OBJECT-BASED IMAGE ANALYSIS FOR THE SPATIOTEMPORAL DYNAMICS OF URBAN INFORMAL SETTLEMENTS: THE CASE OF DEMBELA SUB CITY OF ADAMA, ETHIOPIA

Zenebu Adere Tola

Thesis Submitted to the department of Geomatics Engineering School of Civil Engineering and Architecture (SOCEA)

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

Office of Graduate Studies

Adama Science and Technology University

May, 2024

Adama, Ethiopia

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DECLARATION

I declare here by this research thesis entitled "Object-Based Image Analysis for the Spatiotemporal Dynamics of Urban Informal Settlements: The Case of Dembela Sub City of Adama, Ethiopia" is my own work and has not been submitted to any university for similar purpose. The reference used in this Thesis are dully recognized by proper citations.

Zenebu Adere Tola	________________	________________
Name of student	Signature	Date

RECOMMENDATION OF ADVISORS

I, the major advisor of this thesis, here by certify that I have read the revised version of the thesis entitled "Object-Based Image Analysis for the Spatiotemporal Dynamics of Urban Informal Settlements: The Case of Dembela Sub City of Adama, Ethiopia" prepared under my guidance by Zenebu Adere. submitted in partial fulfillment of the requirements for the degree of Mater's of Science in Geoinformatics. Therefore, I recommend the submission of the revised version of the thesis to the department following the applicable procedures.

Dr. Dejene Tesema	_______________	______________
Major Advisor/Supervisor	Signature	Date

APPROVAL SHEET

I/we, the advisors of the thesis entitled "Object-Based Image Analysis for the Spatiotemporal Dynamics of Urban Informal Settlements: The Case of Dembela Sub City of Adama, Ethiopia" by Zenebu Adere Tola. hereby certify that the recommendation and suggestions made by the board of examiners are appropriately incorporated into the final version of the thesis.

Dr. Dejene Tesema	______________	______________
Major Advisor/Supervisor	Signature	Date

We, the undersigned, members of the Board of Examiners of the thesis by Zenebu Adere Tola have read and evaluated the thesis entitled "Object-Based Image Analysis for the Spatiotemporal Dynamics of Urban Informal Settlements: The Case of Dembela Sub City of Adama, Ethiopia" and examined the candidate during open defense. This is, therefore, to certify that the thesis is accepted for partial fulfillment of the requirement of the degree of Master of Science in Geoinformatics.

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LIST OF ACRONOMY

ACAO	Adama City Administration Office
FGD	Focus Group Discussion
GLCM	Grey Level Co-occurrence Matrix
GR	Green Ratio
IS	Informal Settlement
ITC	International Training Centre
LIS	Land Information System
LULC	Land Use Land Cover
MG	Mean Green
NDBI	Normalized Difference Building Index
NDVI	Normalized Difference Vegetation
NDWI	Normalized Difference Water Index
OA	Over Accuracy
OBIA	Object Based Image Analysis
OE	Omission Error
PA	producer Accuracy
RB (SL)	Relative Border to Slums
RS	Remote Sensing
SAVI	Soil Adjusted Vegetation
SP	Scale Parameter
SPSS	Statistical Package for Social Sciences
UA	User Accuracy

ABSTRACT

Informal settlements are a global concern driven by rapid urbanization and socioeconomic challenges, particularly in developing countries. Factors such as rapid urbanization, high land prices, lack of affordable housing, and economic disadvantages contribute to the growth of informal settlements. The study analyzed the spatio-temporal dynamics of informal settlements in Dembela sub city, from 2012 to 2021 using Object-Based Image Analysis (OBIA). Aerial photographs were used to detect changes in the spatial extent of informal settlements, and qualitative and quantitative data were collected through structured questionnaires to gain insights into the patterns of informal settlements in the study area. OBIA methods were employed, and ECognition software was used to classify built-up and non-built areas. The results revealed a significant expansion of the built-up class, leading to an increase in the area occupied by informal settlements, particularly at the expense of agriculture and bare land classes. Specifically, the area representing informal settlements was 35 hectares in 2012, which increased to 54 hectares in 2017, and further expanded to 79 hectares in 2021, indicating a 3% increase from 2012. The overall accuracy of the classification was determined to be 96.5% with an overall kappa coefficient of 0.95. The results from interview indicate that, the lack of access to formal land was the most significant driving factor, accounting for 32.4% of the responses. This was followed by the absence of formal land transfer by the government (16.7%), migration from rural areas (11.8%), and existing land lease policies (10.8%). Unplanned development activities contributed to about 9.8% of the driving factors. The study concludes that the Object-Based Image Analysis (OBIA) method offers a more comprehensive and contextual approach to remote sensing data analysis compared to other methods. OBIA considers the spatial relationships and properties of objects within the image, leading to improved classification accuracy and the ability to incorporate ancillary data for a more robust and interpretable analysis.

Key words:

Object Based image Analysis, Informal settlement, High resolution images, change detection.

CHAPTER ONE: INTRODUCTION

1.1. Background of the Study

One-third of all urban forms worldwide consist of informal settlements (Samper & Liao, 2023). These settlements have experienced rapid expansion in recent decades due to ongoing socioeconomic changes and urbanization processes. Estimates indicate that nearly 25% of the global urban population currently resides in informal settings (Cinnamon & Noth, 2023). If current trends continue, it is projected that there will be 2 billion people living in informal settlements by 2030 and 3 billion by 2050 (Agyabeng et al., 2022). In addition to making up a sizeable portion of the housing stock in cities, informal settlements are expanding faster than the cities themselves (Nixon, 2020). Most of these cities will need massive collective and coordinated action at all scales, from local to global, to ensure sustainable development. Better and more readily available data are essential, but the role that locals participatory practices must play this situation also depends on our capacity to transform these data useful intelligence to support decision-making at various scales (Soman et al., 2020).

Urbanization is often not accompanied by adequate development of infrastructure, including housing, sanitation, and transportation corridors. This lack of planning when coupled with the large share of informal low-paid employment results in the growth of informal settlements in densely populated urban areas (Ansari, 2020). Informal settlement growth has a very uneven distribution throughout the world. Among the regions of the world identified by the Sustainable Development Goal Regions of the United Nations, Sub-Saharan Africa is exceptional in that its urban population is still anticipated to increase significantly throughout the 21st century (Soman et al., 2020). In Sub-Saharan Africa, informal settlements are expanding in three ways: in number, area, and population, at a rate of 4 to 7 percent year (Mwamhanga, 2013). Informal settlements in Sub-Saharan Africa often arise due to a combination of factors, including poor urban management, weak governance, inappropriate regulations, dysfunctional land markets, social insecurity, economic challenges, and lack of political will(Anulo, 2015). In Ethiopia, the proliferation of informal settlements has emerged as a pressing economic, social, and political concern. These settlements are characterized by substandard living conditions, inadequate housing, and limited access to crucial infrastructure and services (G/selasie, 2019).

Informal settlements, often referred to as slums or shantytowns, are a prevalent feature of rapidly urbanizing cities in many parts of the world. These settlements typically emerge spontaneously and are characterized by a lack of formal land tenure, inadequate housing, limited access to basic services such as clean water and sanitation, and substandard living conditions (Bakhaty et al., 2023). Adama City, located in the Oromia region of Ethiopia, has experienced significant urban growth and transformation in recent decades, leading to the proliferation of informal settlements across its landscape. The phenomenon of informal settlements in Adama City is deeply intertwined with broader socio-economic dynamics, including rural-to-urban migration, population growth (Aredo, 2019). As rural migrants seek better economic opportunities in urban centers, they often settle in informal settlements due to the lack of affordable housing options and limited access to formal land tenure.

Understanding the spatiotemporal dynamics of informal settlements in Adama City is crucial for effective urban planning and sustainable development. Mapping the distribution and growth patterns of these settlements over time provides valuable insights into the underlying drivers of urban expansion and the socio-economic conditions of their residents. Previous studies on informal settlements in most of Ethiopian City have primarily focused on descriptive analyses of their socioeconomic characteristics and living conditions. However, there remains a gap in the literature regarding the spatiotemporal dynamics and environmental impacts of these settlements. By employing geospatial analysis techniques, this study aims to fill this gap by providing a comprehensive understanding of how informal settlements have evolved in Dembela sub city from 2012 to 2021 and their implications for environmental sustainability and urban development.

Through a combination of remote sensing data, Geographic Information Systems (GIS) technology, and socio-economic surveys, this research will contribute to the evidence base for informed decision-making and policy formulation aimed at addressing the challenges posed by informal settlements in study area. By identifying hotspots of informal settlement growth, assessing their socio-economic characteristics, and evaluating their environmental impacts, this study seeks to inform the development of targeted interventions to promote inclusive and sustainable urban development in Adama case study of Dembele sub-City using OBIA.

1.2. Statement of the Problem

Rapid urbanization, lack of affordable housing, rural-urban migration, and increase in population have led to the development of informal settlements, which can be seen as outcomes of industrialization and globalization processes (Bakhaty et al., 2023). The issue of informal settlements is a global phenomenon that affects cities around the world. At a global level, informal settlements represent a significant challenge for urban development and sustainable planning. One of the basic urbanization problems in developing countries is informal settlement. These settlements contribute significantly to urban growth, expanding horizontally instead of vertically. As cities expand horizontally, sustainable development challenges will be increasingly concentrated in urban areas, particularly in developing countries like Ethiopia where urbanization is occurring rapidly. This expansion has ripple effects on infrastructure and service delivery, often leaving slum settlements disconnected from essential physical and social amenities, including employment opportunities (Bank, 2019).

Informal settlements in Ethiopia's urbanization process have arisen due to a range of social, political, and economic issues. These informal settlements are characterized by unauthorized land occupation, illegal subdivision, and a lack of basic services and infrastructure. The main causes include inadequate land management, unclear and ineffective housing policies, corruption, expansion of illegal land markets, and lack of political commitment to address the needs of the poor and homeless (Lirebo, 2006).

The rapid urbanization experienced by Adama City has resulted in the proliferation of informal settlements, presenting complex challenges that demand urgent attention. These settlements often emerge spontaneously and are characterized by a lack of formal land tenure, inadequate housing, and limited access to basic services such as clean water, sanitation, and healthcare. As a result, residents of informal settlements face significant socio-economic vulnerabilities, including poverty, unemployment, and marginalization.

Several studies have been conducted on the topic of informal settlements in Ethiopia. For instance, (Adam, 2014) examined "Informal settlements in the peri-urban areas of Bahir Dar," while (G/selasie, 2019) explored "Factors Contributing for Expansion of Informal Settlements" in Addis Ababa. Additionally, (Aredo, 2019) conducted research on the "Regularization of Urban Informal Landholdings: the Case of Adama City." These studies have primarily focused on factors contributing to the emergence and expansion of informal settlements, as well as the implementation of land regulations to address these challenges. One notable works that were more relevant to this research issue were done by (Abebe et al., 2019) which explored the "Exploiting temporal-spatial patterns of informal settlements using GIS and remote sensing technique" in Jimma City. This study utilized GIS and remote sensing techniques to analyze the spatial and temporal patterns of informal settlements. However, the data used in this study was not of high resolution, limiting the level of detail in the analysis.

However, the above studies have examined the socioeconomic characteristics and living conditions of informal settlements, there is a notable research gap in the longitudinal analysis of their spatiotemporal dynamics. Understanding the trajectories of informal settlement growth, patterns of urbanization, and changes in socio-economic conditions over time is crucial for developing effective policies and interventions to address the challenges posed by these settlements. While there is limited research specifically focusing on informal settlements in Adama city.

To address this gap, this study proposes to employ Object-Based Image Analysis (OBIA) techniques to quantify the spatiotemporal dynamics of informal settlements in the Dembela sub-city of Adama. OBIA provides a powerful approach to extracting and analyzing complex urban features from high-resolution satellite imagery, enabling a more comprehensive understanding of the physical characteristics and changes of informal settlements over time. By leveraging OBIA, this study aims to generate valuable insights into the trajectories of informal settlement growth, patterns of urbanization, and changes in socio-economic conditions over time.

The findings from this study will be particularly useful for planners and decision-makers in Adama, as they currently face challenges in obtaining reliable and up-to-date data on informal settlements. The discrepancies in data from different sources and the lack of dependable information have hindered the development of effective policies and interventions to address the pressing issues faced by residents of informal settlements. By providing a detailed spatiotemporal analysis of informal settlements using OBIA, this research will contribute to evidence-based policymaking and support sustainable urban development in Adama case study of Dembela sub City.

1.3. Objectives of the study

1.3.1. General Objective

The general objective of this study is to assess the spatiotemporal dynamics and Socio-economic impacts of informal settlements in Dembela sub City from 2012 to 2021 using OBIA.

1.3.2. Specific Objectives

The specific objectives that will be attained by the research are to:

1. Identify and Map informal settlement in the study area in 2012, 2017, and 2021.
2. Determine the change in the extent and pattern of informal settlement in the study area between 2012 and 2021.
3. Assess the socio-economic impacts of informal settlement in the study area over the study period.

1.4. Research Questions

Based on the stated specific objectives, the following research questions are raised in the study.

1. How did the trend of informal settlement change during the study period 2012 to 2021 of the city?
2. How did the extent and pattern of informal settlement change between 2012 and 2021?
3. What are the impacts of informal settlement on the socioeconomic in the study area over the study period?

1.5. Significance of the study

The significance of this study lies in its potential to inform evidence-based interventions and policy decisions aimed at addressing the complex challenges posed by informal settlements in Dembela sub City. By employing geospatial analysis techniques and interdisciplinary approaches, this research will provide a comprehensive understanding of the spatiotemporal dynamics and environmental impacts of informal settlements, thereby filling a critical gap in the existing literature. First and foremost, this study will contribute to the body of knowledge on urban development and informality by generating empirical evidence on the distribution, growth patterns, and socio-economic characteristics of informal settlements in study area. This information is essential for policymakers, urban planners, and development practitioners to design targeted interventions that address the specific needs and vulnerabilities of informal settlement residents. Furthermore, the findings of this study were a practical implication for urban planning and management in Adama city and similar contexts worldwide. By identifying hotspots of informal settlement growth and assessing their environmental impacts, policymakers can prioritize resources and implement targeted interventions to improve living conditions, enhance environmental sustainability, and promote inclusive urban development.

Moreover, this study will contribute to advancing the methodological approaches used to analyze informal settlements and their impacts. By leveraging geospatial analysis techniques, remote sensing data, and Geographic Information Systems (GIS) technology, this research will demonstrate the potential of interdisciplinary approaches to address complex urban challenges and inform evidence-based decision-making.

Overall, the significance of this study lies in its potential to contribute to the development of informed policies and interventions that promote inclusive, equitable, and sustainable urban development in Adama City and beyond. By addressing the complex challenges posed by informal settlements, this research has the potential to improve the quality of life for residents, enhance environmental sustainability, and foster resilient cities for future generations.

1.6. Scope of the study

The spatial scope of this study was bounded to Adama City, specifically the Dembala sub-city. Thematically, the study involved conducting a detailed spatial analysis of Adama City to identify and map the locations and extent of informal settlements. The study examined the spatio-temporal dynamics of informal settlement in the Dembala sub-city over a specific timeframe. By analyzing aerial photos, satellite imagery, and available data, the researchers investigated the growth patterns, expansion, and changes in the spatial distribution of informal settlements over time. This analysis provided insights into the evaluation of informal settlements in the city. The study also included assessing the environmental impact of informal settlements in the study area. This assessment contributed to understanding the environmental challenges and implications of informal settlements in the study area. This ensures that the analysis remains focused and contributes to addressing the research questions and objectives of the study, specifically the geospatial analysis and environmental impacts of informal settlements in the study area. the scope and focus of the research, which was centered on conducting a comprehensive spatial analysis of informal settlements in Adama City, particularly within the Dembala sub-city, and evaluating the associated environmental impacts. The researchers had to navigate the available data sources and limitations to ensure the analysis remained relevant and addressed the key objectives of the study.

1.7. Limitation and Delimitation of the Study

The study encountered limitations, particularly in developing countries like Ethiopia where access to high-performance computing resources is limited. As Ethiopia is still in the process of developing its satellite data capabilities, the study had to rely on external sources, such as commercial companies offering high-quality satellite data, which often came with high price tags. The researcher had to utilize available aerial photos taken between 2012 and 2021 due to the lack of affordable high-resolution satellite data. Additionally, some household heads declined to participate, which may have introduced potential bias into the data. Obtaining reliable data from specific sub-cities within the study area proved difficult despite repeated efforts. Regarding the delimitations, the study focused on the Adama City area of the Dembela sub-city, which was the primary geographic focus of the research. The temporal scope of the study utilized aerial photos from 2012 to 2021 as the primary data source, given the limitations in accessing high-resolution satellite data for the study area.

These limitations and delimitations highlight the challenges faced in conducting research on informal settlements in a developing country context, where data availability and quality can be significant hurdles. The researcher had to navigate these constraints and make adaptations to the study design to ensure the most comprehensive and reliable analysis possible with the available resources.

1.8. Operational Definition

Informal settlement: Informal settlements are defined as housing developments in urban or peri-urban areas that lack official approval. These settlements can range from a few dwellings to thousands and are typically marked by insufficient infrastructure, limited access to basic services, unsuitable environments, unregulated and unhealthy population densities, inadequate housing, lack of access to healthcare and education facilities, and ineffective municipal administration (Bint et al., 2022)

Slums: Slums are densely populated urban areas characterized by inadequate and unsanitary housing, poverty, and social disorganization (World Bank, 2002). A key indicator of slum conditions is poor housing, which includes dwellings lacking sufficient light, air, toilet, and bathing facilities. In simpler terms, slums refer to the environmental conditions in urban areas where communities reside (To et al., 2021).

Squatter settlement: Squatter settlements can be defined in various ways, but a common thread is that they are areas where people construct homes in violation of formal regulations pertaining to property rights, zoning requirements, and construction standards (To et al., 2021). The key defining characteristic of squatter settlements is the illegal nature of their tenure.

Squatting: Squatting refers to the act of establishing residential houses without legal claims to the land or permission from the relevant authorities (ANULO, 2015). As a consequence of their illegal or semi-legal status, squatting settlements often lack adequate infrastructure and services.

Object-based image analysis (OBIA): Object-based Image Analysis (OBIA) is a remote sensing technique that involves the analysis and interpretation of digital images based on objects or regions rather than individual pixels. has become one of the most commonly adopted techniques in building studies which generates segmented features from the amalgamation of pixels into homogenous regions and then classifies the regions into individual image objects (Kohli et al., 2012).

1.9. Organization of the Paper

This study was organized into five chapters. The first chapter was the introductory part that included the statement of the problem, the objective of the study, the scope of the study, research questions, the scope of the study limitations, and the organization of the paper. Chapter two deals with a literature review and definitions of terms. Chapter three focuses on the methodology and materials used in this study. Under the subtitle Materials; it describes the research area, data sources, and software programs employed. The subtitle Methodology; outlines the approaches utilized for image rectification, preprocessing, classification, and spatial metrics analysis. Chapter four presents the results and discussions of the study. The final chapter, Chapter Five, concludes the study and provides recommendations based on the research findings.

It summarizes the main conclusions drawn from the study and suggests potential actions or areas for further research based on the results obtained.

CHAPTER TWO: LITERATURE REVIEW

2.1. INTRODUCTION

This chapter reviewed several research projects on informal settlements and environmental impacts that have been carried out by various writers. In essence, the study concentrated on conceptualizing terminology like informal settlement and environmental impact, reviewing theoretical and empirical literature on the various case studies, specifically Spatial of informal settlements (slums); environmental impact of informal settlement, and; general application of geospatial technology like, Satellite Remote Sensing (SRS), Geographic Information Systems (GIS) and others, especially in spatial change analysis. On the other hand, developing a conceptual framework, and identifying research gaps.

2.2. Theoretical literature

2.2.1. Definition Informal Settlement

There is no universal agreement that has been reached concerning what is termed informal settlements. Country-to-country definitions of informal settlement differ significantly based on a range of elements, including social, economic, and environmental aspects. (Mwamhanga, 2013). Construction of dwelling units on a parcel of land without a municipality's legal claim is known as "informal settlement." It can also be referred to as occupying land illegally and conducting unplanned housing constructions that do not comply with the current planning and building regulations of a city (Abebe et al., 2019). According to (Lirebo, 2006), Informal settlements are economically disadvantaged urban areas in developing countries where low-income residents live in substandard housing conditions with limited access to basic services. They can be found on land that is public, private, or even customary, but that has been invaded or developed in violation of zoning, building, and ownership regulations. As Putri, Informal settlements are considered as absence of the formal sector and regulation (Putri et al., 2020)

Informal settlements are among the planet's most common forms of urbanization, accounting for one-third of the total urban form. By the mid-twentieth century, up to three billion people are expected to live in informal urban environments (Samper & Liao, 2023). Informal settlements are common and are typically the product of an urgent need for shelter by the urban poor (Strajhar et al., 2016). Informal settlements are dense settlements comprising communities housed in self-constructed shelters under conditions of informal or traditional land tenure. They are common features in developing countries and are typically the product of an urgent need for shelter by the urban poor. As such they are characterized by a dense proliferation of small, makeshift shelters built from diverse materials, degradation of the local ecosystem, and severe social problems. In Ethiopia, they are known as illegal settlements or commonly “moon shine houses”(Aredo, 2019).

