern of urban growth types using LEI method

Landscape metrics or indices have been commonly used for quantifying landscape patterns. From those metrics or indices landscape expansion index (LEI) is to give a deeper insight of landscape patterns and temporal dynamics. In addition to identifying the types of landscape expansion, LEI can also be used to describe the process of landscape pattern changes within two or more time points. In contrast with traditional landscape indices which only reflect the spatial characteristics at a given time, LEI can capture the information on formation processes of a landscape pattern (X. Liu et al., 2010). By taking urban growth as an example of landscape expansion, these indices are used to identify the spatial modes of urban expansion. Three urban growth types were identified: infilling, edge-expansion and outlying growth. These indices are applied to the pattern analysis of the urban landscape in Dukem, a fast growing town nearest to Addis Ababa city. An infilling type refers to the one that the gap (or hole) between old patches or within an old patch is filled up with the newly grown patch (Fig. 1a). While edge-expansion type, defined as a newly grown patch spreading unidirectional in more or less parallel strips from an edge (Fig. 1b). If the newly grown patch is found isolated from the old, then it would be defined as an outlying type. The LEI index is defined by using the buffer analysis, which can be used in queries to determine which entities occur either within or outside the defined buffer zone.

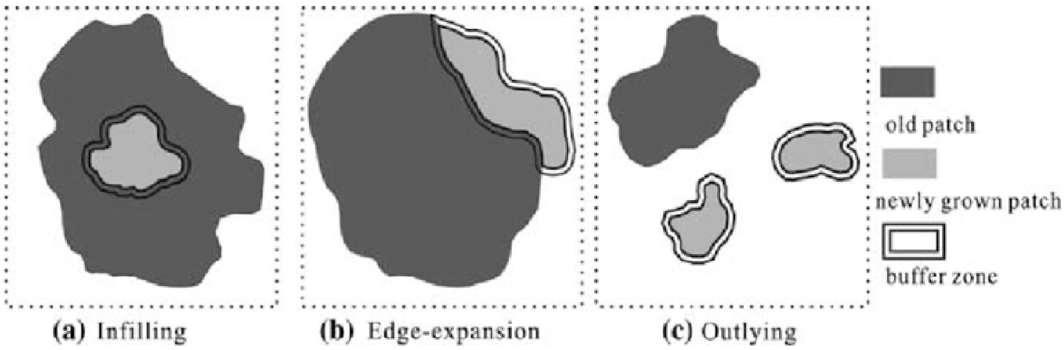

Figure 3.4: Three types of landscape expansion

Source: (X. Liu et al., 2010)

The above Figure describes the buffer zone of new patches with respect to three typical urban growth patterns. A set of rules are defined to identify these growth patterns: (1) if a newly grown patch belongs to the infilling growth, the buffer zone is mostly occupied by the old patch (Figure 1(a)); (2) the area in buffer zone is mixed by vacant land and the original landscape if the newly grown patch is the edge-expansion type (Figure 1(b)) and (3) if the newly grown patch is classified as outlying growth, its buffer zone is composed exclusively of vacant land (Figure 1(c)).

Therefore, the LEI index can be calculated by examining the characteristics of its buffer zone, as shown in Equation:

$$\mathbf{LEI = 100\ \frac{Ao}{Ao + Av}} \quad \text{……………………………………………..…………equation (10)}$$

Where LEI is the landscape expansion index for a newly grown patch, Ao is the intersection between the buffer zone and the old patches and Av is the intersection between the buffer zone and the vacant category. According to this definition based on Liu et al. described, the value of LEI varies from 0 to 100. Urban growth pattern is identified as infilling when LEI > 50, edge-expansion when LEI ranges from 0 to 50 and outlying growth when LEI = 0.

3.5.4. Predicting future urban expansion using CA-ANN model

For predict future urban expansion of Dukem town CA-ANN techniques in Modules for Land-Use Change Simulation (MOLUSCE) plug-in inside QGIS was utilized to estimate spatiotemporal changes and compute the LULC transition between study period intervals (2001–2021), and generated three LULC change maps. Area changes and transition probability matrix using the LULC data and contextual factors was created, which included rows and columns of landscape categories in the start and end years. For transition potential modeling, ANN multilayer perceptron approach was used. As explanatory factors, the DEM, slope, and distance from Road were used. These variables are often utilized in LULC change analysis because they give reproducible data on the physical and anthropogenic influences on LULC dynamics (Muhammad et al., 2022).

Simulated models are used to reduce the dynamics of composite urban structures and make them intelligible in a simple manner. CA-ANN Simulation modules were used to minimize the dynamics of composite urban structures and interpret them in a clear and accessible manner. The MOLUSCE plug-in is perfectly adapted to evaluating spatiotemporal land-use changes, transition potential modeling, and predicting future scenarios. The artificial neural network (ANN) was used in association with cellular automata (CA) to predict the land use changes. Because of its dynamic simulation capacity, high efficiency with limited data, simple calibration, and ability to reproduce different land covers and complicated patterns, CA-ANN was chosen to simulate land use change. ANN was employed in the transition potential modeling to establish trends on the basis of which future prediction will be made (Baig et al., 2022).

Based on the classified LULC data for 2001 and 2011, explanatory variables, and transition matrices, LULC for 2021 was projected. Then to validate the model and prediction accuracy, the MOLUSCE plug-in offers a kappa validation technique and comparison of actual and projected LULC images was made. ANN learning process was applied to project the LULC for 2021. After obtaining satisfactory results from the model validation, I employed LULC data from 2011 and 2021 to forecast the LULC in 2031, and the LULC of 2001 and 2021 for 2041. Finally, the predicted data for 2031 and 2041 were used to forecast LULC for 2051 (Muhammad et al., 2022).

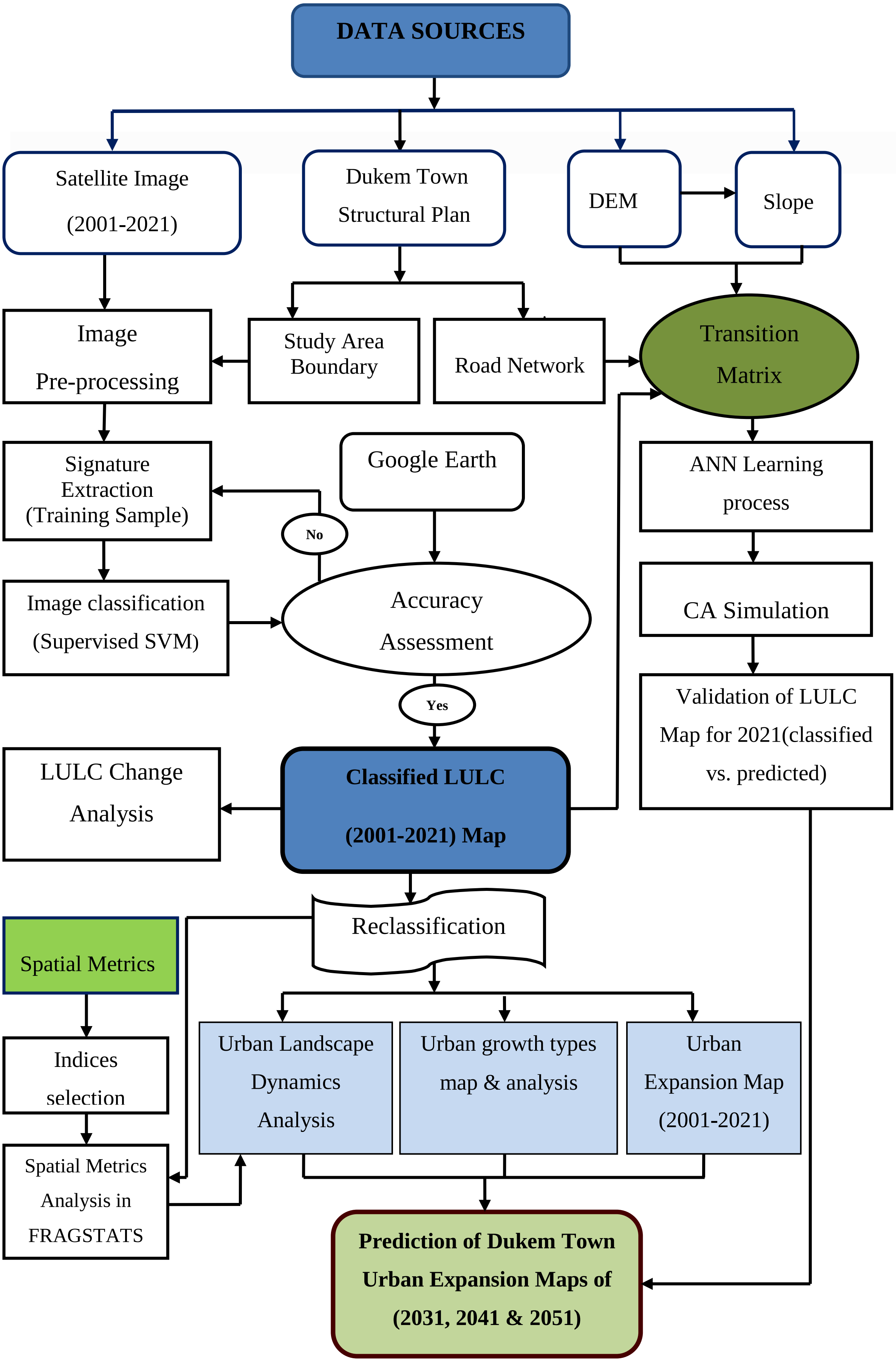

Figure 3.5: Technological scheme of the thesis work

CHAPTER IV: RESULTS AND DISCUSSIONS

This chapter discusses different data sets that were used to examine urban changes in the LULC patterns and modeling of feature Dukem Town. Based on the data gathered, data analysis performed and LULC maps developed for 2001, 2011, 2016 and 2021 years presented in different figures and tables shows the statistical change analysis of LULC over the study period (2001 – 2021). An overall change in LULC of all the four reference years is shown in (figure 4.1, 4.2, & 4.3). Additionally, maps and tables of spatial metrics analysis for urban expansion were created for each LULC years and feature projected maps and tables are presented with analysis.

4.1. Land Use and Land Cover Classification

To accomplish the objectives of the study, LULC of the study area were first classified from Landsat satellite images of 2001, 2011, 2016 and 2021 to compute the LULC change trend of Dukem Town. The images were interpreted or classified into four LULC classes, namely built up, shrub and bushes, Agricultural land and barren land. The LULC maps generated after running a Support vector Machine supervised classification in ENVI 5.3 software. The results showed that, over the study period (2001–2021), the dominant land cover type in the study area was Agricultural land ranging between 57.88% and 70.75% of the total area.

4.2. Accuracy Assessment of the Classification

Accuracy assessment in this study revealed the overall accuracies of 89.51%, 90.2%, 93.63 and 96.77% with the Kappa statistics of 0.857, 0.861, 0.911 and 0.961 were calculated for the four reference years 2001, 2011, 2016 and 2021 respectively. This indicates that all classifications are in acceptable range because an overall accuracy of each year was greater than 85% and kappa coefficient greater than 0.80 represents strong agreement (Landis & Koch, 1977) Is an indicator for a strong accuracy. Hence, the maps met the accuracy requirements for change detection analysis (Merugu & Tiwari, 2013), and there is a positive correlation between the remotely sensed classified samples and the reference data (Merga et al.2022). Results of user's accuracy in this study showed that in 2001 the maximum class accuracy was for Built-up Area (91.17%) and the minimum was for barren land (86.84%). In 2011, user's accuracy ranges from lowest accuracy Agricultural Land (92.30%) to relatively correctly classified Barren Land (87.09%). In 2016, user's accuracy ranges from lowest accuracy Barren Land (95.12%) to relatively correctly classified Built-up Area (91.17%), whereas in the period 2021, it ranges from 100% (Shrub & Bushes) to 94.73% (built-up). Most of the LULC classes have a larger producer's accuracy than overall accuracy almost all are greater than 85% except the class of Shrub & Bushes (83.33%) in 2001. The details of error matrix tables' results are shown in (Table 4.1, 4.2, 4.3 & 4.4).

Table 4.1: Error matrix of classification for 2001

	Reference Map						
	Classified Data	Built-up Area	Shrub & Bushes	Barren Land	Agricultural Land	Row Total	User Accuracy (100%)
Classified Map	Built-up Area	31	0	3	0	34	91.17%
	Shrub & Bushes	0	20	0	2	22	90.90%
	Barren Land	0	1	33	4	38	86.84%
	Agricultural Land	0	3	2	44	49	89.79%
	Column Total	31	24	38	50		
	Producer Accuracy (100%)	100%	83.33%	86.84%	88%		
	Overall Accuracy = 89.51%	Kappa Statistics K ^= 0.8567					

Table 4.2: Error matrix of classification for 2011

	Reference Map						
	Classified Data	Built-up Area	Shrub & Bushes	Barren Land	Agricultural Land	Row Total	User Accuracy (100%)
Classified Map	Built-up Area	30	0	1	0	31	96.77%
	Shrub & Bushes	0	20	0	0	20	100%
	Barren Land	0	0	36	2	38	94.73%
	Agricultural Land	0	1	0	56	57	98.24%
	Column Total	30	21	37	58		
	Producer Accuracy (100%)	100%	95.23%	97.29%	96.55%		
	Overall Accuracy = 96.77 %	Kappa Statistics K ^= 0.961					

Table 4.3: Error matrix of classification for 2016

	Reference Map						
	Classified Data	Built-up Area	Shrub & Bushes	Barren Land	Agricultural Land	Row Total	User Accuracy (100%)
Classified Map	Built-up Area	31	0	3	0	34	91.17%
	Shrub & Bushes	0	21	0	2	23	91.30%
	Barren Land	0	0	39	2	41	95.12%
	Agricultural Land	0	3	0	56	59	94.91%
	Column Total	31	24	42	60		
	Producer Accuracy (100%)	100%	87.50%	92.85%	93.33%		
	Overall Accuracy = 93.63%		Kappa Statistics K ^= 0.911				

Table 4.4: Error matrix of classification for 2021

	Reference Map						
	Classified Data	Built-up Area	Shrub & Bushes	Barren Land	Agricultural Land	Row Total	User Accuracy (100%)
Classified Map	Built-up Area	17	0	2	0	19	89.47%
	Shrub & Bushes	0	19	0	2	21	90.47%
	Barren Land	1	0	27	3	31	87.09%
	Agricultural Land	0	3	1	48	52	92.30%
	Column Total	18	22	30	53		
	Producer Accuracy (100%)	94.44%	86.36%	90%	90.56%		
	Overall Accuracy = 90.2 %		Kappa Statistics K ^= 0.861				

The classifications of satellite image are pixel based classification category, supervised Classification method with support vector machine algorithm for all Dukem Town Land use land cover classes of 2001, 2011, 2016 and 2021.

