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By

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A Thesis Submitted to Bahir Dar University, Institute of Disaster Risk Management and Food Security Studies for the Partial Fulfillment of the Requirements for the Award of a Master's science Degree in Disaster Risk Management and Sustainable Development.

DECLARATION

I **Kibur Zerihun Debeb**, Registration Number/I.D Number **BDU1300679** do hereby declare that this thesis report is my original work and that it has not been submitted partially; or in full, by any other person for an award of a degree in any other university or institution.

Name of student **Kibur Zerihun Debeb** Signature_______________ Date______________

This thesis report has been submitted for examination with my approval as institute supervisor

Name of supervisor **Zerihun Yohannes (PhD) Signature** ___________Date______________

APPROVAL SHEET

The undersigned certify that they have read and hereby recommend to the Institute of Disaster Risk Management and Food Security Studies, Bahir Dar University, to accept the Thesis submitted by Kibur Zerihun, and entitled "**Drivers and Impact of Urban Expansion on Livelihood Asset of Peri-Urban Farmers in Debark Town, Amhara National Regional State, Ethiopia**", in partial fulfillment of the requirements for the award of a Master's Degree in **Disaster Risk Management and Sustainable Development Program**.

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ABSTRACT

Urban expansion-induced displacement is becoming a major concern in Ethiopia, within different parts of the region. Debark is one of rapidly urbanizing town in Amhara region. Therefore, this study was aimed to assess the drivers and impacts of urban expansion on livelihood assets of peri-urban farmers in Debark town. This study was mainly focused on drivers and its impacts on livelihood assets and land use land cover change. Cross sectional survey was applied in three peri urban kebeles of Debark town on 282 (139 displaced and 143 non-displaced) households. The study employed both quantitative and qualitative approach. Multi stage sampling technique was employed to select the study area, kebeles, and sample households. Descriptive statistics, factor analysis, logistic regression model integrated with propensity score matching methods were used to analyze the data. Supervised maximum likelihood classification technique used to map land use land cover change. The results found from key informants indicated that, rural to urban migration, increasing natural population, and economic development were the major drivers of urban expansion. The result found from econometric model showed that the impacts of urban expansion on peri urban farmers' livelihood assets, natural, financial, and social capital were decreased for displaced households at a value of (-0.443), (-0.172), and (-0.166) respectively, with significant and negative value. In contrary, physical capital for displaced households was increased by 0.177. As a result, the average livelihood assets were decreased for displaced households at a value of (-0.159) and significant at p<0.01 indicates at 1% significance levels. The results from land use land cover detection indicated that in the study periods, the built-up area increased at the expanse of cultivated and forest land by +14.8%, 12.1% and 26.9% with corresponding year 2001 to2013, 2013 to 2021 and 2001 to 2021 respectively. Finally, the study recommends that, the urban expansion program should be based on the consideration of livelihood asset of peri urban farmers' analysis before expansion.

Key Words; *Urban expansion, Livelihood asset, Peri-urban, Land use land cover change, Debark.*

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF APPENDICES

LIST OF ACRONYMS AND BBREVIATIONS

ANRS	Amhara National Regional State
CSA	Central Statistics Agency
DFID	Department For International Development
DTAO	Debark Town Administration Office
DDAO	Debark District Administration Office
EU	European Union
FGD	Focusing Group Discussion
GIS	Geographic Information System
GPS	Global Positioning System
HH	Household
LULC	Land Use Land Cover
LULCC	Land Use Land Cover Change
MoARD	Ministry of Agriculture and Rural Development
MSI	Multispectral Instrument
MUDH	Ministry of Urban Development and Housing
OLI	Operational Land Imagery
PUF	Peri_urban Farmers
PCA	Principal Component Analysis
TM	Thematic Mapper
UE	Urban Expansion
UN	United Nations
UNFPA	United Nations Population Fund
USGS	United States Geological Survey
WB	World Bank

CHAPTER ONE: INTRODUCTION

1.1. Background of the study

Before the beginning of the 19th C only 3% of the world's population lived in town of over 5000 people (Tessema, 2017). Through a process Global urbanization is increasing as a result of increase population and rural-urban migration (Admasu *et al.*, 2019; Jiang *et al.*, 2015). According to World Bank (2018) urbanization is a complicated socioeconomic process that modifies the built environment, transforming previously rural resident into urban settlements and moving the spatial distribution of a population from rural to urban areas. Similarly according Berhanu (2018) and Tessema (2017), urbanization is a process by which rural areas are gradually transformed via the dense construction of buildings and infrastructure. As stated by Kleemann *et al.* (2017) and Bonye *et al.* (2021) increasing population growth, rural-urban migration and urban economic development have been observed to contribute to rapid expansion of urban centers worldwide. Moreover, various previously conducted studies such as Bapari *et al.* (2016), Bodo (2019), Abay *et al.* (2020) and Getu and Bhat (2021),indicate that rapid population growth and socio-economic development are major forces intensifying urban expansion.

The world is rapidly urbanizing, particularly fast urbanization at the moment with poorer countries is undergoing (Mohammed *et al.*, 2020). The world's least urbanized region, Eastern Africa, is currently rapidly urbanizing (Dires *et al.*, 2021). Urban populations in developing nations are expected to double by 2030, and urban populations around the world are expected to account for 60% of the total population (Zakari, 2020). At the same time from 32 million in 1950 to over 450 million in 2014, Africa's urban population has increased by 14 times, and it is projected to double by 2030 and quadruple by 2050 (UN, 2018). Urbanization's growing demand for urban land is largely met by transforming rural land on the out skirts of existing built-up areas (Admasu *et al.*, 2019). Because the rate of population growth is linked to the rapid expansion of urban areas, agricultural land has been converted to residential and development use (Ayele and Tarekegn, 2020).

Without a well-managed plan, sustainable development issues become increasingly concentrated in cities as the globe continues to urbanize, especially in lower-middle-income countries where the rate of urbanization is quick and mostly unplanned (Xu *et al.*, 2019). Displacement caused by urban expansion is a bigger issue in developing countries than in developed countries since most people in developing countries live in densely populated peripheral areas and depend on agriculture with dispersed land holdings (Aboda *et al.*, 2019). In recent years, the use of agricultural land for urbanization activities such as residential, commercial, and industrial uses has a negative impact (Kuusaana and Eledi, 2015; Osumanu *et al.*, 2019). It happens because of the urban fabric has more uncontrollably expanded into the surrounding fringes as a result of several of these urban transformation processes (Fitawok *et al.*, 2020). Additionally rapid urbanization is not correlated with economic growth, social transformation, or technological advancement in developing nations (Wondimu, 2020).

However, given that urban expansion is seen as a significant phenomenon, it presents a number of chances for employment, technological advancement, manufacturing, and the provision of goods and services (Güneralp *et al.*, 2017; Selod, 2017; Kötter, 2017). Ethiopia is the second most populous country in east Africa with a population of over 109 million and a total area of 1.1 million km^2 (Teketay *et al.*, 2010; Ayele and Tarekegn, 2020). Despite having one of the least urbanized populations in Sub-Saharan Africa, with only 17 percent of the population is living in cities and towns. Ethiopia has recently gained recognition as one of the world's fastest urbanizing nations, with a growth rate of five percent annually (Wondimu, 2020; Muluwork, 2014). Because in 2018, the total population of the country reached 107,534,882, of which 20.6% were urban inhabitants (Mekuriaw and Gokcekus, 2019).

Due to this urbanization rate Ethiopia’s high rate of land transformation in peri-urban areas is expected to continue (Agegnehu and Mansberger, 2020). The urbanization program in Ethiopia has a severe influence on people's livelihoods, notably those of expropriated landholders, because it is neither participatory nor supportive of farmers on the periphery (Mohammed *et al.*, 2017). Similarly Ethiopian, horizontal urban development and expansion is a complex process that primarily disadvantages peri-urban farmers while primarily benefiting a small number of private investors and residents (Ayele and Tarekegn, 2020). Moreover, urbanization in Ethiopia results in land expropriation and population relocation due to anticipated large-scale land transfers to investors, which have detrimental effects on the environment and the livelihoods of rural communities(Tura, 2018).

Due to the fact that urban expansion-induced displacement is becoming a major concern in Ethiopia, with different levels of concern in different parts of the region Siltan (2019). The disruption to their sources of livelihood caused by urbanization, peri-urban farmers are forced to adopt a new way of life (Fikadu, 2015; Gebregziabher and Yiadom, 2014; Tura, 2018; Teshome, 2021; Mengistu, 2016). At the peri_urban, agricultural lands has been used for Urban settlement due to continues expansion on the surrounding area and this expansion leads to the farmers lose their land, decrease agricultural productivity, displaced from their original land and crime due to mismatch between the land value and their compensation give to the farmers and environmental degradation improper waste management in Debark town (Tame, 2020). As a result, this study gives emphasis to the impact of urban expansion on the livelihood asset of peri-urban households in Debark town of the Amhara region.

1.2. Statement of the Problem

The world we live in today is with rapid urban expansion and its being characterized by an increase in urban population (Mohammed *et al.*, 2020; World Bank, 2018). Particularly many countries in Sub-Saharan Africa have recently experienced urban expansion. Similarly our country Ethiopia is also one of the countries facing the problem of urban expansion in recent years (Tessema, 2017). Urbanization in most countries has historically pushed all forms of agriculture out of the city and into rural areas, considering it too dirty for the glory of the city (Jonga, 2013; Teshome, 2021). Due to that reason peri_urban farmers displacement caused by urban expansion is a bigger issue in developing countries than in developed countries since most people in developing countries live in densely populated peripheral areas and depend on agriculture with dispersed landholdings (Aboda *et al.*, 2019).

Urban expansion is a major indicator of urbanization, urban expansion study is necessary to determine urban expansion followed impact, implement long-term monitoring of urban expansion, in-depth studies of the rate, direction and scale of expansion to identify the corresponding critical driving factors and reveal their variation patterns (Sun *et al.*, 2020). In doing so, land resources can be analyzed in a systematic and reasonable manner to sufficiently balance urbanization and sustainable economic development. Therefore, extracting and analyzing the driving forces of urban expansion is also an essential issue, especially for future land use planning and urban construction (Ge and Cao, 2009). According to Chamling and Bera (2020), assessment of LULC change is highly vital in evaluating the conservation, land use planning, resource management and overall sustainable environmental management.

Urban expansion has a significant impact on environment by producing trash, resource extraction and usage, and land change due to transformed LULC patterns (Enyew, 2019). This means urban expansion is typically characterized by a lack of proper planning or a lack of putting plans into action, leaving cities with a scarcity of the essential infrastructure and services. This is certainly true of many African countries including Ethiopia (Terfa *et al.*, 2020; Gorzelak and Dąbrowska, 2021). Furthermore, land-use and land-cover (LULC) change is a result of rapid urban expansion and significant in transferring information and its impact on urban surface (Balew and Semaw, 2021). In the other way urbanization has serious effects on the livelihood of those who heavily depend on agriculture and its related activities (Nassar *et al.*, 2019).

A number of academics such as Wegedie (2018),Harris (2015), Mkhize *et al.* (2016), Zewdu (2020), Enyew (2021) and Mengistu (2016) have conducted a study on, the impact of urban expansion on displaced farmers' livelihoods and there is a variation in analysis among researchers for example gender, skills, and asset selections such as livestock and tree assets and durable home furniture’s owned by household in response to nonfarm income which are addressed the above researchers. Most of them focused only on livestock and tree assets for impact evaluation. However, livestock and tree asset are not the only focus in area of research interest. Above researchers were used qualitative and descriptive research type than econometric impact modeling.

For example, more recently, the study confined by Enyew (2021) in Debre Tabor town on the impact of urban expansion on the periphery residence. Primary and secondary data were utilized using a mixed research method with a variety of data collection technique. Even though just descriptive statistics were used in this study, no advance models were used for analysis. On the other hand according to Harris (2015) average treatment effect estimation was done on consumption, saving & assets by using Difference in Difference regression. He was found Consumption of the displaced households is increasing. However, the survey analysis with time variation was conducted one year prior to expropriation. Keeping in mind the timing of the survey was conducted within one year after expropriation may be difficult to investigate the real impact and households were permitted to harvest their land before it was taken from them, which means that treated households may still have had stores remaining.

Impact of urban expansion on per urban displaced household in the case of Dessie town studied by Teshome (2021). This study used variables such eucalyptus tree asset, total annual income, and livestock asset variable to estimate the impact of urban expansion on the displaced household. As a result, the goal of this study was to provide new insight by assessing the impact of urban expansion on livelihood assets by combining relevant indicators in each livelihood asset. Furthermore, as in other parts of the country, the urban expansion of Debark town has affected peri_urban farmers by Tame (2020). Therefore, this study was intended to address the major driver and impact of urban expansion on pre urban farmers in debark town.

1.3. Objective of the Study

1.3.1. General Objectives

The general objective of the study was to assess the drivers and impact of urban expansion on livelihood asset, of peri-urban farmers of Debark Town, Amhara National Regional State Ethiopia.

1.3.2. Specific objectives of the study

The specific objectives of this study were to:

1. Determine the extent of land use land cover change in the study area.
2. Identify the major drivers of urban expansion in the study area.
3. Assess the impacts of urban expansion on livelihood assets of peri urban farmers in the study area.

1.4. Research Questions

1. To what extent urban areas are expanded?
2. What are the major drivers of urban expansion in the study area?
3. What are the impact of urban expansion on livelihood assets of peri urban farmers in the study area?

1.5. Significance of the Study

Urbanization and urban expansion in the developing countries like Ethiopia is an issue given attention by scholars, state administration, NGOs, governments, partners and other stakeholders for various reasons. One of the reasons is the need to minimize negative impacts of urban expansion in economic, social and environmental impacts to bring mutual development and symbiotic integration of the rural and urban life. Therefore, this study is used as an input for scholars, state administration, NGOs, governments and partners. On the other hand, the major impacts of urban expansion are a shrinking amount land size like cultivated and grazing land through the development of infrastructures and various development projects. Therefore, urban land use change studies are important tools for urban or regional planners and decision makers to consider the impact of urban expansion. And also, study is served as a baseline for urban policy makers, planners, and urban designers. Furthermore, it is also served as a motivation for further researcher on this topic and provide beginning references for its findings. At the same time, it helps readers to gain knowledge and improved understanding in the issue of urban expansion and its impact on livelihood asset. In addition, it helps for town administration to develop better urban planning techniques to lessen the negative effects of urban expansion and develop positive effects of urban expansion based on facts or findings.

1.6. Scope of the Study

Spatially, the study was carried out in Debark town North Gondar Zone Amhara National Regional State of Ethiopia. The study was addressed only three peri urban namely Mikara, Zebena, and debir kebeles[1]that are found surrounding of Debark town. Thematically, this study considered situation of urban expansion on the peri urban farmers. Specifically, drivers, and its impact on livelihood asset of peri urban displaced household and extent of land use land cover change. To address impact of UE on livelihood asset of displaced peri urban community five capitals and composite /livelihood assets are considered based on sustainable livelihood framework. Each capital has their own proxy indicator that are applied in this research. This research is followed quesi_experimental and cross-sectional research design (one time data collection).

Methodologically, this study used both qualitative and quantitative approaches. Key informant interview was used to collect information on the drivers of urban expansion in the study area. It was analyzed by qualitative approach. Structured questionnaires and Focus group discussion, were also used to collect data on impact of urban expansion on livelihood assets of peri urban farmers. Factor analysis was applied to construct livelihood asset index

[1] Kebele is the lowest administrative unit nest to district in Ethiopia

and binary logistic regression was used to estimate propensity score. Finally, the impact was analyzed by propensity score matching using kernel matching Estimator. In addition, freely available satellite image was used as a primary source of data to examine the impact of UE on LULC and supervised image classification was employed for analysis.

1.7. Limitation of the study

The dynamic nature of urban expansion and the impact on the peri-urban communities was constraint. Because the definition of ‘urban’ varies from country to country, and, with periodic reclassification, can also vary within one country over time, making direct comparisons difficult. However, the study was used by searching different articles, books related with urban expansion in global context. In addition to this the respondents were not easily accessible due to their social engagement and farming activities, in this case, the data collectors were frequently revisited until the respondents are found get relevant evidence. It was also a challenge to get municipality experts for interview. Even if the researchers tolerate and manage all the challenges and adjust free time for municipality experts.

1.8. Organization of the paper

This research was organized in five chapters. Chapter one contains introduction which includes background of the study, statement of the problem, objectives of the study, research question, and significance of the study, scope and limitation of the study. Chapter two contains literature review. Under this, there are concepts and definitions of words, and different related review. Chapter three presents about methodology of the study. Under methodology there are descriptions of the study area, research design, sampling techniques, sample size, data types, and methods of data collection, methods of data analysis. Chapter four describes results and discussion and the last chapter comprises conclusion and recommendation.

CHAPTER TWO: REVIEW of RELATED LITERATURE

2.1. Operational Definition of Related Words and Concepts

Urban: Urban refers to areas characterized by denser population settlement per-unit of land, higher heterogeneity of in habitants (in terms of ethnic background, religious adhere-ship, livelihood Strategies and sources, educational levels etc., greater organizational complexities as well as higher formal social control (Bekele, 2010; Tame, 2020).

Urban expansion: is synonymous with urban sprawl, is the extension of the attentiveness of people of urban settlement to the surrounding area whose function are non-agricultural. Urban expansion is a common phenomenon in both developed and developing countries. However, in developing countries urban expansions are known with negative effect. The major effects contributing for rapid urban expansion in Ethiopia are higher natural population growth, rural to urban migration and spatial urban development (Fekadu, 2015).

Peri-urban community: is agricultural community in rural settlement pattern to which urban set elements expands (Duvernoy *et al.*, 2018).

Livelihood: A livelihood is sustainable when it can cope with and recover from stresses and shocks and maintain or enhance its capabilities and assets both now and in the future, while not undermining the natural resource base (Serrat, 2017).

The propensity score: is defined as the probability that an individual would have been allocated to a particular treatment group as a function of observed baseline characteristics (Lalani *et al.*, 2020).

2.2. Concepts of Urban Expansion

The unexpected and annoying spreading of urban development in areas adjacent to a city's boundaries is known as urban expansion (Mekuriaw and Gokcekus, 2019). It is a continuous process that is not primarily related to industrialization, but rather a combination of all fundamental factors in the process of economic growth and social change (Abebe, 2020). Rapid expansion of urbanization is passing major opportunities' and challenges in front of cities in developing countries (Mekuriaw and Gokcekus, 2019). As the urbanization rate is increasing quickly, urban centers horizontally expand and consume more land (Gashu and Gebre-Egziabher, 2018). Since demographic pressure utilized on natural resource the land has surpassed it carrying capacity, it is quite natural to call it as one of the most formidable challenges for attainment of sustainable development.

Urbanization and urban expansions are considered as a modern way of life which establishes economic growth, population growth and development in the world in general (Enyew, 2021). That means the level of urban expansion, population growth and socio-economic condition of the population is correlated in many countries (Mengistu, 2016). Rapid urban expansion and population growth, mostly in less developing countries, are expected to increase anxiety on agricultural production by expanding urban settlement in price of croplands, competing for resources, and it leads to loss of biodiversity (Gumma *et al.*, 2017). Urbanization is increasing in both developed and developing countries(Adebayo *et al.*, 2021).

However, rapid urbanization, particularly the growth of large cities, and the associated problems of unemployment, poverty, inadequate health, poor sanitation, urban slums and environmental degradation pose a formidable challenge in many developing countries (Mengistu, 2016).According to Nguyen (2018) while the rate of urbanization is the rate at which it grows, and the first urbanization was occurred in North America and Europe over two countries, from 1750 to 1950 with an increase from 10 to 52 percent urban and from 15 to 423 million urbanites. In second wave of urbanization, in the less developed regions, the number of urbanites will go from 309 million in 1950 to 3.9 billion in 2030 (UN, 2015). According to united States of the World Population (UN, 2015), report the impact of globalization on city growth patterns marks a critical difference between past and present transitions.

2.3. Trends of World Urban Expansion

The world is suffering a large-scale process of urban expansion(Angel *et al.*, 2016). In 2018, the global urban land area reached 7.97 × 105 km^2 and 55.2% of the global population exists in urban areas 1.5 times that in 1990 (Gong *et al.*, 2020). While that by 2050, the number of people who live in urban areas is expected to reach 68 (Koroso *et al.*, 2021). The average yearly increase in the urban land area reached 9.7 × 103 km^2 from 1985 to 2015 (Liu *et al.*, 2020). Thus further used an urban extension index, that is, the difference between the average annual rate of urban land and the average annual rate of urban population, to identify urban sprawl (Gao *et al.*, 2016). In terms of the changes in urban expansion speed, developing countries in Asia, Africa, and South America experienced accelerating urban expansion from

1985 to 2015, while developed countries in North America, Europe, and Australia started to slow down (Liu *et al.*, 2020; Güneralp *et al.*, 2020), revealed that the urban expansion speed in China exhibited a downward trend, while that in India exhibited an upward trend. The history of towns in Ethiopia dates back to the 4th century, when Axum, the first governmental and religious hub in the country's north, was formed. Despite the government's failure to construct a well-organized and large-scale urban settlement, it was responsible for the establishment and growth of several towns, particularly in north Ethiopia, such as Axum, Lalibela, and Gondar, which were discovered to be urban centers that served as the country's capitals in the 4th, 11th, and 17th centuries, respectively (Mamuye and Ebabu, 2021; Belay, 2014).

2.4. Urbanization in Africa

Africa is the least urbanized continent, with 43 percent of its population living in cities (UN, 2018). Nonetheless, most African cities are faced by problems related town planned and unrestrained rapid urban growth as informal settlements (Magidi and Ahmed, 2019; Fenta *et al.*, 2017; Kukkonen *et al.*, 2018; El Garouani *et al.*, 2017) become a part of the urban ecosystems (Terfa *et al.*, 2019). Natural population increase (more births than death) and migration are significant factors in the growth of cities in the developing countries (Ahlam, 2017).The non-urban areas are transformed to urban/built-up areas to cope with the demands of the growing populations.

The study done by Willcock *et al.* (2016) have revealed that Africa is suffered the most consequences of the impacts of LULCC, especially the expansion of urban/built-up areas to the loss of other land use types (agricultural and forestland (Schaber *et al.*, 2016). Urban planners make the final decisions since they are in charge of the long- and short-term development and management of cities, towns, villages, and the countryside. Thus, they should have expertise in planning and be able to identify and prevent social, economic and environmental related problems (Ashiru, 2015).

2.5. Urban expansion in Ethiopia

Most cities in Ethiopia have low density but show urban sprawl (Gebrekristos, 2021). This results in inefficient mobility within cities and has an impact on the pricing and rentals of residential and commercial buildings. (World Bank, 2018). Over the last two decades, urbanization and economic development in the country have resulted in extraordinary expansion of metropolitan boundaries, both in big and smaller cities. For example, Addis Ababa's total area rose by 51% between 2007 and 2014. (Ozlu *et al.*, 2015). During this period, the city's rate of urban expansion outpaced its population growth rate (Koroso *et al.*, 2020). The built-up area of Hawassa and Bahir Dar raised by 284% and 148%, respectively, between 2000 and 2015. (Koroso *et al.*, 2021). The alike report showed Ethiopia's total inhabitants was near 90 million in 2015 of which urban population was 18 million people (Weldearegay *et al.*, 2021). However, the urban population is predicted to be 30-35 million in 2025 and 49-55 million in 2035.

According to Admasu *et al.* (2019), farmland conversion enabled boundary extension. As a result, rural land conversion and agricultural loss have become the country's distinguishing features of urbanization. Similarly, urbanization in Ethiopia may not improve household welfare (Mezgebo and Porter, 2017), and it is narrow in generating inclusive job opportunities to all affected and is aggravating economic inequality within the society (Abay *et al.*, 2020). Because most research show that Ethiopia's urban system has become increasingly influenced by political systems and policy issues (Ermias *et al.*, 2019). Furthermore, economic growth has been witnessed, despite agricultural productivity remaining consistently low (Barrett *et al.*, 2017).

2.5.1. The impact of urban expansion on Land use and land cover change

Land use is defined as how land is utilized by people and their habitats, often with an emphasis on land's functional role in economic activities, whereas land cover is a physical feature of the Earth's surface (Mariye *et al.*, 2020). Urban growth and expansion in emerging countries cause a slew of social, environmental, and economic issues by affecting land use/cover patterns, land values, and the concentration of site usage. (Katyambo and Ngigi, 2017; Dadashpoor *et al.*, 2019; Dutta and Das, 2019; Al-Bilbisi, 2019), according to the study, immediate urbanization and a lack of appropriate intensive care and management of urban growth cause a change in the natural ecology of the area and the establishment of more disconnected land use change patterns.

Horizontal expansion and leapfrog development of the town has been risking and destroying important natural resources (Mekuriaw and Gokcekus, 2019). Rapid urban expansion and destructive exploitation of forest has caused critical economic, social and environmental losses having local, national and global implication. The literature also approves that due to rapid urban expansion primary forests in various part of the world, presently estimated 17 million to 20 million hectares of forest, are being vanished every year in developing countries (Mekuriaw and Gokcekus 2019). Urban forests are systems that comprise all forests, corpses, and individual trees located in urban and peri-urban areas; they comprise trees in parks and gardens, forests, street trees, and trees in deserted corners (Borelli *et al.*, 2017).

Recent studies like Seamans (2017)showed that urban and peri-urban forests not only have a beautiful function in the landscape but also play a vital role in alleviating the environmental impact created by urban settlements. Urban area controlling strategy for protecting peri-urban and urban metropolis forests is very important(Bonilla-Bedoya *et al.*, 2020).However, with the expansion of the city and growth of the population the forests including the native species are being uninvolved to meet their demands as well as due to land use change for different urban infrastructure and services (González-García *et al.*, 2020). In the event of urban plan, there is a possibility that urban space expands beyond plan's limit for self-organization due to population raise (Dires *et al.*, 2021). The town enlarges horizontally year to year rather than vertically and consume large tract of rural land (Mekuriaw and Gokcekus, 2019).

Population increase and the prevailing urban development practice in different urban centers of the town contributed significantly for the speedy horizontal expansion (Berhanu, 2018). And this causes the loss of the arable land, and most prominently the loss of the agricultural livelihood of the farmers in the urban fringe of cities/towns harmonizing the loss of arable land to urbanization with preserving a bio-based economy (Kotkin, 2016). Despite the extent of urban expansion and agricultural land loss in various areas of the country, there is limited understanding about the patterns and the fundamental processes of urban conversion of agricultural land at the regional scale (Jiang and Zhang, 2016).Most studies have revealed that urban landscape and land use changes lead to carbon loss (Deyong *et al.*, 2019)and that land use changes have a undesirable impact on urban net primary productivity(Pei *et al.*, 2016)**.**

Table 1: Land use/land cover classes' descriptions

No	LULC classes	Description
1	Built-up	Residential, commercial and services, recreational sites, public installation, infrastructures.
2	Cultivated lands	Areas used for crop cultivation (both annual and perennials), scattered rural settlements, some pastures and plantations around settlements. Sparsely located settlements were included here as it was difficult to separate them from agricultural lands.
3	Forest land	Areas covered with dense growth of trees that include: ever green forests, mixed forest land, deciduous forest lands. Plantations of indigenous specious of trees were also considered here.
4	Grazing land	An area with a main layer of grass and small shrubs covering from10 % to 100 %

Source: Adapted from Ahlam (2017) and Tame (2020)

2.6. Remote Sensing and GIS application in urban expansion

2.6.1. Remote Sensing and GIS

Literally Remote Sensing means obtaining evidence about an object, area or phenomenon without coming in direct contact with it (Waghmare and Suryawanshi, 2017). According to Shao *et al.* (2021), Remote sensing is particularly useful when researchers are observing to study urban expansion. For instance Zhang *et al.* (2017), identifies three ways in which expansion evaluations can be achieved through remote sensing. The field of remote sensing developed from the interpretation of aerial photographs to the examination of satellite imagery, and from local area studies to universal analyses, with advances in sensor system technologies and digital computing (Lippitt and Zhang, 2018).