Hence, based on this premise we can conclude that informal settlement in Ethiopia covers houses that are built on government, communal, or privately held land against the will of the holder and/or without having a development authorization building permit. While the former focuses on the absence of a right to the bare land on which the house is built, the latter focuses on the need for proper planning and building permits (ANULO, 2015). Informal settlements are densely populated areas where communities reside in self-built dwellings, often without formal land ownership (G/selasie 2019).

2.2.2. History of Informal Settlements

The history of informal settlements goes back to the colonial period. Namibia (formerly known as German South West Africa) was separated into the police zone and the northern and northeastern regions during the German colonial era. While the northern and northeastern regions saw the establishment of native population reserves or homelands, the police zone was cleared for white settlement. Outside of these zones, movement was limited (Strajhar et al., 2016).

During the late 19th and early 20th centuries in sub-Saharan Africa, European colonizers established and settled in new settlements, while also changing or expanding existing urban areas to be situated closer to natural resources. This led to increased migration of people from rural to urban areas, as they sought employment opportunities with the newly established industries (Mudau & Mhangara, 2023).

Modern urbanization in Ethiopia has started with the establishment of Addis Ababa. Menelik proclaimed the 1908 land charter of Addis Ababa which recognizes private ownership of urban land. During the regime of Haile Selassie, private ownership of urban land was reemphasized by the 1960 Civil Code. At the time urban land was controlled by few urban elites. During the Military Government, Derg, Proclamation 47/1975 provided land to urban dwellers and such a holding system was known as a permit system. During the Derg regime in Ethiopia, all urban land was transferred to state ownership, and homeless people were allocated 500m2 of land to build a house (as per articles 3.1 and 5 of the proclamation). Additionally, the government nationalized all extra urban houses and provided them to low-income residents at low rental prices. However, this nationalization, rather than solving the housing shortage, led to acute housing shortages and deteriorating housing conditions in all cities across Ethiopia, including the capital Addis Ababa (Chaka, 2018).

According to the above proclamation, urban land was not subject to sale, mortgage, donation, inheritance, and lease and the government became the sole owner of land and collector of rent. The effect was a shortage of housing in major cities because private construction of houses for rental services was shrunken leading to today's urban housing shortage that pushes the poor to Informal settlements and became a headache for the government.

In terms of standard (from slums to standardized residences), location (from suburbs to city centers and secure areas), size (from several small units in settlements for over 50,000 residents), and structure (from single-family homes to multi-story buildings), the history and evolution of informal settlements are diverse and varied. The migration from rural areas, as well as the influxes of refugees and internally displaced persons, have contributed to the sporadic and illegal development of informal settlements in larger cities, among other legitimate causes. In addition to meeting immediate housing needs, many households have turned to illegal real estate investments as a buffer against instability and hyperinflation. These informal settlements often lack adequate roads, basic infrastructure, and social services (To et al., 2021).

2.2.3. Characteristics of informal settlement

Informal settlements are marked by the presence of informal housing, which is characterized by irregular housing arrangements, lack of permission from official authorities, insufficient infrastructure, utilities, sanitation, and environmental impacts. Informal housing refers to housing that does not comply with the laws and regulations established in a specific city or region (G/selasie, 2019). There are numerous methods to characterize informal settlements. According to this perspective, informal settlements have two interconnected aspects. "One is concerned with the actual surroundings and revolves around the home that families occupy, whilst the other is focused on the needs and situations of the families themselves. One aspect of informal settlements focuses on the surrounding environment and the settlement's physical layout, while the other aspect discusses the residents who live there and their socioeconomic problems (To et al., 2021).

Worldwide informal settlements have some common characteristics that enable to differentiate settlements from formal settlements. Thus, according to (CHAKA, 2018), there are essentially three defining characteristics that help us understand Informal settlement: the physical, social, and Legal characteristics as well as the interconnected reasons for each. Physical Characteristics: In Ethiopia, in most areas of informal settlements the access to infrastructure and utilities like water supply, electricity city, schools, and health centers are less compared to those formal ones. Such services are both network and social infrastructure, like water supply, sanitation, electricity, roads and drainage; schools, health centers, marketplaces etc. In general, the physical characteristics describe the settlement based on its inadequacy and/or lack of basic services required by the settlers (Chaka, 2018)

Social characteristics; In informal settlements, the availability of crucial social services such as educational institutions, healthcare facilities, and places of worship is often limited. In Ethiopia, social integration holds significant importance, as reflected in customs like Eder and Ekub, wedding ceremonies, and shared religious and cultural practices that promote communal living. However, the quality of living conditions and low-income levels in these settlements can affect the level of social integration. Despite these difficulties, a strong sense of community and unity persists, cohesion even in squatter areas (G/selasie, 2019)**.**

Legal characteristics: Informal settlements are characterized by the absence of formal land ownership for the land parcels on which homes are constructed. These settlements often occupy undeveloped government or public land, as well as marginal areas such as railway setbacks or unfavorable marshland. The defining feature of squatter housing is the informal nature of land tenure. Residents of squatter settlements typically lack any legal recognition or rights to the land on which their houses are built (Anulo, 2015). These parcels can include unused government or public land, as well as less desirable areas like railway setbacks or marshy land. Squatters take advantage of the land's unproductive state and appropriate it to construct their homes

2.2.4. Major impacts of informal settlement

Informal settlement has impacts on the environment. This is due to poor arrangements of the houses, inadequate supply of infrastructure, utilities, and services, less attention of the governments to access services for the settlers compared to normal dwellers, and less providing of such services has resulted in environmental, social, and economic impacts. Here are some major impacts of informal settlements.

Housing and living conditions: Informal settlements often lack basic infrastructure such as proper housing, sanitation, clean water, and electricity. People living in these settlements often reside in overcrowded and unsafe structures, leading to poor living conditions and increased health risks (Jain et al., 2016).

Poverty and inequality: Informal settlements are often inhabited by marginalized and low-income populations. These settlements perpetuate poverty and exacerbate existing social and economic inequalities. Limited access to education, healthcare, and employment opportunities further entrenches poverty within these communities (UN-Habitat, 2007).

Environmental degradation: Informal settlements often emerge in environmentally sensitive areas such as floodplains, steep slopes, or areas prone to natural disasters. The rapid and unplanned growth of these settlements leads to deforestation, soil erosion, and pollution, causing significant environmental degradation (Ronchi & Arcidiacono, 2019).

Social exclusion and crime: Informal settlements are often stigmatized and marginalized, leading to social exclusion and discrimination against their residents. The lack of formal governance and regulation in these settlements can also contribute to higher crime rates and the proliferation of informal economies (Leonard & Dladla, 2020).

2.2.5. Socio-economic impact

Rapid urban growth in the developing countries has put the city, as a physical and functional entity, under severe pressure. Resources and opportunities have proved inadequate to cope with the population influx, and serious socio-economic problems have emerged. For decision-makers, the core problem is the inability of the city to meet, in conventional terms, the need for employment and shelter. The large numbers employed in the tertiary or service sector and housed in popular settlements are frequently cited in support of this argument. Almost inevitably, such problems are associated with migrants, who are commonly considered to be marginal urban residents in all senses of the word. Spatially, they are often located at the city's periphery, and socially, they seem tenuously linked to its economy and culture. As a consequence, these settlements are viewed with some suspicion by the authorities, as housing for politically unpredictable and unstable groups(To et al., 2021).

The concept of the "culture of poverty" has been stressed, where poverty is not only a state of economic deprivation, disorganization, or the absence of something. It is also something positive in the sense that it has a structure, a rationale, and defiance mechanisms without which the poor could hardly carry on. It is a way of life, remarkably stable and persistent, passed down from generation to generation along family lines. This "culture of poverty" has its own modalities and distinctive social and psychological consequences for its members. As a result, it offers a great foundation for deciding which social research should be prioritized and how development would affect the local social and biophysical environment (Nixon, 2020).

The quality of the urban environment represents a significant contrast between cities in developed and developing nations (G/selasie, 2019). Encouraging a dispersed pattern of urban occupation for housing and infrastructure, the rise of informal settlements for impoverished residents with unstable housing and insufficient public services, the disposal of solid and toxic waste, the extraction of building materials, surface water, and groundwater, the alteration of river courses, flooding, landslides, and environmental stress in conservation areas, green areas, or recreational spaces are some significant environmental processes (Dadi, 2018).

2.3. Empirical literature review

In rapidly growing of world urbanization currently there many studies or researchers are focus on Informal settlement the issues. This empirical literature that focus as global perspective and local perspective.

2.3.1. Global Perspectives

Researchers have employed various geospatial techniques to examine the dynamics of informal settlements and their impact on land use/cover changes in different urban contexts, providing a global perspective on this critical urban issue.

One such study was conducted in Istanbul, Turkey, focusing on mapping informal settlements and their growth patterns(Dubovyk et al., 2011a). The researchers utilized a range of data sources, including land use maps, digital elevation models, informal settlement maps, environmental and transportation data, as well as population and demographic information. They adopted a logistic regression modeling and evaluation approach to generate binary maps of informal settlements for different time periods and analyze the trends and relationships. The researchers found that the logistic regression model, which incorporates spatial explicitness, demonstrated its relevance and consistency when compared to real-world observations, making it a valuable tool in facilitating urban planning processes.

Similarly, (Han et al., 2017)) conducted a study to enhance the understanding of informal settlement formation in the metropolitan fringe, focusing on the Guryong Area (GA) in the Gangnam District of Seoul, South Korea. Through a comprehensive spatiotemporal analysis of topographical characteristics, the researchers examined land-use and land-cover changes in the entire GA from 1950 to 2015, with a specific focus on "spontaneous settlements." The findings revealed that spontaneous settlements were initially dispersed in small clusters but gradually grew into larger and more condensed areas, with their locations shifting from the urban core to the marginal area of the GA. The study highlighted the importance of considering the ecological potential of the urban fringe as an ecotone that connects natural and urban systems, which can be applied to urban planning and policy-making for informal settlements in the metropolitan fringe.

In Oshogbo, Nigeria, (Oyinloye et al., 2018) analyzed the effect of spatial expansion of informal settlements on land use/cover over a period of forty-four years. The study utilized satellite imagery from Landsat (MSS) to examine the changes in land use/cover. The results showed a rapid growth in the built-up area (informal settlement), an increase in cultivation, a decrease in vegetation, and stable water bodies. The findings suggested that housing provision, business purposes, and industrial activities were the major causes of land use change in the study area. To mitigate the effects of land use conversion, the researchers recommended policy measures, including regulating the growth and spread of development and implementing regional development programs.

These empirical studies demonstrate the value of geospatial analysis in understanding the dynamics of informal settlements and their impact on land use/cover changes. The adoption of techniques such as logistic regression modeling, spatiotemporal analysis, and satellite imagery interpretation has provided insights that can inform urban planning and policy-making processes, ultimately contributing to more sustainable urban development.

2.3.2. Local perspective

Several studies have examined informal settlements in different parts of Ethiopia, including a focus on exploring the causes and consequences of squatter settlements. The authors aimed to investigate the causal factors behind squatter settlements and their impact on social, economic, and institutional conditions both for the settlers and the development of the study area. The findings of these studies identified key factors contributing to squatter settlements, such as a shortage of affordable housing and high rental prices, the demand for larger land plots, and an inefficient land administration system. Additionally, the research indicated that squatter settlements have negative effects on both the government and the squatters themselves (Nega, 2021).

Another study utilized GIS and remote sensing techniques to exploit the temporal-spatial patterns of informal settlements (Abebe et al., 2019). The analysis of land use and land cover change (LULCC) revealed that the built-up area accounted for 10.24% (1081.9 ha) of the study area in 1997 and increased to approximately 1160.3 ha by 2007. This transformation from open land and agricultural areas to built-up areas can be attributed to rapid urbanization and the proliferation of slums (Abebe et al., 2019). According to Adane (2016) attempted to demonstrate how to assess the spatial and temporal land use and land cover changes and to identify the causes and consequences of increasing informal settlements in Wolkite town. The findings revealed that the nature of the settlement is determined by a combination of factors such as the monthly income of respondents, previous residence, occupation, and mode of accession of the respondent's current holding. The study also found that informal settlements have expanded alarmingly in the study area at the expense of nearby agricultural fields, causing disorganized infrastructure and a spontaneous network of villages (Adane, 2016).

Alene (2022) examined the determinant factors for the expansion of informal settlements in Gondar. The results of the study revealed that socio-economic, political legislative, administrative, and demographic factors are statistically significant, with the socio-economic dimension being the most influential factor, followed by the political and legislative dimension, and demographic factors contributing the least(Alene, 2022). Finally, (Fantahun, 2016). aimed to assess the causes and impacts of informal settlements on urban development and the environment. The study found that informal settlements largely influence the environment and health status of the residents, causing different pollution problems, degrading natural resources, and affecting the aesthetic value of the city. These scenarios need combating measures to reduce the environmental health problems resulting from informal settlements.

2.4. Research and knowledge gaps

However, while the above-reviewed studies provide valuable insights into the spatiotemporal analyses of informal settlements, they are not sufficient to address the existing and future challenges posed by informal settlements. Although numerous studies have been conducted on informal settlements, the focus has primarily been on their effects on residents and local development. The findings regarding the relationship between changes in imperviousness and informal settlements are inconsistent.

Furthermore, existing studies in Ethiopia that focus on informal settlements often rely solely on social data for analysis, with only a few papers utilizing spatial data such as land use and land cover (LULC) change detection as decision-making tools for urban planners and policymakers. The detection of informal settlements in the aforementioned studies is not clear, and their impacts on urban land use management have not been adequately demonstrated. Additionally, there is a lack of investigation into the spatial distribution and causes of informal settlements in different areas. Some studies primarily concentrate on the impact of scale on land cover fractions within informal settlements, while few have analyzed the formation of informal settlements through LULC shifts within specific urban regions, particularly along the urban periphery. With the exception of one study focused on upgrading informal settlements, others have not provided guidance or measures for upgrading them to formal status.

Moreover, the reviewed studies vary in terms of the duration of the study period, with different time frames ranging from days to years. Additionally, different types of data with varying spatial resolutions have been used. Rapid urbanization has led to the rapid development of structures and pavement, and while attempts have been made to detect informal settlements, only one study specifically utilized LULC data for this purpose.

Presently, Adama City is experiencing uncontrolled urban development, resulting in an increase in informal settlements and environmental issues. These informal settlements have hindered the implementation of master plans, hampering the city's sustainable development. However, a comprehensive examination of the spatiotemporal patterns of informal settlements in Adama City has not been conducted. Therefore, this paper aims to fill this critical knowledge gap by assessing the spatiotemporal dynamics and environmental impacts of informal settlements using high-resolution data, with the goal of promoting sustainable development in Adama City, specifically Dembela sub city.

2.5. Conceptual Framework

The emergence and expansion of informal settlements pose a significant challenge in urban areas worldwide. These settlements are characterized by densely populated housing units that lack basic amenities such as access to safe water, sanitation, infrastructure, and services, as well as secure tenure. The factors contributing to the formation, location, and growth of informal settlements are complex and interconnected. They include inadequate urban planning and management, rapid and uncontrolled population growth, rural-urban migration, insufficient housing provision, and, in some cases, a reflection of historical segregation in certain sub-Saharan African countries. Despite the global trends of economic globalization leading to urban growth and increased opportunities, authorities in developing countries often struggle to keep up with the rising demand for housing and infrastructure.

2.4.1. The role of geospatial technology in informal settlements

1. Geographical information system (GIS)

GIS is a technique or method used by researchers to **process,** analyze, and arrange spatial data. It is used to process all kinds of data or information, including images and visuals. During data analyses and other studies, simple information is needed, and thus, there is a need to break down complex data and reassemble it as required (Dubovyk et al., 2011b). Geographical information system (GIS***)*** assists in improving service delivery to informal settlements. By analyzing the spatial distribution of settlements, GIS can help identify areas lacking basic services like healthcare, education, and sanitation.

2. Remote sensing

One of the biggest obstacles to growth in developing countries is a rapid increase in population. The growth of informal settlements is increasing day by day in developing countries such as India. There is a critical need to identify these informal settlements to serve many urbanization purposes such as improving city planning, identifying the lack of basic facilities such as road connectivity, etc. The Remote Sensing (RS) satellite images are a good source of information to analyze informal settlements. The high-resolution RS images have already proven useful in identifying the informal settlements. According to (BALLIM, 2016). remote sensing is used for a combination of fieldwork and high-resolution aerial photography to identify individual structures in informal settlements through image interpretation. Concluded that remote sensing-based approaches and VHR imagery provide a flexible and useful method to identify and map informal settlements. One of the several approaches that has the potential to address the relatively complex and undefined urban morphology of informal settlements is object-based image analysis (OBIA)

2.4.2. Object based image Analysis

Object-Based Image Analysis (OBIA) is a geospatial technology that can be used in informal settlements to analyze and extract information from satellite or aerial imagery. OBIA takes advantage of both spectral and spatial information to classify and delineate objects or features of interest within an image (Mudau & Mhangara, 2023). The OBIA method is knowledge-based, usually results in a hierarchical categorization, and has been the most popular method over the past ten years. When urban morphology is paired with an image resolution that permits identification, OBIA techniques have been shown to be effective for extracting objects (such as roads and rooftops) at the settlement level (Fallatah et al., 2018). OBIA encompasses the automated image segmentation which produces segments/ image regions which are plausible with reduced level of complexities and detailing(Norman et al., 2021). Object-based image analysis (OBIA) has become one of the most commonly adopted techniques in building studies which generates segmented features from the amalgamation of pixels into homogenous regions and then classifies the regions into individual image objects. The accuracy of the classification is strongly dependent on the choice of segmentation parameters and classifiers in generating a qualitative classified image (Norman et al., 2021) In the context of informal settlements, OBIA can be applied in various ways:

By another hand OBIA also referred as object-oriented image analysis (OOA), or geographic object-based image analysis (GEOBIA) seeks to bridge broader principles of remote sensing, image analysis, and GIS concepts (BALLIM, 2016). Object-based or object-oriented classification uses both spectral and spatial information for classification. The object-based image analysis uses frequently different software's such INVI and Ecognition Developer The object-based approach facilitates analysis of all common data sources, such as medium to high-resolution satellite data, high to very high-resolution aerial photography, lidar, radar and even hyperspectral data. eCognition Developer offers a comprehensive collection of algorithms tailored to the different aspects of image analysis. The user can choose from a variety of segmentation algorithms such as multiresolution segmentation, quad tree or chessboard (Amigo, 2011).

2.4.3. Image Segmentation

The technique of dividing a digital image into several parts is called image segmentation. Segmentation aims to make an image's representation simpler, more interpretable, and easier to study. An image is segmented into a group of segments that together cover the complete image. When considering the ontology of informal settlements and the spatial relationships between the settlement itself and its sub-objects such as buildings, road networks, and vegetation, it becomes evident that image segmentation plays a crucial role (Mudau & Mhangara, 2023). The goal of image segmentation is to generate distinct image objects that represent the settlement areas and their associated sub-objects. In the case of using eCognition, a multi-resolution segmentation method is employed, resulting in two levels of segmentation (Hofmann et al., 2008).

At the top level, the segmentation aims to identify settlement areas and other objects of similar size within the image. This level provides a broader representation of the overall settlement and its immediate surroundings. This network is visualized as a tree-like structure, allowing for a clear depiction of the relationships between objects (Hofmann et al., 2015a).

2.4.4. Rule-based approach

The rule-based approach classification in informal settlements refers to a method of classifying and categorizing objects or features within the settlement based on predefined rules or criteria (Hofmann et al., 2008).This approach involves setting specific rules or thresholds for different classes or categories and applying them to the data to determine the classification. In the context of informal settlements, the rule-based approach can be used to classify different features such as buildings, roads, vegetation, and open spaces. The classification rules are typically based on the spectral, spatial, and contextual characteristics of the objects in the satellite or aerial imagery (Mweni, 2013). A rule-based classification analyses the image objects in line with the set of formulated conditions (rule sets) to assign objects features to a class that best meets the defined specifications. Rule-based classification relies on prior knowledge of the features of interest and allows the analyst to evaluate in detail the spectral similarities and differences between image objects (Xu 2013). However, building a rule set is a time-consuming task as the number of image features greatly challenges the operators to determine the most relevant image features and thresholds (BALLIM, 2016).

2.4.5. Machine learning algorithms

Machine learning algorithms can be used for classification in informal settlement classification to automatically identify and categorize different features or objects within the settlement. These algorithms learn patterns and relationships from labeled training data and apply that knowledge to classify new data. Here are some commonly used machine learning algorithms for informal settlement classification:

Support Vector Machines (SVM): SVM is a popular algorithm for classification tasks. It works by finding the optimal hyperplane that separates different classes in the feature space. SVM can be trained on labeled data with features extracted from satellite or aerial imagery to classify objects such as buildings, roads, and vegetation in informal settlements (Leonita et al., 2018).

K-Nearest Neighbors (KNN): KNN is a simple yet effective algorithm for classification. It classifies new data points based on the majority vote of their k nearest neighbors in the feature space. KNN can be trained on labeled data to classify objects or features in informal settlements based on their similarity to neighboring objects (Smith et al., 2017). These machine learning algorithms can be trained on labeled data, where objects or features within informal settlements are manually labeled or annotated.