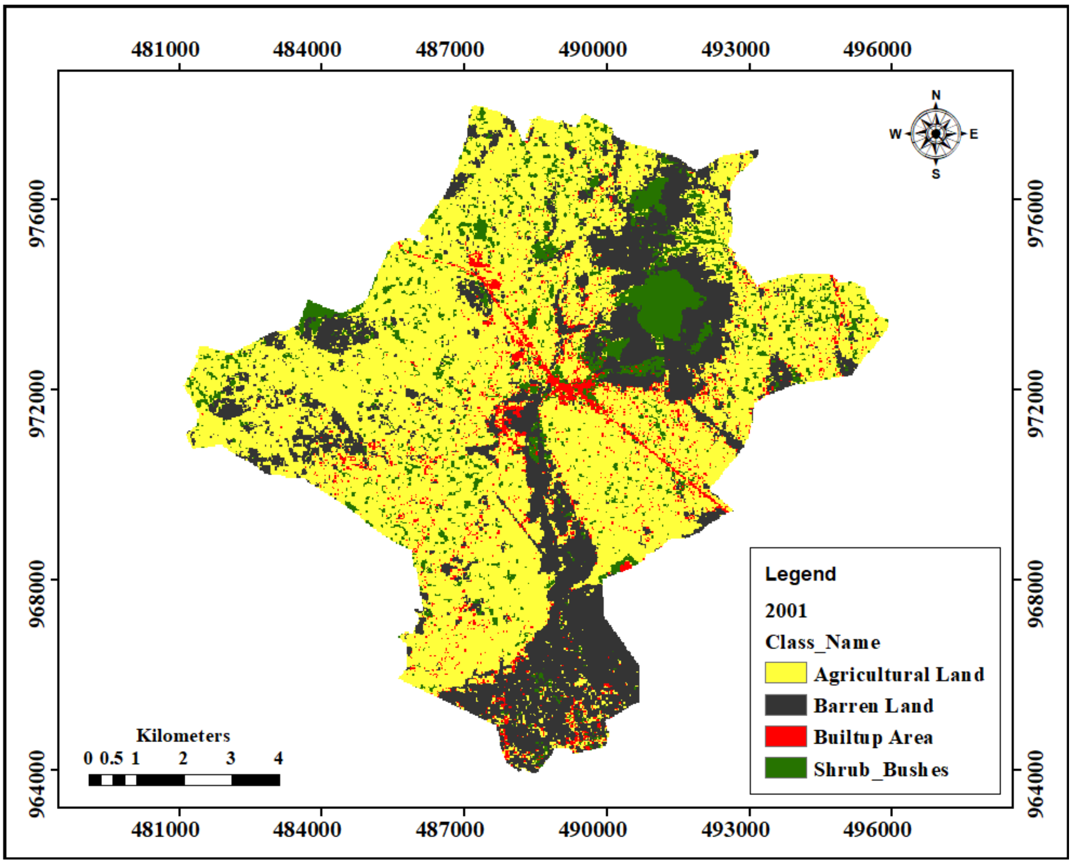

Figure 4.1: LULC map of Dukem town in 2001

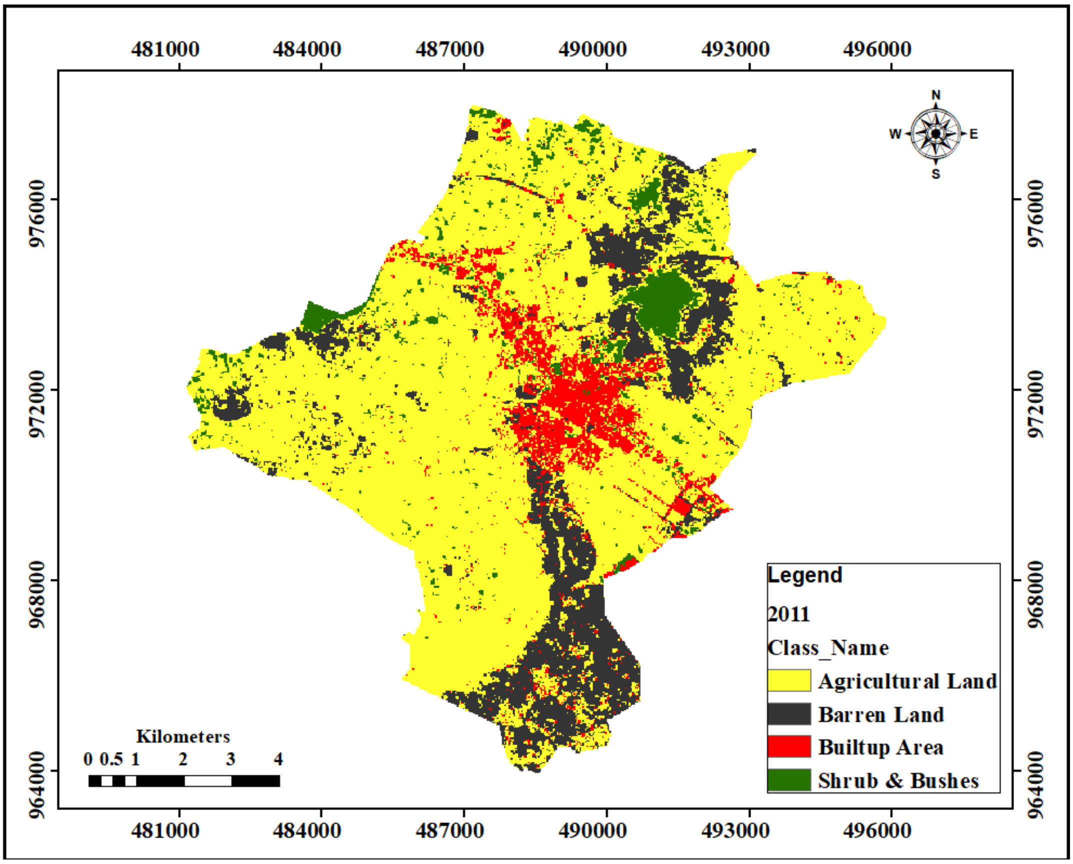

Figure 4.2: LULC map of Dukem town in 2011

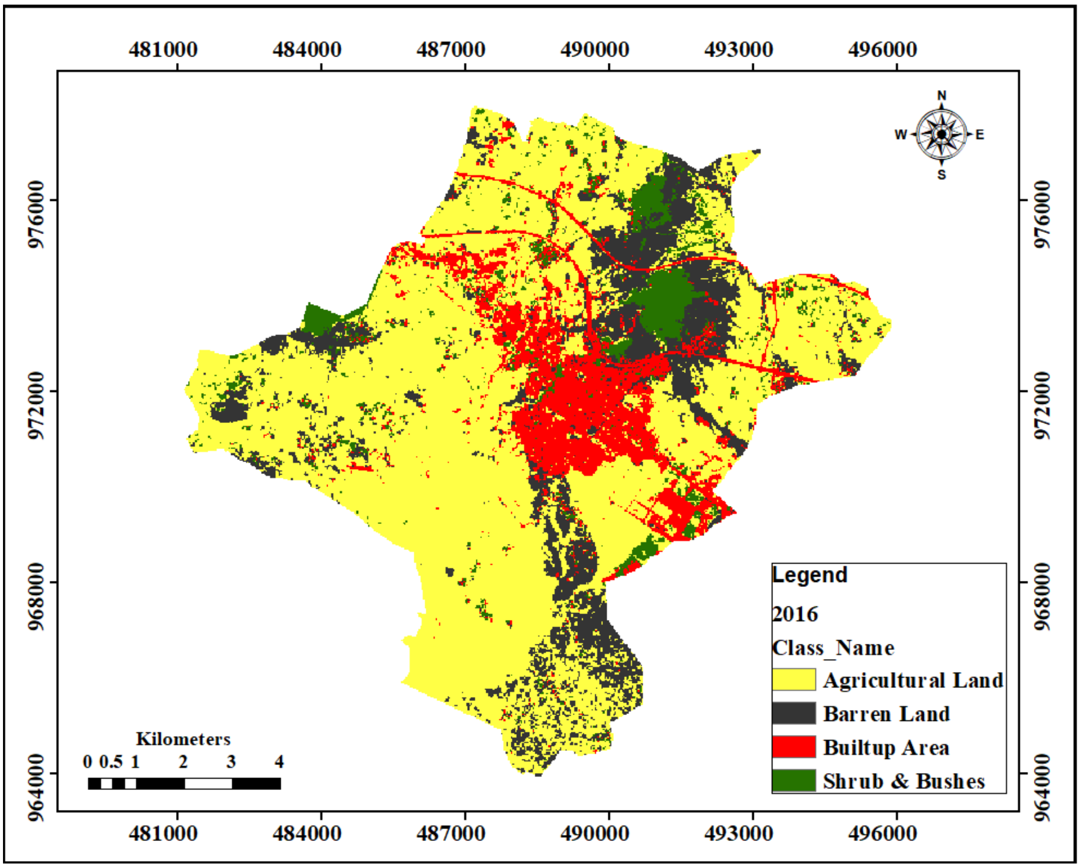

Figure 4.3: LULC map of Dukem town in 2016

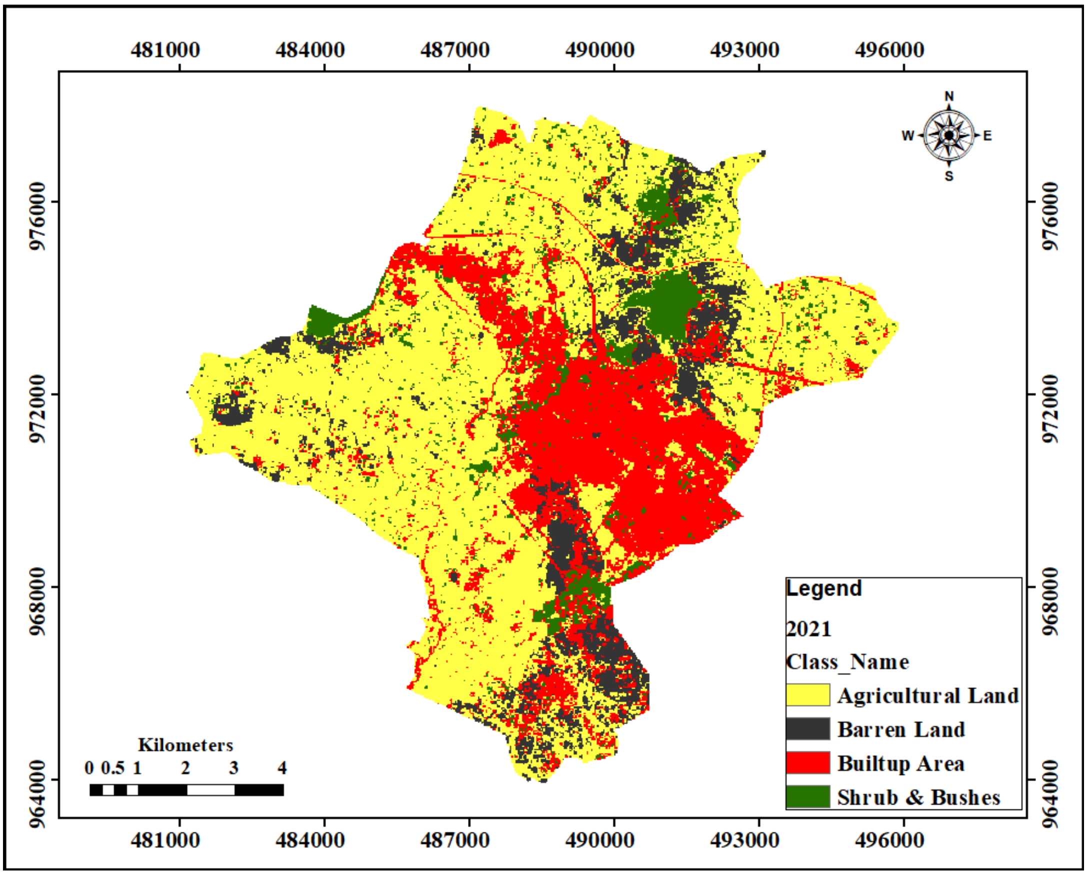

Figure 4.4: LULC map of Dukem town in 2021

4.3. LULC Change Analysis

In this study, four LULC maps were produced for the study period and spatiotemporal LULC dynamic process was analyzed (Table 4.5). Based on the LULC classification, over the past two decades, LULC in study area barren land such as were in continuous decline, while Agricultural land and shrub and bushes classes showed a varying pattern. In general, out of the four LULC classes identified in the study area, only built-up, showed continuous increment over the past 20 years. The extent of change within the study area of the individual LULC categories in hectare (Ha) and the percentage (%) they occupied for 2001, 2011, 2016 and 2021 are presented in Table 4.5.

Table 4.5: Area statistics and % of the LULC units for 2001, 2011, 2016 and 2021

Land Use Type	**2001**		**2011**		**2016**		**2021**	
	Area (Ha)	Area (%)	Area (Ha)	Area (%)	Area (Ha)	Area (%)	Area (Ha)	Area (%)
Agricultural Land	5939.056	61.043	6883.226	70.748	6293.052	64.720	5631.863	57.886
Barren Land	2432.813	25.005	1599.435	16.430	1583.812	16.261	1083.679	11.138
Built-up Area	426.174	4.380	759.939	7.812	1263.633	12.974	2352.671	24.181
Shrub & Bushes	931.197	9.571	486.640	5.002	588.743	6.045	661.027	6.794
Total	9729.24	100.0	9729.24	100.0	9729.24	100.0	9729.24	100.0

In 2001 the study area was dominated by Agricultural land covering 61.04% followed by bare land covering 25% of the study area. Built-up and shrub and bushes shared 4.380% and 9.571% of the total area respectively. In 2011, Agricultural land, barren land and Shrub and bushes covered 70.748%, 16.430% and 5% of the total area respectively. The remaining parts of the area were covered with built-up (7.812%). In 2016 built-up area increased to (12.97%) and the remaining (87.03%) was the share of other LULC classes. In 2021 built-up area increased to (24.181%) and the remaining parts of the area were covered with Agricultural land (57.89%), barren land (11.14%) and Shrub and bushes (6.80%) show in (Table: 4.6 & Figure: 4.5).

Table 4.6: Overall amounts and percentage of LULC Change during 2001-2021

	2001-2011		2011-2016		2016-2021		2001-2021	
Land Use Type	Change (Δ/Ha)	%	Change (Δ/Ha)	%	Change (Δ/Ha)	%	Change (Δ/Ha)	%
Agricultural Land	944.17	9.70	-590.17	-6.03	-661.19	-6.83	-307.19	-3.16
Barren Land	-833.38	-8.57	-15.62	-0.17	-500.13	-5.12	-1349.13	-13.9
Built-up Area	333.76	3.43	503.69	5.16	1089.03	11.20	1926.49	19.80
Shrub & Bushes	-444.56	-4.57	102.10	1.04	72.28	0.75	-270.17	-2.78

Generally, the decreased trends observed in the shrub and bushes, farm land and barren land LULC classes during the study period. Out of the four LULC classes identified in the study area built-up showed increment during the study period. For a better comparison of the change trends occurred in these four study periods are shown in Figure: 4.5.

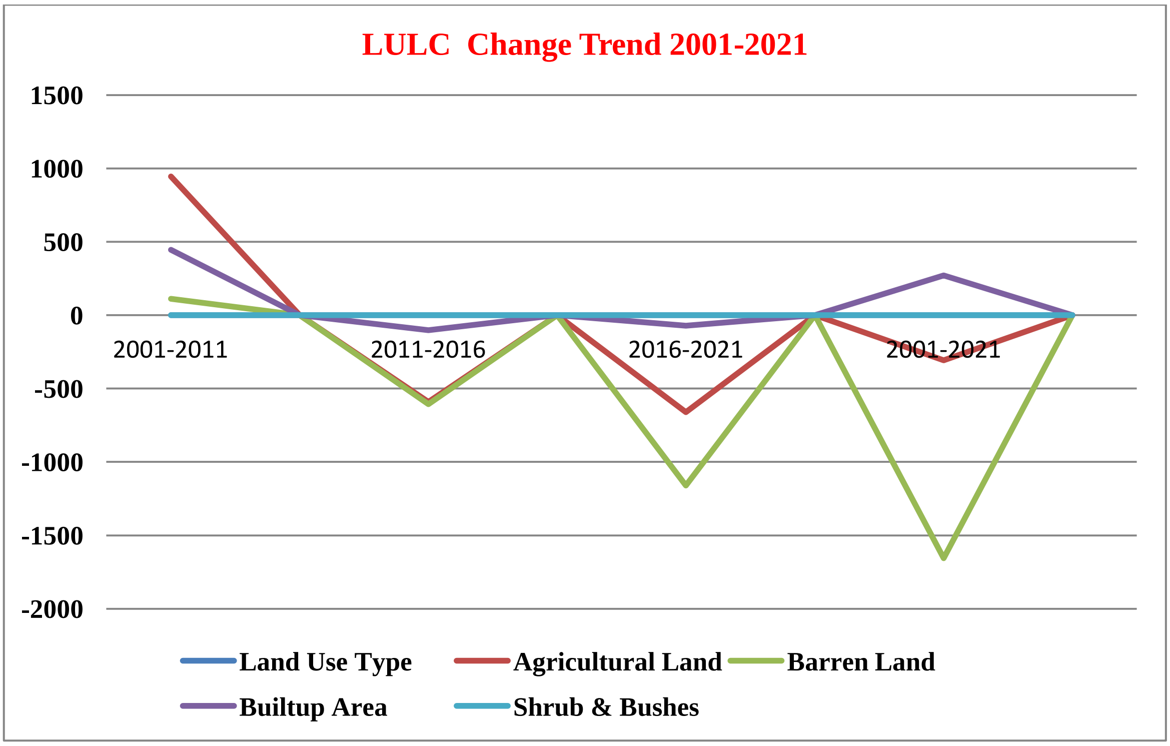

Figure 4.5:Trend of LULC change (2001-2021)

Table 4.7: Dukem Town LULC classes' contributor to net change built up area.

	Changed to Built up area (Ha)			
LULC Classes	**2001-2011**	**2011-2016**	**2016-2021**	**2001-2021**
Agricultural Land	76.43	205.35	339.32	921.1
Barren Land	42.34	115.33	121.47	378.76
Shrub & Bushes	50.22	130.12	234.09	514.43
Total	168.99	450.8	694.88	1814.29

Generally Dukem Town LULC Classes that contribute to Net change in Built up area for two decades (2001-2021), Agricultural Land more contribute (921.1Ha), Shrub & Bushes land contribute (514.43 Ha) and Barren Land is least contribute (378.7Ha).

4.4. Magnitude and Rates of Urban Expansion

Based on equation (7, 8 and 9) magnitude and rate of urban expansion of Dukem town across the study periods are displayed in Table 4.8. The expansion of the built-up area class is evident in the 2021 LULC map shows. The evaluation of class statistics displays that there has been a noticeable urban area expansion within a span of 20 years. As shown in Table 4.8, Dukem town experienced a fast increase of built-up areas, resulting in dramatic transformations in spatial patterns from 2001 to 2021. The highest and the lowest AI occurred from 2016 to 2021 and between the period 2001 and 2011, respectively (Table 4.8). The town, had the highest AI (217.80 Ha) during the year 2016 to 2021. However, the town experienced the least annual expansion rate (5.95%) during 2001 and 2011 period (Table 4.8), whereas in the period of 2016-2021 experienced the highest AER (13.24%). This indicated that the town has higher urban expansion rates especially during the last five years.