Obviously, satellite data, remote sensing, and Geographic Information Systems (GIS) are the most applicable technologies for meeting these needs in the most effective way for urban expansion assessment (Al-Bilbisi, 2017). There are different types of satellite images used to identify horizontal expansion of urban areas. There are many scholars about the application of Geographic Information System and Remote Sensing to measure urban expansion through time (Elhamdouni *et al.*, 2021). However, the use of this technology in some parts of sub-Saharan Africa is still in its beginning because of its high cost and limited accessibility (Kantakumar *et al.*, 2016). The main encounters are the lack of high resolution satellite images mainly Sub-Saharan Africa (Bihamta *et al.*, 2015; Zhang and Su, 2016). Landsat and

Sentinel are freely available satellite images comparatively with the better resolution a possible to investigate urban expansion (Zhao *et al.*, 2015).

2.7. Drivers of Urban Expansion

Various theoretical descriptions tried to see the drivers and consequences of urban expansion mostly on peri-urban agricultural communities. This study was aided from (Briassoulis, 2000a) three theories of urban expansion. Population growth theory argued that an increase in urban population either in natural growth or in rural to urban migration detonates to the adjacent of city. The economic growth theory emphases on the expansion of economic base such as per capita income and employment rate increases request of new housing places and relater infrastructures. In addition, the creations of new industries at urban periphery fired farmers from their land possession. The third reason is government development policies which put emphasis on government's action to use constricting land policies for urban development.

According to this outlook, there may be dissimilarities in regulating development and land use strategies which consequently delay the economic and social phenomenon of urban edge farming communities (Briassoulis, 2000a). Moreover, the nonappearance of proper planning policies and failure to apply such policies are source for unlimited urban expansion that distract zoning structures (residential, commercial industrial, institutional and other land uses) and finally threats urban surrounding agricultural peoples of developing countries. On the other hand, the sociological urban expansion theory emphasized the importance of human agency, social relation, social networks and socio cultural changes in bringing about special, political, economic and other changes (Briassoulis, 2000b; Alemineh, 2019).

By standing from those the above theory major contributing to rapid urban expansion in Ethiopia are higher natural population growth, rural to urban migration and spatial urban development (Berhanu, 2018). The forces or factors include population growth, migration, increasing housing demand, fragmented metropolitan governments, and patterns of infrastructure investments, and the construction of roads (Fekadu, 2015). The causes to rapid population growth in urban residents is improved medicine, vaccination and health service access and in-migration due to pulling factors like employment opportunity, provision of social infrastructure, transportation facility aggravate the expansion of Ethiopian urban centers (Akirso, 2021; Mekuriaw and Gokcekus, 2019).

Additionally search for higher paying employment, better quality of life in terms of health and education, greater diversity of entertainment and lifestyle are grouped as pull factors (Muluwork, 2014). On the other hand Tessema (2017) noticed increasing the demand for the residential house of urban dwellers also another drivers of urban expansion. The Ministry of Urban Development and Housing MoUDH (2015), reported that in Amhara regional state there are more than 150,000 people demanded peri urban land for residential purpose.

2.8. Empirical literature review on Impacts of Urban Expansion

Researchers and institutions have tried to assess the impacts of urban expansion at the household or community levels in the context of livelihood and geospatial analysis in different part of the world. Several studies such as (Mkhize *et al.*, 2016) was conducted the study on the impact of urban growth on agricultural and rural non-farm growth in Kenya and the authors used urban gravity variable that reflects the economic activity of a city to estimate the impact of urban expansion. They found that urban growth also has a large effect on education, followed by commercialization and then on the use of modern varieties. These in turn have a strong impact on agricultural and rural non-farm income.

Similarly the study conducted by Kukkonen *et al.* (2018) was done on urban expansion in Zanzibar City, Tanzania, Analyzing quantity, spatial patterns and effects of alternative planning approaches. They used urban growth prediction models which provide tools for generating such information by predicting future urban expansion patterns and allowing testing of alternative planning scenarios. Based on the results, the urban area of Zanzibar City expanded by 40% from 2004 to 2013. Finally, they found spatial patterns of expansion were largely driven by the already existing building pattern and land-use change.

Al-Bilbisi (2019) conducted a study aimed at assessing, monitoring, and mapping urban land cover using multi temporal Landsat satellite images. Supervised classification technique followed by the post classification comparison change detection approach was used to analyze images. The result indicates that urban area increases were significantly higher in the first 10 years of the study period (i.e., from 1987 to 1997), during which the average annual rate of increase reached 3.33%, while it was 2.04% for the last two decades of the study period (i.e., from 1997 to 2017). Most of the authors those are out of our country used GIS and remote sensing or urban expansion evaluation.

When we come to our country urban expansion in Ethiopian context has been assessed with empirical literatures in regional urban areas. In the case of our county so many authors for instance Fikadu (2015), Mengistu (2016), Tessema (2017), Inki (2018), Mekuriaw and Gokcekus (2019), Abebe (2020), Teshome (2021) and Weldearegay *et al.* (2021), have conducted similar studies on assessing the impact of urban expansion. The summary of those studies is indicated as follows.

Horizontal Urban Expansion and Livelihood Adjustment Problem among Ex-Farmers in the Kebeles Surrounding Jimma Town was studied by (Mengistu, 2016). In this research the author used qualitative research approach and this research result showed that livelihood of ex-peri-urban community has been jeopardized following the urban expansion induced displacement. In the same way by Tessema (2017), and Inki (2018) conducted similar study in different place and they used more mixed research method. They found only adverse impact of horizontal urban expansion without briefing its extent quantitatively on the livelihood of peri-urban.

Additionally, Mekuriaw and Gokcekus (2019) undertook a study to investigate the major consequences of urban expansion in urban areas using qualitative approach. Their result revealed that the trend of urban expansion increases from time to time mostly forest and cultivated land have been changed into different urban development uses such as residential, industrial, and commercial and other various institutions. And also, they documented that urban expansion and associated activities degrade environmental resource, such as surface water and growth wave, air quality and landscape aesthetic and destroy wild life habitats. Moreover, Abebe (2020) assessed the impact of urban sprawl on farming communities over the last 30 years in Dessie town.

This study used Remote Sensing and Geographic Information system for quantifying urban land use and land cover change dynamics and socio-economic data was used to analyze the impacts and factors of urban spread on prei urban farming communities and he found urban expansion program was consumed the peri urban agricultural land for different urban land purpose. Furthermore, Teshome (2021) carried out a study to examine the impact of urban expansion on the displaced households' livelihood in Dessie City. Logistic regression model with propensity score matching was applied estimate the impact of urban expansion on farmer's livelihood. Teshome (2021) used four characteristics like livestock holding, eucalyptus tree assets, durable asset, total income and total expenditure used as an outcome variable. As this result revealed that livelihood of the peri urban areas was negatively affected by urban expansion. In the contrary research confined by Weldearegay *et al.* (2021) examines the consequences of urban expansion on peri-urban farmers' poverty. Inferential statistics, propensity score matching (PSM), was applied to estimate the impact of urban expansion on peri urban displaced farmers. The outcome of this study shows that assessment estimation showed the prevalence of poverty was higher by 5% than non-displaced household.

Livelihood assets

The livelihood assets in the framework are major elements to analyses dynamic processes of socio-economic transformation in peri urban area (Arif *et al.*, 2019). Livelihood assets are not only resources that people use; they are also what give people the capability to act (Banu and Fazal, 2017).

Human Capital: Includes investments in education, health, and the nutrition of individuals. Labor is a critical asset linked to investments in human capital, health status determines people's capacity to work, and skill or experience in something and education determine the returns from their labor (Bawono, 2021).

Natural Capital: Includes the stocks of environmentally provided assets such as soil, atmosphere, forests, minerals, water, and wetlands (Woźniak *et al.*, 2022). In rural communities, land is a critical productive asset for the poor; in urban areas, land for shelter is also a critical productive asset.

Financial Capital: The financial resources available to people, such as savings and supplies of credit(Pomeroy *et al.*, 2020).

Physical Capital (also known as produced or man-made capital): Comprises the stock of plant, equipment, infrastructure, and other productive resources owned by individuals, the business sector, or the country itself (Banu and Fazal, 2017). On the other hand Physical capital refers to the basic material infrastructures needed for any household to have a decent life (Arif *et al.*, 2019; Hulme and McKay, 2013).However, in the present study, the physical capital focus on the village-level infrastructural facilities like the type of housing material, access to blacktop road, availability of market, and drinking facility.

Social capital: An intangible asset is defined as the rules, norms, obligations, reciprocity, and trust embedded in social relations, social structures, and societies' institutional arrangements, which enable its members to achieve their individual and community objectives(Moser, 2021). Social capital is embedded in social institutions at the micro institutional level of communities and households as well as referring to the rules and regulations governing formalized institutions in the marketplace, the political system, and civil society (Arif *et al.*, 2019).

2.8.1. Peri-urban community and urban expansion

Some peri-urban individuals and households benefit from urban growth by taking advantage of many livelihood chances created by the phenomenon, others are harmfully impacted through the loss of livelihoods (Korah *et al.*, 2018). According to Oduro *et al.* (2015) in most developing country the process of urban expansion disturbs the peri urban farmers' livelihoods (Gwan and Kimengsi, 2020). Urbanization also inspires farmers to invest in farm technologies in response to the growing of urban markets, leading to the generation of higher return (Vandercasteelen *et al.*, 2018) which in turn allows farmers to join the middle-income group (Diao *et al.*, 2019).

The difference mechanisms for which weaker subjects experiencing the consequences of environmental deprivation produced by the stronger ones (Kashwan, 2017) are particularly significant in case of land consumption, where the joint effect of economic, social and institutional political factors determines a boost in the housing sector to the detriment of social interest (Bimonte and Stabile, 2017). Agegnehu *et al.* (2016) and Nguyen *et al.* (2017) stated that many households living on the borders of Addis Ababa and other major cities in the country were mandatory to dispose their farmland.

Maintainable urbanization cannot be realized without finding the right balance between urban growth and urban expansion (Koroso *et al.*, 2021). Understanding how fast urban areas expand and urban population change is critical to grasp the evolution of urban settlements (Lei *et al.*, 2021). This, for instance, helps us know how fast peri-urban areas (farmland, forest and protected areas) are being consumed by expanding cities (UN-Habitat, 2018). It might also give us a clue about the cities' land use efficiency. Efficient urban land use is essential to attain 'sustainable urban growth and coordinate economic development and environmental security (Han *et al.*, 2020). The influences of urban expansion are not restricted by city borders. Earlier studies have found that urban actions and urban expansion could suffer heat (Manoli *et al.*, 2019; Du *et al.*, 2015; Zhu *et al.*, 2020) acid which are not forced by city boundaries and can reach up to 10–60 km away from the boundary of current built-up land.

2.9. Impact Evaluation approach

Impact evaluation is the systematic identification of these positive or negative effects, which are intended or not, brought by a given development activity on households and environment (Kasa *et al.*, 2011; Teshome, 2021). The term "impact" describes the extensive and long-lasting economic, social, and environmental effects of an intervention that have an impact on individual or organizational level changes in cognition and behavior that are either anticipated or unexpected, desired or undesirable, direct or indirect, positive or negative (Leeuw and Vaessen, 2009; Frölich and Sperlich, 2019). Urbanization's effects on peri-urban environments and livelihoods can be assessed similarly to other development intervention effects. With this concept in mind, evaluation literatures can be seen into two broad categories: environmental impact assessment, particularly land use and land cover dynamics, and impact of urbanization-induced displacement on peri-urban livelihoods (Kasa *et al.*, 2011).

In this case this research included land use land cover and urbanization induced displacement on peri urban farmer's livelihood. A good evaluation of an intervention is to ask what would happen in the absence of intervention and what would have been the welfare level of particular community or group, households and individuals with intervention. Evaluation involves an investigation of cause and effect in order to identify impact that can be traced back to intervention. The consequence of intervention from other factors is facilitated if control groups are introduced. Control group is a group when a group is exposed to usual condition and consist a comparator group of individuals who did not receive the interventions. But groups having similar characteristics are these receiving the intervention are called treatment group.

Random experiment method of impact evaluation When the group is exposed to some unusual or special condition, it is termed an experimental group. The process of investigating the truth of a statistical hypothesis is relating to some research problem is known as an experiment (Teshome, 2021). Experimental designs, also known as randomization and generally considered the most robust of the evaluation methods.

Non- experimental method of impact evaluation Economists and econometricians have been studying statistical methods for program evaluation with evaluations and types of data should be collected. None experimental estimate in a single post treatment cross section to be correct that need the outcome variable be the same for the absence of participants and none participants in the absence of treatment (Robert, 1991) as cited by Teshome (2021).

Quasi experimental method of impact evaluation: Quasi-experiments are defined as experiments that do not have random assignment but do involve manipulation of the independent variable. It includes a wide range of nonrandomized or partially randomized repost intervention studies (Handley *et al.*, 2018). Quasi experimental methods are alternatives which includes propensity score matching methods, double difference methods, instrumental variable methods and reflexive comparisons (Teshome, 2021).

That means Quasi experimental methods used the treatment and comparison groups are usually selected after the intervention by using none random method. According to Harris (2015) quasi experimental design that is difference in difference method to identify a comparison group as similar as possible to the treatment group in terms of base line or pre intervention characteristics. Whereas in the absence of baseline data there are also different techniques for creating a valid comparing group example propensity score matching by Kasa *et al.* (2011)and Teshome (2021). Similarly, this study was done without baseline data by using propensity score matching impact evaluation method.

2.10. Conceptual frame work of the study

The conceptual framework of this study Figure 1 was developed from the related literature, such as Banu and Fazal (2017), Berhanu (2018) and Alemineh (2019). The study used increase natural population, rural to urban migration and economic development as driving factor of urban expansion. The dependent variables in this study are urban expansion induced displacement of peri urban farmers. Land use land cover and five capitals with composite asset are impact observed factor in this study. Therefore, the study tried to construct a cyclical relationship of each objective.

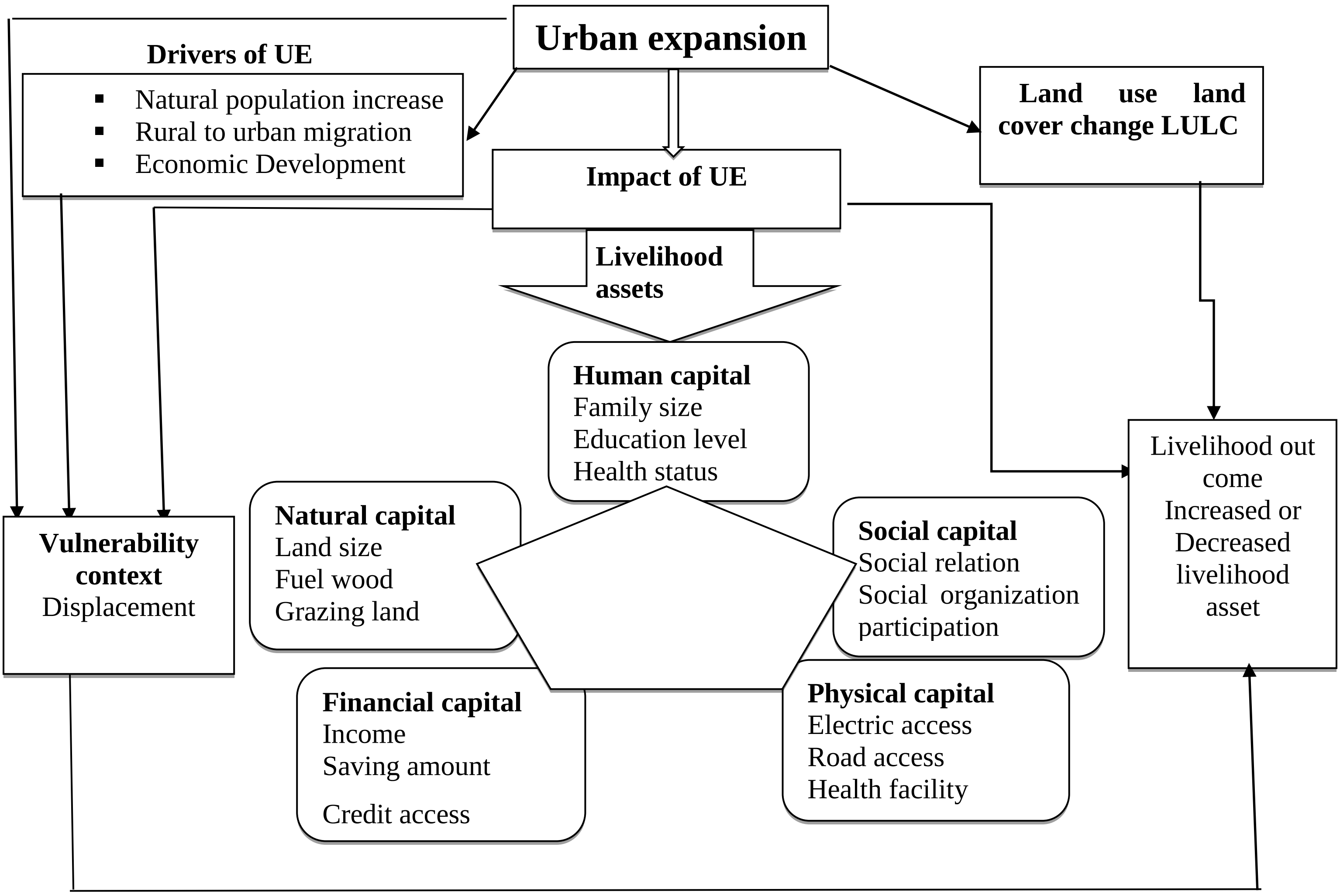


Figure 1: Conceptual Framework of the Study.

Source: adapted from Banu and Fazal (2017) with some modification by authors

CHAPTER THREE: RESEARCH METHODOLOGY

3.1. Description of the Study area

The study area is located in Debark town in Amhara National Regional State (ANRS), Northwest Ethiopia. It is found in debark woreda and it is center of the Semen Gondar Zone. The woreda is bordered in the south by Dabat, in the west by Tsegeda, in the northwest by the Tigray Region, in the north by Adirkay, and in the east by Jana Mora (DWAO, 2022). This woreda is crossed by the Lemalmo Mountains, which form the western near to the semen mountain and Rivers include the Zarima. It is to be found 843 km away from Addis Ababa to northwest. Geographically, the study site lies at 37 ^{0} 40”0:E- 38^{0} '10’0”E longitudes and 12^{0}’ “55” ‘0’ N- 13^{0} “25” ‘0”N latitude and at an altitude ranging from 2750 to2870 meters above sea level (Tame, 2020).

Regarding to climatic condition is large portion of the area receives high annual rainfall ranging from 1000 to 2000 mm in the main and short rainy seasons. The mean annual temperature ranges from -8.950C to 21.140C. The agro ecology the study area is characterized by cool moist mid highlands and tepid moist mid highlands (DWAO, 2022).Study area has an area coverage of 10033 ha with 4 major soil types Chromic vertisols 406.26 ha (7.9 %), dystric cambisols 337.51 ha (6.56 %), dystric nitisols 3873.31 ha (75.3%), and no data 526.79 ha, (10.24%). The main modes of transport of the town are, Taxis, Bajaj (Tri wheel vehicle), bicycles and automobile.

The town serves as social, economic and political center for north Gondar. Administratively, the town is chartered as having two layers of government: city administration and rural kebele administration under woreda administration there are 32 kebele. Based on the 2007 national census conducted by the Central Statistical Agency of Ethiopia (CSA), this woreda has a total population of 159,193 an increase of 31.83% over the 1994 census, of whom 80,274 are men and 78,919 women; 20,839 or 13.09% are urban inhabitants. Debark has a population density of 108.95, which is greater than the Zone average of 63.76 persons per square kilometer (0.39 sq. mi). according to Debark woreda administration office currently the total population of the area is estimated to 198567(DWAO, 2022).

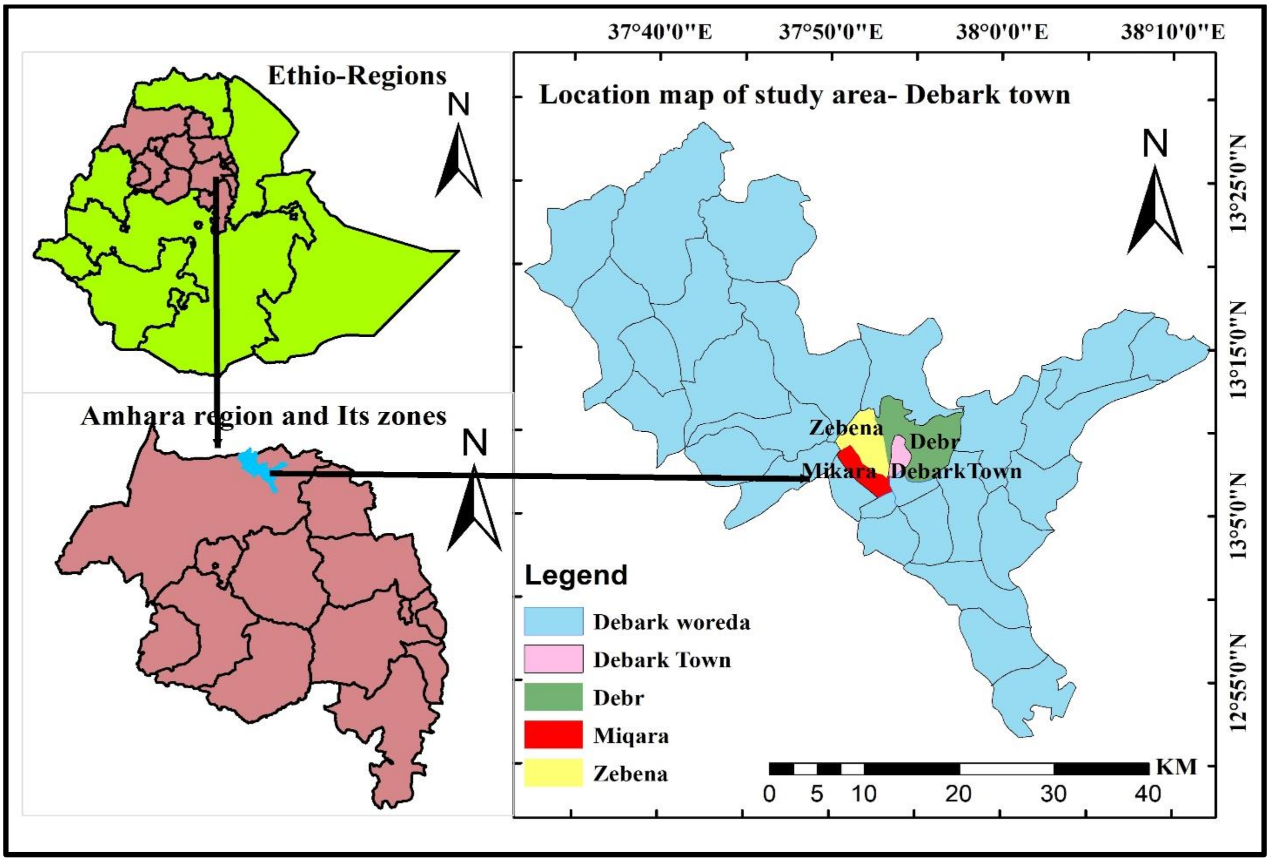


Figure 2: Geographic location of the study area.

Source: Authors production using Ethio-Gis spatial data, (2022)

3.2. Research Design

This study is quesi_experimental research with a cross-sectional research design to make intensive investigation. Both qualitative and quantitative research methods were applied. The study employed household survey using sequential data collection procedures by which the quantitative data was collected through household survey and then the qualitative data was gathered using focus group discussions (FGDs), and in-depth interview of key informants. The purpose of the study is to describe a population or a subgroup within the population with respect to an outcome and a set of situations of urban expansion problems of on displaced peri urban farmers. In this research household is a unit of analysis. The study used samples of displaced household as treatment group and non-non_displaced households as control group.

3.3. Data type and source

The study was revealed based on both primary and secondary data. Primary data gathered from both displaced and non-displaced peri urban farmers household, Key informant's community elders and satellite image from United States geological survey (USGS) the data source for this study. On the other hand, secondary data was collected from Debark woreda agricultural and land administration office, Debark town municipality office and north Gondar zone vital evnt office are used as a source of secondary data of this research. Furthermore, information related to the total number land holder household and displaced household specifically in 2009 that reside in the selected kebele, general information about the infrastructure and facility were collected from those office.

3.4. Sample Size and sampling technique

The multi stage sampling method was employed for this research. At the first stage purposive sampling technique was used to select study area based on the context of urban expansion extent. The study area is classified structurally 3 kebeles and 5peri urban kebeles were near to town and they were affected by urban expansion. So, in the second stage from the total of five peri-urban kebeles three kebeles were selected randomly. In the final stage, the sample households from both urban induced displaced and non-displaced respondents were selected by using random sampling technique operational to the specific number of households from the sampling kebeles. Based on the Debark woreda land administration office the total land holder farmers in three kebele were 952.

However, from the displaced group only in the year 2009 displaces household was used in order to balance equal time duration between the respondent and by considering five years' time interval is better to know the real change of livelihood asset. As a result, 139 households selected from the treatment group and 143 households from comparison group take its proportions of each kebele. A total of 282 samples were selected by using probability sampling techniques.

Representative samples from the households of selected kebeles was based on scientific formula at required degree of confidence. The sample size was determined by considering the 95% confidence level, the degree of variability and level of precision. The formula used to calculate and determine the sample According to Yamane (1967),sample size is:

$$n = \frac{N}{1+N(e^2)} \qquad n = \frac{952}{1+952(0.05^2)} = 282$$

Where n = sample size, N= size of population, and e =desired significance level

The source list is frequently referred to as the "sampling frame" from which the sample is taken. Such a list would be complete, accurate, trustworthy, and pertinent. This list would be used as the sample frame to identify respondents. Following the collection of farmers using the sampling frame, samples are drawn at random from the whole population using simple random sampling, with each sample being chosen with an equal chance according to the needed sample size. While other qualitative data was obtained using non-probability sampling methods by choosing individuals from the population in various non-random sampling procedures to achieve focus group discussions and KII.

Table 2: Sample Size Distributions of Sample Kebeles

Name of the kebelle	Total displaced household	Total of non-displaced household	Proportion of displaced Prop=282/952=0.0869	Proportion of non-displaced Prop=282/952=0.296
Zebena	120	180	120*0.296=36	180*0.296=53
Mikara	180	172	180*0.296=53	172*0.296=51
Debr	168	132	168*0.296=50	132*0.296=39
Total	468	484	139	143

Source: Debark woreda Land Administration Office (2022)

3.5. Methods of data collection

Structured questionnaire, key informant interview, focus group discussion, field observation and remote sensing were a major data collection method in this research.