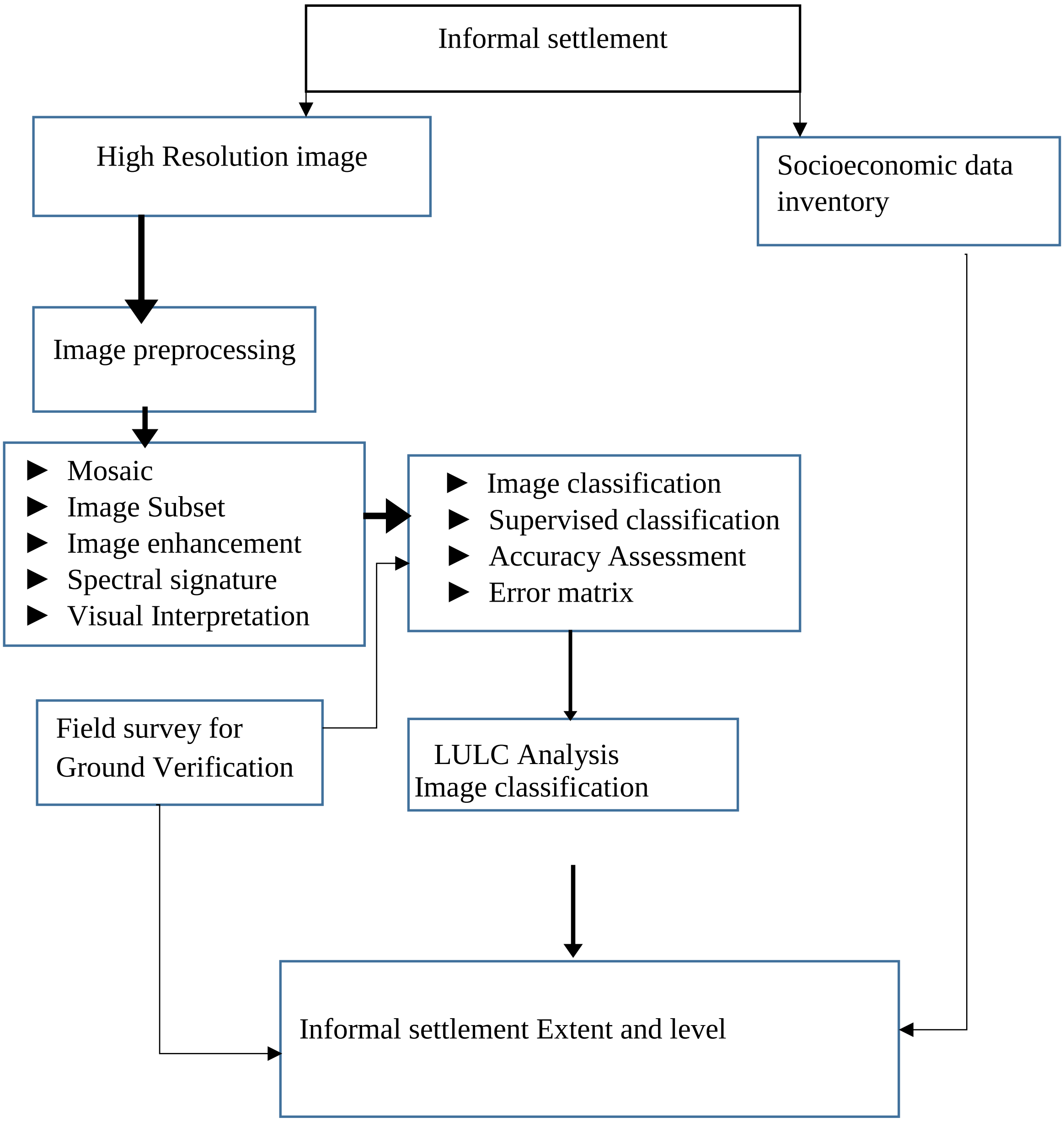

Figure 2. 1: Conceptual frame work of the study

CHAPTER THREE: MATERIAL AND METHODS

3.1. Description of the Study Area

3.1.1. Location Description

Adama city is which located 95 km from Addis Ababa about 8º 35' 00" and 8º 36' 00" N and 39º 11' 57" to 39º 21' 15" E. and at an average altitude of 1620m above the sea level. Its area also 31304 hectares. Adama is situated in the Eastern Shewa region which is part of the central plateau. It is bounded by Boset Wereda in the east, Lome Wereda in the north-west, Duga Bora in the south-west, Dodo Tana Sire Wereda in the south and She kora and Minjar in the north. The city sits between the base of an escarpment to the west, and the Great Rift Valley to the east. Dembela is one of six sub City in Adama city which found southern part of Adama City as shown in map.

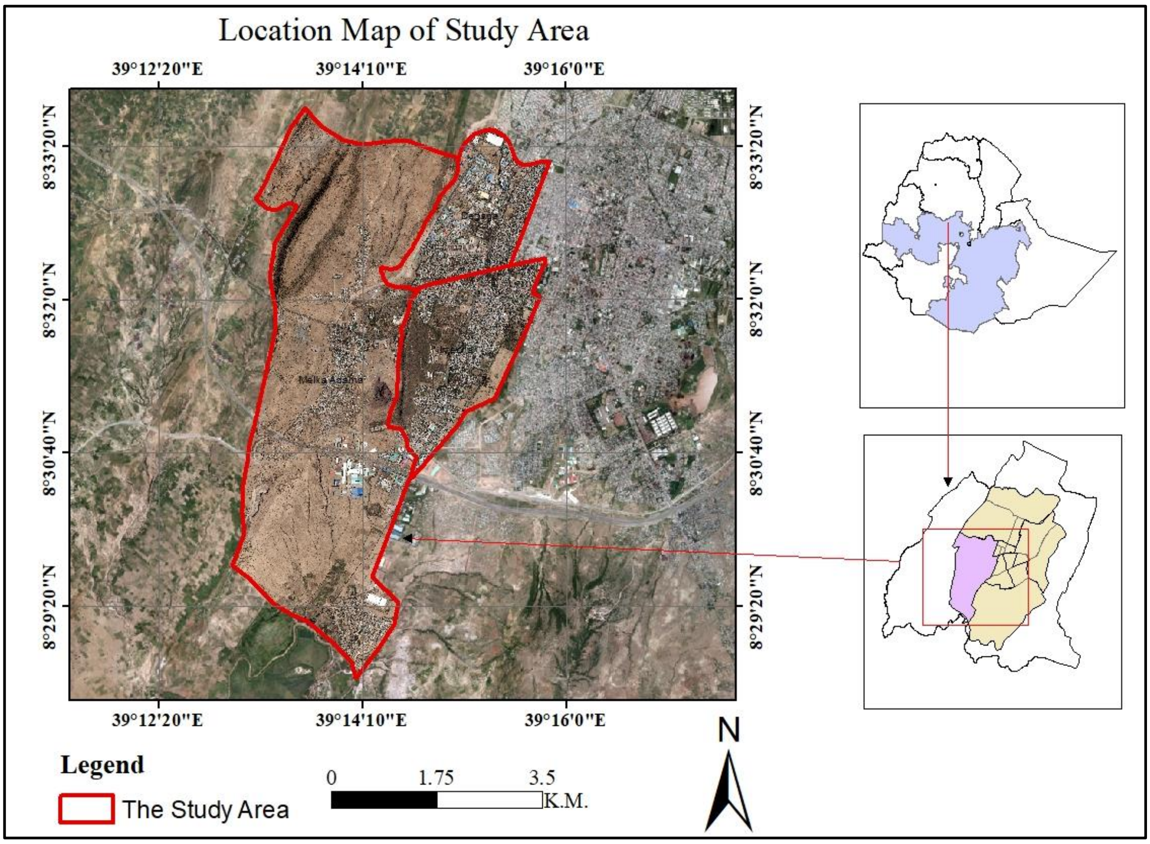

Figure 3. 1. Location map of Dembela sub-City Adama

3.1.2. Topography

Adama City is a low-lying flat terrain surrounded by mountains and ridge topography. The topography of Adama town varies from ground elevations of 1,595m to 1,740m. The southern central part of the town constitutes the lowest areas with ground elevation ranging from 1595masl to 1630masl. Areas with higher altitudes are found from the central to the northern and on the southern verges of the town. The altitude of these areas varies from 1630masl to 1740masl.

3.1.3. Climate and Weather

Adama Average monthly temperatures and weather, sunny and cloudy days. The Annual rainfall and snowfall in Adama 2015-2021. Average monthly temperatures (day and night), Average yearly precipitation (rain and snow), and days of wet weather per month in Adama. Warm, sunny months for a trip to Adama. In general, the City enjoys favorable climatic conditions due to its geographical location surrounded by plateaus that experience moderate temperature and rainfall which is favorable for life. Rainfall mostly occurs in the summer season. It receives abundant and heavy rainfall every year during this season. As reported on socio socio-economic of Adama city during the past five consecutive years, the maximum average and minimum average annual temperature was 29.4o c and 15.8 c in the years 2014/15 and 2012/13 (2007 and 2005 E.C) respectively. Similarly, the maximum annual total and minimum annual total rainfall were 934.8 mm and 736.5 mm in the years 2016/17 and 2012/13(2009 and 2005 E.C) correspondingly sources (Socio-economic Profile of Adama, 2020).

3.1.4. Population

According to the last three consecutive censuses conducted in the country, Adama Town showed a large increase in population. In the first Ethiopian population and housing census, which was held in May 1984, Adama had a population of 77,237. The second population and housing census conducted in 1994 reported that Adama had a total population of 127,842 of whom 61,965 were males and 65,877 were females. According to the third Ethiopian population and housing census which was conducted in 2007 (the most recent year for which data are available), 220,212 people of whom 108,872 males and 111,341 females were inhabited in Adama. Based on this the projected population of Adama Town including four subs urban Ganda’s under the City administration in 2018/19 (2011 E.C) was 433,046 of whom male 216,046 and female 217,000 (Socio-economic Profile of Adama, 2020).

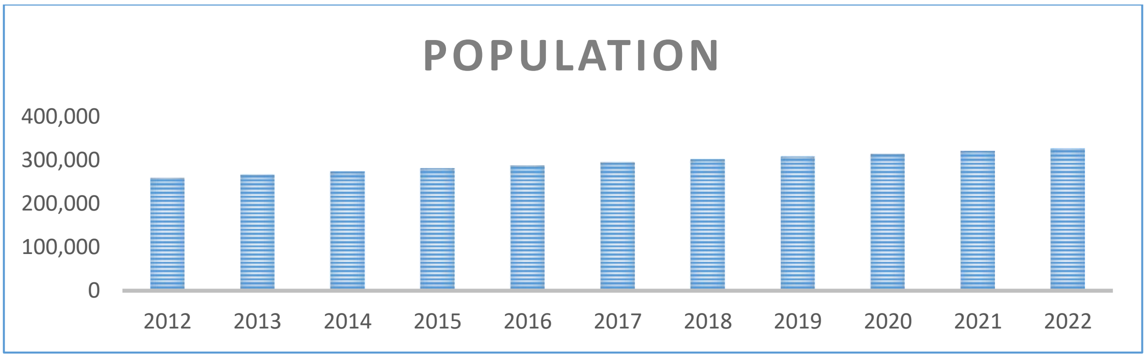

Figure 3.3. Population graph of Adama (sources CSA, projected 2022)

3.2. Data Types and Data Sources

This study incorporates the gathering of both spatial and non-spatial data from actual site visits and secondary data from different sources. Table 3.1 summarizes the data types and sources. Certainly, integrated spatial and non-spatial data in a GIS environment would accommodate the complex, multi-function, and varied nature of formal and informal settlements. These data were obtained from Adama city administration and open source datasets.

Table 3.1: data types and sources

S/N	Data required	Data types	Data sources	Software Process	purpose
1	City Boundary	Shapefile	Adama city Administration	ArcGIS	For limited study area
2	Masterplan of the city	scanned	Adama city	ArcGIS	Evaluation of existing plan
3	Population data	CSV	ESA	Excel& ArcGIS	To determine Population density and take sampling units.
4	Aerial photo	tiff	Adama City/EGII	Ecognition developer &ArcGIS	To detect and identify informal settlement by OBIA
5	DEM	grid	USGS.gov	Global mapper	To show the Elevation map
6	Hand-held GPS with an Accuracy 2m			To collect GCP	for verification

3.2.1. Software used for study

The study used GIS and remote sensing software like ArcGIS 10.8 eCognition developer, and ERDAS IMAGINE 2015 to analyze the extent of informal settlements in Adama city. The software eCognition Developer 9.0 was used for the object classification procedure of this study. As advanced image analysis software, eCognition allows users to develop their rule-sets for algorithm or operation of segmentation and Classification. It allows users to import arbitrary combinations of data types for image segmentation to generate image regions of objects. Various features and algorithms can be analysed and implemented for the extraction. And final results can be exported in raster or vector format. All the rule sets are managed in a process tree and have been saved and reused easily (Trimble, 2014). Other geospatial software will be used for data extraction and preparation of data analysis. SPSS and Microsoft Excel 2019 were used for socioeconomic data analysis and interpretative summary of the software proposed shown in Table 3.2 below.

Table 3. 2. Software proposed for research and its purpose.

S/N	Software description	Purpose of software
1	ArcGIS Version 10.8	For the preparation and analysis of all thematic layers for the study and final mapping.
2	Global Mapper 20.2	To calculate and process elevation data
3	Ecognition Developer v 9.0	For OBIA (image classification)
4	Erdas Imagine v2015	Image pre-processing
5	MS office 2019	For report writing
6	SPSS 26	Analysis of statistical data
7	Google Earth pro	Identify updated timely land coverage and former images

3.3. Sample size determination and sampling method

3.3.1. Sampling Technique and Method

Both probability and non-probability sampling designs were employed in this survey. The target population for the study was selected using a simple random sampling technique, specifically through a lottery system where every item in the population had an equal chance of being included in the sample. This ensured fairness and unbiased representation. Therefore, a combination of probability sampling (simple random sampling) and purposive sampling techniques was utilized in this study to ensure both representative sampling from the target population and the inclusion of key informants relevant to the research objectives.

3.3.2. Sample size determination

This study was conducted in the Dembela sub-city within Adama city, situated in the southwestern part of the city. The selected Sub city comprises a total of three kebeles for the determination of this study purposively. These three kebeles, namely Irecha, Degaga, and Melka Adama were purposively chosen because they were the only ones surrounding the city with the high expanding informal settlement and their infrastructure accessibility. The study population consisted of 398 households out of a total of 79,744 households across these three selected kebeles. The sample size for each kebele was determined based on the proportion of households about the total number of households (79,744) in the three kebeles. To determine the number of sample household heads the formula developed by Yamane's (1967). The population distribution of the target kebeles is described in the tables provided below.

Table 3.3. Sample size distribution in three selected kebele

S/N	Kebele Name	Total HH	HH surveyed	% Households per location
1	Irrecha	38,831	172	43%
2	Degaga	33,734	145	36%
3	Melka Adama	7,179	81	20%
	Total	**79744**	**398**	**100%**

Source: Adama City Administration and (Own survey, 2023)

Yamane's formula is a widely used method for determining sample size in quantitative research studies, especially when the population size is relatively large. The formula is given by: $n = (N)/ (1 + N (e^2))$ ……………………………………… equation (1)

Where: n = required sample size

N = population size (79,744 in this case)

e = margin of error (5)

Calculation using Yamane's Formula:

Given: Population size (N) = 79,744

The margin of error (e) = 5

Now, substitute these values into Yamane's formula to calculate the sample size:

$$n = (79{,}744)/ (1 + 79{,}744(0.05)^2)$$

$$n = (79{,}744)/ (1 + 79{,}744(0.0025))$$

$$n = (79{,}744)/ (200.36)$$

$$n \approx 398.52$$

Therefore, according to Yamane's formula, the calculated sample size for a Total population of 79,744 with a 5% percent Margin error is 398 samples selected out of 79744.

3.4. Data Collection Methods

3.4.1. Primary data collection

Primary data were collected through household surveys, and site observation. To achieve the objectives, the study used different primary data. The study used site observation using GPS to collect field data (location of current informal settlement in the study area as primary data. Also, the study will use the socio-economic data collected through household questionnaires, in-depth interviews, was used for this research as primary data. Before the commencement of data collection, a reconnaissance survey was conducted to obtain general information about the informal settlements in the area. To collect primary data for this study, four data collection tools were utilized: questionnaires, observations, key informant interviews, and focus group discussions. Site observation using hand-held GPS to collect field data (location of current informal settlement) in the study area as primary data.

The researcher physically visited the study area, allowing them to personally engage with the sampled individuals and raise awareness about the research. Initially, questionnaires were distributed to each respective respondent. Subsequently, interviews were conducted and the completed questionnaires were collected. The researcher ensured continuous follow-up throughout the entire process, from the beginning until the end, to maintain a comprehensive data collection approach. As necessary critical observation was also conducted.

Household survey (questionnaires): Information related to household demographic and socio-economic characteristics, extent and types of livelihood asset damaged/loss, and amount of annual income of the household, were collected through household survey. To gather information addressing the research problem, a questionnaire was administered to the households, incorporating both open-ended and closed-ended questions.

The closed-ended questions were designed in table format using Likert scales, enabling the researcher to obtain more consistent and comparable results. This facilitated easier data analysis and interpretation. Additionally, a few open-ended questions were included to allow respondents to express their thoughts, perceptions, challenges, and insights related to the research area.

Key informant interview (kii): key informant interviewees deliberately selected from Individuals believed to have comprehensive knowledge about the area under study gave information. Efforts have been made to include the different spectrum of views from various individuals of different professional and social backgrounds. Consequently, experts from the municipal administration office, and urban development agents, were involved in the key informant interview.

Observation: Observation is a research method that involves systematically selecting, Observing, and documenting the behaviors and characteristics of living beings, objects, or phenomena(Strajhar et al., 2016). In this study, observation was employed as a data collection method because it helps to gather information without relying solely on direct questioning.

3.4.2. Secondary data collection

For this research secondary data was obtained from Adama City Municipality and CSA of Ethiopia. Secondary data, like Aerial photos, satellite images, the Digital Elevation model (DEM), the boundary of the study area (shapefiles), and a scanned master plan of the city were collected from the relevant sources.

3.5. Data Analysis Methods

The data collected from various sources were analyzed and interpreted using both quantitative and qualitative methods. The method was implemented in five main steps: multi-resolution segmentation, object-based classification, and morphological operation, Development of classification ruleset to identify Informal settlement change Analysis accuracy, and Analysis of social impact of informal settlements socioeconomic assessment.

The multiresolution segmentation, object-based classification, and morphological operations were carried out using the eCognition software, while the evaluations of the results of classification and change detection were carried out using the ArcGIS software. Finally, The Analysis of the social impact of informal settlements was performed using a questionnaire and Socioeconomic data done with SPSS software. In the first step of the method, the high-resolution image (ortho photo of study area) was segmented using the multiresolution algorithm segmentation technique employed by the eCognition software. After defining the classes and the class hierarchy, the nearest neighbourhood classification was carried out and then, the classified output was improved using employing a rule-based classification. Next, the morphological opening operation was performed on the final classified image to remove imperfections, and settlement was identified from other classes. The results of both classification and change detection were evaluated using the reference data, which were prepared in this study.

Table 3.4: Description of Imagery data used for the study

S/N	Sensor	Acquisition year	sources	Resolution(m)
1	Ortho photo	2012	ACAO	0.15
2	Ortho photo	2017	ACAO	0.15
3	Ortho photo	2022	ACAO	0.15

3.5.1. Spatial data analysis Indicators to identify informal settlement in the study area

An orthophoto is usually applied in geospatial data establishment and update. Traditional classification based on aerial images is usually reached through visual interpretation, which is very time-consuming.

Table 3.5. Summary of indicators to detect informal settlements

Indicators	**description**	**Level**
Roofing extent of built-up area:	The total area occupied by the building. High density expected.	Object
Residence size	Mean dwellings between <50 m^2 and 380 m^2 are classified as informal settlements.	Object
Vegetation extent	Amount of vegetation present in segments. Expected lack of vegetation.	Settlement
Road segment type and materials	Less road elongation, fewer regular road segments.	Settlement
Texture measures of built-up area	Higher entropy, higher contrast, and lower homogeneity in built-up areas	settlement
Road accessibility	Road width is too narrow for vehicular traffic in informal areas. Roads are not easily accessible, a higher proportion of dead-ends (dangles), and fewer intersecting nodes.	settlement
Building density (dwelling separation)	Lower nearest neighbor distance using the centroid of dwelling polygons	settlement
Proximity to hazards	Hazards include flood zones, hydrologic setbacks, landslides/earthquakes, garbage mountains, point source pollution, airports, energy transmission lines, and major transportation.	Environment
Geomorphology of terrain	Settlements built on gullies, ravines, steep slopes, and unstable soils.	Environment

(Sources adapted from Owen and Wong (2013))

To improve the efficiency, automatic classification methods are introduced. Object-based classification can deal with high-complexity images like orthophoto with high-resolution data. Despite of pixel-based classification that only considers spectral information in one pixel, object-based classification can draw on the feature's information such as texture, context, size, etc. for each segment (Hurskainen & Pellikka, 2004).

3.5.2. Object-Based Image Analysis

The Object-Based Image Analysis (OBIA) technique has been the most common method for informal settlement detection over the past two decades, compared to other image processing approaches (Njoroge, 2016). Object-based image analysis (OBIA) is a powerful tool for mapping informal settlements due to its capacity to incorporate spatial, spectral, and contextual features similar to the interpretation of human cognitive images interpretation(Kohli et al., 2016a). Compared to pixel-based classification, OBIA is beneficial for the classification of slums because the segmentation process generates segments that have additional spectral, geometric, and textural information that is essential for differentiating slums (Njoroge, 2016).

