Analysis of the spatiotemporal dynamics of urban sprawl using Shannon entropy and landscape metrics, Case study Bishoftu City, Oromia, Ethiopia

Birhane Abdisa

A Thesis submitted to the Department of Geomatics Engineering, School Of

Civil Engineering and Architecture

Presented in partial fulfilment of the Requirements for the Degree of

Master‘s in Geo-Informatics Engineering

Office of Graduate Studies

Adama Science and Technology University

May, 2024

Adama, Ethiopia

ANALYASIS OFTHE SPATIOTEMPORAL DYNAMICS OF URBAN SPRAWL USING SHANNON ENTROPY AND LANDSCAPE METRICS. CASE STUDY BISHOFTU TOWN, OROMIA, ETHIOPIA

Birhane Abdisa Dendea

Advisor: Dejene Tesema (PhD.)

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DECLARATION

I declare hereby that this Master Thesis entitled" Analysis of the spatiotemporal dynamics of urban sprawl using Shannon entropy and landscape metrics. Case study Bishoftu town, Oromia, 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.

Birhane Abdisa Dendea	______________________	______________________
Name of Candidate	Signature	Date

RECOMMENDATION

We, the advisor(s) of this thesis, hereby certify that we have read and revised version of thesis entitled" Analysis of the spatiotemporal dynamics of urban sprawl using Shannon entropy and landscape metrics. Case study Bishoftu town, Oromia, Ethiopia". Prepared under our guidance by Birhane Abdisa Dendea submitted in partial fulfilment of the requirements for the degree of Masters of Science in Geo-informatics Engineering. Therefore, we recommend the submission of revised version of the thesis to department following the applicable procedures.

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APPROVAL SHEET

We, the advisors of the thesis entitled "Analysis of the spatiotemporal dynamics of urban sprawl using Shannon entropy and landscape metrics. Case study Bishoftu town, Oromia, Ethiopia". And developed by Birhane Abdisa Dendea, hereby certify that the recommendation and suggestions made by the board of examiners are appropriate incorporated into the final version of the thesis.

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Co-advisor	Signature	Date

We, the undersigned, members of the Board of Examiners of the thesis by Birhane Abdisa Dendea have read and evaluated the thesis entitled "Assessing the spatiotemporal dynamics of urban sprawl using Shannon entropy and landscape metrics. Case study Bishoftu town, Oromia, Ethiopia". And examined the candidate during open defence. This is, therefore, to certify that the thesis is accepted for partial fulfilment of the requirement of the degree of Master of Science in Geo-informatics Engineering.

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TABLE CONTENTS

Table of Contents

LIST OF TABLE

TABLE OF FIGURE

LIST OF ACRONYMS

CA	Class Area
CBD	Central Business District
CSA:	Central Statistical Agency
DEM:	Digital Elevation Model
ED	Edge Density
ERDAS	Earth Resource Data Analysis System
ETM:	Enhanced Thematic Mapper
ETM+	Enhanced Thematic Mapper plus
GIS	Geographic Information System
GCP	Ground control point
GPS	Global Positioning System
LPI	Largest Patch Index
LSI	Landscape Shape Index
LULC	Land Use and Land Cover
NASA	National Aeronautics and Space Administration
NP	Number of Patch
OLI	Operational Land Imagery
PLAND	Percentage of Landscape
RS:	Remote Sensing
SHEI	Shannon entropy index
TM	Thematic Mapper
USGS	United States Geological Survey
US	Urban sprawl
UTM:	Universal Trans Mercator
WGS:	World Geodetic System

ABSTRACT

Urban sprawl is considered as a particular kind of urban growth which comes up with a lot of negative effects. A complex of driving force such as social economic political physical and factor and their interaction cause urban sprawl. Bishoftu city is undergoing rapid changes in the last 3 decades especially in the last decade and needs assessing of urban sprawl and its causative factor. So, this study focuses on the assessing the spatiotemporal dynamic of urban sprawl in Bishoftu City from 1990 to 2022 using Shannon Entropy and landscape metrics. Landsat Satellite data was applied in this research ((TM, ETM+, and OLI/TIRS) for land use/land cover classification and accuracy assessment were applied in four study periods (1990, 2000, 2010 and 2022). Elevation data, major road data, water body data, city center data, health center and educational institute data were used to identify the driving forces of urban Sprawl. The study area is classified in to five classes; water body, bare land, built-up green area, and agricultural land covers. To identify the expansion of built-up areas within the study region, the classified land use/cover data was reclassified into built-up and non-built-up categories. The result showed that an increase in built-up area 1872.81ha, 2479.77ha, 3440.97ha and 4783.14ha in 1990, 2000, 2010 and 2022 respectively this indicate the sprawl pattern of the study area has increased from 1990 to 2022. After reclassified the image multi ring buffer analysis was made at an interval of 3km from the center of city for built-up area. This is used to determine the extent of urban sprawl using the Shannon entropy. The calculated value of Shannon entropy was 0.520, 0.758, 0.861and 0.945for 1990, 2000, 2010 and 2022 respectively. Approach the degree of dispersion or concentration of built up area's development or sprawl was described in this study. FRAG STAS was used to quantify the landscape metrics of Bishoftu city finally; a logistic regression model in IBM SPSS Statistics 25 software was used to identify the driving forces of urban Sprawl from six selected variables. The model identified major roads as a major driver in all years and city centers as a second driver in the period 1990-2010. In the period 2010-2022, educational institutions and health centers emerged as the second-largest drivers.

Key words: *Urban sprawl, Logistic regression, Shannon entropy, spatial metrics, spatiotemporal*

CHAPTER 1 INTRODUCTION

1.1. Background of the study

Historically, in pattern and organization of settlement, human has undergone several changes up to todays (United Nations, 1980). However, it is not known when and where the first settlement begun to grow some anthropologist argues the first settlement began to form approximately in Neolithic period that is the transition from hunting and fishing to agriculture. Some anthropologist argues that settlement began with the adoption of the settled agriculture and people began to identify themselves with place. Following the human development in self-knowledge and ability to induce changes, the other phase of change were the emergence of cities(Gmelch & Kuppinger, 2018) which was the urban idea. By definition, urbanization refers to the process by which rural areas become urbanized because of economic development and industrialization (GGY-HC et al2016). Thus, urbanization can be described as a shift in population from one that is dispersed across small rural settlements in which agriculture is the dominant economic activity towards one where population is concentrated in larger dense and engaged in non-agricultural activities(United Nations 2014).

Urban population change is described by level of urbanization that represents the share of countries total population that lives in urban areas, and by the rate of urban growth which indicates the number of person added to urban population. Globally, the urban population of the world was 30 per cent in 1930 and rapidly increased in to 55 per cent in 2018; and it was projected that 68 per cent will reside in urban zones by 2050(United Nations, 2018).The total population of Ethiopia is more than 107 million with annual growth rate of 2.52 per cents and 20 per cent of urban population while the total urban population of Africa is 42.5 per cent (United Nations, 2018).

Urban expansion and sprawl have been identified as the most significant aspects of urbanization and urban development. In several countries rapid and unplanned urbanization has led to urban sprawl and land use fragmentation (Koroso, 2022). There are multiple challenges associated with urbanization especially when it is not well planned and properly managed. Unpredictable urban growth has resulted in the conversion of land for urban uses exerting pressure on natural resources as open and green ecological spaces gets transformed into residential, industrial and commercial use resulting dispersed and haphazard growth which referred as urban sprawl(Bharath et al., 2017). Inadequately managed urban expansion is combination with unsustainable production and consumption patterns and lack of capacity of public institution to manage urbanization deteriorate sustainably due to urban sprawl, pollution and environmental degradation.

The fact that urban growth induces urban sprawl in both developed and developing countries.Currently, urban sprawl phenomenon has been seen in many of cities both in the developing and developed countries. Urban sprawl is considered as one of a specific kind of urban growth which comes up with a lot of negative effects. A complex of driving forces such as social, economic, political physical factors and their interactions cause urban sprawl. In many studies, the most important reason of urban sprawl is indicated as the increase of demand for dwelling at low density areas. As a result of insufficient demand for dwelling in city centres, there is an increase in building houses at city boundaries (Slaev & Nikiforov, 2013). Another reason of urban sprawl which is as important as the increase of population and demand for dwelling is the role of market. Many researchers which carried out studies on this subject adopt the approach of open market, they defend that the effect of market can be formed since the process of urban sprawl should be directed and managed within specific limits (Slaev & Nikiforov, 2013).

Development of sprawls is now more rapid in developing countries and is a major contributor to the increasing land use changes and conflicts especially in the developing regions of the world(Belal & Moghanm, 2011). For developing countries, sprawl is generally a product of necessity: people migrate to cities in pursuit of better job opportunities, resulting in a growth in population far beyond the city's boundaries (Bekele, 2005). In the case of Ethiopia, urban sprawl is manifested in unnecessary and unlimited outward expansion of urban areas at the expense of other land use classes in a way that contradicts the spatial plan of the city. As the findings of the study conducted by Zemenfes G (2014) in Mekelle city, Ethiopia, the city was sprawling into the nearby rural community as a result of the uncontrolled and unauthorized acquisition and occupation of farmlands; which is mainly related to poor land use and administration policy of the city.

The modern remote sensing techniques, both aerial and satellite-based systems, and their integration with Geographic Information System (GIS) allow us to analyses the data spatially, offering possibilities of the assessment of urban sprawl at a very speedy and repetitive way(Ghosh et al., 2017).Remote sensing alone cannot fully describe the fundamental urban process and patterns hence the need to incorporate landscape metrics

(Magidi & Ahmed, 2019b). These metrics assist in gaining an understanding of the characteristics of the urban landscape for sustainable management of urban environments (Manikandan, 2019). The commonly used composition metrics are Shannon's Diversity Index (SHEI) (Sridhar et al., 2020), and patch richness density (Kpienbaareh et al., 2019). Shannon's entropy reflects the degree of spatial concentration and dispersion of spatial variable and can be used to quantify and differentiate types of sprawl (Araya & Cabral, 2010).

The main cause of urban sprawl in industrialized countries is increasing wages, which lead to people preferring to live on the outskirts of cities, where there are more open spaces and are located at a fair distance from cities. Development of sprawls is now more rapid in developing countries and is a major contributor to the increasing land use changes and conflicts especially in the developing regions of the world(Belal & Moghanm, 2011).

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1.2.Statement of the Problem

Growth of any city can be a good sign of development, but rapid and unplanned urban growth threatens sustainable development when policies are not implemented to protect the environment. On other hand, the way the expansion taken place in land use land cover changes is seen affecting the smaller villages on the periphery, agricultural land without having any basic civic amenities on the city.

As population increases, urban sprawl on a global scale is becoming more apparent than ever. The problem of urban sprawl was restricted to the developed world; but it also exists in developing countries although in a different form. For developing countries, sprawl is generally a product of necessity. People migrate to cities in pursuit of better job opportunities, resulting in a growth in population far beyond the city's boundaries (Bekele, 2005). The city was sprawling into the nearby rural community as a result of the uncontrolled and unauthorized acquisition and occupation of farmlands; which is mainly related to poor land use and administration policy of the city. Generally, as pointed sprawl in Ethiopia is the result of population pressure (both from natural births and migration), however there are other factor. In Ethiopia there is little research in spatiotemporal dynamic of urban sprawl and that determine contributing factor for urban sprawl.

In the case of Bishoftu city, while the researcher developing interest and selecting areas of the study observed that from Cities and Towns nearby Addis Ababa, Bishoftu is one of the rapidly expanding due to its investment, tourism attraction and comfortable for residence due to its location proximity to the capital city of the country adjacent to lakes and is located on the pathway to Adama these have contributed to the rapid expansion of urbanization this issue might leads to urban sprawl. The researcher observed that there is no theoretical understanding for dynamic of urban sprawl on spatiotemporal scale in major and that determine the conterbitung factor of urban sprawl for the study period.

Since Bishoftu city is significantly growing in size with expanding infrastructure and population consequently, there is urgent need to assess the urban sprawl; therefore, this study is relevant to urban planners and community. Urban planners require information related to the rate of growth, pattern, extent and direction of sprawl and causal factor of sprawl to provide basic amenities such as water, sanitation, electricity, etc. Therefore, it is important for urban planners, community and policy makers to understand multidimensional phenomena of urban sprawl and its spatiotemporal dynamics in the city, which can enable effective utilization of resources and allocation of infrastructure by controlling improper enforcement of, land use. Furthermore, the findings of this study are beneficial to reduce the sprawl and its socio –economic and environmental impacts by determining the factor.

1.3.Objective of the Study

1.3.1. General objective

The general objective of this study is to assess the spatiotemporal dynamics of urban sprawl in Bishoftu City from 1990 to 2022 using Shannon entropy and landscape metrics.

1.3.2. Specific objectives

The specific objectives

- To identify the extent and spatial distribution of urban sprawl in Bishoftu City in 1990, 2000, 2010, and 2022
- To determine the changes in the extent and spatial patterns of urban sprawl in Bishoftu City between 1990 and 2022.
- To identify the key factors contributing to urban sprawl in Bishoftu City from 1990 to 2022.

1.4. Research question

1. What is the extent and spatial distribution of urban sprawl in Bishoftu City in the years 1990, 2000, 2010, and 2022?

2. How have the extent and spatial patterns of urban sprawl changed in Bishoftu City between 1990and 2022?
3. What are the key factors contributing to urban sprawl in Bishoftu City from 1990 to 2022?

1.5. Significance of the study

Urbanization and urban growth must be planned, formed, and controlled for cities to completely fulfill their potential to generate wealth, improve the standard of living, ensure citizen health and well-being, and improve environmental efficiency standards. Therefore, GIS and remote sensing play a great role in shaping and managing urbanization by measuring urban sprawl and spatial expansion of urban areas using various techniques of change detection and spatio-temporal satellite images together with, spatial metrics methods to study urban sprawl. Bishoftu is one of the fastest growing cities in Ethiopia. This study will be essential in indicating the past 32 years and current urban sprawl of the city into the surrounding areas. Therefore the study will provide a good understanding about the sprawl of the city and contributing factor for urban planners and city administrators, by measuring built up and various spatial metric indices based on its shape, area, edge, form, number and fragmentation of built up area patches.

1.6. Scope of study

The Geographical scope of this study is Bishoftu City, Oromia, Ethiopia Administrative boundary. Conceptually, this research focuses mainly on an assessment of urban sprawl of 1990, 2000, 2010 and 2022 and determines urban sprawl extent, pattern and direction In addition to this; the study also covers the determination of causative factor using geospatial technologies and landscape metrics.

1.7. Limitations of the study

The historical input data eventually influenced the analysis of urban sprawl's accuracy and reliability. Better simulation outcomes require an understanding of remote sensing data with high spatial resolution. (Sudhira & Ramachandra, 2007). In this study, 30meter resolution Landsat images obtained from USGS earth explorer website (https://earthexplorer.usgs.gov/) has been used. Satellite data may have spatial detection limitations due to spectrum energy mixing, making accurate land use and land cover maps difficult to generate and distinguishing between feature classes. This satellite data may have certain restrictions in terms of the spatial detection of features due to the mixing of spectrum energy in the displayed image. To verify the results of the categorization, further field collected ground control points are required.

Using higher resolution satellites such as SPOT, IKONOS, Quick bird, Geo eye, and World View can provide more detailed information for mapping land use and land cover classes as indicators of urban sprawl.And also factors, which can drive urban sprawl models, was limited by the availability of data.

1.8. Definition of terms

Urban sprawl is the expansion of an urban area outward from its core into low-density suburban or rural areas. It is a form of urban growth characterized by low-density residential housing, commercial development, and office parks that are spread out over a large area. Urban sprawl has been a major concern in many countries, as it can lead to a number of problems, including traffic congestion, air pollution, and loss of open space.

Urbanization is the process by which people move from rural areas to urban areas. It is a global phenomenon that has been occurring for centuries, but it has accelerated in recent decades due to factors such as economic growth, technological advances, and climate change**.** The land is transformed for residential, commercial, industrial, and transportation reasons as a result of this concentration.

Landscape metrics Landscape metrics are quantitative measures used to describe the composition, configuration, and spatial arrangement of landscapes. These metrics are used in landscape ecology, geography, and related fields to assess and analyze various aspects of landscapes, such as habitat fragmentation, connectivity, diversity, and spatial patterns. And Landscape metrics are indeed used extensively in studying urban sprawl.

Shannon's entropy Shannon's entropy, named after Claude Shannon, is a measure of uncertainty or randomness in a dataset. In the context of landscape ecology or land cover analysis, Shannon's entropy is often used as a diversity index to quantify the diversity of different land cover types within a landscape.

Logistic regression Logistic regression is a statistical method used for modeling the relationship between a categorical dependent variable and one or more independent variables. Unlike linear regression, which predicts a continuous outcome, logistic regression is used when the dependent variable is binary (e.g., yes/no, 0/1) or categorical with two or more levels, but representing binary outcomes.

1.9. Organization of the research

The whole thesis is divided into five chapters. The first chapter lays the background of the study providing general introduction about the research work including the problem statement, questions and research objectives, the scope and limitations of the study were also highlighted. The second chapter deals with literature survey in which the related works as have been performed by various other researchers are presented. In the third chapter, information about the chosen study area is given and how the several data layer maps are generated, also outlining the methodology of carrying out the task and the data sources utilized. Chapter 4 presents the findings of this research work and a detailed discussion on the results obtained. Finally, in the fifth chapter, a conclusion is drawn based on the results obtained along with future research possible and recommendations

CHAPTER 2 LITERATURE REVIEW

Literature review in this research is gateway for understanding the concept of Urbanization, urban sprawl, causes of urban sprawl, characteristics, consequences, and methods of measuring, software and algorithm used. Literature review was useful in gathering significant study reports from different scholars.

2.1. Urbanization

The term "urbanization" refers to the rising percentage of people living in urban regions. Its exact definition is "the growing proportion of a country's population living in urban areas (and therefore a declining proportion residing in rural areas)."(Satterthwaite et al., 2010).Urbanization is a process leading to the formation of towns, cities and agglomeration of people and their socio-economic activities in areas classified as urban based on different criteria.

According to Buettner (2015) Countries utilize four general standards to distinguish between urban and rural areas: Administrative criteria refers to the classification of a location as urban; population-related criteria, on the other hand, deal with population size and density; for size, a locality must have a population threshold of 10,000 or more to be considered urban; for density, a locality must have at least 400 people per km2; economic criteria are the substantial presence of non-agricultural activities; and criteria based on urban functions can include things like paved streets, water and sewer systems, electric lighting, and so on. A population that is urban is one in which vast numbers of people are clustered together in very small areas called towns and cities. “Urbanization is a process of population concentration. It proceeds in two ways the multiplication of points of concentration and the increase in size of points of concentration”(Oluwasola, 2007). The physical growth of urban areas can be described both functionally and demographically. The economic functional definition of urbanization relates to the territorial concentration of productive activities (industries and services) as compared to population, while the demographic definition is limited to elements like population size and density. This study looks at urbanization from both a functional and demographic perspective.

