Journal of Agriculture and Environmental Sciences

Research Article

Land-based investment implications on land use land cover change and livelihood of the local community in Northern Amhara Region, Ethiopia

Assefa Belay Mulaw[1,*], Tadesse Amsalu Birhanu[1] and Melkamu Belachew Moges[1]

[1] Institute of Land Administration, Department of Land Administration and Surveying, Bahir Dar University

Corresponding author: assefabelay66@gmail.com

Received: May 30, 2023; Received in revised form: July 31, 2023; Accepted: November 1, 2023

Abstract: *A surge in land-based investment has been taking place in developing countries, including Ethiopia, with the aim to foster economic growth, enhance food security, and reduce poverty. This study sought to investigate the impact of such investments in the western Armachiho district of the Amhara Regional State, Ethiopia, using remote sensing data from 1995, 2010, and 2020 supplemented by socioeconomic surveys and field observation to validate the spatial data. The results revealed significant land use and land cover changes in the district over the past twenty-five years. Forest cover decreased from 60.92% in 1995 to 27.6% in 2010, while water bodies, including rivers, streams, and ponds, declined from 3.04% to 1.4% during the same period. Conversely, built-up areas, bush land, farmland, and bare land exhibited an increasing trend. The observed changes during the initial study period can be attributed to the expansion of land-based investments and illegal farmland encroachment in the area under investigation. The results further indicated that the expansion of such investments during this period had adverse effects on the local community, resulting in the loss of access to farmland, grazing land, and forest products that served as sources of income. The results also demonstrated that the delineation of agricultural investment land, the closure of unproductive land, and the issuance of land-holding certificates have prevented illegal encroachment that contributed to the improvements in forestland cover between 2010 and 2020. Hence, when granting significant amounts of land for land-based investment, it is crucial to consider not only the short-term economic benefits but also the well-being of local communities and the principles of environmental sustainability.*

Keywords: Image classification, Land use change, Livelihood, Remote sensing, Armachiho

Citation: Mulaw, A.B., Birhanu, T.A., and Moges, M.B. (2023). Land-based investment implications on land use land cover change and livelihood of the local community in Northern Amhara Region, Ethiopia. J. Agric. Environ. Sci. 8(2):1-16. https://dx.doi.org/10.4314/jaes/v8i2.1

1. Introduction

In developing nations like Ethiopia, land-based investment has been expanding to enhance economic growth, ensuring food security, and reducing poverty. The government of Ethiopia has encouraged such investments believing that they could help modernize the country's agricultural sector and improve the livelihoods of local people (Guyalo et al., 2021). According to Emelie and Anders (2013), the Ethiopian economy, like the majority of developing economies, heavily depends on natural resources. However, excessive exploitation of these resources over time not only harms the environment but also hinders opportunities for economic growth and subsistence.

Despite having laws and policies in place to safeguard the environment, land-based investments in Ethiopia have negatively affected the ecosystem's resources. Investment in large-scale investment leads to deforestation, improper use of herbicides and pesticides, degradation of soil and water resources, and loss of biodiversity. Agricultural investments have also resulted in forest clearing, a decline in ecosystem services, the loss of local resources for rural livelihoods, and climate change (Alufohai and Oyoboh, 2013; Gebresilase and Amede, 2014; Kareem, 2018; Wenedem, 2021).

The transfer of a significant amount of land for land-based investment has changed the previous land use and land cover in many developing countries, including Ethiopia. This change directly affects the standard of living of the local population (Wendimu, 2015; Agegnehu and Dadi, 2020). Land-based investment can also affect the relationship between the rural population and the environment, which the majority of rural residents rely on. It intensifies deforestation, loss of wildlife habitat and land eviction, and worsens the livelihoods of the local community (Mosisa, 2016; Olya and Okumo, 2017).

According to Khan and Jhariya, (2018), environmental change can be detected based on the dynamic process of land use and land cover change. Land cover refers to the biophysical covering of the earth's surface, while land use is a human modification of the natural environment (Lambin et al., 2003; Oumer, 2009). Land cover includes natural vegetation, water features, soil, and other elements on the ground, and can be easily detected when changes occur (Pandian et al., 2014; FAO, 2016). On the other hand, land use refers to human activities and the various uses of the land (Pandian et al., 2014).

