Analysis of urban spatiotemporal dynamics of Land use land cover and urban sprawl: A case of Dukem Town, Ethiopia

By: - Amare Jembere Gebeyehu

Thesis Submitted to the department of Geomatics Engineering

School of Civil Engineering and Architecture (SOCEA),

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

Geoinformatics Engineering

Office of Graduate Studies

Adama Science and Technology University

Adama, Ethiopia

September, 2022

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Under the Supervision of

Dejene Tesema (PhD)

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DECLARATION

I hereby declare that this research thesis entitled "**Analysis of urban spatiotemporal dynamics of Land use land cover and urban sprawl: A case of Dukem Town, Ethiopia**" is my original work. That is, 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.

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I, the advisor of this thesis, hereby certify that I have read the revised version of the thesis entitled "**Analysis of urban spatiotemporal dynamics of Land use land cover and urban sprawl: A case of Dukem Town, Ethiopia**" prepared under my guidance by Amare Jembere Gebeyehu submitted in partial fulfillment of the requirements for the degree of Master's in **Geoinformatics Engineering**. Therefore, I recommend the submission of the revised version of the thesis to the department following the applicable procedures.

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Name of Major Advisor	Signature	Date

APPROVAL PAGE OF THE THESIS

I, the advisor of the thesis entitled "**Analysis of urban spatiotemporal dynamics of Land use land cover and urban sprawl: A case of Dukem Town, Ethiopia"** and developed by Amare Jembere Gebeyehu hereby certify that the recommendation and suggestions made by the board of examiners are appropriately incorporated into the final version of the thesis.

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We, the undersigned, members of the Board of Examiners of the thesis by Amare Jembere Gebeyehu have read and evaluated the thesis entitled "**Analysis of urban spatiotemporal dynamics of Land use land cover and urban sprawl: 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 **Geoinformatics Engineering**.

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LIST OF ACRONYMS

OLI/TIRS	Operational land imager/thermal infrared sensor
CSA	Central Statistical Agency
EIZ	Eastern Industry Zone
GIS	Geographic Information System
LULC	Land Use Land Cover
NLCD	National Land Cover Database
RS	Remote Sensing
SSA	Sub-Saharan African
UNFPA	United Nations Fund Population
UNHSP	United Nations Human Settlements
CA	Class Area
PZ	Percentage of Zone
LPI	Largest Patch Index
AI	Aggregation Index
ED	Edge Density
EEA	European Environmental Agency
ETM+	Enhanced Thematic Mapper Plus
LSI	Landscape Shape Index
MSS	Landsat Multispectral Scanner
NP	Number of Patches
SHEI	Shannon Evenness Index
SDI	Simpson Diversity Index
PLAND	Percentage of Landscape

ABSTRACT

Urban sprawl, mainly due to rapid urbanization, has become the primary problem in urban growth management, especially in cities in developing countries. Effective planning for its management requires a comprehensive understanding through precise analysis of the dynamics of urban growth and urban sprawl on both spatial and temporal scales. This study aims to analyze the spatiotemporal changes in land use land cover (LULC) due to urbanization and to assess urban sprawl in Dukem Town, one of the emerging towns of the country, from 2000 to 2021. Time series Landsat TM, ETM+, and OLI/TIRS datasets were utilized to prepare LULC maps of the study area for the years 2000, 2010, and 2021 using supervised classification techniques, and the spatiotemporal changes of LULC were investigated based on post-classification comparison. Using the spatial link between pre-growth and newly built components, urban growth types were analyzed. Spatial metrics and Shannon's entropy were used to determine the degree of urban sprawl. The results demonstrate that agricultural land and forest land were negatively impacted by urbanization-induced changes in land use and cover in Dukem Town. A substantial portion of agricultural and forest land were converted to built-up between 2000 and 2021, costing 1,161.58 and 83.97 hectares of land respectively. The spatiotemporal dynamics of urban sprawl have demonstrated incremental tendencies over the past 21 years, with built-up Class Areas (CA) increasing from 858.6 hectares in 2000 to 1,828.79 hectares in 2021. Furthermore, outlying, edge extension, and infilling types of urban growth totaling 534.24, 232.2, and 58.95 hectares of urban area, respectively, were found in the study region over the past 21 years. In conclusion, the study's results showed that the spatiotemporal dynamics of urban sprawl had accelerated over the past 21 years. The Town consequently experiences unprecedented, unanticipated, and rapid expansion, which will last for the ensuing decades. Urban planners must therefore plan ahead in order to execute an effective implementation strategy that will keep up with the rate of urban sprawl.

Key words: Urban expansion, Zonal Metrices, Spatial Metrices, Urban sprawl

CHAPTER ONE

1. INTRODUCTION

1.1. Background of the Study

Urban sprawl has significantly contributed to the conversion of rural to urban land use patterns, as well as the depletion of rural regions (Nejadi et al., 2011). It is the opposite of compact urban development in terms of sprawl, and it is primarily concerned with unplanned and uncontrolled city expansion. The primary challenges associated with urban sprawl have a negative influence on long-term urban growth (i.e., social, environmental, and economic factors). Managing urban expansion is a vital component of long-term urban development (Karppi, 2020).

Urban expansion as dynamic process of land use change is a complicated social/economic phenomenon. It has been linked with details related to topography, transportation, land use, social structure and economic type, but it is generally related to demography and economy in a city (Zornoza-Gallego, 2022). Urbanization as a process of urban expansion is a universal phenomenon in which consists of quick population growth, rise in the proportion of non-agricultural, and conversion in land use from agricultural to built-up (Larsen et al., 2019). The process of urbanization is continuous one and is generally one of the top agendas influenced by various economic activities such as socio-cultural, political, commerce, transportation and industrial activities (Girma and Ababa, 2016). The urbanization process (urban growth and sprawl) is one of the important prime factors of land cover/use change, and it is related to the growth and increase of populations and economic activities. However, it is complicated to present a particular proper describing of urban growth and sprawl that satisfies all the urban planning research community (Kovács et al., 2019).

Recently, African urbanization is characterized by rapid and uncontrolled urban growth. This results in LULC changes and environmental problems (Mengesha, 2017). In Ethiopia urban areas are growing at elevated rate than ever before. This rapid urbanization is accelerated by multi factors such as rural urban migration, natural population growth, economic growth, and favorable government policy (Tegenu, 2010). Urbanization and urban growth are considered as a modern way of life manifesting economic growth and development in many countries (Wedekind, 2011). Many of Ethiopian cities and/ or Towns have experienced rapid horizontal expansion; but which was not properly controlled by appropriate planning intervention, weak implementation capacity, weak institutional

capacity as well as lack of good governance in cities or Towns (Mekuria et al, 2019). As such uncontrolled rapid horizontal expansion of cities/Towns towards the agricultural communities resulted in additional social, economic, environmental and political problems (Debela, 2017).

Analyzing and comprehending the behavior of spatiotemporal changes in urban expansions and patterns is required in urban studies. Geographic information systems (GIS), remote sensing, and ground data from the research region can be used to investigate the urbanization process (Al-shalabi, et al., 2013a; Pradhan et al., 2014a, 2014b). Furthermore, utilizing the aforementioned methodologies, recognizing and mapping types of urban sprawl patterns on landscapes can be accomplished easily (Alsharif et al., 2015). Understanding the dynamics of fast expansion, the evolution of urban sprawl, and measuring the spatial extent of urbanization necessitates the use of a geospatial tool (Araya and Cabral, 2010). Remote sensing has been the most cost-effective method of data collecting for a wide range of applications (Teke et al, 2013). Remotely sensed data from principally Landsat multispectral scanner (MSS), thematic mapper (TM), enhanced thematic mapper plus (ETM+), and Landsat 8 OLI/TIRS have been used to identify, map, and assess urban sprawl and physical expansion of cities (Mushore et al., 2017). As a result, GIS and remote sensing play an important role in shaping and regulating urbanization by monitoring urban sprawl and spatial growth of metropolitan areas utilizing different change detection techniques and spatiotemporal satellite imagery.

1.2. Statement of the Problem

One of the key driving forces behind the construction of today's land-use regimes is urbanization. It nearly invariably entails the change of non-urban to urban land use (Nuissl, et al, 2021). Urban sprawl has resulted in unsustainable urban development patterns from social, environmental, and economic perspectives (Shao et al, 2020). However, urban land-use change may take many different forms, depending on the layout, building density, and rate of change (Siedentop, 2010). The majority of urban sprawl is thought to be low-density growth accompanied by a slew of environmental and socioeconomic difficulties (Paramasivam 2020). There is a rising awareness of and worry about, urban sprawl throughout states and localities. Furthermore, land development has been out of control, with building land spreading at an alarming rate, particularly on the outskirts of several cities (Suzuki et al, 2013).

Actual information on the amount of urban sprawl is very useful for a variety of aspirations, including development activities such as urban planning and management, land and water resource management, service and marketing analysis, and so on. In order to accommodate the expanding population or other urban land uses, urban local governments must devote more time, effort, and attention to being able to employ land resources (Suzuki et al. 2013). The traditional surveying and mapping approach for estimating urban sprawl is time-consuming and costly. As a result, more study is being conducted on mapping and monitoring urban sprawl using Remote Sensing and GIS techniques (Ahmed et al, 2016; Nong et al, 2018; Mosel et al, 2016).

Aside from remote sensing techniques, statistical approaches linked with geospatial technology have been used to measure, estimate, map, and simulate urban sprawl (Suzuki et al. 2013). Shannon's Entropy is one such statistical approach that is utilized as a quantitative assessment of unorganized urban sprawl. The degree of spatial concentration or dispersion of geophysical variables (Xi) among 'n' spatial units/zones is measured using Shannon's Entropy (Hn). The integration of geospatial technologies with statistical measurements is critical for quantifying and estimating urban sprawl. Recently, integrated approaches which use the combination of satellite data that have high spatial accuracy and freely available satellite images with GIS that allows to quantitatively measure the pattern and rate of the rapidly growing Towns and urban areas in a rational and justifiable manner (Dadras et al., 2015; Milad et al., 2017; Li, 2014).

The unlawful occupancy of land is one of the most concerning issues plaguing many developing countries today, and this was plainly seen in Dukem Town (Dadi et al., 2016). Dukem is one of the fastest-growing Towns, yet its growth is increasingly erratic, unplanned, and sometimes results in fragmented development (Abo 2020). Although a number of studies (Zemenfes, 2014; Deribew 2020; Fenta et al, 2017a; Kindu et al, 2020) have been done to measure urban sprawl, their findings explain urban expansion rather than urban sprawl. To that aim, these studies indicated that built-up area increment between specific period of time is regarded as urban expansion and this is taken as a manifestation of urban sprawl. Although the increment of urban area is a manifestation of urban sprawl, these studies unable to determine the actual spatiotemporal dynamics of urban sprawl in terms of direction, location and even the types of sprawls existed in the study region. Zemenfes (2014) have some indication regarding to the direction of sprawl in the city of Mekelle from google earth image. However, this study lacks quantification of the sprawl

dispersion and the study didn't explicitly define the urban sprawl with the help of scientifically proven quantification model. As indicated in Getu (2021) determining the location, distance, and direction of urban sprawl using GIS and Remote sensing approach is paramount significance to have crucial information regarding to the trends of urban sprawl. Dadi et al, (2016) also tried to indicate urban sprawl in the Dukem Town. This study only due attention regarding to the determinant factors of urban sprawl and still didn't recognize the dispersity of urban sprawl in the Dukem Town. Cai et al, (2015) indicated that Shannon entropy model is commonly used techniques to quantify the dispersity of urban sprawl. Spatial metrices are also helpful tools in determining the spatial landscape characteristics of urban sprawl (Das 2019). The most serious concern in recent years has been the proliferation of urban constructions such as residences and commercial complexes on undeveloped land in Dukem Town. Therefore, the primary scientific problem identified in this research work is the uncontrolled urban development in the study region, which has not been quantified yet using Shannon entropy model in previous studies (Dadi et al, 2016). Therefore, this study was aimed to analyze urbanization-induced spatiotemporal changes in land use and land cover and to assess urban sprawl in Dukem Town from 2000 to 2021 using spatial metrics and Shannon's entropy model.

1.3.Objective of the Study

1.3.1.The main objective

To analyze urbanization-induced spatiotemporal changes in land use and land cover and to assess urban sprawl in Dukem Town from 2000 to 2021 using spatial metrics and Shannon's entropy model.

1.3.2. The specific objectives

The specific objectives of this study were:

- To analyze the urbanization-induced changes in land use land cover in Dukem Town from 2000 to 2021.
- To analyze the types of urban growth in the study area from 2000 to 2021.
- To assess the dynamics of urban sprawl in Dukem Town from 2000 to 2021.

1.4.Research Questions

As this study mainly focuses on urban sprawl, the following research questions were set:

- How was the study area's land use and cover change as a result of urbanization between 2000 and 2021?
- What are the primary types of urban growth that took place between 2000 and 2021 in Dukem Town?
- What changes did urban sprawl have between 2000 and 2021 in Dukem Town?

1.5.Significance of the study

GIS and remote sensing play an important role in shaping and regulating urbanization by quantifying urban sprawl and spatial growth of metropolitan areas utilizing different change detection and spatiotemporal satellite images, as well as spatial metrics methodologies. Dukem is one of Ethiopia's fastest expanding Towns, therefore the study has been critical in determining the Town's current sprawl rate during the last two decades, from 2000 to 2021. The finding of this research provides the amount of built-up area converted from non-built-up area (agricultural lands, forest land, and barren lands), as well as the rate of change in urban growth during the last 21 years. More significantly, the study's findings will give urban planners and municipal managers with a better knowledge of the Town's sprawl by assessing several spatial metric indices based on the shape, area, edge, form, number, and fragmentation of built-up area patches. City planners and policymakers may use the research findings to design growth plans that are in harmony with the surroundings.

1.6.Scope of the study

The study's geographic scope is the urban footprint of Dukem Town. The primary goal of the research was to analyze the spatiotemporal changes in land use and land cover due to urbanization and to assess urban sprawl in Dukem Town from 2000 to 2021 using spatial metrics and Shannon’s entropy model. More critically, the scope of this study was narrowed to quantify urban sprawl using spatial and zonal indicators.

1.7.Limitations of the study

As is true in many research, there are certain limitations to the study due to the lack of sufficient data. The fundamental challenge in undertaking urban research in undeveloped

nations such as Ethiopia is a dearth of high-resolution satellite data. Our country, Ethiopia, is not developed enough to create its own satellite data. As a result, the researchers from this country, rely heavily on external sources such as government agencies that provide data of acceptable quality for free or at a low cost, and commercial organizations that provide high quality satellite data at a high and unaffordable cost. In addition, the researcher was obliged to employ Landsat TM and ETM plus satellite images (from 2000 and 2010) as well as Landsat 8 OLI TIRS satellite image (2021). Because of the mixing of spectrum energy in the presented image, this satellite data can have certain limitations in terms of spatial detection of features. This needs the collection of additional ground control points from the field in order to confirm the categorization findings.

1.8.Organization of the paper

The text is divided into five chapters. The first chapter is an introduction to the paper that discusses the study's history, aims, problem statement, research questions, scope of the investigation, limitations of the study, and paper organization. The second chapter is a review of the literature that discusses the general background of urban sprawl, the factors that contribute to urban sprawl, the impacts and consequences of urban sprawl, the process of urban sprawl, the application of geospatial techniques and spatial metrics for urban study, and the measurement of urban sprawl. The procedures and materials are discussed in the third chapter. This section has two subtitles: materials and methods. The subtitle Materials discusses the research area, data sources, and software programs used in the study, whereas the subtitle Methodology discusses all of the techniques used in image rectification, preprocessing, classification, and spatial metrics analysis. The fourth chapter is all about results and debates, and it deals with change detection, all of the spatial metrics analysis results, and zonal metric discoveries. The last chapter covers the study's conclusion and recommendations based on the research findings.

CHAPTER TWO

2. REVIEW OF RELATED LITERATURE

2.1.Definition of terms

Urban sprawl: - "Urban sprawl" is defined as "a type of spatial development characterized by low density (Bueno-Suárez and Coq-Huelva, 2020; Lowry and Lowry, 2014; Sinha, 2018), distributed and discontinuous leapfrog expansion, and land use segregation" (Rosni and Mohd Noor, 2016). Single-use development (Wei and Ewing, 2018), fragmentation (Liu and Meng, 2020), shape irregularity (Aguilera et al., 2011, Keita et al., 2021), inequality/low concentration (Aguilera et al., 2011, Verbeek et al., 2014).

Urbanization: Urbanization is a metropolitan growth that is a response to the often-underappreciated consequences of technical, economic, social, and political factors, as well as an area's physical topography. The pattern of urbanization is defined by a constant concentration of people and activity in big cities (Connolly et al., 2021).

Urban expansion: Urban expansion is defined as the physical pattern of low-density growth of urban areas, mainly into agricultural areas around under certain market circumstances. define urban expansion as an uncoordinated pattern of urban growth in the city periphery, which is described as single land use, low density, and poor connectivity (Zhang et al., 2016).

2.2.Concepts of Urban Sprawl

The rapid development of the geographic range of cities and Towns, frequently typified by low-density residential housing single-use zoning, and growing reliance on the private vehicle for transportation, is known as urban sprawl (Cabral et al., 2013). Urban expansion is the unplanned, unwanted spread of urban development into areas adjacent to a city's outskirts. Metropolitan sprawl is a physical manifestation of low-thickness growth of vast urban regions beneath rural zones. Sprawl violates the principle of urban expansion by implying insufficient planning control over land subdivision. Development is dispersed and robust, with a propensity to discontinuity since it jumps over certain regions, leaving agricultural enclaves. Urban growth is a dynamic aspect that is subject to a variety of activities, including physical, social, and economic ones. These dynamics are primarily responsible for the quick passage of human settlement urbanization. It is a continuous process that is related with the variables underpinning the process of economic growth and

social transformation rather than being primarily associated with industrialization. Rapid urbanization is creating both possibilities and challenges for cities in emerging countries. One of the primary issues is an unavoidable byproduct of the urbanization process (Mekuriaw and Gokcekus, 2019). As the pace of urbanization rises, urban centers horizontally expand and consume more territory. Because population pressure on the natural resource base has exceeded it carrying capacity, it is logical to consider it one of the most challenging challenges to achieving sustainable development (Wassie, S. B. 2020). Overcrowding (slums and shanties) and prolonged unplanned settlement with acute scarcity of infrastructure in one part and unutilized or partially developed unoccupied land in the other portion result from uncontrolled urban expansion (Adam, 2014; Yohannis et al., 2020).

The history of urban sprawl is mostly obscure, with just a little amount of groundwork accomplished. The history of urban sprawl may be traced back to the dawn of civilization (during what is referred to as the first phase of urbanization in the world. Gordon and Yohannis et al., (2020) characterize urban sprawl as leapfrog development, but DiLorenzo (2010) defines it as cancer or viral multiplication. Purvis et al. (2019) believes that in the case of urban sprawl language confusion, describing rather than defining would be more suitable. Over this long period of time, cities evolved from their primitive form to modest harbor/rail-based Towns to the present-day metropolis with skyscrapers adorning landscapes.

By the close of the twentieth century, cities were expanding spatially as a result of rapid urbanization, while the car revolution transformed the primary way of city living in the twenty-first century. Sprawl is a phrase used to describe a sprawling city with low population in the periphery. There is no clear knowledge of what "urban sprawl" is or how it happens since it is a broad word embracing a multitude of difficulties. Despite the attempts of several specialists to define the idea, the following is a fundamental component of most definitions and most people's acceptance of sprawl: Sprawl is the outer spread of an urban zone, and it is particularly significant for rural land on the outskirts of cities. In actuality, urban sprawl, which is apparently done to promote urban expansion, is not suitable for either urban or rural environments. In this view, it has negative implications that inhibit regional long-term development since it is carried out in a disorganized and uncontrolled way. This comprises converting agricultural land to a variety of land uses for sustainable living, such as houses, industrial complexes, and health care facilities (Basudeb, 2010).

The primary drivers of urban development or sprawl are varied arrangements of financial, social, and political authorities in response to a territory's physical topography. Population expansion, migration, rising housing demand, fragmented urban governments, and patterns of infrastructure investment and road building are among the drivers or reasons. Ethiopia's expansion pattern is comparable to that of emerging countries. The causes are fast urban population growth and in-migration owing to pulling forces such as employment opportunities, provision of social infrastructure, and transportation facilities, which exacerbate the expansion of Ethiopian urban centers (Mekuriaw and Gokcekus, 2019).

2.3.Driving factors of urban sprawl

Urban sprawl, which was once a major issue in the developed world, is now a concern for cities in developing countries as well. A variety of reasons contribute to urban sprawl, which has a wide range of environmental consequences. The European Environmental Agency provides the most comprehensive analysis of the causes and drivers of urban expansion (Bhatta, 2010; EPA, 2013). Economic, both macro and micro causes, demographic reasons connected to population increase, greater space and better housing desire, inner-city concerns, transportation-related considerations, and regulatory framework elements were all categorized as key contributors to urban sprawl in the research. All of these are fundamental causes of urban sprawl, and their presence will result in haphazard growth of urban centers, which will manifest in development patterns as urban sprawl. Aside from the above listed factors, modern lifestyle and interest changes in metropolitan cultures are seen to be contributing to urban sprawl (Resnik, 2010). These attitudes and lifestyles include: a desire for new housing and commercial space at affordable prices; a desire for a larger house, which has resulted in an increase in the average size of new houses; the adoption of policies aimed at increasing home ownership levels; and perceptions of higher crime levels and lower crime rates. All of these reasons encourage individuals to live in the suburbs and contribute to urban growth.

2.4.Consequences of Urban sprawl

Following an examination of the characteristics and causes of urban sprawl, we will discuss the good and negative consequences of this phenomena. Regardless of the good features of urban sprawl, the majority of perspectives focus on the bad outcomes. Some of them are related to core-area issues. We may cite difficulties such as poverty concentration, low educational center quality, and a lack of financial resources (Habibi and Asadi, 2011). Sprawl in transportation results in greater commuting, longer travel times, and more

congestion. Households may travel greater distances to obtain better housing, educational facilities, and employment opportunities, and this trend is being accelerated by increased access to infrastructure (Habibi and Asadi, 2011). Infrastructure costs rise as a result of sprawl. Some examples are highways, parking, water, and power bills. Furthermore, it will result in the use of more energy, the creation of pollution, and the removal of lands. Living in these areas has severe psychological and social repercussions. We can distinguish two sorts of emotional costs: access deprivation and environmental deprivation (Habibi and Asadi, 2011). Finally, we may assert that sprawl produces diverse outcomes at three levels of city: new districts, metropolitan regions, and cities. Sprawl has an impact on historic centers and cities by creating new difficulties that result in a loss of competitive power. It results in the preparation of new infrastructures, increased travel, the removal of agricultural land, and a decrease in social connections in new areas. Third, the effects of urban regions on infrastructure expenses, environmental resources, energy consumption, and pollution are growing (Habibi and Asadi, 2011).

The implications of urban sprawl affect both the surrounding rural environment and the inner city (Li, 2012). Bidandi (2020) and the US Environmental Protection Agency (2013) recognized a host of environmental impacts and costs connected with urban expansion. According to Bidandi (2020), who produced 'Understanding Sprawl,' a citizen guide in Canada, the cost of urban development is considerable. The article highlights nine major consequences of sprawl: low density, higher household spending, agricultural land consumption, public health effect, energy consumption, poor water quality, wildlife, and aesthetic expenses. According to Weijers (2012), urban sprawl has three significant effects: "1) the despoiling of countryside, eroding and ruining its characteristics and economy; 2) Sprawl is less efficient than a compact city, as more infrastructure, utilities, and other related services are required; i.e., urban sprawl takes more time for commuters, causes congestion, increases money spent on transportation, loss of agricultural land, and loss of ecologies, to name a few." pp. 23-24 in Weijers (2012).

Low density means high cost, according to Bidandi (2020), which is related to the idea that the cost of providing services increases with distance but decreases with density, and thus it is obviously more expensive to provide roads, telecommunications, electricity, sewerage and pipelines, sanitation, police, and other services for a long distance and large low-density area. Because individuals choose to live in the suburbs while working or doing business in the city, thousands of vehicles are required for mobility. Because these cars consume

billions of liters of fossil fuels each year, they produce millions of tons of pollutants such as carbon monoxide, nitrogen oxides, sulfur oxides, particulate matter, and unburned hydrocarbons. Each type of pollution is harmful to both human health and the environment. This, in turn, contributes to climate change: the use of fossil fuels for transportation and energy produces harmful greenhouse gas (GHG) emissions, the concentration of which is steadily increasing. Each type of pollution is harmful to both human health and the environment. This, in turn, contributes to climate change: the use of fossil fuels for transportation and energy produces harmful greenhouse gas (GHG) emissions, the concentration of which is steadily increasing.

2.5. The Process of Urban Expansion

The cornerstone of growth and the driving factor behind economic success is urbanization. In order for governments and cities to fulfill their economic development goals, urbanization is both necessary and desirable (Scheller, D., & Thörn, H. 2018). According to their finding, almost all nations were urbanized or at least 50% urbanized before attaining middle-income status, and all high-income countries are 70-80% urbanized. No country has ever achieved sustained economic growth without urbanization; countries with higher per capita income tend to be more urbanized, while those with lower per capita income tend to be the least urbanized (UN-Habitat, 2011; Freire et al., 2014). "No nation has succeeded without urbanization, and no prosperous nation is not mainly urban," write Satterthwaite et al. (2010). p. 2810, Satterthwaite and colleagues, 2010. Cities, according to UN-Habitat (2011), are social change vehicles in which new values, ideas, and beliefs may build an alternative development paradigm for people, and urbanization has resulted in fundamental economic growth in the industrialized world.

It indicates that urbanization is the foundation for all economic change. However, for most low-income countries, this appears to be a paradox, for obvious reasons: urbanization and economic growth are relatively modest, although urbanization is at its peak. This is especially true for Ethiopia's objective of becoming a lower middle-income country by 2025 (World Bank, 2015), as the country's urbanization rate is already 20.4 percent in 2017 and 25.4% by 2027. (CSA, 2013). Rapid urbanization in underdeveloped countries, along with low economic growth, puts pressure on municipal, city, and national governments to meet even the most basic urban necessities.