More generally, the total annual increment was 96.32 Ha/year for the study period from 2001 to 2021. From 2001 to 2011, built-up areas of the Dukem town increased by about 33.38 Ha/year. More recently, between the years 2016 to 2021, the study site annually shows 217.80 Ha of annual intensity with urban expansion rate of 13.24% (Table 4.8).

Table 4.8: AI and AER built-up area of Dukem town from 2001 to 2021

Year	Annual intensity(AI) (Ha/year)	Urban Expansion Rate (AER) (% per year)
2001-2011	33.376	5.954
2011-2016	100.738	10.705
2016-2021	217.807	13.237
2001-2021	96.325	8.918

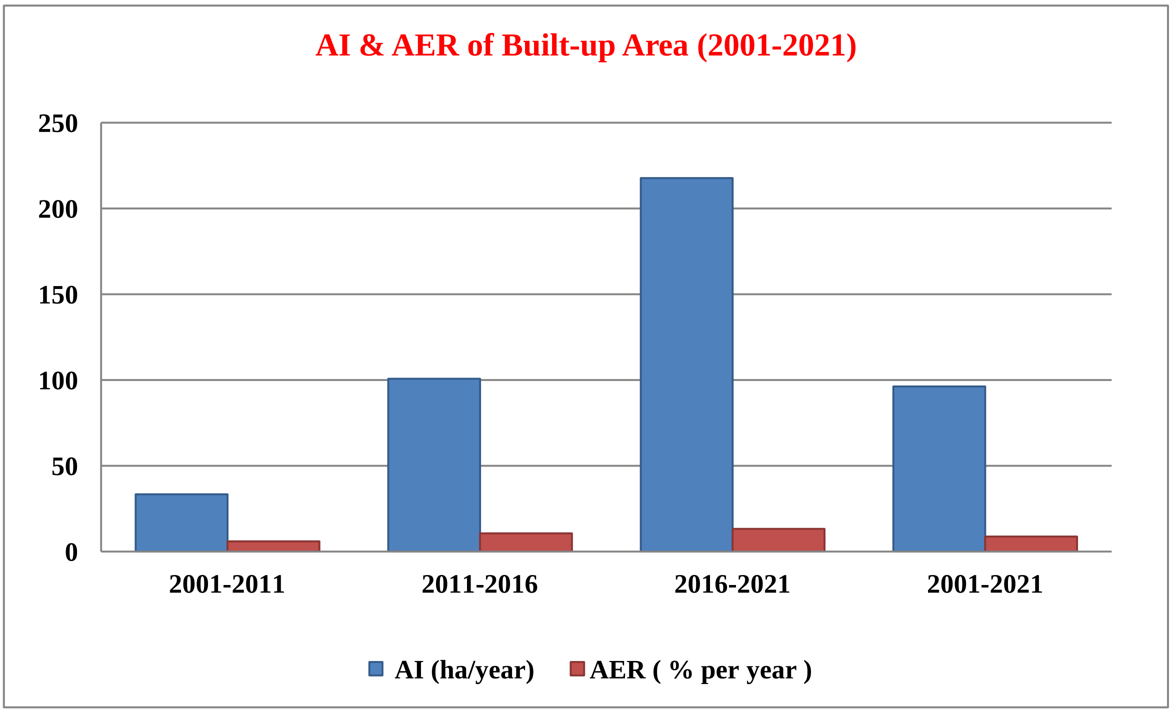

Figure 4.6: AI and annual expansion rates AER of the built-up area from 2001 to 2021.

4.5 Land cover changes of Built up areas

The increment in infrastructure development such as; industrial site, social service, Road, Residential development, business center etc. of Dukem town from time to time has played a major influence for the expansion of built up areas. To examine the spatial extents of built up areas within the four study periods, a reclassification was made to generate land use and land cover maps of built up and non-built up areas as shown in figure 4.7. As clearly seen in table 4.9, the proportion of built up areas in 2001 was 4.38% of the entire study area.

In 2011 the percentage of the built up area is 7.81% the entire area a, which is 3.43% more than before. In 2016 the percentage of built up area was increased by 12.97% and for the periods of 2021 was 2.18% of area coverage.

Table 4.9: Built and non built-up areas (2001- 2021)

Land cover classes	**2001**		**2011**		**2016**		**2021**	
	Area(Ha)	%	Area(Ha)	%	Area(Ha)	%	Area(Ha	%
Built up	426.17	4.38	759.94	7.81	1263.63	12.97	2352.67	24.18
Non-built-up	9303.07	95.62	8969.30	92.19	8465.61	87.03	7376.57	75.82
Total	9729.24	100	9729.240	100	9729.240	100	9729.24	100

The study area has experienced spatial increase of different land use and land cover classes such as; built up areas, due to the corresponding horizontal expansion as well as conversion of land cover classes during the distinct study periods.

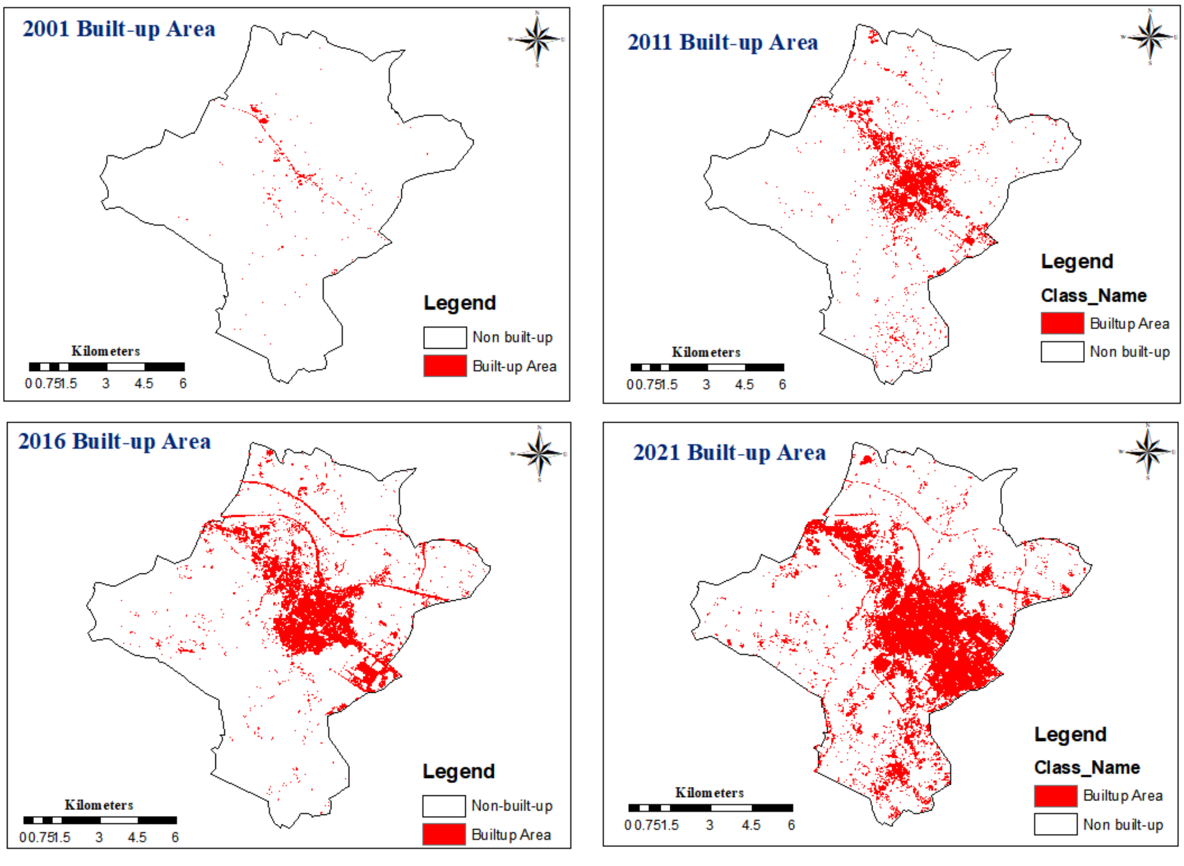

Figure 4.7: Built up and Non-built up area Maps of Dukem town (2001-2021)

The reclassified images in figure: 4.7 showed that there had been a rapid land cover change from non-built up areas to built-up areas. In this study periods, Agricultural land areas and shrub and bushes were the most dynamic classes which contributed to the increase of built up areas. There was a huge increase of built up areas from 2001-2021(4.38% - 24.18% of study area).

The LULC change analysis explores the spatial dynamic variations in the LULC pattern during the study period. The results from 2001 to 2021 show a prominent expansion in urban surface and a shrinking phenomenon in the other LULC. Figure 4.8 show the spatiotemporal change of urban area.

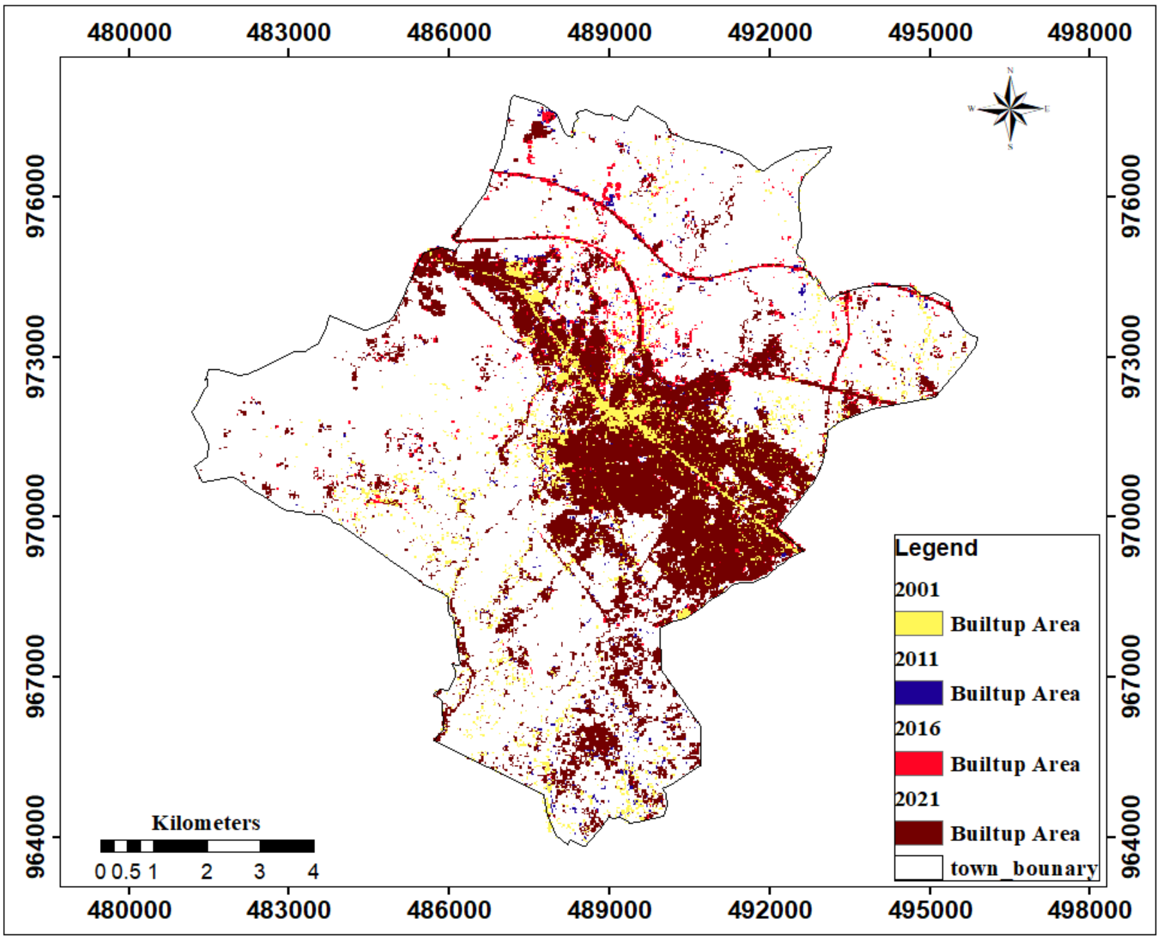

Figure 4.8: Urban Expansion of Dukem Town from 2001to 2021

4.6. Change of Urban Landscape Patterns

Table: 4.10 shows the trends in the annual change of landscape metrics calculated for Dukem town under the study over the past two decades. The fragmentation and complexity of the urban land patches indicated by the DIVISION, COHESION, PLAND, LPI, SHDI CONTAG and LSI varied among the year.

As the result shows the values for PLAND and LPI linearly increases which denotes an increase in the expansion of the constructed areas. Percentage of Landscape (PLAND); is a fundamental measure of landscape composition; specifically, how much of the landscape is comprised of a particular patch type. The PLAND increases from 5.52% in 2001 to 16.40% in 2011, to 53.18% in 2016, while in 2021 the PLAND was drastically increased to 64.75%. Largest Patch Index (LPI) indicates percentage of the area covered by the largest patch of the focal class, built-up area in this case, in the landscape. LPI increased its dominancy from 3.827% in 2001 to about 34.295% in 2021 (Fig 4.9). It shows that the core area of the town center is growing by infill development and merging of patches to already developed built-up area forming more and more continuous urban agglomeration in the landscape.

The overall increasing trend in the values of LSI shows the increasing complexity in the shape and expansion of the urban areas. The increase in DIVISION and decrease in COHESION values indicate that connectedness among urban patches is on the decline due to spatial expansion. On landscape level, SHDI increased while CONTAG decreased sharply indicating urban areas became more dispersed and fragmented over the study period.

Table 4.10: Landscape metrics calculated Value for Dukem Town

LULC (Year)	PLAND	LPI	LSI	DIVISION	COHESION	CONTAG	SHDI
2001	5.517	3.827	28.894	0.719	99.313	85.633	0.594
2011	16.397	48.529	23.657	0.729	99.470	50.957	0.632
2016	53.178	51.775	26.453	0.967	99.604	43.952	0.711
2021	64.750	34.295	32.253	0.998	99.663	52.587	0.802

Growing trend of LPI pushes the town fringe and leads to suburbanization which agrees with the increasing number of patches specifically in the past ten years. When the 34.295% of LPI in 2021 compared with the percentage of built-up area (PLAND) 64.750% (Fig 4.9) in the same year, LPI is almost close to the total built-up area which means the core area of Dukem town and its surrounding is formed a continuous greater urban agglomeration while there is highest fragmentation and spatial expansion of the town in the same year.

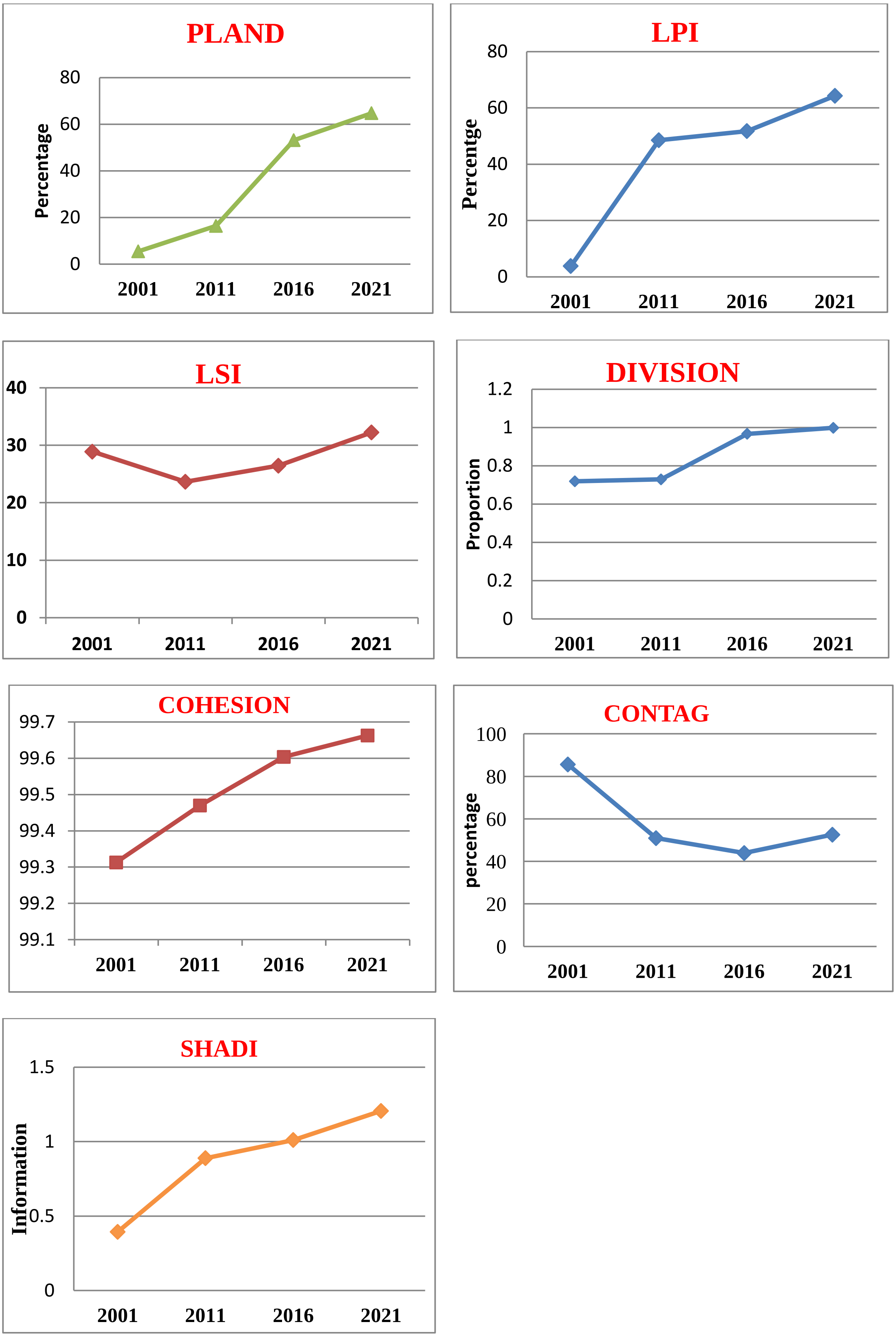

Figure 4.9: Spatial configuration metrics of built-up area from 2001to 2021.