Remote sensing and geographical information systems are reliable tools used to measure the magnitude of changes over time and understand how well the ecosystem is functioning (Musa and Odera, 2015; Alemu et al., 2015). Additionally, these tools can help manage the sustainability of natural resources by providing quantitative data on the exchanges between various land cover categories (Wang et al., 2020). It is important to note that the analysis of changes in land use and land cover is a common practice based on a comparison of recent and earlier data accessible through ground, airborne, and satellite sources. This approach enables the determination of the size of an area and the pattern of alterations, as remote sensing and geographical information systems work together to provide accurate and significant information over time (Nath et al., 2018).

According to Reies (2008) and Quintero-Gallego et al. (2018), changes in land use and land cover are fundamental and obvious landscape characteristics that represent the influence of human disturbances on the Earth's surface. Specifically, statistics from African nations indicate that between 1990 and 2015, 82 million hectares of forestland has been converted into various land uses (Alawamy et al., 2020). Therefore, it is important to examine how land use and land cover have changed over time and understand the trends of modification in order to plan and implement future natural resource management activities (Mariye et al., 2022).

Many studies have been conducted on land use and land cover change in different parts of Ethiopia, including the Amhara region (Abate and Leminih, 2014; Ariti et al., 2015; Hassen and Assen, 2018; Birhane et al., 2019; Tewabe and Fentahun, 2020; Bufebo and Elias, 2021; Buraka et al., 2021). These studies have shown that expansion of agricultural investment, population pressure, climate change, and expanding residential areas were the primary causes of land use and land cover changes. Particularly leasing out large amounts of land for investment raises concerns about changes in land use, deforestation and the environmental effects (Messerli et al., 2014). In addition, as stated by Degife and Mauser (2017), the expansion of large agricultural farms is one of the reasons why forestland cover in Ethiopia continues to experience significant pressure and gradual decline.

According to Alemu et al. (2015), in the Metema district of the Amhara Regional State, an increase in agricultural land resulted in a significant drop in woodland cover from 28.46% in 1985 to 16.66% in 2010. However, comprehensive studies on the impact of land-based investment on land use and land cover change and its implications for the livelihood sustainability of local communities are lacking. Therefore, the overall goal of this research was to examine land-based investment implications on land use and land cover change and the livelihoods of local communities in the western Armachiho district of the Amhara Regional State, where land-based investment is widely practiced.

This research aims to provide valuable insights for policymakers, land managers, and stakeholders by comprehensively evaluating the implications and identifying the key drivers of change. Ultimately, the findings will contribute to the development of sustainable land use policies that prioritize both economic development and the well-being of local communities, while ensuring the long-term environmental sustainability of the area.

2. Materials and Methods

2.1. Description of the study area

This study was conducted in the western Armachiho district of the Amhara National Regional State (ANRS), Ethiopia, which is characterized by the widespread implementation of large-scale agricultural investment (Figure 1). The district is located 382 kilometers from Bahir Dar, the capital city of the Amhara region. Geographically, the district is situated in northwestern Ethiopia, spanning latitudes 12°59'54" to 13°53'24" N and longitudes 36°10'57" to 36°46'3" E, with altitudes ranging from 620 to 850 meters above sea level (Aznaw et al., 2018). Covering a land area of 269,026 hectares, the district is home to a population of 45,583 individuals, comprising 25,239 males and 20,344 females, residing in 17 kebeles (villages), and the population density estimated at 17 people per square kilometer (CSA, 2013).