As a consequence, urbanization is not inherently problematic, and it cannot be both a burden and a benefit for developing countries. Rather, urbanization is a long-term process driven

by rural-urban migration, economic development, and social and cultural transformation. The problem is rapid, unplanned, and uncontrolled urbanization, which causes and exacerbates urban sprawl. The majority of developing countries face two types of urban sprawl: (1) peripherization and (2) suburban sprawl (UN-Habitat, 2011). Peripherization is a sort of urban sprawl defined by an informal and unlawful pattern of suburban area growth paired with a lack of infrastructure, whereas suburban sprawl is characterized by high- and middle-income residential zones linked by individuals rather than public transit.

The process of urban growth may be a difficult one involving many variables. The link between urban growth and environmental, socioeconomic, and population issues has been a focus of urban scientific study (Li et al. 2013; Lu et al. 2013). These environmental and socioeconomic elements, or driving factors, are invariably linked to urbanization and environmental deterioration (Du et al. 2014). As a result, quantifying all of these aspects, coupled with spatial modeling, is critical for assessing planning decisions. When it comes to urban planning objectives, housing has always played an important role in promoting spatial expansion. Housing development has prioritized environmental preservation, sustainable residential development, resource capitalization, and coordinated regional infrastructure (Anthopoulos and Vakali 2012), which has propelled urban expansion beyond local governments' existing spatial land distribution. Human-driven influences on urban transformation may be identified by analyzing elements such as population and household growth, environmental quality, land price, per capita income, and so on (Li et al. 2013; Lu et al. 2013; Chen et al. 2014).

Most studies of the driving forces of urban land transformation fall under one of the two following approaches. Firstly, utilizing local parameters that affect planning strategies and secondly, analysis relies on global parameters like literacy, employment status, and population growth etc. (Mondal et al. 2015). These approaches enable us to identify the causes of LULC change and correlate them in terms of relationships between the considered set of independent variables and the observed phenomenon.

2.6.The relationship between urban Expansion and Urban Sprawl

Urban expansion and development have become important global challenges in recent decades (Parka et al., 2011). They have economic, cultural, and natural consequences, such as increasing infrastructure costs, causing farm and forest land loss, increasing consumption of energy and other environmental resources, raising land prices, causing road crowding and

heavy traffic, and reducing social interaction between people, among other negative environmental consequences. Due to population increase and the construction of new roads, buildings, and other human-made infrastructures and features, the city development authority and city planners are necessary to grasp current growth and to have up-to-date information and maps for future planning (Al-Mashagbah et al., 2012).

Many developing countries have lately witnessed fast urban growth as a result of quick economic advances, resulting in major changes in the landscape (Turok, 2013). Urbanization is widely recognized as one of the most significant drivers of land use and land cover change in human history, as it is connected to population and economic growth (Nuissl, 2021). Land cover in metropolitan areas changes more rapidly in a short period of time than any other feature due to continual urbanization (Jieli et al., 2010). The requirement for large-scale urban expansion entails the encroachment of natural land parcels such as agricultural fields, forestlands, or wetlands (Haregeweyn et al., 2012).

Converting these natural spaces into impermeable built-up lands can have major environmental repercussions, affecting the hydrologic system, biodiversity, and temperature, as well as having a negative influence, such as the urban heat island phenomenon (Haregeweyn et al., 2012). Because urbanization is unavoidable, efforts may be taken to control expansion in the most suitable manner feasible through urban land use planning in order to maintain natural resources as well as people's needs and rights (Soffianian et al., 2010). As a result, accurate mapping of urban environments and monitoring of urban expansion are becoming increasingly important on a global basis (Schneider, A. 2012). Because traditional surveying and mapping methodologies for estimating urban development are costly and time consuming, statistical techniques in conjunction with remote sensing and GIS have been used as an alternative for urban growth studies (Punia and Singh, 2011).

When humans build structures on existing rural or natural regions for residential or commercial purposes, they change the land's usage. Urban growth occurs when the distribution of the human population shifts from low-density village to high-density metropolis (He et al., 2018). According to Bhatta (2010), the boundary of a city or Town may be assessed using morphological or physical criteria, as well as functional or economic elements. This study focuses on the urban sprawl subtype of urban growth. Urban sprawl is a term used to describe the proliferation of low-density developed areas. While there is no agreement on the official definition of urban sprawl, existing literature notes that sprawl is

associated with changes in land use that result in an unplanned and uneven pattern of urban growth, at a rate that exceeds the rate of population growth, driven by a variety of processes and resulting in inefficient resource utilization (Bhatta 2010). This expansion pattern exacerbates traffic congestion concerns such as automotive reliance, higher water consumption, and increased energy demand.

Urban sprawl refers to the expansion of low-density urban communities over huge expanses of land (Cabral et al., 2013). According to Bhatta (2010), sprawl is characterized by "conceptual vagueness" and "challenges in defining." While sprawl is sometimes regarded as spreading outward from a single narrow urban center, Kreuger (2012) challenges this definition by illustrating how sprawl occurs around a single, highly concentrated urban core. Because assessing sprawl using remote sensing imagery is challenging, Bhatta (2010) reviews and compares numerous study approaches on urban sprawl. Bhatta's study indicates that single measurements for identifying sprawl are usually insufficient to determine whether or not a place is growing. Despite the several available techniques, the use of entropy to quantify sprawl is the most reliable and widely used. Though it may not be difficult to see sprawl with the naked eye, quantifying sprawl may be necessary to influence policy and foster sustainable urban growth.

Living has been increasingly difficult to sustain since the influence of urban sprawl on the livelihoods of suburban rural communities, and life has deteriorated from time to time in contrast to their past income level and employment security. The exiles' alternatives are limited to agriculture and local handicrafts. Individuals are exposed to joblessness as a result of the problem, and as a result, society becomes destitute, and they are unable to appropriately support their family. Vu et al, (2017) sought to study if and how displaced people locate new homes. However, little attention has been paid to the situation of displacement and relocation, as well as its impact on the life-making of ex-farmers in Ethiopia's tiny regional cities.

Because what is sprawl to one person may not be to another, not all urban growth is deemed sprawl. "Creating an urban growth model as opposed to an urban sprawl model allows us to quantify the amount of land converted to urban uses and allows the user to select what he or she believes to be urban sprawl" (Rui, 2013). Leapfrog land use patterns, strip commercial development along highways, and very low density single-use projects are all features of rapid urban expansion (Brody, 2013). Sprawl is described as urbanization that happens over

time in either a radial or linear direction surrounding a well-established city (Dhaoui, 2013). Clearly, radial and linear map layouts are merely two of the many possible kinds of sprawl. Land use change evaluations and urban expansion pattern recognition, according to Dhaoui (2013), are essential to appreciate the intricacies of urban sprawl. Human activities contribute to the expansion of highly anthropogenic areas. Urban sprawl causes changes in land use structure, which is followed by the expansion of residential, service, and industrial functions, as well as technical infrastructure. The extent of urban territory's land use patterns is always growing (Senetra et al., 2014).

2.7.Geospatial Techniques

Geospatial techniques have been widely employed to assess changes in land use/cover, notably in urban expansion (Sarker and Rashid, 2013), and urban planning (Hegazi et al., 2015). There are numerous methods for determining land use change in urban areas using satellite photos. Change detection and classification techniques are divided into pre-classification and post-classification processes by Peiman (2011). Pre-classification techniques use several algorithms such as image differencing and image rationing to single or many spectral bands, vegetation indices, or primary components, directly to numerous dates of satellite data to produce "change" vs. "no-change" maps. These methods identify changes but provide no information about the nature of the change (Gong et al., 2015). Post classification comparison procedures, on the other hand, use distinct classes of images captured at different times to create difference maps from which "from-to" change information may be extracted (Mai, 2022). Change detection is the process of detecting differences in the status of an object or phenomenon by seeing it at different time intervals (Panuju, 2020). It is a key tool in monitoring and managing natural resources and urban development because it provides for quantitative examination of the geographical distribution and trends of spatial attributes.

2.7.1. Change detection method

Because of the availability of many current information systems, the definitions of land use and land cover have been used interchangeably in the land use research community. These two phrases, however, describe two distinct situations and meanings. The term "land cover" refers to the observed biophysical cover on the earth's surface, which includes plants, bare soil, hard surfaces, and bodies of water. Land use, on the other hand, is the use of land cover types by humans for agriculture, forestry, habitation, and grazing through affecting land surface processes such as biogeochemistry, hydrology, and biodiversity (Yesuph and Dagnew, 2019).

Changes in land use and land cover became significant as a study issue on global environmental change some decades ago, with the assumption that activities on the earth's surface impact climate. The importance of land use and land cover change on global climate via the carbon cycle was recognized in the early 1980s, with terrestrial ecosystems acting as sources and sinks as a result of the changes. The upcoming volume of the 1991 Global Change Institute of the Office of Interdisciplinary Earth Studies (OIES) will be dedicated to global land use and land cover changes by explaining the major recent trends of changes, their consequences in the environment, human causes on it, as well as data and modeling of changes (Sahalu, 2014). Following that, the scientific community has recognized three fundamental challenges with the help of the International Geosphere and Biosphere Programme (IGBP) and the International Human Dimensions Programme on Global Environmental Change (IHDP). These people recognized the causes of changes in land use and land cover, how to measure them, and how to utilize models to anticipate the changes (Wang et al, 2020).

Changes in land use and land cover induced by the direct and indirect effects of human actions on the environment in order to live a better life. One direct consequence of people is population expansion, which has an effect on land usage, particularly in poorer countries, across longer time frames. As land use and land cover change is a complex process, it may also be driven by the mutual interactions of environmental and social variables at multiple geographical and temporal scales, according to Wang et al (2020).

Wubie et al. (2016) shown that the causes of land use and land cover change may be classified as either direct (proximate) or indirect (underlying). Human activities that originate from the ongoing usage of land and directly modify land cover are examples of direct causes, indicating that humans are driving factors. They are often operated at the local level and explain how and why humans directly modify local land cover and environmental processes. In contrast, indirect causes are basic processes that reinforce the more direct causes of land cover shifts. These factors are the consequence of a complex interplay of social, political, economic, technical, and biophysical forces.

Changes in land use and land cover have a substantial impact on climate change, hydrology, air pollution, and biodiversity. Sahalu, (2014) reported that it induced a variety of microclimatic alterations in their investigation. The increase in global surface temperature is linked to deforestation caused by changes in land usage. This, in turn, generated a significant warming in the urban area, known as an urban heat island. Their research also revealed that water

contamination occurs as a result of land cover shifts from agricultural to habitation (urban areas). It has also been stated that the extinction of forest species has a wide variety of consequences for biodiversity.

Understanding how individuals make land-use decisions, as well as how particular environmental and social elements interact to affect these decisions, is required for identifying the causes and implications of land use and land cover change (Fritsche et al, 2010). Land use change models are useful for understanding the effects of dynamic land use and land cover changes because they give information on land use trajectories by projecting into the future. However, this capability of models is critical for improved environmental management and land use planning (Kozak et al, 2017).

2.7.2. Urban Land use Changes

In a broader sense, urbanization is one of the ways in which human activities alter the global land cover. Although urbanization is a global trend, the United Nations Centre for Human Settlements (Awumbila, 2017) observes that the most visible changes in poor countries are associated with the migration of rural people to cities in quest of better opportunities. Following that, it was expected that the urban population will grow at a 2.3 percent annual rate between 2000 and 2030 (Seto et al., 2012). Residential and commercial land use shifts to rural areas on the fringes of major centers have long been viewed as indicators of regional economic vitality (Fragkias et al, 2010). However, its relevance varies according to the consequences on the environment, rising economic inequities, and social fragmentation. It is the rate of urban population growth. Urban transformational processes, notably the vast worldwide rise in urban population and urbanized area, have an influence on both human and environmental systems at all geographic scales (Chen et al., 2014).

Demographic data has traditionally been used to assess urban sprawl (Steure, 2020). Meanwhile, aerial photography is becoming increasingly important for updating land cover maps. Changes in regional land cover could not be realized in the community since they were caused by human activities. As a result, accurate and up-to-date information is critical for developing strategies for sustainable development and improving city livelihoods. The ability to monitor changes in urban land cover and land use is highly valued by local communities and politicians. Because of the greater availability and better quality of multi-temporal data, as well as new analytical approaches, it is now possible to monitor urban land cover and land use changes, as well as urban sprawl, in a timely and cost-effective manner (Dhanaraj, 2021). As a result, the utilization of satellite data facilitates regional planning and urban ecology.

The demographic process of moving the balance of the national population from "rural" to "urban" regions is referred to as urbanization (Tacoli et al., 2021). Rapid urbanization, one of the most significant social revolutions in the last five decades or more, has resulted in the creation of new types of slums, as well as an increase in squatter and informal housing throughout the developing world's quickly rising cities. According to a 2010 UN-Habitat global assessment of human settlements, urban populations have risen in the last 50 years and will continue to rise in the next 30 years as the number of people born in cities rises and people are displaced from congested rural areas. Because the rate of formal-sector job growth in cities is far slower than the predicted rate of urban labor force increase, the vast majority of these new inhabitants will almost certainly live in slums (UN-Habitat, 2010).

Ethiopian urbanization is a recent phenomenon due to the country's historical factors. Many of Ethiopia's medium-sized cities were built in the nineteenth century for political and military reasons (Terfa et al., 2017). Throughout the nineteenth and twentieth centuries, Ethiopian cities were built around the palace, market, and church, according to Donald Crummey. These institutions provided political, economic, and cultural services (Ambaye et al., 2015). Addis Abeba, Ethiopia's present capital, was founded in 1886, after the foundations of Axum and Gonder in early and medieval Ethiopian history, respectively. Ethiopia has spent most of its history as a place of small Towns and isolated homesteads (Bekele, 2017). According to Richard Pankhurst, Ethiopia's long-term lack of significant urban neighborhoods is due to the royal camp's constant migration. The medieval royal court had a plethora of non-combatants, including spouses, servants, and slaves, armorers, tent-carriers, muleteers, priests, tradesmen, prostitutes, beggars, and even a few children, among others (Ibid). Madlener, on the other hand, claimed that urbanization was unnecessary since it contradicted the current self-sufficient rural culture. By definition, urbanization includes the transfer of extra agricultural land to urban development (Madlener, R., & Sunak, Y. 2011). Nonetheless, contemporary Ethiopian urbanization increased over the twentieth century as a result of political stability (particularly under Emperor Hailesselasi I's reign) and the country's development. Most cities in the country, including Dukem, grew up around an economic center, such as a railway, industrial, or commercial corridor.

2.7.3. Trends of Urban Growth

The globe is seeing the greatest wave of urbanization in history. According to the United Nations Population Fund (UNFPA), significant population increase has been focused in the world's Towns and cities. According to the research, the great bulk of this expansion would be seen in the developing worlds of Africa and Asia, where urbanization is concentrated. Cities drew a large

number of people because they provide more options, such as employment and sources of money, than rural places.

Ethiopia is Africa's second most populous country, with a total population of over 80 million people and an annual growth rate of 3.3 percent. The country has an average yearly urban growth rate of 4.6 percent, which is impressive by global standards (Terfa et al., 2019). Despite the fact that urbanization rates vary depending on the methodology used, Ethiopia's urbanization is low in comparison to other Sub-Saharan African (SSA) nations. Because agriculture is the backbone of the country's economy and the bulk of the population (85%) lives in rural regions, it is obvious that urban expansion will be slow. Agriculture's self-sufficiency also contributed to the reinforcement of rural peasant life from their land. According to the Central Statistical Agency of Ethiopia (CSA), just 16% of the population lives in cities. These are concentrated in small Towns and cities (Schmidt and Kedir, 2011).

2.8.Urban Growth types

Urban growth is synonymous with developed land, and includes residential as well as commercial and industrial land uses that result in a developed or built landscape. When modeling urban growth, it is important looking at the patterns of development on the landscape, rather than referring to relative differences in the density of development. The urban growth model identifies three categories of urban growth: infill, expansion, and outlying with outlying urban growth further separated into isolated, linear branch, and clustered branch growth. The relation (or distance) to existing developed areas is important when determining what kind of urban growth has occurred, however, it must be noted that 30-m pixels do not always identify all roads on the landscape. The urban growth classes can be defined in relation to Forman's (2015) landscape transformation processes. Although the processes themselves are quite similar, the urban growth model defines growth classes from the perspective of a growing urban patch while the landscape transformation processes define fragmentation types as a reduction of non-developed land cover types.

An infill growth is characterized by a non-developed pixel being converted to urban use and surrounded by at least 40% existing developed pixels. It can be defined as the development of a small tract of land mostly surrounded by urban land cover. Ellman (2017) defines infill policies as the encouragement to develop vacant land in already built-up areas. Infill development usually occurs where public facilities such as sewer, water, and roads already exist. Forman (2015) describes attrition as the disappearance of objects such as patches and

corridors. An expansion growth is characterized by a non-developed pixel being converted to developed and surrounded by no more than 40% existing developed pixels. This conversion represents an expansion of the existing urban patch. Expansion-type development has been called metropolitan fringe development or urban fringe development (Heimlich & Anderson, 2014; Wasserman, 2016). When discussing mosaic sequences, Forman (2015) discusses edge development, defined as a land type spreading unidirectionally in more or less parallel strips from an edge. The analogous land transformation class is shrinkage, defined as the decrease in size of objects, such as patches (Forman, 2015).

Outlying growth is characterized by a change from non-developed to developed land cover occurring beyond existing developed areas. This type of growth has been called development beyond the urban fringe (Heimlich & Anderson, 2014). The outlying growth designation is broken down into the following three classes: isolated, linear branch, and clustered branch. Isolated growth is characterized by one or several non-developed pixels some distance from an existing developed area being developed. This class of growth is characteristic of a new house or similar construction surrounded by little or no developed land. Forman (2015) defines perforation as the process of making holes in an object such as a habitat or land type. Linear branch defines an urban growth such as a new road, corridor, or a new linear development that is generally surrounded by non-developed land and is some distance from existing developed land. A linear branch is different from isolated growth in that the pixels that changed to urban are connected in a linear fashion. When discussing mosaic sequences, Forman (2015) defines corridor as a new corridor such as a road that bisects the initial land type. Harvey and Clark (2012) discuss ribbon development, defined as ‘‘segments compact within themselves but which extend axially and leave interstices undeveloped.’’ Forman (2015) defines two land transformation processes that apply to linear branch. The first is dissection defined as the carving up or subdividing of an area using equal-width lines. He also defines fragmentation as the breaking up of a habitat or land type into smaller parcels. Fragmentation also applies to clustered branch. Clustered branch defines a new urban growth that is neither linear nor isolated, but instead, a cluster or a group. It is typical of a large, compact, and dense development. Harvey and Clark (2012) define a similar type of growth called leap-frog development as the ‘‘settlement of discontinuous, although possibly compact, patches of urban uses.’’

2.9.Urban Growth Measurement Using Remote Sensing

Numerous research on measuring urban expansion using remote sensing methods have been undertaken (Alsharif et al., 2015; Belal and Moghanm, 2011; Bhatta et al., 2010; Crowther 2015; Masoumi and Roque, 2015). Typically, urban expansion is quantified using change detection algorithms using categorized land cover images (Bhatta et al., 2010). Natural land cover pixels are classed as impermeable, whereas impermeable surfaces such as roads and buildings are labeled as "developed." However, developed metropolitan environments are more than just impermeable surfaces. Because of the variety of urban infrastructure materials, landscaping, and tree canopy, metropolitan settings have a wide range of spectral fingerprints. This diverse set of spectral fingerprints results in a mixed pixel problem during the categorization process for low to medium resolution satellites such as Landsat (Pena and Brenning, 2012).

Despite the mixed pixel problem's limitations, land cover categorization programs such as the NLCD have been determined to be between 84 and 85 percent accurate between 2001 and 2006 (Wickham, 2013). This accuracy level is suitable for the majority of remote sensing land cover and satellite data categorization research (Qian et al., 2014). The difficulty in assessing low-density residential developments in rural regions, also known as exurban development, is the fundamental restriction of NLCD data for quantifying urban sprawl (Van Berkel et al., 2019). This is due to the tiny disparities between vegetative cover and impermeable surfaces in low-density residential projects, which readily obfuscate data that is not confirmed by ground-truthing.

Qian et al., (2014) contends that finer scale land cover data would be perfect for more accurate estimates of urban sprawl and that NLCD data is not at the proper geographical scale for quantifying urban sprawl. However, Qian et al., (2014) reasoning is limited to a specific urban region in Maryland and may not be applicable to the rest of the country or the rest of the globe. Unlike Qian et al., (2014), Chong et al. (2017) found that NLCD data can be used to measure sprawl depending on the sensitivity of the definition of sprawl. Furthermore, investigations of sprawl utilizing similar Landsat data and classification approaches have proven successful in measuring sprawl (Deka, 2010; Effat, 2015).

2.10. Shannon’s Entropy Approach to Measuring Urban Sprawl

Shannon's entropy on metropolitan areas is used in several research to quantify sprawl over time (Bhatta 2010; Dadras et al., 2015). Shannon's Entropy is one of the most popular

methods used to measure urban sprawl using remote sensing and GIS methods, according to Bhatta (2010), because of its decreased sensitivity to issues relating to the modifiable areal unit problem, where results can vary dramatically depending on the size, shape, extent, and number of regions involved (Bhatta, 2010). According to Chong (2017), the value of relative Shannon's Entropy is "invariant" with the number of areas, unlike other, more traditional techniques of quantifying geographical dispersal. The metric is still affected by the size and form of zones within regions. Because the entropy value would be very low if only one zone were employed throughout an entire metro area, the aggregation effect of coarser scale paired with a small number of zones can have a significant influence on the measure. Furthermore, adopting very different sizes, such as state vs municipal scale, would provide incomparable findings.

Gao et al., (2015) were among the first to use Shannon's entropy to quantify urban expansion in China's Pearl River Delta region. Their study has had a significant impact on subsequent studies of urban sprawl utilizing remote sensing (Bhatta et al., 2010; Singh 2014). They identified urban areas and tracked changes in urban land development over time using principal component analysis on multi-temporal Landsat 21 Thematic Mapper (TM) data. They then established dense land development regions and important roadways in a variety of cities and villages. They then built buffers spreading out from these sites and highways. They compute the urban footprint using a modified version of Chong (2017) Shannon's Entropy equation that takes into consideration the density of land development in the region. Their research discovered a high average Entropy score for all locations tested, indicating that many of the cities analyzed were really spread. The study also discovered that buffer zones located near major roadways produced greater entropy values than buffer zones located in the Town center in several cities and Towns. This suggests that in certain cities, the pattern of sprawl was linked to distance from roadways, but in others, distance from the Town center was assigned to sprawl. The current study examines the urban footprints of the Minneapolis and Chicago MSAs using Gao et al., (2015) modified Shannon's Entropy equation.

Shannon's Entropy, according to Masoumi and Roque, has been used to assess sprawl in India, Iran, China, Egypt, and other developed or rising countries (2015). Masoumi and Roque compare and contrast international Shannon's Entropy studies on urban growth with their own study in Ensenada, Northern Mexico. According to the study, Ensenada has

comparable sprawl speed values to several fast-growing Indian, Portuguese, and Chinese cities, as well as greater intensity values than certain Indian cities. This is significant because, while Masoumi and Roque (2015) were successful in comparing several sprawl studies, there are relatively few research comparing the Shannon's Entropy measure.

The studies Masoumi and Roque (2015) examine utilize different land cover classifications, buffer zone sizes, and satellite sensors for land cover data, but they may be compared since the authors apply a standardized equation to convert entropy to relative entropy. Relative entropy narrows the entropy range from 0 to log(n) to 0 to 1. According to Masoumi and Roque (2015), the degree of dispersion among buffer zones of varied widths and numbers may be measured by converting entropy to relative entropy.

To get the relative entropy, divide the entropy by log (n). The authors caution that the study is limited to affluent or industrialized countries, and there are no comparable investigations in South America or much of Africa. Because the current study finds that different buffer zone sizes and numbers can have a minor effect on the entropy value, Masoumi and Roque's study is primarily used as a reference for the magnitude of change between entropy values over time, with different buffer numbers and sizes, and across different geographical regions around the world.

While the Gini coefficient has typically been employed to explain distribution patterns, this metric presents the modifiable areal unit problem due to its sensitivity to the size and form of the research area Gao et al., (2015). The Gini coefficient is a 0–1 ratio that quantifies the inequality of a distribution (Trapeznikova, 2019). The ratio compares a variable's distribution to a completely uniform distribution. The Gini coefficient is most commonly employed in urban form studies with population or employment density data. The Gini coefficient, like Shannon's Entropy, splits the research region into sub-areas or zones. However, due to the mathematical features of the measure, the size and number of zones have a significant influence on the computation.

The Moran coefficient is another statistic for measuring distribution patterns. The Moran coefficient quantifies high-density zone clustering (Trapeznikova, 2019). The Moran coefficient has a range of -1 to 1, with -1 indicating poor clustering of high-density zones and 1 to 23 indicating substantial clustering of high-density zones. Because of the mathematical features of the measure, the Moran coefficient, like the Gini coefficient, is

very sensitive to the number and size of zones utilized. In contrast, Shannon's Entropy is less susceptible to the changeable areal unit problem since the entropy value is determined by how evenly observations are distributed throughout space rather than the area of the zones (Gao et al., 2015).

Buffer zones are typically established near city centers and traffic networks to assist in calculating "rotten regions of the city-wide range." Distance decay refers to the degree to which distance is engaged in a number of areas, such as development, with a special emphasis on streets and city centers. Researchers may observe how distance influences the location of new and current urban development zones by constructing baths with equal spacing around city centers and roadways (Chong, 2017).