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2.2. Urban sprawl

The migration of people (both rich and poor alike) from the city center to the suburbs in search of a higher standard of living is the phenomenon that properly characterizes urban sprawl. That indicates that while the rich proceed out to lead better lives for themselves, i.e., to escape noise, slums, congestion in traffic, etc., the poor migrate to suburban areas to obtain a better living style because they cannot bear the life standards of the city centers. Moreover, there is a significant association between the effects of urban sprawl and the commute from home to the workplace, transportation infrastructure, distance driving, and traffic congestion.

The term "urban sprawl" was introduced in 1937 by Earle Draper to refer to an unattractive and ineffective type of urbanization; it has been defined in a number of ways in the current context (US), although there is still a bit of confusion.

According to Barnes et al.(2001) and; Wilson et al.(2003) Describing urban sprawl would be more appropriate than defining it.. However, let us see some of the definitions of urban sprawl in the existing literature to understand its complexity; According to Oxford Dictionary, urban sprawl has been defined as the disorganized and unattractive expansion of an urban area into the adjoining countryside this statement is significant as confused and haphazard urbanization and industrialization resulted in series of problems in developing countries(Sudhira et al., 2009). Urban sprawl is characterized by unplanned, uneven growth that is generated by numerous mechanisms and results in ineffective resource use. Such sprawl directly affects the region's land use and land cover since it causes an increase in the amount of paved and built-up area. Generally urban sprawl is the significant or indicator of unplanned, uncontrolled, and haphazard expansion of urban developments or low-density physical expansion of cities into the surrounding non-urban areas(Besussi et al., 2010). Sprawl must be considered in a space-time context as not simply the increase of urban lands in a given area, but the rate of increase relative to population growth. In developing countries, Ardeshiri & Ardeshiri (2011) synthesized the concept of urban sprawl in context of built-up area density, he emphasized the importance of land price and uncontrolled housing leads in lack of government control in land market and building construction, thus resulting in uncontrolled urban sprawl, this study was crucially illustrated by (Habibi & Asadi, 2011a).by pointing out urban sprawl as unusual and excessive growth if cities putting pressure on boundaries and city in context of sustainable development.

In this literature review more focused on six definitions of urban sprawl that was systematically constructed to include physical, morphological, causal, preferential, social and environmental aspects of urban environment and that were adjusted from(Galster et al., 2001) .

2.2.1. Defined by its consequence of uncontrolled growth

Many literary studies illustrate that urban sprawl is mostly caused by unmanaged or uncontrolled urban growth. The study conducted by Hosseini & Hajilou (2019) ,urban sprawl is a result of uncontrolled urban growth and that was mostly affects the outside world, with consequences that are mostly present outside urban peripheries, alongside highways connecting other cities or satellite urban centres.According to Viana et al.(2019) a study on urban sprawl analysis using remote sensing, urban sprawl is not only unplanned and uncontrolled urban expansion, but it is also seen negatively because it is linked to the depletion of complex resources including land, water, air, and health. In other cases, inattention to urban development policies causes urban sprawl rather than unchecked urban expansion.

2.2.2. Defined by its unaesthetic and injustice design

Urban sprawl creates clusters of homogenous design that produce an anaesthetic or unpleasant view; its ugly suburban monotonous housing caused by poor planning or limited autonomy and causes social and economic injustice.

In the context of urban sprawl, defined by its anaesthetic design, urban sprawl is seen as a

Confused and unattractive expansion of an urban or industrial area into the adjoining

Country side. Urban sprawl is visibly ugly as a result of homogenous form of development Gordon & Richardson(1997) defined and critiques urban sprawl as aesthetically unattractive. Bhatta (2010) was Also concerned that urban sprawl can develop additional negative consequences in terms of aesthetic views such as monotonous and ugly suburban landscapes. Urban and rural landscapes should have a strong traditional and distinctive aesthetic value, but urban sprawl distorts it.

2.2.3. Defined by its driving forces

Urban sprawl is the dispersion of residential and employment development, industrial externalities, market forces and neighbourhood incentives that push development further away.

Early literature defined urban sprawl as a product of post-war suburbanization that was highly driven by speculation, taxes and market(Dibble et al., 2019; Franklin & Plane, 2017). Large scale speculation has serious consequences for vacant and ‘leap’ land prices. The situation has formed a discontinuity in urban expansion thus created a leapfrog development. Decades after post war has seen the size and speed of urban sprawl escalate and the main driving forces of urban sprawl are much more diversified. Guan et al. (2020) quantified the urban sprawl index of the Yangtze Economic Belt. The study defined urban sprawl as driven by economy, population and land. The result of the study has concluded that large economic development, rapid population growth, numerous suitable and available pieces of land have been identified as significance factors that contributed to the economic belt and are simultaneously creating sprawl as a by-product. Li & Li(2019) observe the differences and socioeconomic drivers of urban sprawl in China. The study claims urban sprawl is driven by population density; GDP per capita; and industrial structure and has effecting Eco environmental and socioeconomic sustainability

2.2.4. Defined by its pattern of growth

Urban sprawl has a nasty pattern of development spreading further from the city such as leapfrogging, ribbon, strip development and periphery areas.

Ewing(2008) refers to urban sprawl as undesirable land use patterns whether scattered, leapfrog, ribbon or continuous low-density development and at the same time has poor accessibility and lacks functional open spaces. The growth patterns are usually determined by the availability of adjacent land and variations of terrain. Accessibility has a direct correlation with the extent of the scatterednes of the pattern. The more scattered the pattern, the lower their accessibility. Low accessibility increased the travelling and transportation cost. Increased travelling pattern will result in decreased household disposable incomes. a study on the impact of land finance on urban sprawl by Liu et al. (2018) The study defined urban sprawl in multiple forms leapfrogged, low density residential and discontinuous development. The study concluded that local authorities face difficult tasks to gain a budget surplus from sprawled property because of poor public amenities and expensive infrastructures

2.2.5. Defined by its expansive character and excessive growth

Urban sprawls expand excessively, with rapid urbanization and population spread outside their periphery and into rural area, convert and create spatial reorganization and functionality change.

Salvia et al.(2018) argues urban sprawl was formed because of residential overcrowding and increased population in the city centre, resulting in an escalation of development to the outward urban fringe. However, the study indicated concern that urban jobs are still concentrated in the city centre, thus the journey to work contributes to environmental consequences. Salvia et al. also alleged that the trend in countries with recently rising economies such as China, have the highest occurrence of urban sprawl. Aurambout et al.(2018) applied the Averaged Concentric Weighted Urban Proliferation index (ACWUP) and insisted that urban sprawl is a growth that extended once the urban centre becomes extremely crowded. They explained how changes in density and the proportion of development gradually lowers as it occurs further away from an urban centre.

2.2.6. Defined by its consequences to socio-environment

Urban sprawl is associated with low accessibility, extended journey to work in terms of time and distance which eventually make private transportation the only feasible option and inevitably increase carbon release. Wolff et al.(2018) conducted a quantitative study for a European spatial model and highlighted the ecosystem disturbance and decreased quality of air and health when defining urban sprawl. Viana et al.(2019) used a dynamic measure of remote sensing to perform urban sprawl analysis and the result is the region of interest suffered in terms of land, water, air, and health. Kovács et al.(2019) assess urban the expansion of post-socialism Budapest and found that urban sprawl has adverse consequences on the population socially, economically and environmentally.

2.3. Characteristics of urban sprawl

The presence of urban sprawl is worldwide, and it is not exclusive to any particular type of functioning city. Derived from the definition and theory of urban sprawl, the review suggests general characteristics of urban sprawl as below:

2.3.1. Automobile dependence and low accessibility

Dispersed and low-density development decreases the network's accessibility and increases reliance on automobiles(Ewing, 2008). This kind of urban growth also has a significant impact on the price of providing public transportation, which increases its effectiveness and competitiveness(Mendonça et al., 2020). The costly public transportation is because the struggle to consolidate demand and supply at cost efficient level of services in low density and scattered develop

2.3.2. Dispersed and low-density development

Dispersed or scattered and low-density development is urban sprawl most described and recognizable character. The urban sprawl pattern developed in the urban edge, and outside that, reduces in density as they go further away from the urban Centre, in contrast to compact development, which focuses in the urban center.

Urban sprawl's pattern of spread into the surrounding countryside and dispersed or scattered development in rural regions are also crucial elements. Rural agricultural and environmentally sensitive terrain may be encroached upon by this form of development (Deilami & Kamruzzaman, 2017; Nope et al., 2020) . In low-density suburbs, agricultural and Urban land are intertwined with residential and urban infrastructures, as well as dispersed public amenities like health facilities, public schools, and community centers.

2.3.3. Modified travel mode and pattern

The effects of urbanization trends like suburbanization and urban sprawl on mobility and travel behavior have been extensively studied. People can commute a wider distance between residential areas and metropolitan centers due to expressway-upgraded roadways. Urban growth is generally accompanied by an increase in internal transportation route changes, which affect commute times and distances, which in turn affect travel modes and patterns.

In the continental United States Lee (2020) has investigated how traveller trip is impacted by urban sprawl. There are three levels of urban sprawl: lower, middle, and higher. The study develops multivariate regression models relating urban design, commuter journeys, and emissions from road traffic in order to identify the sustainable travel mode and pattern. The conclusion of the study was that lower urban sprawl.

2.4. Factor and Causes of Sprawl

As it was stated, sprawl has some characteristics that differs it from other kinds of urban growth and experts have different viewpoints about its causes. Most of the time considered that urban sprawl has been a major a challenge in developed world but now it has already become a concern for cities in developing countries too. Urban sprawl is caused by different drivers and has in turn a wide range of consequences to the surrounding environment. Urban Sprawl growth is dependent on variety of factors.

The factor and causes of urban sprawl are represented into six categories by considering the definition of urban sprawl.

The categories of factors and causes of urban sprawl include socio-demography, economic, political, physical, environment, and transportation.

Socio-demographic context involved several component like population growth, economic development, proximity to resources and basic amenities(Boori et al., 2015; Jain, 2002).Improvement in socio-demographic factor like growing population and income lead to high demand for housing and other facilities and This situation cause land and housing prices to increase greatly, causing the shifting of lower and middle income city population towards the suburban areas due to a reduced cost of residential properties (Abdullah, 2012; Amato et al., 2015; Rahman, 2016). Jaeger & Schwick,(2014) Determined that sprawl is just not a result of population growth but also of new lifestyles that require more space. Habibi & Asadi, (2011) also summarized the most important factors that encourage sprawl is socio-demographic like population and income growth, followed by other factors such as better accessibility, low price of land and transportation, better infrastructure and public services.

2.5. Type of urban sprawl

There are three types of sprawl, low-density sprawl, ribbon sprawl and leapfrog development sprawl (Harvey & Clark, 1971)

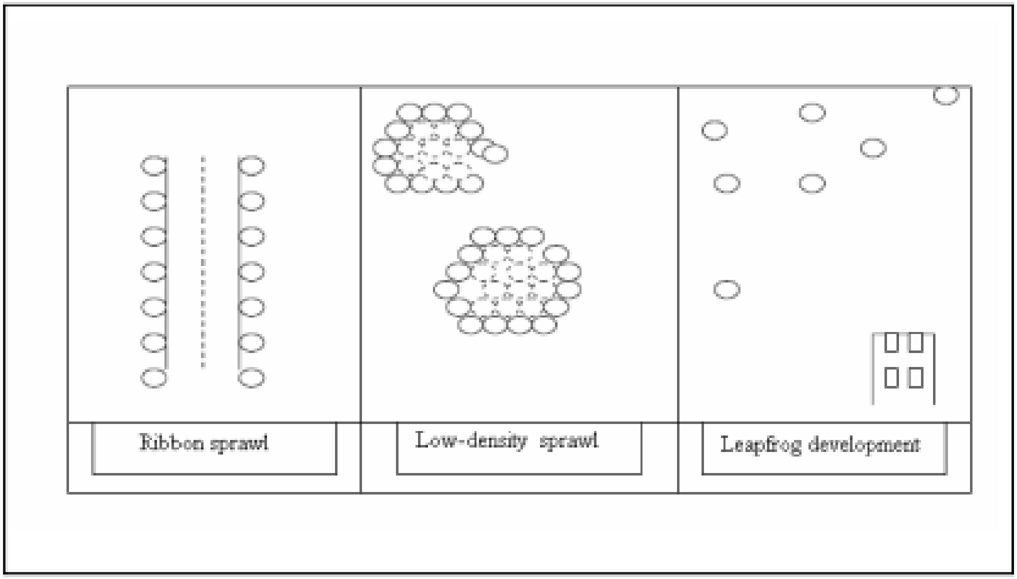


Figure .1 Type of sprawl development

2.5.1. Low density sprawl

Low density sprawl is a phenomenon caused by outward spreading of low-density suburban land use as currently being experienced by many of cities like America as their population becoming bigger and bigger and there is no lack of land supply. This highly consumptive use of land for urban purposes is supported by piecemeal extensions of basic urban infrastructure such as water, sewer, power and roads.

2.5.2. Ribbon Sprawl

Ribbon sprawl is a type of sprawl characterized by concentration of development along major transportation arteries, primarily roads. While development occurs on land adjacent to the major roads, areas without accessibility to the roads tend to remain as green areas, waiting for conversion into urban land uses when land values increase and infrastructure is extended from the major roads.

2.5.3. Leapfrog Development Sprawl

Leapfrog development sprawl is a scattered form of urbanization with disjointed patched of urban land uses, interspersed with green areas. Leapfrog development may be caused by obvious physical limitations such as prohibitive topography, water bodies and wetlands or by more subtle reasons such as differences in development policies between political jurisdictions.

2.6. Consequences of Urban Sprawl

Urban sprawl is generally considered as adverse effect as compared to densely developed city, lacking diversity and economic activities and social infrastructure (Batty et al., 2003). Urban sprawl effect cannot be isolated within single entity, but their effects are accumulated in multiple entities.

2.6.1. Social consequences

Urban sprawl has enormously increased the distance and time taken for journey to work and created a complex web of traffic flows which cause crowding (Wang et al., 2020).

A study on spatial analysis of demographic of Atlanta by Ambinakudige et al.(2017) founds that the type of land use segregation of urban sprawl also aggravating socio-spatial separation there up on and affecting social interaction, formation of urban gaps and racially segregated neighbour hoods. The study also claimed that the socio-spatial separation of urban sprawl would further hinder employment opportunities particularly in the fringe area. Urban sprawl can also cause intensified fiscal disparities among communities, which extend to several aspects of inequality. Suburban wealthy communities have a larger tax reserve, and fewer social service to provide, therefore expanded public service disparities, for example public schools and inner-city services. Another study on how sprawl affect social inequality in America by Lee et al. (2018) investigate whether social well-being and inequality is caused urban sprawl. The study suggests urban sprawl has direct effect in social well-being, and an indirect effect to income inequality. For example, urban sprawl caused long commutes, and this is linked to household disposable income and suppressing social interaction. The study also indicates the growing concentration of social inequality and social segregation is both causes and consequences of other social problems.

2.6.2. Economic consequences

Attention has been given to economic consequences of urban sprawl especially urban decline and reduced urban economic agglomeration. Past research has evidenced connecting urban sprawl with reducing economic agglomeration and productivity in the core urban area. Wolff et al.(2018) suggest urban sprawl seems to have particular impact on economic activity in the core urban area because urban decline had force business and industrial to relocate to the periphery either to reduce operational costs or to accommodate high level business for high inner city society. Since economic sector is linked with geographical factors, only high-level business and services are operating in the core urban area.

In undeveloped country, most people rely on agricultural production and land is a vital resource and assets. A study by Dadia et al. (2016) investigates the impact of urban sprawl in Ethiopia. The agriculture and rural population were extensively affected by residential and infrastructure expansion. The low-density and leapfrog sprawl encroach agricultural lands and has been contrary to the government policies to minimise land conversion, thus undermining the livelihoods and socioeconomic of poverty-stricken population. The loss of arable land and agricultural productivity has severely effecting majority of population because agriculture is the principal occupation and the biggest derived household income. The urbanization has neither come with additional employment nor economic opportunities. The government has unsuccessful to expand industrialized economy, instead the rate of industrial enterprises has reached rock bottom without new employment and the GDP of the country has never been worse. The supposed infrastructure expansion was not benefitted the rural population in term of access to electricity or clean water. What made the matter worst is the converted lands for industrial purposes were not at all even developed.

2.6.3. Political consequences

A continuously increasing number of volumes on development are appearing parallel with the occurrence of sprawl. Urban sprawl has been described in terms of the political structure of urban regions (Egidi et al., 2020). Low density, scattered, and leapfrogged development apparently affect the spatial and locational aspect of local government expenditures. This is due to the increment in providing public services costs to cater for larger area with lower population density. Thus, in order to maintain the quality of service provision in newly urbanizing areas, every now and then, new local governments and special districts are often formed.

Ehrlich et al.(2018) examine urban sprawl and the role of institutional setting in Europe. Urban sprawl in Europe is particularly pronounced and occurs outside functional urban areas. The study founds out a strong link between urban sprawl and local political fragmentation, allowing intervention policy such as land use planning and fiscal incentives to permit suburban development in the periphery.

2.6.4. Environmental consequences

Environmental degradation is the most affected cost associated with urban sprawls that are intensified by the characteristics and pattern of this development. Urban sprawl reduces open space, forest and agricultural land. The low density scattered and leapfrog development requires lengthy infrastructures including road networks, turning absorbent surface into impervious surface. Decreased of open space, forest and agricultural land decreased quality of water sources caused by nonpoint source pollution and sedimentation.

Another study conducted by Manjunatha et al.(2019) where Chicago’s aggressive extension and sprawl of its commercial district have become an environment threat to Illinois basin and Mississippi River, resulting in habitats loss along major rivers threatening the sustainability of wildlife populations. The study by Siles et al.(2018), where urban sprawl causing fragmentation and loss of wetland area are affecting biodiversity and their ecosystem such as specific wildlife and birds.

2.7. Urban Land use land cover of Image Classification

Urban land use land cover classification is the process of assigning land cover types to each pixel in an image of urban area it is used to map the distribution of different land cover types, such as settlement, water body, greenery, bare land etc... Urban land use land cover classification is important for a variety of proposes, including urban planning, environmental management, and disaster response. However, there are two broad types of classification procedure and each finds application in the processing of remote sensing images: one is referred to as supervised classification and the other one is unsupervised classification. These can be used as alternative approaches, but are often combined into hybrid methodologies using more than one method(Richards & Jia, 2006).

2.7.1. Supervised classification

Supervised classification is a common method for land use land cover classification in remote sensing. It involves training a classifier on a set of labelled data, then using the classifier to classify new data. The labelled data is typically collected by field survey or by using other remote sensing data. It is a power full tool for extracting information from remote sensing data. However, it is important to be aware of the challenges associated with this technique in order to achieve accurate and reliable result.

There are a number of different supervised calcification algorithms available, each with its own strengths and weaknesses. The most common algorithms include: Maximum likelihood, minimum distance, K-nearest neighbours. The choice of algorithm depends on the characteristics of the data and the desired level of accuracy.