Field observation and remote sensing data collection tools were applied to address the land use land cover change analysis. In field observation X, Y coordinate point was recorded with the help of GPS. While the land use land cover change assessment of the study area was conducted using Landsat imagery for the two years of 2001, 2013 and sentinel2 for 2021 to cover a period of 30 Years image. Landsat imagery was selected because Landsat has the longest running imagery acquisition dating back to 1972.

Hence, it can provide long term mapping of land use changes and sentinel is recent imagery accusation it was launched in 2015 it is advanced by its higher resolution sensor. The reason to select the year 2001 was during that time there was the starting time of starting housing association of urban dwellers house demanders. The year 2013 was selected to use landsat8 imagery because Landsat5 was used for 2001 and Landsat seven is not working so in order to not use again Landsat5. The images were downloading from the USGS (United States geological survey). Upon downloading, the images the datum was projected to WGS 1984 and referenced to the Universal Transverse Mercator (UTM) Zone 37 North.

Table 3: Characteristics of the satellite imagery utilized

Year	Satellite data type	Sensor	Date of acquisition	Resolution	Source
2001	Landsat5	TM	2001/1/15	30*30	USGS
2013	Landsat8	OLI	2013/1/21	30*30	USGS
2021	Sentinel2	MSI	2021/1/5	10*10	USGS

Source: Computed by the researcher during downloading the image

Key informants were also used to collect primary data. Key informant interviews were held with 6 key informants. Those key informants were selected purposively since they are expected to have deep knowledge about the subject matter interview guides about drivers of urban expansion. The interview was focused on issues related to major drivers of urban expansion in the study area.

Household survey questionnaire was employed to collect the data about the impact of urban expansion from both displaced and non-displaced peri urban farmers household. The questionnaire was primarily prepared in English languages and then translated into Amharic language [2]because the selected respondent for this research was Amharic speaker. Then the data collectors were introduced and clarify the objective of the study to the household head. Finally, it was translated to English language to enter to SPSS for analysis. The items of questionnaire were both closed-ended and open-ended.

The questionnaire was directed to gathered information about the household demographic and social characteristics and the situation of livelihood asset specifically five capitals. For instance, in natural capital fire wood, land size water resource for irrigation and grazing land, in financial capital, occupation, accesses to credit service, total income of the household, total expenditure, livestock, eucalyptus tree, saving amount in the household, loan amount in the household. In social capital social relation, social norm and social organization participation, in physical capital water access, electric power access, road access, and distance to the market and health center access were the proxy variables that were collected from each household.

Therefore, questionnaire was major data collection method to address the impact of urban expansion in the study area. While, focus group discussion was employed in each sampled

[2] Amharic is a mother tongue language for respondent.

kebeles within 8 to 12 members. The data gathered from focus group discussion was used as a supportive and triangulation purposes.

3.6. Data Analysis

Both qualitative and quantitative data analysis method was employed in this study.

3.6.1. Land use land cover change.

In order to address extent of urban expansion and its impact on land use land cover, remote sensing satellite image was used as a raw data as mentioned above in the data collection section. Then ERDASS 2015 and arc GIS were used for managed data processing. image classification method was Maximum likelihood classifier (MLC) appears to be the most commonly used and accurate algorithm for supervised classification (Kumar *et al.*, 2021). In their raw form, as received from imaging sensors mounted on satellite platforms some of the distortions are radiometric distortions, geometric distortion and noise or atmospheric effect. Such errors can be corrected by using pre-processing techniques like radiometric correction, geometric correction and noise removal or atmospheric corrections, which should be applied in raw imageries.

The images used in this study had some distortions like mentioned above. Therefore, these images were perfectly corrected by applying the necessary pre-processing techniques. In supervised classification, the user selects representative samples for each land cover class in the digital image, which is called training sets. Pixels located within these areas, called the training samples, are used to guide the classification algorithm by assigning specific spectral values to a specific class. In addition to this user accuracy assessment, producer and over all accuracy was used for more accuracy assessment. Kappa coefficient is another method for accuracy assessment having a number of advantages over other methods and it is powerful method for comparing the differences between diverse error matrices (Kranjčić *et al.*, 2019) .

Accuracy assessment: In order to assess the quality of the classification process, it is common to compare the classification to geographical data that are presumed to be accurate. The data are typically computed using a set of reference pixels and ground truth data to cross-check the correctness.

Usersaccuracy = Rt/Rs*100---(1)

Where Rt= correctly classified sample locations of the reference data or row and Rs = total number of sample locations of the row.

Producer accuracy C_i/c_t*100--- (2)

Where Ci = correctly classified sample locations of the reference data or column and Ct = total number of sample locations of the column.

Over all accuracy=$\frac{\Sigma xii}{N}*100$-- (3)

Where, *xii* =Number of correctly classified pixels, or the diagonal value and *N*= entire number of pixels in the matrix. Therefore, the confusion matrix method was used to estimate the accuracy of the years 2021 supervised land use/land cover image classification of the study area.

The kappa value is a measure of the agreement between classification and reference data with the agreement due to chance removed (Jensen, 2005). The kappa values, ranging from 0 to 1, divided into 3 groups: 1) those greater than 0.80 represented strong agreement between the classification and reference data; 2) those between 0.40 and 0.80 represented moderate agreement; and 3) those less than 0.40 represented poor agreement. The Kappa coefficient lies typically on a scale between 0 and 1, where the latter indicates complete agreement, and is often multiplied by 100 to give a percentage measure of classification accuracy. So, the kappa value of the classification accuracy computation was employed in this study.

Kappa coefficient is computed as follows (Jensen, 2005) as cited by(Tame, 2020).

$K = \frac{Ts*Tcs-\Sigma(Ct+Rt)}{Ts2-\Sigma(Ct+Rt)}$-- **(4)**

Where:

Ts is the number of total samples in the matrix

Tcs is the number of corrected samples in the matrix

Ct and *Rt* are column totals and row total in the matrix.

E is summation.

LULC change detection analysis: The major LU/LC types in the namely built up, cultivated, forest and grazing land were computed. For land use change detection, forestland is the combination of natural forest and plantation forest similarly grassland and grazing land were group together as grazing land use class. Because they have similar reflectance. Three satellite image dates were employed in this study to analyze the change's temporal distribution. The analysis stage involved computing the total area and its percentage from each date after performing digital picture interpretation of the land cover for each year. Then, for the years 2001, 2013, and 2021, the yearly rate of change in area by hectare and % were determined. The rate of changes in time also computed using equation (Mishra, 2018) as cited by (Tame, 2020).

$$\mathbf{r = q_2 - q_1 / t} \qquad \mathbf{(5)}$$

Were,

- r = Rate of Change
- Q2= Recent year land cover in ha
- Q1= Initial Year land cover in ha and
- t= Interval year between Initial year and Recent

In this section the general methods implemented, applied techniques and the data inputs used throughout this study were explained briefly in the designed in the following flow chart.

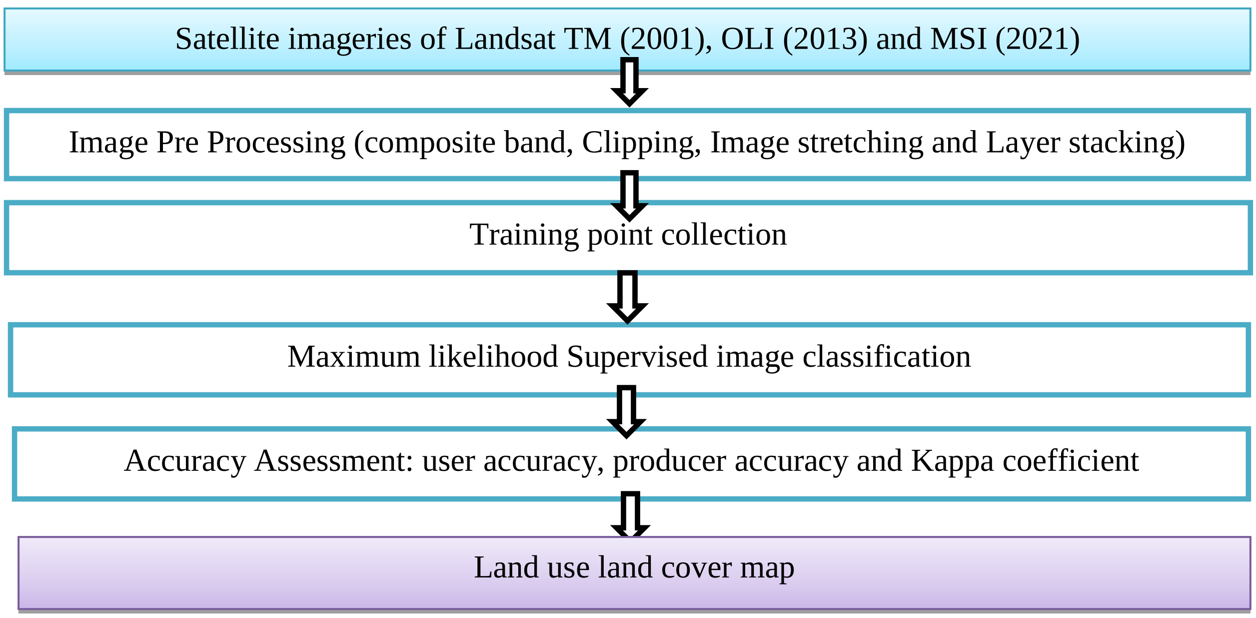


Figure 3: Flow chart showing the procedure followed for land use land cover change.

3.6.2. The drivers of urban expansion

Qualitative analysis method was applied to assess the drivers of urban expansion. The data gathered from KII and FGD were analyzed by thematic analysis in summary and narration form.

3.6.3. Impact of urban expansion on livelihood assets of displaced farmers

Quantitative analysis such as descriptive statistics, factor analysis and econometric model were applied to assess the impact of urban expansion on livelihood assets of displaced peri urban farmers.

Descriptive Statistics

Descriptive statistics such as percentages, standard deviations, mean values, mean differences, frequencies, t-test and chi-square analysis were used in order to work out for the comparison of issues socio demographic characteristic of the respondents between displaced and non-displaced households in the study area based on observed covariates.

Factor analysis

Factor analysis is used to regroup variables into a limited set of clusters based on shared variance and it is easy to create index (Yong and Pearce, 2013). Index can be constructed in different methods for instance, principal component analysis is another method of index constructing way. However, there is little difference between them. The distinction between PCA and factor analysis is that PCA is primarily a technique for reducing the dimensionality of a set of variables, whereas factor analysis assumes the existence of some causal model (Yong and Pearce, 2013). PCA is generally considered exploratory and factor analysis preferred when researchers have some hypotheses about relationships between the variables (Michelson *et al.*, 2013).

For that reason, the study used factor analysis for constructing capital index. In this study, the data are standardized by means of dispersion normalization (i.e., 0–1 standardization) so that the result falls in the range of [0, 1 or 1to100]. According to Liu *et al.* (2018) its linear transformation function is written as: $Factor\ index = \frac{Xi-min}{max-min}$

Before proceeding with any analysis, the entire prerequisite suggested for factor analysis and its family model are checked to examine the variable's factor ability. Among these requirements are Kaiser Meyer-Olkin (KMO) sampling adequacy measures, the Bartlett Test of Sphericity, and the presence of Multicollinearity or not were the basic requirement. The KMO sampling adequacy measure assists in determining whether the surveyed sample is sufficient to run factor analysis and its family or not.

According to Kaiser (1960), as cited in Gambo Boukary *et al.* (2016), if the KMO value is greater than 0.5, factor analysis can be performed. Bartlett Test of Sphericity helps to check if the correlation matrix (R-matrix) resembles the identity matrix. Factor analysis would be valueless with an identity matrix. This means, it helps to see whether the variable in factor analysis is correlated badly or not. The presence of Multicollinearity is tested using the determinant of the R_Matrix (correlation coefficients matrix of the variables in the model). According to Field (2009), Atara *et al.* (2020), the determinant of R-matrix for a good model is expected to be greater than 0.00001. This rule state that an eigenvalue greater than one should be retained for choosing a more useful factor. Therefore, human, natural, financial, physical, social, livelihood asset was constructed based on this situation by applying Factor analysis using principal factors extraction was performed with STATA/SE 14.

3.6.4. Choice of Econometric Model

Logistic regression model

In this research binary logistic regression model was used to estimate propensity score. The logit model was chosen over the linear probability model because it is necessary to assess the likelihood of displacement vs. non-displacement and because predictions made when the response variable is skewed fall beyond the [0 and 1] bounds of probabilities (Caliendo and Kopeinig, 2008). For this research purpose displacement implies urban induced displaced farmers and non-displacement implies non-displaced farmers due to urban expansion.

According to the logistic distribution function for determining the determinant factors of urban induced displaced households could be specified as:

$$P\ (i)\ = (\mathrm{i}) = \frac{1}{1+\mathrm{e}^{-\mathrm{z(i)}}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \ (1)$$

Where P (i) is a probability of household being displaced for I the household and Z (i) is a function of many explanatory variables (Xi) such as observable demographic characteristics. $Z(i)\ =\ 0+\ 1\ x1+\ 2x2+\cdots\ldots\ldots+nxn\ +\ \varepsilon i \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.(2)$ where β_0 is intercept and $\beta_1 \ldots.\ \beta_n$ are unknown slopes /parameter / which are estimated using maximum likelihood, $X_1 \ldots..X_n$ indicates characteristics and εi implies an error term. The probability of households belongs to non-displacement is $1_{\mathrm{P_i}}) = \frac{1}{1+\mathrm{e}^{\mathrm{z(i)}}} \ldots.\ldots\ldots.(3)$

Therefore$\left(\frac{pi}{1-pi}\ \right) = \frac{1+\mathrm{e}^{\mathrm{z(i)}}}{1+\mathrm{e}^{-\mathrm{z(i)}}} = \ \mathrm{e}^{\mathrm{z(i)}}\Big) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.(4)$

$$\text{And}\left(\frac{pi}{1-pi}\right) = \frac{1+e^{z(i)}}{1+e^{-z(i)}} = \frac{\frac{e^{X\beta}}{1+e^{X\beta}}}{1-\frac{e^{X\beta}}{1+e^{X\beta}}} = e^{X'\beta} = e^{\beta 0} + \sum_{i=1}^{n} \beta iXi \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (5)$$

usually, the logit model is written as log-odds ratio. Taking the natural logarithms of the odds ratio of equation (5) was result in what is known as the logit model as indicated as:

$$Ln\left(\frac{pi}{1-pi}\right) = Ln\,[e^{\beta 0} + \sum_{i=1}^{n} \beta iXi] = Z_{(i)}(\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (6)$$

If the disturbance term is taken into account the logit model becomes:-

$$Zi = \beta 0 + \sum \beta iXi + ui \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (7)$$

If a logistic distribution (mean of 0 &1variance of) is considered, we get what is called the logit model.

3.6.5. Test procedure of the model

Model Goodness of fit test: is whether the model fit to this type of data or not. In order to check goodness of fit test classification Tables, the Hosmer and Lemeshow test, and Pearson chi-square test were used.

Multicollinearity test: Since corrective actions can be taken by eliminating a variable, it was possible to rectify specification bias and variable transformation in this study. Multicollinearity among dummy explanatory variables was examined using contingency coefficient and VIF for continuous variables. However, no explanatory variable was removed from the estimated model because the VIF and dependent coefficient analyses showed no significant Multicollinearity issues

Heteroscedasticity test: It can also arise as a result of the presence of outliers, (either very small or very large) in relation to the observations in the sample; constant variance is likely to change. If important variables are omitted from the model, due to skewness in the distribution of one or more repressors included in the model and can also arise because of incorrect data transformation, members may be of different sizes. However, in this research some of the informal and formal methods were used for detecting heteroscedasticity fulfilled. Example the sample size fairly large and much enough variables were used. Moreover, robustness is fairly used to detect the problem.

3.6.6. Econometric analysis using propensity score matching method

According to (Caliendo and Kopeinig, 2008)there are practical steps in implementing PSM. Those are estimation of the propensity scores, choosing a matching algorism, checking on common support, balancing test, and impact estimation after logistic regression results. Based on this, the analysis was implemented in detailed as follows.

Estimating the propensity score (PS)

Propensity score (PS) is the probability of participating in a program given observed characteristics X. Thus, matching procedures based on this balancing score is known as Propensity score matching. Caliendo and Kopeinig (2008) was stated that of binary treatment D_i implies individuals i receive for treated equals one and zero for controlled. The potential outcomes are $W_{i\,/}$ (D_i) for each individual i, where i=1….N, N denotes total population.
In treatment effect of individual "i" can be written as

$$Di \ = \ Wi \ (1) - \ Wi \ (0) \ldots\ldots\ldots\ldots\ldots.\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.. \ (1)$$

Here the fundamental problem arises because only one of the potential out comes is observed for each individual. Hence estimating the individual treatment effect D_i is not possible and then need to concentrate on population Average Treatment Effect (ATE).
The parameter interest i that received the most attention in evaluation literature is the Average Treatment on the Treated (ATT) which is defined as: -

$$TATT \ = \ E\left[\frac{T}{D} = 1\right] = \ E\left[W\frac{1}{D} = 1\right] - \ E\left[W\frac{0}{D} = 1\right] \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. (2)$$

As the counter factual mean for those being displaced E [W (0)/D =1] is not observed since it has to choose a proper substitute for it in order to estimate ATT. Using the mean outcome of non-displaced individuals
E [W (0)/D=1.ATT can be:

$$E\left[W\frac{1}{D} = 1\right] - E\left[W\frac{0}{D} = 0\right] = \text{'I}ATT + E\left[W\frac{0}{D} = 1\right] - E\left[W\frac{0}{D} = 0\right] \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. (3)$$

The difference between the left and 'IATT is the so-called self-selection bias. Thus, the true parameter 'IATT is only identified if $E \ \left[W\frac{0}{D} = 1\right] - \ E \ \left[W\frac{0}{D} = 0\right] = 0 \ldots\ldots\ldots\ldots\ldots\ldots\ldots (4)$

That means ATT = ′IATT+ bias, and if there is no bias ATT = ′IATT. But this can be granted in pure experimental design. However, in quasi-experimental studies this holds true if and only if Conditional Independence Assumption (CIA) holds and Common Support Region (CSR) meet (Caliendo and Kopeinig, 2008) to solve the selection problem stated in equation (3) above.

Another parameter of interest is ATE is defined as ′IATE = $E\ [W\ (1) - W\ (0)]$ … … … … (5) The additional challenge when estimating ATE is both counter factual E [W (1)/D=0] and E [W (0)/D =1] have to be constructed examination of ATE requires that the treatment effect for each individual i is independent of treatment displacement of other individuals or it means stable unit treatment value assumption (Caliendo and Kopeinig, 2008).

Decision to Choose Matching Algorism

Next to propensity score estimation, the researchers have to choose the matching algorithm. There were several alternatives of matching algorism methods. In this study, the choice of matching algorithm was built on the performance criteria such as number of insignificant variables after matching, low pseudo R2 after match, high number of matched sample size and lower standard bias after matching. Matching of urban expansion displaced and non-displaced group households can be conducted based on propensity scores using three matching algorisms as discussed below.

Nearest neighbor matching: an individual from a comparison group was chosen as a matching partner for a treated individual that is closest in terms of propensity score (Caliendo and Kopeinig, 2008). That is, each person in the treatment group chooses individuals with the closest propensity score to them. (From NN1up to NN3) was used as the straightest forward matching estimator in this research.

Caliper matching: Applying caliper matching means that those individual from the comparison group is chosen as a matching partner for treated individual that lies within the caliper (‘propensity range’) and is closest in terms of propensity score was used a tolerance level on the maximum propensity score distance called caliper. (0.5, 0.1& 1) were executed to matching estimator in this research.

Kernel matching: In kernel matching, each person in the treatment group is matched to a weighted sum of individuals who have similar propensity score with greatest weight being given to people with closer scores. All treated units are matched with a weighted average of all controls with weights which are inversely proportional to the distance between the propensity scores of treated and controls. Therefore, in this study (kernel bandwidth 0.1, 0.01& 0.5) was used to match all treated units with a weighted average of all controls with weights which are inversely proportional to the distance between the propensity score of treated and controlled groups. Each had their own advantages and disadvantages up on efficiency and bias. However, each individual were managed properly and produce more or less the same result (Caliendo and Kopeinig, 2008).

Determining the Region of Common Support

From the given set of observable covariates X which are not affected by treatment, potential outcomes are independent of treatment assignment of Un-confoundedness is: -

$$W\ (0), W\ (1)\ \Pi\ D/X, \forall \quad X. \ \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots.\dots\dots\dots.(6)$$

This means selection is solely based on observed characteristics and all variables that influence treatment assignment and potential outcomes simultaneously are observed by the study. The conditioning on all relevant covariates which are all dichotomous; the number of possible matches is two. To deal with these dimensional problems Rosenbaum and Rubin (1983) and Teshome (2021), suggest using the so called balancing score. It means if potential outcomes are independent of treatment conditional on covariates X, they are also independent of treatment conditional on balancing score b(X).

The propensity score P (D=1/X) = P(X) =b(X) i.e., the probability for an individual to participate in a treatment given his observed covariates X, is one possible balancing score. The conditional independence assumption (CIA) based on the propensity score (PS) can be written as (un confoundedness given the P(S): $W(0), W(1) \Pi D/P(X)$ $\dots\dots\dots\dots\dots\dots\dots\dots$ (7)

A further requirement besides independence is the common support or overlap condition. It rules out the phenomenon of perfect predictability of D given X.

Overlap is when $0 \ < \ P\ \left(D = \frac{1}{X}\right) < \ 1 \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots.(8)$

It means that the persons with the same X values have positive probability of being both participants (Heckman, Lalonde, and Smith, 1999) as cited by (Teshome, 2021). An important step was done to check the overlap and the region of common support between treated and controlled groups.

Several ways are suggested in the literature, where the most straightforward one is a visual analysis of the density distribution of the propensity score in both groups. The common support problem can be spotted by inspecting the propensity score distribution, there is no need to implement a complicated formal estimator. Implementing the common support condition ensures that any combination of characteristics observed in the treated group can also be observed among the controlled group (Bryson et al., 2002) as cited by Teshome (2021). For ATT it was sufficient to ensure the existence of potential matches in the controlled group, whereas for ATE it is additionally required that the combination of characteristics was observed from both in the controlled and treated groups (Brysonet al., 2002) as cited by Teshome (2021).

Balancing test: Since the researcher do not condition on all covariates but on the propensity score, the procedure was employed to check if the matching procedure is able to balance the distribution of the relevant variables in both the control and treatment group to compare the situation before and after matching and there was no remain any differences after conditioning on the propensity score. Because there were remedial measures done example dropping variables to matching on the score due to it was not completely successful at the beginning and it was corrected to eliminate differences (Rosenbaum and Rubin; 1983, 1985) as cited by (Damtie *et al.*, 2022).

Impact estimation using (PSM) Analysis

The impact of urban expansion on peri-urban farmers" livelihood asset was measurable to the difference with comparable in households between displaced and non-displaced farmers. However, a household that is displaced and non-displaced was not possible to simultaneously observe in two circumstances. A household at a time can either be displaced or non-displaced. Hence, this study applied a type of non-random experiment assignment the so called a propensity score matching method, which was widely applied as an instrument in the absence of baseline survey data was done for impact evaluation at cross section (Kasa *et al.*, 2011). The PSM technique enabled us to extract from the sample of non-displaced households a set of matching households that give the comparison to the urbanized induced displaced households in all relevant pre-intervention characteristics. In other words, PSM matches each displaced household with a non-displaced household that were almost the same likelihood of displacement due to intervention.

Examining Treatment Effect on treated or Impact Analysis

Given that conditional independent assumption holds assuming that there was a successful overlap between both groups called „strong ignore ability" by Rosenbaum and Rubin (1983). The PSM estimator for ATT can be written in general as:

$$= \text{'}\mathrm{I}_{ATT}^{PSM} = E\left[W1-\frac{W0}{D}-1, P(X)\right] = \left\{E\left[W\frac{1}{D}=1, P(X)\right]-E\left[W\frac{0}{D}=0, P(X)\right]\right\} \dots\dots..(9)$$

To put it in words, the PSM is simply the mean difference in outcomes over the common support, appropriately weighted by the propensity score distribution of participants. Based on this brief outline of the matching estimator in the general evaluation framework it was possible to implement the PSM and hence the plan of impact evaluation on ATT was possible.

Sensitivity Analysis

It was utilized to test the estimated results' sensitivity to changes in the identifying assumptions. Matching estimators may not be robust to a "hidden bias" if unobserved variables simultaneously affect the outcome variable and assignment into treatment. (Rosenbaum, 2002) as cited by Teshome (2021)Thus, "mhbounds" Sensitivity analysis for Average Treatment Effects is achievable. The "rbounds" method focuses on binary outcome variables and "allows the researcher to establish how strongly the unmeasured variable affects the selection process in order to determine the consequences of the matching analysis." Two individuals with the same observed factors X have different chances of obtaining treatment if there is hidden bias.

3.7. Study Variables Definitions, Relationships, Measurements and Hypothesis.

Treatment Variable: in this study dependent variable was displacement of farmers which were represented in the model by a value of 1 = treated if a given households displaced due to urban expansion and 0 = controlled for not displaced households.

Explanatory Variables (independent variable)

The explanatory variables are expected with the association of participation of household in livelihood assets. The explanatory variable is the variable expected to change or influence the dependent variable. According to Lulseged et al. (2011)as cited by Teshome (2021)urban induced displaced household background explanatory variables such as family composition (age of household, sex of household, family size of household , education of household head, and land size are observable characteristics of households

Sex: It is dummy variable for male or female household head which takes value 1 for male 2 for female.

Age of the household: is the age of the household head measured in years.

Family size: the total numbers of people live together in the same house measured in numbers and directly linked to share the household income and consumption expenditure.

Educational status: It is the educational level of the household measured as level of education categorized in to 3 groups.

Health status of household: is their health problem in the household or not.

Shock experience: it is dummy variables and used to identify if the household have shock experience or not.

Livestock: It is a continuous variable and measured in TLU[3].

Land size: Land holding size is the total area measured in hectare possessed by each household.

Credit received: the farmer who has received credit 1, and who are 0, not received.

Social relation: household relation in different community group in different social aspect.

Distance to market: farmers who are found in nearby market places is more benefited in urban expansion than the farmer who found far to the market.

Pure water access: water access measured by households who have pipeline and gage equal one otherwise zero.

Electric Power Access: electric power access measured by households who installed the access to their home equals one otherwise zero

Durables asset[4]: possession of home furniture asset in the household.

Outcome variables

[3] Standardizes different types of livestock into a single unit of measurement. Tape of livestock used in this research corresponding with conversion factor adopted were cow/ox=1, bull=0.8, calf=0.75, horse=1.1, donkey=0.5, sheep/goat=0.06, chiken 0.013 see in appendix one.

[4] Durable asset is apposition of an asset of home furniture in the household and it constructed by factor analysis it used as a proxy variable for physical capital.

(Table 4) presents the relationship, measurement and hypothesis the study variables. To estimate the impact of urban expansion on livelihood asset that included six outcome variables such as human capital[5], natural capital[6], financial capital[7], physical capital [8]and social capital[9]based on sustainable livelihood framework. Composite asset [10]a sum total of 5 capitals and it included as an outcome variable. Moreover, each capital has contained its own indicators as it’s listed below based on the literature (Udayakumara and Shrestha, 2011; Kuang *et al.*, 2020; Martin and Lorenzen, 2016; Mahama and Maharjan, 2019; Kamaruddin and Samsudin, 2014; Shinbrot *et al.*, 2019; Kry *et al.*, 2020; Arif *et al.*, 2019)

[5] Human capital is measured by index through constructed by factor analysis.
[6] Natural capital is measured by index through constructed by factor analysis
[7] Financial capital is measured by index through constructed by factor analysis
[8] Physical capital is measured by index through constructed by factor analysis
[9] Social capital is measured by index through constructed by factor analysis
[10] Livelihood asset it is also measured by index through factor analysis. It used 5 capitals as proxy variable. In this case second step factor analysis was performed.