LSI is a measure of perimeter-area ratio and interpreted as the overall shape complexity of a particular class in the landscape (Mcgarigal, 2015). The increase in LSI shows shape complexity and irregularity of built-up area in the landscape. For this study LSI varies from 23.657 in 2011 when number of patches is lower to 32.253 in 2021 when the number of patches of the built-up area is the highest.

The last index is Shannon’s diversity index (SHDI) was selected to check the general structure of the landscape. These indices are composition metrics that range between 0 and 1. Shannon’s diversity index (SHDI) shows proportional distribution of area among classes and the probability that any two pixels selected randomly, become different patch type. SHDI results obtained from FRAGSTATS range between 0.594 in 2001 to 0.801 in 2021 which means the diversity index is higher in 2001 when all classes have closer proportion of area but decreases in 2021when built-up area dominates the landscape.

4.7. Landscape expansion Index (LEI) and urban growth Types

Based on classification results were shown further used to extract the urban areas of Dukem town for three periods 2001-2011, 2011-2016 and 2016-2021. For calculating LEI firstly, land use data need to be converted into the vector format. Then, the buffer zones of all new patches are generated by executing the program. Buffers can be set at constant or variable distances based on feature attributes. In this paper, the buffers are created by using a constant distance of 1 m. Once the buffer zones of all growth patches have been obtained, they are overlaid with the old urban patches for calculating the area of the old urban patch within the buffer zones (X. Liu et al., 2010). Lastly, the LEI are calculated for each new urban patch according to equation (10). The buffer zones of the new urban patches were automatically generated by the program refers respectively to the infilling type, the edge-expansion type and the outlying type. Based on this finding Figure (4.10, 4.11 & 4.12) shows the spatial distribution of different urban growth types in three periods. Three urban patch growth types were identified by using the proposed indices. Dramatic changes have occurred for the urban landscape of Dukem town from 2001 to 2021 because a great amount of agricultural land use has been transformed into urban land use. The following figure was showed the spatial distribution three urban growth types in a given interval of periods.

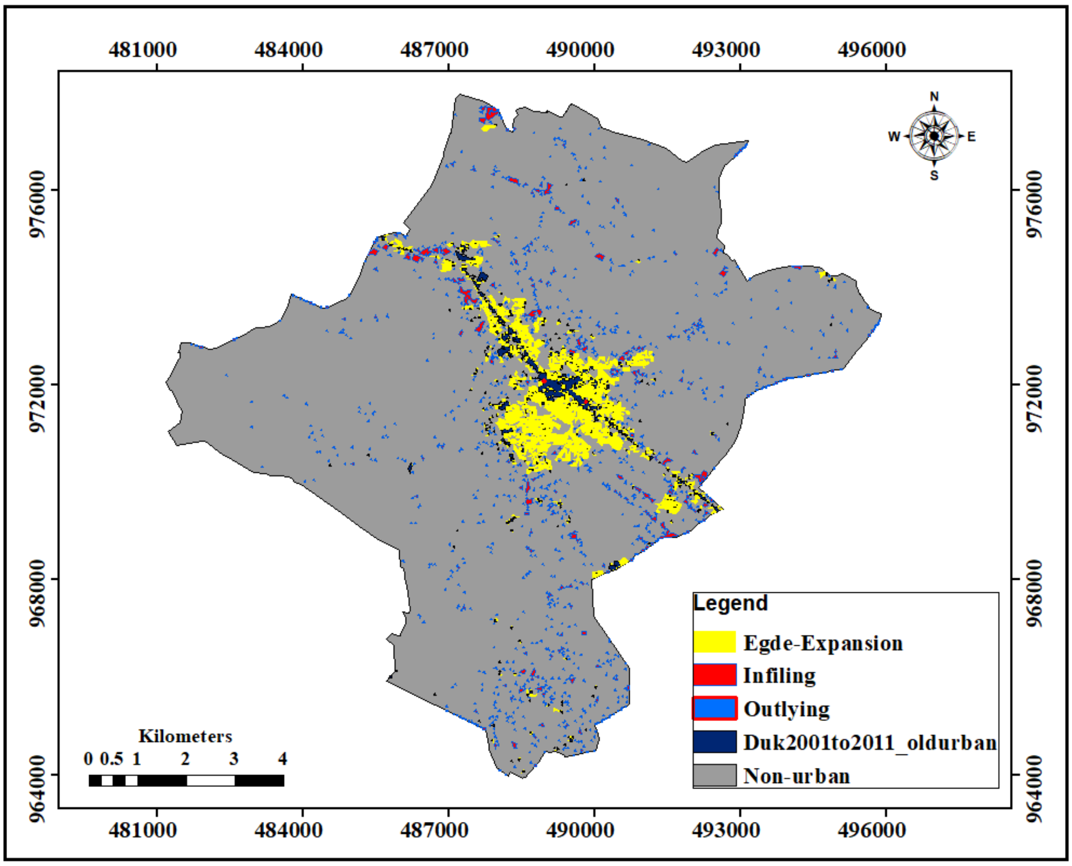

Figure 4.10 : Spatial distributions of urban growth types in 2001-2011

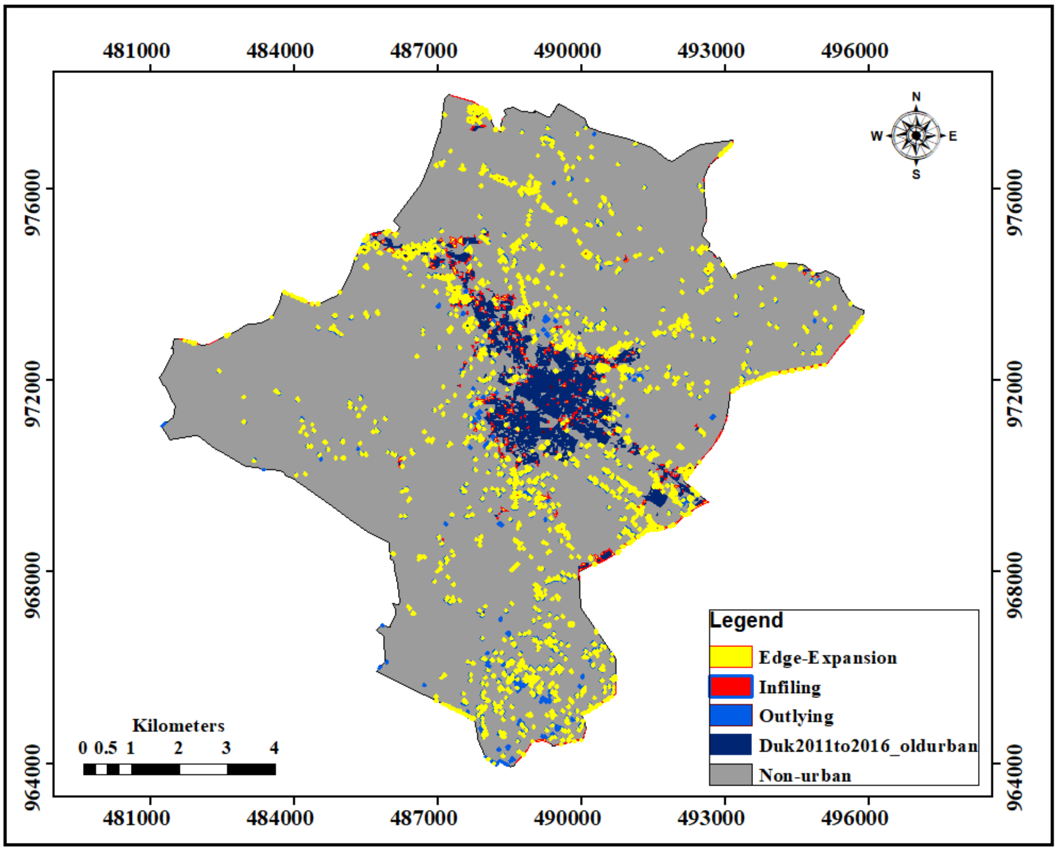

Figure 4.11 : Spatial distributions of urban growth types in 2011-2016

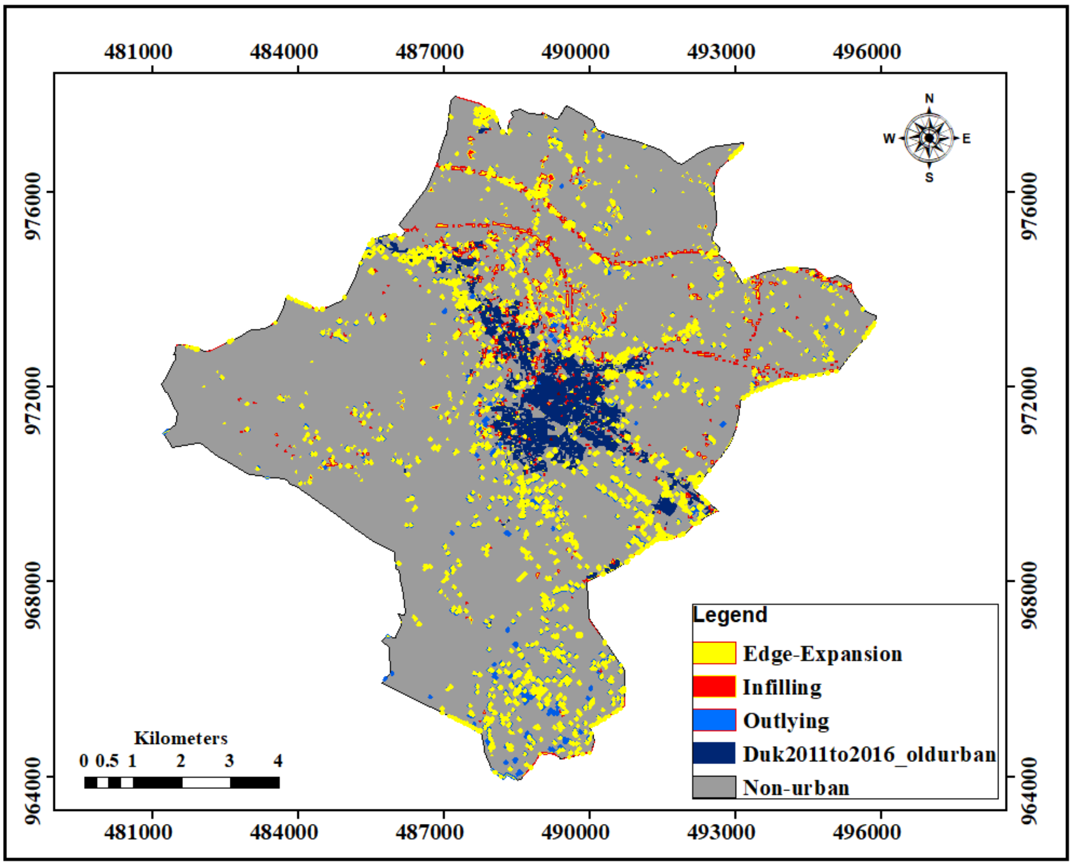

Figure 4.12: Spatial distributions of urban growth types in 2016-2021

The histograms of LEI for three periods were produced to perform a quantitative analysis of the urban growth patterns (Appendix: V). According to the analyses, several thresholds of LEI values were used to determine the urban patch growth types: (1) 50 < LEI ≤ 100, the infilling type; (2) 0 < LEI ≤ 50, the edge-expansion type; and (3) the outlying type if LEI = 0.

4.7.1. Area of three urban growth types during the three periods

According to the equation, the output for the three different urban growth types was calculated using Eq. (10). Each period was color-coded and can be seen in above figures. Infill urbanization involves the densification of vacant spaces among existing urban patches. Edge expansion followed the construction of industry centers and major road networks. Outlying growth, on the other hand, happens on new patches away from the urban core area. The most widespread growth type is the edge-expansion while outlying growth decreased throughout the all periods (Fig. 4.13). Infill growth was very less from 2001 to 2011. During the period 2011–2016, the infill growth was slightly increased, and the edge expansion growth type became more dominant (Fig. 4.13). To characterize the three urban growth types in Dukem town, the area was calculated for three neighboring periods (table 4.11). From 2001 to 2011, edge expansion growth reached its' peak with a coverage area of 181Ha. This incorporated 54.19% of the total newly developed urban patch. During the same period, outlying growths cover area of 136.92Ha (41.023%) and infill growth 15.98Ha (4.79%). In 2011 to 2016 edge-expansion rate continued to grow from expanding a further 342.314Ha. This incorporated 67.96% of the total new growth of that era. During the same period, outlying growth decreased to 21.92 %. Meanwhile, infill growth rate at just 10.11%. The last period 2016–2021 showed the highest infill growth rate at just 16.80%. Edge-expansion continued to be dominant with a 74.56 % share of new urban growth and outlying growth rate was reduced to 8.63%.

Table 4.11: Area of three urban growth types during the three periods (2001–2021)

urban growth types	2001-2011		2011-2016		2016-2021	
	Area(Ha)	%	Area(Ha)	%	Area(Ha)	%
Outlying	136.922	41.023	110.39	21.918	93.9	8.636
Edge-expansion	181	54.189	342.314	67.966	810.662	74.560
Infilling	15.98	4.787	50.944	10.115	182.695	16.803

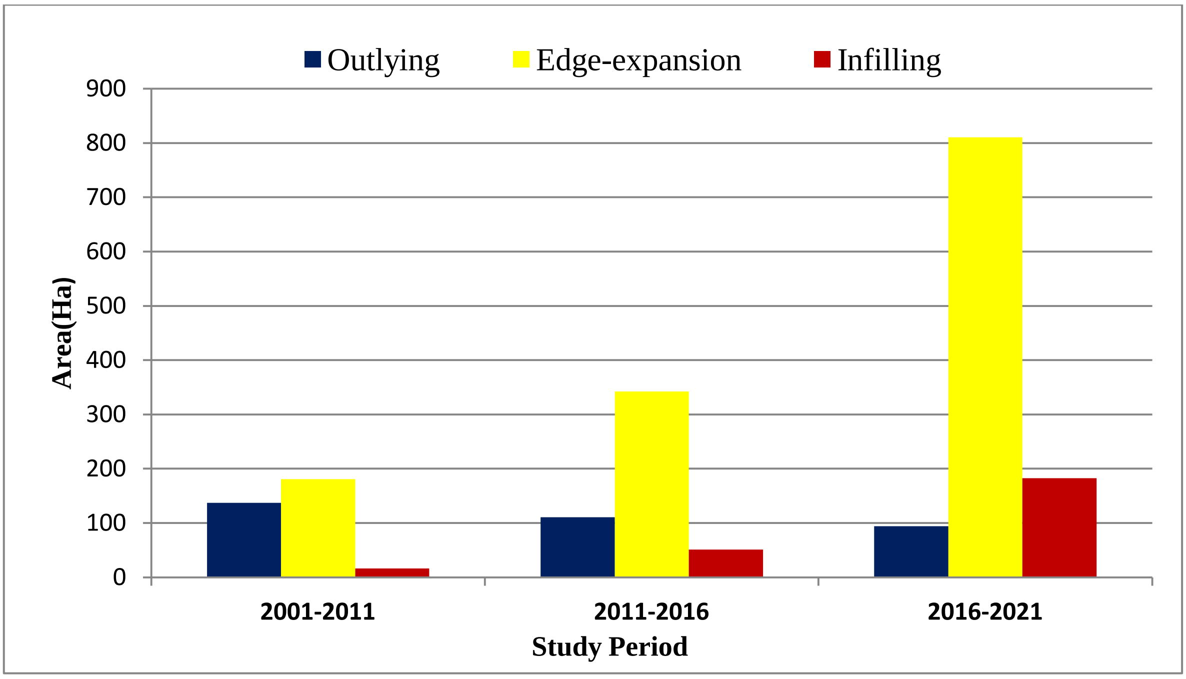

Figure 4.13: Area of three urban growth types during the three periods (2001–2021)

4.7.2. Number of patches (NP) for the three urban growth types

Based on the result, the number of patches (NP) for the three urban growth types recorded some regularity in the temporal patterns (Fig. 4.14). The outlying type had a number of patches 377,286 and 159 in the three periods respectively, showing a remarkably decreasing trend. Number of patches of the edge-expansion type was 498,887 and 1165 throughout study periods respectively, which indicates that outstandingly increased. Meanwhile, it increased gradually to74.56 % in the last period 2016 to 2021. The infilling type had a number of patches 44,132 and 241 during the three periods respectively that shows a remarkable increasing trend (table 4.12).