Shannon's entropy is calculated using buffer zones surrounding the densest concentrated portion of the MSAs. The proportion of variables under investigation in each zone is used to calculate the total dispersion of those variables across all zones. Because of the centrality component of urban sprawl, the city center is not included in the computation. The expansion of built areas out from a central business district or city center, rather than within the city center itself, is referred to as centrality. The next part goes through how to do the computations (Chong, 2017).

2.11. Review of Empirical Studies

Crowther (2015) examines urban land cover change in Pasadena and Inglewood, California, using NLCD data from 1992 to 2001. His work investigates a way for aggregating land cover datasets from 1992 to compare to datasets from 2001, and it compares the aggregated datasets generally. While Crowther's research does not quantify urban sprawl, it does provide a framework for dealing with NLCD statistics and provides insight into the changing environment of a few Southern California communities. Crowther suggests that integrating Census population data with land cover change might provide a helpful indicator for forecasting future land cover change. Pena uses land cover change and population data to calculate urban expansion in Texas' Lower Rio Grande Valley. Pena classifies Landsat 5 images using supervised classification algorithms into three separate urban land cover classes and one unoccupied land cover class. He combines this imagery with dissymmetric population maps based on Census data to investigate the level of increase in the region (low, medium, or high). According to the study, social and demographic changes can have an

impact on the built environment, hence it is critical to incorporate population statistics when considering land cover change.

The bulk of remote sensing-based urban sprawl research focus on emerging nations such as India and China rather than the United States. This is due to the fact that employing traditional surveying techniques for urban sprawl research is sometimes prohibitively expensive and time consuming (Effat and Shobaky, 2015). Using remotely sensed images for urban sprawl measures is frequently less expensive, covers more regions, and may be done at more regular intervals than traditional surveys (Dhanaraj et al., 2021). Satellite remote sensing is becoming a viable alternative to traditional surveying and mapping approaches as radiometric, spatial, and spectral resolutions improve and sensor costs fall. Because of their regular coverage, accessibility, and acceptable geographical, temporal, radiometric, and spectral resolutions, pictures from the Landsat series of satellites are extensively utilized in urban growth studies (Almazroui et al., 2017).

2.12. Research Knowledge gaps

Most of the studies carried out in Ethiopia were focused on assessing urban expansion and its socio-economic impacts on the livelihood of the farming community in the peri-urban areas (Ahlam, 2017; Abebe, 2012; Beka, 2016; Adem, 2010; Efa & Gutema, 2017; Firew, 2010; Tamirat, 2016; Kaleb & Samuel, 2017; Leulsegged et al., 2011 and Shishay, 2011). Their focus is mainly on the expansion of urban areas and their impact on the environment and socio-economic impacts on the livelihood of the farming community in the peri-urban areas in relation to population growth. The finding of those pieces of literature explicitly revealed how the ever-increasing of urban sprawl significantly affects livelihood, socioeconomic and farming activities. Furthermore, much of the studies conducted in Ethiopia to assess urban expansion and sprawl were employed GIS and Remote sensing technologies. To that aim (Eneyew et al, 2018; Bulti et al, 2020; Fenta et al, 2017; Genemo 2012; Belay et al, 2014; Bekele et al, 2010) evaluated the dynamics of urban expansion in different cities of Ethiopia. They all argue that GIS and Remote sensing method is a robust approach in detecting the extents of urban expansion over time series.

Currently, supervised classification (Almazroui et al., 2017; Odjugo et al., 2015) and unsupervised classification (El et al., 2017; Mosel et al., 2016; Peacock, 2014; Nong et al., 2018) techniques have been successfully used to monitor urban sprawl and expansion at various spatiotemporal scales. In addition to this, Shannon entropy and spatial metrics were

employed to quantify urban sprawl and define the various characteristics of sprawl (Deka et al., 2012; Krishnaveni 2020; Stalin, 2019). The Shannon entropy index is a widely used technique for verifying and identifying the disparity of urban sprawl and urban areas (Nkeki, 2018; Das et al., 2016; Muiruri and Odera, 2018; Cai et al., 2015), whereas spatial metrics are useful for quantifying and measuring the spatial characteristics of the landscape (Nkeki, 2018; Das et al., 2016; Muiruri and Odera, 2018; Cai et al (Ramachandra et al., 2014).

In Ethiopia, urban sprawl manifests itself as excessive and limitless outer expansion of urban areas at the expense of other land use land cover. According to the findings of a study conducted by Zemenfes G (2014) in Mekelle, Ethiopia, the city was sprawling into the nearby rural community as a result of uncontrolled and unauthorized acquisition and occupation of farmlands, which is primarily related to the city's poor land use and administration policy. Several studies on urban expansion and urban land use change in Ethiopia have been conducted, with several driving forces as well as the impact on livelihood and the environment (Deribew, 2020; Barow et al., 2019; Fenta et al., 2017a; Kindu et al., 2020; Erasu, 2017; Gebremedhin et al., 2019; Halefom et al., 2018; Gashu and Egziabher, 2018; Fitawok et al., 2020; Terfa et al., 2017). For example, studies conducted by Deribew (2020) in the western fringe of Addis Ababa city, Ethiopia, Barow et al. (2019) in Jigiga Town of Ethiopia, Fenta et al. (2017a), in Mekelle city of northern Ethiopia, Halefom et al. (2018) in Debre Tabor Town of south Gondar zone of Ethiopia recognized rapid urban expansion towards agricultural areas and forest land.

In the research area of Dukem Town, attempts have been made to evaluate urban expansion and its relationship to the urban landscape. Dadi et al. (2016), for example, attempted to examine the influence of urban sprawl on land use change in Dukem Town and found that uncontrolled fast urban development happened at the expense of agriculture and vegetation. Abebe (2012) has carried out research on the spatiotemporal tendencies of urban growth from 1986 to 2010. The study showed a substantial shift in green urban areas due to the fast increase of built-up regions over the study period. Girum (2020) undertook a study that explores urban growth land use land covers (LULC) dynamics in Dukem Town between 2003 and 2019 by identifying driving variables and actors. According to the findings of this study, Dukem Town is quickly increasing, which has resulted in land use land cover conversion into urban usage for various purposes, mainly residential and industrial applications.

Previous research examined the spatiotemporal trends of urban land use change and its influence on the surrounding community, focusing on the physical and proximal characteristics as the primary driving forces of expansion while ignoring the intensity, kind, and size of urban sprawl. These studies, in particular, entirely neglected the important implications of urban sprawl in worsening the land use land cover dynamic in Dukem Town. Furthermore, all previous studies in Dukem Town have not included spatial measurements in their research. As a result, these researches provided a partial conclusion on urban expansion since the complex urban system and its shape, dimension, landscape structure, and growth pattern can be established using these measurements. Despite the fact that these studies were based on satellite data and employed GIS and RS, no metrics were used to assess and quantify the landscape structure and extent of spreading. These were all predicated on detection of land use change, which is insufficient to provide conclusions about the present complex urban sprawl system. Despite the fact that urban sprawl is a regular phenomenon in all cities, Dukem Town has been growing at a quick rate, spanning a big area in a short period of time and rapidly developing new fragmented patches. As a result, this study was done to fill gaps that were previously overlooked as serious difficulties, and it differs from other studies in terms of approach, study period, and data used.

2.13. Conceptual framework

The study employed the conceptual framework that guides the researcher as a roadmap to examine the spatiotemporal dynamics of urban sprawl and its consequences on land use land cover transformation in Dukem Town. The conceptual framework prioritizes urban expansion dynamics, which can have a direct impact on socioeconomic, biodiversity, and forest ecosystems. As shown in Figure 2-1, the spread of urban sprawl from time to time increases the land use land cover conversion rate dramatically. In addition, the increase of urban sprawl in the study region may result in the loss of agricultural fields. The loss of agricultural lands or a decrease in farmland size will have a substantial impact on the community's life. The livelihood conditions can be manifested by shortage of food items and cost of food items increment which are the recent hinders of the country’s development effort.

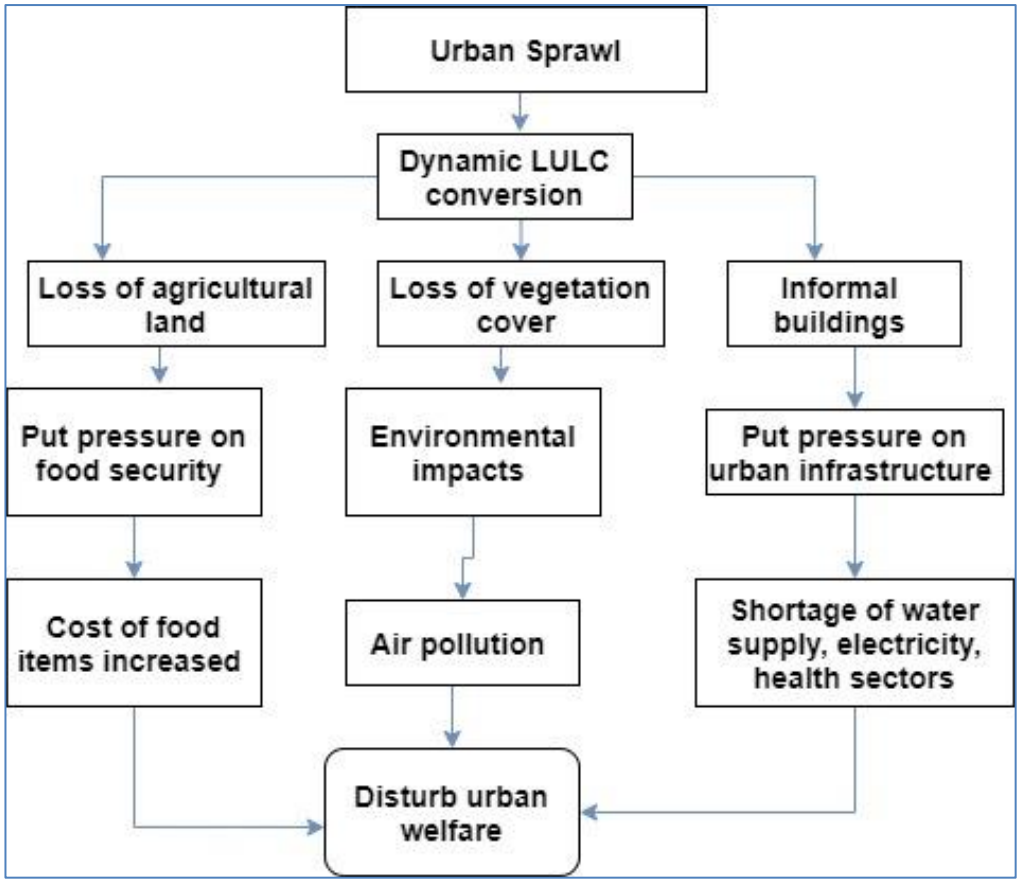

Figure 2-1: Conceptual Framework

The cost of urban sprawl includes not only the loss of agricultural areas, but also the degradation of forest resources for the sake of metropolitan area growth. The most serious concern in today's world, and especially in our nation, is the degradation of ecosystem service value as a result of massive loss of natural resources such as forests. Degradation of forest land resources can cause natural environment disturbances such as air pollution and forest fires, among other things. Furthermore, the rise of urban sprawl leads to an increase in informal construction around cities and Towns. In the instance of Dukem Town, unlawful building development has been prevalent in the last ten years. Illegal building construction can result in the loss of agricultural lands and forest resources, both of which have a direct impact on livelihood circumstances and ecosystem service values. Figure 2-1 provides an overview of the consequences of urban expansion dynamics on land use and land cover changes that have an impact on the Town's welfare. The assumption is that there is a dynamic link between changes in human well-being and urban expansion and other features of land use systems. These connections are depicted in the conceptual framework developed by the author of this study endeavor.

CHAPTER THREE

3. MATERIALS AND METHODS

3.1.Description of the Study Area

3.1.1. Location of the Study Area

Dukem settlement was located 37 kilometers south of Addis Ababa, on the cross-country road leading to Djibouti. The research region is located between latitudes 8°45'25"N and 8°50'30"N, and longitudes 38°51'55"E and 38°56'5" E, encompassing a total area of 9,706.64 hectare. It is situated at a height of 2100 meters above sea level. Dukem is bordered on the east by Bishoftu, the north by Ada'a Woreda, and the south and west by Akaki Woreda. Because of its proximity to Addis Ababa and economic importance, the population is fast increasing. The Town had a population of 25,214 people according to the 2013 National Population and Housing Census (OUPI, 2017).

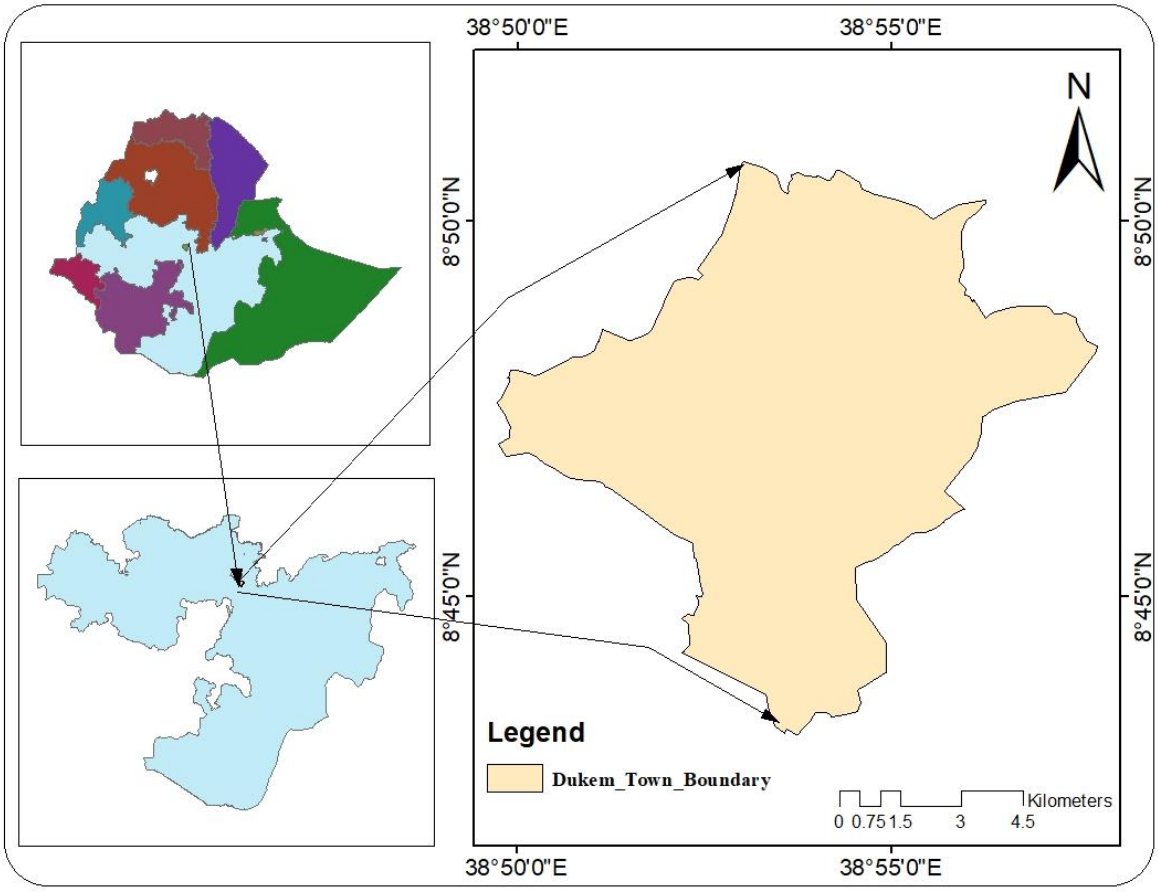

Figure 3-1: Study Area Map of Dukem Town

3.1.2. Physical Characteristic of Study Area

a) Topography

Dukem Town's height ranges from 1890m to 2300m above sea level, with a 410-meter altitudinal range. Rugged topography may be found in the Town's north eastern, northern, and eastern sections (OUPI, 2017).

b) Climate

According to OUPI (2017), the Agro-climatic link between altitude and temperature in Ethiopia shows that Dukem Town's climate is semi-tropical, with temperatures ranging from 150 to 200 degrees Celsius.

c) Slope

Slope analysis is a crucial component in connecting various land uses to a given area's terrain. There are slope classes ranging from 0% to over 20% in the Town. The various slope grades can be found in various locations of Town. The steepest slope class (1-2 percent) is found throughout the Town. It encompasses 2691.6 hectares (63.4 percent) of Dukem's total land area. It includes settlements, commercial activity, and institutions in the southeastern, southern, and central areas of Dukem Town (OUPI, 2017). The slopes of Dukem Town's second greatest slope class range from 5% to 10%. It can be found in several locations throughout the city, particularly in the west. Slope classes ranging from 5% to 10% may also be found in the Town's north-eastern section (OUPI, 2017). The third largest slope class, which covers various areas of Dukem, runs from 0% to 1%. This can be found in abundance in the southwest. Due to the flow direction of Dukam streams from the northeast and flush water from the Eastern Industry Zone, this is the place where floods concentrate (EIZ). Pockets of over 15% slope can be found in the Gimashe upland and the northern parts of Dukem Town. These locations are considered to be one of Dukem's most inaccessible areas. Due to the existence of grass across these areas, they are being used as grazing land. Natural vegetation and eucalyptus trees cover them sparsely (OUPI, 2017)

3.1.3. 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 salty clay soil covers most part of the plain topographic landforms.

Geographic linkage: There is a direct linkage between Bishoftu and Dukem through the highway which radiates from A.A to the Eastern and Southern part of Ethiopia and there is high interaction between of Bishoftu and Dukem Town. Economic linkage: Since Bishoftu is a tourist and also a business center and Dukem is found in a close range to Bishoftu the tourist that go to Bishoftu to tour are serve at Dukem hotels.

3.2.Data types and data source

3.2.1. Satellite data

For this research, Landsat TM, Landsat 7 ETM+, and Landsat 8 OLI/TIRS were freely accessed from the USGS website, and the time interval period of the study was taken into account. The images were collected in December and January since there were no clouds or haze during these months, and the research period lasted from 2000 to 2010. These satellite images were utilized and analyzed to determine urban land use/land cover change in the research region as an indication of sprawl trends. Images obtained during the same approximate annual time range, most likely December and October, were chosen to reduce seasonal vegetation variations and the impacts of shifting sun locations. The availability of multi-temporal data to generate land use/land cover changes is beneficial since it eliminates the issues associated with single-dated land cover information. It also shows the many changes that have happened on the surface of various land-use types. As a result, it is better to identify the dynamism of urban characteristics using several dated data types. However, having multi-date data from the same time of year is difficult, especially in tropical places where cloud cover is widespread (Wilson et al., 2016).

Table 3-1: Satellite image source and type used in this study

Sensor	Path/Row	Special Resolution	Spectral resolution	Year	Source
Landsat TM	168/054	30m	7 bands	2000	www.glovis.gov
Landsat ETM+	168/054	30m	7 bands	2010	www.glovis.gov
Landsat OLI/TIRS	168/054	30m	11 bands	2021	www.glovis.gov

3.2.2. Field data

GPS was used to collect ground data from stratified random sample locations in the field. In this study, 150 ground control points were collected at typical locations for each LULC

class. From 15 February to 20 March 2022, data was collected from Built-up, Barren land, Forest, Green, and Agriculture. The training data was used to generate the LULCC map and to adjust the spectral value for each LULCC class.

3.2.3. Software and tools

Because this study is about detecting urban change and measuring urban sprawl, the software tools ERDAS Imagine 2015, FRAGSTATS 4.2, Zonal Metrics, and ArcGIS 10.8 were mostly utilized for data processing and measuring urban sprawl. ERDAS Imagine is essential software for image preprocessing, enhancement, transformation, classification, and accuracy evaluation. Another notable software application for measuring urban sprawl in geographical measures using identified photos is FRAGSTATS. FRAGSTATS is a new open-source program that produces spatial metrics at a zonal level to quantify urban sprawl in the research region. Other equipment, such as a Garmin GPS 62 and a digital camera, were employed to obtain ground data for assessing the accuracy of categorized photographs.

3.3.Method

3.3.1. Research design

There are several approaches, strategies, and procedures for processing input data in order to provide the needed research output in an effective and adequate manner with the appropriate quality. In fact, the availability of the desired input data, the quality of available information, the strength of logistic support, including the software used, the researcher's experience and skill in manipulating the data, and the necessary funds allocated for the task all influence the choices of general methodology and specific technical arrangements. The availability of information on land use/land cover change, urban sprawl pattern identification, and demographic factors is a necessary necessity for understanding the dynamic phenomena of urban sprawl (Viana et al., 2019).

All downloaded data is processed and projected using the Universal Transverse Mercator (UTM) projection technique. Land use/cover maps were created on ERDAS Imagine 2014 using the Supervised Classification image algorithm. For geographical analysis and the creation of thematic layers, the ArcGIS 10.8.1 software version was also employed. A supervised classification schema was used to investigate built-up change detection, particularly in land use/cover, across a two-decade period (2000 to 2021). The mapping accuracy was assessed using the Error Matrix and the Kappa coefficient technique, and the change matrix was created using ERDAS image 2015.

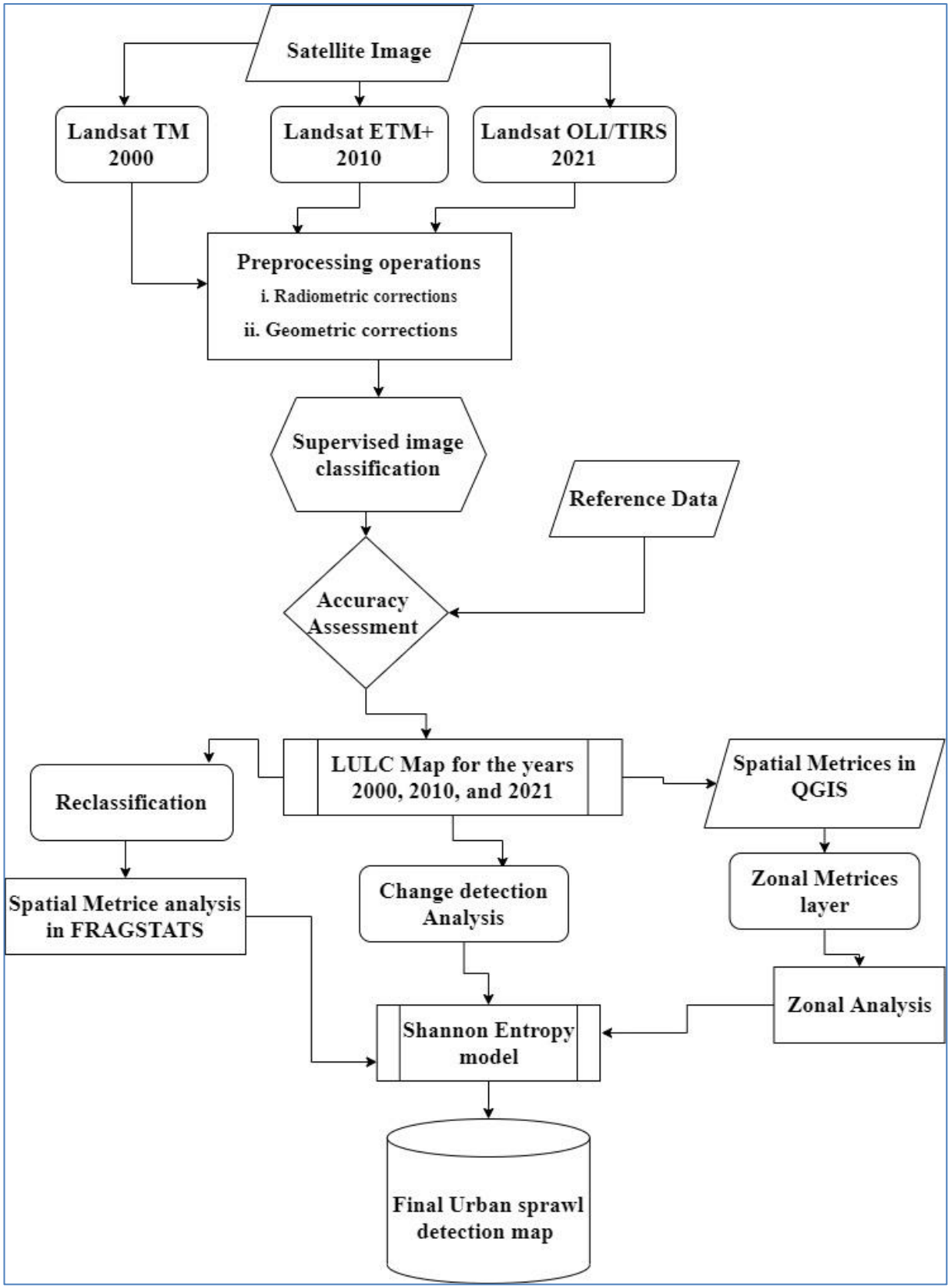

Figure 3-2: Methodological flow chart that depicts the general procedure of analysis

From 2000 to 2021, quantitative areal data on land use/land cover changes, as well as gains and losses in each category, were gathered. A pixel-based comparison was done to create the change information and analyze the changes more effectively. From 2000 to 2021, the matrix displayed the relative gains and losses in the land use/cover category. Field data were collected for two reasons: first, to get GPS data for ground verification of questionable locations, and second, to determine the mapping accuracy of the categorized photos. Using the recode function in the ERDAS Imagine 2015 software, the ground control points were utilized to fix the misclassified regions. A reference dataset of randomly selected 100 points was utilized to test the classification accuracy of all produced outputs.

The classified images provide information on urbanization-induced changes in land use land cover over a two-decade span (2000-2021). Shannon's Entropy was developed using demographic and built-up area information to better comprehend and simulate the urban sprawl dynamics. Shannon's Entropy is commonly utilized to determine the phenomenon of urban sprawl dynamics over time series. High Entropy promotes the emergence of occurrences that contribute to the chaos. The flowchart in Figure 3-2 displays the overall methodological approach employed in this research.