Table 4: Definition of explanatory variable and its expected impact

Outcome variable	**Explanatory Variables**	**Measurement**	**Hypothesis or expected outcome**
Human capital	**Sex**	1 male, 2 female	+
	Age	1n year	+
	Marital status	1,if married and 2,if others[11]	+
	Family size	Number	+
	Educational level	Measured in 4 categories	+
	Health problem	1, if yes 0, no	-
	Employed number	Number	+
	Shock experience	1, if yes 0, no	+
Natural capital	Land size	In heater	-
	Source Fuel wood	Measured in 4 categories	-
	Status of fuel wood	1 if increase 0 if decrease	+
	Grazing land	1 if have, 0 if no	+
	River access	1, if yes 0, no	+
	Village sanitation	1, if yes 0 if no	+
Financial capital	Occupation	Measured in 3 categories	+
	annual income	In ETB	+
	annual expenditure	In ETB	+
	Eucalyptus tree asset	In ETB	-
	Livestock	TLU	+
	Saving amount	In ETB	+
	Loan received	In ETB	-
Physical capital	Distance to urban center	in Km	+
	Water access	1if yes, 0, if no	+
	Electricity access	1if yes, 0, if no	+
	Road access	1if yes 0, if no	+
	Health center access	1 if yes 0, if no	+
	No house in rooms	In number	+
	Durable asset	1 If yes, 0, if no	+
Social capital	Social relation	Measured in 3 categories	-
	Social norm	1if yes 0, if no	+
	Participation in Social organization	1 if yes 0, if no	-
	UID Conflict	1 if yes 0, no	-
Composite /livelihood asset	Human capital	Index	+
	Natural capital	Index	+
	Financial capital	Index	+
	Physical capital	Index	+
	Social capital	Index	+
Treatment variable	Displacement status	1if displaced 0 if not displaced	

Note: + = positive relationship; - = negative relationship.

[11] Others includes that unmarried, divorced, and widowed.

CHAPTER FOUR: RESULTS AND DISCUSSION

This chapter presents the findings of the drivers, impacts of urban expansion on peri_urban household livelihood assets and land use land cover change. The drivers of urban expansion were provided in narration form in the first section. The second objective was to assess the impact of urban expansion on livelihood asset and the last section is the situation of on land use land cover change due to urban expansion. So those three objective findings are provided in this section respectively.

4.1. Descriptive analysis

Demographic and socio-economic characteristics

Sex of Household Heads: From the total respondents 38 (13.48%) were female headed respondents whereas 244 (86.52%) were male headed household respondents. Among the urban induced displaced households 18(12.95%) were female headed and 121(87.05%) were male headed households while the non-displaced households 20(13.99%) and 123(86.1%) were female and male headed households, respectively. Own survey statistical test analysis shows that there was no statistically significant difference between treated and controlled groups regarding to sex of the household (Table 5). This result explained that being male or female doesn't have any role in urban induced displacement of the urban peri urban household.

Education status of Household Head: Own survey result (Table 5) shows that, from the total of 282 sample respondents those 179 (63.48%), 64(22.70%), and 39(13.85%) were uneducated, primary, secondary and above respectively. There was no statistically significance difference between displaced and non-displaced households regarding educational level of household heads.

Marital status: As shown in (Table 5) from the total sample 282 the 217(76%) and 65(23.05) respondents were married and others respectively. There was no statistically significant difference between displaced and non-displaced households regarding marital status of household heads.

Source of fuel wood: Own survey result (Table 5) shows that, from the total of 282 sample respondents those 89(31.56), 78(28.72%), 80(25.53%) and 40 (14.18%) of the household get fuel wood from common forest, private forest, purchasing and private planted tree respectively. Among displaced household 52(37.41), 5(3.60%), 69(49.64%) and 13(9.35%) of the respondent get fuel wood from common forest, private forest, purchasing and private planted tree respectively. from non-displaced household 37(25.87), 73(51.05%), 11(7.65%) and 22(15.38%) of the respondent get fuel wood from common forest, private forest, purchasing and private planted tree respectively. The statistical difference among groups is at 1% significance level. This implies that most of displaced household have got fuel wood by purchasing because they have no more land as non-displaced one.

Credit received: From the total respondents 82(29.08%) have received credit whereas 200 (70.92%) have not received credit household respondents. Among the urban induced displaced households 60(43.17%) have received credit and 79(56.83%) were not receive credit households while the non-displaced households 22(15.38%) and 121(84.62%) were received credit and were not received credit respectively. Own survey statistical test analysis shows there was 1% significant level. Therefore, this result tells us displaced households were more vulnerable than non-displaced households, this may be due to lack of permanent income.

Road access: As shown in (Table 5) the 187 (66.31) respondents were accessible for road whereas 97(33.69) households have not access to road. Particularly 105(75.54) displaced households and 82(57.34%) non displaced households were accessible for road. This result indicates that there is better of access high coverage of road access for displaced household than non-displaced households in the peri urban. In terms of road accessibility, it was statistically significant at 1% level between groups. From this we can understand that urban expansion program was a good opportunity for displaced household in terms road facility.

Social relation: Among the total sample respondents those 173(61.35%) have higher relation while 38(13.48) and 71(25.18%) from both groups were medium and low relation respectively. Among 139 displaced household 55(39.57%), 20(14.59%) and 64(46.04%) were high medium and low respectively. And from the comparison group 118(82.52%), 18(12.59%) and 7(4.90%) were high medium and low respectively. There was statistically significant at 1% significance level between displaced and non-displaced households in terms of social relation. This means displaced households have low social relation than non-displaced because it maybe they ignore themselves from social issue because they may not have money or resource like others.

Participation in social organization: From the total sample respondents those 155(54.96%) were participated in social organization whereas 127(45, 04%) from both groups were not participated in social organization. The displaced household have less participated in social organization relative to non-displaced household. But there was statistically significance difference between displaced and non-displaced households concerning to participation of social organization at 1 % significant level

Village sanitation: From the total sample respondents those 160(56.74%) have there is sanitation problem that related to urban expansion whereas 122(43.26) from both groups were said no visible sanitation problems change and too much worth respectively. There was statistically significance difference between displaced and non-displaced households at 1 %.

Electric access: As shown in (Table 5) from the total 282sample household131 (46.45) respondents have access for electric power whereas the 151 (50%53.55) households have not user of electric power. This result indicates there is lack of access or low coverage of electricity for both households in the urban periphery particularly only 81(58.27%) displaced households and 50(34.97) of non-displaced households were accessible for electric power. From the two groups displaced household has more accessible than non-displaced. In terms of electric power accessibility, it was statistically significant at 1% level of significant between groups.

Health service Access: As shown in (Table 5) the 163(57.80) of respondents were accessible for health center whereas the 119(42.20) of the respondents were not accessible for health center user. Specifically, 102(74.10) displaced households were accessible for health center and 36(25.90) not accessible for health center. In non-displaced households 60(41.96) were accessible and 83(58.04%) not accessible for health center. This result indicates there is good access health facility for displaced households than non-displaced one. However, health service accessibility it was statistically not significant the groups between groups.

Water access: From the total respondents 152 (53.90%) households have accessible, to safe drinking water whereas 130(46.10%) have not access for clean potable water. Among the 139 urban induced displaced households 81(65.47) households have access to clean and safe water and 48(34.53%) have not addressed for safe water. In comparison the non-displaced households 61(43.66%) have received clean water and 82(57.34%) have no access for clean and safe water. Statistically, there is 1 % significant difference between two groups regarding clean and safe water at the household level (Table 5). The displaced peri urban farmers were better users for well supplied clean water than the displaced households. This might be due to non-displaced households were relatively far away to urban center yet not urban water supply program.

Table 5: Descriptive Analysis of Categorical Variables between a groups

Variable	Category	Displaced hh N (%)	Non-displaced hh N (%)	Total N (%)	*X*2	*P value*
Sex	Male	121(87.0)	123(86.01)	244(86.52)	0.1	0.7
	Female	18 (12.95)	20(13.99)	38(13.48)		
Education	Un educated	83 (59.71)	96(67.13)	179(63.48)	2.5	0.29
	primary	37(26.62)	27(18.88)	64(22.70)		
	Secondary& above	19(13.67)	20(13.99)	39(13.83)		
Marital status	Married	111(79.8)	106(74.13)	217(76.95)	1.3	0.25
	Others	28(20.14)	37(25.87)	65(23.05)		
Source of fuel wood	Common forest	52 (37.41)	37(25.87)	89(31.56)	106 .6	0.000***
	Private forest	5(3.60)	73(51.05)	78(28.72)		
	Purchasing	69(49.64)	11(7.69)	80(25.53)		
	Private planted tree	13(9.35)	22(15.38)	35(14.18)		
Credit_recive	Yes	60 (43.17)	22(15.38)	82(29.08)	26.4	0.000***
	No	79(56.83)	121(84.62)	200(70.92)		
Road access	Yes	105(75.5)	82(57.34)	187(66.31)	10.4	0.001***
	No	34(24.46)	61(42.66)	95(33.69)		
Social relation	High	55(39.57)	118(82.52)	173(61.35)	68	0.000***
	Medium	20 (14.59)	18(12.59)	38(13.48)		
	Low	64(46.04)	7(4.90)	71(25.18)		
Parti_sol_orga	Yes	62(44.60)	93(65.03)	155(54.96)	11. 9	0.001***
	No	77(55.40)	50(34.97)	127(45.04)		
Village sanitation	Yes	91(65.47)	69(48.25)	160(56.74)	8.5	0.004***
	No	48(34.53)	74(51.75)	122(43.26)		
Electric access	Yes	81(58.27)	50(34.97)	131(46.45)	15.4	0.000***
	No	58(41.73)	93(65.03)	151(53.55)		
Health center	Yes	102(74.1)	60(41.96)	163(57.80)	29.9	0.000***
	No	36(25.90)	83(58.04)	119(42.20)		
Water access	yes	91(65.47)	61(42.66)	152(53.90)	14.8	0.000***
	No	48(34.53)	82(57.34)	130(46.10)		

***, ** And * implies 1%, 5% and 10% significant level, respectively

Source: Household Survey (2022)

Age of the Household Head: The mean difference between the age of displaced and non-displaced sample household heads was found to be 0.14due to the fact that the mean age of the treated and controlled household heads is 44.56 and 44.41years, respectively. As indicated in table below, statistically, there was no significant difference between displaced and non-displaced households in terms of age. This implies households in the treated and control groups have almost similar distributions regarding the age of the household head.

Family size: The mean difference between the age of displaced and non-displaced sample household heads is found to be 0.12 due to the fact that the mean family size of the treated and controlled household heads is 6.2 and 6.3, respectively. As indicated in table below, statistically, there was no significant difference between displaced and non-displaced households in terms family size.

Durable asset possessed in the household: Durable Asset Owned by the Households includes TV, sofa net, motor cycle, jewelry, carambula, cupboard, mobile, horse cart, and chair all those calculated in durable asset index on average, the value of durable asset owned by displaced and non-displaced households have Birr 0.68 and 0.57, respectively. The mean difference (0.11 in ETB) is statistically significant between the two groups with regard to possession of durable housing furniture's at 1 % (Table 6)

Saving amount in ETB: The survey result shows that, among the two groups the mean difference saving amount in the year 2022 is Birr 881. But displaced households average saving in the same year is Birr 1809 which is below the average saving amount (2691 ETB) of the non-displaced respondents. This revealed the level of savings held by the displaced groups is significantly less than the amount saved by non-displaced households. The difference is statistically significant at 1% level (Table 6). This could be due to there is a connection between saving and shrinking of permanent asset and income sources.

Loan Received amount by Household in ETB: From this data, loan was, on average, received Birr 581 which indicates they have less received credit. However, the displaced households have gained loan, on average, Birr 827.whereas for the non-displaced households is Birr 244. The amount of loan received by displaced household are respondents are higher than non-displaced households and it statistically significant at one percent between two groups (Table 6). So here we can understand that displaced household was more vulnerable to loan because of they may not be have permanent income due to land exploration.

Distance to market and distance to urban center

The mean distance to the nearest urban center of the displaced sample households is 2.0km, whereas for controlled sample households the urban center distance is 3.16 km, respectively. The survey results as indicated in the table below shows, the displaced households are living nearer to urban center than the non-displaced households. Statistically, the nearest distance to urban on average 0.52 km is significant difference at one percent probability level among two groups (Table 6).

Table 6: Descriptive Analysis of continuous Variables between a groups

Variable	Displaced (N=139) Mean (Std. DV)	Non-Displaced (N=143) Mean (Std. Dv)	Differences Mean (Std. Err)	T-value	P-value (Sig.)/
Age	44.56 (9.82)	44.4 (9.69)	-0.14 (1.1)	-0.12	0.55
Family size	6.208 (2.394)	6.3 (2.43)	0.12 (0.28)	0.41	0.67
Durable asset	0.68 (0.3)	0.6 (0.37)	-0.11 (0.04)	-2.7	0.0059***
Saving amount	1809 (2357)	2691 (2294)	881 (277)	3	0.0016***
Loan_amou	827 (1187)	244 (694)	-582 (115.4)	-5	0.000***
Dis_urban center	2.5 (1.01)	3.1 (1.37)	0.52 (0.144)	3.8	0.0001***

***, ** and * indicates 1%, 5% and 10% significance level, respectively. Two-sample t test with equal variances

Source: Household Survey (2022)

Factor analysis

As it is indicated in the method of data analysis part factor analysis was used to create human capital, natural capital, financial capital, physical capital, social capital and composite /livelihood asset index see appendix 2 (A- F) respectively. The Table showed all the statistical requirements for a good factor analysis model are satisfied for outcome variable. After the estimation of outcome variables by using factor analysis T test was performed in each outcome variable to know the difference between displaced and non-displaced groups as shown in the (Table 7) and also the measurement of each outcome variables is index which is in index is a unit less.

4.1.1. Descriptive Analysis of outcome variables

Human capital: The average human capital of the displaced and non-displaced households is 0.52 and 0.48 respectively (Table 7). The mean difference of human capital between the two groups is 0.042 which was not significant. This difference signifies that the displaced households have no difference in terms of human capital from the non-displaced households. This would be due to urban expansion has no significant effect on displaced and non-displaced household regarding to human capital.

Natural capital: The average of natural capital of the displaced and non-displaced households is0.15 and 0.55 respectively (Table 7). The mean difference of natural asset or capital between the two groups is 0.40 which was significant at 1% significant level. As the result shows average of natural asset of displaced household was less than non-displaced household. This would be due to because of land expropriation; decrease land size lack of fuel wood access grazing land decrease for displaced house hold than non-displaced one.

Financial capital: The survey result shows that, among the two groups the mean difference of financial capital was 0.092. But displaced household's average financial asset was0.39 which is below the average financial capital of 0.48the non-displaced respondents. This revealed the level of financial capital held by the displaced groups is significantly less than the financial capital held by non-displaced households. The difference is statistically significant at 1% level (Table7).

Physical capital: On average, the value of physical capital owned by displaced and non-displaced households have 0.46 and 0.38 respectively. The mean difference (0.08) is statistically significance at 1% between the two groups with regard to possession physical asset (Table 7). In this result the level of physical capital held by the displaced groups is significantly greater than the physical capital held by non-displaced households.

Social capital: The result indicates that the average social capital is valued 0.43 and 0.56for displaced and non-displaced households, respectively. Statistically, there was significant mean difference 0.12 at 1% level in terms of social capital as shown in (Table 7). This result shows that the average of social capital was significantly less than that of the non-displaced.

Composite asset: the average of livelihood asset of the displaced and non-displaced households is 0.35 and 0.43 respectively. The mean difference livelihood between the two groups is 0.076 which was significant at 1% significant level. This revealed the level of composite asset held by the displaced groups is significantly less than the livelihood held by non-displaced households.

Table 7: Descriptive Analysis of outcome variables between a groups

Variable	Displaced (N=139) Mean (Std.D)	Non-Displaced (N=142) Mean (Std.Dv)	Differences Mean (Std.E)	T value (t-test)	P-value (Sig.)
Human capital	0.52(0.27)	0.48(0.26)	-0.04(0.03)	-1.3	0.188
Natural capital	0.15(0.25)	0.55(0.19)	0.40(0.19)	20.7	0.000***
Financial capital	0.39(0.23)	0.48(0.23)	0.092(0.027)	3.3	0.0011***
Physical capital	0.46(0.27)	0.38(0.22)	-0.08(0.029)	-2.8	0.0052***
Social capital	0.43 (0.32)	0.56(0.31)	0.12(0.03)	3.2	0.0015***
Composite /livelihood asset	0.35(0.23)	0.43(0.23)	0.076(0.027)	2.78	0.0058***

***, ** and * indicates 1%, 5% and 10% significance level, respectively. Two-sample t test with equal variances.

Source: Household Survey (2022)

4.2. Land use land cover change

Accuracy Assessment

The classification accuracy assessment was accompanied to assess the accuracy of maximum likelihood classifications. In this study, accuracy assessment was performed for the classified maps of all year. Confusion matrices were used to assess classification accuracy using four measures of accuracy such as, user's accuracy, producer's accuracy, overall accuracy and Kappa coefficient. The accuracy of the classified images was checked using ground truth region of interest. The land use land cover classes region of interest was cross checked using ground observation and using Google earth engine. Sufficient accuracy assessment region of interest pixels was taken from each land use land cover type for the analysis.

The overall accuracy assessment, user accuracy, producer accuracy and kappa coefficient of the land use assessment were computed for 2001, 2013 and 2021years. The overall accuracy and kappa coefficient were 95% and 93.6% and 92%, and 93, 99 and 89 corresponding to the year 2001, 2013 and 2021as it indicated in the Table 16. The Kappa statistics of a value greater than 0.80 /80% indicates a strong agreement between the ground truth and classified LULC classes. The result of accuracy assessment showed accuracy in three time period was found more reliable. See appendix 9 each year confusion matrices.

Table 8: Accuracy Assessments of Classified Images

LALC Type	2001		2013		2021	
	UA%	PA%	UA%	PA%	UA5	PA%
Built up land	94	94	91	95	90.6	96.6
Cultivated land	100	91.6	95	91.6	93	93
Forest land	95	100	90	95	90	93
Grazing land	89	94	95	90	93	94
Overall accuracy	95%		93.6%		92%	
Kappa coefficient	93%		99%		89%	

Note: UA= user accuracy, PA= producer accuracy,

Source: Own competition, April (2022)

Overall accuracy: This is computed by dividing the total correct number of pixels (i.e., summation of the diagonal) to the total number of pixels in the matrix (grand total). In some empirical studies (Dega *et al.*, 2022; Taye *et al.*, 2019; Alburshaid and Mangoud, 2021) it is noted that the accuracy value of 90.83% and it is required for effective and reliable land cover change analysis. Depending upon the purpose of the land cover map, different people use different accuracy levels. The study's confusion matrix result of all the derived land use/land cover maps has revealed, (95, 93.6 and 90) corresponding to the year 2001, 2013 and 2021 respectively. Overall accuracy levels of more than the minimum accuracy threshold defined by Dega *et al.* (2022).

Producer accuracy: Producer's accuracy refers to the number of correctly classified pixels in each class (category) divided by the total number of pixels in the reference data to be of that category (column total) (Damtie and Mengistu, 2022; Tiwari *et al.*, 2021). This value represents how well reference pixels of the ground cover type are classified. In this study the maximum class accuracy was built-up area which are 96.6%, whereas the minimum class accuracy was cultivated land and forest which is 93%, how the other classes within each land class has a good accuracy.

User accuracy: Users accuracy refers to the number of correctly classified pixels in each class (category) divided by the total number of pixels that were classified in that category of the classified image (row total) (Tiwari *et al.*, 2021). The probability that a pixel classified into a particular category truly corresponds to that category on the ground is represented by this value. Results of user's accuracy in this study showed that in 2021 the maximum class accuracy of grassing land was 93, and the minimum was forest land class with accuracy of 90%.

Kappa analysis: Kappa coefficient, which is one of the most widely measures in addressing the discrepancy between the actual agreement and change agreement, was also calculated (Foody, 2020).The kappa coefficients obtained for the classified imageries 88.9 % or 0.889 for the year 2021.

4.4.1. Land Use Land Cover Change classification

In this study there were four major LULC classes' namely built-up land, cultivated land, forest land and Grazing land from 2001 to2021were detected. In general, the analyzed LU/LC patterns in the study indicated that there was significant land use land cover change between the three time series data over 2001, 2013 and 2021 (Table 9)

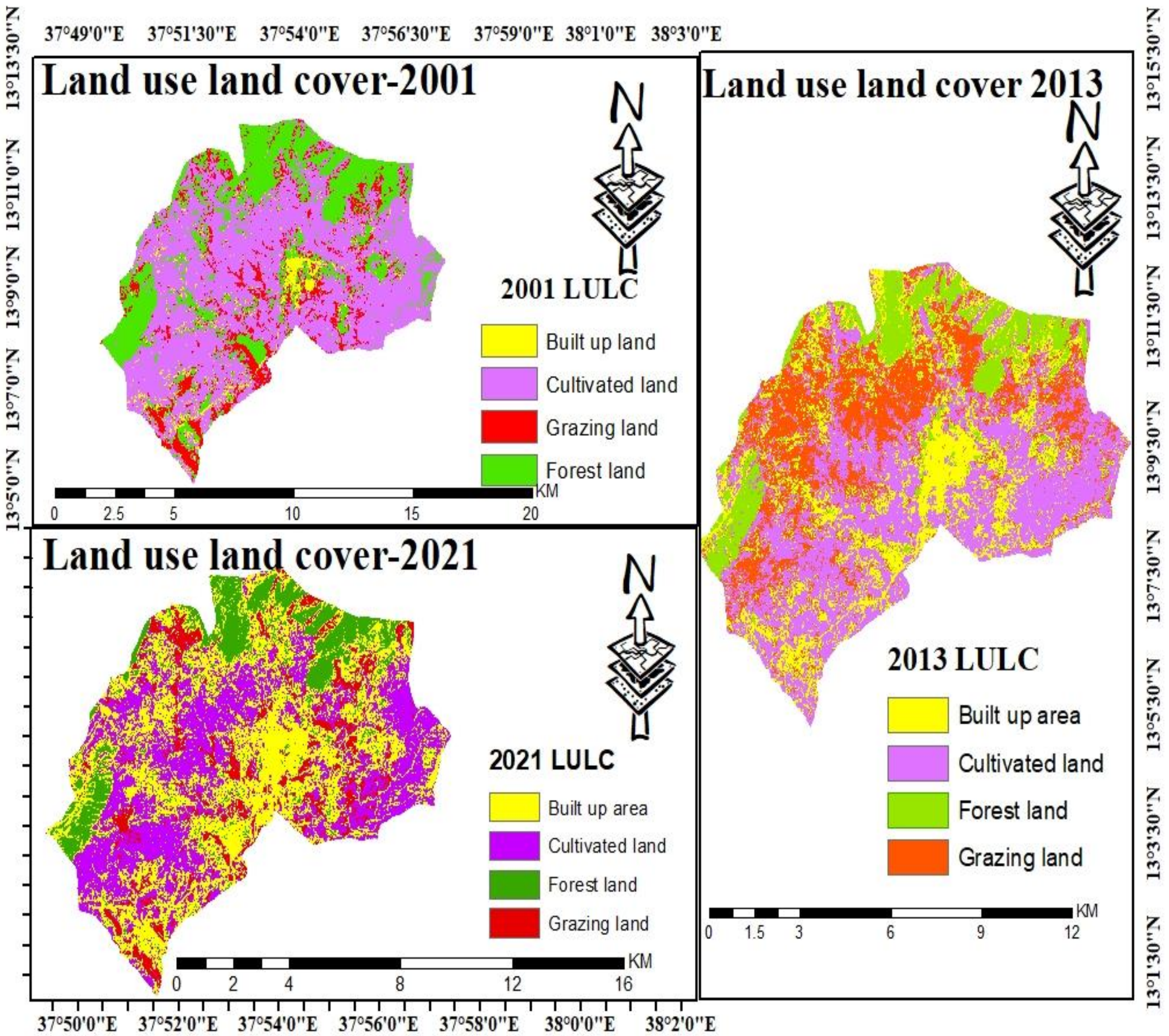


Figure 4: Land Use Land Cover Classification Map

Source: Authors production using MLC, (2022)

Built up land

Built up land use class had smaller area coverage than cultivated land in the year 2001. However, it increased steadily in a referenced period (Table 9). Built up land rate change increased by +89 ha, 39 ha, and 163ha from 2011 to 2013, 2013 to 2021, and 2001 to2021 respectively (Table 10) this might be the increased in population size associated with the demands of additional settlement in the rural areas and mood of scarce settlement rather than populated. The result was similar to (Fenta *et al.*, 2017) that reported increased built up area due to urban expansion in Mekelle city northern Ethiopia. Moreover, the study result in line (Mamuye and Ebabu, 2021) they reported that built up increased by 3287.97ha from 2001 to 2019 due to urban expansion in worabe town and as (Inki, 2018) documented 365ha was built up land was increase from 1997 to 2017 .

Table 9: Land use and land cover Coverage from 2001 to 2021

	Land use and land cover Coverage from 2001 to 2021		
	2001	2013	2021
LU Type	Hac (%)	Hac (%)	Hac (%)
Built up land	1654.5 (16.5)	3136 (31.3)	4357 (43.4)
Cultivated land	6190 (61.7)	4939 (49.2)	4202 (42)
Forest land	1163.5 (11.6)	805 (8)	795 (7.9)
Grazing land	1024 (10.2)	1153 (11.5)	679 (6.7)
Total	10033 (100)	10033 (100)	10033 (100)

Source: Authors production from confusion matrix, (2022)

Cultivated land

In the analyzed LULC change for the study area revealed that cultivated land was predominant land use class in the year 2001 and showed slightly reduced over the period of (2001_2013) and (2013_2021) and 2001_2021 as it is indicated in (figure 5). In those years cultivated land use class coverage was changed from 6190 ha (61.7 %) in 2001 to 4939 ha (49.2 (Table 9). Similarly, it had decreased rate of change by -33 hectare over twenty years of 2001_2021 (Table 10).

The decrement of cultivated land could be urban expansion due to population growth increases associated housing demand, for different infrastructure project and lands for expansion of industry and institution. In addition to this the reduction of cultivated land would be leads landlessness to farmers and reduced crop productivity and the farmers maybe obligate to live in poverty. This result was in line with (Ahlam, 2017)cultivated land were declined in -13.3% in the year between 2000 up 2016 due to urban expansion and expansion of road project program in kutaber town Amhara region Ethiopia.

Forest land

There was a decrement of forestland area coverage of the studied area from 1163.5(11.6%) ha to 805(8%) ha in 2001 to 2013 and from 805 (8%) ha to 795(7.9%) ha in 2013 to 2021 referenced years (Table 9). This might be associated with the conversion forest land to build up land due to urbanization. As key informant mentioned that the reason for the decrement of forest because the demand of income, energy, and construction purpose was increased throughout the year. This result was in line with (Tame, 2020) forest land was reduced -216.24ha -4.21% in the year 1999 to2019 and (Mamuye and Ebabu, 2021) reported that forest cover of the study area in the year 2009 was 3798.27 ha (24.2 %) but it was changed to 1358.01ha (8.6%) by the year 2019. Therefore, due to urban expansion 2440.17 ha (15.6%) of the forest was cleared mainly for residential and commercial purposes.