In summary the selection of the OBIA method for the analysis of informal settlements is driven by its ability to effectively capture the heterogeneous and complex nature of these environments, its capacity to extract detailed structural and morphological characteristics, its support for hierarchical and multi-scale analysis, the integration of ancillary data and expert knowledge, and the improved transferability and scalability of the approach. These key advantages make OBIA a compelling choice for the in-depth understanding and analysis of informal settlements. The basic steps of running eCognition Software are schematically shown in (Figure#3.4) to achieve the goals of the OBIA application in the information process.

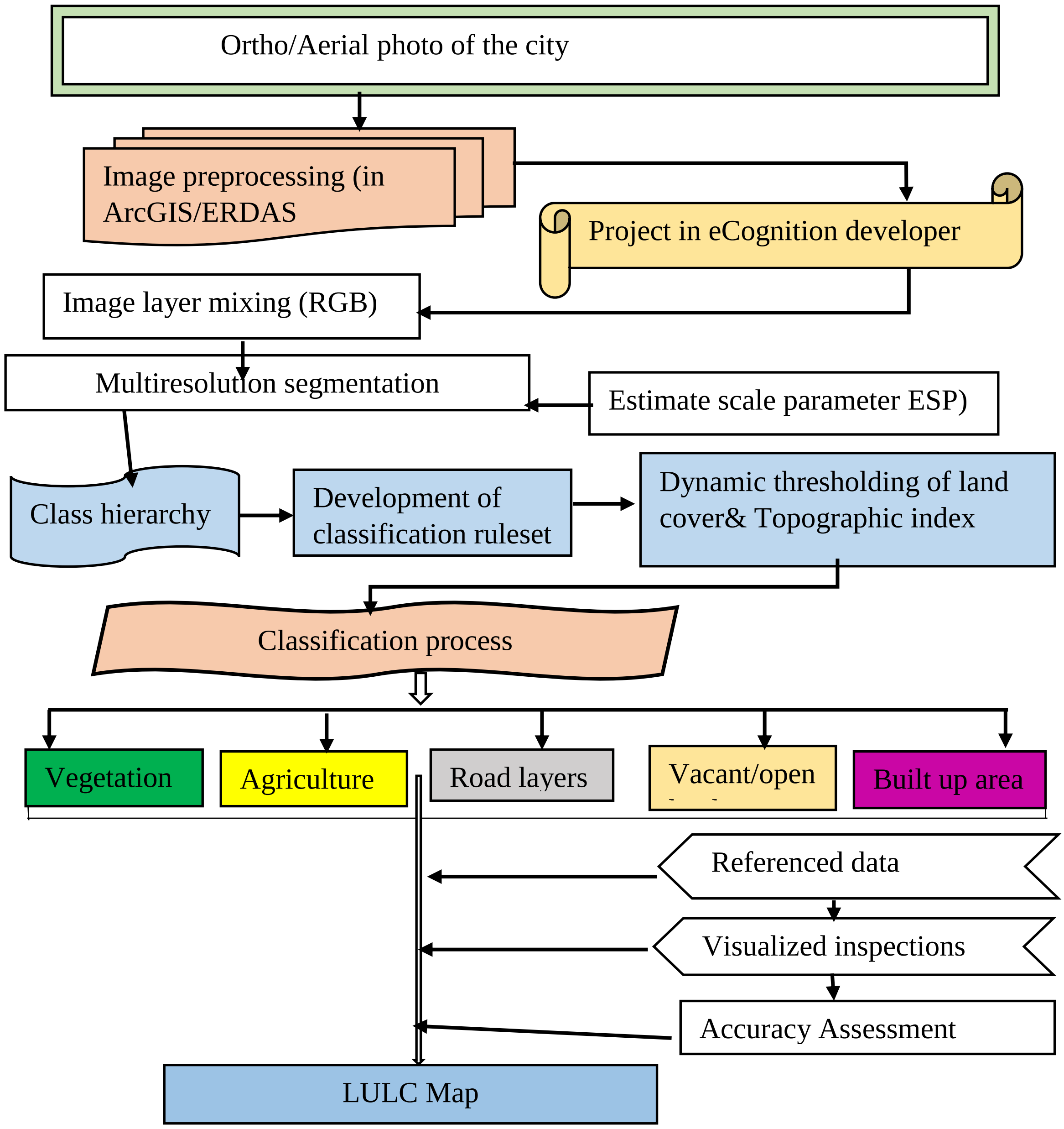

Figure 3.4. Work flow of OBIA application in the information process.

Segmenting images to select target areas or objects, especially when distinguishing between formal and informal settlements, can be a multi-step process that often utilizes advanced image analysis software like eCognition.

1. Data Acquisition: Obtain high-resolution satellite or aerial imagery covering the area of interest. Ensure the imagery is up-to-date and of sufficient quality to distinguish between different settlement types.

2. Preprocessing: Apply necessary preprocessing techniques, such as atmospheric correction, to enhance the quality and consistency of the imagery. Pan-sharpen the imagery to combine high-spatial resolution panchromatic data with lower-resolution multispectral data, improving the overall spatial detail.

3. Image Segmentation: In eCognition, use the multi-resolution segmentation algorithm to create image objects (segments) based on spectral and spatial characteristics. Adjust the segmentation parameters, such as scale, shape, and compactness, to find the optimal balance between under-segmentation and over-segmentation. Ensure the segments accurately represent the boundaries of individual buildings, informal settlements, and other relevant features.

4. Feature Extraction: Analyze the characteristics of the image objects, such as spectral, textural, and geometric features, to distinguish between formal and informal. settlements Formal settlements often exhibit more regular shapes, larger building sizes, and more homogeneous spectral signatures compared to informal settlements. Informal settlements may show more irregular shapes, smaller building sizes, and higher spatial and spectral heterogeneity.

5. Classification: Employ supervised or unsupervised classification techniques to categorize the image objects into different settlement types (formal, informal, etc.). For supervised classification, create training samples representing the characteristics of formal and informal settlements, and then apply a classifier such as Random Forest or Support Vector Machine. For unsupervised classification, use clustering algorithms like k-means or ISODATA to group the image objects based on their spectral and spatial similarities.

6. Accuracy Assessment: Evaluate the accuracy of the settlement type classification by comparing the results to ground-truth data, such as field observations or high-resolution imagery. Calculate metrics like overall accuracy, user's accuracy, and producer's accuracy to assess the reliability of the classification.

The use of eCognition software, or similar object-based image analysis (OBIA) tools, is particularly useful in this process. eCognition provides a robust set of algorithms and tools for image segmentation, feature extraction, and classification, allowing for a comprehensive and efficient analysis of settlement patterns.

3.5.3. Segmentation

The first step in OBIA is to segment the satellite or aerial imagery into meaningful objects, such as individual buildings, roads, and open spaces, rather than working with individual pixels. This is typically done using a multi-resolution segmentation algorithm, which starts with single-pixel objects and iteratively merges them into larger objects based on their spectral, spatial, and textural similarities. The algorithm considers the heterogeneity within each object and the heterogeneity between objects and attempts to minimize the overall heterogeneity to create homogeneous objects (Medhi & Saha, 2019). The segmentation process is controlled by parameters like scale, shape, and compactness, which can be adjusted to capture the characteristics of informal settlements, such as their irregular shapes and patterns. By dividing the image into homogeneous segments, OBIA allows for the processing and analysis of only the relevant parts of the image, , which can improve the accuracy and efficiency of the analysis of informal settlements (Norman et al., 2021).

The segmentation uses several properties of image regions including texture, average intensity, and boundary (Ansari, 2020). This segmentation method has the capability to incorporate a wide range of image properties, including spectral, texture, spatial, shape, size, prior knowledge, and contextual characteristics, into the object delineation process (Fallatah et al., 2019). The general steps followed in image segmentation using eCognition developer are shown in Figure 3.5

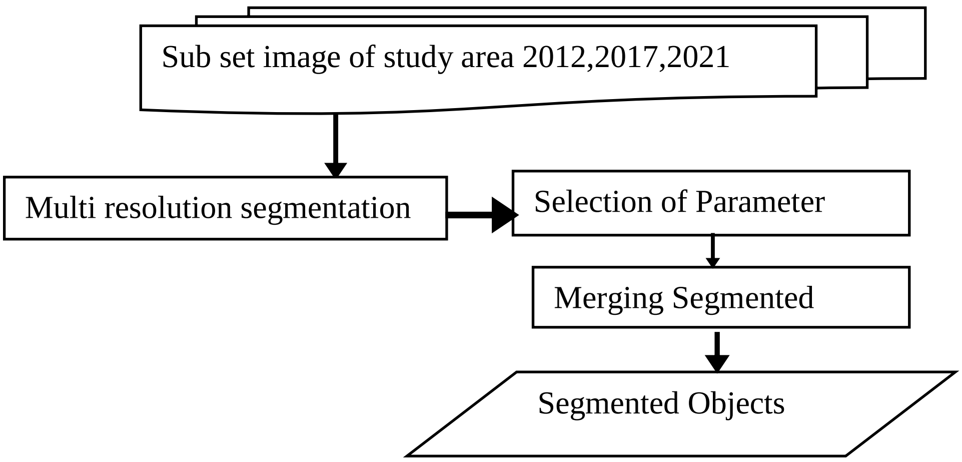

Figure 3.5: flowchart of the segmentation process

The first step in Extracting informal settlement indicators via OBIA is to generate segments by automatically grouping the pixels in the image into coherent groups to form segments based on the degree of homogeneity (Csillik et al., 2014). Indicators of informal settlements were then Identified and assessed. In this study, the available Blue (B), Green (G), and Red (R) image bands with spatial resolution of 0.15m were used for the segmentation. Later these indicators were grouped to provide formal vs informal settlement mapping. To this end, three parameters are optimized to segment objects: scale (SP), shape (W shape), and compactness.

Parameters scale: The scale parameter determines the highest allowed heterogeneity level of the image objects and affects the average object size. The higher the scale parameter value, the larger the image objects become.

The parameter Shape/Colour: This parameter adjusts the effect of shape vs. Colour homogeneity on the generation of image objects. The higher the shape value, the less spectral homogeneity influences the object generation.

The parameter Smoothness/Compactness: Determines the compactness or smoothness of the resulting object. With a selected shape value, the user can influence the compactness or smoothness of the final object.

A variety of segmentation algorithms such as multiresolution segmentation, quadtree, or chessboard are provided in eCognition. A multiresolution segmentation algorithm was chosen for the image segmentation process in this project. It presents homogeneous areas in larger objects whereas heterogeneous areas are in smaller ones. The results of segmentation can be defined by users with scale parameters. The scale parameter regulates how much the homogeneity of the object will be. The smaller the scale is, the more heterogeneous the objects are (eCognition9.0: Guided Tour Level 1).

3.5.4. Object-based Image Classification

Object-based land cover classification was performed by eCognition 9.0 software. The extraction results presented six land cover types. After completing the segmentation operation, the image was classified to extract the defined land cover classes. Six land cover types were considered focusing on the essential land cover types including built-up area Informal settlement, vegetation, open/vacant land, Road networks, and agricultural land were used as the classification scheme. As shown in Figure 3.6 the decision tree classification consisted of six steps. Table 3.5. show detailed land use land cover description.

Table 3.6. The definitions of Land Use/Land Cover classes.

S/N	Classes	description
1	vegetation	Area covered by grasslands, forests, croplands, small shrubs, and sparse and dense trees.
2	Vacant/Open land	Exposed soil with neither grass, trees, nor built-up structures, relatively open areas covered by low vegetation like bushes and grass. Parking lots and bare ground were also included.
3	Other urban Building	Housing units with regular layout patterns, residential, commercial, and industrial were categorized into the building class.
4	Informal settlement	Densely built housing units that are contiguous
5	Agriculture land	Comprises places where crops are grown, both annuals and perennials.
6	Road networks	Include freeways, highways, tertiary or local roads

Segmentation was followed by classification at levels 1 and 2. After performing the segmentation process, the next step involved classifying the image objects at levels 1 and 2. The segmentation process generates numerous image objects, each having distinct characteristics and features that can be calculated and utilized for classification purposes. These calculated features provide valuable information for distinguishing and categorizing the image objects into different classes at both level 1 and level 2 of the classification process.

I. Classification at Level 1(Classification at object level): The first step of the classification process at Level 1 (Object Level) apply appropriate segmentation algorithms and parameters to segment image objects. For each object, feature values such as spectral values, shape characteristics, texture, size, and contextual relations are computed based on the purpose of classification (Kohli et al., 2016a). Rule-based classification, also known as the membership function classifier, can be used to assign image objects to the desired class by integrating prior knowledge. A sequence of steps defining the class membership conditions forms a ruleset where each step comprises a condition/rule leading to the classification of the respective class. Several steps may be required to classify a single class. All these steps were executed by the eCognition developer.

Classification of the segmented image was performed in two steps. First, the non-built-up classes such as Agriculture, Vacant land, and vegetation were classified. These classes were useful in defining contextual relationships for the characterization of built-up and also to avoid misclassifications. For the classification of built-up areas, spectral measures and texture were used. The spectral feature Mode(R), which calculates and returns the most frequently occurring pixel value in the red band for an object, was first used to classify built-up areas. The remaining built-up areas, comprising mostly dark-roofed or old buildings, were then classified using texture analysis. Previous studies have shown the usefulness of texture features for effective built-up classification (Kohli et al., 2016b). Use of Mode(R) helped avoid false positives from bare soil. The results of level 1 were further used for the classification of slums at level 1. The shape characteristics used in the classification process served to detect the size and simplicity of the roof structures in informal settlements. This shape-based analysis helped differentiate the informal settlement areas from the formal built-up regions (Leonita et al., 2018).

Table 3.7. Definitions of the parameters used in the classification.
For details (Sources Ecognition reference book (Trimble 2014).

S/N	parameter	Description	Definition
1	Brightness	Brightness of object	The mean intensity of all image bands for an image object
2	Mode(R)	Mode for red band	Returns the most frequently occurring pixel value per object in the red band
3	GR	Green ratio	An index to measure vegetation, defined as (green / (red + green + blue))

4	NDVI	Normalized difference vegetation Index	An index developed to measure vegetation, defined as NIR-Red)/ (NIR + red)
5	GLCM	Grey level co-occurrence matrix	Proximal combinations of pixel brightness values (grey level) within a particular band of an image.
6	RB(SL)	Relative border to slums	The ratio of the shared border length of an image object (with a neighbouring image object assigned to a defined class) to the total border length.
7	MG	Mean Green	The mean intensity of all pixels forming an image object in the green band.
9	Area	Area of object	The number of pixels forming an image object.

II. Classification at Level 2(Classification At the settlement level): At the settlement, texture measures can be used to represent the contrast between formal and informal settlements. Settlement-level indicators are physical characteristics of informal settlements that describe the overall shape, form, or density of the respective settlement. These indicators include the relative density of building structures and the absence of regular road networks and vegetation. Further indicators are the orientation of built structures (Gevaert et al., 2017). The density of structures in informal settlements can vary from one settlement to another. Used the level 1 (object level) classification results to calculate the spatial metrics for the V-I-S for level 2 settlement primitives. The built-up class, in this study, is synonymous with the impervious class as it includes building roofs and other impervious materials Area, in terms of the size of segments, is useful in identifying and characterizing slums. steps involved bringing level 2 classification results to level 1 to get a final classified map together with other classes (Kohli et al., 2016a).

III. Classification At the environmental level: This level is also known as the Landscape level (Sirueri, 2015) cited in (Fallatah et al., 2019). The general location characteristics of informal settlements in the surrounding area are analysed. This spatial level of Analysis does not reflect a diverse urban landscape in terms of a mixture of different land uses (Wurm & Taubenböck, 2019). Further factors that extend beyond the site itself are important, for example, hazards due to flood plains and marshy conditions(Kohli et al., 2012). Informal settlements are primarily developed on vacant land in undesirable locations close to rivers or services, in low-lying areas, or on steep slopes. Areas prone to environmental disasters may also be used for informal settlements (Shekhar, 2012). The integration of location characteristics such as proximity to rivers, roads, or railway lines in the OBIA classification process has been proven to enhance the detection of informal settlements (Shekhar, 2012).

The methods for the above three levels provide the opportunity to integrate local knowledge through the selection of relevant attributes and the adjustment of parameters for each selected attribute to local conditions. This research focuses on the level 1 (object) and at level 2 (settlement) levels, as they are the most relevant concerning high-resolution images. Both can be directly extracted from an image of the proposed year, while for the environment level, additional data are used i.e. socioeconomic data collected through interview and questioner.

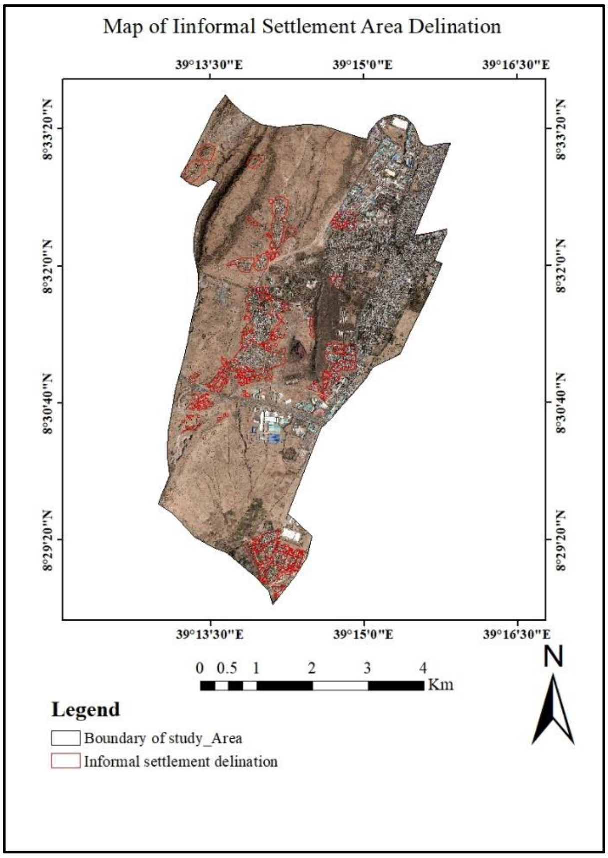

Figure 3.6. Informal settlement delineations provided are displayed on the Arial photo image

3.5.5. Accuracy assessment and Confusion matrix

Accuracy assessment is a process used to evaluate the performance and accuracy of a classification. It involves comparing the classified or predicted results with reference data, which serves as ground truth. The accuracy assessment provides quantitative measures and metrics to assess the correctness and reliability of the classification. One common tool used in accuracy assessment is the confusion matrix, also known as an error matrix. It is a tabular representation that summarizes the classification results by comparing the predicted classes with the reference classes. The confusion matrix provides insights into the types and frequencies of errors or misclassifications made by the classification model. From the confusion matrix, various accuracy metrics can be derived, such as overall accuracy, producer's accuracy, user's accuracy, and Kappa coefficient. These metrics provide a comprehensive assessment of the classification performance, including measures of correctness, reliability, and agreement between the classified results and the reference data.

Overall accuracy represents the proportion of correctly classified samples out of the total samples, providing a general measure of the classification's correctness. Producer's accuracy (also known as sensitivity or recall) measures the proportion of correctly classified samples within each class, indicating the ability of the classification model to identify true positives. User's accuracy (also known as precision) measures the proportion of correctly classified samples among the predicted samples for each class, indicating the reliability of the classification results.

An overall evaluation of the classification result's correctness is provided by the Kappa coefficient and overall accuracy. Commission error (CE), omission error (OE), over-accuracy (OA), producer accuracy (PA), user accuracy (UA), and kappa coefficient(Segmentation et al., 2016). The Kappa coefficient is a statistical measure that considers the agreement between the classified results and the reference data, considering the possibility of chance agreement. It provides a measure of how much better the classification performed compared to random assignment, indicating the classification's superiority beyond chance. In summary, accuracy assessment involves comparing the classified or predicted results with reference data and utilizing the confusion matrix and various accuracy metrics to evaluate the performance and accuracy of the classification or prediction model. The confusion matrix provides a detailed breakdown of the classification results, while accuracy metrics offer quantitative measures of correctness, reliability, and agreement.

$$OA = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}}$$

$$PA = \frac{\text{Number correctly identified in a given map class}}{\text{The number actually in that reference class}}$$

$$UA = \frac{\text{Number correctly identified in a given map class}}{\text{A number claimed to be in that map class}}$$

$$\text{F-score} = 2 * \frac{(PA*UA)}{(PA+UA)}$$

Kappa coefficient: The Kappa coefficient is a statistical measure commonly used in accuracy assessment to evaluate the performance of a classification process. It considers the contribution of random chance when assessing the accuracy of the classification. During image classification, pixels are not assigned to classes randomly. However, the Kappa coefficient considers the probability of random assignment and compensates for chance agreement in the classification results. It provides a measure of how much better the classification performed compared to what would be expected by randomly assigning pixels to their correct categories.