3.3.2. Data analysis method

The collected satellite images were previously geo-referenced and radiometrically adjusted. Image classification was then used to begin image processing inside the administrative boundaries of Dukem Town. Only four classes were chosen based on the scope of the research and visual interpretation of satellite imagery. These were forest land, barren land, agricultural land and built-up area. Based on spectral differences across classes, supervised classification using maximum likelihood was used. The ERDAS IMAGINE 2015 program was used to classify land use and land cover classes. The next stage was to conduct a land cover change detection analysis after defining the land cover classes. Change detection analysis comprised of post classification procedures. Land cover change detection is the process of assessing the spatial and temporal dynamics of a given land use land cover type. This was done through overlying the classified satellite imageries and analyzing by image differencing algorithm in Arc GIS 10.8.1 software. This study employed change detection analysis within ten-year interval. To that aim, the first post classification analysis involves differencing the classified image of 2000 with the classified image of the year 2010. The second post classification analysis was differencing the classified image of 2010 with classified image of 2021. The last post classification analysis was differencing the earlier

classified image of 2000 with the classified image of 2021. This can be done in raster calculator of Arc GIS environment.

Following the spatiotemporal study of land use and land cover, the next stage is statistical layer production and zonal metric analysis. Using the ZonalMetrics Toolbox, this is done primarily to address and assess the direction and location of urban sprawl in the research region. ZonalMetrics toolbox is a new open-source tool created in Python script by Adamczyk and Tiede (2017) that can be incorporated as a toolbox in QGIS. It is an extremely useful Python utility with specific features for computing spatial metrics at the zonal level. The tool computes selected spatial metrics such Class Area (CA), Number of patches per class (NPC), Zone Area (ZA), Percentage of zone (PZ), Total Class Edge (TE), Edge Density (ED) and Shannon Diversity Index (SHDI) indices in FRAGSTATS per specified zones. The following utilities are accessible in the toolbox. The first is that it accepts vector-based category layers created by the user for direct analysis. Second, it offers landscape metrics meant to calculate inside any user-defined zone, such as ordinary gridded zones, administrative zones, and environmental zones. Finally, it offers features to construct particular zones (pies, hexagons) to serve as statistical zones.

As a result, two major layers are required as input for each tool in the toolbox to produce zonal metrics. The first is the input layer, which contains categorical data, such as thematic maps created by image classification, and metrics are calculated exclusively for certain classes. The zonal layer for which the metrics will be calculated is the second. Using the study area map layer as an input, the user may produce hexagonal or pie statistical layers, or they can simply utilize the administrative zones. For this study, the pie statistical zones developed for the study area using ZonalMetrics Toolbox were determined to be more suited for displaying change over time than the hexagonal zones since they radiate from the study area's center. Due to the design of the research area, the pie zones split the study area into zones of similar size and width but varying length. These pie zones are used to examine the change in built-up area over time. To construct zonal metrics for the years 2000, 2010, and 2021, eight pie statistical layers were created. Class area, Number of patches, largest patch index, Landscape Proportion, Patch density, Edge density, Simpson Diversity Index and Shannon Evenness Index were selected to calculate spatial metrices of built-up area over the study region. Based on these spatial metrices analysis, the spatiotemporal distribution of built-up area was investigated with special emphasis on how the built-up is spreading over the study period.

3.3.3. Land Use/Land Cover Description

To facilitate sample collection and classification, land use/land cover nomenclatures must first be created and defined in order to develop and define the various land use/land cover classes. Despite the paper's focus on built-up regions, the land use/land cover map of the research areas was originally constructed using the land use/land cover classifications shown in Table 3-2. The land use/land cover classes used in this research are based on the AFRICOVER categorization method, which is extensively used in East African countries (García-Álvarez, 2022). The researcher adjusted the descriptions of some of the land use/land cover classes for the sake of simplicity, taking into account the study area's land use/land cover variety. As a result, four primary land use/land cover nomenclatures were employed to create the final land use/land cover map of the research area: Built-up areas, agricultural lands, forest land, and barren fields.

Table 3-2: Description of land use land cover classes used in this research work

No.	LULC classes	Description
1	Agricultural lands	Arable areas that are irrigated or rain-fed, cropland with permanent crops, farming, and fallow fields
2	Built-up areas	Residential, industrial, and commercial units, road and railway networks, and other connected areas comprise the continuous and discontinuous urban fabric.
3	Forest lands	Forests, both natural and man-made, grasslands, woodland shrubs, and poorly planted trees
4	Barren lands	All vacant spaces, sands, rocky areas

Source: (García-Álvarez, 2022)

3.3.4. Landsat image preprocessing

As a prerequisite for performing change detection analysis, digital image processing of Landsat images is performed (Abd El-Kawy et al., 2011). It is vital to enhance human understanding of digital pictures. Before the picture data analysis step, procedures such as importing, geometric and atmospheric correction, layer sacking/merging, image enhancement, mosaicking, sub-setting, and sharpening must be completed. Image enhancement is also used to boost an image's brightness. Histogram equalization was used to adjust the image contrast of various brightness levels. Geometric error is created mostly

by the projection system of picture data collected from multiple sensors, and it may be addressed by projecting the image to a common projection system.

3.3.5. Image classification

Image classification is the process of categorizing digital pixel values into several thematic classes (Carneiro et al., 2012). In digital image classification, spectral information of digital numbers in one or more spectral bands was used to try to categorize each element into discrete groups using spectral information. During the image classification process, several spectral signatures were assigned to picture data based on reflectance attributes. The image class's objective was to allocate every pixel in an image to a certain class or theme. Although there are several image data categorization techniques, the two most frequent methodologies for producing LULC maps are supervised and unsupervised methods (Luo et al., 2017). The supervised image classification approach is often used since it delivers more accurate results than the unsupervised method (Rafiei et al, 2017).

A human analyst trains the signature, groups the signatures, and then uses a software algorithm to categorize each signature into distinct themes in supervised image classification. As a consequence, for this investigation, the supervised image classification approach was applied. In this work, a supervised classification using Maximum likelihood classification was performed based on spectral differences across various classes. These distinctions were used to divide the LULC class of the study area into separate classes using a known identity of a specific area in remotely sensed data using a combination of such fieldwork collected data, aerial photography, personal experiences in the site, and questioning of elders who have lived in the area for a long time, as well as a high-resolution Google earth image. When working with low-resolution images, this strategy helps to eliminate mistakes in pixel mixing Landsat images and has a considerable influence on the study's LULC classification accuracy. These approaches were used to develop the LULC thematic layer and picture categorization.

3.3.6. Accuracy assessment

After every satellite image classification analysis, an accuracy evaluation is required to determine whether or not the classification process attained its objectives. The degree of connection between observation and actuality is measured by accuracy (Rwanga, 2017). It refers to determining the level of accuracy of the final categorized map produced by image classification. This may be accomplished by producing a random collection of points and

comparing the picture's land-cover map to that produced in the field, i.e., an image map with reference data (Ayele et al., 2018). According to Rwanga (2017), existing maps, large-scale aerial photos/images, and field inspections can be used to collect reference data for accuracy evaluation. The most often used techniques of assessing accuracy include producer's accuracy, user's accuracy, overall accuracy, and the Kappa coefficient (Rwanga, 2017). All of these strategies are used to evaluate categorization activity performance over all years.

Producer Accuracy: quantifies the percentage of properly categorized pixels in a sample data set or, more indirectly, identifies mistakes of omission for a certain class. It is derived by dividing the total number of samples in the reference data or column by the number of correctly categorized locations.

$$Producers\ accuracy = \left(\frac{Ci}{Ct}\right) * 100 \qquad \text{Equation (3-1)}$$

Where Ci is the number of properly categorized sample sites in the reference data or column, and Ct denotes the total number of sample locations in the column.

User Accuracy: evaluates the likelihood of each category listed on the map being represented on the ground. It alludes to a mistake of commission in a certain category. Users' accuracy can be calculated as;

$$Users\ accuracy = \left(\frac{Ri}{Rt}\right) * 100 \qquad \text{Equation (3-2)}$$

Where Ri denotes the number of correctly identified samples in the row and Rt is the total number of samples in the row.

Overall Accuracy: also known as Percent Correctly Classified (PCC), this statistic simply reflects the overall accuracy of the data and is computed as the sum of the diagonal divided by the total number of samples (n).

$$Overall\ Accuracy = \left(\frac{Sd}{n}\right) * 100 \qquad \text{Equation (3-3)}$$

Where Sd is the sum of the values along the diagonal and n is the total number of samples.

Kappa Statistics: Kappa statistics is another measure of accuracy evaluation that provides a more accurate estimate than overall accuracy since it can regulate the PCC index and utilizes off-diagonal data to construct the coefficients. Kappa coefficient scores that are less than one suggests great agreement between the categorized map and reference data. ERDAS

Imagine 2015 evaluated the accuracy of identified images from all years- 2000, 2010, and 2021. The categorization for the years 2000, 2010, and 2021 is assessed by randomly picking 150 points from their respective images.

3.3.7. Reclassification

In FRAGSTATS, this is a technique for measuring urban sprawl using a spatial metric system. In the ArcGIS spatial analyst tool, the class values of categorical maps must be reclassified as positive integers and the background value as negative integers. This is especially significant when using FRAGSTATS to construct spatial metric indices of built-up area. Because FRAGSTATS computes the background cells with the focused classes until we alter the background class value to a negative integer, the outcome is completely different. To put it another way, FRAGSTATS considers cells with positive class values to be inside and cells with negative class values to be outside. The newly classified maps were fed into FRAGSTATS to create spatial metric indices.

3.3.8. Spatial metrics

Zonal Metrics: These are spatial metrics that are used to determine certain numerical indices at the zonal level. They are new spatial measures in 'The Zonal Metrics Python Toolbox,' a new open-source program developed by Adamczyk and Tiede (2017) with specific functionality for generating landscape metrics at the zone level. The source code is free and available to the public, and it may be altered using ArcGIS 10.2 or later. The research region is split into user-specified zones in zonal metrics, and statistics are produced per zone.

Patches: are surface regions that differ from their surroundings in nature or appearance (Coulson, 2010) and are one of the primary elements that comprise a landscape as well as the building blocks of spatial metric computation. Patches must be defined in reference to the topic under study. Patches, regardless of size, are discrete built-up area polygons surrounded by non-built-up settings such as agricultural, open spaces, or green regions in this research.

Patch Level Metrics: These are spatial metrics that compute the spatial character and context of individual patches. Class and landscape metrics are built on patch-level data. They are statistics that describe certain patches. Patch level metrics describe the area, perimeter, form, core area, and other characteristics of patches in the landscape.

Class Level Metrics: These are metrics or statistics produced for total patches of a certain class and are fragmentation indices for the class under consideration (McGarigal, 2015). Patch measurements are used with averaging or weighted average to produce class metrics. They quantify the number and geographical layout of built-up patches in the urban environment, revealing the breadth and fragmentation of each built-up patch. For this study, class-level metrics relate to spatial indices produced for the built-up class, and the majority of the metrics chosen fall into this category for the simple reason that the study's main emphasis is the fragmentation and sprawl of built-up territory.

Landscape Level Metrics: These are spatial metrics that are calculated to characterize the entire landscape or all classes in the landscape. They illustrate the landscape's spatial layout. Landscape-level metrics quantify the spatial connection of landscape patches, i.e., spatial composition and configuration (Coulson, 2010). Landscape metrics, according to Frank et al., (2012), are divided into two types: those that measure landscape composition and those that quantify landscape layout.

Landscape composition: refers to the quantity or percentage of patch kinds of classes, including patch richness (number of classes), patch evenness (abundance of classes), and patch variety, but does not include patch spatial features (Lausch et al., 2015).

Landscape Configuration: refers to the spatial properties of patches, such as their organization, location, or orientation within a class or landscape (McGarigal, 2015). Patch and edge size, form complexity, core area, aggregation index, and other configuration metrics are examples.

3.3.9. Dynamics of urban sprawl Measurement Using Shannon's Entropy model

Many attempts have been made to measure sprawl dynamics (Nazarnia et al., 2019). One of the most commonly used approaches, in most urban sprawl studies, is to integrate Shannon's Entropy with GIS tools. This is a relatively straightforward and efficient approach to analyzing urban sprawl dynamics. Shannon's entropy is used to measure the degree of spatial concentration and dispersion of urban sprawl, defined by geographical variables (Ozturk,2017). The entropy value varies from 0 to 1. A minimum value of 0 is obtained if the distribution is maximally concentrated in one region while an evenly dispersed distribution across space gives a maximum value of 1. The dispersion of built-up areas from a city center or road network leads to an increase in the entropy value. This gives a clear

idea to recognize whether land development is more dispersed or compact. Shannon's entropy (En) is given by;

$$En = \sum_{i}^{n} pilog(\frac{1}{pi}) / \log(n) \quad \text{Equation (3-4)}$$

Where;

$Pi = Xi / \sum_{i}^{n} Xi$ and *xi* is the density of land development, which equals the amount of built-up land divided by the total amount of land in the *i*th zone in the total zone of *n* zones.

3.3.10. Types of urban growth

To classify the types of urban growth in Dukem Town, the study used the method of literature review and based on the framework of (Duong et al., 2018). A metric T was defined for calculating the ration between the length of common edge of newly developed urban patches and existing urban patches as:

$$T = \frac{L3}{P2} \quad \text{Equation (3-5)}$$

Where; L3 is the total length of edge for the existing urban patch and P2 is the perimeter of newly developed urban patch.

The value of T is between 0 and 1. If T > 0.5, it means that at least 50% of the new urban patches is surrounded by the old urban square, and it represents the infilling type; if T is between 0.3 and 0.4 the new urban patches develop from the edge of the old urban covers, and the common length is less than 50% of its frontier. This type is edge expansion or shrinkage (Basudeb, 2010); if T is between 0 and 0.3, it means that the new urban areas have no spatial association with the old urban patches, and this is outlying type with outlying urban growth further separated into isolated, linear branch, and clustered branch growth (Sun et al., 2011). The distance to existing developed areas is important when determining what kind of urban growth has occurred (Basudeb, 2010).

Table 3-3: Categories of urban growth based on Metric T values

Metric T value	Types of urban growth
T >= 0.5	Infilling type
0.3 <= T <= 0.4	Edge expansion
0 <= T <= 0.3	Outlying

CHAPTER FOUR

4. RESULT AND DISCUSSION

4.1. Results

4.1.1. Land use land cover in 2000

Agricultural land, Built-up, Barren land, and forest were the principal land use land cover types in 2000. As shown in the table, agricultural land accounts for the biggest proportion of all categorized land use land cover covering an area of 8237.34 hectares and contributing 84.72 percent. The study region is well-known for its surplus production during the year 2000 and that is why agricultural land use is the dominant land cover in the area. On the other side barren land is the least proportion of all categorized land use land cover covering an area of 11.97 hectares and contributing 0.12 percent. The area covered by forest and built-up is 618.84 hectares (6.36 percent) and 855.27 hectares (8.80 percent), respectively. The Town has the smallest area coverage in the year 2000 compared to the overall size of the study area. The primary reason for a limited percentage of Towns is because urbanization was not increased as much as another land cover in 2000. In 2000, the forest cover was well dense, accounting for 6.36% of the total area of other land use land cover classifications. This is owing to the fact that deforestation was supposed to be quite low in 2000, and the population was not as densely packed as it is now.

Table 4-1: Area and percentage of land use land cover classes in the year 2000

LULC Class	Area (Ha)	Percent
Agricultural land	8237.34	84.72
Built-up	855.27	8.80
Forest	618.84	6.36
Barren lands	11.97	0.12

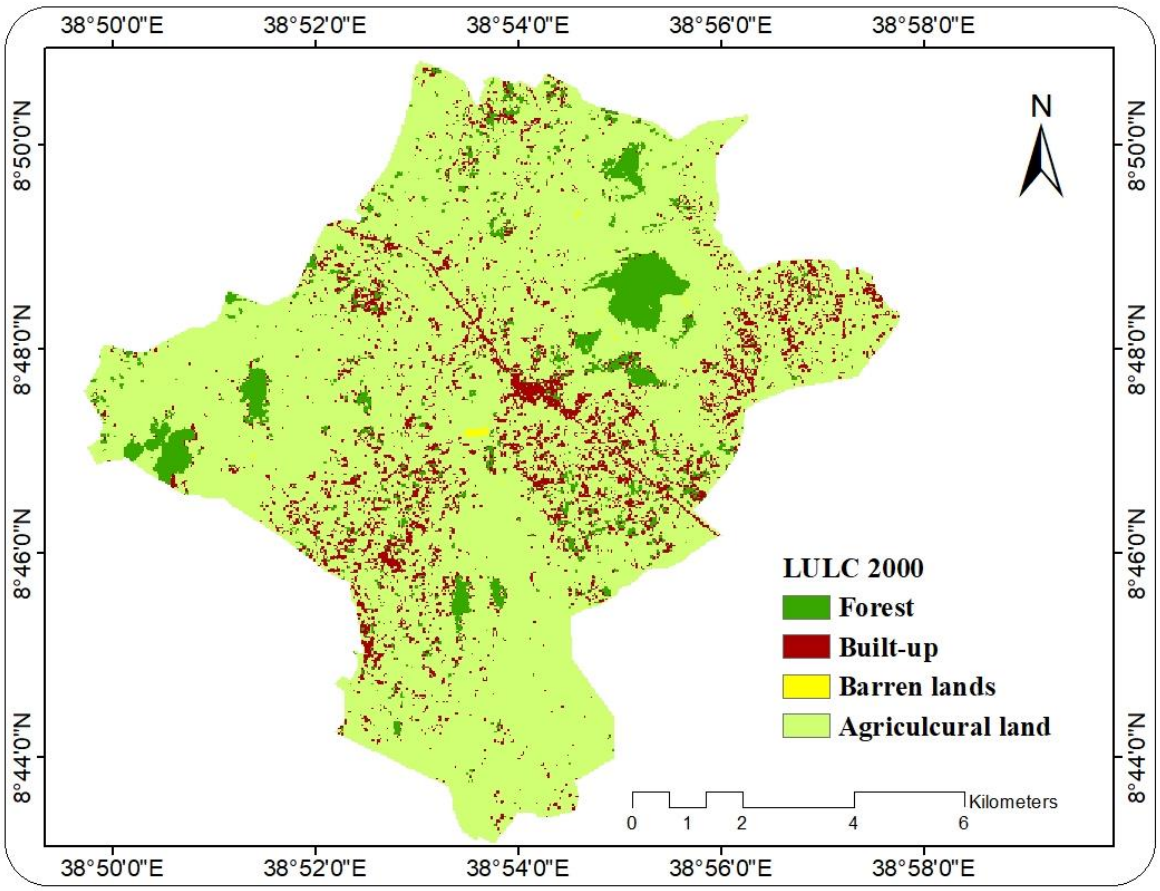

Figure 4-1: Land use land cover map of 2000

4.1.2. Land use land cover classes of the year 2010

As seen in the table, agricultural land accounts for the biggest proportion of all categorized land use land cover, covering an area of 7057.71 hectares (72.58 percent). The built-up has been expanding since 2000, with an area covering 1558.62 hectares in the year 2010. It has been doubled by half percentage from 855.27 hectares to 1558.62 hectares between the years 2000 and 2010. The incremental patterns of the built-up in the study area demonstrate that urbanization has been much introduced in the year 2010 and industries began to expand in the southern part of the study region. Barren land and forest land represent 661.05 hectares (6.80 percent) and 446.04 hectares (4.59 percent) of the total land area. The forest area coverage decreased by 1.77 percent from the year 2000 because much of the forest was identified in the mountain and delineated as a protected area. The built-up area shows an incremental trend from the year 2000 to 2010 with an area coverage of 1558.62 hectares (16.03 percent) and makes the second-largest land cover next to agricultural land. The primary cause for the increase in built-up area coverage between 2000 and 2010 is that urbanization occurred significantly more in 2010 than in 2000.

Table 4-2: Area and percentage of land use land cover classes in the year 2010

LULC Class	Area (Ha)	Percent
Agricultural lands	7057.71	72.58
Built-up	1558.62	16.03
Barren lands	661.05	6.80
Forest	446.04	4.59

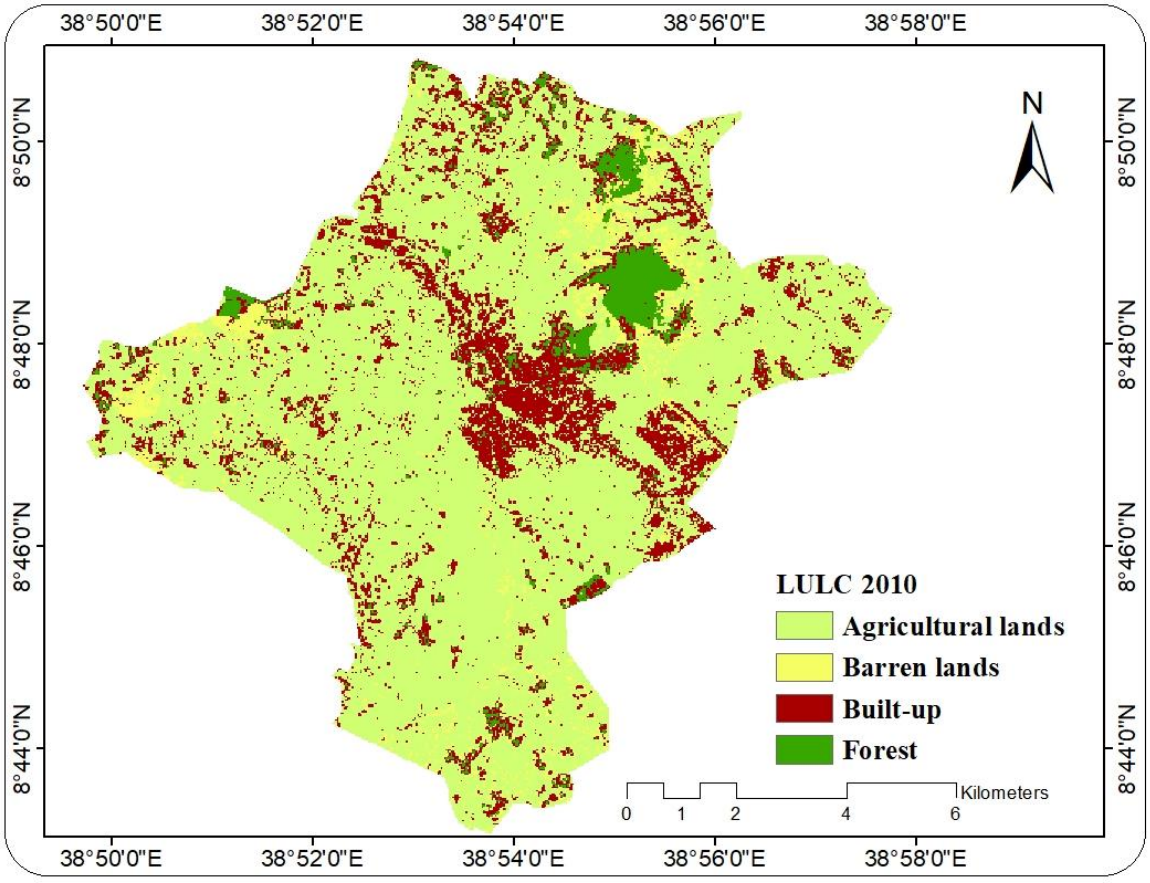

Figure 4-2: Land use land cover map of 2010

4.1.3. Land use land cover classes of the year 2021

Agriculture also has the biggest coverage in the study area's 2021 LULC classification, relative to the other classes. It occupied 5872.61 hectares (60.40%), followed by built-up, barren land, and forest, which occupied 3130.99 hectares (32.20%), 361.71 hectares (3.72%), and 358.11 hectares (3.68%), respectively. When compared to the other LULC classes, barren terrain and forest had the lowest coverage in the research region in 2021. It is apparent that the built-up area has risen considerably since 2021. The built-up area has

more than doubled by a half percentage point, from 16.03 percent in 2010 to 32.20 percent in 2021. It is clear that the built-up area coverage has been increasing incrementally throughout the previous two decades, from 2000 to 2021. In that regard, the built-up area coverages in 2000, 2010, and 2021 were 855.27 hectares, 1558.62 hectares, and 3130.99 hectares, respectively. In addition, forest land area coverage has fallen from 446.04 hectares in 2010 to 358.11 hectares in 2021. This is because forest land has been converted to other land cover groups, primarily agricultural and built-up areas.