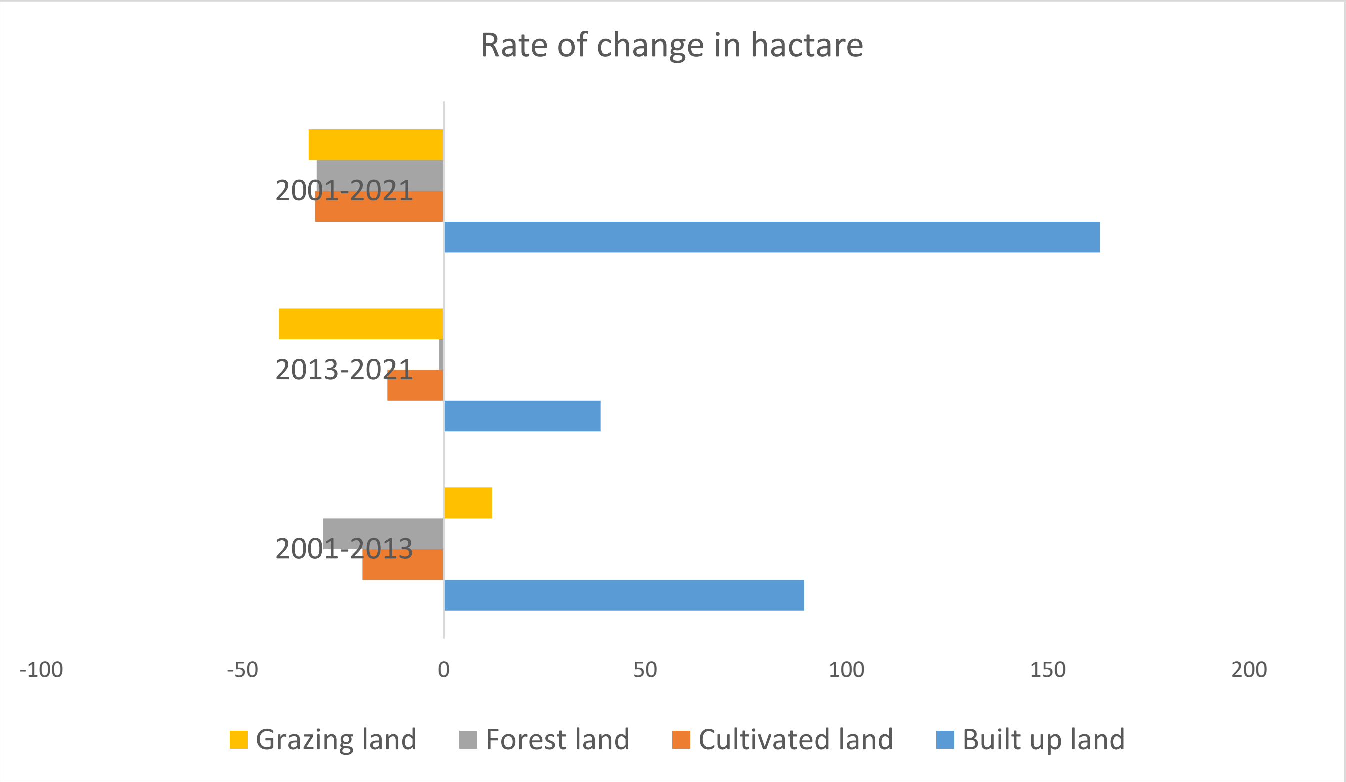


Figure 5: Rate of change land use land use land cover change

Grazing land

As (table 9) the result revealed that grazing land had the lowest area converge in 2001year 1024 (10.4%) which was relatively less coverage than other land uses. However, this land use class showed slightly increment between the year 2001to 2013 by 12 hectare. On the other hand, it was decreased by -33.6 ha from 2001 to 2021 suggestion years (Table 10). The reason for a decline in grazing land might be the increased population size that changed grazing land to cultivated land and settlement. This result is similar with (Ahlam, 2017) in which grazing land were declined by-16.075 ha -18.3% in the year between 2000 up 2016 due to urban expansion.

Table 10: Rate of change of land use land cover in the study area.

	Rate of change of land use land cover change from 2001 to 2021		
	2001 to 2013	2013 to 2021	2001 to 2021
LU type	Hac	Hac	Hac
Built up land	+89.5	+38.9	+163
Cultivated land	-20.2	-14	-32
Forest land	-30	-1.24	-31.6
Grazing land	+12	-41	-33.6
Total	0 (0)	0 (0)	0 (0)

Source: Authors production from confusion matrix, (2022)

4.4.2. Rate of change in the year 2001, 2013 and 2021 in the study area

there was an increase of built-up areas of +89.9 ha, in the year 2001 to 2013 but the land use land cover in cultivated land, forest land, and grazing land was significantly declining with -20.2 ha , -30 ha, and +12 ha, respectively. The land use and land cover change between 2013 and 2021 also revealed an increase in built-up areas of +38.9 ha, but a decline in the usage of cultivated land, forest land, and grazing land by -14 ha, -124 ha, and -41 respectively. Land use and land cover data from the years 2001 to 2021 also revealed that while built-up areas expanded by 163 ha, other land uses decreased by -32 ha, -31.6 ha and -33.6 hectares.

4.3. The Drivers of Urban Expansion in the Study Area

According to the data gathered from key informant interviews there are three major drivers of urban expansion in the study area.

1. Rural to urban migration: According to the administration office, debark woreda comprises 32 kebeles, and the woreda administration office has been headquartered in Debark town, which is the center of the north Gondar zone, since 2018. The main engine of urban expansion in Debark town is rural-to-urban migration. People migrate from various rural kebeles due to various push and pull factors. For example, based on the push factors of poverty, landlessness, violence, or crime in rural areas, this finding is consistent with Berhanu (2018). On the other hand, the pull factors for rural to urban migration included job opportunities, access to improved infrastructure such as clean water, electricity, roads, schools, telecommunications, health care, and other urban amenities. This result also in line with Inki (2018) and Ibido (2020).

2. Increasing Natural Population: In the study area, it is also major driving factor of urban expansion. In this study interview questions were prepared for the key informants in the health office regarding trends in birth and mortality over the previous five years in the study area. However, the health expert informant stated that because we only record mother and baby events, there isn't a complete document in our office for your data. They suggested that the office of vital events might have a complete document on this subject. Even while medical professionals claimed that improved immunization rates and easier access to other healthcare facilities, such as quick ambulance service for mothers and other injured individuals, were too blamed for the recent natural population growth. As a result, over the previous five years, there have been fewer deaths and more births. The average yearly records for Debark town in 2021 showed 1850 births and 310 deaths, according to the North Gondar Zone vital evnt office (2022).

Even though the office does not have all the necessary documents, the trend of population growth over the last five years. The study tried to find confirmation on this issue from the housing and construction office of Debark Town, and that office informed that there has been rapid population growth during the previous five years. Additionally, there is a greater need for housing, as the DTHC office demonstrates. Since 2008, the land of peri-urban kebeles such Mikara, Zebena, debir, kino, and dildy that are close to the town has been expropriated by 84 housing associations, each of which has 40 members. Therefore, increase natural population was one of the major drivers of urban expansion. So this result was in line with (Berhanu, 2018; Bodo, 2019; Fekadu, 2015).

3. Economic development: As several studies such as Mekuriaw and Gokcekus (2019), Berhanu (2018) and Dires *et al.* (2021) shows economic development is one of the crucial case or driver of urban expansion in different place. Similar to other locations, urban expansion in Debark town is mostly fueled by economic development. As the Debark Town Administration Office indicate that, the town has grown rapidly over the past 20 years, particularly since it was chosen as the official location for the North Gondar Zone

Administration. The town administration begins a variety of development projects to expand the town by collaborating with private investors, non-governmental groups, and official bodies. Therefore, the municipality office uses 3560 hectares of land for this development activity, consumed from peri-urban kebeles. This result is also consistent with Berhanu (2018) and Mekuriaw and Gokcekus (2019). At the same time focus group discussion result was similar with this.

4.4. Econometric results

This section outlines the entire procedure used to determine how the urban expansion has affected the assets and lives of displaced households. Fitting the binary logistic regression, estimating the PS(predicting probability), matching across covariates (using various matches), selecting the matching algorithm, discarding off-support observations, performing a balancing test, analyzing Multicollinearity, and performing a sensitivity analysis were the practical steps.

Goodness of fit test: Binary logistic model was used to estimate propensity score point for two comparison group. Evaluating goodness of fit is an important step in the assessment of the adequacy of a regression model. Pearson chi-square test, Hosmer and Lemeshow test, and classification table were used to observe the fitness of the model. According to Fagerland and Hosmer (2017)Pearson chi-square test, Hosmer and Lemeshow test, and classification table, are greater than 0.05,0.05 and correctly classified >90.3% respectively. Therefore, the model fits well as it indicated in (table 8) Pearson chi-square test, Hosmer and Lemeshow test and classification table 0.14, 0.996 and 94.33% respectively that means fail to rejection H_o.

Table 11: Logistic model for displacement status, goodness-of-fit test

Testing criteria	**Number of observations**	**number of covariate patterns**	**Prob > chi2**
Pearson chi2(264) =289	**282**	**282**	**0.14**
Hosmer-Lemeshow chi2(8) =1.28	**282**	**Number of groups=10**	**0.996**

Source: Household survey (2022)

Multicollinearity test: Variance inflation factor (VIF) was applied to test for the presence of Multicollinearity problem among the explanatory variables as shown in Appendix 4 (A). The mean VIF was 1.73 which is less than 10. There was no explanatory variable dropped from the estimation model since no serious problem of Multicollinearity was detected from the

VIF results. Contingent coefficient evaluation also checked for categorical variables which implies all are below the tolerance limit see appendix 4 (B).

Heteroscedasticity test: it is attest that used to detect the occurrence of outliers in the data. Heteroscedasticity test revealed that chi2 (1) = 0.29 and Prob > chi2 = 0.591, Ho: Constant variance. This test resulted in fail to rejection of the non-existence of heteroscedasticity hypothesis (since Prob>chi2=0.591) which indicates insignificant and there was no heteroscedasticity problem see appendix 4 (C). However, robust standard errors were estimated in the logit model to tackle heteroscedasticity problem in the data.

4.4.1. Impacts of urban expansion on peri urban farmers livelihood assets

Estimation of Propensity Score by Logit model

The propensity score was generated using the logit model. The control groups were utilized in propensity score matching to analyze what happened in the absence of urban expansion in treated group. PSM was used to collect data from a group of units that had not been displaced as a result of urban expansion, allowing the program's effectiveness to be assessed by comparing the results to those of displaced groups. The propensity scores were used to prevent the bias that was introduced by using a matching method to select control units that were similar to the treated units. This enabled for the estimation of the program intervention's impact (Tsega, 2012) as cited by Teshome (2021). To ensure that the score was not biased by treatment or anticipation of treatment, pre-intervention covariates were utilized to estimate it.

Looking the estimated coefficients in the table 8 below, the pseudo-R2 value is 0.313. The pseudo-R2 indicates how well the repressors overall fitness to explain the displacement probability. Observing into the estimated coefficients, the result indicates that urban expansion induced displacement was significantly influenced by nine explanatory variables namely durable asset, distance to urban center, credit received, health access, participation in social organization and social relation were statistically significant at 1 % and road access and electric access were significant at 5%.

Table 12: Logistic regression results of households displaced by urban expansion

```
Logistic regression                             Number of obs     =        282
                                                Wald chi2(17)     =      74.27
                                                Prob > chi2       =     0.0000
Log pseudolikelihood = -134.09587               Pseudo R2         =     0.3139
```

disp_sta	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
age	.0384922	.0261004	1.47	0.140	-.0126636	.089648
familysize	-.1335588	.1196185	-1.12	0.264	-.3680068	.1008893
sor_fuwd	.1667521	.1393938	1.20	0.232	-.1064548	.439959
educ_level	.3093537	.2707714	1.14	0.253	-.2213485	.8400559
marital_status	-.6348829	.430168	-1.48	0.140	-1.477997	.2082309
savi_amou	-.0000893	.0001018	-0.88	0.380	-.0002888	.0001102
loan_amou	.0001121	.0002006	0.56	0.576	-.000281	.0005052
mmx_dur	1.353259	.4808228	2.81	0.005	.410864	2.295655
dis_ur	-.89553	.2586903	-3.46	0.001	-1.402554	-.3885063
cred_receiv	1.056417	.4066348	2.60	0.009	.2594272	1.853406
Helth_acc	.5836634	.3282055	1.78	0.075	-.0596075	1.226934
rod_acsse	.7417193	.3876186	1.91	0.056	-.0179992	1.501438
water_acc	.6689945	.4123988	1.62	0.105	-.1392922	1.477281
elec_acc	.607746	.3443102	1.77	0.078	-.0670897	1.282582
parti_soc_orga	-.7965339	.3281438	-2.43	0.015	-1.439684	-.1533838
social_relation	.7043672	.2528724	2.79	0.005	.2087464	1.199988
vilag_sanit	.6831005	.3173532	2.15	0.031	.0610996	1.305101
_cons	-2.810677	1.509776	-1.86	0.063	-5.769783	.148429

Source: Household Survey (2022)

Note: sor_fuwd = source of fuel wood, educ_level=saving amount in the household, loan_amount=loan received amount in the household, mmx_dur, dis_ur=distance to urban center, cred_receiv= is the household received credit or not, health_acc= is the household get health service access or not, water_acc=is the household get access or not, elec_acc= is the household get electricity or not, Parti_sol_orga=is the household participated in different social organization or not, social_relation = the level of households social relation, vilag_sanitation= is there village sanitation or not.

From these observed covariates, we can infer that the variables have explanatory power on displacement due to urban expansion has impact in the farmers‟ livelihood asset in the study area. The rest of the variables were not statistically significant (Table 9). As the regression in logit model shows it was likely to say that majority of the households who were involved in urban induced displacement had better to access health service, road access and they also possess relatively more durable asset regarding the pre-program intervention. In addition, they were more credit receiver and they were nearest to the urban center relatively to the non-displaced households. However, the parameter estimates of this regression in the above model need not to interpret because urban expansion affects all peri urban households in the targeted villages where decision to displacement is not an issue to these covariates regarding selection to displacement. But this procedure is necessary to generate the propensity score. The propensity score is used to create best matches between the two groups conditional on sharing similar pre-intervention covariates.

Determining the Region of Common Support

Common support method was one of the matching methods of observed mean outcome of untreated to estimate the mean of counterfactual outcomes of the treated being were not treated. The common support estimation was improved by dropping the comparison observations whose estimated propensity score was greater than the maximum or less than the minimum of the treated group propensity scores. (Figure 4) shows, the distribution of the households with respect to estimated propensity scores. In case of treated households, most of them are found in the center side of the distribution and they are partly found in the right side of distribution. On the other hand, most of the controlled households partly found in the left side of the distribution and are partly found in the center. However, one can visually observe that there are considerable wider areas in which the distribution of propensity score of both groups shares sufficient common support region.

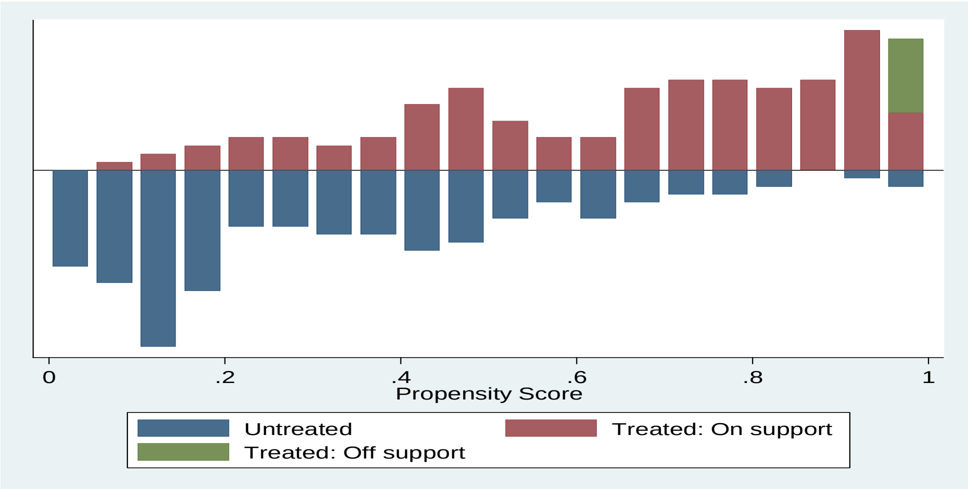


Figure 6: Common support region both treated and control

Source: Computed based on Household Survey (2022)

Moreover, both treated and controlled groups‟ lies between 0 and 1 and fall to the common support region indicating that there was sufficient to ensure the existence of potential matches in the control group. Regarding this analysis, any combination of characteristics observed in the treatment group can also be observed among the control group.

Distribution of Propensity Score Matching

The following output shows that the identified region of common support is [0.0056664, 0.9912922] and the final number of blocks is 5, and the balancing property is satisfied. In (table 10), the description of the estimated propensity score in region of common support shows that the average of the mean propensity score of the controlled and the treated groups before matching were 0.306and 0.684 and standard deviation were 0.23and 0.25respectively. The minimum and the maximum of the controlled group were0.00566 and 0.09828 respectively and of the treated groups were 0.09554 and 0.9912 respectively.

Table 13: Distribution of propensity score matching before matching

Group	N	Mean	Std. Dev.	Std. Err	Minimum	Maximum
Untreated	143	.306	0.232	.01924	.00566	0.9828
Treated	139	.684	0.251	.02133	0.09554	0.9912
Total	282	.492	0.306	.0182	0.0506	0.9912

Table 14: Distribution of propensity score matching after matching

Group	N	Mean	Std. Dev.	Std. Err	Minimum	Maximum
controlled	143	0.314	0.235	0.019	0.0796	0.988
Treated	139	0.676	0.244	0.020	0.0144	0.978
Total	282	0.492	0.299	0.017	0.0144	0.988

Source: Household Survey (2022)

As it indicated in Table 10, the distribution of propensity score matching estimates after matching of the controlled and treated groups, the minimum of the estimated propensity scores were0.0796 and 0.0144respectively and the maximum were 0.988and 0.978. The common support of the total was lay between [0.0144and 0.9888]. Out of this support the households were discarded in the matching exercises. In other words, households whose estimated propensity scores were less than 0.0144and larger than 0.988 are not considered for the matching exercise. Individuals outside of this range must be ignored, and the treatment's impact on them cannot be predicted. Due to this limitation, only 5 treated households were eliminated. This demonstrates that while computing the impact estimator, the study does not need to exclude a large number of non-displaced and displaced household from the sample.

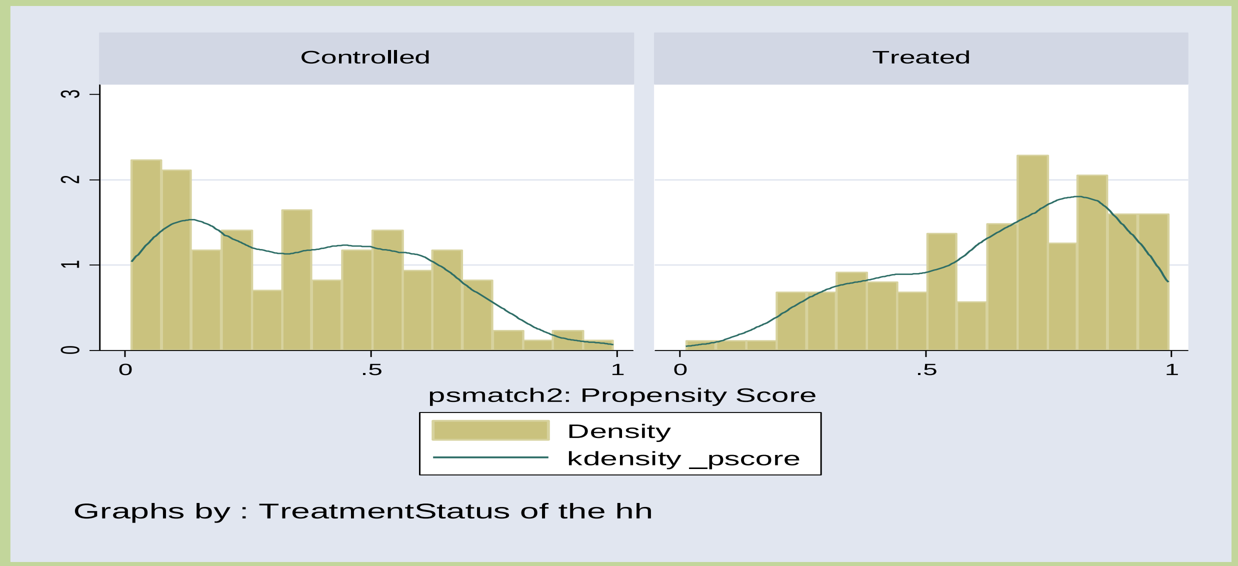


Figure 7: Kernel Density Distribution Result
Source: Computed based on Household Survey (2022)

The output of this command as shown in Figure 5, it is likely possible to observe visually the quality of overlap by considering the kernel density distribution that was checked by using graphical diagnosis of the covariate's distribution. We can see that propensity scores mean distribution tend to be higher in the treated than the untreated. However, because of the limits of bounds to 0 and 1 on the propensity score, both distributions are skewed to left and relatively very close support was executed after matching at the right to (0.988) which was reduced from (0.991).

Decision to Choose Matching Algorism: As it indicated in the methodology section among several matching alternatives, three alternative matching estimators were tried. From three alternative matching estimator kernel matching was applied for this study to matching the treated and controlled households in the common support region (Table 12). The final selection of a matching estimator was influenced by many criteria such as the equal means test, also known as the balance test (Caliendo and Kopeinig, 2008) pseudo-R^2,mean bias and matched sample sizes. A matching estimator that balances most explanatory variables (i.e., produces insignificant mean differences between the two groups after matching), has a low pseudo R^2 value low mean biased after matching, and produces a high matched sample size is preferred. Table 12shows the estimated results of nearest neighbor, caliper and kernel matching estimator of tests of matching quality was based on the performance criteria mentioned above. after looking into the results from own econometric computing matching estimation procedures, it was found that kernel band width (0.1) was the best estimator for this research since it was produce largest sample size (277) with the Pseudo-R2 value (0.044) , least mean bias(9.7%) which is less than 20% and equal means test or in this research case the mean balancing test of the number of all 17 explanatory variables were tends to almost equal mean between controlled and treated groups after matching with no statistically significant mean differences as shown in the insignificant statistical test and p-value among the matched groups of displaced and not-displaced households. Thus, we can conclude that, the balancing is good since the separate results in the t-test for all covariates are insignificant after matching.

Table 15: Performance matching estimators' values before &after matching

Matching estimator	Performance criteria					
Nearest Neighbor	Balancing test	Pseudo-R^2		Matched	Mean bias	
		Before	After	Sample Size	Before	After
NN (1)	14	0. 313	0.069	277	43	9
NN (2)	15	0. 313	0.066	277	43	10.3
NN (3)	16	0. 313	0.052	277	43	10.3
Caliper						
0.1	15	0.313	0.069	277	43	11
0.01	15	0.313	0.039	236	43	7
0.5	16	0.313	0.069	277	43	10.3
Kernel						
Bandwidth 0.1	17	0.313	0.044	277	43	9.6
Bandwidth 0.01	16	0.313	0.022	236	43	6
Bandwidth 0.5	14	0.313	0.095	277	43	18.1

Source: Household Survey (2022)

Given to the above criteria and base on selecting the best matching estimator, the following estimation results and discussions are the direct outcomes of the kernel matching algorithm based on a kernel band width of 0.1 since it was better to match all treated unit with a weighted average of all controlled with weights. Subsequently, the weighted averages of all not-displaced households in the control group are used to construct the counterfactual outcome; kernel matching has an advantage of lower variance because more information is included in the analysis (Heckman et al., 1998) as cited by Teshome (2021).

Balancing Test of P score and Covariates Analysis

As previously stated, the primary goal of propensity score estimation is not to provide a precise forecast of treatment selection, but rather to balance the distributions of key factors in both groups. The balancing powers of the estimations were determined by considering different test methods such as the reduction in the mean standardized bias between the matched and unmatched households, equality of means using t-test and chi-square test for joint significance of the variables are the commonly used balancing tests in propensity score matching analysis. The standardized bias results for the models were within the acceptable limit of less than 20%.

The PSM model showed a standardized before matching is in range of 1.5% and 153.1% and after matching the total reduction bias of covariates obtained by matching procedure lies between 1.8 % and -19 % which are much below the critical level of 20 percent suggested by Rosenbaum and Rubin (1985) see (Table 13). On the other hand, the t-test used to assess the quality of the matching and no variable is expected to have a p-value of less than 0.05 after the matching is showed. The result indicated that no covariate variable had a statistically significant difference after matching. The process of matching thus creates a high degree of covariate balance between the treatment and control samples.

Table 16: Propensity Score and covariates balancing

Variable	Unmatched Matched	Mean Treated	Mean Control	%bias	%reduct |bias|	t-test t	t-test p>|t|	V(T)/ V(C)
_pscore	U	.68209	.30902	153.6		12.90	0.000	1.02
	M	.67085	.66112	4.0	97.4	0.33	0.742	1.01
age	U	44.561	44.413	1.5		0.13	0.898	1.01
	M	44.179	44.803	-6.4	-320.2	-0.53	0.597	1.01
familysize	U	6.2086	6.3287	-5.0		-0.42	0.677	0.96
	M	6.1642	6.672	-21.0	-323.0	-1.63	0.104	0.81
sor_fuwd	U	2.3094	2.1259	17.9		1.50	0.134	1.23
	M	2.2836	2.1359	14.4	19.5	1.28	0.202	1.96*
educ_level	U	1.5396	1.4685	9.8		0.82	0.413	0.99
	M	1.5522	1.5395	1.8	82.0	0.14	0.891	0.85
marital_status	U	1.2014	1.2587	-13.6		-1.14	0.255	0.84
	M	1.194	1.2331	-9.3	31.9	-0.78	0.438	0.87
savi_amou	U	1809.8	2691.6	-37.9		-3.18	0.002	1.05
	M	1868.9	1926.6	-2.5	93.5	-0.20	0.842	1.01
loan_amou	U	827.96	244.99	60.0		5.05	0.000	2.92*
	M	814.09	1001.1	-19.2	67.9	-1.27	0.205	0.95
mmx_dur	U	.68476	.57194	33.1		2.78	0.006	0.68*
	M	.67702	.72424	-13.9	58.1	-1.23	0.219	0.95
dis_ur	U	1.6345	2.028	-63.2		-5.31	0.000	0.88
	M	1.6507	1.7633	-18.1	71.4	-1.62	0.106	1.26
cred_receiv	U	.43165	.16783	58.9		4.95	0.000	1.60*
	M	.41791	.44892	-6.9	88.2	-0.51	0.614	0.94
Helth_acc	U	.70504	.44056	54.5		4.57	0.000	0.80
	M	.69403	.73642	-8.7	84.0	-0.77	0.444	1.09
rod_acsse	U	.76978	.57343	41.9		3.51	0.001	0.78
	M	.76119	.72405	7.9	81.1	0.68	0.497	0.98
water_acc	U	.65468	.44056	43.3		3.63	0.000	0.87
	M	.64179	.63267	1.8	95.7	0.15	0.884	0.80
elec_acc	U	.58273	.36364	44.2		3.71	0.000	0.99
	M	.57463	.50787	13.5	69.5	1.08	0.279	0.94
parti_soc_orga	U	.46043	.65035	-38.2		-3.21	0.001	1.16
	M	.47761	.43206	9.2	76.0	0.74	0.463	1.08
social_relation	U	1.7482	1.3007	65.1		5.47	0.000	1.03
	M	1.7313	1.7923	-8.9	86.4	-0.61	0.541	0.57*
vilag_sanit	U	.65468	.48951	33.3		2.79	0.006	0.86
	M	.64179	.61374	5.6	83.0	0.47	0.640	0.92

NB; U = unmatched, M= matched

Source: household survey (2022)

Table 17: Chi-square Test for Joint significant

Sample	Ps R2	LR chi2	p>chi2	MeanBias	MedBias	B	R	%Var
Unmatched	0.313	122.52	0.000	43.0	40.1	150.8*	1.10	17
Matched	0.044	16.48	0.559	9.6	8.8	50.2*	1.21	11

Source: Household Survey (2022)

Finally, the joint significance and pseudo R2 scores of the models was checked. If the pseudo R2 decreases and approaches 0, it indicates that a successful balance has been reached. The result in (Table 14) signifies that after matching there is fairly low Pseudo R2 value was reduced from 0.313 to the lower insignificant value of 0.044and overall bias was reduced satisfactorily from 43% to 9.6% after matching or there is insignificant (9.6%) mean difference between the two groups. the likelihood ratio (LR) results after matching were insignificant indicating the covariates are not determining the urban expansion impact on livelihood asset of the households. All of the above tests suggest that the matching algorithm that has been chosen is relatively best with the data at hand. Thus, it is possible to precede estimation of ATT for those urban induced displaced households.