By incorporating chance agreement into the assessment, the Kappa coefficient provides a more robust evaluation of classification accuracy. It helps to determine the extent to which the classification results are reliable and whether they surpass the expected performance based on random chance. A higher Kappa coefficient indicates a stronger agreement between the classification and the true categories, suggesting a more accurate classification outcome. The resulting Kappa measure compensates for chance agreement in the classification and provides a measure of how much better the classification performed in comparison to the probability of randomly assigning of pixels to their correct categories. is theoretically expressed as:

$$K = \frac{\text{observed accuracy} - \text{chance agreement}}{1 - \text{chance agreement}} \dots\dots\dots\dots\dots\dots \text{equ (1)}$$

$$\frac{\dot{K} = N \sum_{i=1}^{r} \mathrm{XN} - \sum_{i=1}^{r} (Xi + X + i)}{N^2 - \sum_{i=1}^{r} (Xi + X + i)} \dots\dots\dots\dots \dots\dots\dots\dots\dots\dots\dots \text{equ (2)}$$

Where,

r = the number of rows in the error matrix

xii = the number of observations in the row i and column i

xi+ = total of observations in row i

x+I = total of observations in column i

N = total number of observations included in matrix

3.5.6. Morphological analysis of informal settlements and ruleset

The concepts of urban density, access, mix, and interface have long been a critical issue of concern in architecture, urban design, and planning theory (Juwita & Dwisusanto, 2022). The OBIA method has been used to identify these indicators to detect informal settlements with some degree of success. This study evaluates the utility of these indicators for Dembela sub City in selected areas. As the author explains in the conceptual framework for this research, we adopt the informal settlements ontology which is useful for understanding the relationship between images and actual informal settlement characteristics (Kohli et al., 2016a). This multi-scale approach assesses the variable nature of informal settlements across different contexts, by considering a set of indicators at different scales for informal settlements(Kohli et al., 2012) (see Table 3.8).

Table 3.8. Ruleset Summary and the quantitative classification criteria with the sequence from top to bottom.

SN	Classification Steps	Ruleset
1	Generate object primitives at Leve11	Multiresolution segmentations (SP=50 Wshape= 0.5 Wompts=0.5)
2	Classify road vacant land and Agriculture	Assign class using thematic layers
3	Classify Vegetation	GR> 0.42
4	Classify Shadows	Brightness <310
5	Classify built-up	Mode(R) >360, GLCM >3.6
6	Generate settlement Primitives at level 2	Multiresolution segmentations (SP=100 Wshape= 0.5 Wompts=0.5)
7	Classify Slums	Area > 14,000, built-up > 50%, Veg < 30% and Irregular road networks

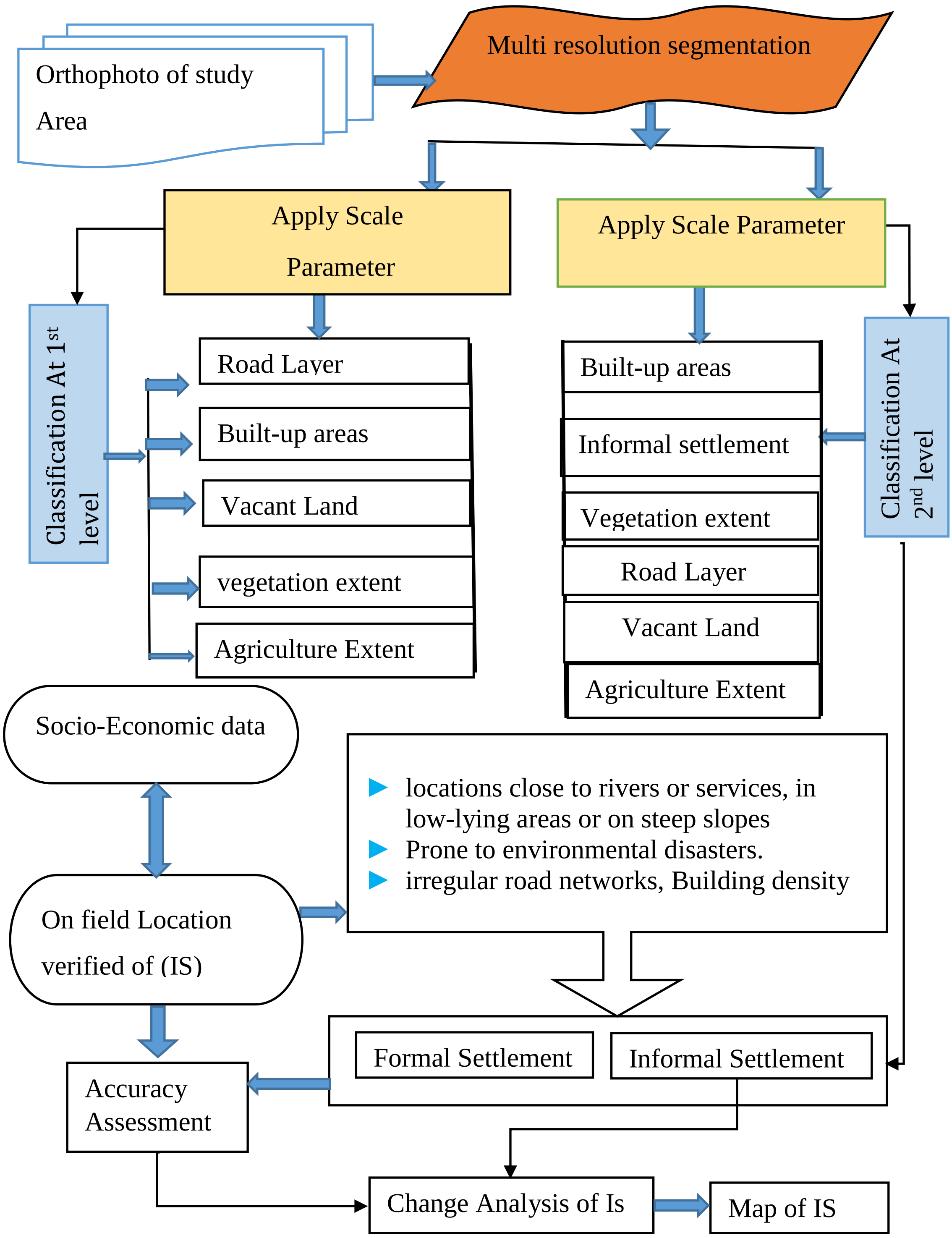

Figure 3.7: Flow chart of OBIA ruleset structure for mapping and identifying informal settlements indicators in study area.

3.6. Determine the change in the extent and pattern of IS in the study area.

To determine the change in the extent and pattern of informal settlements (IS) in the study area, spatial data related to these settlements will be extracted and integrated for comprehensive analysis. Geospatial information will be utilized to obtain the necessary data for the study. An analytical method will be developed to assess and characterize the extent and pattern of informal settlements in study area. The method will involve using object-based image analysis (OBIA), which is a technique available in software such as eCognition developer. OBIA starts by grouping neighboring pixels into spatial clusters, creating homogeneous areas that can be processed for classification (Hofmann et al., 2015b).

Remote sensing and OBIA methods have proven to be effective in analyzing urban areas, including informal settlements. These methods, also known as object-oriented image analysis or geographic object-based image analysis (GEOBIA), offer improved capabilities for analyzing complex urban environments. They enable the inclusion of spatial, spectral, and contextual characteristics, allowing for a more comprehensive and accurate interpretation of the data, similar to human cognitive image interpretation.

By applying OBIA and utilizing the spatial data, the changes in the extent and pattern of informal settlements over time can be assessed. The analysis will provide insights into the expansion, contraction, or spatial redistribution of these settlements in the study area. By comparing the results with previous data or reference information, trends and patterns of change can be identified and characterized. Through this approach, the study aims to gain a better understanding of the dynamics and transformations of informal settlements in the study area. The use of OBIA and geospatial information will enhance the accuracy and reliability of the analysis, facilitating a comprehensive assessment of the changes in the extent and pattern of informal settlements in study area.

3.7. Assessment of the environmental and social impacts of IS in the study area

To evaluate the environmental and social impacts of informal settlements in the study area of various methods was employed. These methods include the use of questionnaires, key informant interviews, and critical literature reviews. Questionnaires were distributed to gather data directly from residents of informal settlements and expert. These questionnaires were designed to capture information regarding the environmental and social impacts experienced by the residents over the study period. The responses obtained from the questionnaires were provided valuable insights into the specific challenges and issues faced by the community. Key informant interviews were conducted with individuals who possess expert knowledge or experience in the field of informal settlements. These interviews was provided a deeper understanding of the environmental and social dynamics, as well as the underlying causes and potential solutions related to informal settlements in the study area. Focus group discussions (FGDs) will be organized with groups of residents from informal settlements.

Additionally, a critical literature review was conducted. This review also involved examining existing research, publications, reports, and relevant documentation on informal settlements, both locally and internationally. The review helped researcher to identify key themes, trends, and findings related to the environmental and social impacts of informal settlements. It will also explore theories and concepts related to informality and government interventions in addressing this phenomenon. Furthermore, existing directives, land management manuals, regulations, and reports on the situations of informal settlements were thoroughly reviewed and analyzed. The analysis was conducted both quantitatively and qualitatively to address the research questions and provide a comprehensive understanding of the environmental and social impacts of informal settlements in the study area.

Overall, through the combination of questionnaires, key informant interviews, FGDs, critical literature review, and analysis of relevant documents, this assessment aims to shed light on the specific environmental and social challenges posed by informal settlements in the study area of Adama city. The general work flows of the study illustrate as bellow fig#3.8

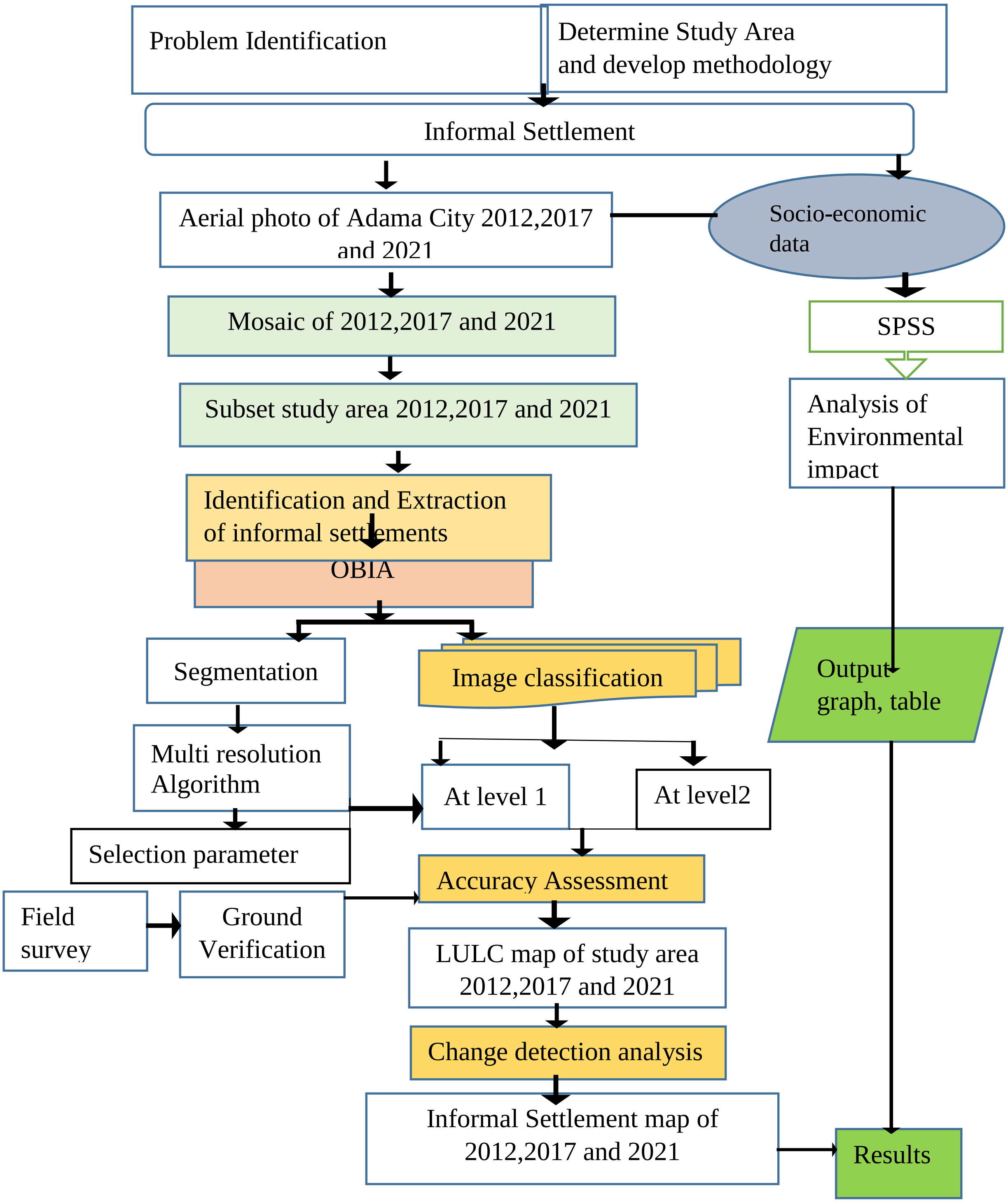

Figure 3. 8. Methodology workflow

CHAPTER FOUR: RESULTS AND DISCUSSION

4.1. Results

4.1.1. Land Use Change and Informal Settlement Mapping of the Study Area

The The study first segments the aerial photos from 2012, 2017, and 2021 to compute the land use change and identify informal settlement in the study area. The multiresolution segmentation was conducted at two levels using eCognition Developer software. At Level 1, the segmentation was done with a scale parameter value of 50, indicating a high level of detail considered during the process. The shape and compactness parameters were both set to 0.5, striking a balance between preserving the original shape of objects and achieving a certain level of smoothness, as well as ensuring an intermediate level of compactness for the resulting segments. At Level 2, the segmentation was performed with a scale parameter value of 100, allowed for the identification of more detailed object boundaries, particularly within the built-up areas, to better distinguish formal and informal settlements. again using 0.5 for both the shape and compactness parameters. By maintaining the shape and compactness parameters at 0.5 for both segmentation levels, the process aimed to balance the preservation of the original object shapes and the desired level of smoothness and compactness in the resulting segments. This approach was chosen to ensure that the segmented objects would be suitable for the subsequent classification process. The sample values generated from the segmentation results are presented in the figure below.

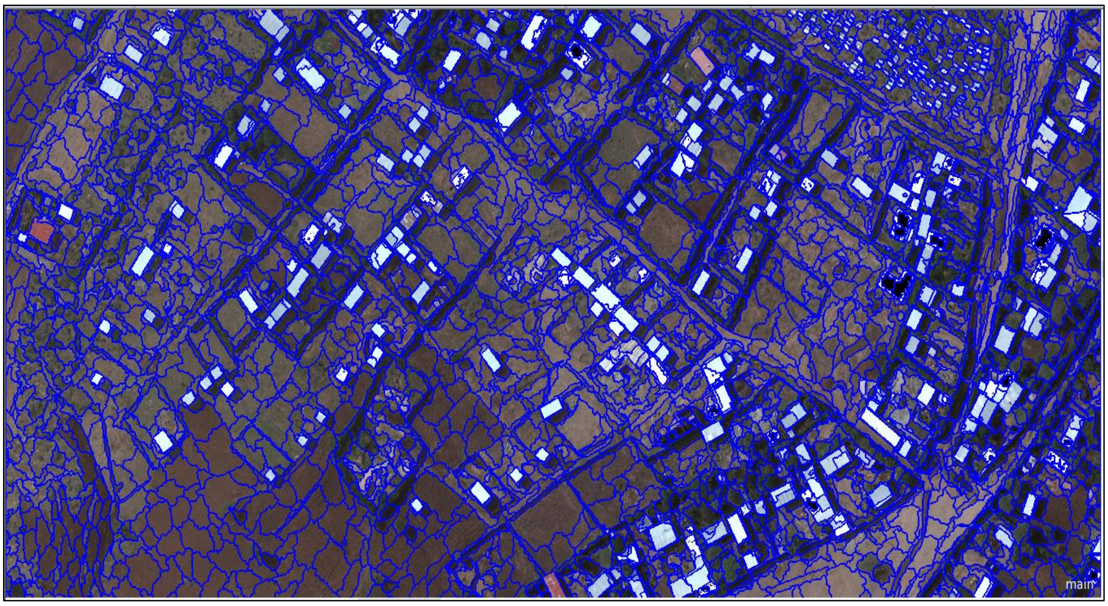

Figure 4.1. Multi-resolution Segmentation result of 2012

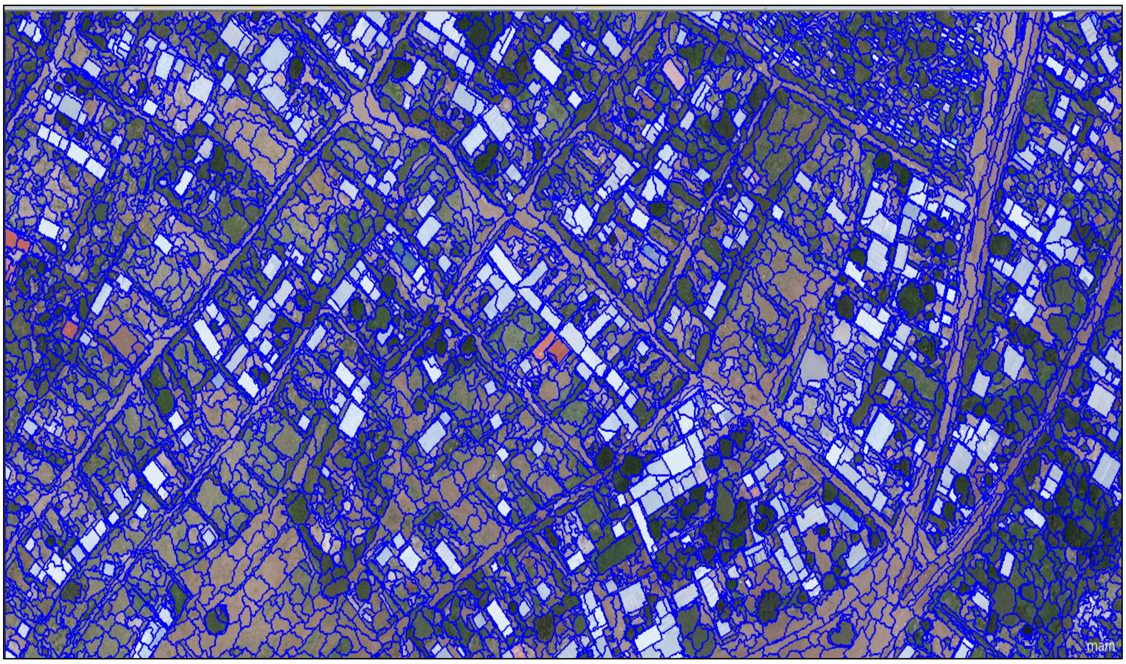

Figure 4.2. Multi-resolution Segmentation result of 2017

(Source aerial photo image classification and author, 2024)

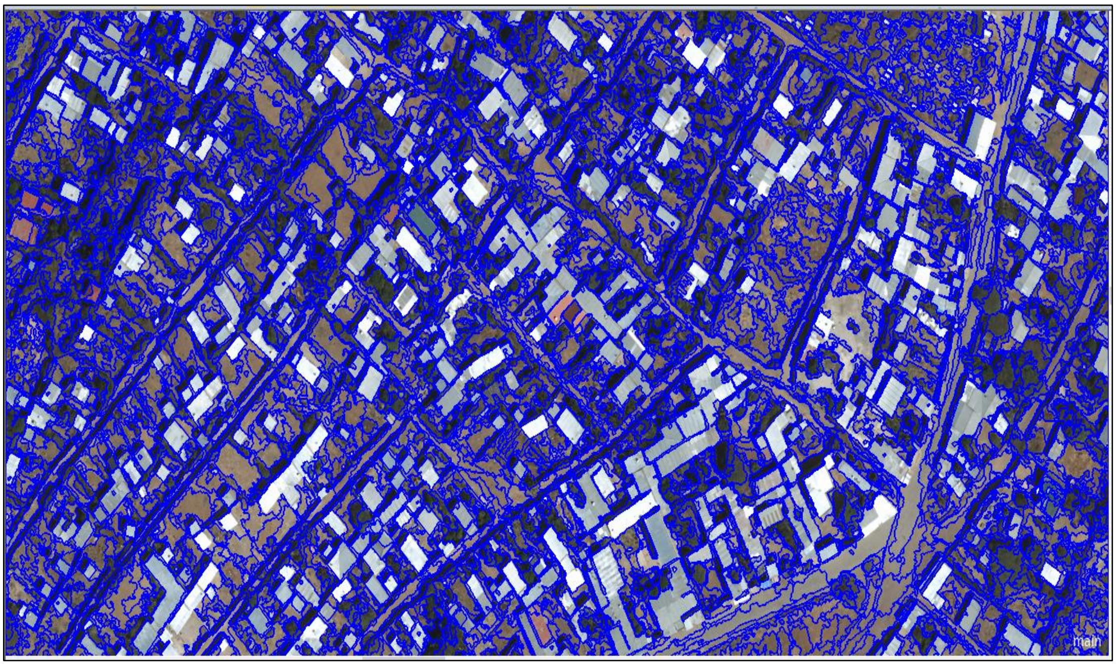

Figure 4.3. Multi-resolution Segmentation result of 2021

(Source aerial photo image classification and author, 2024)

4.1.2. The Extent and Patterns of Land Use Change and Informal Settlement Growth

The image classification in eCognition was based on the segmentation results and user-defined class descriptions incorporating spectral, spatial, and contextual features. The study utilized past and recent aerial photo data from 2012, 2017, and 2021 to assess the extent and patterns of land use change and informal settlement growth over the study period. In this classification process, quantitative criteria were used, as outlined in Table 3.8. The classification began with assigning image object classes, which included the road layer, vegetation, agriculture, vacant land, and built-up areas. Using brightness values and the green ratio, the non-built-up areas, such as agricultural land, vacant land, and vegetation, were classified. This approach allowed for the differentiation of these land cover types based on their spectral and spatial characteristics.