2.7.2. Unsupervised classification

Unsupervised classification is a method for land use land cover classification in remote sensing that does not required labelled data. It involves clustering the data into groups based on their similarity. The clustering is than assigned to classes based on their characteristics. There are a number of different unsupervised calcification algorithms available, each with its own strengths and weaknesses. The most common algorithms include: K-means clustering, Hierarchical clustering and Density based clustering.

2.8. Measurement of Urban Sprawl

According to different literature urban sprawl is a multidimensional phenomenon that requires a different set of measures for each dimension. Most urban sprawl measures recommended in the literature can be divided into five major groups: growth rates, density, spatial-geometry, accessibility, and aesthetic measure.

2.8.1. Growth Rates

The phenomenon known as urban sprawl is characterized by faster population growth rates in the suburbs than in the center metropolis.(Jackson, 1985). The "Sprawl Index" (SI) or "Sprawl Quotient" is another widely used growth-rate metric. It is the ratio of the population growth rate in a given area to the growth rate of built-up areas. Urban sprawl is implied by a quotient greater than 1.

2.8.2. Density

Densities come in a variety of forms, with numerous measurement methods and scales available. Density can be defined as the proportion of an urban activity to the total area that it occupies. The amount of residential units, residents, or workers can be used to characterize urban activity. The most widely used sprawl metric that accurately captures the phenomenon is this one.

2.8.3. Spatial-Geometry

This constitutes the largest group of measures. There are numerous geometric measures, most of which have been adopted from ecological research(K. McGarigal, 1995; Turner, 1989) or from fractal geometry (Torrens & Alberti, 2000). The structure and composition of the urban landscape are the two primary features that can be quantified using geometric and ecological criteria. The term "configuration" describes the urban built-up area's geometry, while "composition" describes its degree of variety. As long as an urban area's land-use mix is more homogeneous and segregated and its geometric configuration is irregular, scattered, and fragmented, it will be said to be sprawling.

Bekele.(2005)Some common measures 20 in this category are leapfrog or continuity(Galster et al., 2001),measure of circularity, fractal dimension and Mean Patch Size (MPS). All of these authors quantified the level of scatter and fragmentation of the urban landscape. The percentage of different land-uses quantifies its level of heterogeneity(K. McGarigal, 1995). In these types of measurements, two indicators that can be used for the determination of the composition and configuration can be seen deeply.

(A) Land Use and Land Cover Change Analysis the study of detecting changes in an object's (or phenomenon's) condition over time is known as "change detection." In order to detect changes, many time steps will be employed, utilizing various multitemporal data sets of a region, which can be accomplished through remotely sensed data. The following uses of change detection are effective: analyzing changes in land use, tracking shifting cultivation, evaluating deforestation, researching variations in vegetation phenology, analyzing seasonal variations in pasture productivity, assessing damage, and assessing other environmental changes.

(B) Landscape Metrics Landscape metrics are used to describe and quantify the structure of urban landscapes (the composition and arrangement) and the spatial relationships (Walz, 2011). The pattern of a landscape is expressed by the “size, shape, arrangement and distribution of individual landscape elements. The reason for using metrics in spatial analysis is to record the structure of an urban landscape quantitatively on the basis of area, shape, edge lines, diversity and topology-descriptive mathematical ratios” (Walz, 2011).Landscape metrics are quantitative measures of spatial structures and patterns which can be used to describe urban sprawl. These indexes are a collection of unit-less metrics that quantify and analyze landscape patches on the basis of geometric shape, complexity and compactness. The landscape metrics are grouped into the levels of heterogeneity which are further grouped in to the aspect of landscape pattern.

2.8.4. Accessibility

Sprawl is defined as a condition of poor accessibility followed by the massive use of private vehicles. Accessibility can be quantified by measuring road length, road areas, and the traveling times of households. Another way to measure accessibility is to calculate the fractal 21 dimensions of road networks(Benguigui, 1995). Some ecological measures are useful to measure accessibility like "Mean Proximity Index" (MPI).

2.8.5. Aesthetic Measures

Urban sprawl is often considered a boring, homogenous form of development. Being subjective by definition, it is difficult to measure and quantify the aesthetics of sprawl (Frenkel & Ashkenazi, 2008). However, several recent studies have attempted to define archetypes of urban development or sprawl, such as residential sprawl or strip-malls sprawl, and to compare various landscapes to those types.

2.9. GIS in Urban Sprawl Research

The complexity of urban sprawl systems makes it difficult to adequately address their changes using a model based on a single approach. Allen & Lu (2003) it is ideal to use a tool such as a GIS as part of the research on urban sprawl because of its capacity to handle many different types of spatial data. A GIS will not only allow for powerful visualization of urban sprawl within the study area by providing maps, but it will also allow for an in depth analysis of the data by providing the capability to examine all of the data in one system, therefore facilitating the measurement of urban sprawl. In another study it was concluded that Landsat TM images coupled with entropy integrated GIS was successful in measuring and monitoring urban sprawl patterns when the area is large and land use changes quickly Yeh & Li (2001) and Yeh & Li(1998) employed a Shannon's entropy technique with the integration of remote sensing and GIS.

2.10. Remote Sensing in Urban Sprawl Research

Remote Sensing is advanced technique of collection of data from space borne technique or airborne technique without having any physical contact in the earth surface(Campbell & Wynne, 2011) . RS provides flexibility of multispectral, multi temporal, multi resolution data, which are valuable assets for urban analysis, urban modelling and urban sprawl modelling as well. Due to its nature of timely, cost effectiveness, high temporal frequency, this technique was widely used for urban modelling, land use land cover change detection and variety of other urban study related field(Araya & Cabral, 2010). Urban growth/urban sprawl growth can be monitored properly with the application of GIS and RS. .RS technology with the advent of different platform and different sensors provides historical and recent satellite image which is valuable assets for urban growth analysis. Fichera et al. (2011) used integrated technique of GIS and RS for land cover classification and land cover change analysis for determining urban sprawl growth phenomena. Analysing time series of archive and recent satellite image data can generate LULC change and also predict future urban growth. RS technique can be used for measuring variety of morphological structure of cities development, urban sprawl extent, density and shape(Webster, 1995).

Remote sensing technology is indispensable to deal with the dynamic phenomenon. It is also a tool for determining the existence of urban sprawl. Without remote sensing data, one may not be able to monitor and estimate urban sprawl effectively over a time period, especially for a passed time period (Jat et al., 2008).Using remote sensing for detecting urban change and urban sprawl, many scholars have conducted extensive research over several decades (Bhatta, 2010; Chettry & Surawar, 2021; Manikandan, 2019).

2.11. Spatial metrics method

Recently there are other methods applied to measure urban sprawl and spatial metrics is one of the most important mechanisms used by different experts in the field. Spatial metrics is the main methodology applied to measure urban sprawl. Spatial metrics was first developed in ecological landscape to assess habitat loss and ecological fragmentation (K. McGarigal, 2015), but in recent times there are a number of works done applying the same methodology in urban area to assess the pattern of developments and to quantify urban sprawl. Spatial metrics use patches as a basic unit or element to measure landscape structure and pattern(Knaap et al., 2005; K. McGarigal, 2015).

Patches are defined as discreet areas of homogeneous environmental conditions in a landscape (L. McGarigal & Marks, 1995; Reis et al., 2016). The shape, size and division or isolation of patches is important characteristics to measure a landscape under investigation. There are hundreds of spatial metrics indices but only tens of these indices are selected for urban sprawl measurement purpose by many researchers.

Quantify several aspects of landscape configuration and composition these metrics can be divided into the following three categories

2.11.1. Shape irregularity

Shape irregularity includes the metrics that assess whether an urban settlement has a regular or even shape or if, on the contrary, it has a complex shape with a ragged edge. They can be used to characterize a single patch (e.g. fractal dimension or shape index) or at the landscape level (e.g. Landscape shape index, edge density or area weighted mean patch fractal dimension). The metrics most often used to analyses shape irregularity are area weighted mean patch fractal dimension, edge density, area weighted mean shape index and landscape shape index.

2.11.2. Fragmentation metrics

Fragmentation metrics measure the extent to which urban settlements or patches are close together (aggregated) or dispersed (fragmented). These metrics are used at the landscape level. A fragmented landscape is normally characterized by a higher number of patches, with a smaller average size and located further away from each other. The metrics mostly used to measure fragmentation are mean patch size, number of patches, patch density and contagion index.

2.11.3. Diversity metrics

Diversity metrics focus more on the composition of the urban landscape rather than on its shape. The most used metrics are Shannon's diversity and evenness indexes, which measure the distribution of different patch types (for instance land use types) throughout the urban area. Other metrics include the largest patch index, measuring the relative importance of the largest patch (which may be useful to study for instance the importance of the urban centre), and the compactness index, which uses a concept of compactness based on both fragmentation and shape irregularity.

The change of built-up areas using only the remote sensing data can not reveal the real patterns of urban sprawl, thus landscape metrics are utilized to create quantitative measures of spatial patterns on a map or a remote sensing image (Integrated remote sensing technology on the spatial patterns of urban sprawl requires a combination of landscape perspectives for understanding)(Magidi & Ahmed, 2019a).

2.12. Application of Entropy in Urban Sprawl

Entropy concept was first formulated by German physicist Rudolph Clauses, in second law of thermodynamics (Clausius et al., 1867).Statistical characteristics to entropy were first given by Claude Shannon as a scientific domain (Cabral et al., 2013). Shannon defined entropy as a property of particle, where bits are used as symbol and entropy is defined as logarithm of possible outcome of arrangement of bits, with relative proportion of message. Entropy is a measurement of disorder or uncertainty in a system. In urban sprawl, entropy can be used to measure the degree of spatial heterogeneity and the degree of mixing between different land uses. It can also be used to identify areas of urban sprawl and to assess the impact of sprawl on the environment and on human health. Entropy with integration of GIS and RS can be used for modelling urban sprawl (Yeh & Li, 2001). Shannon‘s entropy (h) is used to calculate dispersion or concentration of spatial variable (xi) among zones. Use of Entropy after integration of GIS and RS technique has been most effective tool for measuring urban sprawl(Sun et al., 2007) .Implication of Shannon‘s Entropy with application of GIS and RS can calculate degree of spatial concentration or dispersion of urban sprawl(Yeh & Li, 2001).

2.13. Empirical literature review

Urban growth and urban built-up area expansion in large cities and small town is increasing is leading to urban sprawl. Assessing urban sprawl, determine the extent and pattern as well as analyze the causative factor of urban sprawl is the subject of this research.

2.13.1. Global perspectives

According to the Study conducted by Bhat et al. (2017) This study's main focus is on how urban sprawl affects the dynamics of land use and cover. This study examines how migration, a primary driver of population growth, leads to significant increases in built-up and urban areas and declines in agricultural land, open space, and water bodies.

according to Biney & Boakye. (2021) in Sekondi-Takoradi metropolitan assembly Water body decreased from 1991 to 2002, but increased in 2008 and decreased in 2018.

Afifi (2013) Utilizing remote sensing and GIS, assess the risk of urban sprawl and how it affects agricultural land in the greater Cairo area. Ascertain the study area's primary land degradation process is urban sprawl.

Eko (2012) the findings in this study indicate that urban sprawl has impacted negatively on agricultural lands.

Raziq et al.(2016) investigate rapid increase of urbanization modified the natural landscape and affected the water drainage system of the city which leads to become a flood when rain is occurs. The result is the built up and water body increased, while agricultural land and barren land are decrease in the city of Peshawar Khyber Pakhtunkhwa Pakistan.

Padmanaban e t al. (2017) examines the amount and quality of urban sprawl would negatively affect Chennai's natural resources and land. Urban ecosystem services are predicted to degrade due to increased landscape fragmentation and projections regarding the US's extent and level over the next 12 years. Indicators and measurements from this study help to track the US in Chennai.

Mohammady & Reza (2016) Discover that ANFIS approach had the best ROC value and goodness of fit among the three models (ANFIS, ANN (I) and ANN (II)) for urban sprawl modeling and they differentiate factor influence number of urban cell in 3*3 neighborhoods is greater than the influence of other factor and slope had the lowest impact on Tehran Megacity for urban sprawl.

Grigorescu et al. (2019) The study area's findings indicate that population growth is the factor contributing most significantly to urban sprawl, with mountainous regions, the expansion of forested areas, and wetlands having the lowest likelihood of this phenomenon. Future built-up area expansion is more likely to "consume" arable lands, grasslands, permanent crops, and agricultural complex production patterns due to the expected transition of diverse land use/cover categories. A few studies distinguish between different factors influencing urban sprawl, however all of the above-mentioned focused studies show that population increase (migration) is the primary cause of urban sprawl.

2.13.2. Local perspectives

Now days the use of Remote Sensing and Geographic Information Systems techniques has become important for quantifying the degree of urban sprawl, mapping, monitoring, and managing urban land-use/land cover changes. Mapping urban sprawl provides a picture of where this type of growth is occurring, and helps to identify the environmental and natural resources threatened by such sprawls, and it also suggests the likely future directions and patterns of sprawling growth.

There are limited number of studies conducted on quantifying the extent and detecting the pattern of urban sprawl in Ethiopia using GIS and Remote Sensing. Contrary to this there are quite significant number of studies conducted on the impact of urban sprawl in altering land uses especially the impact it has on consumption of agricultural land on the outer skirts of cities.

A study conducted by Shifera (2018) quantified the rate of urban sprawl and mapping, and evaluated the general sprawling characteristics of Addis Abeba and its surrounding areas with regard to land use detection and urban sprawl mapping. Due to the existence of Entoto Hill and the protected eucalyptus forest, the study area's urban sprawl is most pronounced in the south along the outlet to Debre Zeyte Road, and it is least apparent in the north.

similar study was conducted in Ethiopia by Dadia et al. (2016) employing GIS to examine the main causes of urban sprawl and how they affect the conversion of land use in the peri-urban kebeles of Dukem town, one of the towns in the Oromia Special Zone that wraps around Addis Ababa city.

Another study of urban sprawl in Ethiopia was conducted in Debre Berhan town which is located north-east of Addis Ababa by Zewdu (2011) . The study's conclusions indicated how the area's fast population pressure has caused uncontrolled growth, which has subsequently contributed to urban sprawl.

The study conducted by Kassa(2014) On his studied the rate and effect of sprawling of Addis Ababa city. According to the study, compared to other outlets, the rate of urban sprawl along the Mojo and Jimma outlets which run south of Addis Ababa and lead to Adama city is significant, having an impact on the local population as well as the surrounding regions. Like other studies, this one focused on how urban growth has changed land use and cover, rather than clearly showing the sprawl pattern.

The Study Conducted by Bekele(2005) For countries that are developing, sprawl is typically the result of compelled migration, with people moving to cities in search of greater opportunities for employment, which causes population increase well outside of city limits. Urban sprawl in Ethiopia is characterized by the unnecessary and uncontrolled outward growth of urban areas at the expense of other land use classes, which runs counter to the city's spatial plan.

As the findings of the study conducted by Zemenfes G (2014) in Mekelle city, Ethiopia, the city was sprawling into the nearby rural community as a result of the uncontrolled and unauthorized acquisition and occupation of farmlands; which is mainly related to poor land use and administration policy of the city

Another analysis was made on the urban sprawl susceptibility of the town of Shashamanne using remote sensing and GIS techniques by Uka(2012) this study focused on quantify and measure the urban sprawl, an assessment was made on the extent and rate of land use/land cover (lulc) change using multi-temporal Landsat images and Shannon's entropy index. This study investigate that the study area has undergone a tremendous change in urban growth and pattern during the study period. Predominantly at the expense of agricultural lands and vegetated areas in the hinterlands, built-up area was increased from 1977 (in 1986) to 2677 ha (in 2000) and further rose to 4329 ha (in 2011). Shashamanne town was expected to have sprawl pattern types of ether linear/strip along highways, or expansion/cluster, or leapfrog as common to other urban canters in the world. However, in reality, the town has rather had irregular sprawl pattern type that is termed here as amoeboid shape. This is to mean that sprawl phenomenon in the study areas was of a variable irregular pattern showing the combination of the three sprawl patterns: linear/strip along highways, expansion/cluster and leapfrog. The analysis made on urban sprawl susceptibility revealed that, of the total area of the study site 1023 ha (8%), 5279 ha (41%) and 394 ha (3%) were respectively, highly, moderately and marginally susceptible to sprawling. This implies that large areas that are currently reserved as informal green spaces, fertile farming lands and other natural resources have been threatened.

Another study was conduct by Manikandan(2019) The goal of this study was to measure the patterns and trends in the spatiotemporal aspects of urban expansion in Sub-Saharan African cities that are rapidly rising, like Adama. According to the study, Adama's urban growth is spreading. Furthermore, as cities and towns continue to expand, large-scale migration and population expansion are the main causes of this tendency. These results provide compelling evidence that a well-defined urban planning policy is necessary for the overall process of urban growth.

The study conducted by Kebebew et al.(2019) Is concerned with analysing the spatio-temporal land use/cover change, extent and pattern of urban sprawl of Lagatafo Laga Dadi town. The analysis was carried out based on satellite imageries of two decades (three periods). It was concluded that the built up showed great horizontal expansion and uncoordinated growth pattern resulting in putting burden on the town administration to provide the necessary infrastructure. Hence, an increase in urban expansion and sprawl led to higher loss of agricultural land which negatively affected the pattern of land use. Because of its geographical location and sharing a boundary with one the sprawling East African city, Addis Ababa, Laga Tafo Laga Dadhi town is expected to be highly affected by competing interests from both formal and informal developments. The landscape around the town encourages further sprawling development on one hand and the area is equally suitable for agriculture on the other. The study also demonstrated the role of integrated application of GIS and remote sensing in quantifying and mapping the extent and pattern of urban sprawl through different time periods.

The study conducted in Bahir Dar, Northwest Ethiopia. By Getu & Bhat (2021) The purpose of this study was to evaluate and monitor the spatiotemporal dynamics of urban sprawl and its growth pattern over the previous 35 years in Bahir Dar, Northwest Ethiopia. Spatial landscape metrics, Shannon's entropy index, and post-classification comparison between the Landsat TM and OLI datasets can all be used in this study. The study's conclusions showed that over the studied periods, the built-up area grew near the area covered by forests and agriculture. It demonstrated the presence of highly heterogeneous and dispersed sprawl that progressively moved outside of the central business district (CBD).Inadequate preparation and application of sustainable urban planning and management policies can lead to a number of socio-economic and environmental issues, including the fast expansion of cities and subsequent urban sprawl.

CHAPTER 3: MATERIALS AND METHODS

3.1. Description of the study area

3.1.1. Geographical Setting

Bishoftu city's geographical/astronomical/ location is $8^0 45^1$- $8^0 47^1$ North latitudes and $38^0 56^1$-39^0 longitude and covers about 20,574.45 hectares of area. It is found in the Oromia Region, East Shewa zone of Ada'a Wereda. It is located at a distance of 47 km south East of Addis Ababa, and 52 Km from Adama. The city is bordered by kebeles such as Erer Selassie, Godino and Koftu in the North, with Ude and Giche Garababo in the south, in the East with Hidi and Dembalo; in the West with Dire town peasant association, and in North West with Dukam Town Administration.