4.4.1.1. Average Treatment on Treated

In order to answer this study estimating average treatment effect on treated is evaluated the main impacts of urban induced displacement on outcome variables for displaced households. This study demonstrates that, rather than variations in the observed covariates, the wellbeing of farmer's livelihood asset of the peri urban household may be systematically altered by the displacement (i.e., urban expansion). After controlling for the differences in demographics, utilities, services and asset endowment characteristics of the urban induced displaced and non-displaced households, it has been found that, on average, the displaced households of Natural capitals financial capital social capita and Composite asset/Livelihood asset of the household is reduced.

The estimated evidence showed that there is a statistically significant effect on outcome variables. The result is interpreted as the average impact of urban expansion on displaced household livelihood asset is reduced by (**-.159)** at 1% significant level as compared to non-displaced. This might be due to those displaced households' loss possession of natural capital financial capital and social capital. The estimation result presented in table 15 provides supportive evidence that, the urban expansion has negative correlation and significant effect on the peri_urban household's livelihood asset, such as natural, financial, and social capitals at a value of (**-0.443)**, (**-0.172)** and (**-0.166**) respectively.

Table 18: Average treatment effect on treated (ATT)

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
hum_capital	Unmatched	.522188011	.479945266	.042242746	.032052001	1.32
	ATT	.51709669	.512519437	.004577254	.054248133	0.08
natu_capital	Unmatched	.15218427	.552450246	-.400265975	.019319366	-20.72
	ATT	.148245135	.59148822	-.443243086	.036612376	-12.11
fina_capital	Unmatched	.397354655	.489832733	-.092478078	.027969362	-3.31
	ATT	.393149845	.565350635	-.17220079	.047698079	-3.61
phy_capital	Unmatched	.46842733	.384723883	.083703447	.029728061	2.82
	ATT	.465643265	.287724197	.177919068	.047477955	3.75
social_capital	Unmatched	.439242944	.562076815	-.122833871	.038354118	-3.20
	ATT	.443607501	.610024534	-.166417032	.064617285	-2.58
composite_asset	Unmatched	.353822037	.430634536	-.076812499	.027621857	-2.78
	ATT	.358472898	.517315909	-.158843011	.046866402	-3.39

Source: Household Survey (2022)

The results indicate that being a displaced is significantly decreased farmer's household livelihood asset status. May be this impact is occurred due to loss their cultivated land, reduced fire wood availability, gained more credit, decreased income, losses social relation in the community and stop participation in social organization due to urban expansion program intervention. This result was in line with Wegedie (2018); Alemineh (2019) and Teshome (2021) and Weldearegay *et al.* (2021). However, the average difference of human capital and physical capital were increased. But there not significance difference between two groups in terms of human capital.

Whereas the result also signifies that physical capital on average possessed by displaced households as compared to the non-displaced households is increased by (**0.177)** at 1% significance level. This implies that, displaced households have owned more physical capital indicators like access to infrastructure. Because they are found nearest to the urban center so they may get improved better infrastructure than controlled group and purchasing more durable home furniture and constructing number of home rooms during compensation of displacement when they received cash payment. This result is consistent with Tessema (2017) there is infrastructural improvement after displacement. Similarly focus group discussant finding in this study was in line with this quantitative result.

4.4.1.2. Checking Robustness of Average Treatment Effect on treated

The strength of the propensity score-matching model for average treatment effect on treated was found to be good. Psmatch2 was used to check the robustness of the ATT for the outcome variables on livelihood asset. As it is presented in appendex9 independent variables were used to estimate the outcome variable livelihood asset which are found to be, jointly, statistically significant with Z value, for human, natural, financial, physical, and social is (**1.6**), (-**10.48**), (-**4.5**), (**4.43**), and (-**3.05**) and P value less than one percent for all outcome variable expect human capital it is not significant. Similarly, the livelihood asset revealed that at less than 1% significant level. Therefore, the result was supports the ATT result livelihood asset it is done in (Table 15).

Sensitivity Analysis

The sensitivity analysis Rosenbaum bounds (2002) As cited by Teshome (2021) calculates for average treatment effects on the treated to test whether the presence of unobserved heterogeneity (hidden bias) between treatment and control cases which allows us to determine how strongly an unmeasured confounding variable may affect selection in the treatment. If there are unobserved variables that simultaneously affect assignment into treatment and the outcome variable, a hidden bias might arise to which matching estimators are not. In this study, under the assumption of no hidden bias, indicating a significant treatment effect sensitivity analysis was carried out on the estimated average treatment effect using alternative matching estimators for only significant outcome variables since testing sensitivity analysis for insignificant outcome indicators is meaningless.

The results were performed sensitivity analysis at gamma 0.1, 1, 2 and alpha level (0.95, confidence interval). The results indicated in Appendices 4(D to H) for each significant outcome indicators such as (natural, financial, physical, social and livelihood asset) shows the effect of the program is not changing though it was stable between upper and lower bounds implies insensitive regarding these outcome indicators. Thus, it possible to concluded that our impact estimates (ATT) of households‟ human, natural, financial, physical, social and livelihood asset were insensitive to unobserved selection bias and were the result of the effect of the urban expansion program.

CHAPTER FIVE: CONCLUSIONS AND RECOMMENDATIONS

5.1. Conclusions

The aim of this study was to assess the impact of urban expansion on displaced households' livelihood asset in Debark Town Amhara National Regional State of Ethiopia. Hence, this study considered drivers of urban expansion, impact of urban expansion on displaced peri_urban farmers livelihood asset and land use land cover change. So, for addressing these objectives appropriate methodology was employed. Thus, selected key informants and elders from the sample kebele for discussion to identify the drivers of urban expansion. As result, achieved from them, natural population growth, rural to urban migration and economic development were the pre dominant driving factor of urban expansion. On the other way, propensity score matching method was employed to assess the impact of urban expansion on livelihood asset of displaced households.

However, before estimating the impact, the outcome variable such as human, natural, Financial, Physical and social capital were created by using factor analysis. Because it is impossible to measure them directly. After created those variable total composite/ livelihood assets was generated from those five capitals by applying second step of factor analysis. Then after this step those five capitals and composite asset were used as an outcome variable. Then logistic regression model was applied to estimate the propensity score by using the selected covariates and PSM was used to assess the impact urban expansion. The result showed that average composite asset of urban induced displaced households was significantly smaller than the non-displaced households by (**-0.159**) at 1% significant level.

Similarly, the average impact of urban expansion on displaced household in terms of natural, financial and social capita was decrease by at a value of (**-0.443**), (**-0.172)** and (**-0.166**) respectively as compared to non-displaced and the impact that urban expansion is statistically significant at 1% significance in kernel methods of estimator. On the other hand, the average physical capital displaced households were significantly greater than the non-displaced at a value of (**0.177**) and values is significant at $p<0.01$. This implies that the proxy variables of physical capital (electric power access, pure water access, health service access durable asset ownership, and distance to urban center) were increase to displaced household than non-displaced household.

However, by contradicted with this the proxy variables included in natural, financial and social capitals decreased due to urban expansion to displaced households than non-displaced households. Thus, it is possible to conclude that since displaced households" are less potential to spend sustain their life due to depletion of livelihood assets they are unprotected from shock, fall to ensure food security and the instability of livelihood asset status was critical problem in the study area. The other lesson, which we can infer from the results that the observed negative and significant difference between urban induced displaced and non-displaced households indicated the impact of urban expansion needs careful management.

Satellite images for the year 2001, 2013 and 2021 were used to prepare the LULC maps, and analyze urban expansion changing aspects. In the last twenty (20 years), built-up area increased by 2702.5 ha and mostly gain from cultivated land. Other land uses decreased by 1988 ha (-19.7%), 369 ha (-3.7%), and 346 ha (grazing areas) (-3.5 percent). Area coverage of built up are in the year 2001, 2013 and 2021 was 1654.5, 3136 and 4357 respectively. This land use land cover change result also showed livelihood asset are decreased because built up land is increased rapidly at the expense of other land use land covers.

5.2. Recommendations

The study revealed that urban expansion has negative impact on livelihood assets. It finds that, natural, financial and social capital are significantly reduced and physical capital is increased to displaced household than non-displaced household. Based on this fact the following recommendations have been made:

- Urban expansion has a positive impact on physical capital and is used to build other livelihood assets. So urban expansion programmers and planers should be focused on how to sustain the livelihood asset of peri urban displaced household through providing sustainable source of revenue, market and alternative production opportunities.

- Financial capital is decreased because of cultivated land consumed to urban use and the farmers' household have faced a big problem. Therefore, town administration staff should provide training, continuous follow up and extension services, business development services for those displaced household farmers to leave their former livelihood strategy facilitate different new business options.

- How much, when should be expanded could be based on the criteria in reality of planning to be directed by policy direction and hence benefited displaced farmers from urban development.
- The study also indicates that the responsible body should test the ways of program implementation procedure and people's perception at the ground level. Unless the program improves the way of expansion it may be continued adversely affect the displaced household.
- Regarding to this study impact of urban expansion is evaluated by using PSM method without base line data by comparing two groups. This study followed the cross-sectional approach to measure the impact of urban expansion on livelihood assets of displaced households. Therefore, it recommends longitudinal survey with institutional base line data by using difference in difference method which is very important to estimate the impact of urban expansion.
- Since this study was limited in scope so, it recommends for future researcher to study the adversely impact of urban expansion on natural resource such as deforestation, flood, erosion due to the conversion of land and deposits of wastes.

REFERENCES

Abay, K., Tiberti, L., Mezgebo, T. G. & Hailu, M. (2020). Can Urbanization Improve Household Welfare? Evidence from Ethiopia. *Evidence from Ethiopia (May 14, 2020). Partnership for Economic Policy Working Paper*.

Abebe, J. T. (2020). An Impacts of Urban expansion on the Livelihood of Farming Community in Peri-Urban Areas of Dessie Town Using GIS and Remote Sensing Techniques. *Journal of Higher Education Service Science and Management (JoHESSM),* 3.

Aboda, C., Mugagga, F., Byakagaba, P. & Nabanoga, G. (2019). Development induced displacement: A review of risks faced by communities in developing countries. *Sociology and Anthropology,* 7**,** 100-110.

Adebayo, T. S., Ramzan, M., Iqbal, H. A., Awosusi, A. A. & Akinsola, G. D. (2021). The environmental sustainability effects of financial development and urbanization in Latin American countries. *Environmental Science and Pollution Research***,** 1-14.

Admasu, W. F., Van Passel, S., Minale, A. S., Tsegaye, E. A., Azadi, H. & Nyssen, J. (2019). Take out the farmer: An economic assessment of land expropriation for urban expansion in Bahir Dar, Northwest Ethiopia. *Land Use Policy,* 87**,** 104038.

Agegnehu, S. K., Fuchs, H., Navratil, G., Stokowski, P., Vuolo, F. & Mansberger, R. (2016). Spatial urban expansion and land tenure security in Ethiopia: Case studies from Bahir Dar and Debre Markos peri-urban areas. *Society & Natural Resources,* 29**,** 311-328.

Agegnehu, S. K. & Mansberger, R. (2020). Community involvement and compensation money utilization in Ethiopia: Case studies from bahir dar and debre markos peri-urban areas. *Sustainability,* 12**,** 4794.

Ahlam, Y. (2017). Urban expansion and its impact on the livelihood of peripheral farming communities: The case of Kutaber town. *Amhara region, Ethiopia (MSc. Thesis), Addis Ababa University, Addis Ababa*.

Akirso, N. A. (2021). Squatter Settlement: Costs and Contributing Factors in Jimma Town, Oromia National Regional State, Ethiopia. *European Review Of Applied Sociology,* 14**,** 11-19.

Al-Bilbisi, H. (2019). Spatial monitoring of urban expansion using satellite remote sensing images: A case study of Amman City, Jordan. *Sustainability,* 11**,** 2260.

Al-Bilbisi, H. H. (2017). Land Use/Cover Change Detection in Arid and Semi-Arid Areas of Northeastern Jordan Using Landsat Images. *Jordan Journal of Social Sciences,* 10.

Alburshaid, E. & Mangoud, M. (2021). Spatio-temporal land use analysis and urban growth dynamic prediction in the kingdom of Bahrain.

Alemineh, Y. T. (2019). Government Strategies and Implementation Challenges on Evicted Farming Households in Ensuring Sustainable Livelihoods: The Case of Gondar City-peripheral Rural-Communities. Gondar, Ethiopia.

Angel, S., Blei, A. M., Parent, J., Lamson-Hall, P., Galarza-Sanchez, N., Civco, D. L. & Thom, K. (2016). Atlas of urban expansion—2016 edition. *Areas and densities. Cambridge, MA: NYU Urban Expansion Program at New York University, UN-Habitat, and the Lincoln Institute of Land Policy*.

Arif, M., Srinivasa RAO, D. & GUPTA, K. (Year) Published. Peri-urban livelihood dynamics: a case study from Eastern India. Forum Geografic, 2019.

Ashiru, P. (2015). The roles of Planners in the Built Environment. Olabisi Onabanjo University.

Atara, A., Tolossa, D. & Denu, B. (2020). Analysis of rural households' resilience to food insecurity: Does livelihood systems/choice/matter? The case of Boricha woreda of sidama zone in southern Ethiopia. *Environmental Development,* 35**,** 100530.

Ayele, A. & Tarekegn, K. (2020). The impact of urbanization expansion on agricultural land in Ethiopia: A review. *Environmental & Socio-economic Studies,* 8**,** 73-80.

Balew, A. & Semaw, F. (2021). Impacts of land-use and land-cover changes on surface urban heat islands in Addis Ababa city and its surrounding. *Environment, Development and Sustainability***,** 1-35.

Banu, N. & Fazal, S. (2017). A pragmatic assessment of livelihood status in the peri-urban interface: A case from developing India. *Asian Geographer,* 34**,** 1-23.

Bapari, M. Y., Haque, M. E., Chowdhury, M. K. I. & Islam, M. J. (2016). Impacts of unplanned urbanization on the socio–economic conditions and environment of Pabna Municipality, Bangladesh. *Journal of Environment and Earth Science,* 6**,** 105-114.

Barrett, C. B., Christian, P. & Shiferaw, B. A. (2017). The structural transformation of African agriculture and rural spaces: introduction to a special section. *Agricultural Economics,* 48**,** 5-10.

Bawono, S. (2021). Human capital, technology, and economic growth: A case study of Indonesia. *Journal of Asian Finance, Economics and Business*.

Bekele, F. (2010). *The Impact of Horizontal Urban Expansion on Sub-Urban Agricultural Community Livelihood: The Case of Tabor Sub-City, Hawassa city, SNNPRS, Ethiopia.* Msc. Thesis Addis Ababa University, Addis Ababa, Ethiopia.

Belay, E. (2014). Impact of urban expansion on the agricultural land use a remote sensing and GIS Approach: A Case of Gondar City, Ethiopia. *International Journal of Innovative Research and Development,* 3**,** 129-133.

Berhanu, K. (2018). *Impacts Of Horizontal Urban Expansion On The Surrounding Rural Farming Communities: The Case Of Debre Berhan, North Shewa, Amhara Region.*

Bihamta, N., Soffianian, A., Fakheran, S. & Gholamalifard, M. (2015). Using the SLEUTH urban growth model to simulate future urban expansion of the Isfahan metropolitan area, Iran. *Journal of the Indian Society of Remote Sensing,* 43**,** 407-414.

Bimonte, S. & Stabile, A. (2017). Land consumption and income in Italy: a case of inverted EKC. *Ecological Economics,* 131**,** 36-43.

Bodo, T. (2019). Rapid urbanisation: theories, causes, consequences and coping strategies. *Annals of Geographical Studies,* 2**,** 32-45.

Bonilla-Bedoya, S., Mora, A., Vaca, A., Estrella, A. & Herrera, M. Á. (2020). Modelling the relationship between urban expansion processes and urban forest characteristics: An application to the Metropolitan District of Quito. *Computers, Environment and Urban Systems,* 79**,** 101420.

Bonye, S. Z., Aasoglenang, T. A. & Yiridomoh, G. Y. (2021). Urbanization, agricultural land use change and livelihood adaptation strategies in peri-urban Wa, Ghana. *SN Social Sciences,* 1**,** 1-23.

Borelli, S., Conigliaro, M., Quaglia, S. & Salbitano, F. (2017). Urban and Peri-urban agroforestry as multifunctional land use. *Agroforestry.* Springer.

Briassoulis, H. (2000a). ``Analysis of land use change: theoretical and modeling approaches, inWeb Book of Regional Science Ed. S Loveridge, Regional Research Institute, West Virginia University, Morgantown, WV.

Briassoulis, H. (2000b). Analysis of land use change: theoretical and modeling approaches, the web book of regional Science. *Regional research institute, West Virginia University, USA.*

Caliendo, M. & Kopeinig, S. (2008). Some practical guidance for the implementation of propensity score matching. *Journal of economic surveys,* 22**,** 31-72.

Chamling, M. & Bera, B. (2020). Spatio-temporal patterns of land use/land cover change in the Bhutan–Bengal foothill region between 1987 and 2019: study towards geospatial applications and policy making. *Earth Systems and Environment,* 4**,** 117-130.

Dadashpoor, H., Azizi, P. & Moghadasi, M. (2019). Land use change, urbanization, and change in landscape pattern in a metropolitan area. *Science of the Total Environment,* 655**,** 707-719.

Damtie, Y. A., Berlie, A. B. & Gessese, G. M. (2022). Impact of water hyacinth on rural livelihoods: the case of Lake Tana, Amhara region, Ethiopia. *Heliyon,* 8**,** e09132.

Damtie, Y. A. & Mengistu, D. A. (2022). Water Hyacinth (Eichhornia crassipes (Mart.) Solms) Impacts on Land-Use Land-Cover Change Across Northeastern Lake Tana. *Journal of the Indian Society of Remote Sensing***,** 1-12.

Dega, M. B., Emana, A. N. & Feda, H. A. (2022). The Impact of Catchment Land Use Land Cover Changes on Lake Dandi, Ethiopia. *Journal of Environmental and Public Health,* 2022.

Deyong, Y., Hongbo, S., Peijun, S., Wenquan, Z. & Yaozhong, P. (2019). How does the conversion of land cover to urban use affect net primary productivity? A case study in Shenzhen city, China. *Agricultural and Forest Meteorology,* 149**,** 2054-2060.

Diao, X., Hazell, P., Kolavalli, S. & Resnick, D. (2019). *Ghana's economic and agricultural transformation: Past performance and future prospects*, Oxford University Press.

Dires, T., Fentie, D., Hunie, Y., Nega, W., Tenaw, M., Agegnehu, S. K. & Mansberger, R. (2021). Assessing the Impacts of Expropriation and Compensation on Livelihood of Farmers: The Case of Peri-Urban Debre Markos, Ethiopia. *Land,* 10**,** 614.

Du, E., De Vries, W., Liu, X., Fang, J., Galloway, J. & Jiang, Y. (2015). Spatial boundary of urban 'acid islands' in southern China. *Scientific reports,* 5**,** 1-9.

Dutta, I. & Das, A. (2019). Application of geo-spatial indices for detection of growth dynamics and forms of expansion in English Bazar Urban Agglomeration, West Bengal. *Journal of Urban Management,* 8**,** 288-302.

Duvernoy, I., Zambon, I., Sateriano, A. & Salvati, L. (2018). Pictures from the other side of the fringe: Urban growth and peri-urban agriculture in a post-industrial city (Toulouse, France). *Journal of Rural Studies,* 57**,** 25-35.

DWAO (2022). Debark woreda Adminstration Office descripition of debark

El Garouani, A., Mulla, D. J., El Garouani, S. & Knight, J. (2017). Analysis of urban growth and sprawl from remote sensing data: Case of Fez, Morocco. *International Journal of Sustainable Built Environment,* 6**,** 160-169.

Elhamdouni, D., Arioua, A. & Karaoui, I. (2021). Monitoring urban expansion using SVM classification approach in Khenifra city (Morocco). *Modeling Earth Systems and Environment***,** 1-6.

Enyew, F. B. (2019). Assess the Impact of Urban Expansion on the Periphery Residence in Debre Tabor Town in Case of Kebele 01. *Science,* 5**,** 143-156.

Enyew, F. B. (2021). Assess the Impact of Urban Expansion on the Periphery Residence in Debre Tabor Town in Case of Kebele 01. *Science,* 5**,** 143-156.

Ermias, A., Bogaert, J. & Wogayehu, F. (2019). Analysis of city size distribution in Ethiopia: Empirical evidence from 1984 to 2012. *Journal of Urban Management,* 8**,** 237-244.

Fagerland, M. W. & Hosmer, D. W. (2017). How to test for goodness of fit in ordinal logistic regression models. *The Stata Journal,* 17**,** 668-686.

Fekadu, T. (2015). Urban Expansion And Its Effects On Peripheral Farming Communities: The Case Of Hosanna Town. *Hadiyazone, Snnpr, Ethiopia*.

Fenta, A. A., Yasuda, H., Haregeweyn, N., Belay, A. S., Hadush, Z., Gebremedhin, M. A. & Mekonnen, G. (2017). The dynamics of urban expansion and land use/land cover changes using remote sensing and spatial metrics: the case of Mekelle City of northern Ethiopia. *International Journal of Remote Sensing,* 38**,** 4107-4129.

Field, A. (2009). Discopering statistics using SPSS, thrid edition.

Fikadu, T. (2015). Urban Expansion and Its Effects on Peripheral Farming Communities: The Case of Hosanna Town, Hadiya Zone, SNNPR, Ethiopia. *Haramaya University, Haramay*.

Fitawok, M. B., Derudder, B., Minale, A. S., Van Passel, S., Adgo, E. & Nyssen, J. (2020). Modeling the Impact of Urbanization on Land-Use Change in Bahir Dar City, Ethiopia: An Integrated Cellular Automata–Markov Chain Approach. *Land,* 9**,** 115.

Foody, G. M. (2020). Explaining the unsuitability of the kappa coefficient in the assessment and comparison of the accuracy of thematic maps obtained by image classification. *Remote Sensing of Environment,* 239**,** 111630.

Frölich, M. & Sperlich, S. (2019). *Impact evaluation*, Cambridge University Press.

Gambo Boukary, A., Diaw, A. & Wünscher, T. (2016). Factors affecting rural households' resilience to food insecurity in Niger. *Sustainability,* 8**,** 181.

Gao, B., Huang, Q., He, C., Sun, Z. & Zhang, D. (2016). How does sprawl differ across cities in China? A multi-scale investigation using nighttime light and census data. *Landscape and Urban Planning,* 148**,** 89-98.

Gashu, K. & Gebre-Egziabher, T. (2018). Spatiotemporal trends of urban land use/land cover and green infrastructure change in two Ethiopian cities: Bahir Dar and Hawassa. *Environmental Systems Research,* 7**,** 1-15.

Ge, Y. & Cao, F. (Year) Published. A study on the driving forces of urban expansion using rough sets. International Conference on Computational Science and Its Applications, 2009. Springer, 176-188.

Gebregziabher, Z. & Yiadom, K. S. (2014). The impact of urban sprawl on the livelihood of fringe farmers in Mekelle, Ethiopia. *growth,* 4.

Gebrekristos, T. (2021). Urbanization and Development in Ethiopia: Policy Issues, Trends and Prospects. *Economic Development, Population Dynamics, and Welfare***,** 93.

Getu, K. & Bhat, H. G. (2021). Analysis of spatio-temporal dynamics of urban sprawl and growth pattern using geospatial technologies and landscape metrics in Bahir Dar, Northwest Ethiopia. *Land Use Policy,* 109**,** 105676.

Gong, P., Li, X., Wang, J., Bai, Y., Chen, B., Hu, T., Liu, X., Xu, B., Yang, J. & Zhang, W. (2020). Annual maps of global artificial impervious area (GAIA) between 1985 and 2018. *Remote Sensing of Environment,* 236**,** 111510.

González-García, A., Palomo, I., González, J. A., López, C. A. & Montes, C. (2020). Quantifying spatial supply-demand mismatches in ecosystem services provides insights for land-use planning. *Land Use Policy,* 94**,** 104493.

Gorzelak, M. & Dąbrowska, D. (2021). Environmental & Socio-economic Studies.

Gumma, M. K., Mohammad, I., Nedumaran, S., Whitbread, A. & Lagerkvist, C. J. (2017). Urban sprawl and adverse impacts on agricultural land: A case study on Hyderabad, India. *Remote sensing,* 9**,** 1136.

Güneralp, B., Lwasa, S., Masundire, H., Parnell, S. & Seto, K. C. (2017). Urbanization in Africa: challenges and opportunities for conservation. *Environmental research letters,* 13**,** 015002.

Güneralp, B., Reba, M., Hales, B. U., Wentz, E. A. & Seto, K. C. (2020). Trends in urban land expansion, density, and land transitions from 1970 to 2010: a global synthesis. *Environmental Research Letters,* 15**,** 044015.

Gwan, A. S. & Kimengsi, J. N. (2020). Urban expansion and the dynamics of farmers' livelihoods: Evidence from Bamenda, Cameroon. *Sustainability,* 12**,** 5788.

Han, X., Zhang, A. & Cai, Y. (2020). Spatio-Econometric Analysis of Urban Land Use Efficiency in China from the Perspective of Natural Resources Input and Undesirable Outputs: A Case Study of 287 Cities in China. *International Journal of Environmental Research and Public Health,* 17**,** 7297.

Handley, M. A., Lyles, C., McCulloch, C. & Cattamanchi, A. (2018). Selecting and improving quasi-experimental designs in effectiveness and implementation research. *Annual review of public health,* 39**,** 5.