Table 4-3: Area and percentage of land use land cover classes in the year 2021

Class Name	Area (Ha)	Percent
Agricultural land	5872.61	60.40
Built-up	3130.99	32.20
Barren land	361.71	3.72
Forest	358.11	3.68

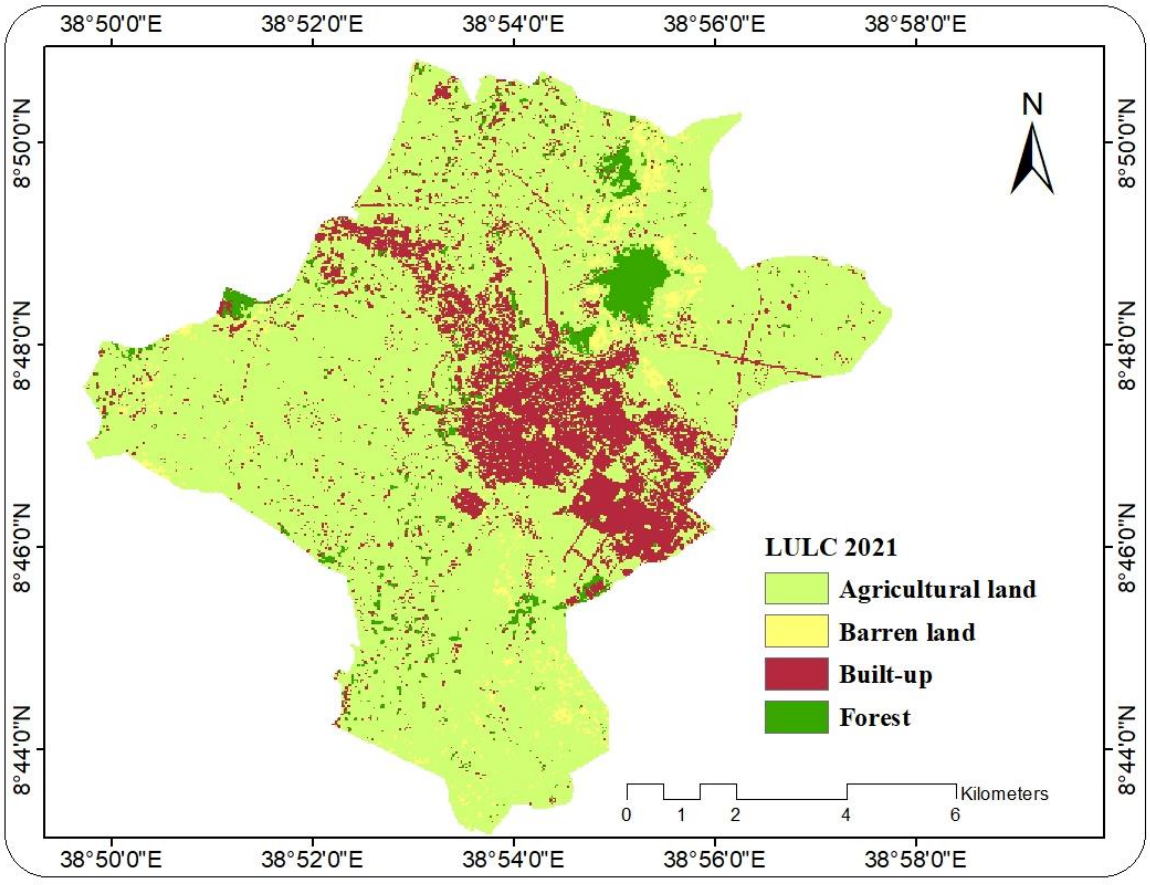

Figure 4-3: Land use land cover map of 2021

4.1.4. Change detection matrix between 2000 and 2010

The change detection table below shows change matrices that show what has been modified. The table's first row represents the starting stage of LULC classes in 2000, while the column represents the final stage of LULC classes in 2010. The table's diagonal values demonstrated that the values in both times images are the same. The class change, unlike the diagonal values, indicates the total modified image areas of each LULC in the initial phases. While the column's class value depicts the final stage image area of each LULC class, the row depicts the starting stage image area of land use land cover classes. The changing area of the agricultural area towards the built-up area is the highest in the change detection matrix, with 1213.06 hectares in the study area, as shown in (Table 4-4). Forest land was also converted to agricultural land, barren land, and built between 2000 and 2010, covering an area of 264.81, 15.05, and 97.99 hectares, respectively. Furthermore, barren land was also converted to agricultural land, forest, and built-up between 2000 and 2010, covering an area of 5.65, 0.24, and 3.90 hectares, respectively.

Table 4-4: Change detection matrix between 2000 and 2010

		LULC classes of 2010				
		Agriculture	Barren lands	Forest	Built-up	Grand Total
LULC classes of 2000	Agriculture	6345.71	589.28	200.68	1213.06	8348.73
	Barren lands	5.65	0.33	0.24	3.90	10.12
	Forest	264.81	15.05	217.33	97.99	595.19
	Built-up	546.45	5.82	18.43	181.91	752.61
	Grand Total	7162.62	610.48	436.68	1496.86	9706.64

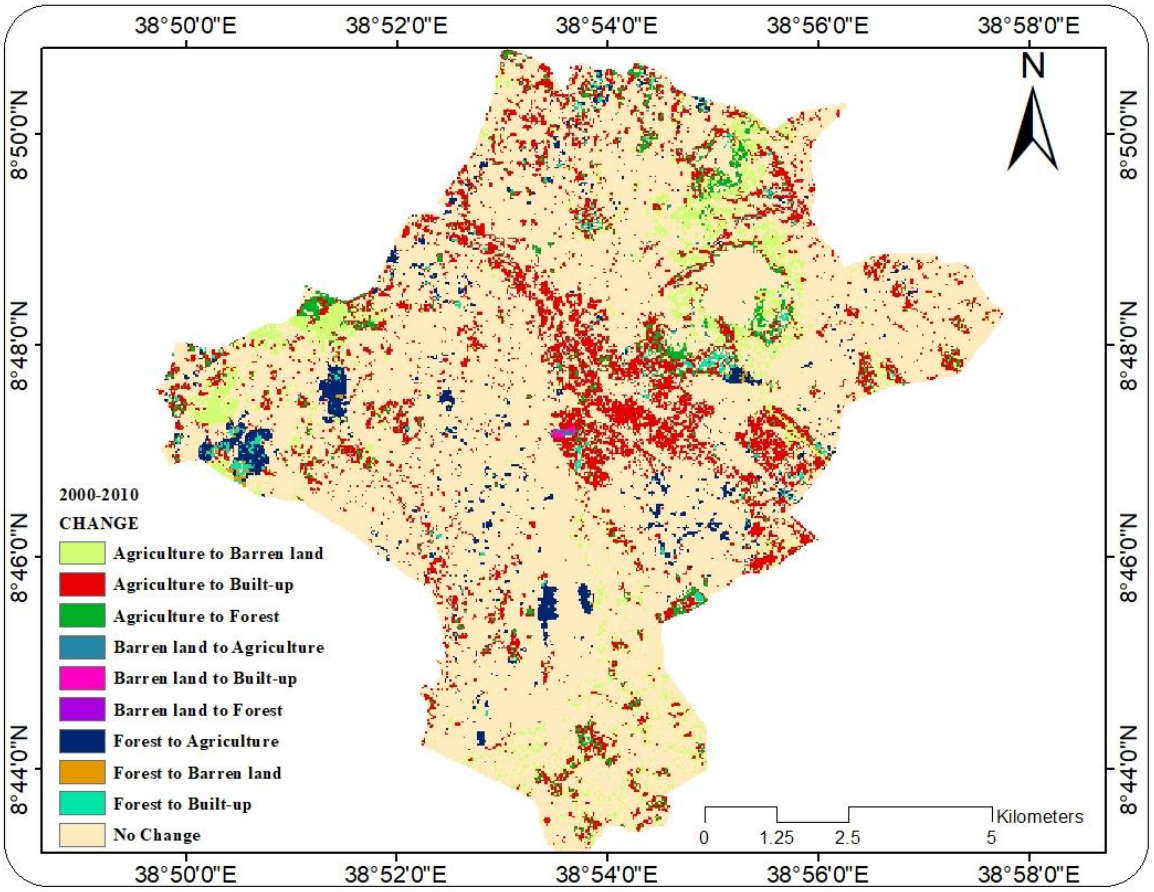

Figure 4-4: Change detection map between 2000 to 2010

4.1.5. Change detection matrix between 2010 and 2021

Between 2010 and 2021, the conversion of agricultural land to built-up land was picked as the highest land-use conversion rate. Between 2010 and 2021, huge areas of rural land were turned into built-up areas as a result of industrial growth. 787.87 hectares of agricultural land were turned into built-up areas at ten-year intervals. Furthermore, agricultural land was changed to other land use land cover classifications. It is clear that 180.91 hectares of agricultural land and 89.02 hectares of forest land were converted, respectively. Conversion of barren areas to agriculture, on the other hand, was the second-highest conversion rate between 2010 and 2021. Within ten-year intervals, 437.35 hectares of barren soils were transformed into agriculture. This is because agricultural growth is the most significant factor influencing deforestation and land degradation in the Dukem Town study region. Furthermore, between 2010 and 2021, a large amount of forest land was converted to cultivation. Approximately 176.39 hectares of forest land were degraded and converted to agricultural land. A little amount of forest land was also turned to barren ground and built up with 3.03 and 45.27 hectares, respectively. From this perspective, the conversion of

agricultural land to built-up land had the highest conversion rate between 2010 and 2021. This demonstrated that urban growth was mostly enhanced at ten-year intervals. The presence of urban growth is critical in evaluating the extent of urban sprawl in the studied region.

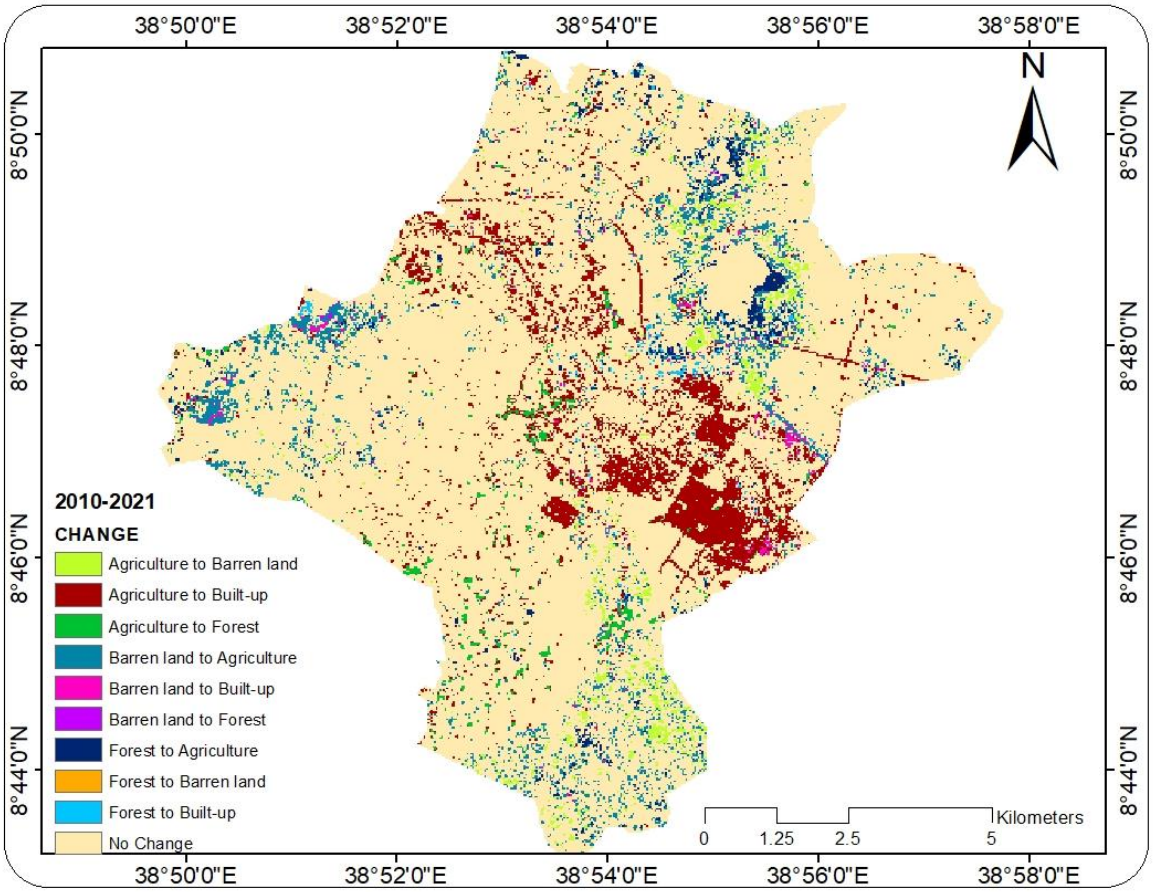

Figure 4-5: Change detection matrix between the years 2010 to 2021

Table 4-5: Change detection matrix between 2010 and 2021

		LULC classes of the year 2021				
		Agriculture	Barren land	Forest	Built-up	Grand Total
LULC classes of 2010	Agriculture	6105.16	180.91	89.02	787.87	7162.96
	Barren lands	437.35	126.90	5.14	41.06	610.45
	Forest	176.39	3.03	212.39	45.27	437.07
	Built-up	48.78	11.27	36.21	600.74	697.00
	Grand Total	6767.68	322.10	342.76	1474.94	9706.64

4.1.6. Change detection matrix between 2000 and 2021

The change detection matrix indicates that the trends of LULC over the last twenty-one years were very dynamic. Some land-use classes were converted to the other land cover classes in an abnormal way and this is the reason that the conversion was said to be devastating. To that extent, agricultural land experienced a high conversion rate towards each land use land cover class namely into the built-up, forest, and barren lands. Subsequently, agricultural land was converted to built-up, forest, and barren lands with an area of 1161.58, 156.38, and 307.01 hectares respectively. From this conversion rate agricultural land to built-up was said to be very high and it accounts for 1161.58 hectares. Within the last 21 years, urbanization has proven some incremental trends. To that end, agricultural land was raised for urban development and 1161.58 hectares of land was converted from agriculture to built-up. On the other side, a significant number of forests were degraded and converted into agricultural lands. Thus, forest land cover was converted to agricultural land with 330.92 hectares in the last twenty-one years. Furthermore, some areas of forest land and barren lands were converted into the built-up area. Thus, 83.97, and 5.74 hectares of forest land and barren lands respectively were converted into built-up areas over the last 21 years. This shows that urban expansion within the last 21 years was clearly seen by degrading the forest land, barren lands, and Agricultural lands over the study region.

Table 4-6:- Change detection matrix between the years 2000 to 2021

		LULC classes of 2021				
		Agriculture	Barren land	Forest	Built-up	Grand Total
LULC classes of 2000	Agriculture	6725.56	307.01	156.38	1161.58	8350.53
	Barren lands	2.82	1.50	0.06	5.74	10.12
	Forest	330.92	10.55	170.04	83.97	595.49
	Built-up	510.16	2.82	15.89	223.59	752.46
	Grand Total	7569.46	321.88	342.36	1474.88	9706.64

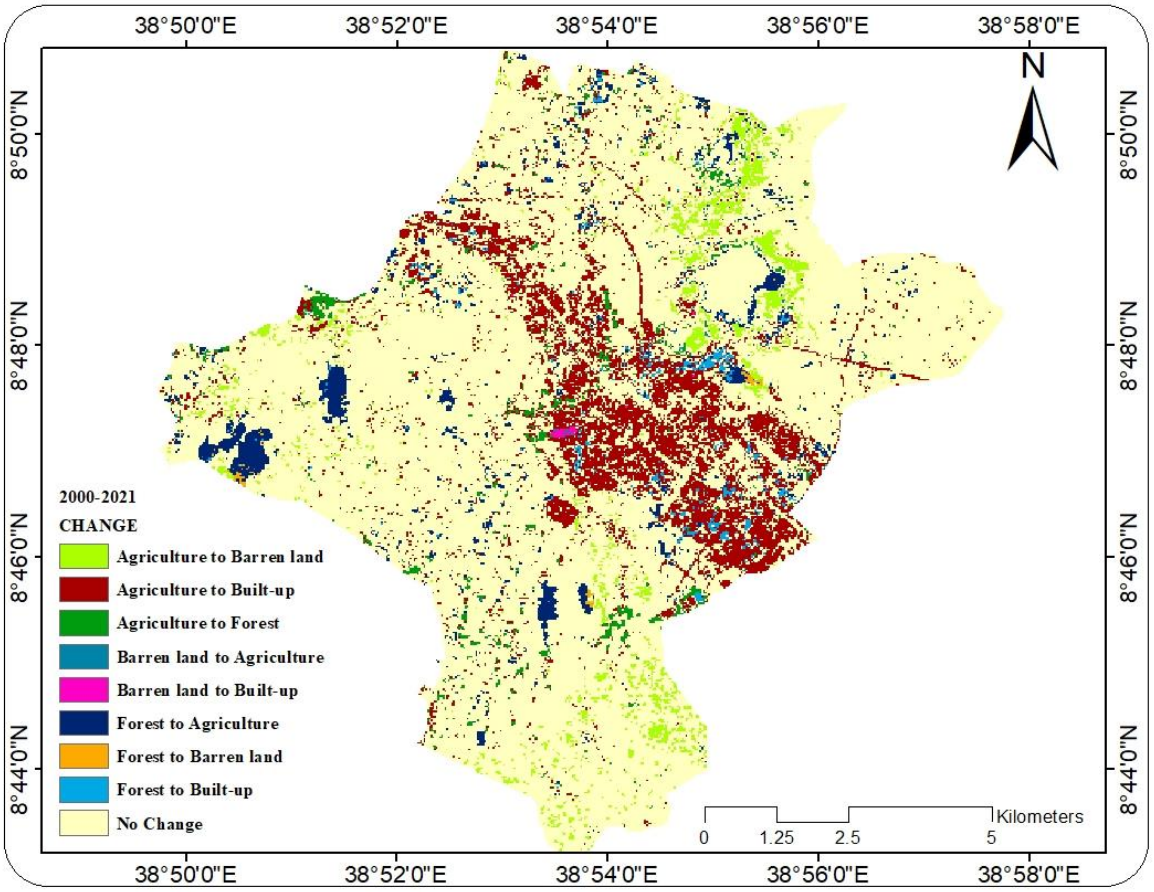

Figure 4-6: Change detection map between the years 2000 to 2021

4.1.7. Accuracy assessment

Land-use and land-cover accuracy assessments for 2000, 2010, and 2021 years were produced. The results of the classification revealed that the ground verification points coincide with a classified image with an overall classification accuracy of 80%, 83.33%, and 87.50% for the years 2000, 2010, and 2021, respectively. The overall land-use and land-cover classification Kappa statistics for the study periods were 0.76, 0.80, and 0.85 for the years 2000, 2010, and 2021 respectively. According to the literature, a result value of more than 70% overall accuracy is considered appropriate for classification accuracy. A kappa statistic value of greater than 0.75 suggests excellent or very good agreement, but a range of 0.40 to 0.75 indicates fair or better accuracy, and a value of less than 0.4 indicates poor correlation. Table 4-7 shows the complete information on overall image classification, kappa statistics, producers, and users' accuracy.

Table 4-7:Statistical information of accuracy assessment for the years 2000, 2010 and 2021

	2000		2010		2021	
Class Name	Producers accuracy	Users accuracy	Producers accuracy	Users accuracy	Producers accuracy	Users accuracy
Agricultural land	75.56%	85.00%	80.49%	82.50%	81.82%	90.00%
Forest	54.55%	80.00%	62.50%	100.00%	72.73%	80.00%
Built-up	74.42%	80.00%	96.77%	75.00%	94.74%	90.00%
Barren lands	96.43%	77.00%	93.55%	72.50%	89.74%	87.50%
Overall	80.00%		83.33%		87.50%	
Kappa statistics	0.76		0.80		0.85	

4.1.8. Spatial metrices analysis to assess urban sprawl dynamics from 2000 to 2021

To quantify urban sprawl over the study region of Dukem Town, different spatial metric indices were calculated from the classified image of the three decades. Spatial metrics method is a new way of measuring urban sprawl from categorical maps. To calculate the landscape metric indices from the classified image, the classified image has to be categorized into different zones. A Python toolbox of ZonalMatrice in ArcGIS was applied for the calculation of zonal landscape metrics. Accordingly, the classifeied image was catagorized into eight (8) zones so as to take advantges for data analysis easly (Figure 4-7). After generating landscape zones for the classified image for the years 2000, 2010, and 2021, QGIS was employed to create spatial metrices. LecoS plugin tool was used to create spatial metrice. LecoS tool contains several analytical functions for land scape analysis which is taken from statistical software. The tool computes several spatial indices from categorical maps and produce the output in comma delimited (CSV) file format. QGIS calculates distance metrics in meters and area metrics in hectares the units were converted into the desired unites. Selected built-up area indices obtained after QGIS analysis and the results were analyzed in detail in the next portion. Spatial metrics in general whether patch, class or landscape fall into two main categories: those that measure composition and those that measure configuration of the categorical map (Meeli, 2013; McGarigal, 2015). Therefore, the results of spatial indices obtained from QGIS are interpreted based on these categories.

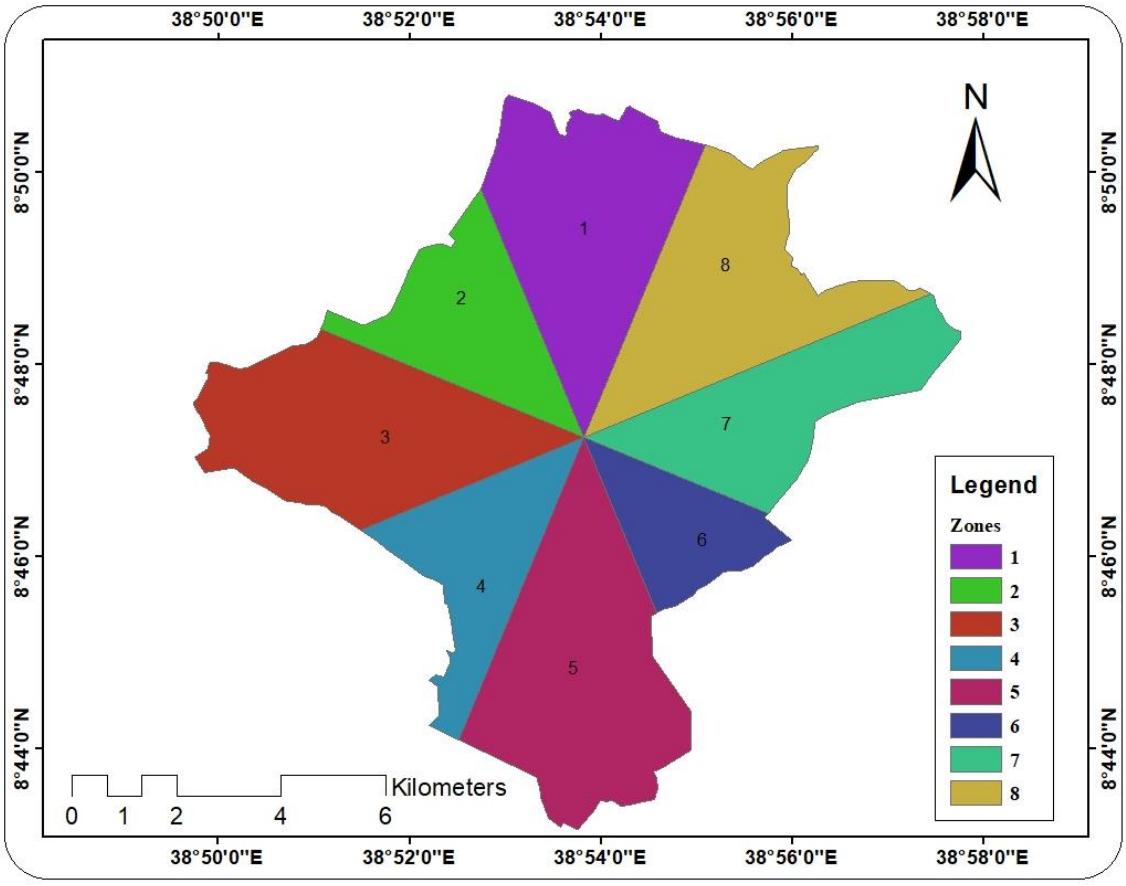

Figure 4-7: Pie Spatial matrices zones created using ZonalMatrice tool

Table 4-8: Class metrices of built-up area for the years 2000, 2010, and 2021

	Class Metrices					
Years	LP	CA	ED	NP	PD	LPI
2000	0.34	858.60	0.0647	2158	0.0002	8.69
2010	0.55	1241.56	0.0746	1898	0.0002	35.02
2021	0.64	1828.79	0.0602	1722	0.0001	96.47

4.1.8.1.Class Area

Class Area is the total of the areas of all patches of the same kind. The QGIS LecoS plugin tool computes the class area using the map unit of meter. For the purposes of analysis, the metric unit is divided by 10,000 to yield the hectare. Class area is a metric of landscape composition that specifies how much of the landscape is made up of a given patch type. Class area is employed in the calculations for various class and landscape metrics, including

landscape percentage and biggest patch index, in addition to its direct interpretative value. CA is a number between zero and infinity, and as CA approaches zero, the patch type becomes increasingly rare in the landscape. CA equals Total Area when the entire landscape is made up of a single patch type, i.e., when the entire picture is made up of a single patch. Table 4-8 shows the CA area of the study region with the unit hectare. The CA of built-up area in 2000 was 858.60 hectare, as shown in the table. This suggests that the built-up area has a CA of 858.60 hectare in comparison to other land cover patches. After 10 years, the CA of built-up area has expanded drastically from 858.60 to 1241.56 hectare. Between 2000 and 2010, urban sprawl dynamics in the study region was quite strong, with the core section of the Town being heavily occupied by the CA of built-up area.

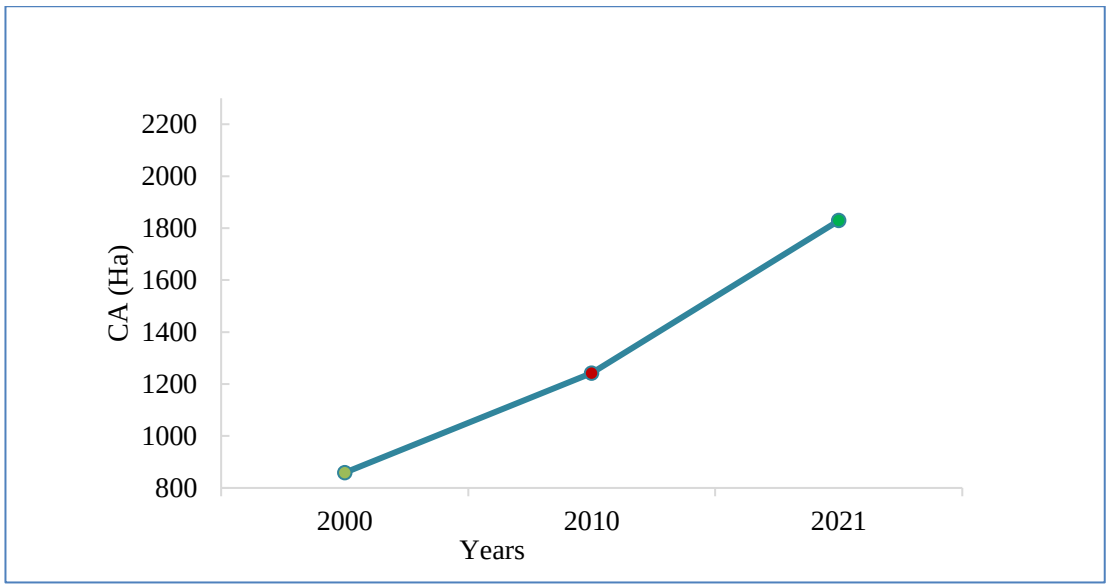

Figure 4-8: Class Area of built-up for the respective two decades (2000, 2010, and 2021)

It is stated that urban spawl will rise when the CA increases over a specific time period. Subsequently, between 2010 and 2021, the CA of built-up area increased from 1241.56 hectares to 1828 hectares. According to literatures, the growing and increasing patterns of CA are the main indicators of urban sprawl dynamics.