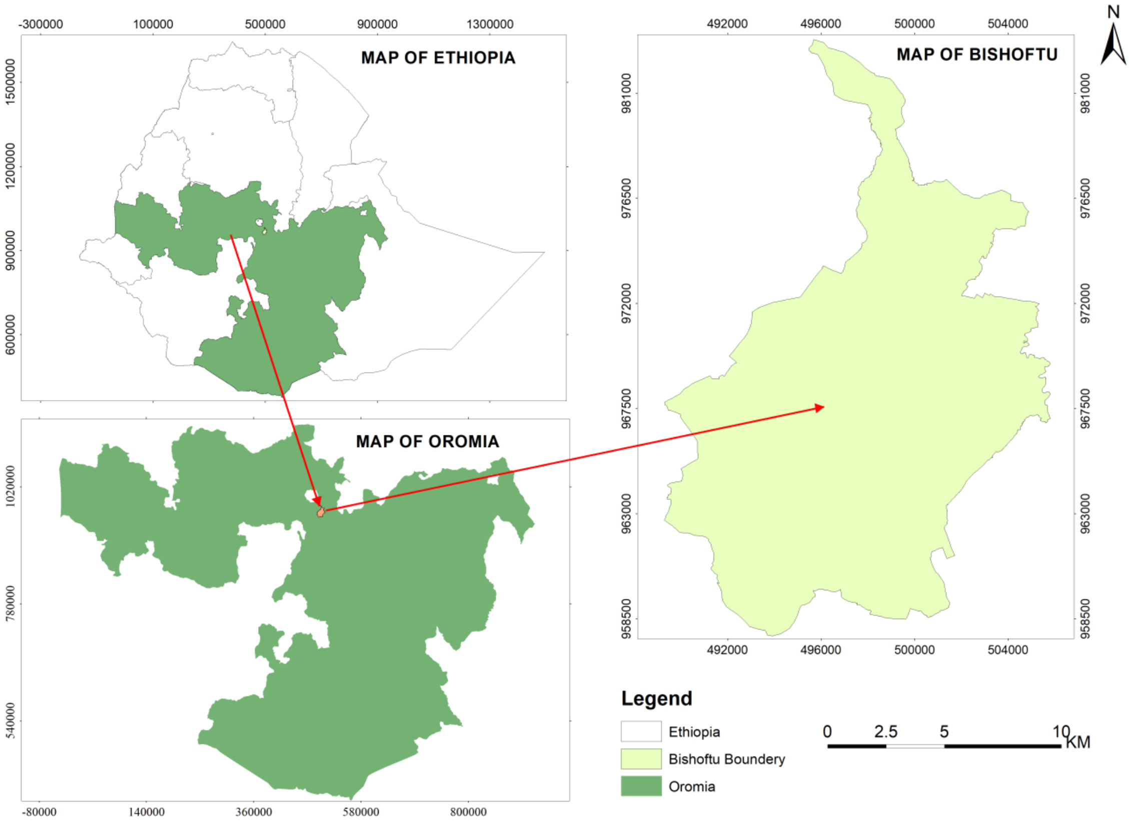


Figure 0.2 Study area

3.1.2. Topographic Features /Landscape

The typical description of the topographic land form of Bishoftu city and its environment comprises vast plain areas, swampy and water bodies, soft, rounded hips and hilly mountains, steep and rounded hills, and associated undulating dissected areas. The southern portion of the city is largely associated with and characterized by undulating and rugged terrains whereas; the eastern is to a large extent plain area. The altitude of Bishoftu city is ranging from 1748m-1955m high above mean sea level. Therefore the city is situated at an average elevation of 1851.5m above sea level. More flat areas constituted the largest proportion in terms of area coverage. Such areas are found in the eastern, northern, and north western expansion directions. On the other hand, Babo Gaya, Gara Beru, and Soroba, hills can be categorized as slightly steeply, rounded hills that are non-accessed through motor able transport modes.

The central part of the city where the lakes are found is surrounded by higher elevations ranging from 1856-1893m with few lower altitudes to access the lakes. Altitude of the water levels of the lakes also varies accordingly. The water level of Lake Kuriftu is located at elevation of 1858m above mean Sea level while the water level of Hora Arsedi Lake is located at elevation of 1,844 m above mean Sea level. This shows that the altitudinal difference between the two lakes is 14m and this indicates that siltation is one of the problems of Lake Kuriftu besides diversion of water course from its natural flow. The water level of Lake Babo-gaya is found at altitude of 1,752m above mean sea level. The water level of both Bishoftu and Green lakes is found at similar elevation of 1848m above mean sea level.

Having the above topographic features, the general elevation of the town ranges from 1746m to 1995m. The altitude is generally higher in the south western part of the city and gradually declines to east directions for few distances and then increases again to the same direction. Altitude declines gradually from north to south direction for few distances and then increases elevation again from north to south direction. The greatest proportion of the altitude of the city ranges between 1893 to 1930 meters and almost covers western, northern, and south western parts of the city.

3.1.3. Population

The city population growth is rapidly increasing by more than 4% annually. Based on administration data currently population size of the city is projected to be 256,594 of which 131,329 male and 125,265 female. The two main factors for the increment of this population are rural urban migration and fertility. In the city, migration (rural to urban) / urban to urban/ has predominant role in changing the population characteristics and reflects the urbanization rate. Much of the population growth has been the result of internal migration and expansion of different pulling factors. Change in population growth accelerates the demand for land and the dynamics in land-use/land cover changes and also the main reason for urban sprawl.

3.2. Material and software

In this research various software‘s and materials were used for different purposes in order to achieve the proposed objective. There are a number of different kinds of methods, strategies and techniques to process input data to generate the required output with desired quality.

3.2.1. Data Types and Source

In today's world, different commercial and government organizations provide a vast variety of data at different scales at the local, regional, and national levels. The United States Geological Survey (USGS) is a known source of free satellite images covering large areas and a veritable treasure trove of information.The main problem in developing countries like Ethiopia is lack of high resolution satellite images such as IKONOS and Quick Bird because of their expensive price. For this reason, Landsat images, Landsat Thematic Mapper (TM), Landsat Enhanced Thematic Mapper Plus (ETM+) and Landsat-8 Operational Land Imager (OLI), for the years 1990, 2000, 2010 and 2022, respectively are obtained from USGS Earth Explorer For all years, high quality cloud free images were selected from row 54 and path 168, full scenes. The season of the year was preferred to get cloud free images for ease of classification and facilitate comparison in post-classification activities. Way that the cloud covers will not exceed 10%. The images were also of the same level of spatial resolution 30m which make it convenient for comparison of changes and patterns that occurred in the time under consideration. Additionally, The DEM used to Estimated Slope to analyze driving forces of urban Sprawl is downloaded from SRTM-USGS centre.

City centers and major roads were derived from VHR Google Earth image. Other data such as administrative boundaries location of Educational Institute and Health center were obtained from City municipality. All dataset in this study will use geometrically referenced to the WGS 1984, UTM zone 37 projection systems. The detail description of the characteristics all images which will use in this study is summarized in the following Table

Table 0.1 Data type and source

No	Data type	Source	Resolution
1	Landsat5TM 1990	USGS earth explorer	30
	Landsat7ETM 2000		30
	Landsat7ETM 2010		30
	Landsat 8 OLI2022		30
2	Administrative boundary	Bishoftu City	-
3	DEM	USGS earth explorer	30
4	Road network	Google earth image	
5	Slope	Estimated from DEM	30
6	City Centre	Google earth image	-
7	Water body	Google earth image	30
8	Health centre	Municipality of Bishoftu city	-
9	Educational Institute	municipality of Bishoftu city	-
10	Industry	municipality of Bishoftu city	
11	GCP	Field observation	-

3.2.2. Software used

To achieve the objectives of these studies, some excellent software has been utilized. Data gathering; organizing, analysis, interpretation, and presentation are all done with the help of this software. The study's software and its objectives are shown in the following table.

Table 0.2.Software used

NO	Name of software	Purpose
1	QGIS	Data processing and thematic map preparation
2	ERDAS Imagine 2015	For processing and analyzing satellite Image and For classification
3	FRAGSTAT 4.2	Urban Sprawl assessment
4	Google Earth Pro	Use as a base map in visual image interpretation,
5	Microsoft office Word v.2016	Writing, chart preparing, graphs and statistical analysis.
6	Power point	For preparing of final thesis presentation
7	Digital Camera	For the capturing of photos
8	SPSS	For data analysis

3.3. Method of Data processing

In this study the method used to achieve the objective of the research will began with the acquisition of satellite imager for the year of 1990, 2000, 2010and 2022 from USGS.

3.3.1. Pre-processing

The need for image pre-processing curtails from the fact that satellite images are subject to geometric and radiometric distortions. Pre-processing is a data removal technique used to improve raw data into a format that is useful and well-organized, and its goal is to improve the image data set that has unwanted noises and distortion and enhance some image properties for the further research.

It is used to eliminate the external noises in the images by image de-stripping, bit errors and scan line correctors (Navin & Agilandeeswari, 2020). It also involves in the correction of brightness, pixel brightness correction, image filtering, image segmentation, image restoration. The spatial enhancement techniques include blending of the images, filtering, and sharpening, stacking, feature extraction.

3.3.1.1. Geometric correction

Geometric correction often referred to as Image Warping is the computerized manipulation of image data to precisely adjust a given projection surface or shape in the image. It is made to correct the inconsistency between the locations coordinates of the raw image data, and the actual location coordinates on the ground or base image.

3.3.1.2. Radiometric correction

The capacity to translate digital numbers captured by satellite imaging equipment into tangible units is known as radiometric correction. The units of measurement are either apparent top-of-atmosphere reflectance or radiance (W/m2/sr/µm). a method of enhancing an image's visual quality by adjusting pixel values that don't correspond to the object's reflectance or spectral emission.

3.3.1.3. Atmospheric correction

Atmospheric correction is the most important part of the pre-processing of satellite remotely sensed data and any blunder produces in accurate results. It is the process of removing the scattering and absorption effects of the atmosphere on the reflectance values of images taken by satellite or airborne sensors.

3.3.2 .Layer staking

Layer stacking is a process for combining multiple images into a single image. In order to do that the images should have the same extent (number of rows and number of columns), which means you will need to resample other bands which have different spatial resolution to the target resolution. In other words, all images/bands should have same spatial resolution to be able to perform layer stacking. However, combining images/bands increase the final stacked image size, and consequently increase the processing time later when you do your analysis. In this study Landsat5, Landsat7 and Landsat8 have been used for layer stacking the duration between 1990 and 2022; (1990, 2000, 2010 and 2022).

Landsat5 carried two instruments' MSS (multi spectral scanner) and thematic mapper TM. MSS contains four spectral bands (visible green, visible red, near infrared and thermal-infrared) and TM contains 7 spectral bands (visible red, visible green, visible blue, near infrared bands, two mid-infrared bands and thermal-infrared). Due to the application of the data thermal-infrared band is excluded in this study. While the other hand, Landsat7 enhanced thematic mapper plus (ETM+) collect data in eight spectral bands, the panchromatic band (band8) is additionally included as compare with landsat7. To match the resolution of the data to landsat5, panchromatic band (band 8) is not included in this study. And alsoLandsat8 is applied in this study (operational land imager and thermal infrared sensor). Operational land imager collects data in nine spectral band (short-wave infrared 1 and 2, Coastal aerosol and Cirrus cloud additionally included as compare with Landsat7) and the thermal infrared collects in two thermal-infrared 1 and 2. All Landsat5, Landsat7 and Landsat8 layer stack spatial resolution applied in 30m. Based on the launch dates of the satellites, Landsat 5 was used to acquire the 1990 data, Landsat 7 was used to acquire the 2000 and 2010 data, and Landsat 8 was used to acquire the 2022 data for this study.

3.3.3. Sub-setting of Study area

Image extraction is the first step of image pre-processing. It is possible to reduce the image's prominence and remove any unnecessary components. The project field must be eliminated from the full image in order to reduce the size of the image file and only include the region of interest (AOI). This does more than just clear the image of the extraneous information. But it expedites the process because there is less data to manage. This is crucial when working with multiband data, such as Landsat TM imaging. We refer to this reduction of data as a sub setting. At this point, the utilization of Arc GIS and ERDAS IMAGINE software was essential. During this process, the project region was trimmed across each Landsat scene (Bishoftu shape file). It needs to be completed following the formation of a composite image or layer stacking.

3.4. Method of data analysis

3.4.1 Image classification

Following the processing of the satellite images, one of the study's actual duties is image classification, which serves as the basis for a process of built-up extraction. Classification is one of the seven change detection mechanisms, and supervised classification was employed for this study. Supervised classification requires the selection of training areas to get accurate classification output. It is profoundly based on the quality and quantity of training samples to produce good quality classification results. In supervised classification, identifying feature cover types, selecting high-quality and sufficiently numerous training sample sets is the time consuming and one of the major challenges that the investigators face during digital image analysis to producing highly accurate classification results. As the main objective of the study is measuring urban sprawl of the city, only five main land-use/cover categories were selected for the purpose: built-up area, agricultural area, green area, barren land/open space and water body (Table 3) Classification nomenclatures were selected according to Anderson et al. (1976) and the categories were made same for all 1990, 2000, 2010 and 2022 images .The classification process began by selecting training areas with careful observation of the images and feature cover types within the images.

Table0.3 the final land cover classification scheme for study area.

No	LULC	Descriptions
1	Built-up	Includes all residential, commercial, and Industrial developments and transportation. Areas under construction are also included.
2	Water	Includes all water bodies (rivers, lakes, gravels, streams, canals and reservoirs.
3	Barren land	Includes a surface with no or little vegetation, open land, exposed soil, rocks and sand(eroded gullies)
4	Vegetation	Includes all forest vegetation types (evergreen, deciduous and wetland), and non-forest vegetation futures that are not typical of forest (pasture grasslands and recreational grasses.
5	Agricultural	Includes all agricultural lands (both annuals and perennials) .

3.4.2. Accuracy Assessment

Accuracy assessment is a compulsory activity after any satellite image classification analysis to know whether or not the classification process met its objectives. Accuracy assessment in remote sensing is the processes of evaluating the accuracy of land classification or other remote sensed product it is an important step in ensuring that the result of satellite image classification reliable and can be used for decision making.

3.4.2.1. Producer's Accuracy

Producer accuracy is a measure of the accuracy a classification system that is based on the producer’s estimate of the true class of each pixel. It is calculated as the proportion of pixel that is correctly classified by the system.

It refers to the number of correctly classified pixels in each class (category) divided by the total number of pixels in the reference data to be of that category (column total). This value represents how well reference pixels of the ground cover type are classified.

$$\mathrm{PA} = \frac{\sum \mathrm{TCSij}}{\mathrm{TSci}}$$

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

3.4.2.2. User's Accuracy

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

$$\mathrm{UA} = \frac{\sum \mathrm{TCSij}}{\mathrm{TSri}}$$

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

3.4.2.3. Overall Accuracy

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

$$\mathrm{OA} = \frac{\sum \mathrm{TCSij}}{\mathrm{TS}}$$

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

3.4.2.4. Kappa Coefficient

The Kappa Coefficient is used to equate the precision of a grouping to that of simply assigning values at random. The Kappa Coefficient can be somewhere between -1 and 1. The classification is no different than a random classification if the value is 0. The classification is significantly worse than random if the number is negative. A value close to 1 indicates that the classification is significantly better than random. (Jennes etal (2007).

$$\mathrm{K} = \frac{(\mathrm{TS}\times\mathrm{TCS}) - \sum \mathrm{TScjTSri}}{\mathrm{TS}^2 - \sum(\mathrm{TScj} - \mathrm{TSri})}$$

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

TScj is the total number of pixels in column j and

TSri is the total number of pixels in the row i.

3.4.3. Reclassification

Reclassification is the process of assigning new values to pixels in a raster dataset according to predetermined standards or procedures. This can be carried out to rectify mistakes or aggregate values for more effective analysis after completing image classification (ArcGIS, 2022). Reclassification can be helpful when we wishes to add new values to the input raster, make a raster's information simpler, or give a raster priority, sensitivity, or preference values.

To assess the density and expansion of built-up areas in the study area during the four time periods, imageries were reclassified into built-up and non-built-up land areas and maps were generated. This method was followed for all the selected year LULC maps (1990, 2000, 2010 and 2022). In this study Agricultural land, water body, bare land and green area land use land classification were reclassified to non-built up area and built-up area is not changed its classes for all selected year (1990, 2000, 2010 and 2022).

3.4.4. Multi Ring Buffer Analysis

A multi-ring buffer creates a large number of buffers spaced apart from the input characteristics. It was used to create buffers (zones) around the size of the research area boundary in ArcGIS at a 3 km interval around the city center.

Multi ring buffer requires different parameters. It includes input features, output feature class, distance, buffer unit, field name, dissolve option and others. In this study multi-circular buffer was created by 3km interval around the city center to calculate the Shannon entropy.

3.5. Identify urban sprawl

It is not difficult to quantify urban expansion using data from remote sensing. But measuring the sprawl is difficult (A. G.-O. Yeh & Li, 2001). The most effective and widely use approach for urban sprawl measurement is Shannon entropy. Shannon's entropy is capable of measuring "the degree of spatial concentration or dispersion of a geographical variable. They overlaid urban land using images to measure the density of land development in a set of buffer zones that were created around city centers and along roads. They calculated the value of entropy to measure the density of land development among zones; the degree of urban sprawl was then determined by examining whether land development in a city or town was dispersed or compact(Yeh & Li, 2001) .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. The value of entropy is always between 0 and 1 and is calculated by using equation 3.1. A value of 0 indicates that the distribution of built-up areas is very compact (concentrated, aggregation), while values closer to 1 reveal that the distribution of built-up areas is dispersed spatial distribution. Higher values of entropy indicate the occurrence of sprawl. Half-way mark of entropy (0.5) is generally considered as threshold. If the entropy value crosses this threshold the city is considered as sprawling.

$$En = \sum_{i}^{n} pi \, log\left(\frac{1}{Pi}\right) / \, log(n) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots .3.1$$

Where pi= $^{xi}/_{\sum_i^n xi}$ and xi is the density of land development, which is equal to the amount of built-up land divided by the total amount of built-up land in the ith of n total zones(Tewolde & Cabral, 2011). Because the distribution of a geographical phenomenon can be measured and determined using entropy, the difference in the entropy between time t and t + 1 can be used as an indicator of the magnitude of the change in the urban sprawl by calculating the difference in the dispersity in Eq 3.2 (Yeh & Li, 2001).

$$\Delta \mathrm{En} = \mathrm{En}(\mathrm{t}+1) - \mathrm{En}(\mathrm{t}) \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots . . 3.2$$

Where ΔEn is the difference between the relative entropy values from two time periods, $En(t + 1)$ is the relative entropy value at time period$(t + 1)$, and $En(t)$is the relative entropy value at time period t. Therefore, the Relative Shannon Entropy (RSE) value for each and the overall ring buffers for each of the years 1990, 2000, 2010, and 2022 have been calculated to identify the urban sprawl.