The classification process continued with the identification of built-up areas. Given the highly textured nature of urban scenes in high-resolution images, the classification of built-up areas employed texture-based metrics, such as the Grey Level Co-occurrence Matrix (GLCM), which utilized the blue and red bands. The GLCM entropy value in the blue band was used to classify the built-up areas. Additionally, the mean layer intensity values in the blue and green bands were utilized to distinguish between built-up areas that were not slums and other built-up areas, with the formal built-up objects having higher values in these two layers compared to other built-up objects. The brightness feature was also employed to separate formal from informal settlements, as the formal built-up areas are generally brighter due to the construction materials used. Furthermore, the spectral characteristics of the image, including GLCM Texture measures, were used to separate the formal from informal built-up areas, with the GLCM Contrast of band 3 being utilized for this purpose. After separating the formal built-up areas, the remaining built-up areas were classified as informal settlements.

Thus, finally the image was classified in to road layer, vegetation, agriculture, vacant land and built-up areas. This classification results were used a basis for the level 2 classification. The figure below shows the classified built up, vegetation another classes at level 1.

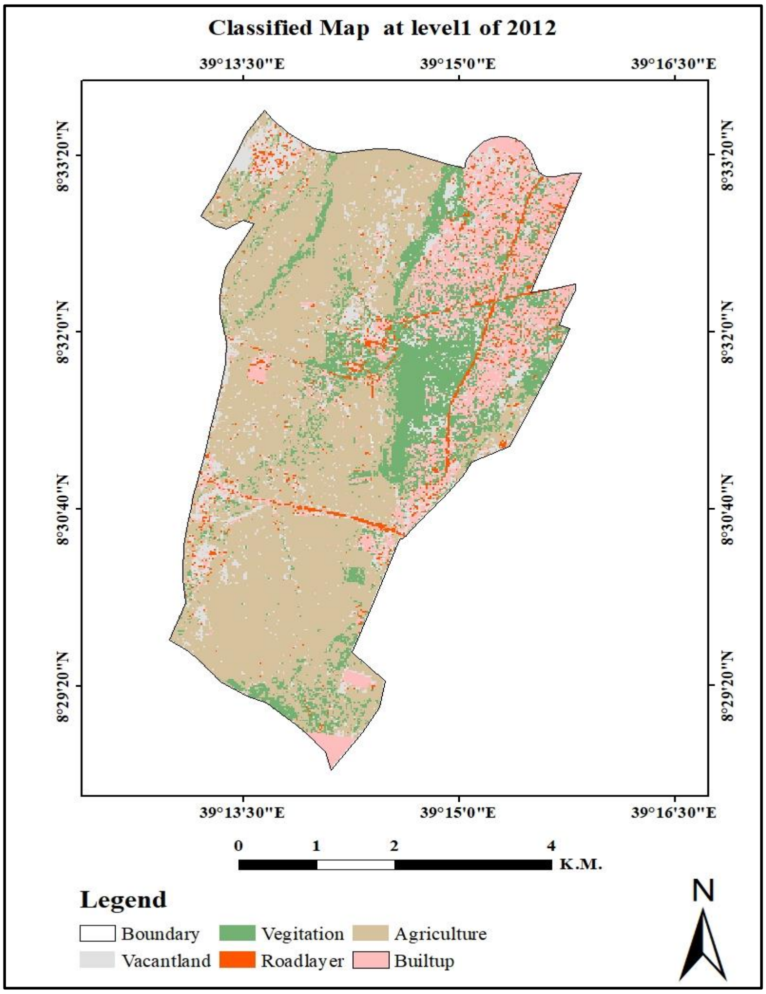

Figure4.4: Classification of image at level 1 results of 2012 in study area

(Source aerial photo image classification and author, 2024)

In 2012, classification at level 1 the land use and land cover distribution in the area was as follows: Agriculture covered the largest portion at 52, built-up areas accounted for 13%, road layers constituted 5.4% of the area, vacant land made up 12% and Vegetation covered 18% of the lands. The below table detail of area and percentage as shown;

Table 4-1: Area and percentage of classification at level 1 in the year 2012

Class _Name	Area(ha)	Percent
Agriculture	1415	52
Built-up	352	13
road layer	148	5.4
vacant land	339	12
Vegetation	488	18

(Source aerial image classification and author computation, 2024)

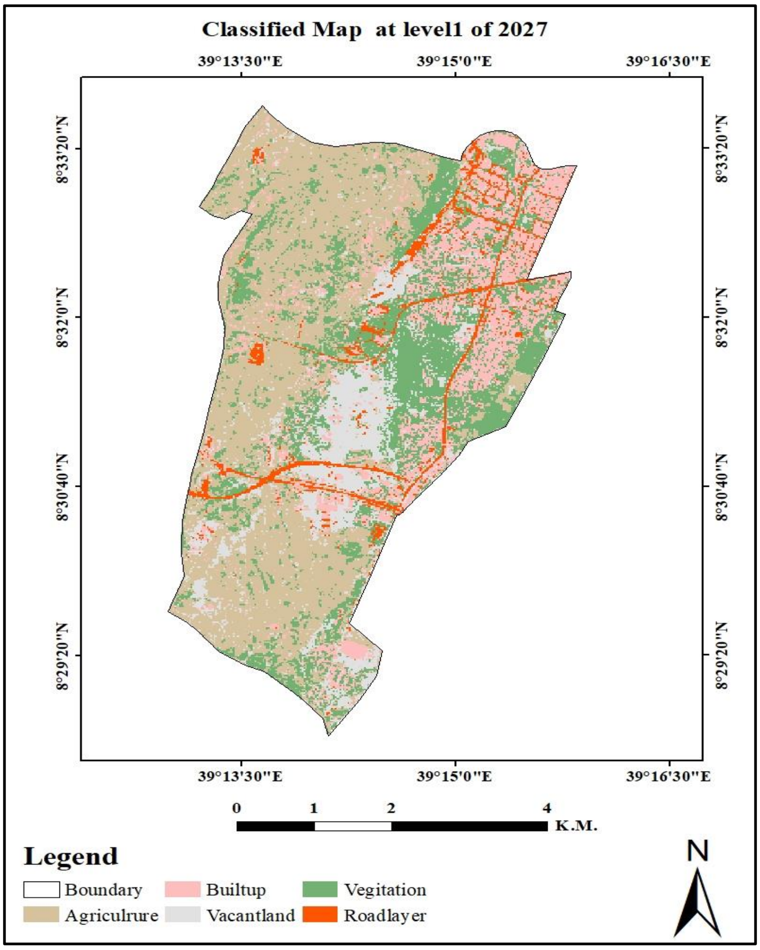

Figure 4.5: Classification of image at level 1 results of 2017 in study area

(Source aerial photo image classification and author, 2024)

The provided below table presents data on the area and percentage of land cover classes at level 1 for the year 2017. The dominant land cover class was agriculture, covering an area of 1,111 hectares, which accounted for 40% of the total. Built-up areas constituted 529 hectares and road layers occupied 157 hectares, accounting for 6% of the total. Also, vacant land and Vegetation covered 406, 531hectares of the total area.

Table 4-2: Area and percentage of classification at level 1 in the year 2017

Class _Name	Area(ha)	Percent
Agriculture	1111	40
Built-up	529	19
Road layer	157	6
vacant land	406	15
Vegetation	531	19

(Source aerial image classification and author computation, 2024)

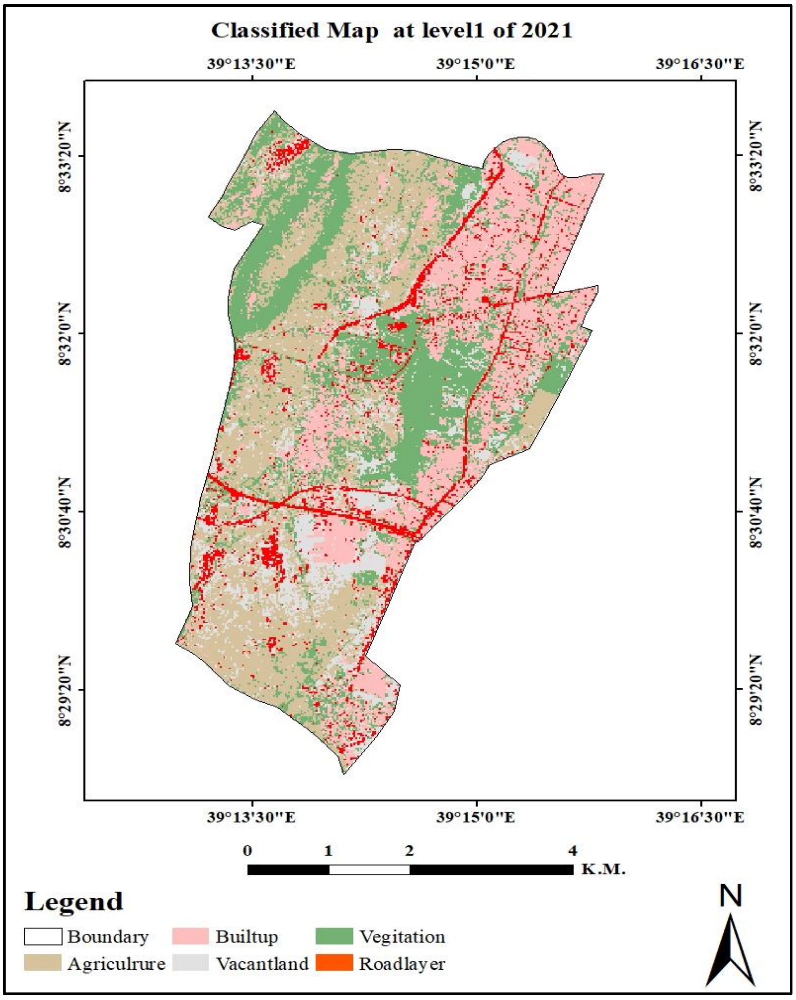

Figure 4.6: Classification of image at level 1 results of 2021 in study area

(Source aerial image classification and author, 2024)

The data from 2021 shows land cover distribution. Agriculture accounted for 29% of the total area, while built-up areas expanded to 21%. Road layers represented 8% of the land, vacant land accounted for 19%, and vegetation covered 22%. These changes indicate a decrease in agricultural land, ongoing urbanization, the presence of transportation infrastructure, and the importance of preserving natural vegetation.

Table 4-3: Area and percentage of classification at level 1 in the year 2021

Class _Name	Area(ha)	Percent
Agriculture	806	29
Built-up	614	21
Road layer	215	8
vacant land	509	19
Vegetation	608	22

(Source aerial image classification and author computation, 2024)

4.1.3. Implications of Land Use Change and Informal Settlement Growth in the Study Area

The study involved a two-step process to differentiate between formal and informal settlement areas at Level 2 classification. First, segmentation was performed using specific parameters to generate homogeneous texture segments. The second step then utilized criteria like irregular texture, area, relative area, and presence of super objects to distinguish between formal and informal settlements. The segmentation representing informal settlement areas was largely composed of compact building structures. Segments with large relative built-up areas (greater than 50%), irregular road networks, and low vegetation coverage (less than 30%) were classified as informal settlement patterns. The final image classification at Level 2 successfully incorporated these techniques to effectively distinguish between formal and informal settlement characteristics within the study area.

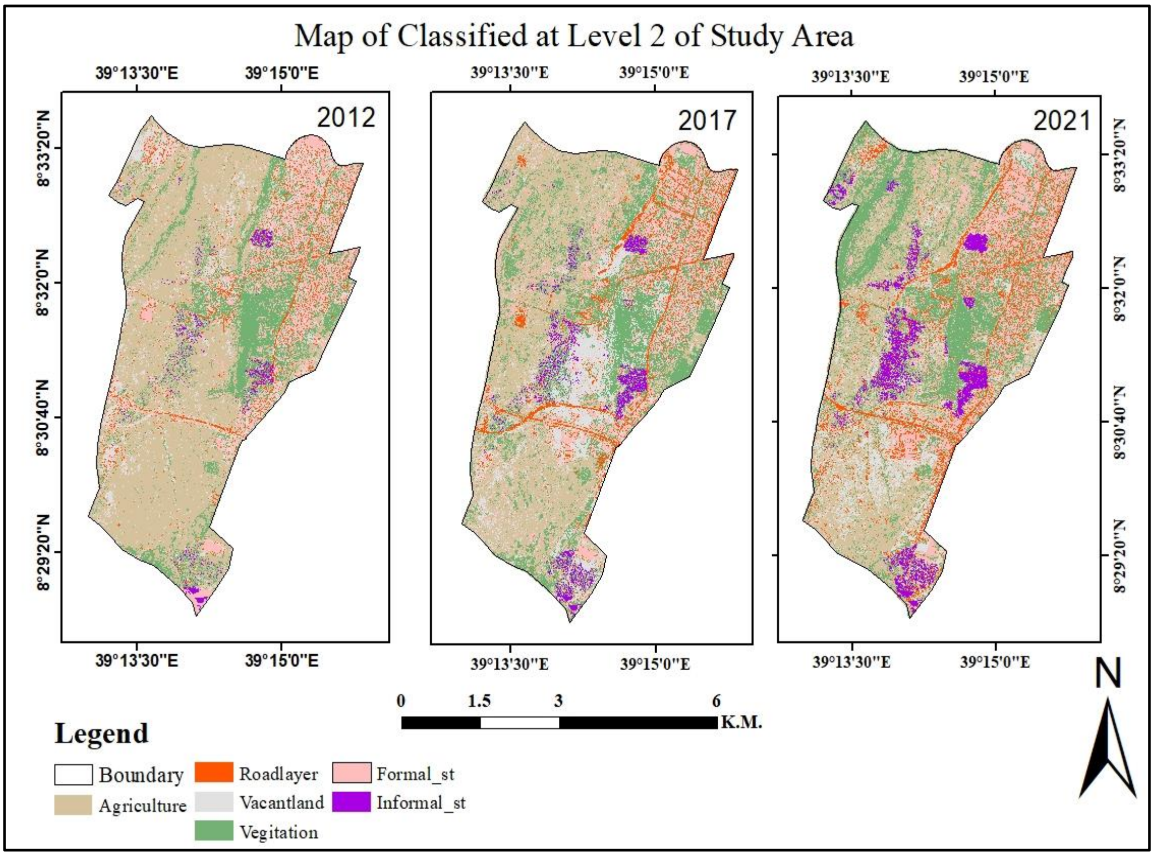

Figure 4.7: *Classification of image at level 2 results of from2012 to 2021 in study area. (Source aerial image classification and author, 2024)*

Table 4.4: Area and percentage of land use land cover *Classes at level 2* in the year 2012 to 2021

	2012		2017		2021	
Class Name	Area(ha)	Percent	Area(ha)	Percent	Area(ha)	Percent
Agriculture	1415	52	1111	40	806	29
Built-up	317	12	475	17	535	19
Informal Settlement	35	1.3	54	2	78.5	3
Road layer	148	5.4	157	6	215	8
Vacant land	339	12	406	15	509	19
Vegetation	488	18	531	19	608	22

(Source aerial image classification and author computation,2024)

The provided table presents data on the area and percentage of land use and land cover classes for the years 2012, 2017 and 2021. In 2012, agriculture was the dominant land cover class, covering 52% of the total area, followed by vegetation at 18%, built-up areas at 12%, vacant land at 12%, road layers at 5.4%, and informal settlements at 1.3%. By another hand in 2017 revealed a dynamic and diverse landscape within the study area. Agriculture emerged as the dominant land use class, covering 40%. Built-up areas accounted for 17%, reflecting the ongoing process of urbanization and human settlement. The presence of informal settlements, representing 2% of the land, underscored the challenges associated with unregulated housing and the need for improved planning and infrastructure. The rest classes 6% of Road coverage, the existence of vacant land comprising 15% while only 19% area covered by Vegetation in 2017.

In 2021, Agriculture covered an area of 806.hectares, representing 29% of the total land area. Built-up areas occupied 534 hectares, accounting for 19% of the total area. Informal Settlements covered 78 hectares, representing 3% of the total area. This class denotes areas with unregulated housing and limited amenities. The Road layer class encompassed 215 hectares, making up 8% of the total area. Vacant land covered 509 hectares, comprising 19% of the total area. Vegetation accounted for 608 hectares, representing 22% of the total area. Together, the table and figure provide valuable information about the distribution and composition of land use and land cover classes in 2021.

4.1.4. Accuracy Assessment

The accuracy assessment conducted for the years 2012, 2017, and 2021 provides valuable insights into the accuracy of the land cover classification process. To assess the accuracy of the classification process in terms of analyzing the error or confusion matrix. The table presents the results in terms of producer accuracy, user accuracy, overall accuracy, and overall kappa values for different land cover classes. In 2012, the classification process showed moderate accuracy. The built-up class had a producer accuracy of 0.83, indicating that 83% of the reference pixels belonging to this class were correctly classified. The user accuracy for the built-up class was 0.77, meaning that 77% of the pixels classified as built-up were correctly classified. Similar patterns were observed for other land cover classes, with varying levels of accuracy. The overall accuracy for 2012 was reported as 92.1%, indicating that 92.1% of all the pixels were correctly classified across all land cover classes. The overall kappa value of 0.89 suggested a substantial level of agreement between the classified and reference data.

In 2017, there was notable improvement in accuracy compared to 2012. The built-up class showed significant progress, with a producer accuracy of 0.97 and a user accuracy of 0.972. The overall accuracy increased to 93.75%, indicating an improvement in the classification process. The overall kappa value also increased to 0.921, suggesting a higher level of agreement between the classified and reference data. By 2021, the accuracy of land cover classification further improved. The built-up class achieved perfect producer accuracy (1.00) and a user accuracy of 0.92. This indicates significant progress in correctly classifying built-up areas. The overall accuracy increased to 96.5%, demonstrating a higher level of accuracy in the land cover classification process. The overall kappa value reached 0.95, indicating a strong level of agreement beyond chance.

Overall, the accuracy assessment results show a positive trend of improvement in the accuracy of land cover classification over time. The classification process achieved higher accuracy in 2017 and 2021 compared to 2012, particularly in correctly classifying built-up areas. The overall accuracy and kappa values consistently indicated a high level of agreement between the classified and reference data, suggesting the reliability and effectiveness of the classification process.

Table 4.5: Statistical Information Accuracy Assessment for the year 2012 to 2021

Class Name	2012 Producer Accuracy	2012 User Accuracy	2017 Producer Accuracy	2017 Use Accuracy	2021 Producer Accuracy	2021 User Accuracy
Built-up	0.83	0.77	0.97	0.972	1.00	0.92
Informal Settlement	0.95	0.96	0.90	0.9	0.96	0.96
Road layer	0.91	1	0.94	0.88	0.91	1
Agriculture	0.77	0.91	0.96	0.92	0.91	0.91
Vegetation	1.00	0.88	1.00	1.00	1.00	1.00
Vacant land	1	0.9	0.88	0.93	1.00	1.00
Overall accuracy		92.1		93.75		96.50
Overall kappa		0.89		0.92		0.95

(Source aerial image classification and author computation,2024)

4.1.5 Change detection from 2012 to 2021

The provided table below presents the change detection of Classification of image at level 2 between the years 2012 and 2021. From 2012 to 2017, there was a decrease in the area of agriculture by 304 hectares, representing an 11% reduction. This decline indicates a shift away from agricultural activities during that period. Similarly, from 2017 to 2021, agriculture experienced a further decrease by 305 hectares, or 11%, indicating an ongoing trend away from agricultural land. Built-up areas, on the other hand, showed an increase of 158 hectares or 6% from 2012 to 2017, and an additional 60 hectares or 2% from 2017 to 2021. This suggests urbanization and development, with land being converted for built-up purposes. Informal settlements experienced a slight increase, with an additional 19 hectares or 1% from 2012 to 2017, and a further 25 hectares or 1% from 2017 to 2021. This indicates the growth of informal housing in the area.

Road layers also saw an increase in area, with 9 hectares or 1% from 2012 to 2017, and a significant rise of 58 hectares or 2% from 2017 to 2021. This reflects the expansion of transportation infrastructure to accommodate growing mobility needs. Vacant land showed an increase of 67 hectares or 2% from 2012 to 2017, and a further 103 hectares or 4% from 2017 to 2021.

This suggests areas without current development or land waiting for future use or planning decisions. Vegetation witnessed growth, with an increase of 43 hectares or 2% from 2012 to 2017, and an additional 78 hectares or 3% from 2017 to 2021. This highlights efforts toward environmental conservation and the preservation of natural vegetation.

Overall, the changes in land use and land cover between 2012 and 2021 indicate a decrease in agriculture and an increase in built-up areas, informal settlements, road infrastructure, vacant land, and vegetation. These changes reflect the dynamics of urbanization, infrastructure development, and environmental considerations in the region over the given time period. The table below shows the detail change detection in the year of 2012 to 2021.