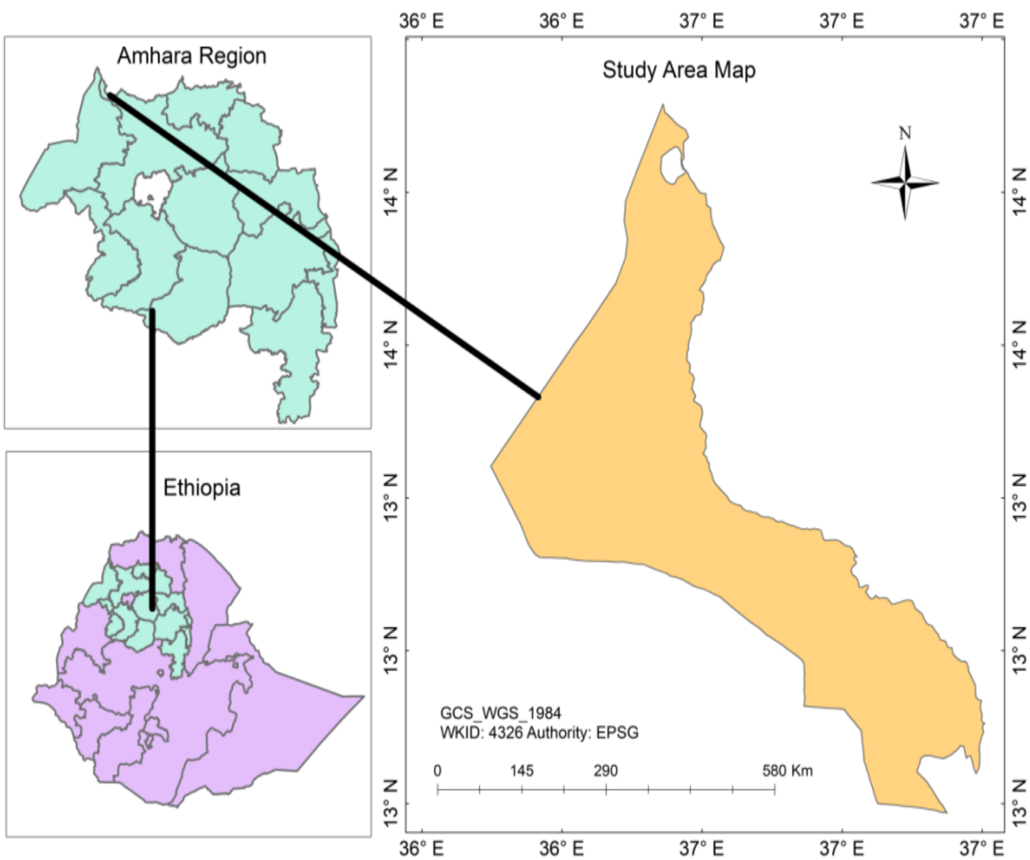

Figure 1: **Location map of the Study Area**

2.2. Research Methods

The research applied a mixed-method research approach to fulfill the research objectives. The utilization of a mixed method as outlined by Creswell and Creswell (2022), allows for the collection of quantitative and qualitative data from multiple sources. This approach facilitates data triangulation, thereby enhancing the overall quality of the data during analysis and interpretation.

2.2.1. *Study site selection, sources of data, and sampling method*

Western Armachiho district was purposefully selected for this study due to its significant contribution of over 44% to the region's large-scale land-based investment (BoLAU, 2020; CSA, 2021). Among the 17 kebeles in the district, land-based investment is carried out in 9 kebeles. To assess the impact of this investment on land use, land cover change, and local livelihoods, two kebeles (Midregent and Terefwork) with land-based investment and three kebeles (Zemenmeriq 01, 02, and Mahrish) without such investment were included in the sample. The research employed a combination of qualitative and quantitative data obtained from primary and secondary sources. Primary data were collected from remote sensing and GIS sources, key informant interviews, focus group discussions, and field observations. The focus groups, key informant interviews, and household surveys provided insights into the pre-intervention land use types, visible indicators of land use change, primary drivers of forest cover change, conservation strategies employed, and the impact of large-scale investment on local livelihoods. The sample size for the study comprised 343 households, drawn from both investment-affected and non-affected kebeles, and the sample size was determined using the formula described by Slovin (1960) as indicated below [1].

$$n = \frac{N}{1+N(e)^2} \qquad [1]$$

Where n represents the sample size; N is the sampling frame (2418 households); 1 is the probability of the event occurring; and e is the desired level of precision (5% margin of error).

Accordingly sample size was 343. The sample households from each kebele were computed using the proportional sampling method following the formula described by Kebede et al. (2021) indicated below [2].

$$ni = \frac{Ni*n}{\Sigma Ni} \qquad [2]$$

Where ni = sample from the i^{th} kebele, Ni = total population in the i^{th} kebele, ΣNi = sum of population of the five sample Kebles, and n = total sample from the district.

Taking into account the ratio of male and female-headed households in the sampling frame, male and female-headed households were included in the sample, and the sample households were picked out using a systematic random sampling method (Table 1).