4.1.8.2.Largest Patch Index

LPI is calculated by dividing the area of the largest patch of the appropriate patch type by the overall landscape area and multiplying it by 100 (to convert to a percentage). LPI is the proportion of the landscape that is covered by the biggest patch. The Patch Index ranges from zero to one hundred (0-100). When the biggest patch of the appropriate patch type becomes increasingly tiny, LPI approaches zero. When the whole landscape consists of a

single patch of the relevant patch type, LPI goes to 100; that is when the biggest patch accounts for 100 percent of the landscape. At the class level, the biggest patch index estimates the percentage of total landscape area occupied by the largest patch. As such, it is a straightforward indicator of dominance. In the year 2000, the Largest Patch Index of built-up area was 8.69 percent, as shown in Table 4-8. This means that built-up areas account for about 8.69% of the dominance of all equivalent landscape patches in the research region. Within a ten-year period, the Largest Patch Index grew to 35.02 percent in 2010.

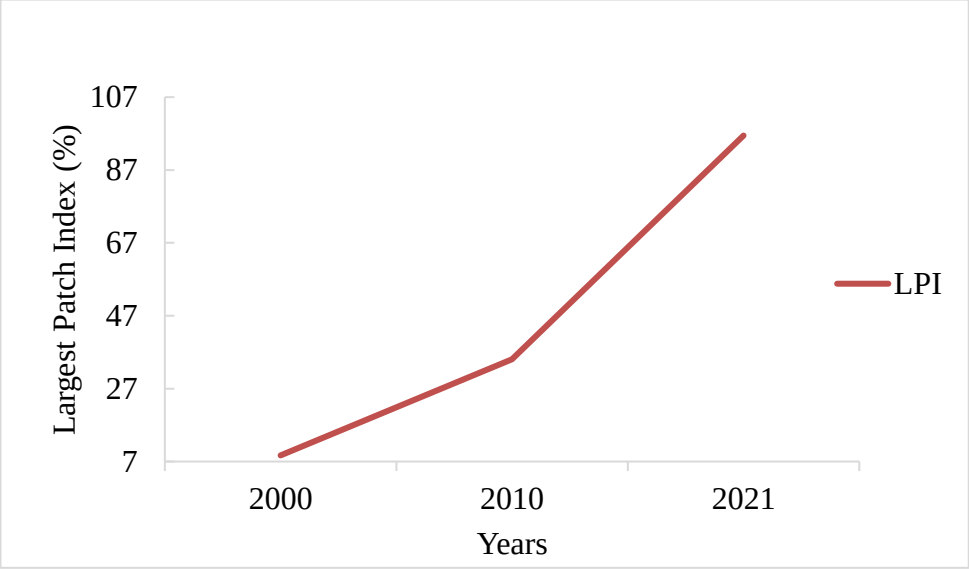

Figure 4-9: Largest Patch Index values of built-up area for the years 2000, 2010, and 2021

The increase in Largest Patch Index values showed that built-up area dominates in comparison to the previous year of 2000. Simultaneously, from 2010 to 2021, the built-up area's Largest Patch Index values climbed considerably. It was raised from 35.02 percent to 96.47 percent. The class dominance of a certain patch increased as the number of the Largest Patch Index climbed. Thus, the class domination of built-up regions has expanded dramatically during the previous 21 years. The dominance of built-up regions during the previous 21 years demonstrated that urban sprawl is extremely persistent in the studied area.

4.1.8.3.Landscape Proportion

Landscape Proportion (LP) is the sum of the areas (hectares) of all patches of the same patch type divided by the total landscape area (hectares) multiplied by 100 (to convert to a percentage). Landscape Proportion (LP) is the proportion of the landscape that is made up of the matching patch type. The proportionate abundance of each patch type in the landscape is quantified by the percentage of the landscape. It, like total class area, is a metric of landscape composition that is useful in quantifying urban sprawl. However, because

Landscape Proportion is a relative metric, it may be a better indicator of landscape composition than class area when comparing landscapes of different sizes. The analysis of matrices indicated that the composition of the built-up area increased from 2000 to 2021. In that regard, the Landscape Proportion in 2000 was 34%. As a result, the built-up area accounted for 34% of the total patch area. Between 2000 and 2010, the built-up area composition expanded to 55 percent, representing a 21 percent incremental tendency.

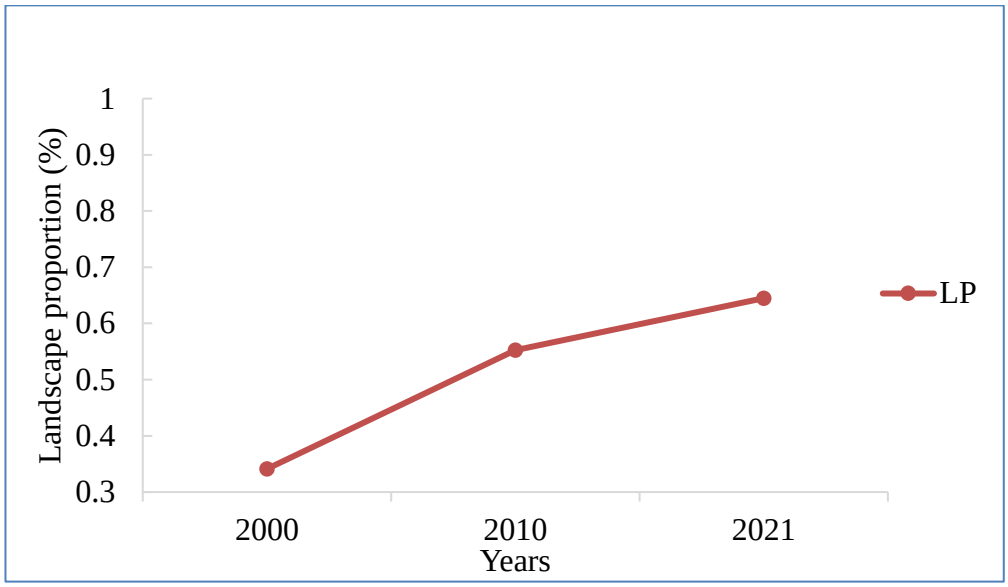

Figure 4-10: Landscape Proportion (LP) of the built-up area between the years 2000, 2010, and 2021

According to this perspective, urban sprawl circumstances between 2000 and 2010 were noteworthy since the makeup of built-up regions changed considerably. Between 2010 and 2021, the built-up area's composition increased to 64 percent. However, the composition of built-up area is significantly lower than in prior years (2000-2010). Between 2010 and 2021, the built-up area expanded by only 9%. This demonstrates that the urban sprawl condition persisted between 2000 and 2010.

4.1.8.4.Edge Density

Edge Density (ED) is another spatial configuration statistic that quantifies the density of all built-up class edge segments (m) per hectare. ED is related to landscape fragmentation, and ED grows when a landscape is fragmented into smaller parts. According to this study, ED increased significantly from 647.15 per hectare in 2000 to 746.74 per hectare in 2010, an almost 5% rise indicating urban area fragmentation. One of the finest geographical indicators for characterizing urban spread in a terrain under examination is the growing degree of ED. Figure 4-11 demonstrates that ED increased the most in 2010, coinciding with the largest number of patches in the same year. However, the number of ED admissions fell

by 7% between 2010 and 2021. This demonstrates that the fragmentation of built-up regions has lessened, and the urban sprawl dynamics between these years has been described as low in comparison to earlier years. The aggregate evidence demonstrated that the study region has seen significant urban sprawl dynamics during the previous 21 years. The indices shown on the line graph below (Figure 4-11) indicate the presence of intermediate urban sprawl in the research area.

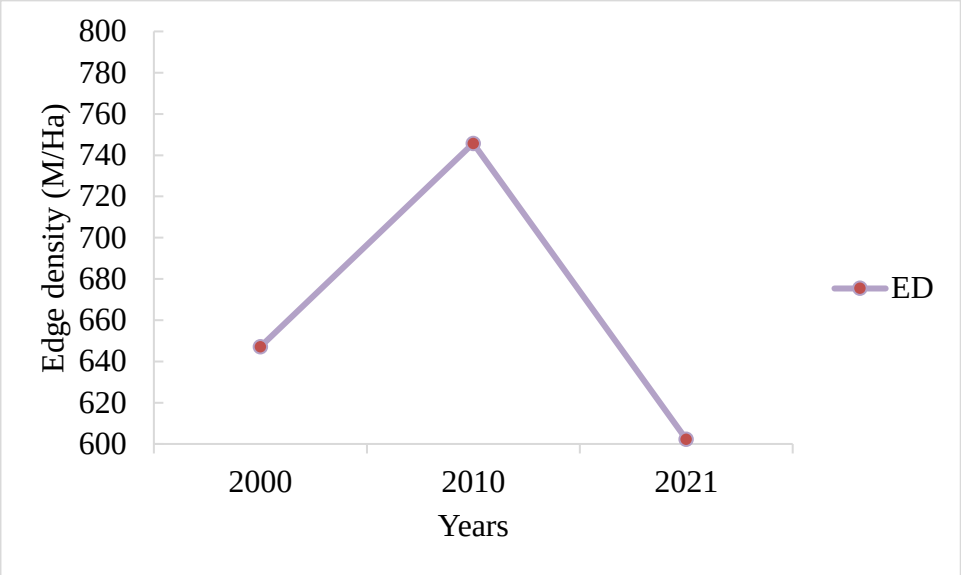

Figure 4-11: Edge Density of the built-up area over the years 2000, 2010, and 2021

4.1.8.5.Number of Patches

Another spatial composition measure that best represents urban sprawl and built-up area fragmentation is the Number of Patches (NP). The number of patches of a certain patch type is a basic measure of the patch type's subdivision or fragmentation. Although the number of patches in a class is vital to quantifying urban sprawl, it frequently has minimal interpretative value on its own since it transmits no information regarding patch area, distribution, or density. In fact, if the overall landscape area and class area remain constant, then the number of patches transmits the same information as patch density or mean patch size and maybe a helpful index to analyze. However, a number of patches are likely to be most useful as the foundation for computing additional, more interpretable metrics. NP simply denotes the number of distinct urban patches and demonstrates how the land, particularly the built-up region, has been fragmented into patches or smaller parts. After filtering by area, the results for the Number of Patches were 2158 for 2000, 1898 for 2010, and 1722 for 2021. NP was 2158 in 2000 but reduced to 1898 in 2010 with 260 patches, indicating patch combining into the main built-up area in subsequent years. Furthermore,

NP in 2021 was 1722, a reduction from 1898's 176 patches, and this is attributed to the integration of many patches into the main built-up region in 2021.

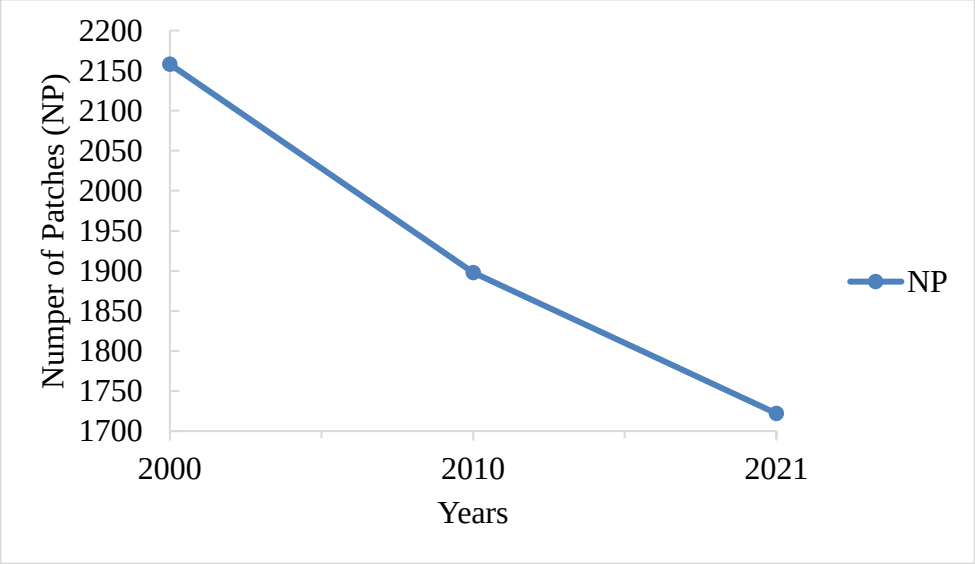

Figure 4-12: Number of patches of the built-up area over 2000, 2010, and 2021

From this perspective, it is possible to conclude that the built-up area has been consolidated during the previous 21 years, resulting in a decrease in the number of separate patches. The southern half of Town, in particular, is dominated by an industrial zone. The big size industry zones may contain many smaller patches, resulting in a drop in NP across the research region. The diminishing and growing NP trends led in urban sprawl in two ways. Initially, if the NP of a built-up area rose over a given time period, the incidence of fragmentation led urban sprawl to rise. Second, if the NP of the built-up area decreases within the set time limit, the NP building blocks will combine to form the greatest class area. This also results in the most urbanization in the studied region. According to this study, the number of NP in the built-up area decreased between 2000 and 2021. This is due to the merging of the smallest patches into the largest patch, which resulted in an increase in urban sprawl in the study region.

4.1.8.6.Patch Density

Patch density is a limited, but fundamental, aspect of landscape pattern. Patch density has the same basic utility as a number of patches as an index, except that it expresses a number of patches on a per unit area basis that facilitates comparisons among landscapes of varying sizes. Of course, if the total landscape area is held constant, then patch density and the number of patches convey the same information. Like a number of patches, patch density often has limited interpretive value by itself because it conveys no information about the

sizes and spatial distribution of patches. The results of spatial metrices analysis revealed that, PD of built-up area was 1.93, 1.59, and 1.41 for the years 2000, 2010, and 2021 respectively. The results of PD indicate the decreasing trend over the last 21 years study period. This is due to the fact that PD is largely depend on the NP observed per each landscape patches.

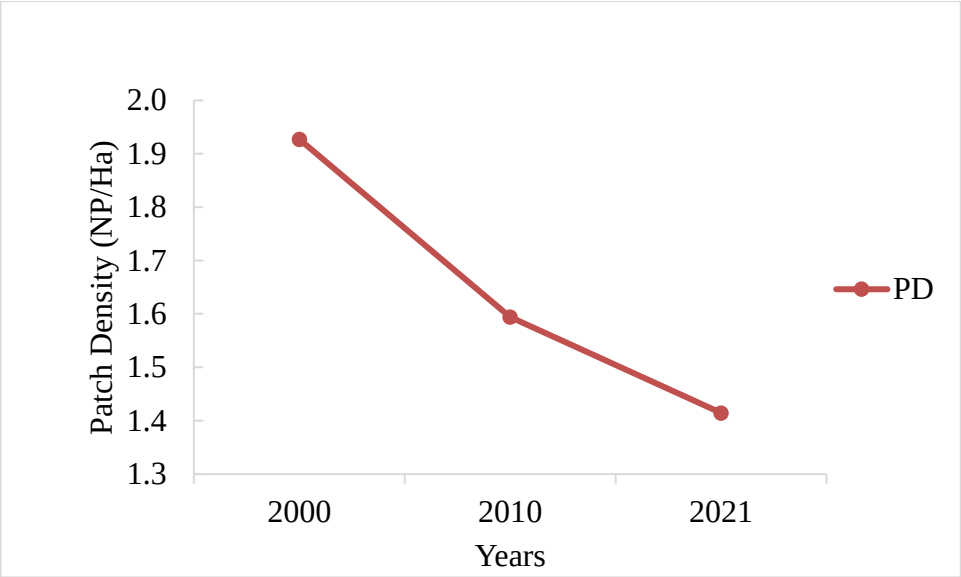

Figure 4-13: Patch Density of built-up area over the years 2000, 2010, and 2021

4.1.8.7.Shannon Evenness Index

SHEI equals minus the sum of the proportionate abundance of each patch type multiplied by that percentage across all patch types divided by the logarithm of the number of patch types. The observed Shannon's Diversity Index divided by the maximum Shannon's Diversity Index for that number of patch types. SHEI values vary from 0 to 1. As the distribution of area among the different patch types grows more unequal, SHEI approaches zero (i.e., dominated by 1 type). When the distribution of area across patch types is exactly even, SHDI reaches 1. (i.e., proportional abundances are the same). Shannon's evenness index is written in such a way that an even distribution of patch types results in maximum evenness. As a result, evenness is the inverse of dominance. Shannon's evenness index values for 2000, 2010, and 2021 were 0.388, 0.613, and 0.531, respectively. The evenness distribution of built-up area was not near to one in the year 2000. It was 0.388, indicating that the complement dominance of built-up area was fairly low. This indicates that urban sprawl was quite modest in 2000 compared to the other research periods. The evenness index values of built-up area were enhanced from 0.388 to 0.613 in 2010. The complement domination of built-up area was plainly seen and closely approximated 1. As the Evenness

index nears one, the built-up area entirely dominates the class area. This results in a very high level of urban sprawl between 2000 and 2021. However, in 2021, the Shannon evenness index of built-up area was reduced from 0.613 to 0.531. This demonstrated that urban sprawl dynamics between 2010 and 2021 was not as damaging as it had been during the prior study period (2000-2010). This is not to say that the status of urban sprawl will be particularly low in 2021. The occurrence of urban sprawl was highlighted by the Shannon evenness index of 0.531. The Shannon evenness index of built-up area is clearly seen in the following table (Table 4-9) and line graph (Figure 4-14) for the years 2000, 2010, and 2021.

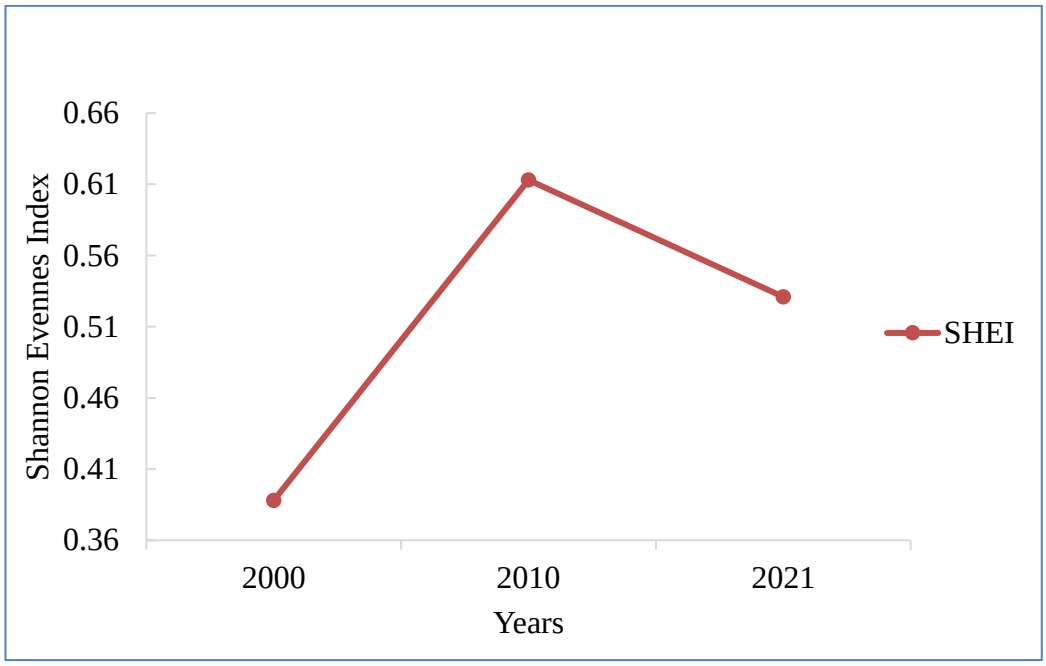

Figure 4-14:- Shannon Evenness Index of built-up area for the three study periods

Table 4-9: Shannon and Simpson Diversity Indices of built-up area (2000, 2010, and 2021)

	Indices	
Years	SHEI	SIDI
2000	0.388	0.27
2010	0.613	0.44
2021	0.531	0.381

4.1.8.8.Simpson Diversity Index

Simpson's diversity index is another prominent diversity metric for quantifying urban expansion. Simpson's index is less susceptible to the presence of unusual types and has a far more obvious interpretation than Shannon's index. The value of Simpson's index, in particular, shows the likelihood that any two pixels chosen at random will be distinct patch kinds. Simpson Diversity Index values, like Shannon Evenness Index values, range from 0 to 1. When there is only one patch in the landscape, SIDI equals zero (i.e., no diversity). As the number of various patch types (i.e., patch richness, PR) rises and the proportionate distribution of area across patch types becomes more equal, SIDI approaches 1. SIDI values from the QGIS landscape ecology tool range from 0.27 in 2000 to 0.44 in 2010, indicating that the diversity index is greater in 2010 when all classes have a similar share of area, but declines to 0.381 in 2021 when built-up area dominates the landscape.

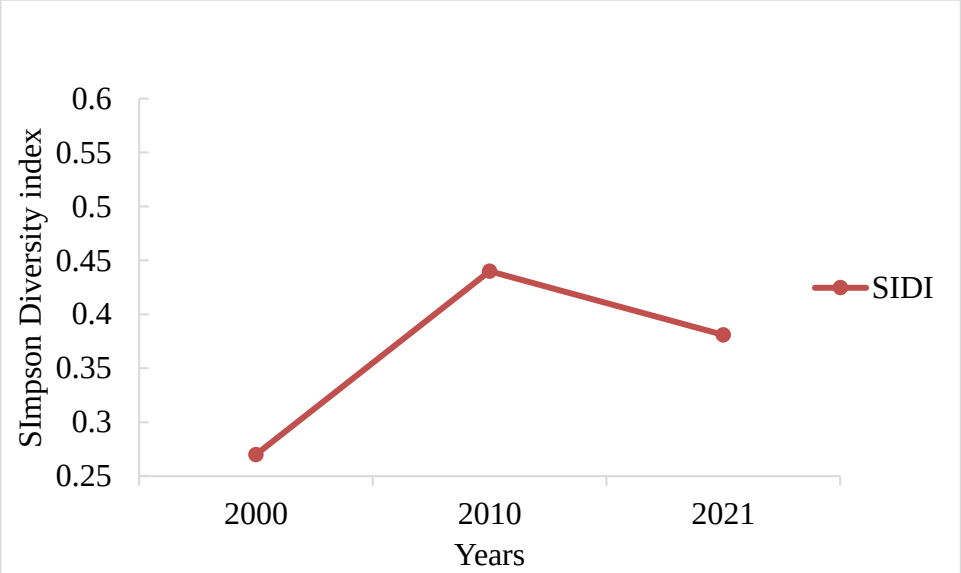

Figure 4-15: Simpson Diversity Index of built-up area for the three study periods

4.1.8.9.Zonal metrices

The use of the zonal measure is another key way for quantifying urban sprawl dynamics. The direction, location, and amount of urban sprawl in Dukem Town were investigated using a zonal metric analysis. This approach is mostly used to assess the spatiotemporal dynamics of urban sprawl of built-up areas. The spatial component is handled by separating the research area into zones and measuring the direction, location, and amount of urban sprawl in the landscape, whilst the temporal dimension is addressed by time series analysis of each zone. The categorized maps of each year were split into 8 pie zones in order to quantify urban sprawl in ZonalMetrics Tool. For each year, a zonal metric analysis was

performed to generate four primary indices for built-up area: total Class Area (CA), percentage of built-up inside each zone (PZ), and Edge Density (ED) each zone.