Table 3.6: Change Detection in land use land cover from 2012 to 2021

	Change					
	2012_2017		2017_2021		201_2021	
Class Name	Area(ha)	Percent	Area(ha)	Percent	Area(ha)	Percent
Agriculture	-304	-11	-305	-11	-609	-23
Built-up	158	6	60	2	218	8
Informal Settlement	19	1	25	1	44	2
Road layer	9	1	58	2	67	3
Vacant land	67	2	103	4	170	6
Vegetation	43	2	78	3	120	4

(Source aerial image classification and author computation,2024)

4.1.6. The Extent and Pattern of Informal Settlement Growth in the Study Area

From 2012 to 2021, there was a spatial change in the extent and pattern of informal settlements. The area occupied by informal settlements increased, indicating their growth over time. The specific changes in the spatial distribution and patterns of informal settlements would require further analysis and data representation to provide a comprehensive description.

The bar char in the 4.8 illustrates informal settlements area (Ha) for the years 2012, 2017 and 2021. The Y-axis represents the area covered while the X-axis represents the year. It can be seen that the change from year 2012 to 2017 was 35 ha from 54 ha while that from 2017 to2021 was from 54 ha to 79 ha. This is a clear upward trend in the increase of informal settlements in the study area

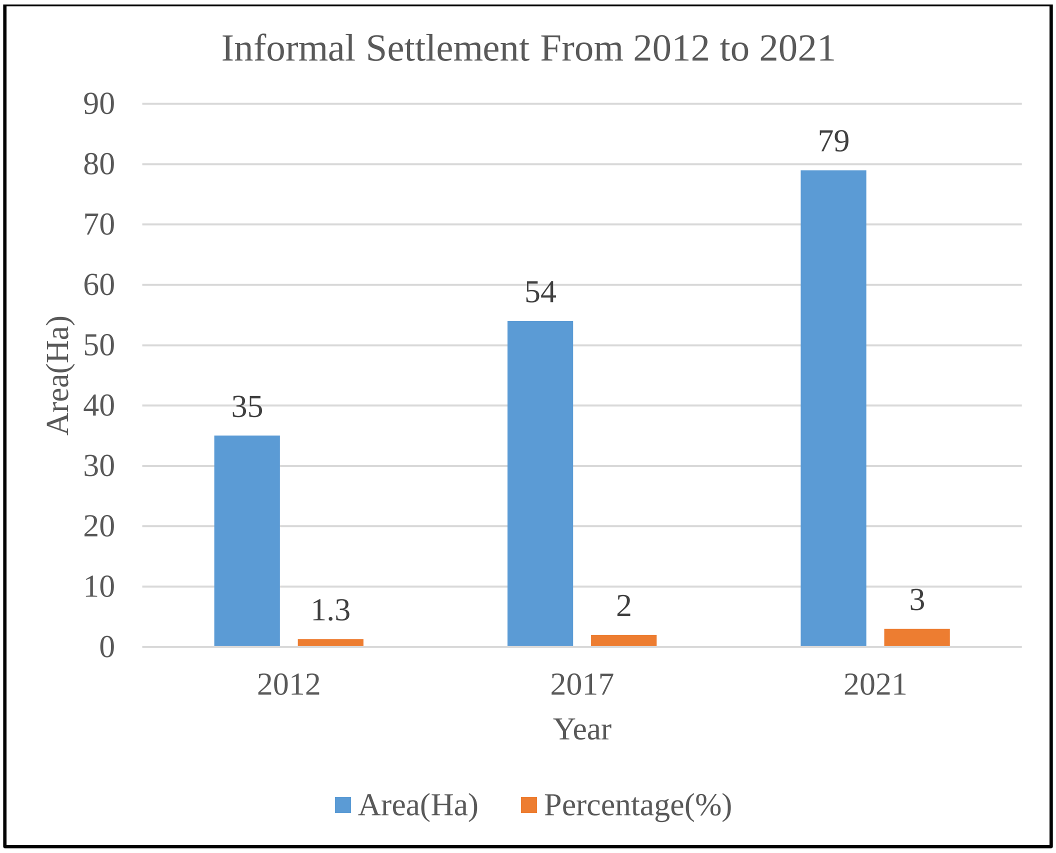

Figure 4.8. Informal settlements Area in (Ha) and Percentage for the year 2012 to 2021 (Source aerial image classification and author analysis)

Figure 4.9 show that map represents the spatial extents informal settlements for the year 2012to 2021. The areas in purple shows the area covered by these settlements. It can be seen that these settlements tend to increase from 2012 to 2021 by just looking at the extent they cover in each of map shown. Together, the graph and map provide a comprehensive understanding of the change in the extent and pattern of informal settlements in the study area. The data highlights the substantial growth of informal settlements, both in terms of area and density, between 2012 and 2021. This suggests a significant transformation in the urban landscape, potentially driven by factors such as population growth, urbanization, and socio-economic dynamics.

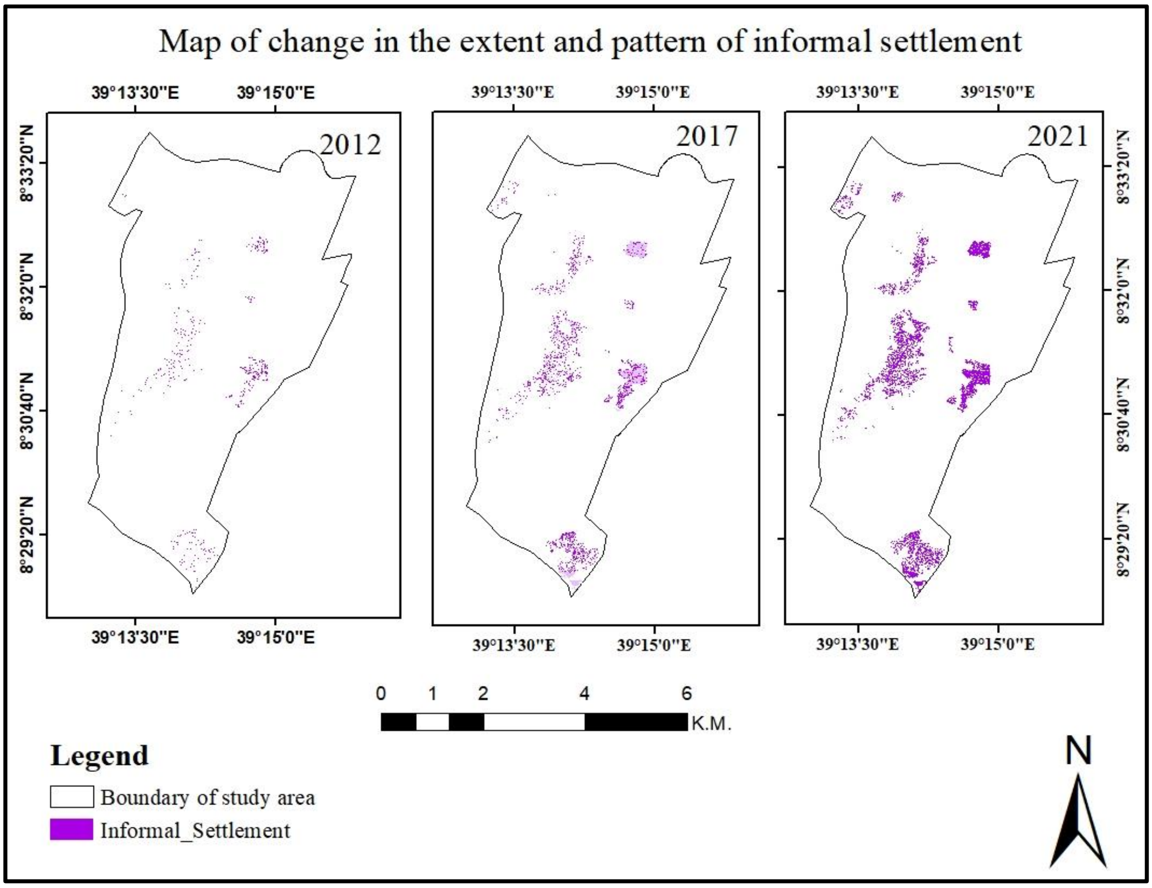

Figure 4.9. Final Map of spatial change in the extent and pattern of informal settlement from 2012 to 2021

(Source aerial image classification and author analysis)

4.2. Assessing the socio-economic impacts of informal settlement

This subsection analyzed, interpreted and discussed the socio-economic impact of informal settlement using socio-economic data.

4.2.1. Descriptive Analysis of Demographic Characteristics of Respondents

The demographic data consist of Gender, Age, household head, marital status, educational level, income level and family size of the respondents. The descriptive statistics mainly the frequency analysis was used to examine the demographic characteristics of respondents.

4.2.2. Age of the Household heads (respondent)

The table (4.7) result showed that 10 (9.8%) of the respondents were between the age of 18-29, 38 (37.3%) of the respondents were between the ages of 30- 40, 36 (35.3) of the respondents were between the age of 41 - 55, and 18 (17.6%) of the respondents were above the age 56 years old. In this regard, the result indicated that the majority of the respondent was between the age group of 30-40 and above 41 years respectively.

This implies that out of the total sample resident household heads interviewed, majority 37.3 percent are active work forces and it needs effective land policy at urban areas that can respond to the needs of those people formally, that is formal affordable land and housing supply for all income levels of urban residents, and reduce rates of informal settler.

Table 4.7: Age of Respondent

Variable	Category	Frequency	Percentage
Age	18-29	10	9.8
	30-40	38	37.3
	41-55	36	35.3
	Above 56	18	17.6
	Total	102	100.0

Source: own survey and computation, 2023

4.2.3. Gender and marital status of the squatter Household Respondent

Gender of respondents: As clearly shown in table 4.8, out of the total number of 102 sample Informal household heads interviewed, (76) 74.5 percent of the household heads are males and the remaining (26) 25.5 percent are females. This indicates that majority of the squatter household heads are males.

***Marital Status of the Respondents*:** As indicated in table 4.8 below, out of the total interviewed squatter household heads, 82.4 percent were married, and 17.6 percent were single. This indicates that the government responses towards the squatters should take this situation of squatter households in to consideration.

Table 4.8: Gender and Marital status of Respondent

Variable	Category	Frequency	Percentage
Gender	Male	76	74.5
	Female	26	25.5
	Total	102	100.0
Marital Status	Single	18	17.6
	Married	84	82.4
	Total	102	100.0

Source: own survey and computation, 2023

4.2.4. Family Size of the Respondents

The importance to knowing family size of the respondents helps the author to provide useful and reasonable recommendation. The computed data collected from the respondents indicates that 13.7 percent had a family size of less than three persons, 33.3 percent with a family size ranging from 3-5 persons and the remaining 52.9 percent with a family size of more than five persons. Therefore, the government response towards the existing squatters' settlements should take the family size of the squatters in to consideration. Unless such issues are carefully analysed and responded, the decisions may lead to economic, social and political crises of the country.

Table 4.9. Family size of the Respondents

Variable	Category	Frequency	Percentage
Family Size	less than three	14	13.7
	three - five	34	33.3
	five and above	54	52.9
	Total	102	100.0

4.2.5. Education Background of the Squatter Household

With regard to education background of the respondents, the data computed and shown in the table indicated that out of the total squatter household heads interviewed, more than half of them were high school complete and above. Among them 15.7 percent were holders of first degree and above and 23.5 percent were 12+ and Certificate holders. Out of the total house hold heads interviewed, only 14.7 percent were with no educated. This may imply that low education is not a reason for squatting. See table 4.10 given below for more information about general information about sample squatter house hold's heads interviewed.

Table: 4.10. Education Background of the sample squatter Households

Variable	Category	Frequency	Percentage
Education Level	Illiterate	15	14.7
	Primary School	47	46.1
	12+ and Certificate	24	23.5
	First Degree and Above	16	15.7
	Total	102	100.0

Source: (Own survey and computation, 2023)

4.2.6. Employment Situations of the Squatter Household heads

With regard to employment status of the squatter household heads interviewed, the majority 81.4 percent of interviewed household heads are employed. The rest 18.6 percent were not employed. The entire squatter household heads can be employed formally or informally and earn money. The table 4.11 also indicates that out of total squatter households' heads interviewed, 61.5 percent or 51 household heads are employed formally and the remaining 38.5 percent or 32 household heads employed informally. This indicates that proliferation of Informal settlements in the city is not because of lack of employment opportunities.

Table 4.11. Employment situation of the respondents

Variable	Category	Frequency	Percentage
Employment Status	Employed	83	81.4
	Unemployed	19	18.6
	Total	102	100.0
Employment Condition	Formal	51	61.5
	Informal	32	38.5
	Total	83	100

Source: (Own survey and computation, 2023)

4.2.7. Average Monthly Expenses of the Squatter Household heads

The objective of enquiring the average monthly expense of the squatter's households was to estimate the average monthly income level of the respondents. I have preferred to collect data on average monthly expense to average monthly income because I understood that the respondents may not be willing to tell me their correct average monthly income. Basically, it is believed that the total expense is less than total income of a household.

As indicated in table 4.12, the interview result shows that no squatter household spends less than 1000 Birr in a month for regular life. Thus, all the squatter households spend 1000 Birr or more on average in a month for their regular life. Out of the total interviewed squatter household heads, the average monthly expense of 37.3 percent is 1,000 Birr up to 2,000 Birr. The average monthly expenditure of majority of the interviewed households for their regular life activities falls in a range of 2001 Birr up to 4,000 Birr; which is 14.7 percent of the total sample households. The average monthly expenditure of 21.6 percent of the whole interviewed households is 4,001 Birr up to 5,000 Birr. On average, monthly for total family members of each household and average monthly expenditure of 26.5 percent of Total households is more than 5,000 Birr.

Table 4.12. Average Monthly Expenses of the Household heads

Variable	Category	Frequency	Percentage
Average Monthly Income	Less than 1000	0	0
	1001-2000	38	37.3
	2001-4000	15	14.7
	4001-5000	22	21.6
	5001 and Above	27	26.5
	Total	102	100.0

Source: (Own survey and computation, 2023)

4.3. Urban Morphology based Indicators for Informal settlements

Site Condition: Regarding Proximity to high-voltage power line the slums mostly occupied the poorest quality lands as no formal systems were put in place to provide affordable serviced land for the new entrants into cities. In many cases, the only recourse the poor had were swamps, steep slopes, refilled quarries and garbage dumps. Similarly, settlements spilled over to service reserves like railway safety zones, land under high voltage power lines and on road reserves. The results from respondents show 33.3 percent indicate settlements are close to high voltage powerline. Sample photo taken from site observation show in figure 4.1a and 4.1b. So as government with ministry of housing have to develop a policy that will provide a guideline in terms of how they deal with such cases within informal settlements. ***As respondent responses*** 43.1%, site on Steep slope and Flood Zone. The rest 18.6% and 4.9% are Proximity to (railway lines, Highways and Major Roads) and Proximity to hazardous industries respectively.

Neighbourhood Location: in Neighbourhood Location indicators majority show 55.9% are such as; Connected to infrastructure in neighbourhood area and 44.1 % of the total show informal settlement are Close to neighbourhood of low incoming socioeconomic status. This show urban informal settlement expanded through low income of socioeconomic area.

Table 4.13. Site condition and Neighborhood location of informal settlement.

Indicators	Measurement	Frequency	Percent
Site condition	Proximity to hazardous industries	5	4.9
	Proximity to high-voltage power line	34	33.3
	Steep slope and Flood Zone	44	43.1
	Proximity to railway lines, Highways, Major Roads	19	18.6
	Total	102	100.0
Neighbourhood Location	Connected to infrastructure in neighbourhood area	57	55.9
	Close to/inside neighbourhood of low incoming socioeconomic status	45	44.1
	Total	102	100.0

Source: (Own survey and computation, 2023)

The settlement close to high voltage power line in study area illustrated in Figure 4.11.

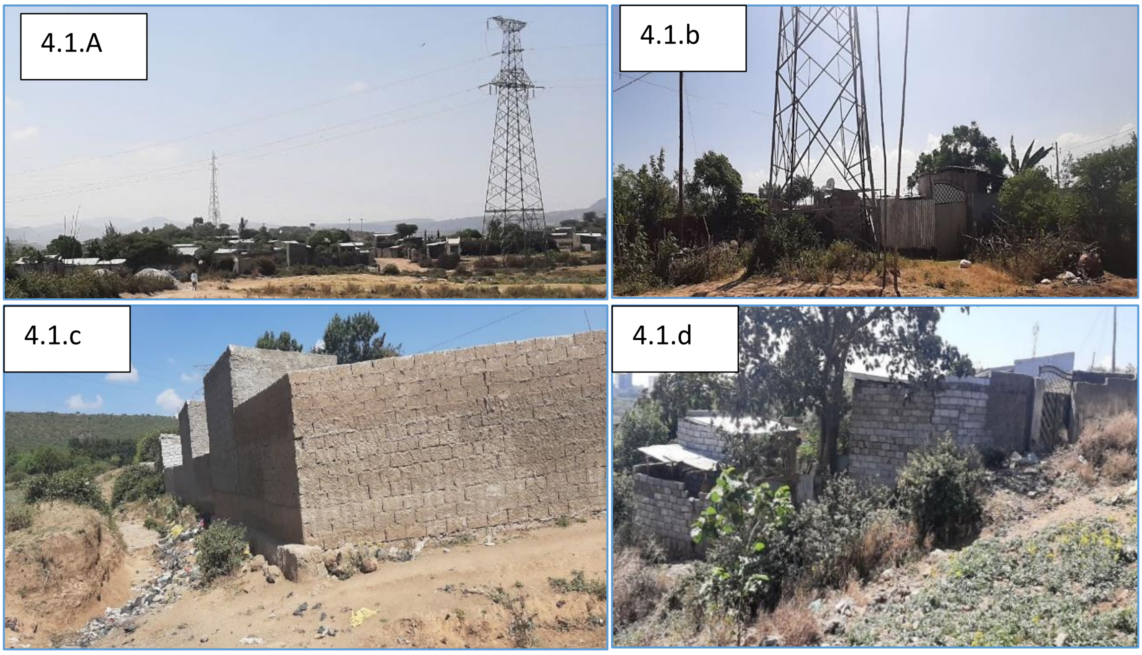

Figure 4.11. (a) and (b)show different residents and settlements near to high-voltage of power line. (c) deforestation/land degradation and flood zone (d)show that settlement build on steep slope with recommended building material

(Sources: site visiting and photo taken by Author,2023)

4.4. Major driving factors for informal settlement in study area

Table 4.20. indicates that the interviewed squatter households occupied the unauthorized land for the only reason that they did not have access to formal land. As the explanation of most of the respondents, government could not supply affordable land and house for all income levels of the urban residents and the respondents also could not afford the exaggerated formal housing market.

Table 4.14. Major driving factors informal household occupied unauthorized land

Major Driving factors	Frequency	Percentage
Lack of access to formal land	33	32.4
Migration from Rural Areas	12	11.8
Expensive Land Price	14	13.7
Absence of formal land Transfer by a government	17	16.7
Unplanned Development Activities	10	9.8
Need for wide area	2	2.0
Another reason	3	2.9
Total	102	100.0

Source: (Own survey and Computation, 2023)

Data collected from the household survey through questionnaire, and interview revealed that informal settlements were Lack of access to formal land (32.4%), absence of formal land transfer by a government (16.7%), Expensive Land Price (13.7%), Migration from Rural Areas (11.8%) and Unplanned Development Activities only contributes for about 9.8%.

Among the causes of informal settlements in Ethiopia, high rate of population growth, rural to urban migration, and the inability of the local government in providing the land and housing necessities are some of the major ones (Abagissa, 2019). Accordingly, the income disparity; the rise in the lease price of urban land, and the meager compensation paid to peri-urban farmers during their land's expropriation are among the key economic drivers for the growth of informal settlements. According to data obtained from expert's interview shows that unemployment and unable to pay the land lease price immensely contributed for the increasing number of informal settlements. The respondents also confirmed that the city has land use related problems such as insecurity of tenure, large land stocking by individuals and unfair compensations for land owners (who occupied the land before urban expansions).

4.5. Socio-economic Impacts of informal Settlements

Municipal officials have identified key Socio-economic issues in informal settlements, including Lack of basic service, pollution from indiscriminate waste disposal and burning, lack of adequate sanitation and water infrastructure, and the absence of open public spaces. These complex challenges require comprehensive interventions to address the interconnected problems and improve the living conditions of the residents.

4.5.1. Socio-economic Challenges of Informal Settlements

According to general interviewed of respondents and local knowledge show that the major challenge expected are leading by 41.2 % of Roads and drainage which are below minimum levels. Secondly 31.4 of Electricity, and other social service are below minimum levels. And the rest 27.5% of Social infrastructure, like water supply and sanitation which are below minimum levels responded by household interviewed. This show low quality of existing Roads and drainage infrastructure are high challenge in informal settlement. Table 4.15 show the summary of percentage of socioeconomic problem/expected challenges and Environmental impact.

Environmental problem: as shown in table 4.15 primary environmental impact in informal settlement 40.2% are Pollution from Solid and Liquid Wastes were increasing throughout the time. 37.3 % show There is unhealthy living conditions and hazardous locations of informal settlement. The last 22.5% show Land degradation and deforestation Expanded which is previously showed in figure 4.12.