Harris, A. (2015). Expropriation, compensation and transitions to new livelihoods: Evidence from an expropriation in Ethiopia.

Hulme, D. & McKay, A. (2013). Identifying and measuring chronic poverty: Beyond monetary measures? *The many dimensions of poverty.* Springer.

Ibido, M. N. (2020). Pollution Control 2020-Urban expansion and its impact on peri-urban household: The case of Gelan and Dukem Towns, Ethiopia-Mesfin Nigussie Ibido-Nanjing Agricultural University. *Journal of Nuclear Energy & Power Generation Technologies,* 4**,** 1-2.

Inki, A. B. (2018). Impact of urban expansion on the livelihood of periphral community : in the case of holeta town.

Jiang, L. & Zhang, Y. (2016). Modeling urban expansion and agricultural land conversion in Henan Province, China: An integration of land use and socioeconomic data. *Sustainability,* 8**,** 920.

Jiang, Y., Fu, P. & Weng, Q. (2015). Assessing the impacts of urbanization-associated land use/cover change on land surface temperature and surface moisture: A case study in the midwestern United States. *Remote Sensing,* 7**,** 4880-4898.

Jonga, W. (2013). Dilemmas of Urban Development: A Survey of Addis Ababa City Residents' Opinion on Urban Agriculture. *Available at SSRN 2233445*.

Kamaruddin, R. & Samsudin, S. (2014). The sustainable livelihoods index: A tool to assess the ability and preparedness of the rural poor in receiving entrepreneurial project. *Journal of Social Economics Research,* 1**,** 108-117.

Kantakumar, L. N., Kumar, S. & Schneider, K. (2016). Spatiotemporal urban expansion in Pune metropolis, India using remote sensing. *Habitat international,* 51**,** 11-22.

Kasa, L., Zeleke, G., Alemu, D., Hagos, F. & Heinimann, A. (2011). Impact of urbanization of Addis Abeba city on peri-urban environment and livelihoods. *Sekota Dry Land Agricultural Research Centre of Amhara Regional Agricultural Research Institute: Addis Ababa, Ethiopia*.

Kashwan, P. (2017). Inequality, democracy, and the environment: A cross-national analysis. *Ecological Economics,* 131**,** 139-151.

Katyambo, M. M. & Ngigi, M. M. (2017). Spatial monitoring of urban growth using GIS and remote sensing: a case study of Nairobi metropolitan area, Kenya.

Kleemann, J., Inkoom, J. N., Thiel, M., Shankar, S., Lautenbach, S. & Fürst, C. (2017). Peri-urban land use pattern and its relation to land use planning in Ghana, West Africa. *Landscape and Urban Planning,* 165**,** 280-294.

Korah, P. I., Nunbogu, A. M. & Akanbang, B. A. A. (2018). Spatio-temporal dynamics and livelihoods transformation in Wa, Ghana. *Land use policy,* 77**,** 174-185.

Koroso, N. H., Lengoiboni, M. & Zevenbergen, J. A. (2021). Urbanization and urban land use efficiency: Evidence from regional and Addis Ababa satellite cities, Ethiopia. *Habitat International,* 117**,** 102437.

Koroso, N. H., Zevenbergen, J. A. & Lengoiboni, M. (2020). Urban land use efficiency in Ethiopia: An assessment of urban land use sustainability in Addis Ababa. *Land Use Policy,* 99**,** 105081.

Kotkin, J. (2016). *The human city: Urbanism for the rest of us*, Agate Publishing.

Kötter, T. (2017). Risks and opportunities of urbanisation and megacities. *Proceedings of the FIG Working Week, Athens, Greece, http://www. fig. net/pub/athens/papers/ps02/ps02_2_kotter. pdf.*

Kranjčić, N., Medak, D., Župan, R. & Rezo, M. (2019). Support vector machine accuracy assessment for extracting green urban areas in towns. *Remote Sensing,* 11**,** 655.

Kry, S., Sasaki, N., Datta, A., Abe, I., Ken, S. & Tsusaka, T. W. (2020). Assessment of the changing levels of livelihood assets in the Kampong Phluk community with implications for community-based ecotourism. *Tourism Management Perspectives,* 34**,** 100664.

Kuang, F., Jin, J., He, R., Ning, J. & Wan, X. (2020). Farmers' livelihood risks, livelihood assets and adaptation strategies in Rugao City, China. *Journal of environmental management,* 264**,** 110463.

Kukkonen, M. O., Muhammad, M. J., Käyhkö, N. & Luoto, M. (2018). Urban expansion in Zanzibar City, Tanzania: Analyzing quantity, spatial patterns and effects of alternative planning approaches. *Land Use Policy,* 71**,** 554-565.

Kumar, R., Rai, A., Mishra, V. N., Diwate, P. & Arya, V. (2021). Performance Evaluation of Supervised Classifiers for Land Use and Land Cover Mapping Using Sentinel-2 MSI Image.

Kuusaana, E. D. & Eledi, J. A. (2015). Customary land allocation, urbanization and land use planning in Ghana: Implications for food systems in the Wa Municipality. *Land Use Policy,* 48**,** 454-466.

Lalani, N., Jimenez, R. B. & Yeap, B. (2020). Understanding propensity score analyses. *International Journal of Radiation Oncology, Biology, Physics,* 107**,** 404-407.

Leeuw, F. L. & Vaessen, J. (2009). Impact evaluations and development: NONIE guidance on impact evaluation.

Lei, Y., Flacke, J. & Schwarz, N. (2021). Does Urban planning affect urban growth pattern? A case study of Shenzhen, China. *Land Use Policy,* 101**,** 105100.

Lippitt, C. D. & Zhang, S. (2018). The impact of small unmanned airborne platforms on passive optical remote sensing: A conceptual perspective. *International Journal of Remote Sensing,* 39**,** 4852-4868.

Liu, X., Huang, Y., Xu, X., Li, X., Li, X., Ciais, P., Lin, P., Gong, K., Ziegler, A. & Chen, A. (2020). High-spatiotemporal-resolution mapping of global urban change from 1985 to 2015. Nature Sustainability, 3 (7), 564–570.

Liu, Z., Chen, Q. & Xie, H. (2018). Influence of the farmer's livelihood assets on livelihood strategies in the western mountainous area, China. *Sustainability,* 10**,** 875.

Magidi, J. & Ahmed, F. (2019). Assessing urban sprawl using remote sensing and landscape metrics: A case study of City of Tshwane, South Africa (1984–2015). *The Egyptian Journal of Remote Sensing and Space Science,* 22**,** 335-346.

Mahama, T. A. & Maharjan, K. L. (2019). Determining the nature and spatial-temporal changes of the livelihood asset pentagon and its relationship with livelihood opportunities in Ghana. *Community Development,* 50**,** 460-483.

Mamuye, F. & Ebabu, D. (2021). Analysis of urban horizontal expansion and its impact on the surrounding land using GIS and remote sensing: a case of Werabe town.

Manoli, G., Fatichi, S., Schläpfer, M., Yu, K., Crowther, T. W., Meili, N., Burlando, P., Katul, G. G. & Bou-Zeid, E. (2019). Magnitude of urban heat islands largely explained by climate and population. *Nature,* 573**,** 55-60.

Mariye, M., Mariyo, M., Changming, Y., Teffera, Z. L. & Weldegebrial, B. (2020). Effects of land use and land cover change on soil erosion potential in Berhe district: A case study of Legedadi watershed, Ethiopia. *International Journal of River Basin Management***,** 1-13.

Martin, S. M. & Lorenzen, K. (2016). Livelihood diversification in rural Laos. *World Development,* 83**,** 231-243.

Mekuriaw, T. & Gokcekus, H. (2019). The Impact of Urban Expansion on Physical Environment in Debre Markos Town, Ethiopia.

Mengistu, T. (2016). Horizontal Urban Expansion And Livelihood Adjustment Problem Among Ex-Farmers In The Kebeles Surrounding Jimma Town: The Case Of Derba Kebele. *European Scientific Journal,* 12.

Mezgebo, T. & Porter, C. (2017). From rural to urban, but not through migration: Household livelihood responses to urbanization in Northern Ethiopia. *Journal of Agricultural Economics (in progress).*

Michelson, H., Muñiz, M. & DeRosa, K. (2013). Measuring socio-economic status in the millennium villages: the role of asset index choice. *The Journal of Development Studies,* 49**,** 917-935.

Mkhize, H. P., Johnson, T., Samboko, P. C. & You, L. (2016). The impact of urban growth on agricultural and rural non-farm growth in Kenya.

Mohammed, I., Kosa, A. & Juhar, N. (2017). Urbanization in Ethiopia: Expropriation Process and Rehabilitation Mechanism of Evicted Peri-Urban Farmers (Policies and Practices). *Int. J. Econ. Manag. Sci,* 6.

Mohammed, I., Kosa, A. & Juhar, N. (2020). Economic linkage between urban development and livelihood of peri-urban farming communities in Ethiopia (policies and practices). *Agricultural and Food Economics,* 8**,** 1-17.

Moser, C. O. (2021). Mothers, daughters, fathers and sons: intergenerational family social capital and inequalities in Guayaquil, Ecuador. *Environment and Urbanization,* 33**,** 193-210.

MoUDH (2015). Highlights about Ethiopian Urban Local Governments

Financial Management System report.

Muluwork, B. B. (2014). *An assessment of livelihood and food security of farmers displaced due to urban expansion.* Mekelle University.

Nassar, M., Levy, R., Keough, N. & Nassar, N. N. (2019). Agricultural land use change and its drivers in the palestinian landscape under political instability, the case of Tulkarm City. *Journal of Borderlands Studies,* 34**,** 377-394.

Nguyen, H. M. (2018). The relationship between urbanization and economic growth: An empirical study on ASEAN countries. *International Journal of Social Economics*.

Nguyen, P., van Westen, A. & Zoomers, A. (2017). Compulsory land acquisition for urban expansion: livelihood reconstruction after land loss in Hue's peri-urban areas, Central Vietnam. *International Development Planning Review,* 39**,** 99.

Oduro, C. Y., Adamtey, R. & Ocloo, K. (2015). Urban growth and livelihood transformations on the fringes of African cities: A case study of changing livelihoods in peri-urban Accra. *Environment and Natural Resources Research,* 5**,** 81.

Osumanu, I. K., Akongbangre, J. N., Gordon, N., Tuu, Y. & Owusu-Sekyere, E. (Year) Published. From patches of villages to a municipality: time, space, and expansion of Wa, Ghana. Urban Forum, 2019. Springer, 57-74.

Ozlu, M. O., Alemayehu, A., Mukim, M., Lall, S. V., Kerr, O. T., Kaganova, O., Viola, C. O., Hill, R., Hamilton, E. & Gapihan, A. T. (2015). Ethiopia-Urbanization review: urban institutions for a middle-income Ethiopia. The World Bank.

Pei, F., Li, X., Liu, X., Wang, S. & He, Z. (2016). Assessing the differences in net primary productivity between pre-and post-urban land development in China. *Agricultural and forest meteorology,* 171**,** 174-186.

Pomeroy, R., Arango, C., Lomboy, C. G. & Box, S. (2020). Financial inclusion to build economic resilience in small-scale fisheries. *Marine policy,* 118**,** 103982.

Rosenbaum, P. R. & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika,* 70**,** 41-55.

Schaber, C., Wékel, J. & Zdiara, A. (2016). New planning culture in German cities-topics, priorities and processes. *A documentation by Darmstadt University of Technology in cooperation the German Association of Cities and the Federal Institute for Building, Urban and Environmental Research. Retrieved form: http://www. staedtetag. de.*

Seamans, G. S. (2017). Mainstreaming the environmental benefits of street trees. *Urban Forestry & Urban Greening,* 12**,** 2-11.

Selod, H. (2017). Opportunities and challenges of urbanization, planning for an unprecedented. *DEC Policy Research Talk.*

Serrat, O. (2017). The sustainable livelihoods approach. *Knowledge solutions.* Springer.

Shao, Z., Sumari, N. S., Portnov, A., Ujoh, F., Musakwa, W. & Mandela, P. J. (2021). Urban sprawl and its impact on sustainable urban development: a combination of remote sensing and social media data. *Geo-spatial Information Science,* 24**,** 241-255.

Shinbrot, X., Jones, K., Rivera-Castañeda, A., López-Báez, W. & Ojima, D. (2019). Smallholder farmer adoption of climate-related adaptation strategies: The importance of vulnerability context, livelihood assets, and climate perceptions. *Environmental management,* 63**,** 583-595.

Siltan, D. (2019). The Impact of Development Induced Displacement on the Livelihood of Small Holder Farmers; the Case of DejenWoreda Rural Kebeles. *Int. J. Sustain. Dev. Res,* 5**,** 9-17.

Sun, W., Shan, J., Wang, Z., Wang, L., Lu, D., Jin, Z. & Yu, K. (2020). Geospatial analysis of urban expansion using remote sensing methods and data: A case study of Yangtze River Delta, China. *Complexity,* 2020.

Tame, M. (2020). *Urbanexpantion and livelihood management problems of sorrounding farmers in debark town ,Amhara regional state.* . uog.

Taye, B., Gebre, S. L., Gemeda, D. O. & Getahun, K. (2019). Using geospatial techniques in the selection of potential ecotourism sites in Menz-geramidir district, Ethiopia. *Ghana journal of geography,* 11**,** 201-227.

Teketay, D., Lemenih, M., Bekele, T., Yemshaw, Y., Feleke, S., Tadesse, W., Moges, Y., Hunde, T. & Nigussie, D. (2010). Forest resources and challenges of sustainable forest management and conservation in Ethiopia. *Degraded Forests in Eastern Africa.* Routledge.

Terfa, B., Chen, N., Liu, D., Zhang, X. & Niyogi, D. (2019). Urban expansion in Ethiopia from 1987 to 2017: characteristics, spatial patterns, and driving forces. Sustainability 11 (10): 2973.

Terfa, B. K., Chen, N., Zhang, X. & Niyogi, D. (2020). Urbanization in small cities and their significant implications on landscape structures: The case in Ethiopia. *Sustainability,* 12**,** 1235.

Teshome, A. (2021). *The Impact Of Urban Expansion On The Peri-Urban Farmers Livelihood: The Case Of Dessie City.*

Tessema, M. W. (2017). Impact of urban expansion on surrounding peasant land the case of Boloso Sore Woreda, Areka Town, SNNPR, Ethiopia. *Global Journal of Human-Social Science Research,* 17**,** 53-65.

Tiwari, J., Sharma, S. & Patil, R. (2021). Accuracy assessment of land use land cover mapping of a watershed of Narmada basin using Remote sensing and Geographical Information System. *JNKVV***,** 42.

Tura, H. A. (2018). Land rights and land grabbing in Oromia, Ethiopia. *Land use policy,* 70**,** 247-255.

Udayakumara, E. & Shrestha, R. (2011). Assessing livelihood for improvement: Samanalawewa reservoir environs, Sri Lanka. *International Journal of Sustainable Development & World Ecology,* 18**,** 366-376.

UN-Habitat (2018). SDG Indicator 11.3. 1 Training Module: Land Use Efficiency. UN-Habitat Nairobi, Kenya.

UN, D. (2015). World urbanization prospects: The 2014 revision. *United Nations Department of Economics and Social Affairs, Population Division: New York, NY, USA,* 41.

UN, D. (2018). United Nations, Department of Economic and Social Affairs, Population Division (2018). *World urbanization prospects: The*.

Vandercasteelen, J., Beyene, S. T., Minten, B. & Swinnen, J. (2018). Big cities, small towns, and poor farmers: Evidence from Ethiopia. *World Development,* 106**,** 393-406.

Waghmare, B. & Suryawanshi, M. (2017). A Review-Remote Sensing. *engineering research and application,* 7.

Wegedie, K. T. (2018). Communities in Peri-Urban Area of Bahir Dar City Amahara, Ethiopia. *Communities,* 9.

Weldearegay, S. K., Tefera, M. M. & Feleke, S. T. (2021). Impact of Urban expansion to peri-urban smallholder farmers' Poverty in Tigray, North Ethiopia. *Heliyon***,** e07303.

Willcock, S., Phillips, O. L., Platts, P. J., Swetnam, R. D., Balmford, A., Burgess, N. D., Ahrends, A., Bayliss, J., Doggart, N. & Doody, K. (2016). Land cover change and carbon emissions over 100 years in an A frican biodiversity hotspot. *Global Change Biology,* 22**,** 2787-2800.

Wondimu, H. (2020). The Subsequent Challenges of the Slum and Squatter Settlements: In the City of Addis Ababa. *Habtamu Wondimu.(2021). THE SUBSEQUENT CHALLENGES OF THE SLUM AND SQUATTER SETTLEMENTS: IN THE CITY OF ADDIS ABABA. European Journal of Research Development and Sustainability,* 2**,** 24-34.

World Bank (2018). United Nations Population Division. World Urbanization Prospects: 2018 Revision.

Woźniak, G., Hutniczak, A. & Dettmar, J. (2022). "Natural Capital" Concept–A New Approach to Environmental Management and Post-industrial Landscapes. *Green Scenarios: Mining Industry Responses to Environmental Challenges of the Anthropocene Epoch.* CRC Press.

Xu, G., Dong, T., Cobbinah, P. B., Jiao, L., Sumari, N. S., Chai, B. & Liu, Y. (2019). Urban expansion and form changes across African cities with a global outlook:

Spatiotemporal analysis of urban land densities. *Journal of Cleaner Production,* 224**,** 802-810.

Yamane, T. (1967). Statistics: An introductory analysis.

Yong, A. G. & Pearce, S. (2013). A beginner's guide to factor analysis: Focusing on exploratory factor analysis. *Tutorials in quantitative methods for psychology,* 9**,** 79-94.

Zakari, I. S. (Year) Published. Bridging data gap for understanding emerging issues in Niger: challenges and opportunities in the era of smart cities and smart villages. 2020 IEEE International Conf on Natural and Engineering Sciences for Sahel's Sustainable Development-Impact of Big Data Application on Society and Environment (IBASE-BF), 2020. IEEE, 1-7.

Zewdu, A. A. (2020). Impacts of Urban Growth on Bahir Dar City. *Canadian Social Science,* 16**,** 41-50.

Zhang, L., Weng, Q. & Shao, Z. (2017). An evaluation of monthly impervious surface dynamics by fusing Landsat and MODIS time series in the Pearl River Delta, China, from 2000 to 2015. *Remote sensing of environment,* 201**,** 99-114.

Zhang, Q. & Su, S. (2016). Determinants of urban expansion and their relative importance: A comparative analysis of 30 major metropolitans in China. *Habitat international,* 58**,** 89-107.

Zhao, S., Zhou, D., Zhu, C., Sun, Y., Wu, W. & Liu, S. (2015). Spatial and temporal dimensions of urban expansion in China. *Environmental science & technology,* 49**,** 9600-9609.

Zhu, L., Huang, Q., Ren, Q., Yue, H., Jiao, C. & He, C. (2020). Identifying urban haze islands and extracting their spatial features. *Ecological Indicators,* 115**,** 106385.

APPENDIX

Appendix1: Livestock Conversion Factor (TLU)

Livestock type	Conversion factor	Livestock type	Conversion factor
Cow/Ox	1.00	Sheep/Goat	0.06
bull	0.80		
Heifer	0.75	Donkey Young	0.35
Calf	0.20	Chicken	0.013
Horse/Mule	1.1		

Source: adapted from(Teshome, 2021)

Appendix 2: Egenvalue for 5capitals and livelihood asset

A: Egenvalue for human capital index

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	2.78467	1.86159	0.5569	0.5569
Factor2	0.92308	0.23246	0.1846	0.7416
Factor3	0.69062	0.17574	0.1381	0.8797
Factor4	0.51488	0.42814	0.1030	0.9827
Factor5	0.08674	.	0.0173	1.0000

LR test: independent vs. saturated: chi2(10) = 708.45 Prob>chi2 = 0.0000

Bartlett Test of Sphericity: Chi-Square 705.914, df (10), Sig. (p = .000). Kaiser-Meyer-Olkin Measure of Sampling Adequacy = 0.705 determinant of R-matrix = 0.079

Source: household Survey (2022)

B:Egenvalue for natural capital index

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	1.57048	0.43077	0.2617	0.2617
Factor2	1.13971	0.15089	0.1900	0.4517
Factor3	0.98882	0.03626	0.1648	0.6165
Factor4	0.95257	0.14124	0.1588	0.7753
Factor5	0.81133	0.27424	0.1352	0.9105
Factor6	0.53709	.	0.0895	1.0000

LR test: independent vs. saturated: chi2(15) = 86.08 Prob>chi2 = 0.0000

Bartlett Test of Sphericity: Chi-Square 85.773, df (15), Sig. (p = .000). Kaiser-Meyer-Olkin Measure of Sampling Adequacy = .544 determinant of R-matrix = 0.735 LR test: independent

Source: household Survey (2022)

C: Eigenvalue for financial capital index

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	2.73805	0.82827	0.3912	0.3912
Factor2	1.90978	1.06747	0.2728	0.6640
Factor3	0.84232	0.18359	0.1203	0.7843
Factor4	0.65872	0.12305	0.0941	0.8784
Factor5	0.53568	0.24192	0.0765	0.9549
Factor6	0.29376	0.27207	0.0420	0.9969
Factor7	0.02169	.	0.0031	1.0000

LR test: independent vs. saturated: chi2(21) = 1286.84 Prob>chi2 = 0.0000

Bartlett Test of Sphericity: Chi-Square 1289.565, df (28), Sig. (p = .000). Kaiser-Meyer-Olkin Measure of Sampling Adequacy = 0.510 determinant of R-matrix = 0.010

Source: household Survey (2022)

D:Egenvalue for physicall capital index

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	1.84533	0.38347	0.2636	0.2636
Factor2	1.46185	0.32426	0.2088	0.4725
Factor3	1.13759	0.24053	0.1625	0.6350
Factor4	0.89706	0.14773	0.1282	0.7631
Factor5	0.74933	0.14651	0.1070	0.8702
Factor6	0.60282	0.29679	0.0861	0.9563
Factor7	0.30602	.	0.0437	1.0000

LR test: independent vs. saturated: chi2(21) = 269.40 Prob>chi2 = 0.0000

Bartlett Test of Sphericity: Chi-Square 262.434, df (21), Sig. (p = .000). Kaiser-Meyer-Olkin Measure of Sampling Adequacy = 0.560 determinant of R-matrix = 0.0381

Source: household Survey (2022)

E:Egenvalue for social capital index

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	1.93236	0.76740	0.3865	0.3865
Factor2	1.16496	0.28666	0.2330	0.6195
Factor3	0.87831	0.24804	0.1757	0.7951
Factor4	0.63027	0.23617	0.1261	0.9212
Factor5	0.39410	.	0.0788	1.0000

LR test: independent vs. saturated: chi2(10) = 198.75 Prob>chi2 = 0.0000

Bartlett Test of Sphericity: Chi-Square 198.032, DF (10), Sig. (p = .000). Kaiser-Meyer-Olkin Measure of Sampling Adequacy = .563 determinant of R-matrix = 0.491

Source: household Survey (2022)

F: Eigenvalue for livelihood asset

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	2.00318	0.67527	0.4006	0.4006
Factor2	1.32792	0.49350	0.2656	0.6662
Factor3	0.83441	0.15478	0.1669	0.8331
Factor4	0.67964	0.52479	0.1359	0.9690
Factor5	0.15485	.	0.0310	1.0000

LR test: independent vs. saturated: chi2(10) = 406.44 Prob>chi2 = 0.0000

Bartlett Test of Sphericity: Chi-Square 404.98, df (10), Sig. (p = .000). Kaiser-Meyer-Olkin Measure of Sampling Adequacy = 0.518 determinant of R-matrix = 0.234

Source: household Survey (2022)

Appendix3: Model goodness of fit test

```
. estat gof

Logistic model for disp sta, goodness-of-fit test

       number of observations =       282
 number of covariate patterns =       282
            Pearson chi2(264) =       289.00
                  Prob > chi2 =         0.1391


. estat gof, group(10)

Logistic model for disp sta, goodness-of-fit test

  (Table collapsed on quantiles of estimated probabilities)

       number of observations =       282
             number of groups =        10
      Hosmer-Lemeshow chi2(8) =         1.28
                  Prob > chi2 =         0.9958
```

```
. estat classification, cutoff(0.11)

Logistic model for disp_sta

              -------- True --------
Classified |         D            ~D  |      Total
-----------+--------------------------+-----------
     +     |       138            15  |        153
     -     |         1           128  |        129
-----------+--------------------------+-----------
   Total   |       139           143  |        282

Classified + if predicted Pr(D) >= .11
True D defined as disp_sta != 0
--------------------------------------------------
Sensitivity                     Pr( +| D)   99.28%
Specificity                     Pr( -|~D)   89.51%
Positive predictive value       Pr( D| +)   90.20%
Negative predictive value       Pr(~D| -)   99.22%
--------------------------------------------------
False + rate for true ~D        Pr( +|~D)   10.49%
False - rate for true D         Pr( -| D)    0.72%
False + rate for classified +   Pr(~D| +)    9.80%
False - rate for classified -   Pr( D| -)    0.78%
--------------------------------------------------
Correctly classified                        94.33%
--------------------------------------------------

.
```

Appendix 4: Asumtoins of the model fit

A: Multicolinarity test for explanaratory contineous variabel

Variable	VIF	1/VIF
familysize	2.76	0.362031
age	2.35	0.426415
savi_amou	1.75	0.570456
loan_amou	1.34	0.747819
dis_ur	1.11	0.900035
mmx_dur	1.06	0.939246
Mean VIF	1.73	

B:Multicolinarity test for explanaratory catagorical variabele variabel/contigenty coficcent

	disp_sta	sor_fuwd	educ_l~l	marita~s	cred_r~v	Helth_~c	rod_ac~e	water_~c
disp_sta	1.0000							
sor_fuwd	0.0896	1.0000						
educ_level	0.0409	-0.0842	1.0000					
marital_st~s	-0.0319	0.0462	-0.2024	1.0000				
cred_receiv	0.3058	0.0020	-0.2106	0.1203	1.0000			
Helth_acc	0.2807	-0.0027	0.0451	0.0514	0.1223	1.0000		
rod_acsse	0.1925	0.0700	0.1062	0.0191	-0.0888	0.0237	1.0000	
water_acc	0.2288	0.1398	0.1861	-0.0017	-0.2068	0.0903	0.4095	1.0000
elec_acc	0.2336	-0.0509	0.1509	-0.0595	0.0299	0.0450	0.3179	0.4049
parti_soc_~a	-0.2053	0.0520	0.0280	0.0447	-0.1110	-0.0919	0.1239	-0.0650
social_rel~n	0.3105	0.0827	-0.1349	0.1013	0.4688	0.2195	-0.1300	-0.1208
vilag_sanit	0.1737	0.1215	-0.0592	-0.0897	0.0863	0.1846	-0.0015	0.0540

	elec_acc	parti_~a	social~n	vilag_~t
elec_acc	1.0000			
parti_soc_~a	-0.0286	1.0000		
social_rel~n	-0.1015	-0.0870	1.0000	
vilag_sanit	-0.1338	-0.0999	0.1748	1.0000

C:Hetrocedastiycity test

```
. hettest

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of disp_sta

         chi2(1)      =     0.29
         Prob > chi2  =   0.5916
```

D: Sensitivity Analysis for Estimated ATT natural capital (Rbounds)

```
. rbounds natu_capindx , gamma (1 (0.1)2)

Rosenbaum bounds for natu_capindx (N = 282 matched pairs)
```