Table 4-10: Zonal composition of built-up area coverage in hectares starting from 2000 to 2021

Zones	Built-up area (Ha) coverage each year			The changed area between study periods		
	2000	2010	2021	2000-2010	2010-2021	2000-2021
Zone 1	108.99	297.3	242.8	188.31	-54.5	133.81
Zone 2	75.51	158.0	173.9	82.49	15.9	-61.61
Zone 3	65.25	177.2	79.3	111.95	-167.9	14.05
Zone 4	152.37	96.8	72.3	-55.57	-24.5	-80.07
Zone 5	57.24	148.1	102.2	90.86	-45.9	44.96
Zone 6	95.22	96.0	330.4	0.78	182.39	235.18
Zone 7	195.03	280.4	339.0	85.1	58.6	143.7
Zone 8	108.99	292.9	184.0	183.91	-108.9	75.01

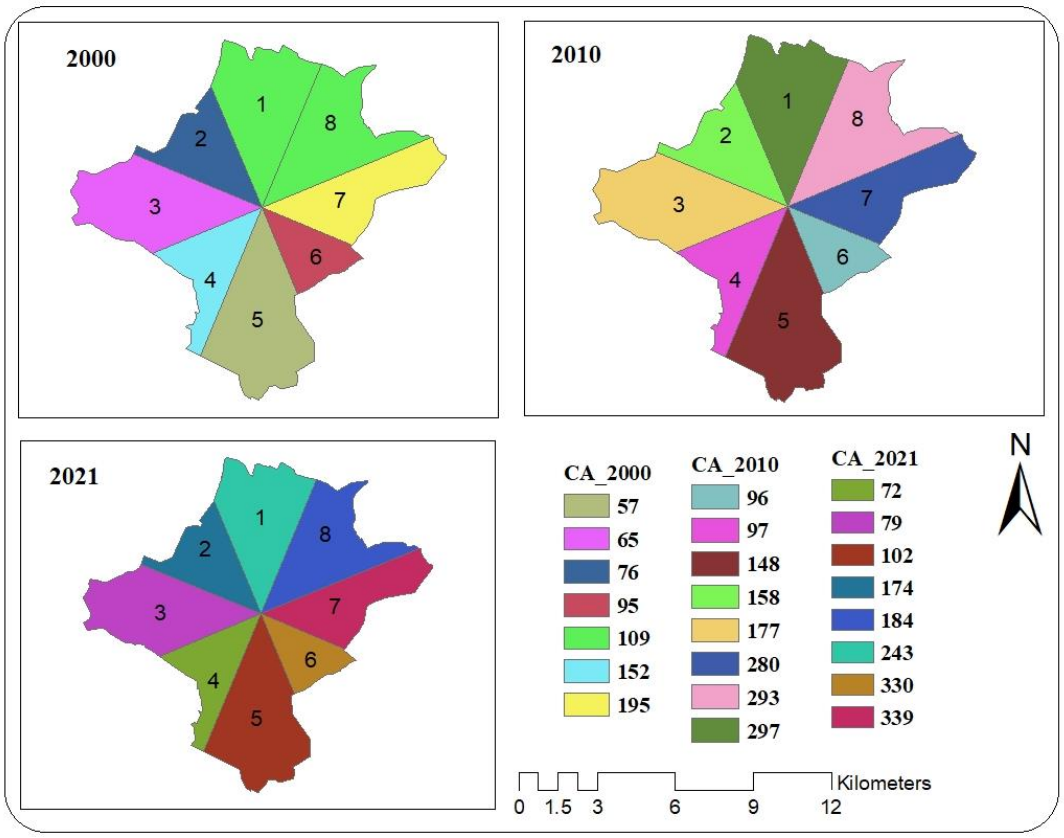

Figure 4-16: Class Area (CA) of each metrices zones for the years 2000, 2010, and 2021

Class Area (CA) is one of the key indicators that assess the amount of change or urban sprawl per zone and is computed each year. In the year 2000, the CA of built-up area in zone 7 was quite high, approaching 195 hectares. The maximum CA of the built-up area shows that urban sprawl inside zone 7 is significantly higher than in the other zones. Zone 7 is located to the east of Town, according to the pie split of zones. As a result, the eastern side of Dukem Town has suffered substantial urban sprawl in comparison to the rest of the Town. Zones 5, 3, and 2 on the other hand, had relatively low CA area coverage in the year 2000. Zones 3 and 2 are in the Town's northwestern region, while zone 5 is in the Town's southern part. This means that in the year 2000, the south and northwestern parts of the study region had relatively little urban sprawl. Zones 1 and 8 have approximately identical CA of built-up around 108 hectares and are displayed in figure 4 with the same color. These zones were found to the north of the research region.

In 2010, zone 1 CA of built-up increased significantly from 108 to 297 hectares, with a 188-ha incremental trend. In comparison to the prior year of 2000, the northern edge of the study zone witnessed extremely significant urban sprawl. Furthermore, the CA of zones 7 and 8 were deemed extremely high, with 280 and 292 hectares, respectively. As a result, it is possible to conclude that urban sprawl was seen in the northeastern half of the research territory.

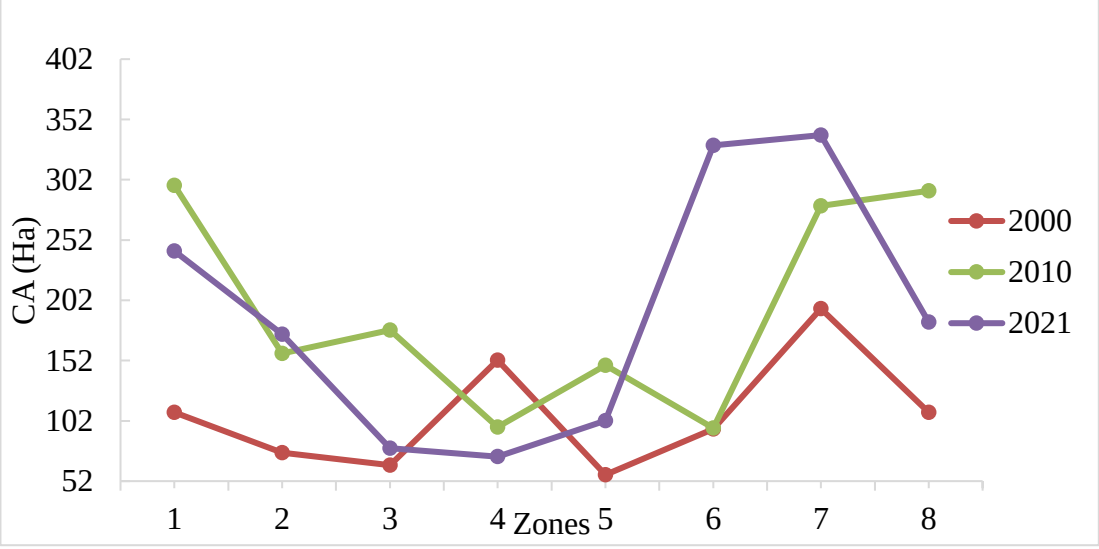

Figure 4-17:Class Area (CA) of eight built-up area zones in the years 2000, 2010, and 2021.

Zone 4's built-up area decreased by 55 hectares between 2000 and 2010, from 152 to 96 hectares. As a result, zone 4, located in the southwestern part of Town, had very little urban sprawl. The CA of built-up in 2021, on the other hand, indicates a downward trend in zones

1, 3, 4, 5, and 8, with -54.5, -167.9, -24.5, -45.9, and -108.9 hectares, respectively. The CA of built-up suggested that the Town's urbanization has been most noticeable throughout the past 21 years of observation. Zone 6 CA has a larger extent than the other corresponding zones, having a total area of 235 hectares. As a result, the southeast sector of the research region is densely populated, resulting in an incremental trend of urban sprawl during the last 21 years. Furthermore, the CA of built-up in zone 7 is substantially greater than in zone 6, and it is next to zone 6. As a result, over the past 21 years, urban sprawl has dominated zones 6 and 7.

Another indicator of urban sprawl in the study region is the proportion of built-up area per zone. PZ is computed by dividing the total built-up area by the total zone area and multiplying the result by 100. PZ denotes the percentage of built-up area in each zone over the research period. It depicts the growth of built-up areas in each zone during the last 21 years. The PZ of the research region over zone 7 is extremely high, approaching 23% in comparison to the similar zones. A large proportion of built-up area per zone reflects how much built-up area dominates a particular zone. As seen in Figure 4-18, the eastern half of Town, zone 7, is experiencing substantial urban sprawl in comparison to the other zones in the year 2000. Zone 5 PZ values indicate that the proportion of built-up area was very low across the research zones. The urban sprawl on the southern boundary was believed to be relatively modest at this stage. The PZ of the built-up area across zones 1 and 8 indicates an incremental tendency in 2010 compared to the preceding year in 2000. As seen in Figure 4-18, urban sprawl persisted in the northern portion of the research region. Zones 6 and 5, on the other hand, have the same PZ values and are colored the same on the map. In comparison to the rest of the equivalent zones, these zones have an extremely low proportion of built-up land. Having a low PIZ implies that urban sprawl in these specific zones was minimal. In 2021, the share of built-up land in zones 6 and 7 was relatively high, nearing 22% of the total. As a result, urban sprawl was prevalent in these areas. According to PZ statistics, urban sprawl has been consistent during the previous 21 years. To that degree, urban expansion has spread to the eastern portion of the study region, which is classified as zones 6 and 7.

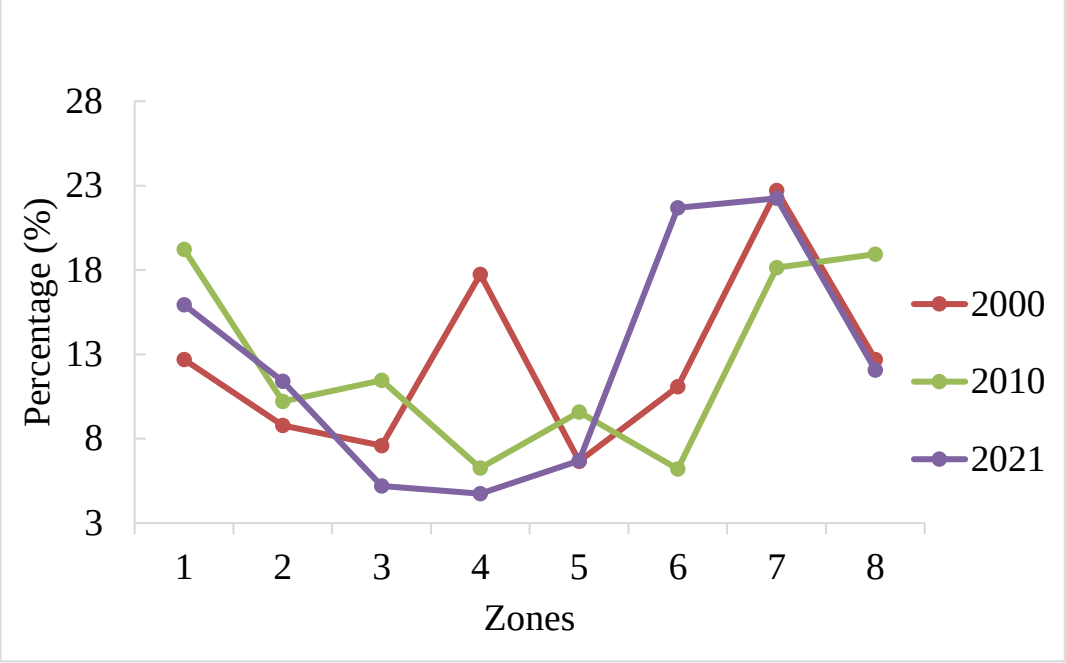

Figure 4-18: Percentage of built-up area per zone over the years 2000, 2010, and 2021

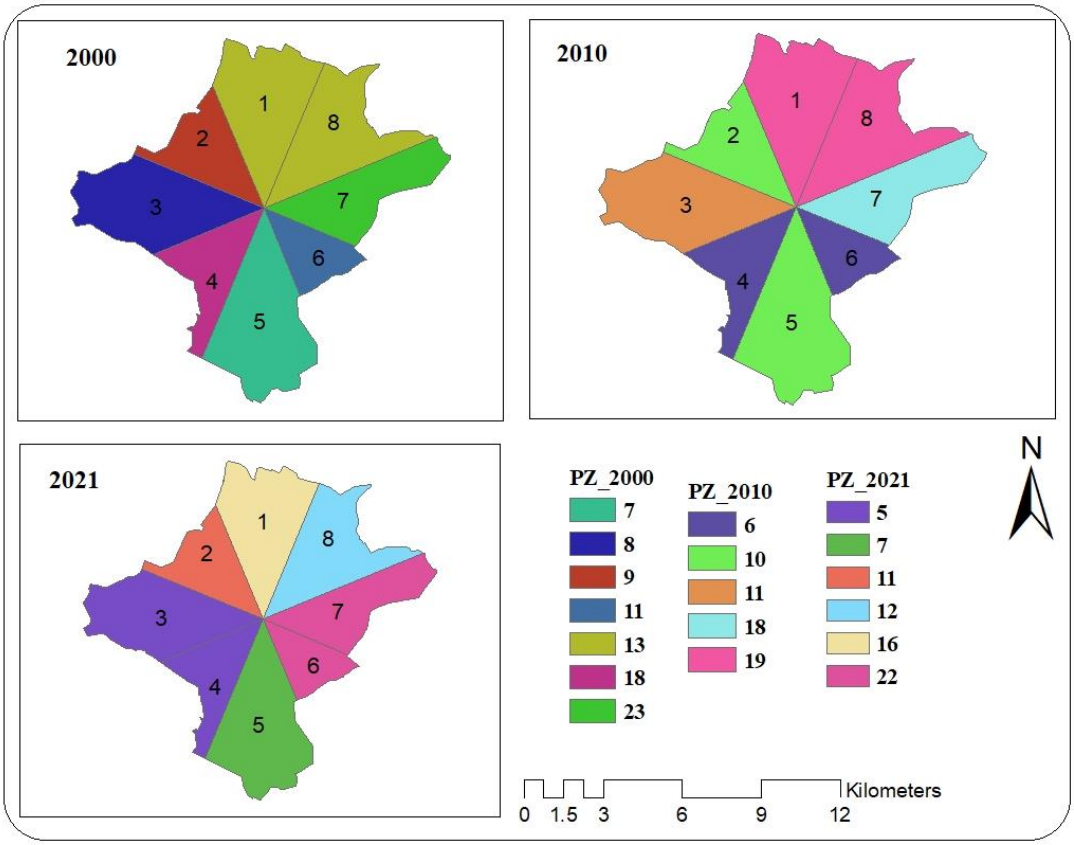

Figure 4-19: Percentage of built-up area per zone over the years 2000, 2010, and 2021

Another indicator of urban sprawl is edge density (ED) per zone. In general, ED is proportional to the overall edge length and zone area. It is computed in ZonalMetrics Toolbox as the total edge length (m) divided by the zone area and stated in terms of a user-

defined land extent, such as 1, 100, or 1000 hectares. Edge length (m) per hectare is calculated for this investigation. As a result, ED calculates the amount of edge length per hectare of land for each particular year in the urban environment. ED, like TE, has a similar association with landscape fragmentation; as a landscape's partition into smaller areas rises, so does ED. As shown in Figure 4-20, ED for the years 2000 and 2010 follows an almost same pattern, with a lower increase per hectare in 2010. However, the level of ED grew in the majority of statistical zones in 2010, with the exception of zones 5 and 3, which have lower ED values of 53.2 and 85.2 m per hectare, respectively. The outcome in 2021 is quite evident and bold: ED climbed significantly, and the 2021-line graph seemed higher than prior years. Except for two zones, zones 5 and 3, the ED per statistical zone is larger than 200m per hectare. This demonstrates that urban sprawl and urban landscape fragmentation happened in all directions in 2021.

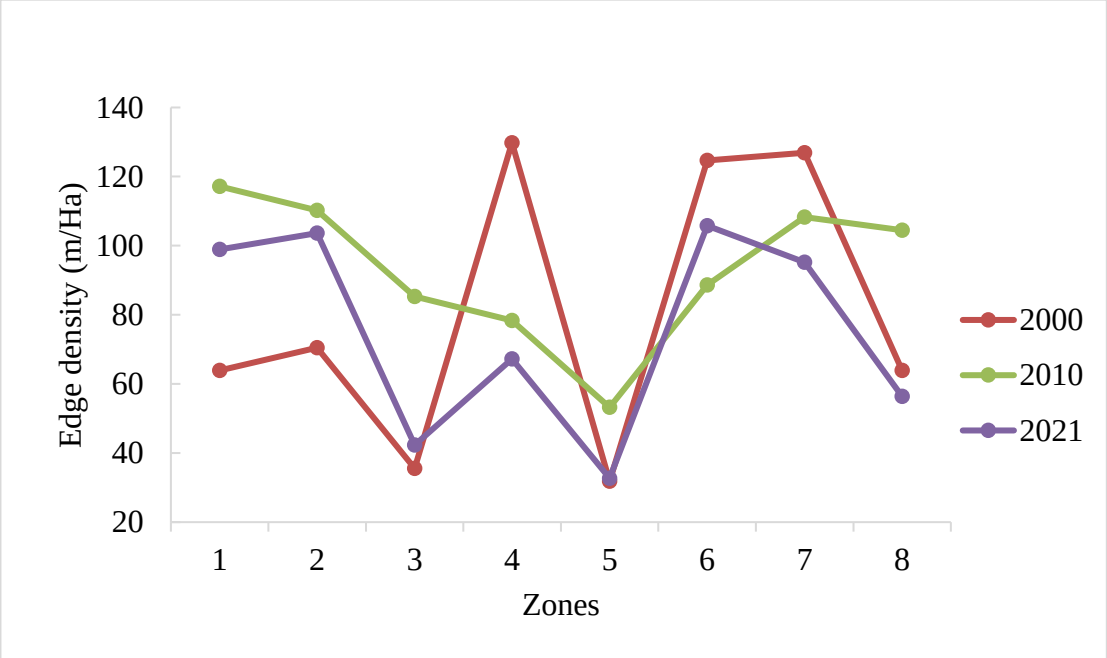

Figure 4-20: Edge Density of built-up area per zone over the years 2000, 2010, and 2021

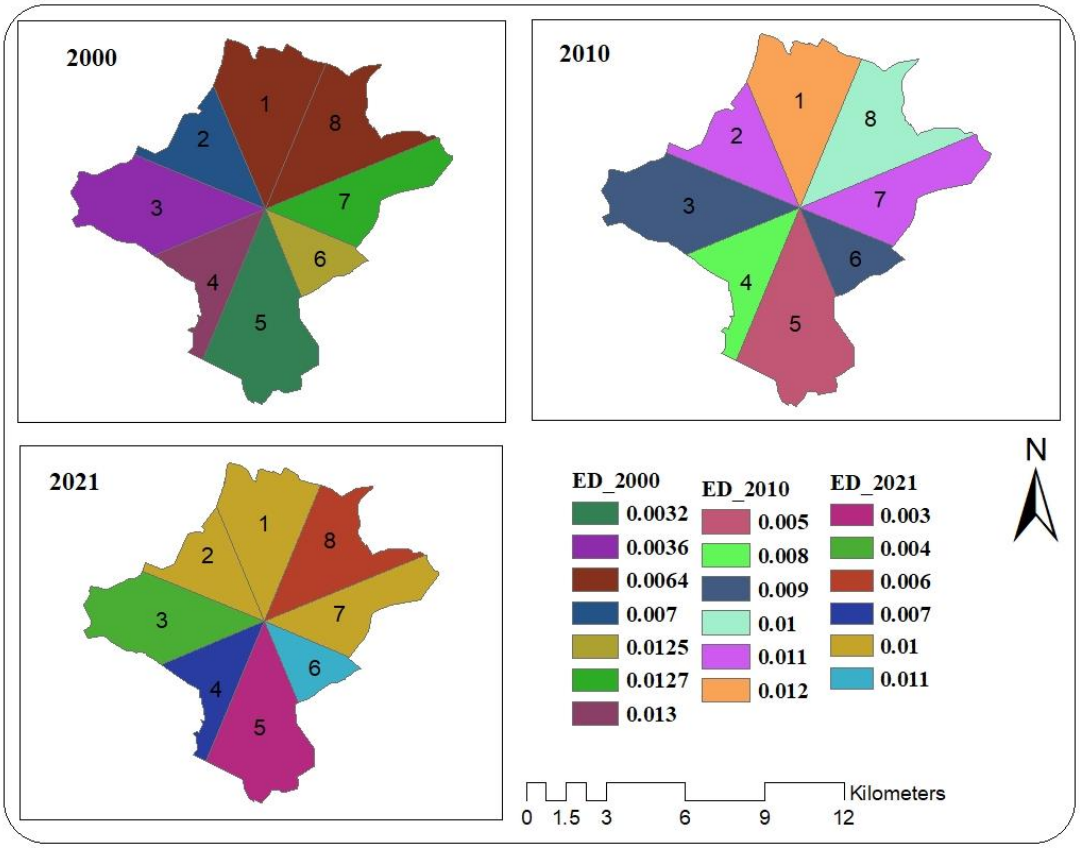

Figure 4-21: Edge density of built-up area per zone over the years 2000, 2010, and 2021

4.1.9. Spatiotemporal dynamics of built-up area over the last 21 years

Several landscape metrics were used to determine the pace of urban sprawl dynamics in the research area. The first and important metric to define the geographical and temporal distribution of built-up area over Dukem tow was CA dynamics across each of the eight zones. To distinguish the built-up region from the rest of the land use class, the built-up area is mask out using QGIS software. Pie zones produced in ZonalMatrice were superimposed to analyze the spatiotemporal dynamics of built-up area over the research region. In the year 2000, built-up area is dispersed throughout all zones, as seen in Figure 4-22. Zones 4, 6, 2, and 7 in particular showed built-up area domination. The other zones, especially zones 5, 3, 1, and 8, have relatively low built-up CA dominance.

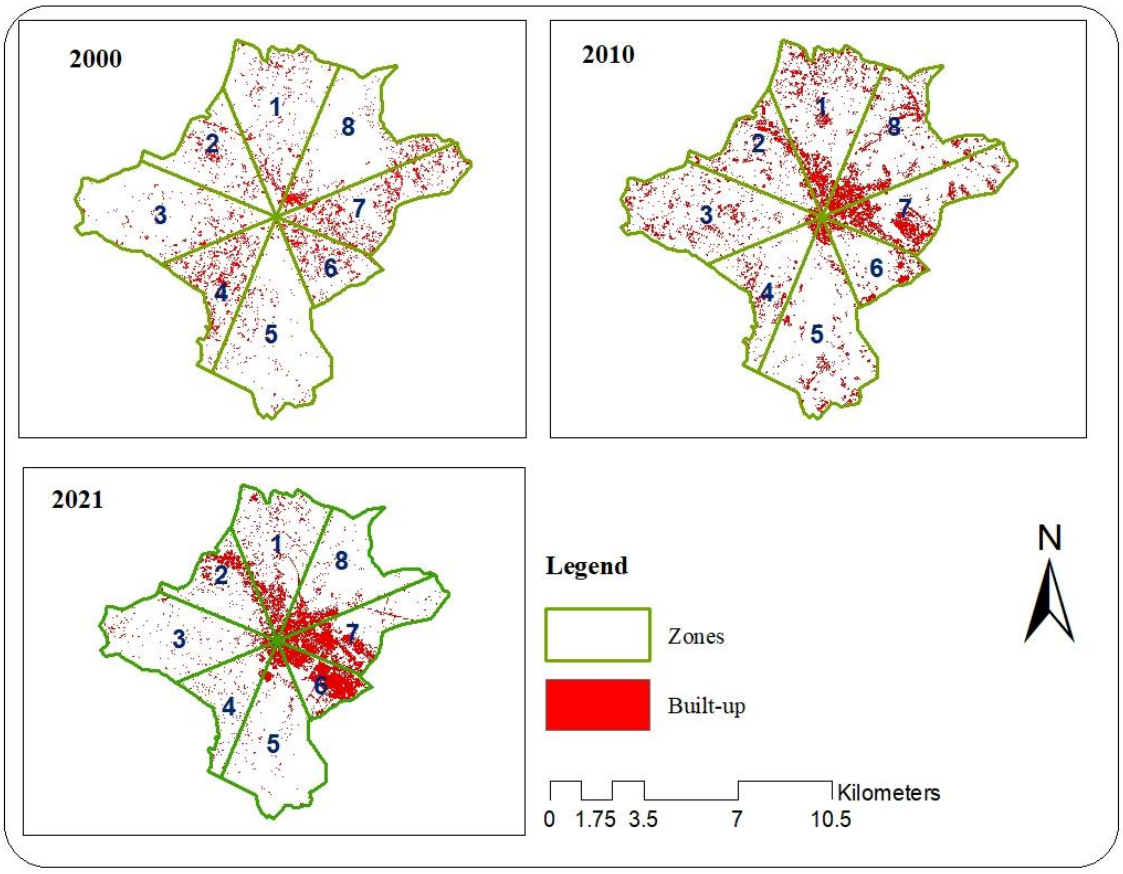

Figure 4-22: Spatiotemporal dynamics of urban sprawl over the last 21 years (2000, 2010, and 2021)

High CA dominance was closely related to the spread of urban sprawl. From this perspective, it is possible to infer that urban sprawl was fairly limited in the year 2000. In contrast, in 2010, the distribution of built-up area was expected to concentrate at the center margin of three metric zones, namely zones 7, 8, and 1. This is related to the merging of multiple patches into the biggest patch. As a result, the remaining zones, especially zones 5, 4, and 6, saw relatively modest fragmentation rates. These data numbers clearly show the spread of urban sprawl over the research territory using three metrics zones. On similar trend, the spatiotemporal dynamics of built-up area was also more concentrated near the center of the Town. To that extent, the entire and central part of the Town was highly dominated by the built-up area. As indicated in Figure 4-22, the spatiotemporal dynamics of urban sprawl over the study region is persistent through the entire part of the Town and elongated to north western part of the study area. To conclude, the spatiotemporal dynamics of urban sprawl over the study period of 2000, 2010, and 2021 revealed an incremental trend.

4.2.Urbanization-induced changes in land use land cover conversion

4.2.1. Decreasing trends of agricultural land due to urbanization-induced changes

The desire for cheap permanent uses over large areas of land in the form of residential and industrial uses, malfunctioning institutional setups, development of infrastructural facilities, movement of human resources to urban centers, population growth, and gaps in policy documents all contribute to the development of urban sprawl (Marshall & Randhawa, 2017; Tassie, 2018). Urbanization is an inescapable process that alters the landscapes of outlying areas as part of development. Uncontrolled and fast urban-to-rural migration has a number of negative environmental consequences. Abdulai et al., (2021) identified some of these impacts, including biodiversity loss, disruption of the hydrologic cycle, soil nutrient compaction, increased susceptibility of rural people to various types of disasters, and changing land cover due to human-induced actions. According to Abdulai et al. (2021), when agricultural land is urbanized, it significantly slows livelihoods and disenfranchises individuals who reside near urban areas since they cannot manage their holdings. This further leads in communities lacking land and resources, harming the country's overall growth. When these conditions are paired with catastrophic weather events caused by climate change, the country's food security suffers in the long term. It is obvious that the urbanization of the study region of Dukem Town has had a substantial impact on agricultural land covering. As shown in Figure 4-23, agricultural land area coverage was quite high in 2000, accounting for 1213.06 hectares. Following that, the agricultural area coverage was reduced to 787.87 hectares in 2010. However, agricultural land was grown to 1161.58 hectares between 2010 and 2021. This is due to the deterioration of forest area in the northern section of Town, which leads to some agricultural growth. Overall, agricultural lands have fallen from 1213.06 hectares in 2000 to 1161.58 hectares in 2021 throughout the previous 21 years of observation.