Table 1: Sample size by household head sex and treatment type

Households	Treated		Untreated		Total
Male-headed	Count	153	Count	156	309
	%	90.5	%	89.7	901
Female-headed	Count	16	Count	18	34
	%	9.5	%	10.3	9.9

2.2.2. *Image preprocessing and classification*

In this study, the images were uploaded for pre-processing to prepare the data for classification using the Google Earth Engine (GEE) cloud-computing platform. During the initial pre-processing stage, specific bands from Landsat 5 (TM), 7 (ETM+), and Landsat 8 (OLI) were selected using GEE (Table 2). It is worth noting that all retrieved images from the archive shared the same coordinate system. As the data had projected to WGS 84 UTM zone 37, there was no need to perform a new projection of the Landsat satellite images. For the classification process, a random forest (RF) algorithm was utilized, which is widely recognized for its effectiveness in multi-class classification and yields superior results compared to other algorithms (Noi and Kappas, 2017; Valero and Atehorta, 2019; Nitze et al., 2012). The random forest algorithm, as described by Fawagreh et al. (2014), is a supervised machine-learning algorithm that constructs decision trees based on various samples and aggregates their majority votes for classification purposes. This study employed 100 trees using a black-box approach (Kulkami and Lowe, 2016; Fawagreh et al., 2014). Each tree was created using a random sample selection, and a random subset of input predictors was used at every tree node to generate new nodes or classes. To determine the signature value for each land use or land cover type, six distinct categories were identified (Table 3). The 120 training sites (20 for each category) were selected to train the classification model using ground truth data collected through GPS. To evaluate the accuracy of the image classification for the year 2020, ground truth data was gathered using the Global Positioning System (GPS) and combined with Google Earth images.

Table 2: Characteristics of the Landsat images used in the study

Satellite image	Sensor	Resolution (m)	Bands used	Acquisition Date	Source
Landsat 5	TM	30*30	1,2,3,4,5,7	05/11/1995	USGS
Landsat 7	ETM+	30*30	1,2,3,4,5,7	04/01/2010	USGS
Landsat 8	OLI	30*30	2,3,4,5,6,7	18/02/2020	USGS

Table 3: Description of land use and land cover types

LULC types	LULC Description
Farmland	Area fixed to main rain-fed crop production, mostly oil seed cereals and smallholders and large-scale investors grow pulses
Forestland	Areas covered by trees forming closed or nearly closed canopies with Acacia and *Boswellia papyrifera* predominant species.
Bush land	Small trees, bushes, and shrub covering the land, and in some cases, such land mixed with grasses, and less dense than forestland.
Built-up	Areas composed of rural villages and small towns as residential, commercial sites and roads, fences and sometimes covered with trees
Bare land	Land, which is mainly covered by exposed soils; and barren area influenced by human intervention and natural phenomena.
Water body	Rivers, streams, ponds and reservoirs.

Source: Adapted from Alemu et al. (2015)

2.2.3. *Accuracy assessment*

Accuracy assessment is a crucial stage in evaluating the categorized images for each land use and land cover class (Congalton and Green, 2009; Adedeji et al., 2015). For the image of 2020, 120 random sample points were constructed using ArcGIS 10.7 and collected from the field with the aid of a handheld GPS (Bufebo and Elias, 2021). An error matrix was generated to compare the categorized image with the reference image. The overall accuracy was calculated based on Lillesand (2008) using the formula [3].

$$OA = \left(\frac{x}{y}\right) * 100 \quad [3]$$

When, OA represents the overall accuracy, x denotes the number of correct values found on the diagonals of the error matrix, and y represents the total number of reference points.

The accuracy assessment was conducted specifically for the 2020 image, as the signatures were collected for this particular year. In GEE, the remaining years were classified using the classifier based on reflectance values for each land cover type generated from the signatures obtained from the 2020 image.

The Kappa coefficient is a measure that quantifies the discrepancies between the actual agreement of the classified map and the chance agreement of random classifiers when compared to the reference data (Fung and Drew, 1988; Congalton, 1991; Jensen, 1996).

$$\hat{K} = \frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r}(x_{i+} * x_{+i})}{N^2 - \sum_{i=1}^{r}(x_{i+} * x_{+i})} \quad [4]$$

Where K is the Kappa coefficient, r is the number of rows in the matrix, xii is the number of pixels belonging to the actual data class i, and column i, xi + are the marginal totals of row i, x + i are the marginal totals of column i, and N is the total number of observation (Table 6).