3.6 Quantify urban sprawl Extent using landscape metrics

Calculation of landscape metrics for determination of urban sprawl extent was computed using built-up areas of the years 1990, 2000, 2010 and 2022. The study of landscape ecology examines how ecological processes interact with spatial and temporal patterns. One of the primary reasons why urban sprawl is a concern is that the spatial organization of urban development will have social, economic, and environmental consequences over a variety of temporal scales.

By applying the theory of landscape ecology to urban sprawl, what is it and what its effects can be better understood. In particular, using landscape ecology's tools allows us to store, manipulate and display spatial and temporal data at appropriate scales. It can provide finer grain data that include more information concerning urban sprawl. Landscape metrics or indices can be defined as quantitative indices to describe structures and patterns of a landscape. The change of built-up areas using only the remote sensing data can not reveal the real patterns of urban sprawl, thus landscape metrics are utilized to create quantitative measures of spatial patterns on a map or a remote sensing image

3.6.1. Selection of spatial Metrics to measure urban sprawl

Spatial metrics method is the methodology to be applied in this study to measure urban sprawl using FRAGSTATS version 4.2 Software.

FRAGSTATS is the software package for calculating landscape metrics i.e., composition and configuration of landscape. Spatial metrics are quantitative measures of spatial structures and patterns that can be used to describe urban sprawl (Weijers, 2012). According to (McGarigal, 2015)FRAGSTATS computes several spatial statistics representing area, shape and perimeter (edge) at the patch, class, and landscape levels, i.e., levels of heterogeneity. FRAGSTATS accepts only raster data and gives statistical data as an output.

FRAGSTATS compute a number of spatial metrics that measure urban sprawl with some criteria and parameterization by the user. Most of these metrics are redundant and calculate almost similar values. Therefore, it is responsibility of the user to select appropriate metrics for his/her purpose. Hence, here the selections of indices listed below were based on their purpose and the fragmentation they calculate. In FRAGSTAS, the user needs to select spatial metrics, specify common tables, select analysis parameters, parameterize patch, class and landscape metrics, before using the software. All were set according to instructional manual and purpose of study. .

The selection of spatial metrics is determined by three main factors (Kupfer, 2012)

1. Data requirements and calculation clarity
2. structural and functional properties of a landscape
3. Simplicity of interpretation of the indices.

For this specific study a group of five metrics were selected based on the literature review and the potential of each metrics to best describe urban sprawl.

1,Class Area Metrics (CA); Class area is one of the most intuitive and straightforward metrics used to measures the landscape composition i.e. how much the land scape metrics composed to the particular land use land cover patch. For the study of urban sprawl extent CA metrics was used to determine increase in urban class(Padmanaban, et al., 2017).

$$CA = aij\left(\frac{1}{10{,}000}\right)$$

Where aij: area in (M^2) of patch ij

2, Number of Patches (NP); Refers to the number of built-up patches in meter/hectare in the landscape and selected to measures level of fragmentation of built-up area of the study area. An increase in number of patches in time series study, indicate an in increase in fragmentation, sprawling urban area(Rutledge, 2003).However, it conveys no information about area, distribution or density of patches.

$$NP = N$$

Where N: is total number of Patches.

3, largest patch index (LPI): quantifies the total landscape area in project area which is comprised by largest patch. LPI can simply be understood as measure of dominance of patch in overall landscape. Having LPI value close to zero indicates corresponding patch size increasingly small, whereas larger patch size indicates entire land scape is dominated by particular patch type (McGarigal, K., 2015).

$$LPI = Max$$

4, Landscape shape Index (LSI): is a standardized measure of total edge or edge density that adjusts for the size of the landscape. LSI equals ¼ (adjustment for raster cells) times the sum of the entire landscape boundary and all edge segments (m) within the landscape including the patch type in focus divided by the square root of the landscape area (M^2) including any internal boundary. LSI =1 when the landscape is comprised of a single square patch of the corresponding patch type (built up class) and increases when the shape of the landscape becomes irregular or as the edge length of the corresponding patch type increases in the landscape(Gezahegn Aweke, 2013).

5, Percentage of Landscape (PLAND): is the proportional abundance of each patch type in the landscape. It is a measure of landscape composition at class level and indicates the percentage of the corresponding class under study or each class in the landscape. PLAND is calculated as the sum of the areas (m2) of all patches of the focal class, divided by total landscape area (m2), multiplied by 100 (to convert to a percentage).

$$\mathrm{LAND(Pi)} = \frac{\sum_{\mathrm{j}}^{\mathrm{n}} \mathrm{aij}}{\mathrm{A}}$$

Where Pi = proportion of the landscape occupied by patch type (class) i

aij = area (M^2) of patchij. A = total landscape area (M^2) 2. The result ranges between 0 and 100.focal class, divided by total landscape area (M^2) multiplied by 100 (to convert to a percentage).

3.7. Logistic Regression Modelling and Driving Forces of Urban Sprawl

Logistic regression is one of the most popular approaches to modelling (to predict the probability of an event occurring). This model can be used in modelling and explaining the relationship of a number of (Xs) independent variables to a dichotomous single dependent variable (Y), which represents the occurrence or non-occurrence of an event (Kleinbaum et al., 2010). Logistic regression also describes the combined effects of several factors (Kleinbaum et al., 2010).

The spatial urban expansion is the dependent variable represented in a raster binary map. A value of 1 on the produced probability map indicates the presence of urban sprawl, and a value of 0 indicates the absence of urban urban sprawl. The probability of urbanization for each cell in the raster map was produced based on the following logistic regression.

$$y = a + b_1x_1 + b_2x_2 + \cdots \dots \dots . + b_n$$

$$y = \log_e(p/1 - p) = \log it(p)$$

$$p(z = 1) = e^y/1 + e^y$$

Where x1, x2... xn are explanatory variables.

The utility function y is a linear combination of the explanatory variables representing a linear relationship. The parameters b1, b2…. bn are the regression coefficients to be estimated. If z is denoted as a binary response variable (0 or 1), value 1 (z=1) means the occurrence of a new unit (i.e. the transition from a rural unit to an urban unit), and value 0 (z=0) indicates no change. P refers to the probability of occurrence of a new unit, i.e. z=1. Function y is represented as log it (P), i.e. the log (to base e) of the odds or likelihood ratio that the dependent variable z is 1. As the y value increases, probability P inevitably increases(Huang et al., 2009b).

3.7.1. Preparation of input data for logistic regression model

For each of the four study periods, factor maps or independent variables have been generated for the regression analysis.

These maps are prepared in GIs software environment. All the input data are in raster format in a cell size of 30x30 so as to match the resolution of Landsat images.

1. **Dependent variables** in this model four binary land cover maps of 1990, 2000, 2010 & 2022 are used as dependent variables to carry out the logistic regression analysis. These

maps are classified into two land cover classes 0 & 1. 0 represents non-built up land cover class whereas 1 represents built up land cover class. The conversion rule is based on the assumption that land cover changes from non-built up to built-up land. This is due to the fact that the possibility of land cover to change from built up to non -built up is very unusual or rare in developing countries like Ethiopia.

2. **Independent variables** six independent variables are finally screened out based on literature review and the data I gate. Those are distance from major roads, distance from town centers, distance from water body, slope, and health center and education institute. However, due to unavailability of data that covers the whole study area the population data are removed from the model.

3.8. Methodology

TO encounter the objective of this research The fallowing activities conducted in this portion include acquisition of satellite images for four years 1990, 2000, 2010 and 2022, pre-processing, image classification and categorical map generation, accuracy assessment, reclassification, Multi Ring Buffer, calculation of spatial metric indices Calculation of Shannon Entropy from categorical maps generated from satellite images to quantify urban sprawl And Logistic Regression Model.

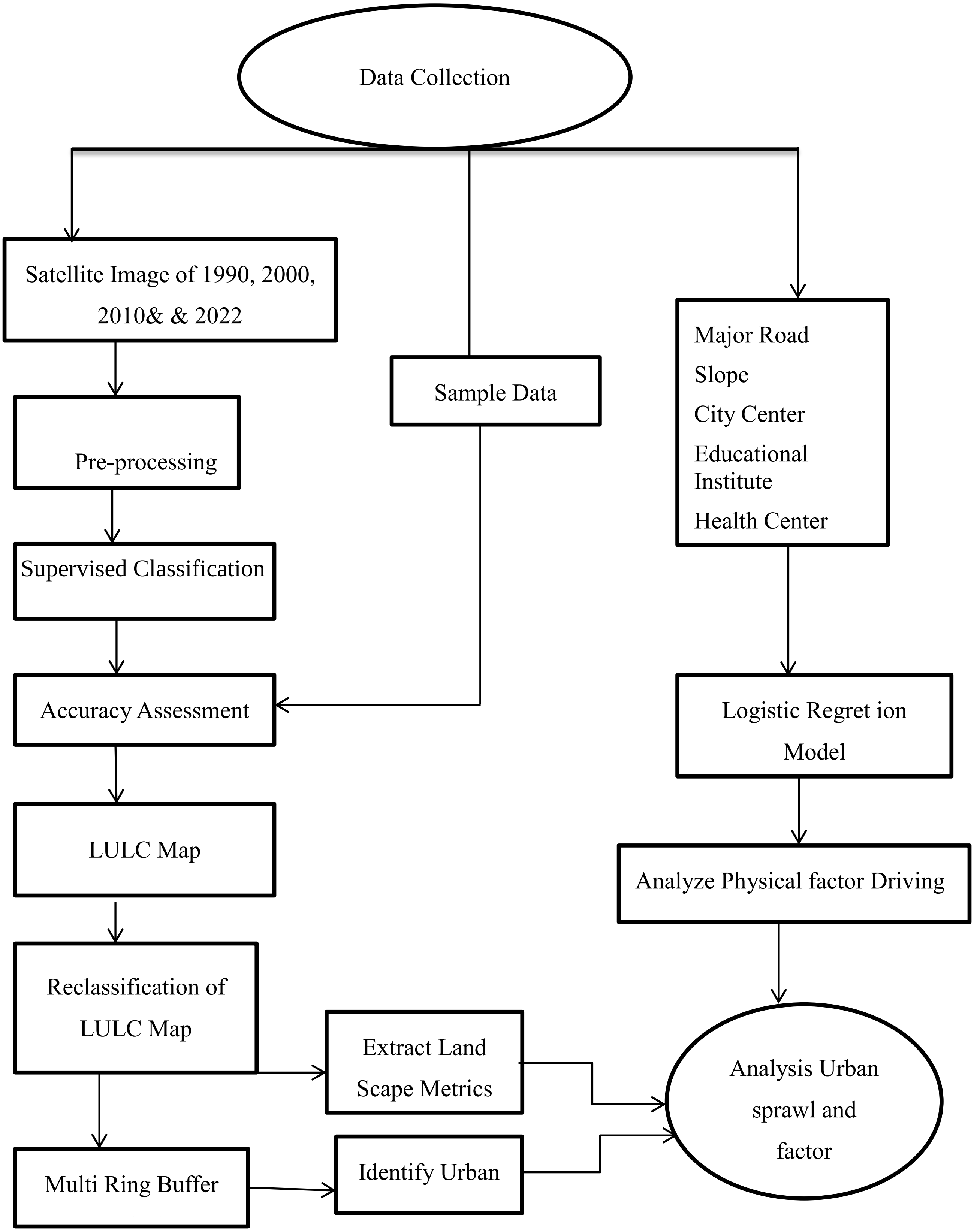


Figure 2.1 Methodology of the study

CHAPTER 4: RESULTS AND DISCUSSION

4.1. Spatio temporal land use land covers (LULC)

The change of land use land cover pattern is actual the reason for occurrences of urban sprawl. Sprawling area are the area where the conversion on the agricultural land, green area and bare land. So that The LULC change analysis results explain the historical LULCC and the change dynamics in each land cover class. The study results would significantly help urban planners and decision makers to determine the nature, position, and rate of change of urban sprawl in the study area and also used to generate built up area map for assessment of spatio temporal of urban sprawl. In this study the classified land use/land cover maps of 1990, 2000, 2010, and 2022 were generated using the supervised Classifications and maximum likelihood algorithm Using ERDAS IMAGINE 15 software packages for all images. The process of classifying an image involves evaluating each pixel's reflectance and properly identifying which signature it most closely resembles. Twenty consistent training samples have been selected for one class with the objective of getting more accurate LULC classes. Five LULC classes were identified in the study area for the specified period 1990–2022.Training samples for each class were collected from each image. The outcome displays that the land use land cover pattern of Bishoftu city has changed radically between 1990 and 2022; with the built-up areas experiencing continuous growth over the last study periods displays the spatial distribution of each LULC in 1990, 2000, 2010, and 2020. Figure 4.1 depicts the maps of various stages each land cover class has undergone, with each stage having a different rate and quantity of change. The quantitative result is presented in Table 4.1, which shows the statistics of the five LULC classes and the change dynamics during the four-time periods.

Table 4.1 LULC Class and area Coverage of study area from (1990-2022)

Classification	Area 1990		Area 2000		Area (ha) in 2010		Area in 2022	
	%	Ha	%	Ha	%	Ha	%	ha
Bare Land	18.57	3844.08	12.04	2493.99	16.22	3355.65	11.45	2362.68
Water body	3.33	688.50	3.36	695.43	2.89	598.32	2.84	586.35
Built up area	9.05	1872.81	11.97	2479.77	16.63	3440.97	23.17	4783.14
Green Area	11.51	2258.19	6.45	1335.33	7.73	1598.49	5.20	1073.97
Agricultural Land	58.15	12036.42	66.18	13706.91	56.52	11691.90	57.34	11837.61

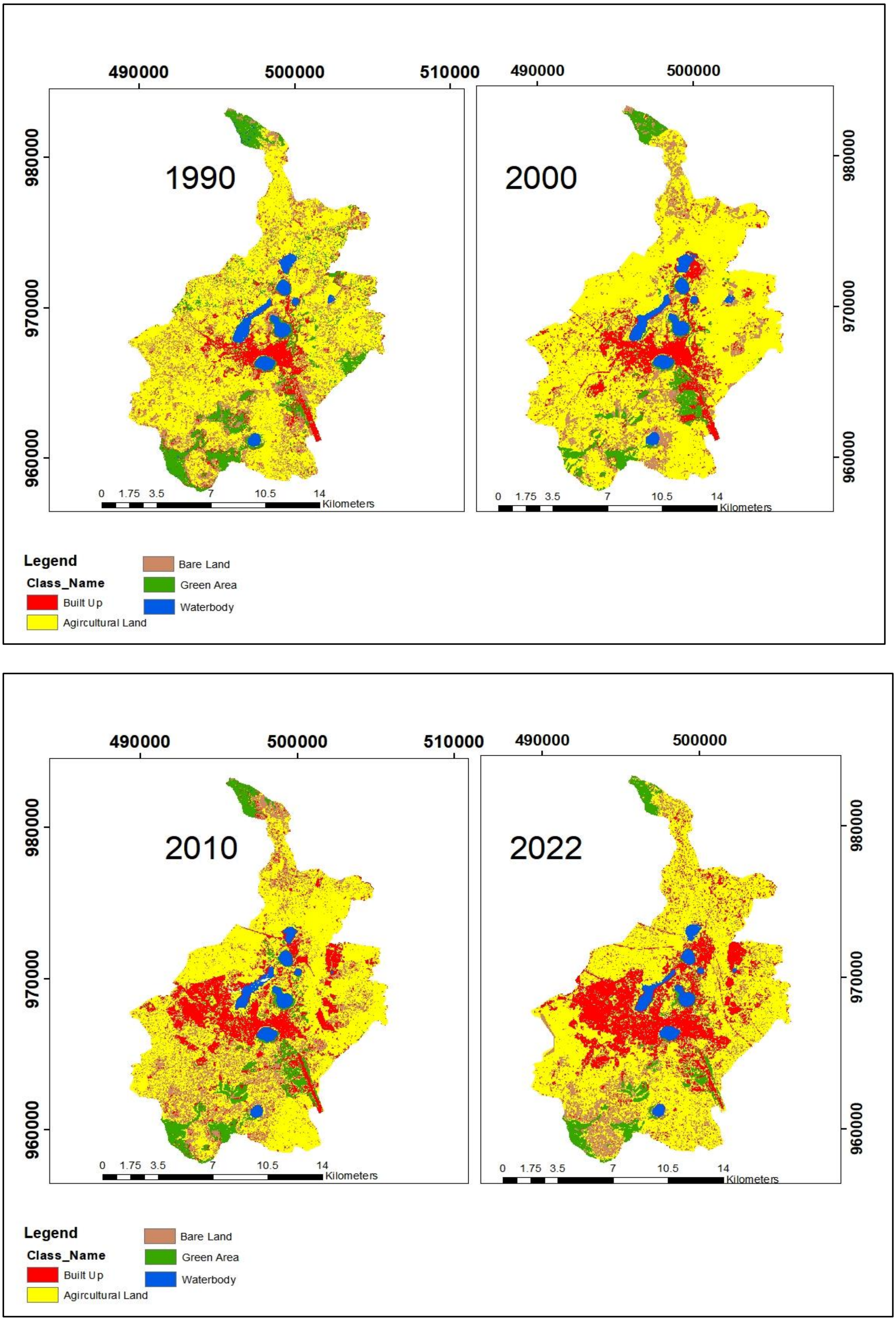


Figure4.1Supervised classification of study area map

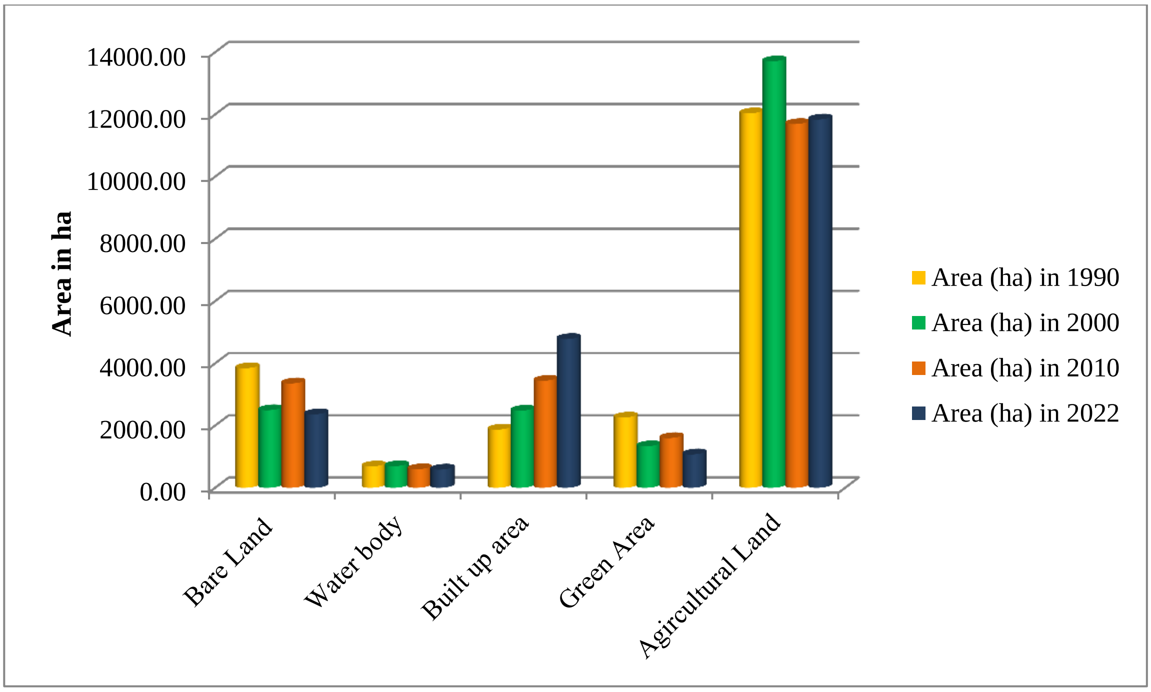


Figure 4.2 Land use Land cover distribution and changes in the study area

4.2. Accuracy assessment

Stratified random sample points were used to assess the classification results. It divides the research study area into strata according to the different land use classes, and then randomly selects samples from each stratum. This guarantees that samples are available for each land classification. To compute omission error, commission error, over all accuracy and kappa coefficient sample points are essential. The following table 4.2 shows the producer's accuracy, user's accuracy, over all accuracy and kappa coefficient value.