Table 4.15. Socio-economic impacts of informal settlement

Variable	Category	Frequency	Percentage
Socio-economic Impacts	water supply and sanitation are below minimum levels	28	27.5
	Electricity, and other social service are below minimum levels.	32	31.4
	Roads and drainage are below minimum levels.	42	41.2
	Pollution from Solid and Liquid Wastes were increasing throughout the time.	41	40.2
	There is unhealthy living conditions and hazardous locations	38	37.3
	Land degradation and deforestation Expanded.	23	22.5
	Total	102	100.0

Source: (Own survey and computation, 2023)

4.5.2. Road Accessibility and Condition in Informal settlements

Roads facilitate easier access to essential services like education, healthcare, and banking. Over time, this can lead to a more educated workforce, better health outcomes, and increased financial inclusion all critical factors for economic development. Out of the total squatter's household's heads interviewed, 82.4 percent had access to road and only 17.6 percent of the interviewed squatter's houses did not have access to road.

Table 4.16. Road accessibility

Variable	Category	Frequency	Percentage
Road Accessible	Accessible	84	82.4
	Not Accessible	18	17.6
	Total	102	100.0

Source: (Own survey and computation, 2023)

Responses of the Informal settlement household heads interviewed and my observation reveal that there is a road quality problem in expansion areas in Dembela sub city. Even though some respondents evidenced that there is problem of road quality in their settlements, the information from city government and some informants as well as my observation reveal that the city government has been working on provision of roads in accordance with urban plan of the city regardless of informality issue as most squatters are mixed with old possessions. Figure 4.12 show different types of road narrow and very small width which not use vehicle close between two households' fences.

Figure 4.12. Road Condition InInformal Settlements (in Dagaga kebele (05)

(Source: Photo taken by the Author, 2023)

Adama city has had a massive growth of informal settlements forming a belt around the urban core. Because of the unplanned nature of these areas there has been very poor road infrastructure development, with narrow, unpaved roads constituting the road infrastructure. The researcher has observed that most roads' conditions in both planned and non-planned areas are almost similar. Since majority of Unauthorized housing constructions on government land mixed with old possessions without title-deeds, the city administration is providing infrastructures for both settlements in a similar manner as per its capacity allows.

I) Width of the Roads

As shown in table 4.11, from squatter households' heads interviewed, 25.5% percent responded that their houses are accessible to roads having a width of less than 10 meters. This may reduce demolition if regularization is required. while the remaining 74.5% percent houses of the respondents were accessible to roads having a width of less than six meters. As I observed during data collection time, there are roads having a width of 3 ,4 metres which is not suitable for driving vehicle.

Table 4.17. Width of the road accessible to house of the respondent

Variable	Width in meter	Frequency	Percentage
Width of the road	Less than 6m	76	74.5
	6m-10m	26	25.5
	Total	102	100.0

Source: (Own survey and Computation, 2023)

4.5.3. Drainage Lines in Informal settlements

Urban Drainage system are one of the indicators of road quality. As clearly shown in the (Table 4.17) below, 91.2 percent of the responses of the interviewed household heads indicated that there are no drainage lines in their settlements and that exposed them to critical flooding. But the situations were seen in both formal and informal settlements almost in a similar manner.

Table 4.18. Availability of drainage lines in Informal settlements

Variable	Category	Frequency	Percentage
Drainage line Availability	There is drainage problem	93	91.2
	There's is no drainage problem	9	8.8
	Total	102	100.0

Source: (Own survey and Computation, 2023)

Drainage line gives excess water a place to go to prevent it from building up and causing floods. A series of above-ground drains, underground pipes, and open-air ditches combine to safely transport runoff to an area better suited to hold it, like streams, creeks, rivers, bayous, and oceans. Figure 4.4. show Sample poor drainage system in informal settlement area, this may cause high flooding in during rainy season.

Figure 4.13. Sample photo of poor drainage in informal settlement and no drainage system

4.5.4. Availability of drinkable Water in Informal' Settlements

As clearly shown in table 4.18, responses of the interviewees indicated that 42.2 percent of the total households' heads did not have private water connections in their compounds. But 13.7 percent of those who did not have private or source of water connections in their compounds get potable water from their neighbour or public bono and the remaining two percent get water from other sources.

Table 4.19. Availability of water in individual Household compound

Variable	Water Availability	Frequency	Percentage
Water Availability	Available	8	7.8
	Not Available	43	42.2
	There're no sources of water connection	14	13.7
	From Neighbourhood	17	16.7
	From public bono	18	17.6
	Another	2	2.0
	Total	102	100.0

Source: (Own survey and Computation, 2023)

4.5.5. Availability of electricity in Informal' Settlements

As indicated in table 4.19, out of the total squatter households' heads interviewed, 6.9 percent responded that they had private electric meter. But from those without private electric meter. 13.7 percent responses there's no source of Electric service for those do not have private electric meter connection, 16.7 percent get electric service from their neighbour and the remaining households were using another means like solar.

Table 4.120. Availability of electric meter in the house of squatter household.

Variable	Electric power Availability status	Frequency	Percentage
Electricity Availability	Available	7	6.9
	Not Available	55	53.9
	Source of Electric service for those do not have private electric meter connection.	14	13.7
	From Neighbourhood	17	16.7
	Another	9	8.8
	Total	102	100.0

Source: (Own survey and Computation, 2023)

The absence of reliable electricity impedes the ability of informal settlement dwellers to escape poverty and live safe, healthy, productive lives: without reliable power, students struggle to study after dark, workers struggle to perform their jobs, and everyone faces personal safety threats when public spaces are not illuminated after dark. While another settlement use unrecommended electric pole in informal settlements in area. This show that such access is inaccurate and largely illegal.

4.6. Discussion

This section discusses the performance of spatial analysis of change of informal settlement and environmental impact. The spatial analysis of change from 2012 to 2021, a time span of almost 9 years. Segmentation results of aerial photos from 2012, 2017, and 2021 using eCognition Developer were analysed. The multiresolution segmentation was conducted with a scale parameter value of 50, for the classification at level 1 and 100 for classification at level 2 indicating the level of detail considered during the segmentation process. The shape and compactness parameters were set to 0.5 to balance the preservation of object shape, smoothness of segment boundaries, and achieving an intermediate level of compactness. The segmentation results provided a visual representation of the objects and their boundaries for each year.

The classification results indicate the successful application of object-based image analysis (OBIA) to assess land use changes in the study area from 2012 to 2021. The result obtained suggests that although object-based classification is effective in differentiating classes which have similarities such as formal and informal settlements A hierarchical approach comprising the two levels of ontology, the object level and the settlement level, was used in an object-based image analysis environment. The object level represented the basic land cover features. The parameters GR, Brightness, Mode(R) and Grey Level Co-occurrence Matrix (GLCM) were useful for basic land cover classification of road layer, vegetation, agriculture, vacant land, built-up areas, respectively.

The results of the image classification at level 1 reveal the distribution of land use and land cover classes in the study area for the years 2012, 2017, and 2021. In 2012, agriculture covered the largest portion of the area at 52%, followed by built-up areas at 13%, road layers at 5.4%, vacant land at 12%, and vegetation at 18%. In 2017, agriculture remained the dominant land cover class, covering 40% of the total area, while built-up areas accounted for 19%, road layers for 6%, vacant land for 15%, and vegetation for 19%. By 2021, there were noticeable changes in the land cover distribution, with agriculture covering 29% of the area, built-up areas expanding to 21%, road layers representing 8%, vacant land accounting for 19%, and vegetation covering 22%. These changes indicate a decrease in agricultural land, ongoing urbanization, the presence of transportation infrastructure, and the importance of preserving natural vegetation.

At level 2, the classification focused on distinguishing between formal and informal settlement areas. The process involved segmenting the image based on texture and using criteria such as area, relative area, and the existence of super objects. The results showed that informal settlements accounted for a small proportion of the total area, ranging from 1.3% in 2012 to 3% in 2021. The dominant land use class remained agriculture, followed by built-up areas, road layers, vacant land, and vegetation.

The classification accuracy was assessed using producer and user accuracy measures, as well as overall kappa values. The accuracy assessment revealed high levels of agreement between the classified land cover classes and the reference data for all three years. The overall kappa values increased from 0.89 in 2012 to 0.92 in 2017, and further to 0.95 in 2021, indicating improved accuracy and reliability of the classification over time. The high kappa values suggest that the classification results were highly reliable, enabling robust analysis of land use and land cover changes.

The analysis of spatial change in the extent and pattern of informal settlements from 2012 to 2021 reveals a significant increase in the presence of these settlements in the study area. The map clearly shows the expansion of informal settlements over the years, with the purple areas representing the areas covered by these settlements. By comparing the data presented in Table 4.8 and the bar chart in Figure 4.8, it is evident that there has been a continuous upward trend in the growth of informal settlements. The change in the extent of informal settlements is visually depicted in Figure 4.9, which displays the final map illustrating the spatial patterns of informal settlements from 2012 to 2021. The map clearly demonstrates the expansion and proliferation of these settlements over time.

The findings suggest that the study area has experienced rapid urbanization and population growth, leading to the emergence and expansion of informal settlements. The factors driving this trend may include limited affordable housing options, rural-urban migration, and socioeconomic dynamics. The increase in informal settlements raises concerns about issues such as inadequate infrastructure, lack of basic services, and challenges in urban planning and management.

The demographic characteristics of the respondents in the study on Informal settlement households. The results indicate that the majority of the respondents were between the ages of 30-40 and above 41 years. It was found that 74.5% of the household heads were males, while 25.5% were females. Furthermore, 82.4% of the respondents were married, and 17.6% were single. In terms of family size, 13.7% had a family size of less than three, 33.3% had a family size ranging from 3-5, and 52.9% had a family size of more than five.

The major driving factors for informal settlements in the study area, include the lack of access to formal land, and migration from rural areas, expensive land prices, and absence of formal land transfer by the government, unplanned development activities, and the need for a wider area. These factors were identified through a household survey and interviews conducted in the area. According to the data collected, the lack of access to formal land was the most significant driving factor, accounting for 32.4% of the responses. This was followed by the absence of formal land transfer by the government (16.7%), expensive land prices (13.7%), migration from rural areas (11.8%), and existing land lease policies (10.8%). Unplanned development activities contributed to about 9.8% of the driving factors.

These findings align with the causes of informal settlements in Adama, which include high population growth, rural to urban migration, and the inability of local governments to provide sufficient land and housing. Economic factors such as income disparity, rising lease prices, and inadequate compensation for peri-urban farmers during land expropriation also contribute to the growth of informal settlements. The city also faces land use-related problems, including insecurity of tenure, individuals hoarding large amounts of land, and unfair compensation for landowners affected by urban expansions. Overall, these driving factors highlight the complex socio-economic and policy challenges that contribute to the growth of informal settlements, while the need for effective urban planning strategies, policies, and interventions to address the growth of informal settlements and ensure sustainable and inclusive urban development in the study area.

The findings suggest the need for effective land policies, affordable housing options, and consideration of the specific characteristics of squatter households in urban planning and government responses. Based on the available information, informal settlements face various challenges related to their site conditions and lack of infrastructure and social services. These settlements often occupy poor-quality lands such as swamps, steep slopes, and garbage dumps. Additionally, they are located in proximity to high-voltage power lines, railway lines, highways, and hazardous industries. These site conditions pose risks to the residents.

In terms of infrastructure and social services, informal settlements struggle with inadequate roads, drainage systems, water supply, sanitation, and electricity. These deficiencies contribute to socio-economic problems and impact the overall living conditions in these settlements. Pollution from solid and liquid wastes, unhealthy living conditions, and land degradation/deforestation are some of the environmental impacts observed in informal settlements.

To address these challenges, there is a need for government policies and strategies that focus on improving site conditions, providing affordable serviced land, and developing guidelines for dealing with such cases within informal settlements. It is crucial to invest in infrastructure, social services, and community participation to uplift the living standards and well-being of the residents in these settlements. Based on the available information, road accessibility and condition in squatter settlements pose challenges. The majority of households have access to roads, but the width of the roads is often inadequate. Road quality problems, such as narrow and unpaved roads, are observed in both planned and non-planned areas. Drainage lines are lacking in most settlements, leading to flooding issues. Access to drinkable water and electricity is limited, with a significant percentage of households lacking private connections. These infrastructure deficiencies can impact the quality of life and development opportunities for residents.

CHAPTER FIVE: CONCLUSIONS AND RECOMMENDATIONS

5.1. Conclusions

The main objective of this study is to assess the spatiotemporal dynamics and Social impacts of informal settlement using OBIA from 2012 to 2021. The methodology employed segmentation followed by hierarchical classification, utilizing the morphology of the built environment as a basis for detecting generic informal settlements. Object based image analysis indeed offers a promising potential in feature classification and object detection respectively and most importantly integration of various data sources for spatial analysis. The output produced from the OBIA method became a major input for identification of informal settlement in the study area. The combination of geospatial analysis and the OBIA classification output proved beneficial in this identification process. Notably, the OBIA approach exhibited higher accuracy levels, leveraging texture analysis in conjunction with spatial metrics on aerial photographs of the city of Adama. The method showcased promise in effectively identifying informal settlements, with the classification process guided by contextual knowledge in the form of a local informal settlement.

The spatial analysis of informal settlements and their social impact in the study area from 2012 to 2021 provided valuable insights into urban transformation dynamics. The application of object-based image analysis (OBIA) using eCognition software enabled successful classification and monitoring of land use and land cover changes, with a focus on tracking the growth and expansion of informal settlements. The classification results revealed significant changes, including a decrease in agricultural land, ongoing urbanization, expansion of transportation infrastructure, and the importance of preserving natural vegetation. At a more detailed level, the classification distinguished between formal and informal settlement areas, showing that informal settlements accounted for a small but steadily increasing proportion of the total area, rising from 1.3% in 2012 to 3% in 2021. The accuracy assessment demonstrated high agreement between the classified land cover and reference data, with overall kappa values improving from 0.89 in 2012 to 0.95 in 2021.The analysis of spatial change in informal settlements showed a significant increase in their presence and expansion within the study area during 2012-2021. The driving factors behind this growth include lack of access to formal land, existing land lease policies, rural-urban migration, expensive land prices, unplanned development, and the need for wider living space. underscored the need for effective land policies and affordable housing options to address the growth of informal settlements. The challenges faced by these settlements included poor site conditions, inadequate infrastructure, and limited access to social services. Informal settlements often occupied marginal lands and were exposed to environmental risks. The lack of proper roads, drainage systems, water supply, sanitation, and electricity further compounded the living conditions in these areas.

To address these challenges, government interventions should focus on improving site conditions, providing affordable serviced land, and developing comprehensive guidelines for dealing with informal settlements. Investments in infrastructure and social services are crucial to improve the living standards and well-being of the residents. Additionally, addressing the driving factors behind the growth of informal settlements, such as the lack of access to formal land, expensive land prices, and rural-urban migration, requires a multi-faceted approach that considers socio-economic and policy dimensions. Overall, the spatial analysis and associated findings shed light on the complex dynamics of informal settlements, emphasizing the importance of integrated planning, inclusive policies, and sustainable development strategies to address the challenges they pose and improve the lives of their residents.

5.2. Recommendations

Spatio-temporal analysis proves to be a valuable approach for enhancing our understanding of informal settlement (IS) development. By employing this methodology, decision-makers and urban planners can gain insights that contribute to informed decision-making and facilitate productive discussions with stakeholders regarding IS issues. However, the availability and quality of data play a crucial role in effectively applying spatio-temporal analysis to study IS development. This research recommends the following;

- ❖ The study effectively employed an Object-Based Image Analysis (OBIA) approach to evaluate the spatiotemporal patterns of informal settlements. This methodology was found to be robust and suitable for conducting similar assessments of informal settlements in other Ethiopian cities.
- ❖ Leverage geospatial analysis techniques, remote sensing data, and GIS technology to demonstrate the potential of interdisciplinary approaches in addressing complex urban challenges and informing evidence-based decision-making.

- ❖ The insights from this study can inform evidence-based interventions and policy decisions aimed at addressing the complex challenges posed by informal settlements in Adama city and other similar contexts in Ethiopia.
- ❖ Contribute to the body of knowledge on urban development and informality by generating empirical evidence on the distribution, growth patterns, and socio-economic characteristics of informal settlements in Adama city. This information is essential for policymakers, urban planners, and development practitioners to design targeted interventions.
- ❖ Serve as a valuable resource for stakeholders, including government agencies, non-governmental organizations, and community-based organizations, working to address the challenges of informal settlements in Adama City. Provide a nuanced understanding of the drivers and consequences to facilitate collaboration and coordination for holistic and sustainable solutions.
- ❖ Encourage and facilitate active community participation in housing construction and decision-making processes related to informal settlements.
- ❖ Incorporate informal settlements into the city's formal urban planning processes and implement in-situ upgrading programs.
- ❖ Develop and implement clear, uniform, and well-planned land regularization procedures to provide secure tenure for informal settlement residents.
- ❖ Expand the availability of affordable housing options and provide financing mechanisms, such as public sector loans and microfinance, to support low and middle-income groups.

Overall, these recommendations aim to enhance the accuracy and comprehensiveness of analyses, contribute to more effective and holistic approaches in managing and addressing informal settlement challenges, and promote inclusive, equitable, and sustainable urban development in Adama City and beyond.

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APPENDICES

Appendix: [1]

Template of Questionnaire survey

ADAMA SCIENCE AND TECHNOLOGY UNIVERSITY

SCHOOL OF CIVIL ENGINEERING AND ARCHITECTURE

GEOINFORMATICS ENGINEERING (MSC) PROGRAM 2023 G.C

QUESTIONNAIRE SURVEY OF THE RESEARCH ON OBJECT-BASED IMAGE ANALYSIS FOR THE SPATIOTEMPORAL DYNAMICS OF URBAN INFORMAL SETTLEMENTS: THE CASE OF DEMBELA SUB CITY OF ADAMA, ETHIOPIA

This questionnaire is intended to collect data on the research “Object-Based Image Analysis for The Spatiotemporal Dynamics of Urban Informal Settlements”: The Case of Dembela Sub City of Adama, Ethiopia. You have been identified as a potential respondent. Therefore, you are kindly requested to complete the questionnaire honestly and responsibly. The study is purely academic so that all the information will be kept confidential.

Thank you in advance to your kind cooperation!

General direction

1. No need to write your name on the paper.
2. Please read all instruction of the questionnaire
3. To give your own answer put a tick “✓”or “X” mark on space provided in the box.

I. Background Demographic information of Respondent

1. **Gender:** □ Male □ Female
2. **Age:** □ 20- 30 □ [31 – 40] □ [41 – 50] □ 51 and above
3. **Marital status:** □ Single □ Married
4. **Education level**: □ uneducated □ Primary school □ TVET/Diploma □ first Degree □ Master's Degree □ above
5. **Occupation:** □ Self- employed □ Private employee □ public servant □ Government employee □ Farmers
6. **Level of Income:** □ High □ Middle □ Low None
7. **Name of your Sub City/Kebele**_______________________

II: Questionnaire for Informal Settlements Residents

1. What has your experience been like living in this informal settlement, especially with the lack of services?

____

____

____

2. Do you think that this area is suitable for residential purposes? If not please state your reasons.

____

____

____

3. Which Socio-economic challenges do you think are more prevalent in this area?

____

____

____

Part III: Questioner for Expert survey

Urban Morphology based Indicators for Informal settlements

In the following section, kindly provide information on each of the indicators based on your context, please use the knowledge of informal settlement from your city/area. The following questions related to environmental problem of informal settlement; kindly indicate the level of agreement 1 to 5. (**5) for strongly Agree (4) for Agree (3) undecided (2) for disagree (1) for Strong Disagree**

Please circle the number that represents the site condition of an Informal settlement in your context.

Indicator	Measure	**1**	**2**	**3**	**4**	**5**
Site condition	Proximity to hazardous industries					
	Proximity to high-voltage power line					
	Steep slope					
	Proximity to railway lines, Highways, Major Roads					
	Flood Zone					
Neighborhood location	Connected to infrastructure in neighborhood area					
	Close to/inside neighborhood of low incoming socioeconomic status					
	Close to neighborhood of middle/high incoming socioeconomic status					

II. Questions related to socio-economic and environmental challenges

Please indicate your responses to each of the following statements regarding

Indicate with a √ in the appropriate answer box, according to the following code definitions:

Please rate your response as follows: Degree of agreement

(**5) for strongly Agree (4) for Agree (3) for undecided (2) for disagree (1) for Strong Disagree**

S N	Socio-economic problems	Degree of agreement				
		1	**2**	**3**	**4**	**5**
1	Social infrastructure, like water supply, sanitation, electricity, roads and drainage; are below minimum levels.					
2	Rapid urbanization and influx of people into urban areas were major causes of informal settlement					
3	Inefficient public administration, inappropriate planning and inadequate land administration were the main causes of informal settlements.					
4	Pollution from Solid and Liquid Wastes were increasing throughout the time.					
5	There is unhealthy living conditions and hazardous locations					
6	Land degradation and deforestation Expanded.					

III) Questions related to Major driving factors for informal settlement

(5) for strongly Agree (4) for Agree (3) for undecided (2) for disagree (1) for Strong Disagree

S/N	Major Driving factors	1	2	3	4	5
1	Migration from Rural Areas					
2	Expensive Land Price					
3	Absence of Formal Land Transfer by A Government					
4	The Level of Economic Status					
5	Unplanned Development Activities					

II. Interview Questions for Municipal Officials

Do you think that informal settlements are suitable for residential purposes? If not, why?

1. What are the environmental challenges do you think are more prevalent in informal settlements?

2. What are the sources of socio-economic challenges experienced in informal settlements?

3. What do you think are the possible solutions to the negative impacts which informal settlements have on the social?

4. What measures have the local municipality taken to help reduce pollution in the Adama informal settlement?

THANK YOU