2.2.4. *Land use/land cover change detection*

Land use and land cover (LULC) change detection, facilitated by remote sensing data, serves as a vital source of information for various decision support systems. The detection of changes in land use and land cover contributes to land conservation, sustainable development, and effective water resource management, among other aspects (Tewabe and Fentahun, 2020). To analyze changes, it is crucial to determine the specific transformations occurring between different categories of LULC types, as highlighted by Shiferaw and Singh (2011). For the analysis of land use and land cover change detection, Alemayehu et al. (2019) presented a formula to calculate both the extent and patterns of changes within and between periods. Three distinct methods were employed in this study:

1. The total LULC was computed by subtracting the area of the first year from the area of the last year. Positive values indicated an increase in land use and land cover, while negative values represented a decline in magnitude.

2. The percentage of LULC change is derived by dividing the total LULC result by the area of the original year. This calculation provided insights into the relative extent of change.

3. The annual rate of LULC change was determined using the formula r = (Q2 - Q1) / t, where r denotes the rate of change, Q2 represents the recent year's LULC in hectares, Q1 corresponds to the initial year's LULC in hectares, and t signifies the time interval between the initial and recent years.

3. Results and Discussion

3.1. Dynamics of land use and land cover change

The study area's land use and land cover units were classified into six classes (Table 3) and changes over time were analyzed using satellite images from three periods (1995, 2010, and 2020). The findings presented in Table 4 and Figure 2 reveal the distribution of land cover types in 1995, with forestland, bush-land, and farmland occupying the majority of the area at 60.92%, 19.28%, and 15.72%, respectively. By 2010, there was a noticeable increase in bush land, farmland, and built-up areas, accounting for 34.5%, 25.95%, and 9.66%, respectively, while forestland experienced a substantial decline to 27.4%. Additionally, the results demonstrate a decline in bush land, farmland, and water body coverage to 22.27%, 18.71%, and 0.27%, respectively, in 2020, while forestland showed an increase to 44.31% with an annual growth rate of 6.2% (Tables 4 and 5). Throughout the study period, the built-up area coverage expanded to 32.57%, while forest cover experienced a decline to -27.25% (Table 4).

The outcomes of the household survey, key informant interviews, and focus group discussions provided valuable insights into the drivers behind the observed land use and land cover changes in the study area. Expansion of land-based investment was identified as the primary factors contributing to these changes. These findings shed light on the dynamic nature of land use and land cover in the study area, and underline the need for sustainable land management practices to address the challenges posed by population growth and investment expansion.

Table 4: Area and proportion of LULC in western Armachiho District in 1995, 2010 and 2020

	1995		2010		2020		Change 1995-2020	
LULC types	Area (ha)	%	Area (ha)	%	Area (ha)	%	Area (ha)	%
Built-up area	1013.61	0.38	25983.02	9.66	34029.06	12.65	33,015.45	32.57
Bush land	51860.6	19.28	92822.07	34.5	61265.14	22.77	9404.54	18.13
Farm land	42284.42	15.72	69810.2	25.95	50344.37	18.71	8059.95	19.06
Forest land	163881	60.92	73710.47	27.4	119222.27	44.31	-44,658.73	-27.25
Bare land	1807.72	0.67	2930.24	1.09	3438	1.28	1630.28	90.18
Water body	8179.45	3.04	3770.8	1.4	728	0.27	-7451.45	-91.09
Total area	269026.8	100	269026.8	100	269026.8	100		