Table 4.2 Summary of error matrices for LULC maps of 1990, 2000, 2010 and 2022

Land class	Producer's Accuracy				User's Accuracy			
	1990	2000	2010	2022	1990	2000	2010	2022
Bare land	0.84	0.98	0.89	0.98	0.86	0.98	0.94	0.96
Water body	0.98	0.88	0.80	0.85	0.94	0.88	0.90	0.90
Built Up	0.96	0.98	0.96	0.90	0.92	0.90	0.92	0.88
Green area	0.88	0.90	0.96	0.98	0.88	0.92	0.80	0.90
Agricultural land	0.90	0.92	0.90	0.90	0.94	0.96	0.93	0.94
Over all accuracy	0.911		0.931		0.898		0.918	
Kappa statistics	0.887		0.912		0.870		0.895	

The above table shows that the overall accuracy is 91.1%, 93.1%, 89.8% and 91.8 for 1990, 2000, 2010 and 2022 LULC maps. The other one is kappa statistics for reference years; it is 88.7%, 91.2%, 87.0% and 89.5% for 1990, 2000, 2010 and 2022 LULC maps. According to (Congalton & Green, 2019) the value of kappa numbers greater than 0.8 signify a solid agreement and good classification performance between the categorized land use map and reference data.

4.3. Built up change from 1990-2022

Built up area is one of the most important indicators to measure urban sprawl for this study, so the classification accuracy is needed for built up area extraction.

The built up area of four time periods was extracted from the image after classification. The classified image was reclassified in to two classes (built up and non-built up areas).

Were as Non-built up includes bare land, agricultural land, water body and green area. And built up only includes built up area itself on the classified image.

The following figure 4.5 describes that; built up and non-built up area; the result shows a remarkable increase in the built up area from 1990-2022.

The area covered by built up in 1990 was only 11.7% (2408.58ha), and non-built covers 88.3% (18167.04ha) of study area. Built-up was dramatically increased in 2022 to 24.72. 24.8% (5099.85ha) and in contrary to this non-built area highly decreased in 2022, it covers 75.2% (15475.77ha). The following table 4.3 shows the four period built and non-built up areas in hectare.

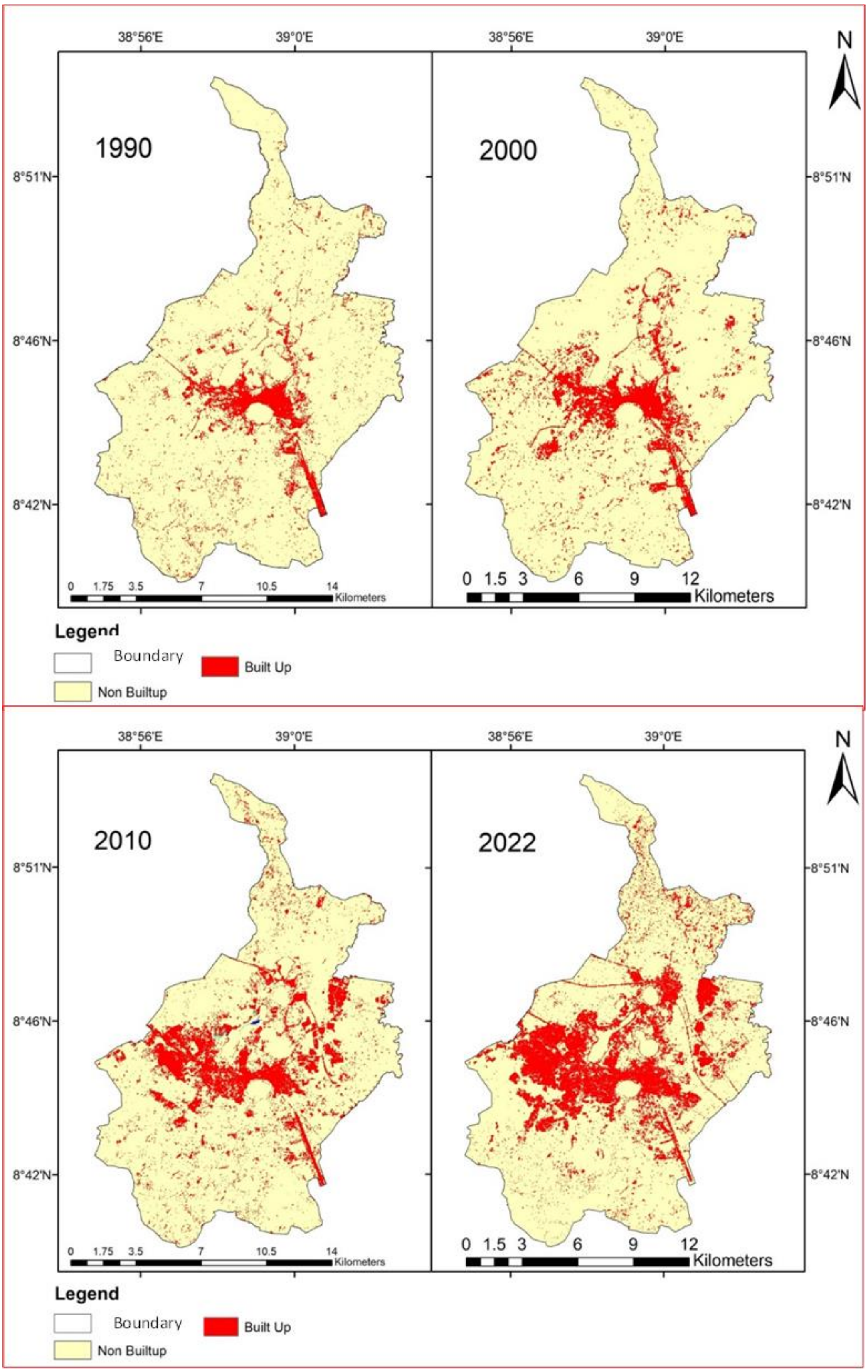


Figure 4.3 Reclassified LULC maps of 1990, 2000, 2010 and 2022

Table 4.3 Built up and non-built up area four time periods

	1990		2000		2010		2022	
Classes	Area in ha	Percent	Area in ha	Percent	Area in ha	Percent	Area in ha	Percent
Built up	1872.81	9.05	2479.77	11.98	3440.97	16.62	4783.14	23.11
Non Built up	18827.19	90.95	18231.66	88.08	17244.36	83.31	15860.61	76.62

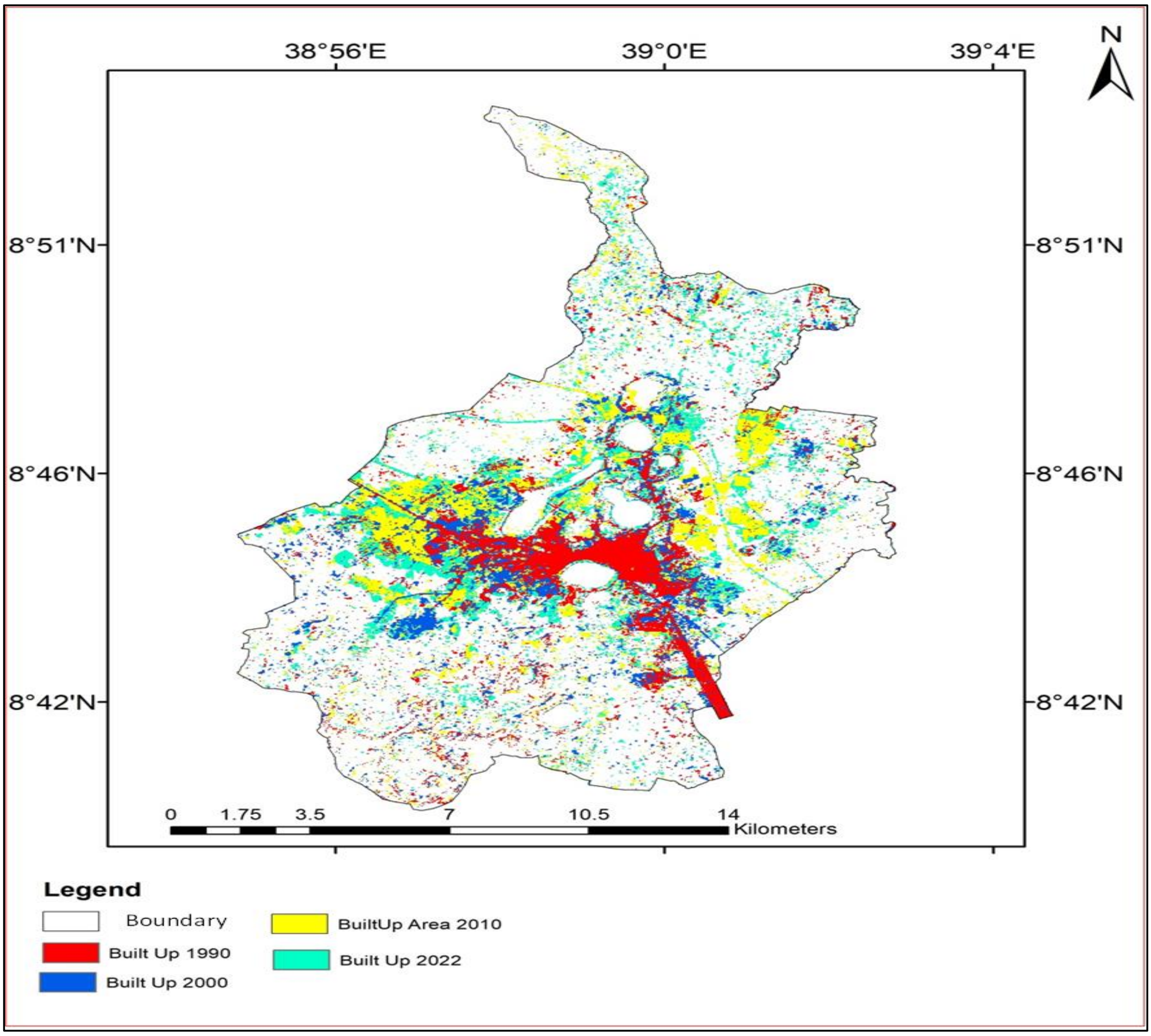
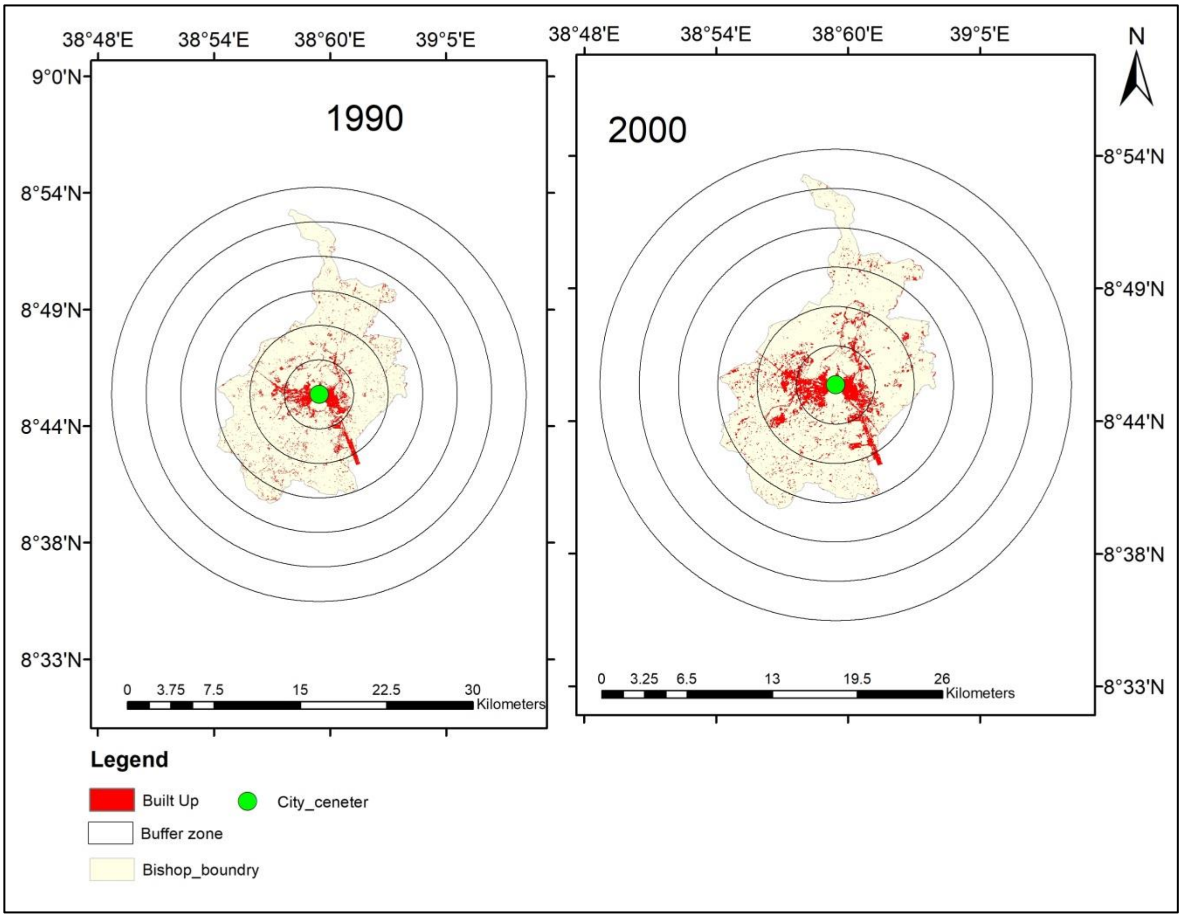


Figure4.4 Map of spatio temporal built-up of Bishoftu from 1990-2022

4.4. Multi-ring buffer analysis

Multi Ring Buffer Analysis technique was applied for creating buffers (zones) with 3 km interval around the city's centre; figure 4.5 reveals that the buffer zone covers 17km from the centre of the city to end of the buffer zones.



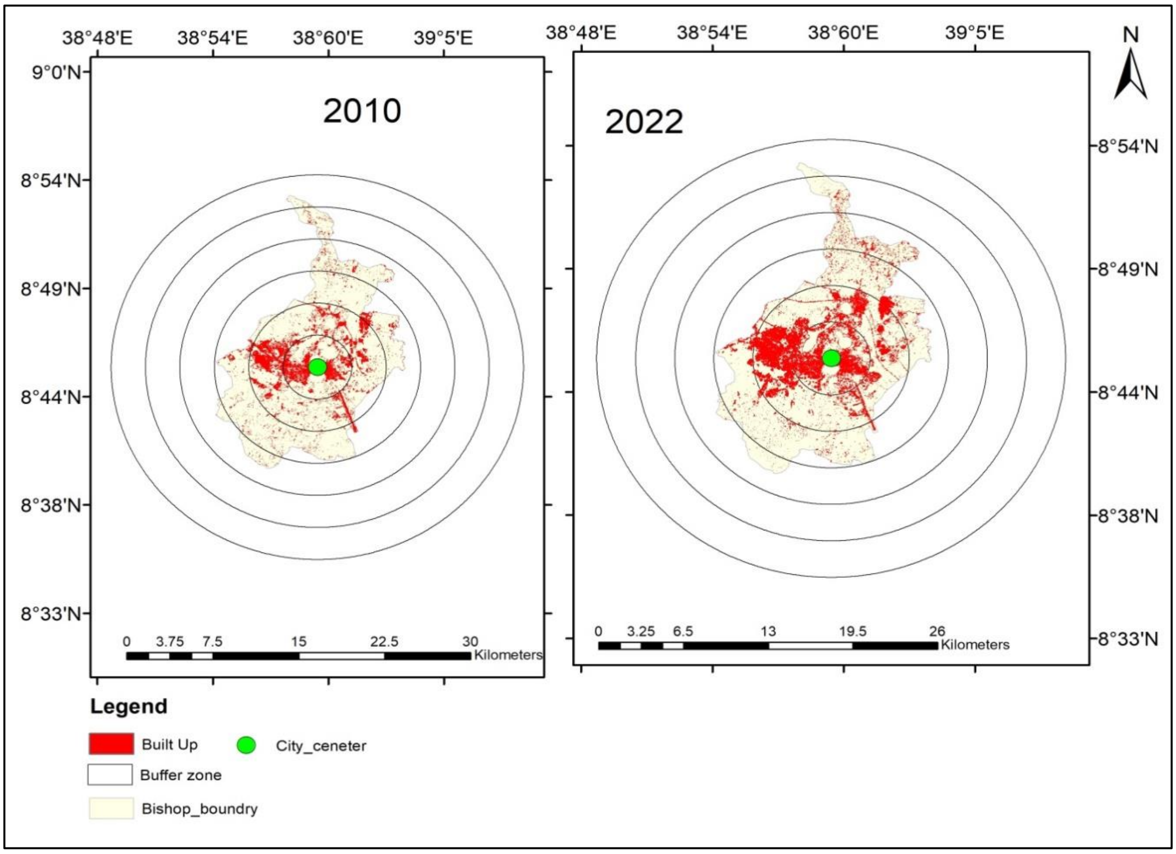


Figure 4.5 multiple ring buffer created by 3km zone from the center of the city 2022

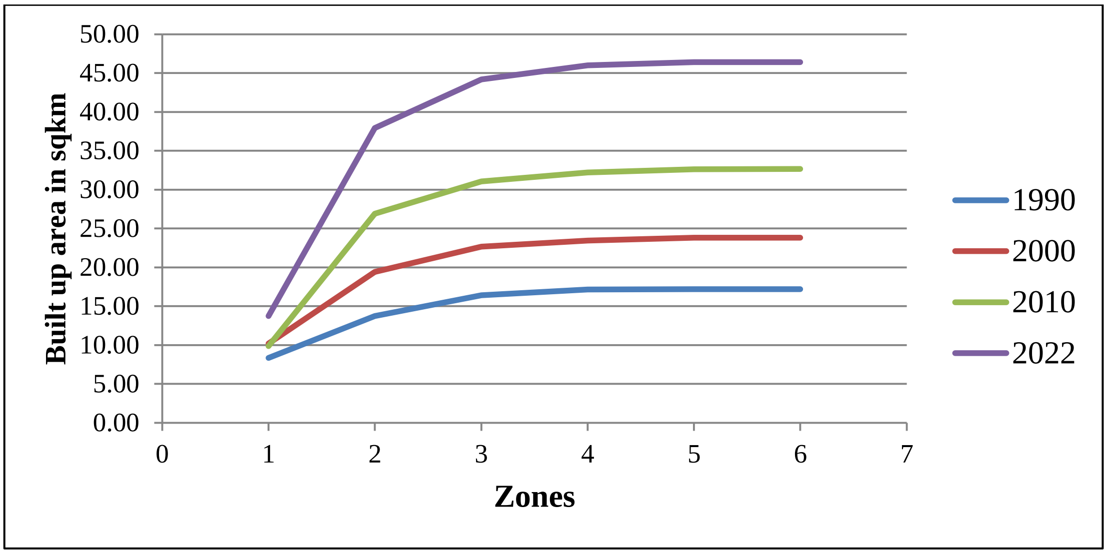


Figure 4.5 the relationship between buffer zone and built-up area

4.5. Shannon entropy

The research area is divided into 6 zones by using 3km buffer zone based on the administrative boundary (Bishoftu boundary). The built-up region of study area and its

Environs have grown quickly from the CBD (center of urban growth) in all directions, as seen in the figures below (Fig. 4.5). The rapid expansion of urban sprawl in study area is being caused by this unchecked and unlawful growth of built-up area. Below Figure 4.6 examines and represents the spatiotemporal distribution of built-up area across the study period (1990 – 2022). This reveals that, in comparison to the earlier study period, built-up regions had become more dispersed in recent years. This built-up area density can be used to analyze Urban Sprawls; the city center showed the highest density numbers, whereas the outside rings had the lowest built-up area density. The entropy values have been calculated across all zones, and are summed up for each time period for the research area, the calculated value of Shannon entropy reveals that, the value is range from 0.52 to 0.945. Based on definition of Shannon entropy value, the 1990 value of Shannon entropy shows low urban sprawl. However, there is an increase for Shannon entropy value in four periods of study time. The obtained value is 0.520, 0.758, 0.861 and 0.945 for 1990, 2000, 2010 and 2022. The dispersal of built-up areas will lead to an increase in the entropy value, which gives a clear idea to recognize whether land development is processing towards a more dispersed or compact pattern. Values for the years 2000, 2010and 2022 was above 0.5, demonstrating dispersion of the built-up area, which is a sign of urban sprawl. Such high entropy values confirm that land development was spreading over the urban fringe and into the surrounding rural areas. It shows the rate of urban sprawl grew dramatically between 1990 and 2022.The deviation between two different period of time value identify the change in the degree of dispersal of land development or urban sprawl; table 4.4 shows Shannon entropy value and changes in Shannon entropy.