Gamma	sig+	sig-	t-hat+	t-hat-	CI+	CI-
1	0	0	.352401	.352401	.32234	.379958
1.1	0	0	.344146	.362563	.311149	.389151
1.2	0	0	.332062	.368948	.298302	.39945
1.3	0	0	.323369	.379202	.288283	.407387
1.4	0	0	.313638	.385587	.276502	.415672
1.5	0	0	.306685	.395515	.264327	.423426
1.6	0	0	.297044	.400116	.256975	.433732
1.7	0	0	.290848	.405653	.24604	.440338
1.8	0	0	.280595	.413796	.240508	.448996
1.9	0	0	.272841	.417783	.229635	.455101
2	0	0	.26419	.423934	.223159	.463387

E: Sensitivity Analysis for Estimated ATT Financial Capital (Rbounds

Rosenbaum bounds for fina_capindx (N = 282 matched pairs)

Gamma	sig+	sig-	t-hat+	t-hat-	CI+	CI-
1	0	0	.438683	.438683	.407346	.469206
1.1	0	0	.427371	.449123	.396555	.480722
1.2	0	0	.417445	.458957	.387129	.491272
1.3	0	0	.40817	.468374	.378508	.500242
1.4	0	0	.399974	.477129	.370066	.507925
1.5	0	0	.392697	.484741	.36239	.515773
1.6	0	0	.385828	.492545	.355686	.523445
1.7	0	0	.379382	.499312	.349054	.529776
1.8	0	0	.373489	.505076	.342689	.536872
1.9	0	0	.367675	.510852	.336683	.543388
2	0	0	.36213	.515983	.331327	.549771

F: Sensitivity Analysis for Estimated ATT Physical Capital (Rbounds)

Rosenbaum bounds for phy_capindx (N = 282 matched pairs)

Gamma	sig+	sig-	t-hat+	t-hat-	CI+	CI-
1	0	0	.420382	.420382	.385936	.452299
1.1	0	0	.408346	.431617	.372704	.464733
1.2	0	0	.396991	.442396	.361412	.475587
1.3	0	0	.386938	.450937	.351	.484889
1.4	0	0	.37739	.460643	.341992	.493538
1.5	0	0	.368527	.469765	.333242	.500411
1.6	0	0	.359805	.476718	.325696	.508894
1.7	0	0	.352328	.483878	.317917	.51662
1.8	0	0	.345556	.489944	.311076	.524106
1.9	0	0	.339183	.495933	.304246	.530283
2	0	0	.332926	.500694	.297773	.536717

G: Sensitivity Analysis for Estimated ATT Social Capital (Rbounds)

Rosenbaum bounds for social_capindx (N = 282 matched pairs)

Gamma	sig+	sig-	t-hat+	t-hat-	CI+	CI-
1	0	0	.497145	.497145	.466594	.52619
1.1	0	0	.491525	.504351	.459002	.544511
1.2	0	0	.47778	.512696	.44872	.553169
1.3	0	0	.469998	.525715	.442095	.565405
1.4	0	0	.461768	.536416	.425344	.57582
1.5	0	0	.454855	.547615	.409543	.586372
1.6	0	0	.447737	.554237	.405352	.602027
1.7	0	0	.443125	.563947	.398492	.609849
1.8	0	0	.430839	.570535	.392595	.621564
1.9	0	0	.41778	.581805	.387819	.640006
2	0	0	.409427	.587371	.383387	.658118

H: Sensitivity Analysis for Estimated ATT livelihood asset (Rbounds)

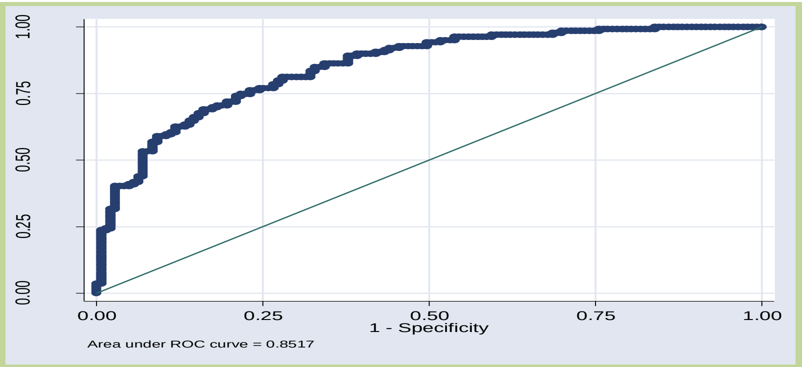
Rosenbaum bounds for livel_assetindx (N = 282 matched pairs)

Gamma	sig+	sig-	t-hat+	t-hat-	CI+	CI-
1	0	0	.388225	.388225	.360045	.416612
1.1	0	0	.378165	.398347	.349785	.427452
1.2	0	0	.368997	.407552	.340023	.437222
1.3	0	0	.360803	.415789	.331232	.445692
1.4	0	0	.353257	.423799	.322893	.454425
1.5	0	0	.345601	.431765	.31492	.462325
1.6	0	0	.338757	.438468	.30744	.469408
1.7	0	0	.332174	.444821	.30037	.476653
1.8	0	0	.326149	.451017	.293391	.483318
1.9	0	0	.320266	.457007	.287124	.489724
2	0	0	.314534	.462665	.281189	.495674

* gamma - log odds of differential assignment due to unobserved factors
sig+ - upper bound significance level
sig- - lower bound significance level
t-hat+ - upper bound Hodges-Lehmann point estimate
t-hat- - lower bound Hodges-Lehmann point estimate
CI+ - upper bound confidence interval (a= .95)
CI- - lower bound confidence interval (a= .95)

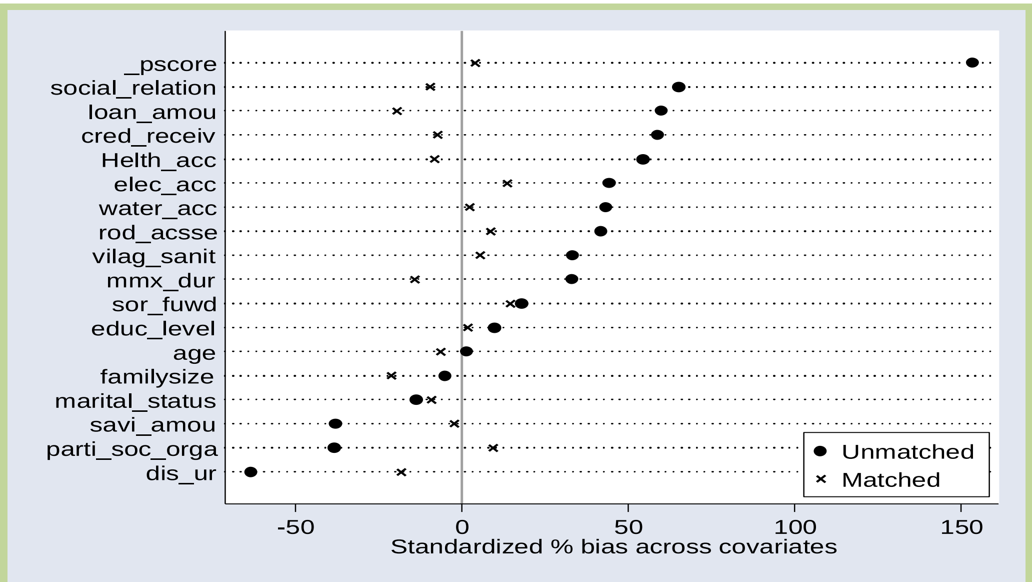
Source: household survey (2022)

Appendix5: Receiver operating characteristics curve

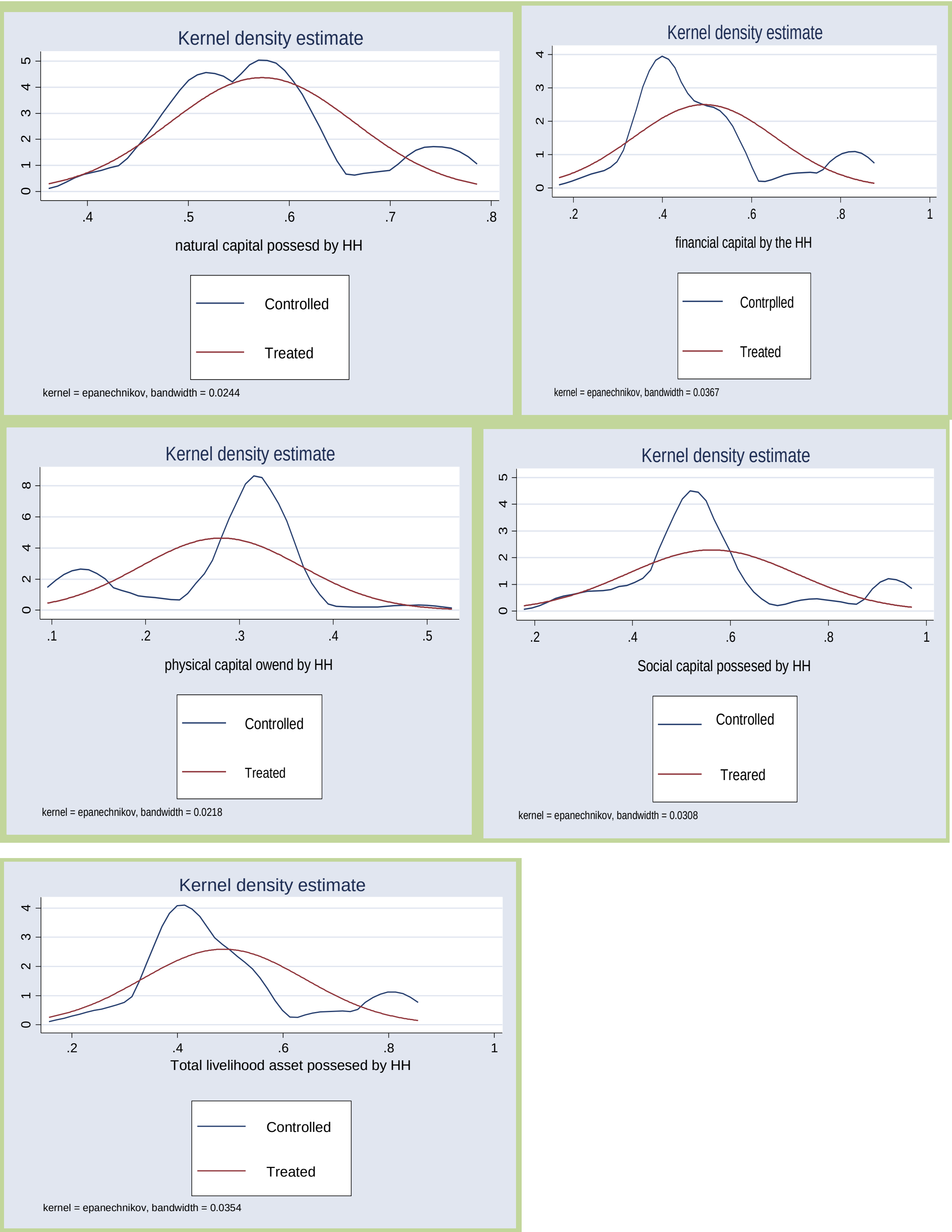


Source: household survey (2022)

Appendix 6: Standardized% bias across covariates graph



Appendix7: Kdensity Distribution of Outcome Indicators for Treated & Controlled



Source: household survey (2022)

Appendix8: Confusion matrix for land cover map of 2001 to 2021

A: Confusion matrix for land cover map of 2001

Classified land	Built up land	Cultivated land	Forest land	Grassing land	R. total	U. A

Built up land	17	1	0	0	18	94.
Cultivated land	0	22	0	0	22	100
Forest land	0	0	20	1	21	95.3
Grassing land	1	1	0	17	19	89.
Column total	18	24	20	18	80	
Producer A.C	94.	91.6	100	94.		

Over all accuracy 17+22+20+17/80*100 =95%

Kappa coefficient (K) =

(80*76)-18*18+24*22+20*21+18*19/ (80[2)] -18*18+24*22+20*21+18*19*100 =93

B: Confusion matrix for land cover map of 2013

Classified land	Built up land	Cultivated land	Forest land	Grassing land	R. total	U. A
Built up land	21	1	0	1	23	91%
Cultivated land	0	22	1	0	23	95.%
Forest land	1	0	20	1	22	90.%
Grassing land	0	1	0	19	20	95%
Column total	22	24	21	21	88	
Producer A.C	95.5%	91.6%	95%	90%		

Over all accuracy 21+22+20+19/88*100 =93.6%

Kappa coefficient (K) =

(88*82)-22*23+24*23+21*22+21*20/ (88[2)].22*23+24*23+21*22+21*20*100 =90.8%

C: Confusion matrix for land cover map of 2021

Classified land	Built up land	Cultivated land	Forest land	Grassing land	R. total	U. A
Built up land	29	0	1	1	32	90.6%
Cultivated land	2	26	1	0	28	92.8%
Forest land	2	0	27	1	30	90%
Grassing land	1	1	0	28	30	93%
Column total	30	28	29	33	120	
Producer A.C	96.6	92.8	93	84.5		

Over all accuracy 28+29+27+26/120*100 =91.6%

Kappa coefficient (K) =

(120*110)-33*30+30*32+29*30+28*28/ (120[2)].33*30+30*32+29*30+28*28*100 =88.9

Appendix9: Robustness of Average treatment effect for the treated-on outcome variable.

hum_capindx	Coef.	AI Robust Std. Err.	z	P>|z|	[95% Conf. Interval]	
ATET						
disp_sta (displaced vs non displaced)	-.0957766	.0595493	-1.61	0.108	-.2124911	.0209379

natu_capindx	Coef.	AI Robust Std. Err.	z	P>|z|	[95% Conf. Interval]	
ATET						
disp_sta (displaced vs non displaced)	-.4609454	.0440016	-10.48	0.000	-.5471869	-.3747038

fina_capindx	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
ATET						
disp_sta						
(displaced vs non displaced)	-.249749	.053741	-4.65	0.000	-.3550795	-.1444185
		AI Robust				
phy_capindx	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
ATET						
disp_sta						
(displaced vs non displaced)	.1848994	.0417331	4.43	0.000	.103104	.2666948

social_capindx	Coef.	AI Robust Std. Err.	z	P>|z|	[95% Conf. Interval]	
ATET						
disp_sta						
(displaced vs non displaced)	-.2256303	.0739166	-3.05	0.002	-.3705042	-.0807564
		AI Robust				
livel_assetindx	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
ATET						
disp_sta						
(displaced vs non displaced)	-.2419988	.0529094	-4.57	0.000	-.3456994	-.1382982

Source: Household Survey (2022)

BAHIR DAR UNIVERSITY,

INSTITUTE OF DISASTER RISK MANAGEMENT AND FOOD SECURITY STUDY

DEPARTMENT OF DISASTER RISK MANAGEMENT AND SUSTAINABLE DEVELOPMENT

Appendix 10: Household Survey Questionnaire

This plan questionnaire is set By Kibur Zerihun Debeb; a student in the Department of Disaster Risk Management and Sustainable Development at Bahir Dar University Institute of Disaster Risk Management and Food Security Study.

Statement for the respondents:

Title of the study: "Driver and impact of Urban Expansion on Peri-Urban Community in Debark woreda, Amhara Regional State, Ethiopia".

Objectives of the study: to study urban expansion drivers, the effect of urban expansion on livelihood asset in displaced peri-urban communities, and land use land cover change that related to urban expansion and to recommend favourite solutions to policymakers. The study is conducted only for academic purpose/s. Therefore, your frank responses are vibrant for the success and reliability of the study. Feel free and be confident in that it has no other purposes and your responses are kept intimate; hence, you are kindly requested to respond to all the questions accordingly. Are you voluntarily participating in this interview? (1). Yes [**]** (2). No **[]**

If the answer is **"**No**"** stop the interview here________________Thank you in advance!

Questionnaire code______Name of interviewer_____________________

Date of interview _______________ D D/MM/YY, hour________

Part 1: Demographic Data of Household

1	2	3	4	5	6
Age of HH	Sex of HH	Family size	Marital status	Level of education	How long you staying in the Kebele (in year)
	1)Male 2)Female		[1]=Married [2]=others	[1] uneducated [2] = Primary [3] = Secondary and above	

Part 2: impact of Urban Expansion on livelihood asset of displaced Peri-urban farmers

1. Are you displaced from your land? 0) no 1) yes
2. If yes, when___________
3. How much your land size in hectare ---------?
4. How much your land productivity per hectare in Quintal__________?

1. Natural capital

1.1 land Asset Ownership

1 Landholding in (hectare)

Land possessed by the household	Response	
	[1] yes	[0] no
1 do you have crop land		
2 do you have grazing land		
3 do you have forest land		
4 do you have irrigated land		

<u>1.2 Forest resources</u>

1. How do you see firewood supply is after displacement? (1). yes [] (0).no []
2. What are the sources of firewood in your household? (1). common forests [] (2). Private forest/shrubs [] (3). Purchasing [] (4). Own planted trees [] (5). Other(specify)_____
3. Do you see village sanitation problem after urban expansion? 1) yes [] 0) no

1.3 Water resources asset

1. What is/are the sources of drinking water in your households? (1). pipeline [] (2). River, pond, spring, lake [] (3.) Other/specify____________
2. How much time to fetch water from the water sources to your households? (/hr/min)
3. Is there any river in your locality? 1) yes [] 2) no []
4. If yes, had you used for irrigation? 1) yes [ ] 2) no [ ]

2. Financial capital

2.1 Income and consumption

1. What is/are the main livelihood/s of the family? (1). Crop production [ ] (2). Livestock keeping [] (3). Forestry (4). Petty trade [ ] (5). Construction/carpentry [ ] (6). Handcraft [ ] (7). Daily labours [ ]
2. Is there a change in source of income in the last 5 years? 1) Yes 2) [ ] no [ ]
3. What are the main sources of your income? 1) Petty trade 2) Handicraft 3) Daily worker 4) Sales of firewood and charcoal 5) Livestock sales 6) Sales from crop 7) Forestry product sales 8) Sales from honey &honey product 9) Sales from honey &honey product
4. How much money do you earn from on farm income including crop production, animal production and forest production per year on average? __________
5. How much money do you earn from off farm income including in daily labour, patty trade and others per year on average? _________
6. How much money do you earn from remittance income per year on average? _________
7. How much money do you pay for food item expenditure per year on average to feed your family (such as? ________
8. Teff, Maize, Sorghum, Wheat, Barely, Peas, Beans, Chickpea, Lentils------------------ETB
9. , Milk, butter, Beef, Egg, Honey------------ ETB
10. Coffee Sugar, Oil, Pepper and Others------------ETB
11. sum total annual expenditure in -----------ETB
12. How much annual expenditure of the sum total for each of the non-food items in amount such as
13. Kitchen equipment, Charcoal, Fuel wood, Kerosene, Sop/moon------ -------------ETB
14. Water fee, medical expenses, School fee, Transport expenses, Drinks, Rents, Farm implements, Farm oxen, Animal feed, veterinary, service----------- -----ETB,
15. labour cost, Chemical, Seed, Fertilizer-----------------ETB
16. Building materials and Others------------------ETB
17. Non-food items total value ------------------------in ETB.
18. How much money do you pay for non-food item expenditure per year on average AD displacement? _________
19. How much is the productivity of your annual crops in **quintal**?
22. Sale of eucalyptus tree in number -------- yearly cash ---------------in ETN

2.2 Livestock asset ownership

S.N	The livestock type	number of livestock possessed	Multiplied by conversion factor	Total
1	Ox			
2	Cow			

3	bull			
4	Heifer			
5	Calf			
6	Sheep			
7	Horse/			
8	Donkey			
9	Hen			
10	Other			
11	Total			

2.3 Credit and saving issue

1 Are there credit institutions in your localities? (1). Yes [ ] (0). No [ ]
2 If yes, how much time to reach the nearest credit institutions? (hrs./mins) ________
3 Have you received any type of credit 5 year? 1) Yes [ ] 0) No [ ]
4 If yes, A) where? __________1) Service cooperatives [ ], 2) Friends and relatives [ ], 3) Local money lender [ ], 4) Rural institutions [ ] 5) Banks, 6) others [ ]
B) How much was it? __________What was the interest rate? _______________

6. If no why? 1) Fear to repay [ ], 2) High interest rate [ ], 3) Lack of collateral, 4) No one to give credit [ ] 5) No need for credit [ ], 6) others_______________
7. What are the basic sources of marketing information? 1) Radio [ ], 2) Merchants/traders [ ], 3) Development /Extension Agents [ ], 4) Friends /relatives/neighbours [ ], 5) others
8. How much was your total saving amount/in any bank or in ACCI, at home in pocket and in traditional saving like Equib in ETB? ____________
9. How Mach loan do you received?

3. **Physical capital**

3.1 Quality of house status

1. Nature of the house you live in. 1) grass roofed [ ]
   2) corrugated iron sheet with wood and mud [ ] 3) blocket-wall with cemented floor [ ] 4) other [ ] specify_________
2. Number of housing rooms ___________

3.2 Transport, access to market and communication issue

1. What types of transport your households use to travel to your canter the town?
   (1). Car [ ] (2). Bajaj [ ] (3). On foot or Animals [ ]
2. Do you access rod?
3. Distance to urban centre in km? ___________
4. Distance to market in km? __________
5. How much time to reach public transport station/main road? in hr/min __________
6. Do you have mobile phone? (1). Yes [ ] (0). No [ ]
7. Do you have radio or tap? (1). Yes [ ] (0). No [ ]

8. Do you have jewellery? (1). Yes [ ] (0). No [ ]
9. Do you have horse cart? (1). Yes [ ] (0). No [ ]
10. Do you have television? (1). Yes [ ] (0). No [ ]
11. Do you have table or chair? (1). Yes [ ] (0). No [ ]
12. Do you have Bajaj? (1). Yes [ ] (0). No [ ]
13. Do you have motor cycle? (1). Yes [ ] (0). No [ ]
14. Do you have carambula? (1). Yes [ ] (0). No [ ]
15. Do you have cupboard? (1). Yes [ ] (0). No [ ]

3.3. Energy sources indicator

1. What is /are the source/s of cooking energy? (1). Traditional fuel (fire wood, dung cake, charcoal) [ ] (2). Biogas, kerosene, Electricity [ ] (3). Others/specify ________
2. What is/are your source/s of lighting energy? (1). fuel wood, crop residue, dung cake, charcoal [ ] (2). Biogas, candle, Battery kerosene, Electricity (3). Others/specify ________

3.4 Utilities: supply of utilities received to the household:

1. Electric city 1) yes [ ] , 0) no [ ]
2. potable water supply 1) yes [ ], 0) no [ ]
3. Health centre access 1) yes [ ], 0) no [ ]
4. **Social capital:**

4.1 Networking and relationship indicator

1. Is urban expansion sociality accepted in your community?1) Yes [ ] 0) No [ ]
2. Do you think urban expansion is affect your social norms? 1) Yes [ ] 0) no [ ]
3. Have you ever faced conflict due to UE? 1) Yes [ ], 0) No [ ],
5. How is the degree of your ties to relatives and neighbours before displacement? (1). Good relationship increases [] (2) Good relationship decrease/ in conflict [ ] (3). No change[ ]
6. How is the degree of your ties to relatives and neighbours after displacement? (1). Good relationship increase [ ] (2) Good relationship decrease/ in conflict [ ] (3). No change [ ]
7. Had you got help from relatives and neighbours like (crop harvesting, ploughing, marketing, livestock herding, and house construction before displacement)? (1). Yes [ ] (0). No [ ]
8. Had you got help from relatives and neighbours like (crop harvesting, ploughing, marketing, livestock herding, and house construction after displacement displacement)? (1). Yes [ ] (0). No [ ]
9. What do you expect will be the households‟ life next year? 1) Much better [ ] , 2) somewhat better [ ] , 3) the same [ ], 4) somewhat worse [ ],

4.2 social Organizational indicators:

1. Do you participate in different social organization in your community? 1) yes 0) no
2. Religious organization 1) zikir 2) Senbete
3. Community based organization 1) eddir 2) equib
4. Farming work coordination’s 1) farmers cooperatives 2) webera/Debbo

5 Human capital

1. Is there health problem in your household? 1) yes / 0) no
2. Had you faced shock before this time? 1) yes 0) no

3. How many families’ member is employed in your household? ___________

Improvements or worsens due to urban expansion in household life?

What improvements or worsens do you feel due to urban expansion in household life?

No	Improvements in the household	1)yes	0)no	Worsens in the household	1)yes	0)No
1	better saving amount	[ ]	[ ]	jobless family member	[ ]	[ ]
2	able to own new business	[ ]	[ ]	reduce livestock asset	[ ]	[ ]
3	able to own more livestock	[ ]	[ ]	reduce livestock asset	[ ]	[ ]
4	able to own more livestock	[ ]	[ ]	life is risky due to no permanent income	[ ]	[ ]
5	able to own new business	[ ]	[ ]	have too many loans	[ ]	[ ]
6	better job opportunity	[ ]	[ ]	money & durable asset reduced	[ ]	[ ]
7	better infrastructure &utility service	[ ]	[ ]	family consumption style decline	[ ]	[ ]
8	better health and education for hh	[ ]	[ ]	money & durable asset reduced	[ ]	[ ]
9	better consumption style of hh	[ ]	[ ]	decline saving amount	[ ]	[ ]

Appendix 11: Question for the Key Informant and Focus Group Discussants

1. Address _______kebele___________ 2. Level of education_________

A: Interview Guideline to Question to health expert.

1. Do you think that Debark town is expand rapidly? Explain
2. What are the major drivers of urban expansion in Debark? ____________________
3. Do you think natural population increase is the major driver of urban expansion in Debark?
4. In so many scholars mentioned natural population increase is the major driver of urban expansion because improved medicine increases fertility and decreased mortality. Is it true in your area? If yes how many births and death were recorded from the past 5yeas up to 2014 E.C for comparison?

Fertility __________? Mortality ______________?

5. Do you think that urban expansion has health effect on peri urban community? If yes how____

B: Interview Guideline to Municipality Experts

1. Address _______kebele___________ 2. Level of education_________

1. Do you believe that Debark town is rapidly expanding? History of town expansion, how about the status of urban expansion, infrastructural facilities, socioeconomic conditions and livelihood asset

2. In so many scholars mentioned natural population increase, rural to urban migration and economic development are the major driver of urban expansion. Is it true in your area? If yes
3. How many peoples increase since 2009 E.C_________________?
4. What was the reason of peoples to migrate rural to urban in your area? ______________
5. What are the new infrastructure, institutions, private and governmental organizations that constructed to show the economic development of the town expansion since 2017 ____
6. Do you know how was the status of land use land cover change in the past 10 years ago in this area explain
7. Which type of land is more reduced due to UE_________________________________?
8. How do you express the landholder's expropriating procedures for urban expansion program towards to per urban community; Regards to notification, participation, family members right and else
9. How was feeling of landholders during the time of expropriating; are they volunteer, any cases for their reaction (if any) ____?

The End Thank you for your cooperation

C: FDG Guideline to peri-urban displaced community Elder

1. What is urban expansion means in your opinion?
2. Discussion regards to urban expansion condition of town; historical expansion of town, demographic situation (vocally), conditions regards to infrastructural facilities, socioeconomic characteristics there before and at time of the survey
3. Discussion on livelihood condition of households before urban expansion; income sources they repeatedly engaged in, access of job opportunities.
4. Discussion on social relation of the peri-urban community after displacement

Thank you for your cooperation