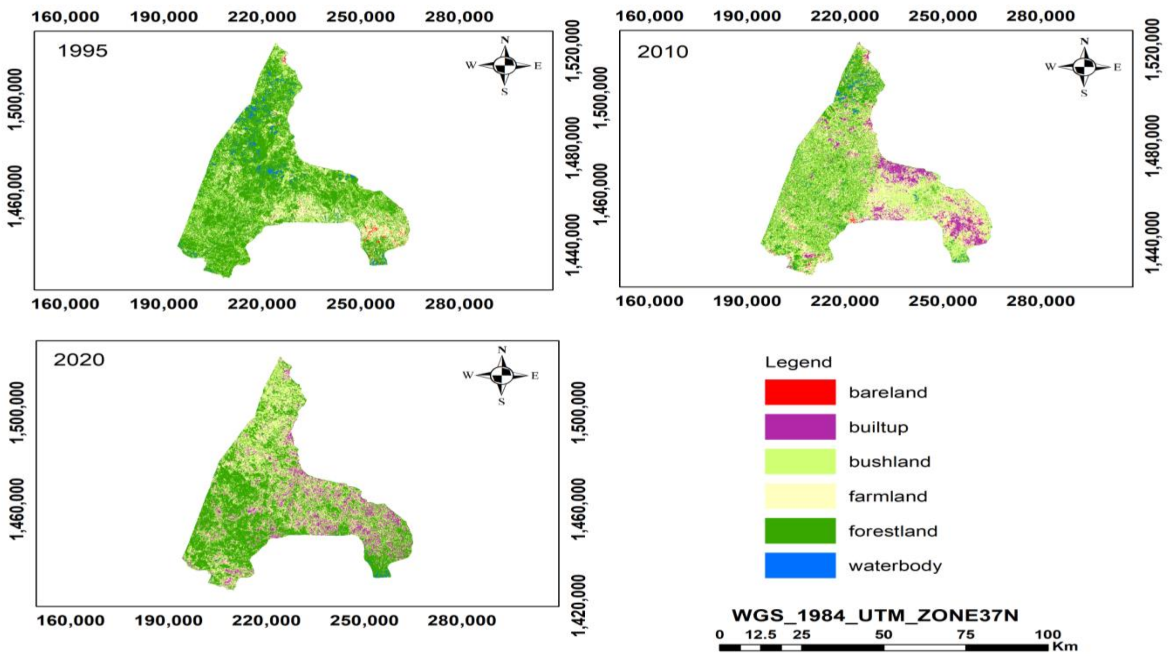

Figure 2: LULC map of western Armachiho district from 1995 to 2020

Table 5: Area and proportion of LULC in western Armachiho District in 1995, 2010 and 2020

Land cover	1995-2010		2010-2020		1995-2020	
	ha/yea	%	ha/year	%	ha/year	%
Built-up	1664.63	164.2	804.6	3.1	1320.6	130.3
Bush land	2730.76	5.3	-3155.7	-3.4	376.2	.73
Farmland	1835.1	4.3	-1946.6	-2.8	322.4	.76
Forestland	-6011.4	-3.7	4551.2	6.2	-1786.4	-1.1
Bare land	74.8	4.1	50.8	1.7	65.2	6
Water body	-293.9	-3.6	-304.3	-8.1	-298.1	-3.6

3.2. Classification Accuracy Assessment

A confusion matrix serves to measure the classification accuracy assessment of the 2020 image (Table 6). The overall accuracy, producer accuracy, user accuracy, and kappa statistics are provided in the matrix. The matrix's diagonal elements indicate successfully categorized values, whereas the off-diagonal entries reflect poorly classified values. The 2020 image's overall accuracy and kappa statistics computed are 99% and 0.99, respectively. These values show a high level of agreement and accuracy between the classified image and the reference data. The high overall accuracy illustrates the classification algorithm's efficacy in accurately assigning land use and land cover categories to picture pixels. The accuracy evaluation results, as shown in Table 6, provide confidence in the classification image's reliability for the year 2020. These findings contribute to the credibility of the land use/land cover change analysis and its applicability for monitoring and decision-making purposes.

Table 6: LULC classes and accuracy assessment of the image of 2020

Classified Data	Built-up	Bush land	Farm land	Forest land	Bare land	Water body	Row Total	User's accuracy (%)
Built-up	**20**	0	0	0	0	0	20	100
Bush land	0	**20**	0	0	0	0	20	100
Farmland	0	1	**19**	0	0	0	20	95
Forestland	0	0	0	**20**	0	0	20	100
Bare land	0	0	0	0	**20**	0	20	100
Water body	0	0	0	0	0	**20**	20	100
Column Total	20	21	19	20	20	20	120	
Producer's accuracy (%)	100	95.2	100	100	100	100		

Note: the overall accuracy and kappa statistics were 99%.

3.3. Land use/land cover conversion patterns from 1995-2010 and 2010-2020

Tables 7 and 8 provide clear evidence of substantial land use and land cover conversions within the study area. The tables present the extent of changes that occurred between different periods, specifically from 1995 to 2010 and from 2010 to 2020. The data presented in Tables 7 and 8 illustrate the magnitude of land use and land cover transformations that took place over the specified time intervals. These changes reflect the dynamic nature of the study area and highlight the shifting patterns of land utilization and coverage. The information provided in these tables is valuable for understanding the trends and dynamics of land use and land cover changes in the study area. By quantifying the conversions between different land use and land cover types; these findings contribute to a comprehensive understanding of the evolving landscape and its implications for various environmental and developmental considerations.