Table 4.4 Shannon entropy value and changes in Shannon entropy for four study periods

Year	Shannon Entropy Value	Change in Shannon entropy
1990	0.520	Base year
2000	0.758	0.23
2010	0.861	0.103
2022	0.945	0.084

4.6. Landscape Metrics

In ecological research, landscape metrics are employed to analyze the variability of land use, land cover pattern, or landscape diversity. The built-up areas of the year 1990, 2000, and 2010 and 2022 were used to calculate the landscape metrics for determining the pattern of urban sprawl. The calculation of landscape value is used to determine the level of urban sprawl measurement. The examination of landscape pattern distribution for a certain land use land cover on a regional or global scale can be done through the application of built-up area patch indices and density indices. In this study, from 1990 to 2022, the study area of urban sprawl was measured using five landscape measures. To quantify and identify patterns of land use and land cover change in the Research area. The whole period of study time is, 1990 to 2000, 10 years period; 2000 to 2010, 10 years period and 2010 to 2022, 12 years period.   The following are landscape used for the determination of urban sprawl

1,Number of Patches

In order to quantify the degree of built-up area fragmentation within the study area, the number of patch refers to the total number of built-up patches, measured in meters per hectare. A growing number of patches in a time series analysis suggests a more fragmented and expansive metropolitan area. Fragstats 4.2 software was used to compute the metrics in this study. In this study, the value of NP (number of patches) increased steadily from 2328 in 1990 to3022 in 2000. Again the value of NP rose from 3022 in 2000 to 3674 in 2010, demonstrating an increase over two distinct periods. Similarly, between 2010 and, NP further climbed from 3674 in 2010 to3737 in 2022.Marking a consistent rise throughout all study periods. This sustained growth strongly suggests significant urban sprawl expansion between 1990 and 2022. The following table 4.5 and figure 4.8 reveals the value of NP for four study periods.

Table 4.5 the number of patches for built up area in the year of 1990, 2000, 2010 and 2022

Year	NP	Difference in NP
1990	2328	Base year
2000	3022	694
2010	3674	652
2022	3737	63

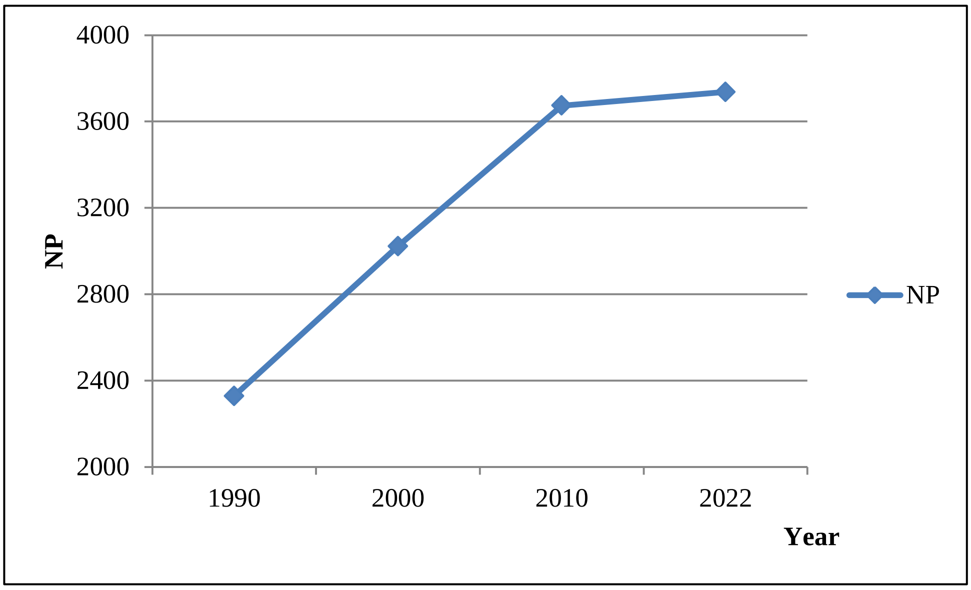


Figure 4.6 Number of Patches in four periods

2, Class Area Metrics (CA)

Class Area Metrics (CA) quantifies the amount that each landscape metric contributes to the specific land use land cover patch, or the composition of the landscape. Because CA measures are a significant consequence of habitat loss and vegetation fragmentation, they were used in this study. Based on table 4.6 value of CA from 1872.81 in 1990 to 4783.14 in 2022, there has been a noticeable growing trend in the value of CA. This indicates an increase of more than 155% during the course of the study.

The first rise is moderate between 1990 and 2000 (2479.77), but between 2000 and 2010 (3440.97), there is a more noticeable increase, and by 2022 (4783.14). This implies an increasing rate of urban sprawl from 1990 to 2022 and it rises concerning questions about sustainability, resource management, and community development. Figure 4.8 reveals the CA of year.

Table 4.6 Class Area for built-up area in the year of 1990, 2000, 2010 and 2022 (ha)

Year	CA	Difference in CA
1990	1872.8	Base year
2000	2479.8	606.96
2010	3441	961.2
2022	4783.1	1342.17

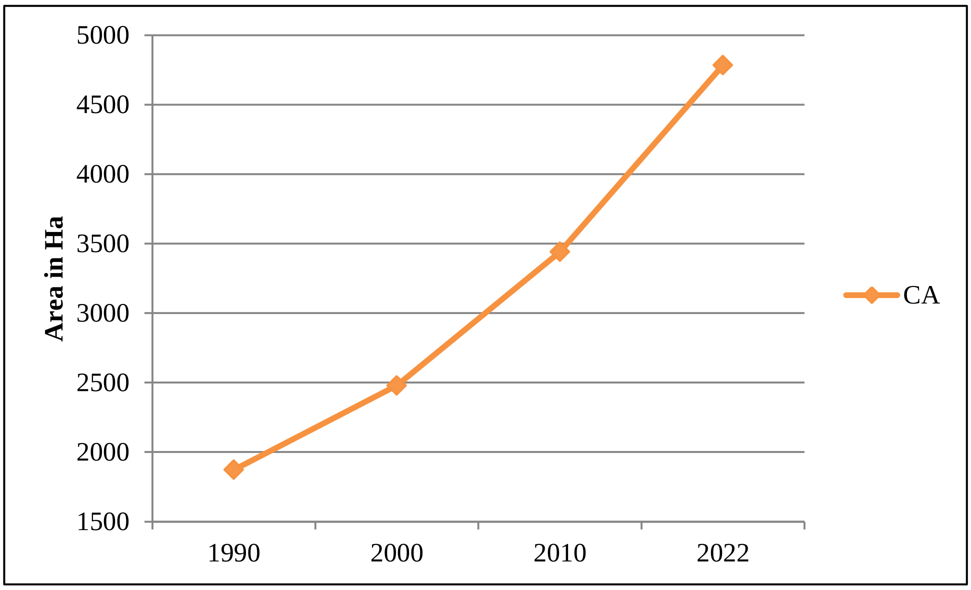


Figure 4.7 Class area metrics in four study periods

3, Largest patch Index (LPI)

The largest patch index (LPI) measures the entire landscape area in the study area. LPI is essentially a measure of a patch's dominance in the larger landscape. A low LPI value implies shrinking patch sizes, while a high value suggests landscape dominance by a single patch type. LPI starts at 3.367 in 1990 and marks a sharp 6.1818 increase by 2000.

Likewise, from 2000 to 2010, the value increases by a moderate 5.3%. In contrast, between 2010 and 2022, LPI shows a dramatic surge of over 58.9%, more than half times the rate of increase observed during the previous decade. This suggests a significant acceleration in the pace of landscape consolidation over the past twelve years. The following table 4.7 shows LPI of four periods of years and their difference.

Table4.7 Largest Patch Index (LPI) for four time periods and their differences.

Year	LPI	Difference in LPI
1990	3.367	Base year
2000	6.1818	2.8148
2010	6.5333	0.3515
2022	11.0984	4.5651

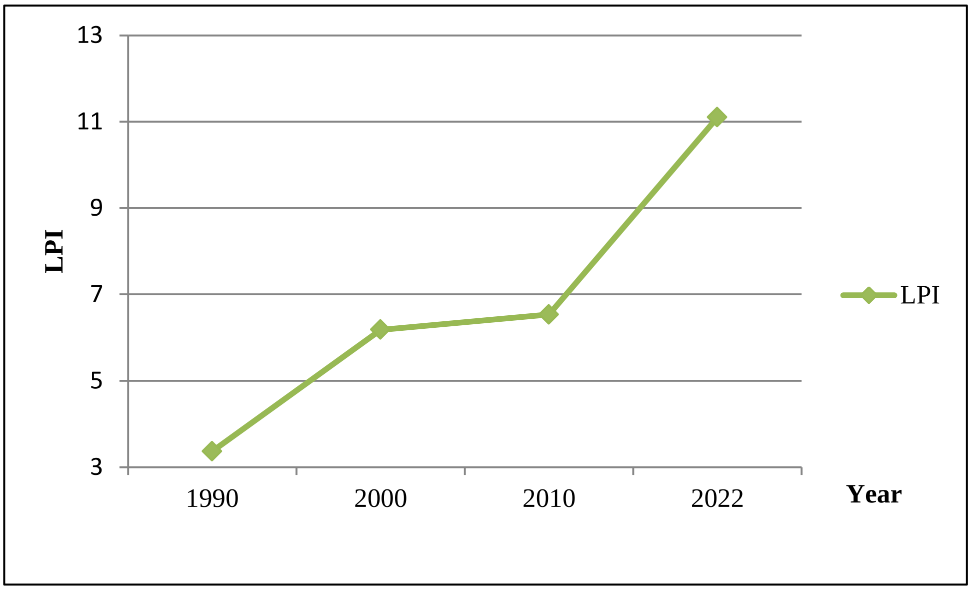


Figure 4.8 Largest Patch Index metrics in four study periods

4, Landscape Shape Index (LSI)

The Landscape Shape Index (LSI) measures the amount of edge or boundary present within a landscape, relative to its overall size. It's calculated by taking a quarter of the total length of all edges within the landscape, including both external boundaries and internal edges between different patch types, and dividing that by the square root of the landscape's total area. The computed value of LSI by using Fragstat4.2 software (table 4.8) was 50.09

for 1990, and it increases by 15.2% in 2000 (57.45). Similarly, it increases by 1.0% from 2000 to 2010 study periods. However, the values of LSI highly increase from 2010 to 2022. It increases by 3.04% from two study periods of time.

Table4.8 Landscape Shape Index (LSI) for built-up area in the year of (1990-2022)

Year	LSI	Difference in LSI
1990	50.0994	Base year
2000	57.4589	7.3595
2010	57.5952	0.1363
2022	59.3418	1.7466

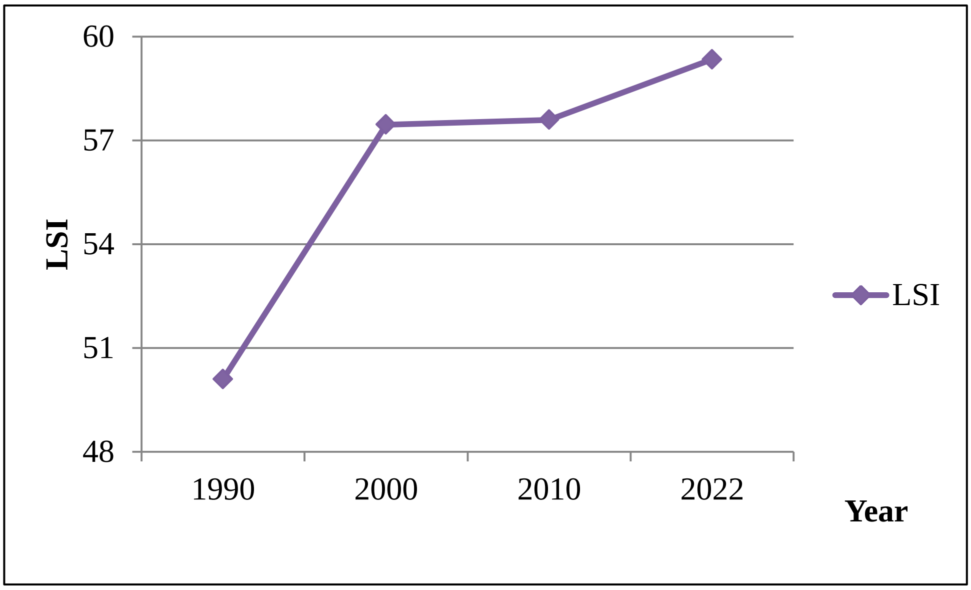


Figure 4.10 Largest Shape Index metrics in four study periods

5, Percentage of Landscape (PLAND)

PLAND describes how much of a landscape is made up of a specific type of area, like buildings. It's like a pie chart for a whole landscape, showing what percentage belongs to each type of "slice." This gives us a simple percentage breakdown of how much space each type takes up. Based on the values in Table 4.9, the PLAND in the study area increased from 9.04% in 1990 to 11.97% in 2000 and continued to rise to 16.63% in 2010, reaching 23.2% by 2022. These trends, along with all other analyzed metrics, reveal a pattern of concerning rapid and unmanaged urban expansion radiating outward from the city center, suggesting a potentially unhealthy trajectory for the city's growth.

Table4.9Percentage of Landscape (PLAND) for built-up area in the year of (1990-2022)

Year	PLAND	Difference in PLAND
1990	9.0474	Base year
2000	11.973	2.9256
2010	16.6348	4.6618
2022	23.1699	6.5351

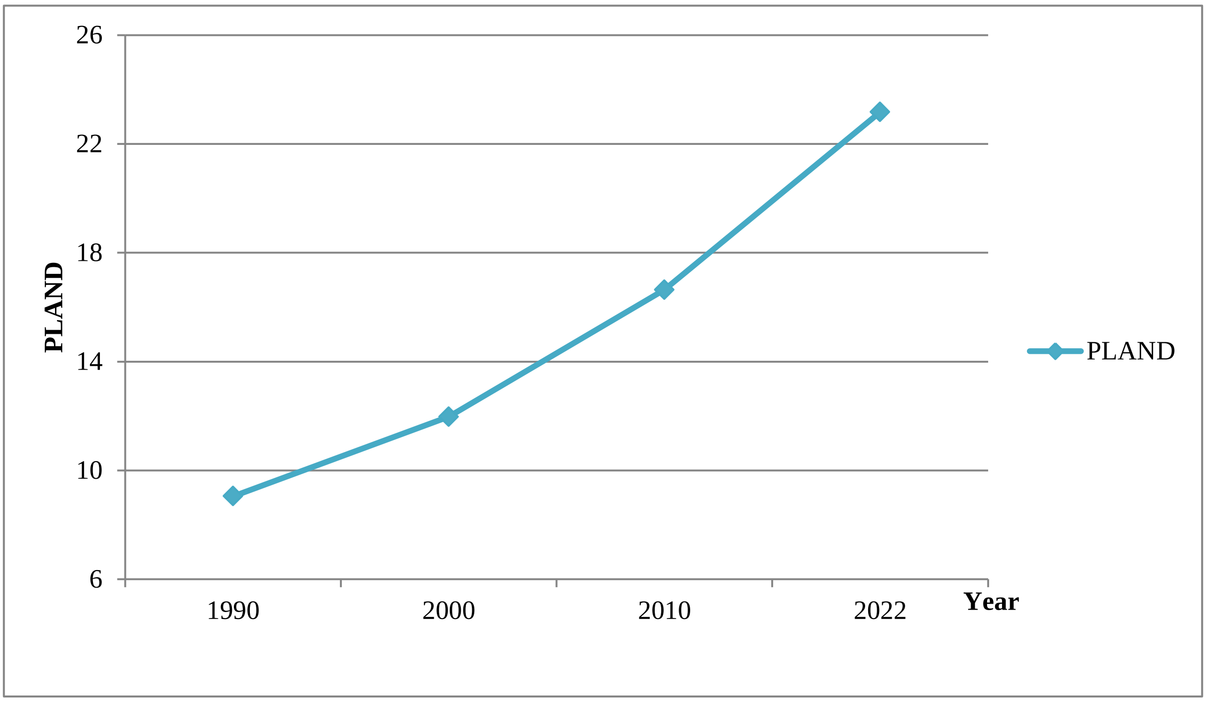


Figure 4.9 Percentage of Landscape metrics in four study periods

4.7 Driving Forces of Urban Sprawl and Logistic Regression Modeling

Rural to urban (built-up to non-built-up) land conversion was applied using logistic regression. The dependent variable is binary (0 and 1) and the explanatory variable were discussed in 3.89 section. All predictors were prepared using ARCGIS to minimize spatial dependence, spatial sampling was implemented. Finally, binary logistic regression was processed using IBM SPSS 25. The following Table 4.10 and Figure 4.12 summarize the selected predictor variables of this study.