Table 4.12: Spatial distribution of urban growth types in terms of the number of patches

urban growth types	2001-2011	2011-2016	2016-2021
	Number of patches	Number of patches	Number of patches
Outlying	377	286	159
Edge-expansion	498	887	1165
Infilling	44	132	241
Total	919	1,305	1,565

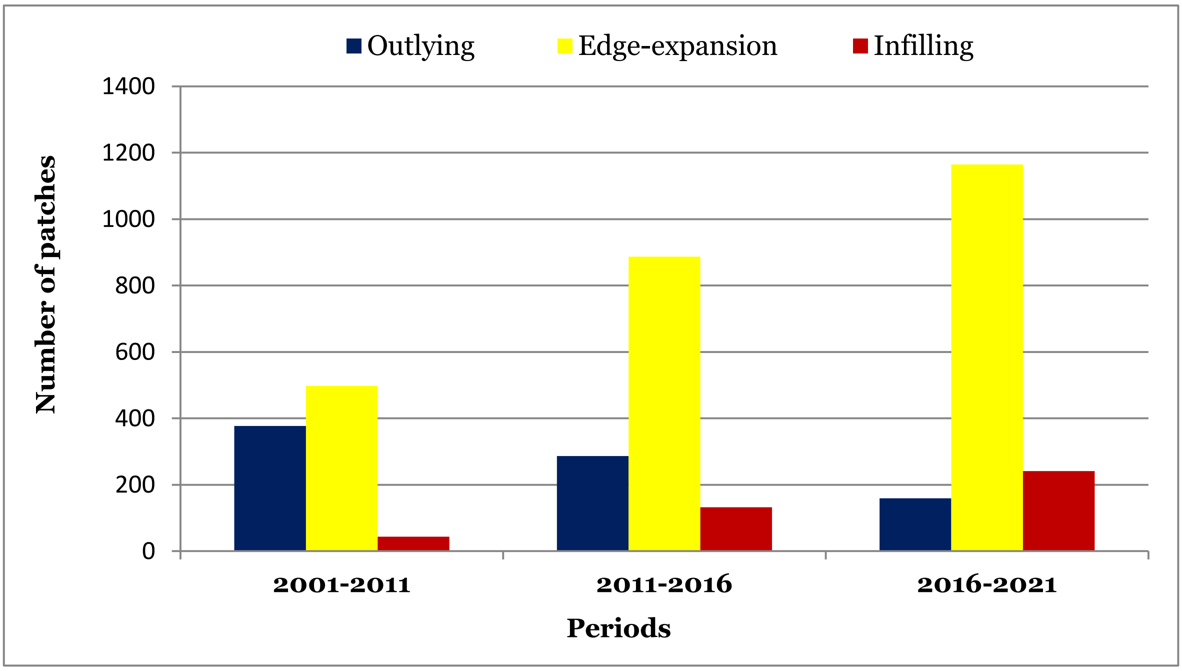

Figure 4.14: number of patches for the three urban growth types in the three periods

4.8. Selection of Spatial Variables for CA-ANN Model

According to transition matrix analysis revealed that, there was a significant growth in Urban Land surface was mainly due to Agricultural Land, green area and barren land fragmentation. All these transitions were based on physical and socioeconomic driving factors. Researchers mostly use these spatial factors to investigate LULC dynamics. Table: 4.13 shows the prospective Cramer's V value of each spatial variable. The Cramer's V value suggests that the variables are ideal for transition potential modeling, as their values are more significant (Muhammad et al., 2022). The CA-ANN simulation was performed to obtain the predicted LULC maps from the years 2031 to 2051. This maps are must be having fixed extent, pixel size and coordinate. First all vector data converted to raster data to be able to deal with plug-in. The same coordinate system for all layers which are (WGS_1984_UTM_Zone_37N) was set and applied resample process for all layers to determine the same pixel size, in this study I was set pixel size as (30 M). According to the values, the selection of physical and socioeconomic explanatory variables is more effectual, i.e., DEM: 0.08; slope: 0.22; and distance from road: 0.85.

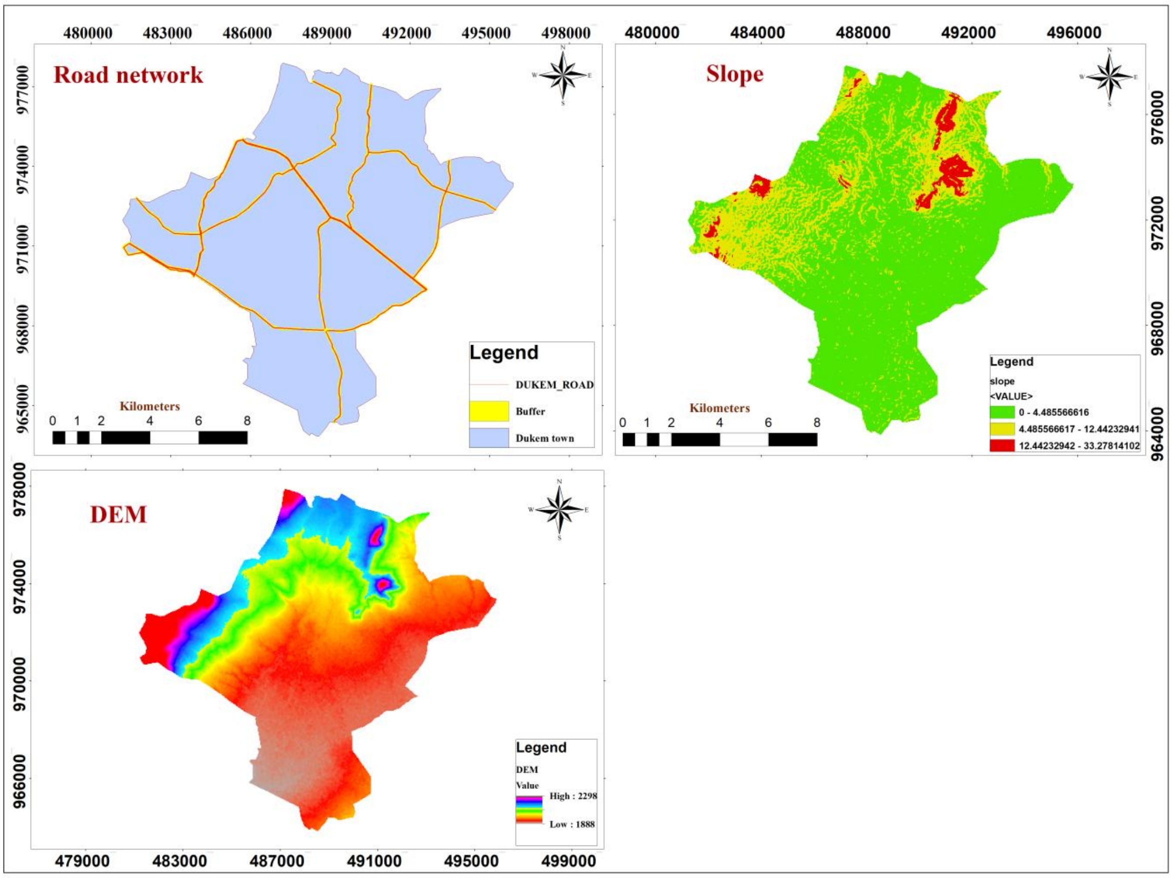

Figure 4.15: Spatial variables map for prediction.

Table 4.13: Cramer's V value of spatial variables

Spatial Variables	Person's Correlation	Cramer's V
DEM	0.0681	0.0775
Slope	0.2733	0.2253
Distance from roads	0.8011	0.8534

4.9. Transition Potential Modeling and Model Validation

A transition potential matrix was generated in the study periods (2001–2011) to create the change map. The MOLUSCE plug-in integrates some well-known algorithms for transition potential modeling, such as the ANN (multilayer perceptron), weights of evidence, multi-criteria evaluation, logistic regression, and CA algorithm, for future simulation. The spatial variables for model calibration were chosen based on their relatively strong association with LULC, as measured by Cramer's coefficient (Muhammad et al., 2022).

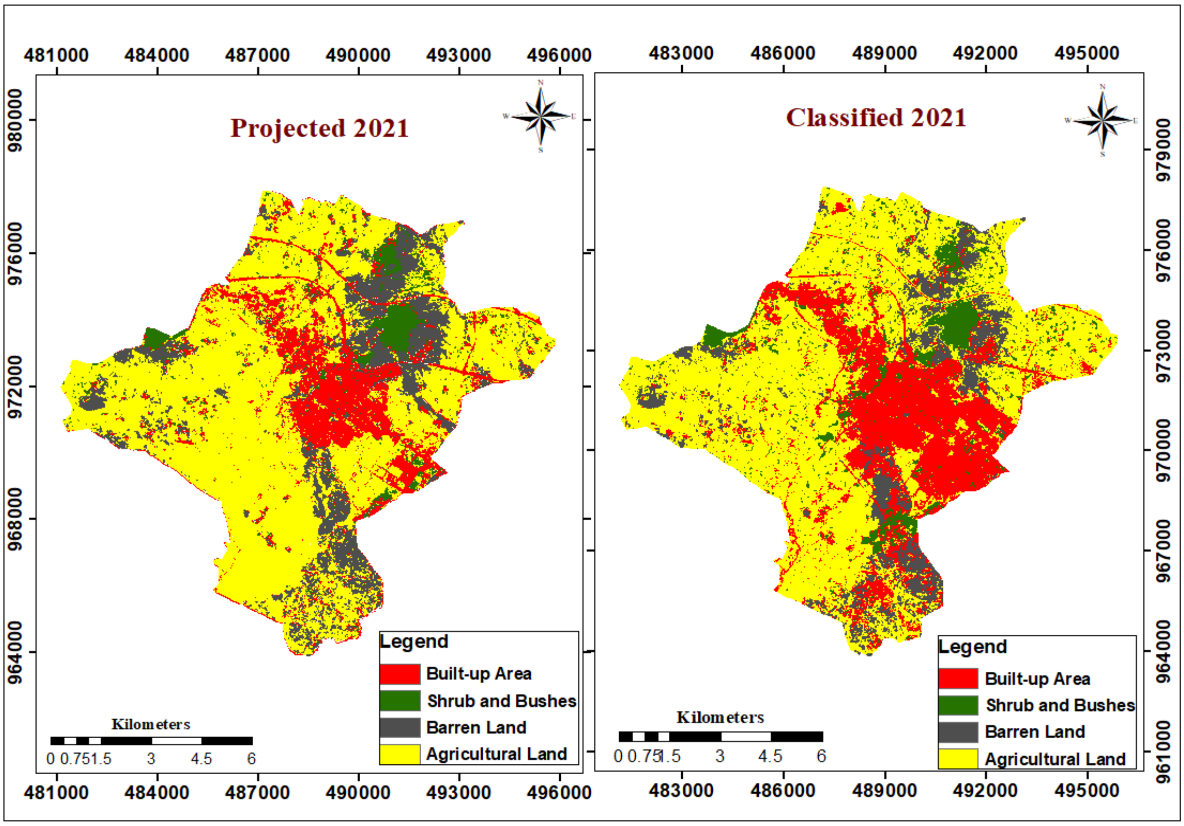

Figure 4.16: Classified and projected LULC of 2021

The transition potential model is trained based on the LULC maps of 2001 and 2011, as well as spatial parameters to produce the predicted map of 2021. For this study CA-ANN approach for transition potential modeling and prediction was used. LULC data from 2001–2021 along was used with spatial variables to project LULC for 2021 and obtained a validation kappa value of 0.9158. After obtaining the projected LULC, we compared the actual LULC of 2021 with the projected data and obtained an overall accuracy of 71.81% and an overall kappa value of 0.53. Figure 4.17 and Table 4.14 show the actual and forecasted maps and statistics for 2021.

Table 4.14: classified and projected LULC of 2021

LULC Category	**Classified 2021**		**Projected (Simulated) 2021**	
	Area(km^2)	**Area (%)**	**Area(km^2)**	**Area (%)**
Built-up Area	23.52	24.18	19.56	20.10
Shrub & Bushes	6.61	6.79	4.75	4.88
Barren Land	10.83	11.13	13.70	14.08
Agricultural Land	56.33	57.89	59.28	60.93
Kappa Value	ANN		0.96372	
	Validation		0.9158	

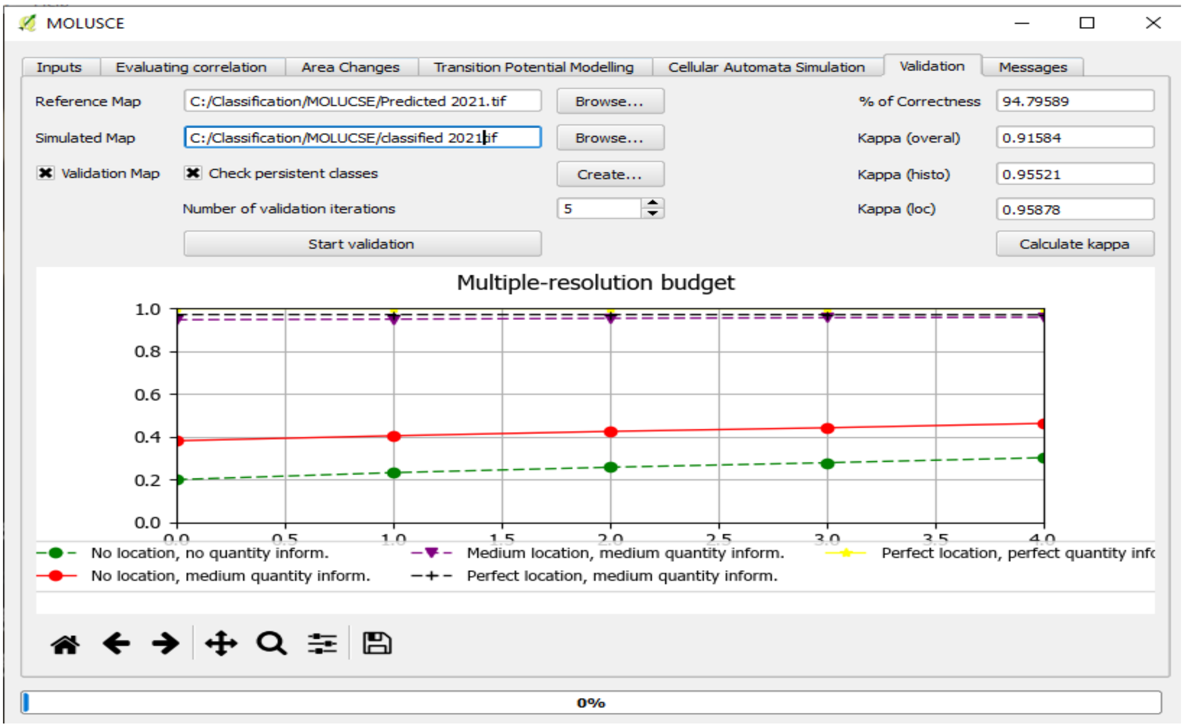

Figure 4.17: validation of Classified and projected LULC of 2021.

4.10. Prediction of LULC

After obtaining satisfactory results from model validation, next step are predicted the LULC for 2031, 2041, and 2051. For this purpose I was conduct the temporal LULC data from 2011 and 2021, the spatial variables, and the transition probability matrix (Appendix III) to predict the LULC for 2031 and obtained a kappa value of 0.67. Furthermore, the LULC of 2001 and 2021, including the explanatory variables and transition matrix (Appendix III), were used for the prediction of 2041, and I obtained a kappa value of 0.58. Finally, the last year prediction of 2051 LULC based on the projected data for 2031–2041 is done and the transition matrix (Appendix III) and obtained a kappa value of 0.71. (Figure 4.18, 4.19 and 4.20) and Table 22 represent the map, area statistics, and overall validation kappa of the predicted LULC of 2031, 2041, and 2051.