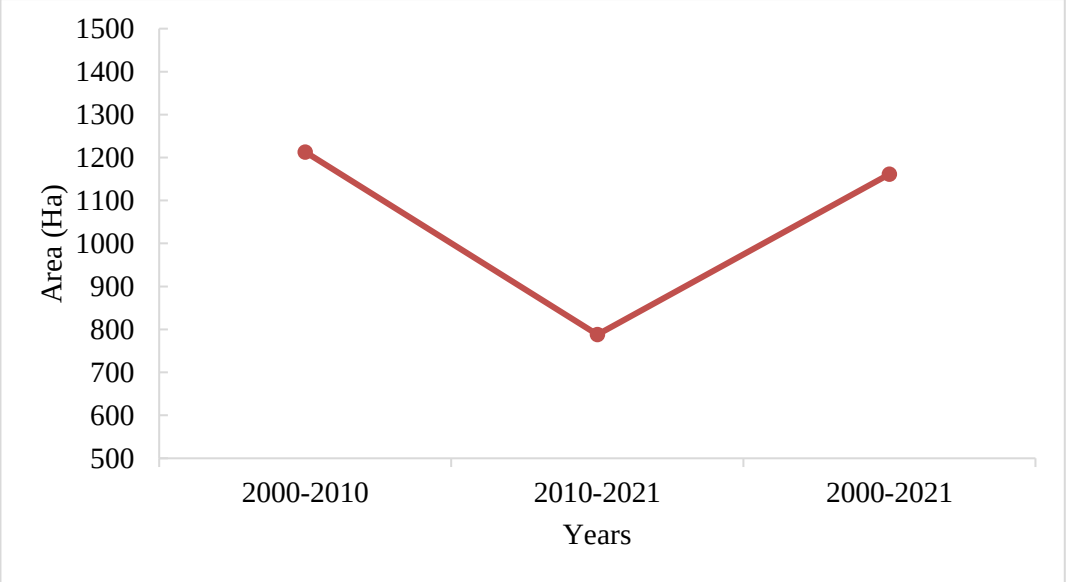

Figure 4-23: Changed area from agricultural lands to built-up for the years 2000, 2010, and 2021

4.2.2. Decreasing trends of forest land due to urbanization-induced changes

Given the consequences of vegetation clearance, it is assumed that the amount and quality of surviving forest fragments in urban areas will reflect their environmental conservation status (Biao et al., 2010). The processes involved with environmental conservation can be deduced from patterns of plant composition and distribution, as well as land uses, according to landscape ecology principles. This technique allows structural patterns to be analyzed using landscape measures or indices such as forest quality based on size, shape, isolation, succession stage, and anthropic bounds (Hardt et al., 2013a, 2014). The current status of environmental protection is closely linked to land use history, which may be defined by identifying and comprehending the driving factors of changes witnessed through time (Plieninger et al., 2016). Understanding the dynamics of these changes might help with future conservation planning and assessment, such as developing trend scenarios to minimize or reduce negative consequences (Whitlock et al., 2017). Forests throughout metropolitan landscapes have evolved along with the issue of urban expansion. Forest fragmentation is a kind of habitat deterioration that has been extensively researched (Hanski et al. 2013).

The forest coverage in the study region of Dukem Town is located at the north eastern part near the small plateau and to the southwestern edge of the Town. As indicated in the Figure 4-24, the forest land degradation due to urban expansion is predominantly high between the years 2000 and 2010. Forest land was not only subjected for clearance for the sake of urban expansion and forest land is highly susceptible for the expansion of agricultural lands.

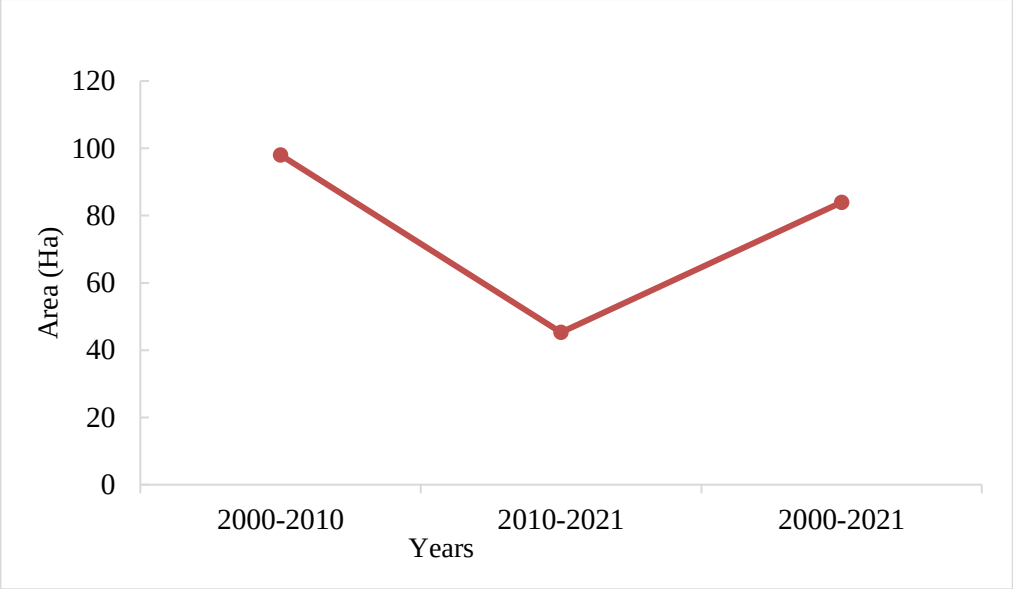

Figure 4-24: Impacts of built-up area expansion on the forest land

The northern portion of the forest land near the small plateau is highly degraded due to farmland expansion near the forest region as of field observation of the researcher. A large amount of forest land was cleared between the years 2000 and 2010. The land use land cover change dynamics significantly affects the forest ecosystem at large scale. To that aim, over a time series a number of forest land area coverage was converted to other land use type. The amount of rate of change of forest land to different land use system is not always the same. Literatures indicates that the conversion of forest land to agriculture takes the lion share of conversion rate. This is to mean that, the world forest ecosystem was put endanger due to agricultural expansion for the sake of food security. Coming down to the Dukem Town, a large amount of forest land was converted to agricultural land, barren land, and built between 2000 and 2010, covering an area of 264.81, 15.05, and 97.99 hectares, respectively. To quantify the impacts of urban growth over the forest region, it is important to understand how much area of forest land is converted to urban area. Between the years 2000 and 2010, a large amount of forest land nearly 97.99 hectares were cleared for the sake of urban expansion. This is the largest conversion rate compared to the overall study periods (2000-2021). Modest amount of forest land was also cleared between the years 2010 and 2021 with 45.27 hectares. Forest degradation due to urban growth is said to be reduced between the years 2000 and 2010. Over the last 21 years, a total of 83.97 hectares of forest land was converted to built-up area.

4.3.Types of urban growth in Dukem Town

Detailed analysis of the newly expanded urban areas revealed the general trends of urbanization process and pointed out the configuration of the different urban growth types in Dukem Town between 2000 and 2021. The types of three kind of urban growths are depicted in Table 4-11. The results of the table shows that the types of urban growth in Dukem are similar to framework of Hai et al., (2019). These three types of urban growth have been visualized in this study including infilling type, edge expansion and outlying type.

Infilling type

As for the infilling type, its area was smallest in urban growth. It was prominent where expansion occurred in the infilling of the remaining open spaces within urban areas. This study has revealed that the infilling urban growth regions consist of zone three and five wards. These urban zones were transformed from non-urban lands particularly from agricultural lands within the urban region. Infilling urban growth type was covered an area of 58.95 ha from the total area coverage of urban growth types. In terms of infilling urban growth, the relatively corresponded to sustainable urban growth types (Roberto et al., 2012).

Table 4-11: Types of urban growth in Dukem Town with their relative area coverage

Zones	Metric T	Types of urban growth	Area Coverage in hectare
Z1	0.39	Edge expansion	133.83
Z2	0.36	Edge expansion	98.37
Z3	0.71	Infilling	14.04
Z4	0.15	Outlying	80.10
Z5	0.53	Infilling	44.91
Z6	0.22	Outlying	235.17
Z7	0.04	Outlying	144.00
Z8	0.04	Outlying	74.97

Edge expansion

The edge enlargement sprawl, which was practically saturated and compact, was the second major urban growth type in the study region. Edge expansion emerged mostly in the adjacent urban fringe. This type of urban growth was observed in zone one and two with an area coverage of 133.83 ha and 98.37 ha respectively. Zone 1 has experienced more agricultural land in the previous year of 2000 and then built-up area was expanding in due consideration of their edge. The most urban growth type, which accounted for more than half percent of the total urban growth areas, was the edge expansion in zone 1 and 2, where land was ready to develop from the edge of the pre-developed area.

Outlying

The outlying urban growth, which includes insolated type, linear branch and nucleated branch, has been the summing almost 534.24 ha of the whole sprawl types. Outlying urban growth type is considered to be the majority urban growth type in the study region. Development outside the main urban region was a reflection of rural Towns adopting strategies to establish development or industrial zones. Outlying characterized the newly scattered development that was far away from the pre-developed urban zone. In this regard, zone 4, 6, 7, and 8 were experienced outlying urban growth types.

4.4.Discussion

In Dukem Town, urbanization-induced changes in land use land cover were analyzed from 2000 to 2021. For the research periods of 2000, 2010, and 2021, Landsat imagery was utilized to establish land use land cover classes. Agricultural land, built-up land, barren land, and forest were the most common land use land cover categories over the three research periods. In the year 2000, the built-up area coverage was the least in comparison to the whole size of the study area, accounting for 855.27 hectares (8.80 percent). The fundamental explanation for the low proportion of built-up area is because urbanization did not rise as much as other land cover in 2000. (Abebe, 2012) published similar findings that quantified the association between population increase and urban growth. To that point, the researcher discovered that the Dukem Town area coverage was quite modest in comparison to other land use land cover classes in early 1986. The percentage of built-up area expanded extremely by 62 percent as the population doubled in two ten-year periods. This remark is supported by the findings of this investigation, which found that built-up area coverage was quite low in the early 2000s, with proportional coverage of 8%.

From 2000 to 2010, the built-up area coverage rose considerably. Between 2000 and 2010, it more than quadrupled by half, from 855.27 hectares to 1558.62 hectares. The incremental patterns of built-up in the research area show that urbanization was heavily introduced in 2010, and industries began to grow in the study region's southern section. According to Dadi et al. (2016), approximately one-third of the total area was allocated to housing, while industries and storage accounted for 148.8 ha (22.8 percent) and 86.2 ha (13.3 percent), respectively. This provides insight into the primary land use category from which land demand arises. According to Bibri et al., (2020), a fundamental difficulty that urban centers in developing nations confront in order to ensure sustainable and healthy urban expansion

is a lack of early knowledge about the extent of existing urban lands and the quality of urban growth forecast.

In the recent year 2021, the built-up area has risen dramatically. The built-up area has more than doubled from 16.03 percent in 2010 to 32.20 percent in 2021, a half percentage point increase. The built-up area coverage has noticeably expanded during the previous two decades, from 2000 to 2021. The built-up area coverages in 2000, 2010, and 2021 were 855.27 hectares, 1558.62 hectares, and 3130.99 hectares, respectively. According to Girum (2020), the establishment of industries and manufacturing, population increase, and players such as private investors were all important factors in Dukem Town's spectacular urban expansion. Furthermore, Asfaw (2018) underlines that the resulting LULC dynamics provide a tough urban planning and management problem, owing to a lack of appropriate urban development management approaches. Dekum Town is a key location for showing the issues of shifting land use land cover. The expansion of the built-up area has come at the price of forest degradation and agricultural land loss. As a result, the rapidly increasing built-up region was poorly managed, resulting to chaotic land development and a variety of urban anomalies (Gallaso et al, 2019). The forest, on the other hand, has been deteriorated during the previous 21 years. The covering of forest land has decreased from 446.04 hectares in 2010 to 358.11 hectares in 2021.

Numerous studies have shown that unsustainable agricultural land conversion on the fringes of cities has had negative implications by reducing farmlands and crop yields, jeopardizing local people's livelihoods (Azadi et al., 2012; Rudi et al., 2012). Belay (2014) investigated the influence of urban growth on agricultural land using remote sensing and GIS. Based on Landsat imagery produced between 1966 and 1999 and 1999 and 2004, the study found that the rate of urban growth over agricultural land was 113.32 km2 in the 13-year interval and 106.26 km2 in the 5-year interval. This demonstrates that the rate of urban growth is accelerating. As a result, agricultural land has been lost. In general, the faster urbanization occurs, the more agricultural land is lost.

Agricultural land, as noted in (Holden et al., 2010; Agegnehu et al., 2016; Muhabaw & Gashu, 2019), is a critical economic resource for the development of rural living in a country like Ethiopia, where agriculture employs the vast majority of the population. When agricultural land in peri-urban areas is converted to built-up land through horizontal urban expansion, it has an impact on land use value. According to Tuyen (2013) and Bekele (2010), urbanization has both positive and negative effects on farmers in peri-urban areas.

The negative repercussions, however, are more publicly highlighted since this growth is typically unplanned or uncoordinated, and hence the negative consequences outnumber the positive ones. Land conversion and displacement, particularly in developing countries, are not seen negatively by any activities that have taken place on it. However, it may have a detrimental impact on displaced households in terms of interruption of livelihoods as well as social and cultural repercussions (Nigusie, 2011; Muluwork, 2014).

Aside from studies on land use/land cover change detection, there are studies that quantify, estimate, map, and model urban sprawl dynamics using statistical approaches and GIS technologies (Viana et al. 2019). Shannon's Entropy is one such statistical approach that is utilized as a quantitative assessment of unorganized urban sprawl dynamics. The degree of spatial concentration or dispersion of geophysical variables (Xi) among 'n' spatial units/zones is measured using Shannon's Entropy (Hn). Landscape metrics, which provide information about the configuration of land cover classes and the landscape, can be used to obtain changes in urban structures and patterns. Landscape metrics are algorithms used to describe and quantify the spatial characteristics of patches, class areas, and the entire landscape (Xiang et al. 2018).

The spatiotemporal dynamics of urban sprawl in Dukem Town were quantified and measured using landscape metrics. Class Area (CA) was one of the spatial metrics indexes that measured an area's total built-up expansion. It counts the number of built-up pixels every time step. According to the findings of the investigation, the CA of built-up area in 2000 was 858.60 hectare. After 21 years, the CA of built-up area has skyrocketed from 858.60 to 1828.79 hectare. Between 2000 and 2021, urban development in the study region was very high, with the CA of built-up area occupying a large portion of the Town's center. It is said that as the CA rises over a given time period, urban spawl will rise. As Shi et al, (2012) pointed out, the incremental trend of CA for built-up area was an important indication of urban sprawl dynamics. The expansion of urban sprawl will be dramatically increased when the composition of urban structure changes. The findings of this research clashed with Shi et al, (2012) ideas, which said that when the CA of built-up rose during a given time period, it is feasible to identify the spread of urban sprawl.

Furthermore, the number of patches indicates the number of unique urban patches and shows how the land, particularly the built-up zone, has been broken into patches or smaller pieces. The analysis of spatial metrics indicated that the number of patches in 2000, 2010, and 2021 was 2158, 1898, and 1722, respectively. NP was 2158 in 2000 but had dropped to 1898 in

2010 with 260 patches, showing patch blending into the main built-up area in later years. Furthermore, NP in 2021 was 1722, down from 176 patches in 1898, owing to the merger of numerous patches into the main built-up zone in 2021. Similar findings were observed by (Seto et al. 2012), demonstrating that changing NP trends are not the main indicator of urban sprawl dynamics. Because it has no information on the area, the patch disparity, or the density. Aside from that, Alexakis et al. (2011) stated that NP offers information on the number of new patches developed during a certain time period. According to their findings, the freshly formed patches were the most important indicators of urban sprawl. In this study, the NP were combined to form the biggest patch across the study region in the previous 21 years. Aside from that, the freshly formed patches were also seen in various areas of Dukem Town, notably the northwestern boundary. Over the course of 21 research periods, urban sprawl persisted in that particular place.

The Largest Patch Index was another geographical statistic employed to evaluate urban sprawl in the research region. The Largest Patch Index, as shown in the results section, is the ratio of the area of the largest patch in the landscape to the entire landscape area. LPI approaches 0% when the biggest patch in the landscape becomes increasingly tiny. It reaches 100% when the entire terrain is made up of a single patch. According to the findings of this research, the largest patch index of built-up area in the year 2000 was 8.69 percent. The Largest Patch Index increased to 35.02 percent in 2010 during a ten-year period. Compared to the previous year of 2000, the increase in Largest Patch Index values demonstrated that built-up area dominated more in 2010. Simultaneously, the built-up area's Largest Patch Index values increased significantly from 2010 to 2021. It was increased from 35.02 to 96.47 percent. According to Eiden et al. (2012), the incremental patterns of LPI throughout time series analysis are a key predictor of urban sprawl. According to Garouani et al, (2017), the class domination of a certain patch rose as the number of the Largest Patch Index increased, causing the spread of urban sprawl to become more important. This study's findings were consistent with the scholarly literature mentioned above. To that aim, the class dominance of urban areas has grown considerably during the last 21 years. The domination of built-up areas during the past 21 years revealed that urban sprawl is quite persistent in the examined area.

Furthermore, the Shannon Evenness Index was used to quantify the increasing dominance of built-up area during the previous 21 years. As a consequence, the values for Shannon's Evenness Index in 2000, 2010, and 2021 were 0.388, 0.613, and 0.531, respectively. In the

year 2000, the built-up area distribution was far from even. It was 0.388, suggesting that built-up area had a low complement dominance. This demonstrates that, in comparison to the other research periods, urban sprawl was very limited in 2000. In 2010, the built-up area evenness index was increased from 0.388 to 0.613. The complement dominance of built-up area was clearly visible and approached 1. When the Evenness index approaches one, the built-up area completely dominates the class area. Between 2000 and 2021, this leads in a very high amount of urban sprawl. Sun et al. (2013) used SHEI landscape metrics to quantify the growth of urban sprawl. According to their findings, built-up areas were more concentrated in the heart of Town, causing built-up areas to totally dominate other patches. The complimentary dominance of built-up area over other similar patch types drives urban sprawl spread. In accordance with this information, the research region's SHEI demonstrated that urban sprawl dominated the center and eastern parts of the study territory.

CHAPTER FIVE

5. CONCLUSIONS AND RECOMMENDATION

5.1.Conclusions

The main objective of this research work was to analyze the spatiotemporal changes in land use and land cover due to urbanization and to assess urban sprawl in Dukem Town from 2000 to 2021 using spatial metrics and Shannon's entropy model. To achieve the desired objective, three unique years were chosen: 2000, 2010, and 2021. The satellite images were then collected and processed to create categorized maps that may be used as input. The approach used consists of three major parts. The first stage involved image preprocessing, classification, and the generation of category maps. The second part involved selecting acceptable spatial metric indices, computing indices, detecting urban expansion changes, and describing the research area's urban sprawl. The last phase involved creating zonal statistical layers and computing area and edge metrics to quantify the location, quantity, and direction of urban sprawl at the zonal level. GIS and remote sensing software tools, as well as other zonal and spatial metric tools, were employed in an integrated strategy to complete all operations. The final results were divided into three categories: urbanization-induced changes of land use land cover, spatial and zonal metrics analysis result that comprehend spatiotemporal dynamics of urban sprawl, and types of urban growth persisted in the study area.

Three types of urban growth have been visualized in Dukem Town including infilling type, edge expansion and outlying type. As for the infilling type, its area was smallest in urban growth. It was prominent where urban growth occurred in the infilling of the remaining open spaces within urban areas. This study has revealed that the infilling urban growth regions consist of zone three and five wards. These urban zones were transformed from non-urban lands particularly from agricultural lands within the urban region. Another urban growth type is edge enlargement, which was practically saturated and compact in the study region. Edge expansion emerged mostly in the adjacent urban fringe. This type of urban growth was observed in zone one and two with an area coverage of 133.83 ha and 98.37 ha respectively. The last urban growth type is outlying, which includes insolated type, linear branch and nucleated branch with the summing of 534.24 ha of the whole urban growth types. Outlying characterized the newly scattered development that was far away from the pre-developed urban zone.

To map the lay of the urban environment in land-use/cover categories, a post classification change detection method was performed. As a result, four primary land-use classes were chosen, and the area covered by each was estimated for each study period. The built-up Class Area (CA) was computed in hectares using categorical maps, and the findings were 858.60 in 2000, 1241.56 in 2010, and 1828.79 hectares in 2021. In other words, the proportion of built-up area (PLAND) was about 34%, 55%, and 64% of the entire study area in 2000, 2010, and 2021, respectively. Agricultural and forest land have fallen 24.32 percent and 2.68 percent, respectively, from 2000 to 2021. Similarly, the barren land/open areas contributed significantly, but it waxes and wanes over time. This is clear evidence that Dukem Town is expanding at the cost of agricultural and forest land.

The spatiotemporal dynamics of urban sprawl in Dukem Town was quantified using Spatial Metrics method. The results of spatial metrics indices demonstrated that urban sprawl in Dukem Town was mostly persistent. Number of Patches (NP) are key indications for subdividing built-up land into pieces in this regard. The Largest Patch Index of built-up area was 8.69 percent in 2000. The Largest Patch Index increased to 35.02 percent in 2010 during a ten-year period. In compared to the previous year of 2000, the increase in Largest Patch Index values demonstrated that built-up area dominated. Simultaneously, the built-up area's Largest Patch Index values increased significantly from 2010 to 2021. It was increased from 35.02 to 96.47 percent. As the number of the Largest Patch Index grew, so did a patch's class domination. The domination of built-up areas during the past 21 years revealed that urban sprawl is quite persistent in the research region. This is an indicator that the biggest patch is expanding in size, producing a continuous urban agglomeration in the city center. That is, although the number of patches increases year after year, fragmenting the outlying areas, the largest patch at the core grows larger and larger.

The Zonal Metrics level analysis was also utilized to assess the direction and precise locations of urban sprawl across the research region. In the year 2000, the CA of built-up area in zone 7 was around 195 hectares. The greatest CA of built-up area inside zone 7 demonstrates that urban sprawl is substantially greater than in the other zones. In the year 2000, however, Zones 5, 3, and 2 had relatively low CA area coverage. Zones 1 and 8 have almost comparable CA of built-up of 108 hectares and are colored the same in figure 4. The zone 1 CA of built-up area rose dramatically from 108 to 297 hectares in 2010, with a 188-hectare incremental trend. Zones 7 and 8 were assessed to have highly high CA, with 280 and 292 hectares, respectively. Between 2000 and 2010, the built-up area of Zone 4 declined

by 55 hectares, from 152 to 96 hectares. As a result, zone 4, located in the city's southwest, had virtually little urban expansion. In contrast, the CA of built-up in 2021 shows a declining tendency in zones 1, 3, 4, 5, and 8, with -54.5, -167.9, -24.5, -45.9, and -108.9 hectares, respectively.

Edge density (ED) per zone is another metric of urban expansion. ED is often related to total edge length and zone area. As shown in the results section, ED follows a nearly same pattern between 2000 and 2010, with a smaller growth per hectare in 2010. However, the bulk of statistical zones' ED levels increased in 2010, with the exception of zones 5 and 3, which have lower ED values of 53.2 and 85.2 m per hectare, respectively. PZ is also an important metric for measuring urban sprawl in Dukem. Zone 7's PZ is unusually high, nearing 23% when compared to similar zones. A high proportion of built-up area per zone represents the amount of built-up land that dominates a certain zone. A low PIZ indicates that urban sprawl was modest in these specific zones. In 2021, the proportion of built-up land in zones 6 and 7 was rather high, approaching 22% of the total. According to PZ data, urban sprawl has been steady during the last 21 years. To that extent, urbanization has expanded to the study region's eastern half, which is divided into zones 6 and 7.

The impacts of urban growth on land use land cover change were also investigated in this research work. To quantify urban growth effects on land use land cover, two major land use land covers were selected. In the study region of Dukem Town, urban growth is costing agricultural and forest land area at large expense. To that extent, 1213.6 hectares of agricultural land was converted to built-up between 2000 and 2010. Moreover, 787.87 hectares of agricultural land was converted to built-up area between 2010 and 2021. At the end, 1161.58 hectares of agricultural land was converted to built-up area between 2000 and 2021. Furthermore, between the years 2000 and 2010, a large amount of forest land nearly 97.99 hectares were cleared for the sake of urban growth. This is the largest conversion rate compared to the overall study periods (2000-2021). Modest amount of forest land was also cleared between the years 2010 and 2021 with 45.27 hectares. Forest degradation due to urban growth is said to be reduced between the years 2000 and 2010. Over the last 21 years, a total of 83.97 hectares of forest land was converted to built-up area.

5.2.Recommendation

The following recommendation points are forwarded from the research findings: -

- The study's findings indicated that the spatiotemporal dynamics of urban sprawl has accelerated in the previous 21 years. This results in extraordinary, unplanned, and quick growth of the Town, which will continue in the next decades. Furthermore, investigations show that all of the master plans developed to steer urban development activities have been poorly implemented. As a result, it is essential that urban planners prepare ahead of time in order to keep up with the rate of urban expansion through appropriate implementation.

- It is also stated that the Town is expanding quantitatively in the east, north east, south, and north west directions towards fertile agricultural areas. As a result, agricultural and forest areas have reduced significantly during the last 21 years. As a result, city planners must look inside and vertically to accommodate infill development and assure appropriate horizontal expansion of the city in order to minimize agricultural land loss and the impact of urban sprawl on urban ecology.

- The spatial and zonal metric approach was utilized to successfully assess spatiotemporal dynamics of urban sprawl by computing the number of patches, CA, ED, LPI, PLAND, SHEI, and other landscape metrics. Most Towns in Ethiopia are prone to urban sprawl on occasion. As a result, the approach presented in this research work was robust and appropriate for comparable urban sprawl assessments in other Ethiopian cities.

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APPENDICES

Appendix I: Photographs during data collection time.