Table4.10Selected predictor's variable of the study area

Variables name	**Description**
Mroad	Distance from the cell to the nearest Road
City_C	Distance from the cell to the nearest City Center
WB	Distance from the cell to the nearest water Body
Industry	Distance from the cell to the nearest industrial site
Ed and HC	Distance from the cell to the nearest Educational Institute and Health center
Slope	Slope of the study area

Note: a) Slope b) City center c) major road d) water body e) Educational institute and Health center f) Industry

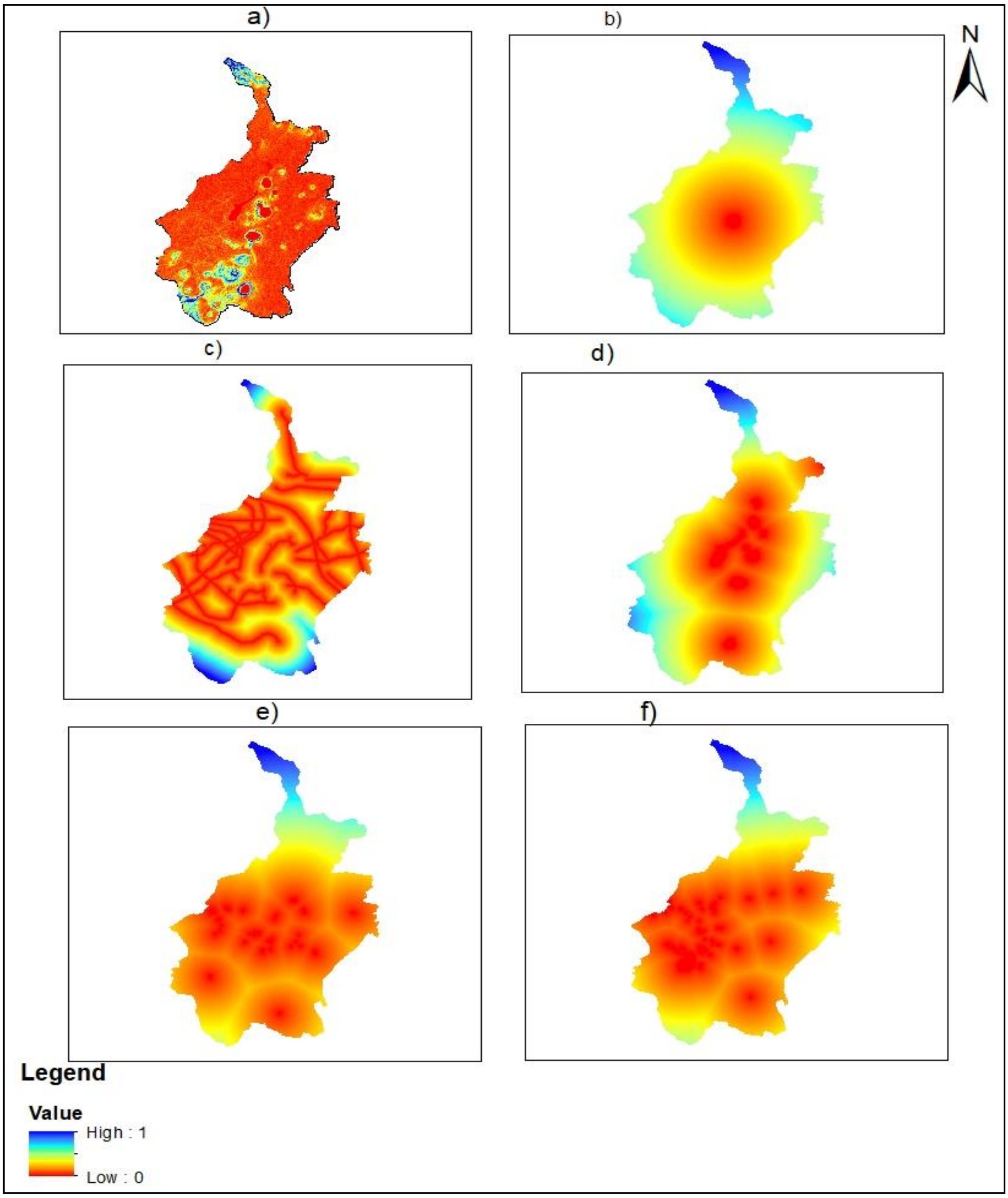


Figure4.10 Standardized selected explanatory variables of the study area

4.7.1 Multicollinearity analysis

Multicollinearity diagnostics have been performed for each set of variables utilized in various time periods in order to remove redundant variables from the model and preserve the stability of the coefficient. Using the statistical software tool SPSS 25, the analysis is performed by iteratively regressing one of the dependent variables against the other six variables. The result depicted that distance to industry and distance to health center and education independent variables affected in multi-collinearity. The analysis expects that the value of VIF less than 5 indicates no collinearity; however the value greater than five indicates high multi-collinearity. To remove multi collinearity from the variables, there are two options; the first one is removing high collinearity variable from the list and if the variables are important in the analysis, we combine two high collinearity variables and take the average of two variables. For this study, two variables are combined and average value is taken for the analysis. The following shows the value of VIF of three periods.

Table 4.4 the value of multi-collinearity (VIF) in the variables

Variables	1990-2000	2000-2010	2010-2022
M road	1.307	1.307	1.307
WB	2.147	2.147	2.147
City centre	4.533	4.533	4.533
Slope	1.222	1.222	1.222
Average (ED and Ind)	3.700	3.700	3.700

4.7.2 The result of the models

The rural-urban (non-built-up to built-up) of 1990-2000, 2000-2010 and 2010-2022 were analyzed respectively and results were presented in Table 4.11, Table 4.12 and Table 4.13. The regression analysis model was estimated by using maximum likelihood algorithm. The result depicted that distance from the cell to the nearest (road, water body, city center, average (educational institute and health center, industry)) and slope explanatory variables are included in the study. The logistic regression model was statistical significant $X^2(5)=130.889$, for $p<0.005$ for 1990-2000, $X^2(5)=219.407$, for $p<0.005$ for 2000-2010 and $X^2(5)=69.480$, for $p<0.005$ for 2010-2022. The model explained 53.7% for 1990-2000, 42.8% for 2000-2010 and 43.3% for 2010-2022 Nagelkerke (R^2) of the variance in rural to urban transition and correctly classified 97.1% for 1990-2000, 92.6% for 2000-2010 and 88.4% for 2010-2022. Increasing major road, city center, average (industry and (health center and education)) value associated with a reduction in the likelihood of built-up area (in other word, when the value of major road, city center and average (industry and (Health center and educational institutes)) distance increases built-up decreases and vice versa) for

1990-2000. Because the significant value is <0.05. The values of coefficient (B) for all variables are negative and these indicate that the relation between explanatory variables and dependent variables are inverse relationship.

Table 4.5 Variables in the Equation (1990-2000)

		B	S.E.	Wald	df	Sig.	Exp(B)	95%C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	MRoad	-.184	1.029	.032	1	.036	1.202	.160	9.039
	WB	-.766	1.041	.542	1	.462	.465	.060	3.574
	City_C	-2.387	1.304	3.350	1	.027	.920b	.007	1.184
	slope	-2.403	1.511	2.530	1	.112	.090	.005	1.747
	Average(ED and Ind)	-11.227	2.237	25.188	1	.000	.006	.000	.001
	Constant	-1.288	.241	28.657	1	.000	.276		

a. Variable(s) entered on step 1: MRoad, WB, City-C, slope, Average EDandInd. (B is coefficient Exp(B) is odds ration)

Increasing slope, major road, water body, city center and average (industry and health center) value associated with a reduction in the likelihood of built-up area (in other, when the distance far from the of major road, slope, water body, city center and average (industry and health center and education) transition from rural to urban built-up decreases and vice versa in 2000-2010.

Table 4.6 Variables in the Equation (2000-2010)

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	MRoad	-5.062	.793	40.771	1	.000	2.930	.001	.030
	WB	-2.077	.606	11.748	1	.001	.813	.038	.411
	CityC	-1.071	.897	1.425	1	.023	2.920	.503	16.952
	slope	-3.304	1.059	9.743	1	.002	.737	.005	.292
	AverageEDandInd	-5.674	1.022	30.796	1	.000	.693	.000	.025
	Constant	-.880	.176	25.094	1	.000	.415		

a. Variable(s) entered on step 1: MRoad, WB, CityC, slope, Average ED and Ind.

The significant value of major road, water body, city center, slope, average (Industry and Education and health center) value is 0.000, 0.023, 0.014, 0.024 and 0.032, which it indicates that the major road, water body, city center, slope and average (Industry and Education and health center) associated with a reduction in the likelihood of built-up area (in other, when the distance far from the of major road, water body, city center, slope and average (Industry and Education and health center) transition from rural to urban built-up decreases and vice versa).

Table 4.7 Variables in the Equation (2010-2022)

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	MRoad	-2.162	.420	26.487	1	.000	2.115	.051	.262
	WB	-.512	.428	1.432	1	.023	.599	.259	1.387
	City_C	-.998	.681	2.146	1	.014	.969	.097	1.401
	slope	-.106	.532	.039	1	.024	.900	.317	2.552
	Average ED and Ind	-.291	.589	.245	1	.032	1.338	.422	4.243
	Constant	-1.290	.132	96.110	1	.000	.275		

a. Variable(s) entered on step 1: MRoad, WB, City, slope, AverageEDandInd.

Based on the above result we can identified the derive forces and it is depicted in Table 4.14. In period of 1990-2000, the major driven force of city growth is major road and next is city center.

Table4.8 Major driving force of urban sprawl in three periods

	Level of Driven force		
Variables	1990-2000	2000-2010	2010-2022
Mroad	1st	1st	1st
WB	3rd	3rd	4th
City-C	2nd	2nd	3rd
Slope	5th	4th	5th
Average ED and Ind	4th	5th	2nd

4.7.3 Model evaluation

An essential phase in logistic regression modeling is model evaluation. The most common kind of evaluation technique is percentage accurate prediction (PCP). Out of the sampled pixels in the model, it indicates the proportion of accurately predicted pixels. When we have alternative models for prediction, this helps us decide which one to utilize. The value of PCP for 1990-2000, 2000-2010 and 2010-2022 as described in model result part the correct predicted value for 1990-2000 is 97.1%, for 2000-2010 is 92.6% and for 2010-2022 is 88.4% respectively.

4.8 Discussion

This study used Landsat 5, Landsat 7 and Landsat 8 imagery for land use/land cover classification. Sample data collected over four years (1990, 2000, 2010 and 2022) using Google Earth was used to assess the accuracy of the land use/land cover classification for the study area. In addition, elevation data, road data, water body data, data on city centers, industries, health centers, and educational institutes were used to identify the drivers of urban growth using a binary logistic regression model. After data acquisition, pre-processing was performed on the Landsat image; including layer stacking, sub setting the image to the study area, radiometric correction, and geometric correction. The pre-processed Landsat image with stacked layers was then classified using a supervised image classification technique in ErdasImagine2015. The study area is basically classified to five classes (built up, agricultural land, bare land, green area and water body). The result depicts that bare land, water body, built up area, green area, and agricultural land covers in 1990 LULC map shows 3844.08ha (18.57%), 688.50ha (3.33%), 1872.81ha (9.05%), 2384.01ha (11.51%) and 12036.420ha (58.15%). In 2000 LULC map bare land, water body, built up area, green area, and agricultural land covers 2493.99ha (12.04%), 695.43ha (3.36%), 2497.77ha (11.97%), 1335.33ha (6.45%) and 13706.91ha (66.18%). The LULC map of the other study year 2010 shows 3355.658ha (16.22%) covered by bare land, 598.32ha (2.89%) covered by water body; 3440.97ha (16.63%), 1598.49ha (7.73%) and 11691.44 (56.52%) were covered by built up area, green area and agricultural land respectively. The classified LULC map of 2022 reveals that 2362.68ha (11.45%) study area is covered by bare land, while586.35ha (2.84%) of study area was covered by water body and built up area, green area and agricultural land covers the study area by 4783.14

(23.17%), 1073.97ha (5.20%) and 11837.61ha (57.34%) respectively. (Getu & Bhat, 2021) in their study classified study area in ix main classes (built-up area, water body, forest, wet land and open space). (Sun et al., 2007) classified the image of study area to three; built up, non-built up and water body.(Tewolde & Cabral, 2011) Also in their study, they classified land into six classes: built-up, grazing land, irrigation, plantations, rainfed, and water bodies. This shows us the classification of image of land use land cover is based on environmental condition and the application of the classification. The other study also classified the image by different classes; (Huang et al., 2009).

Followed by image classification, accuracy assessment was performed in ERDAS Imagine 2015for image classification; producer's accuracy, user's accuracy, over all accuracy and kappa statistics were applied in this study. The basic accuracy measurement kappa statistics value for four years is 0.887 for 1990, 0.912 for 2000, 0.87 for 2010 and 0.895 for 2022. To identify changes in land cover classification between the four study years, change detection was applied to clearly determine these differences. This study aimed to identify the expansion of built-up areas within the study region. Therefore, the classified images from all four years were reclassified into built-up and non-built-up categories. To identify the sprawl of the urban, multiple-ring buffer was applied in 3km radius and Shannon entropy technique was applied to identify the level of sprawl. The result Shannon entropy depicts 0.520, 0.758, 0.861 and 0.945 for 1990, 2000, 2010 and 2022. To analyze the variability of land use cover pattern or landscape diversity spatial metrics was applied for four study years using Fragstats 4.2 software. The software computed number of patches, class area metrics, largest patch index (LPI), Largest shape index (LSI), percentage of landscape (PLAND) and others. This study was applied the above mentioned five spatial metrics to determine extent of urban sprawl. Finally, to identify the driven force of urban growth logistic regression model was applied in SPSS 25 software. Data was Pre-processed spatial data in ArcGIS and saved in CSV format. The final processed data identified the driven of urban Sprawl for three periods (1990-2000, 2000-2010 and 2010-2022). The result showed that major road is the main driven for urban growth in the study area for all periods; however city center is the second driven force in periods of 1990-2000 and 2000-2010. The average value of Education institute, health center and Industry was the second driven center in period of 2010-2022. Water body was is the third driven force in periods of 1990-2000 and 2000-2010 City center for period of 2010-2023. Getu & Bhat (2021) uses producer accuracy, user's accuracy, over all accuracy and kappa statistics for accuracy assessment and in the same manner they use Shannon entropy to calculate the level of urban sprawl in the study area .and finally this study applied logistic regression model to identify driven force. Xie et al. (2005) spatial logistic regression model to identify the driven force of urban expansion; however the selected explanatory variables have some variation as compared with this study. Cheng & Masser, 2003; Huang et al., 2009; Macandza, 2022; Wu & Zhang, 2013) uses their selected explanatory variables to identify the driven force of urban expansion.

CHAPTER FIVE CONCLUSION AND RECOMMENDATION

5.1. Conclusion

Currently, urban sprawl phenomenon has been seen in many of cities in the developing and developed countries. It is considered as a particular kind of urban growth which comes up with a lot of negative effects. This study focuses on Analysis of the spatiotemporal dynamic of urban sprawl using geospatial technologies and landscape metrics in Bishoftu town from 1990 to 2022. Landsat5 and Landsat7 and Landsat8 imagery was applied to land use land classification. The study area is basically classified to five classes (built up, agricultural land, bare land, green area and water body). The result depicts that built up land covers in 1990, 2000, 2010 and 2022 were 1872.81ha (9.05%), 2497.77ha (11.97%), 3440.97ha (16.63%) and 4783.14 (23.17%). While the bare land covers in four periods are 3844.08 ha (18.57%), 2493.99 ha (12.04%), 3355.658 ha (16.22%), and 2362.68 ha (11.45%),. Again, water body covers in four study years are 688.50ha (3.33%), 695.43ha (3.36%), 598.32ha (2.89%) and 586.35ha (2.84%). The other classified class green area covers in four study years are 2384.01ha (11.51%), 1335.33ha (6.45%), 1598.49ha (7.73%) and 1073.97ha (5.20%). Lastly, the agricultural area covered in a four year are 12036.420ha (58.15%), 13706.91ha (66.18%), 11691.44 (56.52%) and 11837.61ha (57.34%). Based on the above results, we can conclude that a larger portion of the study area was dedicated to urban agriculture, and built-up area land saw a rapid increase during the four years of the study.

To identify the expansion of built-up areas within the study area, classified images from all four years were reclassified into built-up and non-built-up categories. Subsequently, the Shannon entropy technique was applied in a 3km buffer zone, along with spatial metrics, to identify the level of sprawl. The results show that the Shannon entropy values for the four study years (1990, 2000, 2010, and 2022) are 0.520, 0.758, 0.861, and 0.945. These entropy values indicate a rapid increase in the level of urban sprawl from 1990 to 2022. In addition to Shannon entropy index, landscape metrics were also used to identify the presence of urban sprawl and determine its extent. Five Land scape matrices were used and overall result show that Bishoftu city has experiencing a change in its landscape over the past 32 years. Followed by Shannon entropy and spatial metrics, six variables (Distance from the cell to the nearest road, Distance from the cell to the nearest City Center, Distance from the cell to the nearest water Body, Distance from the cell to the nearest industrial site, Distance from the cell to the nearest Educational Institute and Health center and Slope of the study area) are selected to identify the driven force of urban expansion. The result showed that major road is the main driven for urban growth in the study area for all periods; however city center is the second driven force in periods of 1990-2000 and 2000-2010. The average value of Education institute, health center and Industry was the second driven center in period of 2010-2022. Water body was the third driven force in periods of 1990-2000 and 2000-2010.City center for period of 2010-2023. In other, the leading driven forces of urban expansion based on selected variables is major road. Therefore, we can conclude that the major driven force for urban expansion in their ascending order are major road (for all periods), city center (1900-2010), water body (1990-2010), average of education and health center and Industry (1990-2000)) and slope (2000-2010). Average of education and health center and Industry (2nd in 2010-2022), city center (3rd in 2010-2022), water body (4th 2010-2022) and slope are the last.

5.2. Recommendations

This study reveals Analysis the spatiotemporal dynamic of urban sprawl using Shannon Entropy and landscape metrics.

Thus, the following recommendations are hereby made:

- ✓ Uncontrolled urban expansion is a serious issue for the study area. Therefore, the local government should consider implementing this study with minor modifications.
- ✓ Obtaining essential data is crucial for any study, but acquiring some essential data can be challenging. Stakeholders should prioritize data organization and accessibility for future researchers.
- ✓ Future researchers should prioritize identifying more effective techniques to pinpoint the driving forces behind urban expansion for a clearer understanding of the issues.

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