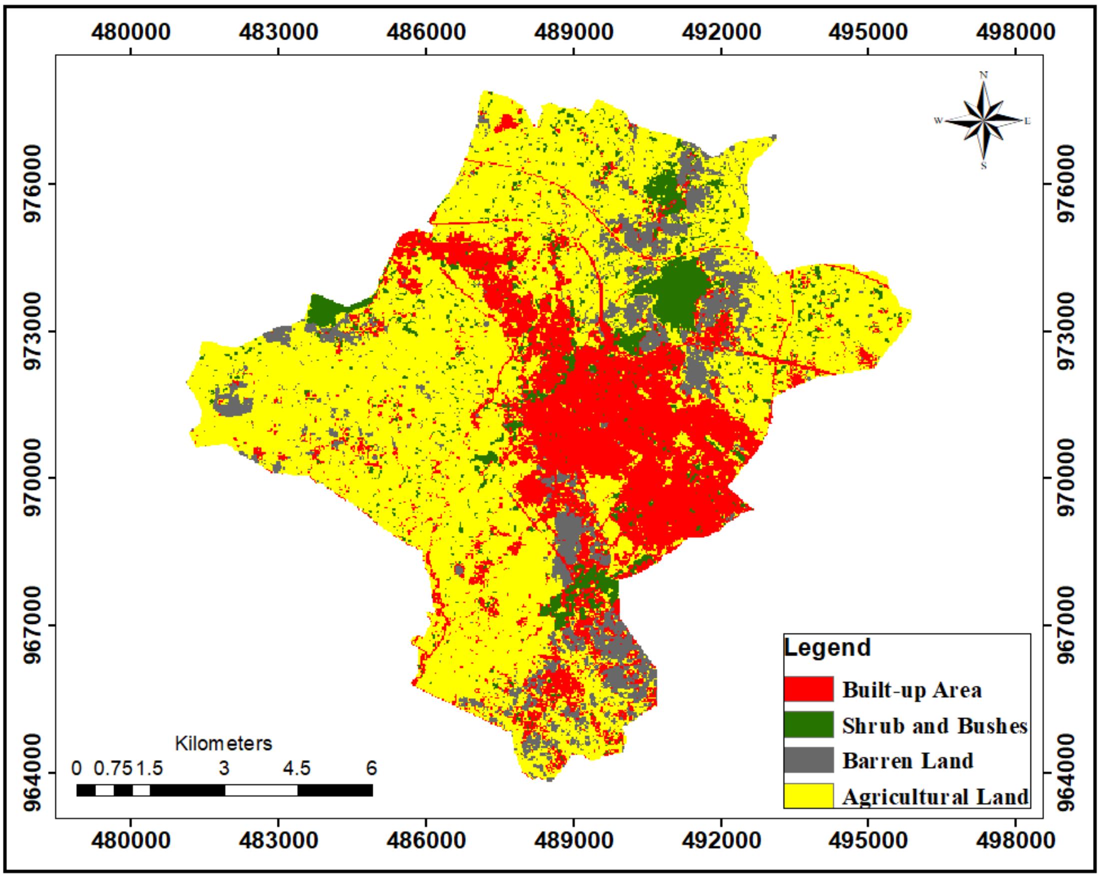

Figure 4.18: Prediction of LULC Map Dukem Town 2031

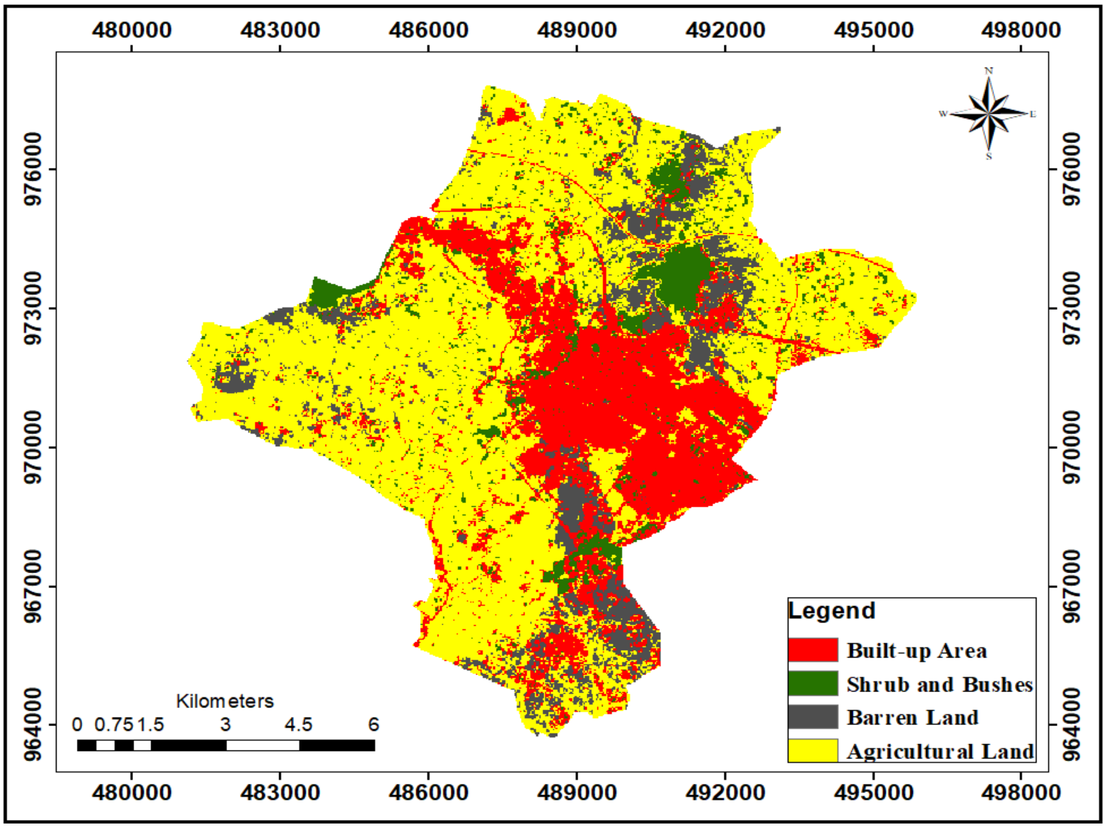

Figure 4.19: Prediction of LULC Map Dukem Town 2041

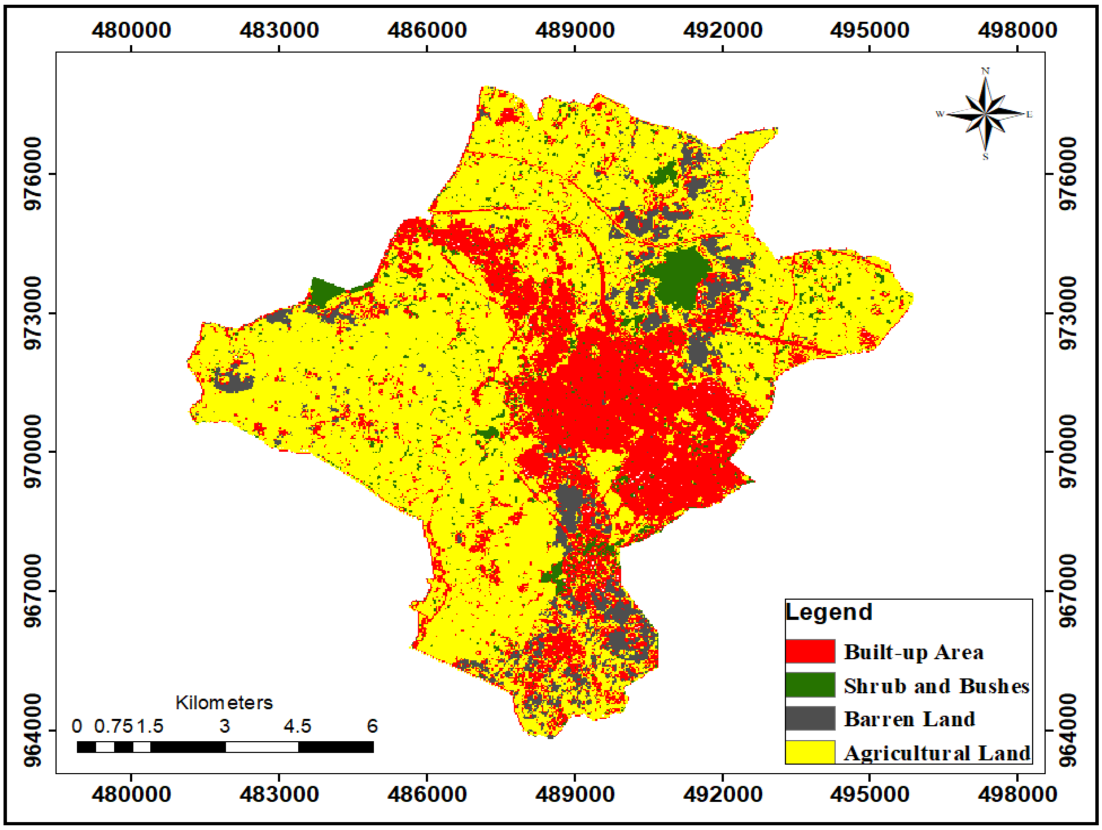

Figure 4.20: Prediction of LULC Map Dukem Town 2051

Using CA-ANN approach transition potential of 2011-2021 future projected Dukem Town LULC was conducted. As a result, in 2031 LULC will contains 26.74Km^2 (27.8%) of Built-up area, 6.41 Km^2 (6.59%) of Shrub & Bushes land, 55.19 Km^2 (56.73%) of Agricultural land and 8.95 Km^2 (9.20%) of Barren Land. In 2041 LULC will contains 28.22Km^2 (29.00%) of Built-up area, 6.91 Km^2 (7.10%) of Shrub & Bushes land, 54.38 Km^2 (55.90%) of Agriculture land and 7.78 Km^2 (8.00%) of Barren Land. As well as, in 2051 will contains 32.59Km^2 (33.49%) of Built-up area, 5.75 Km^2 (5.91%) of Shrub & Bushes land, 52.60 Km^2 (54.07%) of Agriculture land and 6.35 Km^2 (6.53%) of Barren Land.

Table 4.15: Predicted LULC statistics (2031, 2041, and 2051)

LULC Category	projected Periods					
	2031		2041		2051	
	Area(km^2)	Area (%)	Area(km^2)	Area (%)	Area(km^2)	Area (%)
Built-up Area	26.74	27.48	28.22	29.00	32.59	33.49
Shrub & Bushes	6.41	6.59	6.91	7.10	5.75	5.91
Barren Land	8.95	9.20	7.78	8.00	6.35	6.53
Agricultural Land	55.19	56.73	54.38	55.90	52.60	54.07
Kappa Value	0.96372					

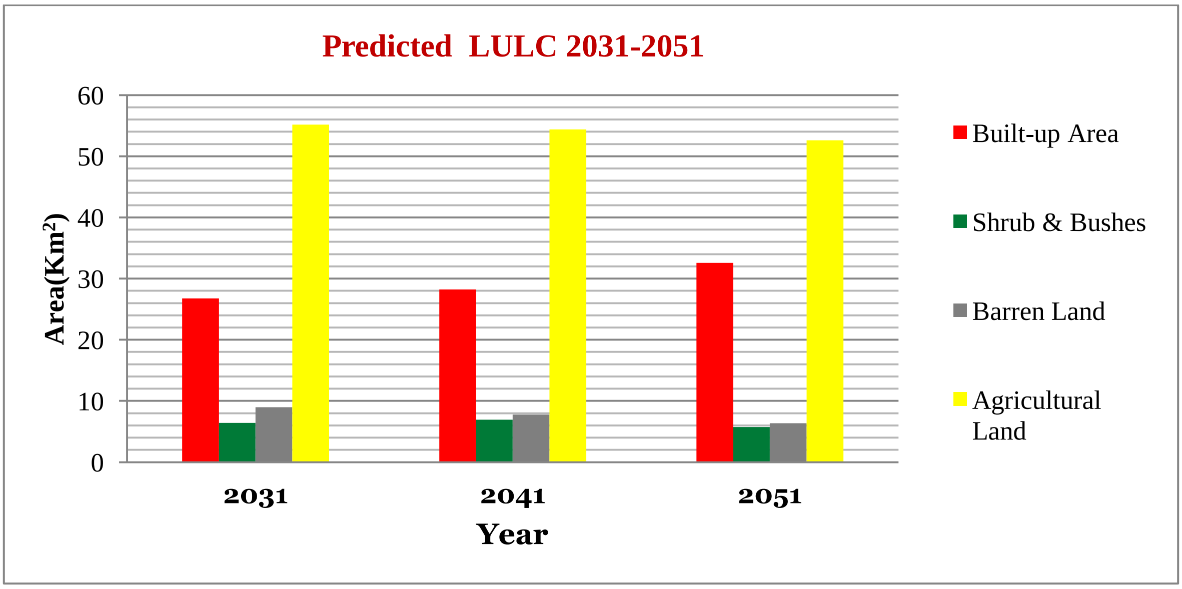

Figure 4.21: Dukem town Predicted LULC from 2031 to 2051

According to predicted result the Built-up area is increased from 23.52Km^2 (24.18%) in 2021 to 26.74Km^2 (27.8%) in 2031G.C, increased from 26.74Km^2 (27.8%) in 2031 to 28.22Km^2 (29.00%) 2041G.C and increased from to 28.22Km^2 (29.00%) in 2041 to 32.59Km^2 (33.49%) 2051G.C this is predicted result by considering factors and constraints. Built-up area land use land cover type is increasing in an alarming rate over the study periods. While the major contributors are Agricultural land, Barren land and Shrub and Bushes land cover types.

4.11. Prediction of Change

In Dukem Town, urban land use land cover changes are dramatically increased for the last two decades and, as the future simulation results obtained, it will increase to 3.22 km^2 in 2031, 1.48 km^2 in 2041 and 4.37 km^2 in 2051.Nevertheless, other LULC such as Barren land, Agriculture land and Shrub and Bushes land are decreased within 2021-2051. Analyzing prediction of temporal changes within a set of LULC categories requires the use of the transition matrix for extracting transition change of LULC. Table 4.16 show the spatiotemporal area and percentage change in all LULC categories.

Table 4.16: Temporal changes from 2021 to 2051

LULC Category	**2021-2031**		**2031-2041**		**2041-2051**	
	Area(km^2)	Area (%)	Area(km^2)	Area (%)	Area(km^2)	Area (%)
Built-up Area	3.22	1.526	1.48	0.233	4.37	1.62
Shrub & Bushes	-0.20	-0.490	0.50	-0.528	-1.16	-1.039
Barren Land	-1.88	-1.564	-1.17	-0.507	-1.43	-3.098
Agricultural Land	-1.14	0.788	-0.81	0.924	-1.78	2.623
Kappa Value	0.91902		0.96372		0.87494	

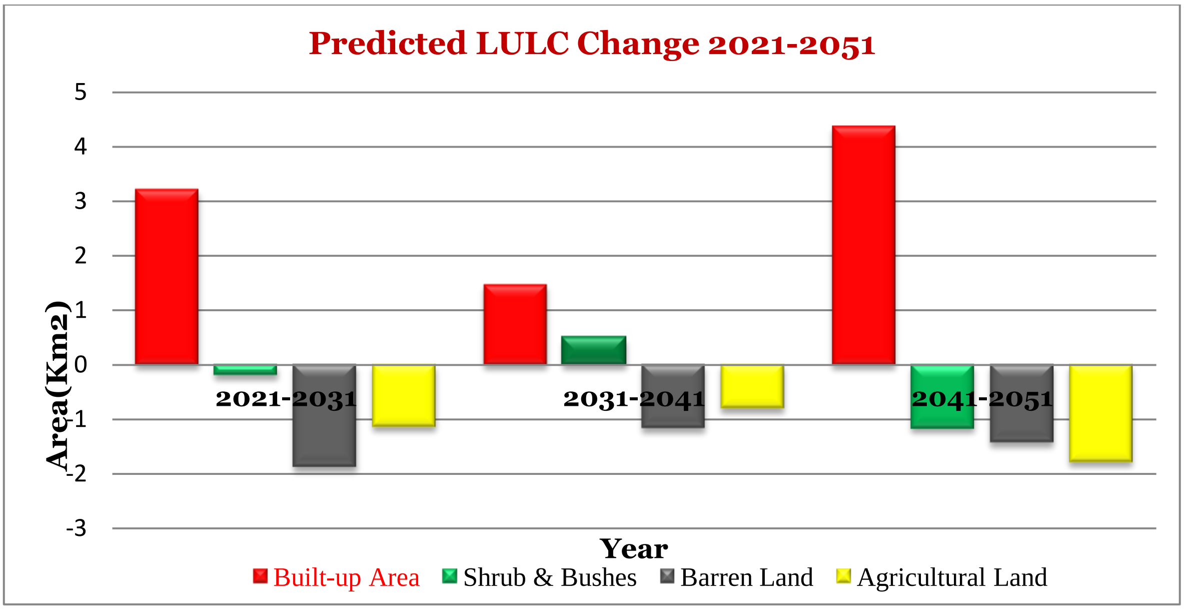

Figure 4.22: Dukem town Predicted LULC Change from 2021 to 2051

The LULC change analysis explores the spatial dynamic variations in the LULC pattern during the study period. In fact of this results from 2021 to 2051 show a notable expansion in urban surface and a dwindling phenomenon in the other land. Figure (4.23, 4.24 & 4.25) shows transition of LULC classes of Dukem town.

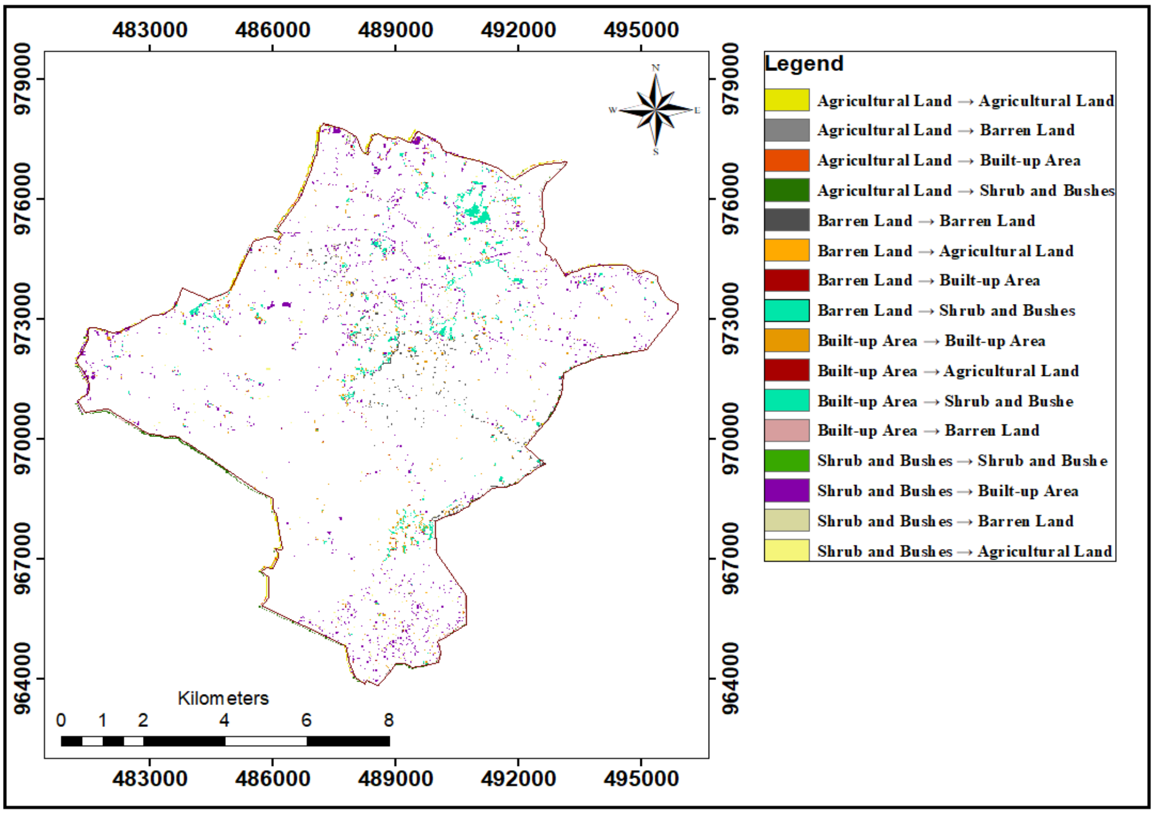

Figure 4.23: Dukem Town predicted change map 2021–2031.

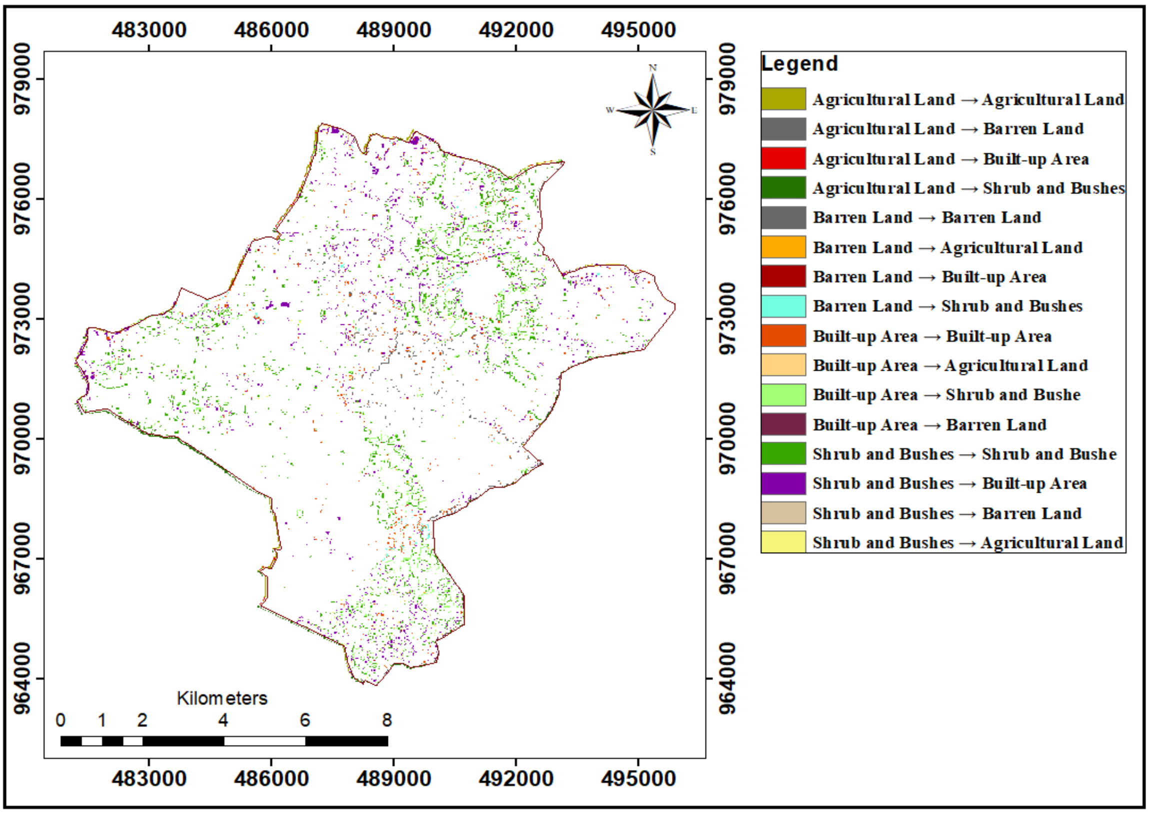

Figure 4.24: Dukem Town predicted change map 2031-2041.

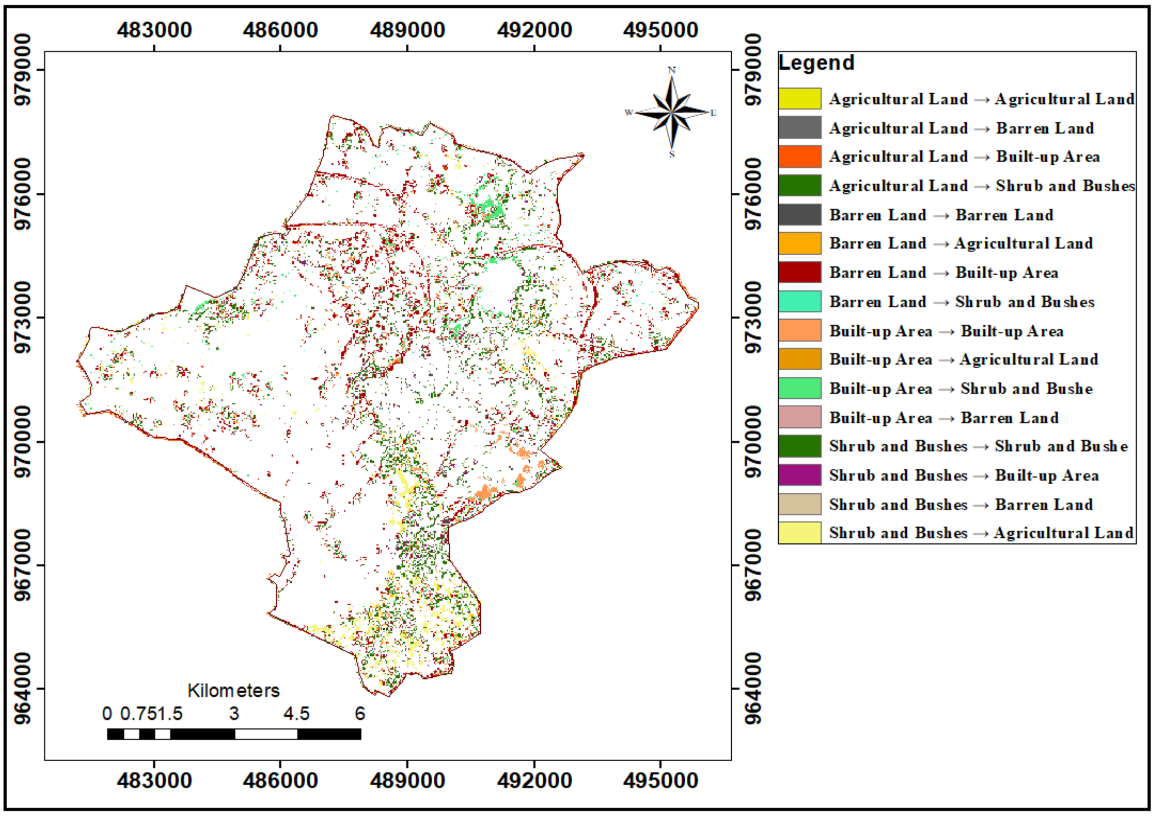

Figure 4.25: Dukem Town predicted change map 2041-2051.

4.12. Discussion

Land use and land cover changes have wide range of consequences at all spatial and temporal scales. Because of these effects and influences it has become one of the major problems for environmental change as well as natural resource management. Identifying the complex interaction between changes and its drivers over space and time is important to predict future developments, set decision making mechanisms and construct alternative scenarios.

This study aimed at analysis of Dukem Town Urban expansion and feature view. So, based on result of this study Dukem Town urban land use changes is increased by 1926.498Ha (19.8%) within Two decades (2001-2021) and increased 907Ha (9.31%) for future three decades (2051). The rapid urban expansion over the past two decades, the spatiotemporal patterns of urban expansion varied among each decade. The extent, direction, and location of urban expansion in each decade have mainly been associated with variances in their physical setting, administrative conditions, demography, policies, and urban master plans. most of the large and medium-sized cities, for example, major chain cities (Jiao, 2015), Cairo, and Kigali (Xu et al., 2019) have grown in a compact form with an inner core and minimally scattered manner on the outskirts. However, in Dukem town, such characteristics were not uniformly noted and much more irregular pattern was found.

As Table 4.8: shows that the town had the highest Annual Intensity (217.80 ha) during the year 2016 to 2021.Whereas, the town experienced the least annual expansion rate (5.95%) during 2001 and 2011 period, As well as in the period of 2016-2021 experienced the highest AER (13.24%). This indicated that the town has higher expansion rates. Annual intensity is high and annual expansion rate is less when the finding of this result was compared to (Berhanu; et al., 2020).

In this study by applying landscape expansion index (LEI) urban growth types in Dukem town for three periods was investigated. As a result, the analyses has demonstrated that the proposed landscape expansion index (LEI) can be used to identify various growth types, i.e., infilling, edge-expansion, and outlying. The study indicates different spatial expansion modes shows during the whole period. Accordingly, during the entire study period (2001-2021) the edge expansion type became the dominant growth type which is 54.198%, 67.966% and 74.56%. While outlying expansion was decreased during the entire study periods which were initially 41.023% and than 21.918 % and 8.636 %. The rest growth type is infilling type of growth which was the least type of urban growth however; it increases continuously on a given entire periods that was 4.787%, 10.11%, and 16.80%. The finding of this result was slightly similar in the case of edge-expansion and different urban growth form of infill and outlying with compared to Addis Ababa city as (Busho et al., 2021) discussed in their research article. However, the urban growth characteristic of Dukem town more of it has the same trend from findings in Dongguan for four periods in China from 1988 to 2006 (X. Liu et al., 2010), which found during entire period outlying was decrease and edge-expansion and infilling types of urban growth was increases.

Predicted Dukem Town urban land use land cover change result are obtained by considering the Factors and Constraint as constant (not dynamic) and calculate changes within the Boundary of study. In 2051 Built-up area is 3259Ha (33.49%), Shrub & Bushes is 575Ha (5.91%), Agriculture land is 5260Ha (54.07%) and Barren land is 635Ha (6.53%). Based on this predicted result the Built-up area is increased from 2352.671Ha (11.206%) in 2021to 3259Ha (33.49%) in 2051. Built-up area land use land cover type is increasing in an alarming rate over the years. While the major contributors are Shrub land, Agriculture land and Forest land cover types. The result of prediction of this study was different when we compare trend with Linyi city in china (Muhammad et al., 2022), which found variation in built-up surface growth during the predicted period.

The population of Dukem Town was rapidly increased from 24,024 in 2007 to 162,233 in 2021 showing that the population of the Town has increased by more than six times within the less than two decades and if population growth with this rate the total Population of Dukem town became 468,204 Population in 2051. Rapid Population growth is increase Urban Land use land cover Changes. Dukem Town implement urban housing development program called Integrated Housing Development Program (IHDP) gives land for many Governmental workers such as Teachers, Police, and lawyer etc. to improve housing access to low and middle income residents of urban areas also increase urban land use land cover (Dukem Town Communication office, 2022). Eventually, unexpected changes in LULC, notably urban expansion and the loss of agricultural land may put the environment, food security, and natural resources at risk. In order to help policymakers analyze the change in LULC intensity and the socioeconomic factors that affect it as well as to promote environmental conservation and sustainable development policies, spatiotemporal and prospective LULC simulation results have been conducted.

5. CONCLUSION AND RECOMMENDATIONS

5.1. Conclusion

In general, this study was analyzed spatiotemporal LULC changes based on temporal Landsat data, and projected future scenarios based on driving factors in Dukem town. The town faces the challenge of agricultural land, environmental deterioration, and water quality depletion as a result of fast urban expansion and fragmentation of forest and green areas. These factors intensify the difficulties associated with sustaining regional development and environmental conservation. Modeled and predicted landscape patterns using solely physical and socioeconomic elements in this study. Additionally, agriculture and development policies can be linked to promote sustainable urbanization. It is advised that future studies use more factors and data to investigate their effects on landscape patterns.

The result of LULC analysis revealed that, over the study period (2001–2021), the dominant land cover type in the study area was Agricultural land ranging between 57.88% and 70.75% of the total area. However, Dukem Town Urban LULC change is increasing in an alarming rate over the years. While the major contributors such as Agriculture Land, Shrub and Bushes land and Barren Land decreased by 307Ha, 270Ha, and 1349Ha respectively within the last two decades. Dukem Town loss Protected Forest Land, Shrub Land and Prime Agricultural Land, this result becomes deteriorating Environmental quality and Climate change, reduced Farmland.

Selected spatial metrics indices show that there is a fast Change of Urban Landscape Patterns in study period of time. Largest Patch Index (LPI) in percentage also shows a growing trend from 3.827% in 2001 to about 34.295% in 2021. This is a good indication that largest patch is growing more and more in size forming a continuous urban agglomeration at the town center. That is, while the number of patches increase at every year leading fragmentation of the edging areas, the largest patch is growing bigger and bigger at the center.

During the entire study period (2001–2021), the urban area expanded mainly as edge expansion it increased from 54.198% in 2001-2011 to 74.56% in 2016-2021. Outlying growth decreased from 41.023% in 2001-2011 to 8.636% in 2016-2021. As well as infilling types of growth was slightly increased rate through interval of study period 4.787% in 2001-2011 to 16.80% in 2016-2021.

Overall, the result of this study shows that urban expansion of Dukem town area highly increased from 426.174 Ha (4.4%) to 2352.671Ha (24.2%) in last two decades (2001-2021) and for future three decades 2674Ha (27.8%) in 2031, 2822Ha (29.00%) in 2041 and 3259Ha (33.49%) in 2051. In view of the fact that Dukem town located nearest Addis Ababa city and rapid population growth the expansion of squatter houses in the town is becoming a big challenge on the capacity of the Local government. As demonstrated in this study geospatial technology can play a crucial role in urban Expansion Analysis and help to get up-to-date information about the urban land use. In addition to this, CA-ANN approach for transition potential modeling has been shown to be a flexible and realistic tool for predicting Urban Expansion in the study.

5.2. Recommendations

This portion is committed to the recommendation part of the paper. The deals with urban Expansion change detection, satellite image utilization, urban planning, and spatial metrics method.

- The results of the study show that, the pace of urban Expansion in Dukem Town is rapid, especially in the last five years with a growth rate of 11.20%. This causes unparalleled, unplanned and rapid expansion of the city that will continue in the coming decades. Furthermore, studies indicate that all the master plans formulated so far to guide urban development activities suffered from lack of proper implementation. Therefore, planners must be give attention to plan ahead and handle up with the pace of urban growth with proper implementation.
- Urban land has expanded rapidly in Dukem town. This expansion is largely horizontal towards edges of town without monitoring and planning expansion. This type of expansion is consuming large coverage of land. due to this fact, to realize sustainability of effective land use the town policy maker, urban planners and other concerned bodies are consider and early set the direction to control the town land use process.
- Application of satellite images for urban growth change detection has been successful to show the spatiotemporal expansion of urban areas. Due to lack of high resolution data, the researcher made use of different satellite images such as Sentinel and Landsat images to get a better spatial resolution out of it and facilitate feature extraction.

Nevertheless, if availability of high resolution data source such as SPOT, IKONOS and Quick Bird is possible, future studies can also be made based on these images to get spatial metric indices less than 5m resolution.

- Highly growing of settlement affects LULC not only the town, it may affects out of the boundary of the town that means putting pressure on the nearby rural kebeles and there should be strategic planning acquired to monitor and control this expansion of the town from the concerned governmental and non-governmental bodies or responsible concerned stack holder.
- Regarding on environmental effect Dukem Town Urban planner, Land administration offices and Environmental protection offices must be considered Health Care of people who lived nearest to industrial zones during site selected for Housing development to solve the society problems and avoid risks.
- For future researchers should investigate the underlying causes and environmental impact of landscape transformation due to urbanization processes in Dukem town. As well as, they should look into other spatial metrics and future studies use more factors and data to investigate their effects on landscape patterns.

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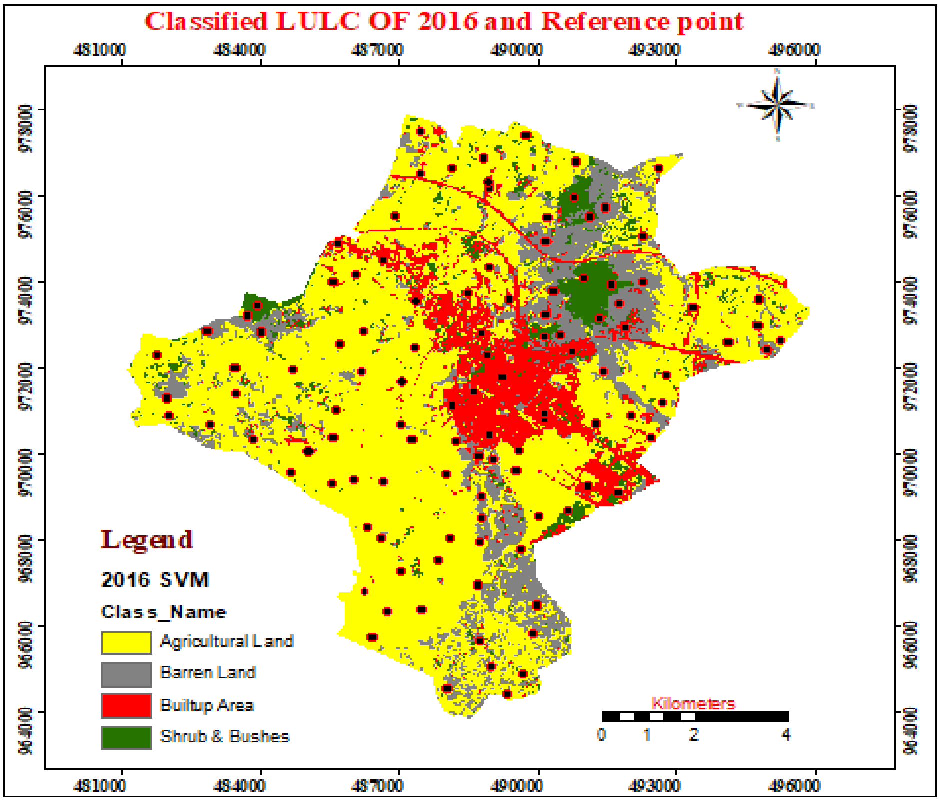
APPENDICES

Appendix I: population number of Dukem town by kebeles in 2014 E.C

No.	Keble names	Male	Female	Total
1	Melka Dukem	22,726	21,940	44,666
2	Teddeche	18,936	18,283	37,219
3	kotiche	18,181	17,552	35,733
4	Gogecha	15,913	15,360	31,273
5	Oda Nabe	1,358	1,176	2,534
6	Yatu	1,200	1,121	2,321
7	Wejitu	1,865	1,746	3,611
8	Gimashe	2,221	2,665	4,876
	Total	**82,400**	**79,843**	**162,233**

Source: (Socio-economic profile of Dukem town, 2021)

Appendix: II Example of Reference/ GCP Points and classified image of 2016



Appendix III: Transition Matrix table of all LULC years

a) Transition Matrix of 2001-2011

Transition matrix

	Agricultural Land	Shrub and Bushes	Barren Land	Built-up Area	5
Agricultural Land	0.792135	0.003559	0.003043	0.000837	0.000426
Shrub and Bushes	0.000143	0.436963	0.511524	0.075542	0.075828
Barren Land	0.200000	0.548910	0.216426	0.153823	0.180841
Built-up Area	0.020171	0.423224	0.455927	0.400143	0.220535

Update tables   Create changes map

0%

b) Transition Matrix of 2011-2016

Transition matrix

	Agricultural Land	Shrub and Bushes	Barren Land	Built-up Area
Agricultural Land	0.892135	0.033559	0.013043	0.200837
Shrub and Bushes	0.030143	0.346963	0.911524	0.075542
Barren Land	0.034900	0.458910	0.016426	0.153823
Built-up Area	0.020171	0.423224	0.455927	0.400143

Update tables

0%

c) Transition Matrix of 2016-2021

MOLUSCE

Inputs | Evaluating correlation | Area Changes | Transition Potential Modelling | Cellular Automata Simulation | Validation | Messages

Class statistics   sq. km.

	Class color			Δ	%	%	Δ %
0	Built-up	23.57 sq. km.	7.56 sq. km.	-16.01 sq. km.	24.2830639728	7.78730513277	-16.49575884
1	shru& b...	7.03 sq. km.	4.84 sq. km.	-2.19 sq. km.	7.24273834027	4.98324764867	-2.2594906916
2	Barren	11.06 sq. km.	15.95 sq. km.	4.89 sq. km.	11.4008288491	16.4394561716	5.03862732249
3	Agricult...	55.39 sq. km.	68.70 sq. km.	13.31 sq. km.	57.0733688379	70.789991047	13.7166222091

Transition matrix

	0	1	2	3
0	0.270630	0.025961	0.132844	0.570565
1	0.027781	0.372244	0.096597	0.503377
2	0.017649	0.004777	0.739880	0.237694
3	0.014248	0.028075	0.071464	0.886213

Update tables   Create changes map

0%

d) Transition Matrix of 2021-2031

Transition matrix

	Agricultural Land	Shrub and Bushes	Barren Land	Built-up Area
Agricultural Land	0.492135	0.053559	0.023043	0.200837
Shrub and Bushes	0.040143	0.346963	0.011524	0.075542
Barren Land	0.000900	0.65223	0.016426	0.153823
Built-up Area	0.023003	0.673224	0.455927	0.400143

e) Transition Matrix of 2031-2041

Transition matrix

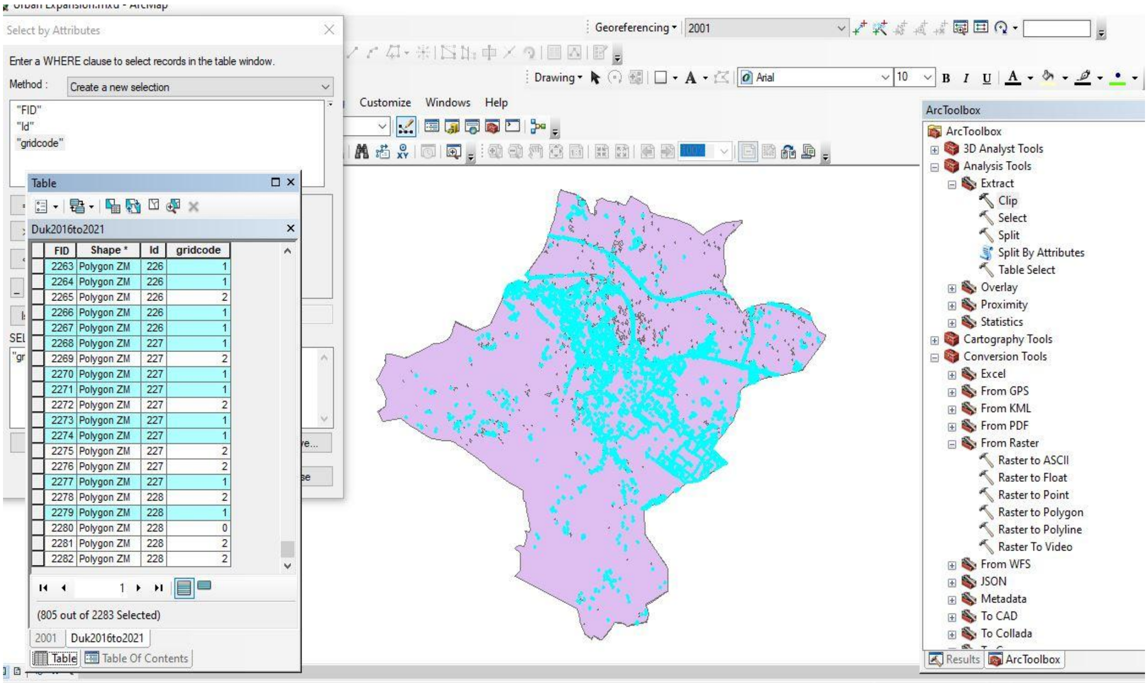
	Agricultural Land	Shrub and Bushes	Barren Land	Built-up Area
Agricultural Land	0.992135	0.023559	0.023043	0.400383
Shrub and Bushes	0.440143	0.201003	0.011524	0.075542
Barren Land	0.003100	0.222234	0.016426	0.053823
Built-up Area	0.00003	0.003224	0.005927	0.000363

f) Transition Matrix of 2041-2051

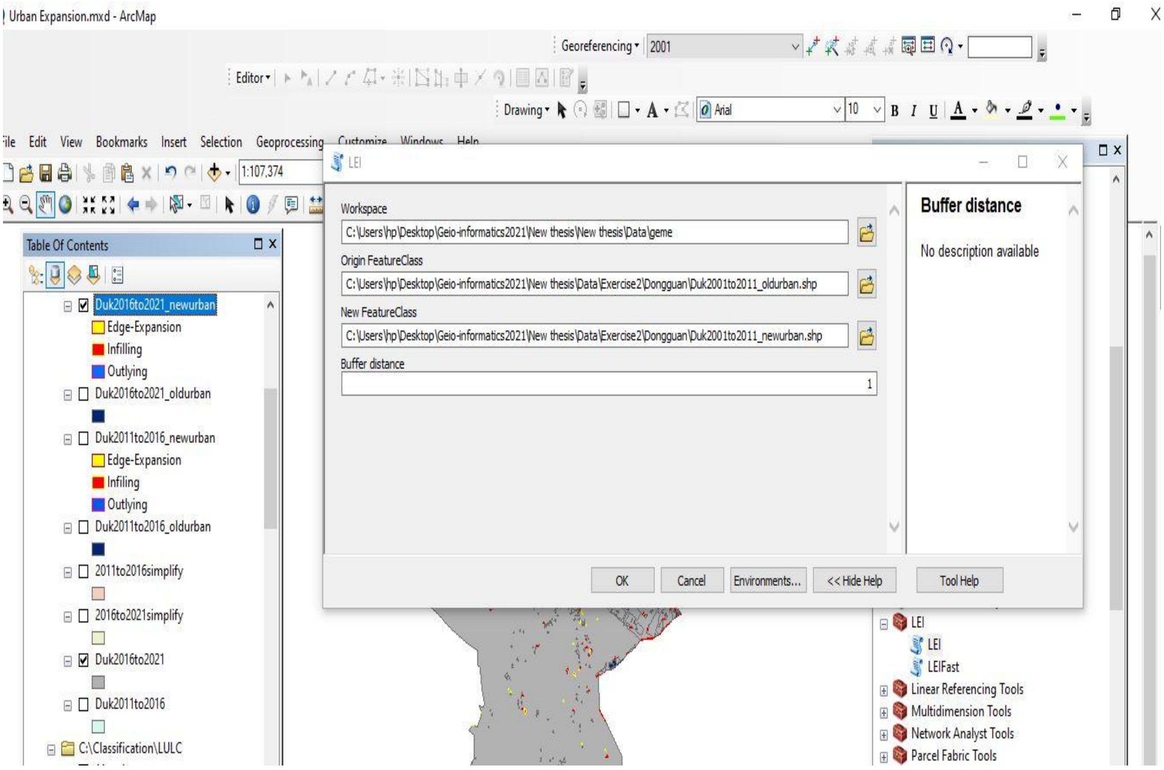
Transition matrix

	Agricultural Land	Shrub and Bushes	Barren Land	Built-up Area
Agricultural Land	0.892135	0.013559	0.000303	0.700383
Shrub and Bushes	0.540143	0.601003	0.011524	0.075542
Barren Land	0.000100	0.034234	0.016426	0.053823
Built-up Area	0.00001	0.003224	0.005927	0.080363

Appendix IV: New urban Area selection for LEI process & generating urban growth

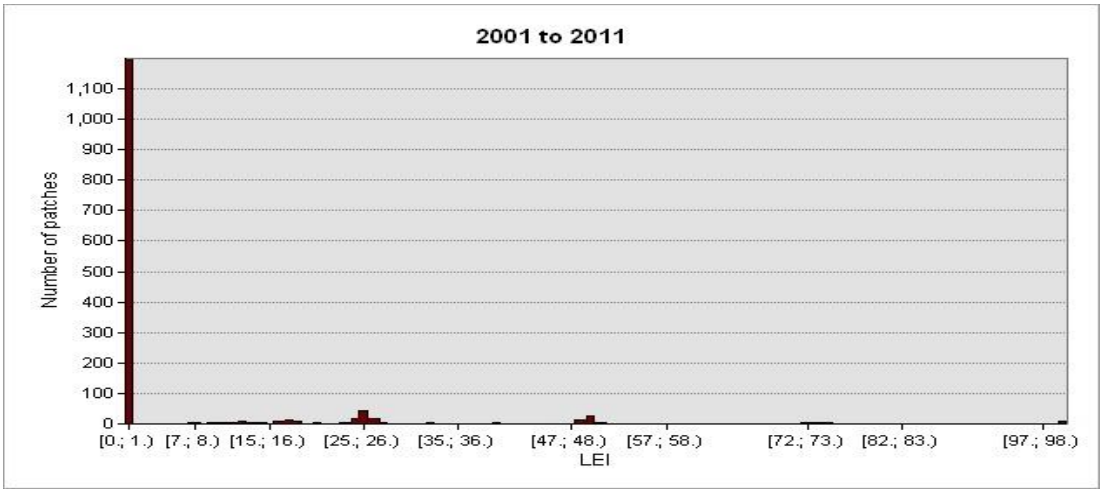


Appendix IV: LEI generating urban growth of Dukem town

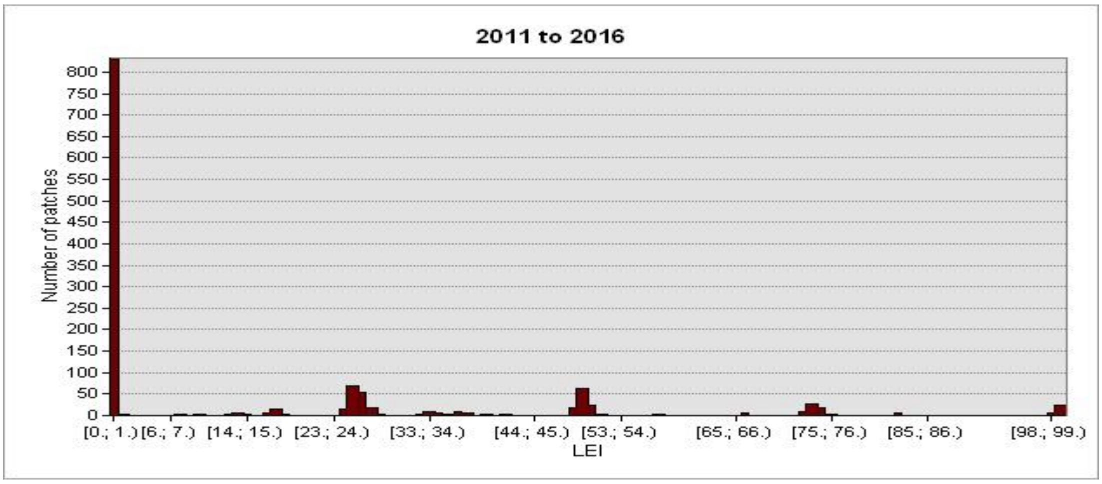


Appendix V: Landscape Expansion index (LEI) chart

a) LEI Number of patches of 2001-2011



b) LEI Number of patches of 2011-2016



c) LEI Number of patches of 20116-2021