Table 7 presents the notable conversions of land use and land cover types within the study area during the period from 1995 to 2010. The table indicates that various land cover types underwent significant changes, resulting in the conversion of substantial land areas. Specifically, the data reveals that within this period, an area of 3,946.33 hectares of bush land, 80,033.06 hectares of farmland, 12,866.46 hectares of forestland, 740.23 hectares of bare land, and 601.87 hectares of water bodies converted into built-up areas. These conversions were accompanied by a remarkable increase in the built-up area, primarily at the expense of forestland, which experienced a dramatic decline in forest cover of 27.4%. Furthermore, the data highlights that the largest gain in the built-up area was observed from forestland (49.2%), followed by farmland (30.6%) and bush land (15.1%). Conversely, the built-up area underwent transformations into other land uses and land cover types, primarily driven by the consolidation of scattered villages to facilitate infrastructure development. The conversions resulted in losses of 32.4% in bush land, 39.3% in farmland, 20.5% in forestland, 2.7% in bare land, and 5.2% in water bodies (Table 7). These findings indicate that while the built-up area expanded throughout the entire study period, a considerable portion of it was converted into farmland, followed by bush land and forestland.

The area of bush land increased from 19.28% in 1995 to 34.5% in 2010 (Table 4), with an annual rate of change of 2,730.8 hectares (Table 5). During the 1995–2010 period, bush land experienced gains of 262.11 hectares, 10,883.22 hectares, and 59,817.65 hectares from built-up areas, farmland, and forestland, respectively. Notably, the majority of the gain in bush land was conversions from forestland accounting for 80.9% of the total gain of 73,902.97 hectares (40.7%). According to the Western Armachiho District Office of Agriculture (Wada, 2020), extensive removal of forest cover to create additional cultivable land resulted in forestland conversion into bush land during this period. Furthermore, 3,946.33 hectares, 12,919.86 hectares, 14,639.08 hectares, 253.6 hectares, and 598.9 hectares of bush land were converted into built-up areas, farmland, forestland, bare land, and water bodies, respectively (Table 7). The analysis also reveals that an area of 19,502.83 hectares of bush land remained unchanged during the 1995–2010 periods.

Farmland area increased from 15.72% in 1995 to 25.95% in 2010, with an annual increase rate of 1,835.1 hectares (Tables 4 and 5). Farmland expansion during this period was mostly due to the expansion of large-scale land-based investments, a resettlement program, and illegal intrusion by farmers migrating from highland areas in the North Gondar zone. Table 7 shows that agriculture acquired 53,128.7 hectares, primarily from forestland (72.5%) and bush land (24.3%), for a total gain of 29.3% in farmland. During the same period, 8,003.06 hectares, 10,883.32 hectares, 5,846.09 hectares, 705.47 hectares, and 237.89 hectares of cropland were converted into built-up areas, bush land, forestland, bare land, and water bodies, respectively (Table 7). The conversion of agriculture into bush land was the most substantial (42.4%), followed by built-up areas (31.2%). Furthermore, the data shows that a total of 16,608.59 hectares of cropland remained constant between 1995 and 2010.

The forest area coverage declined from 60.92% in 1995 to 27.4% in 2010, with an annual diminishing rate of 6,011.4 hectares per year. A study conducted in the Gambella Regional State by Olya and Okumo (2017) reported that large-scale agricultural investments were a major driver of land use and land cover changes and had adverse effects on local livelihoods. The conversion matrix presented in Table 7 demonstrates that forestland underwent significant conversions, with 12,866.46 hectares, 59,817.65 hectares, 38,493.6 hectares, 861.08 hectares, and 1,888.51 hectares transformed into built-up areas, bush land, farmland, bare land, and water bodies, respectively. The largest conversions of forestland occurred into bush land (52.5%) and farmland (33.8%), while built-up areas accounted for 11.3% of the total loss, resulting in a substantial reduction of 113,927.3 hectares (62.8%), which is a large reduction that significantly affects the whole environment in terms of forest cover. Conversely, forestland experienced gains from bush land (14,639.08 hectares), farmland (5,846.09 hectares), and water bodies (2,976.36 hectares) during the 1995–2010 periods, contributing to 13.1% of the total gain in forestland. Overall, significant conversions into other land uses and land cover types were observed in the built-up area, bush land, farmland, and forestland during the years between 1995 and 2010. The analysis also indicates that an area of 49,953.7 hectares of forestland remained unchanged during the same period.

Table 7: Land Use/Land Cover conversion matrix from 1995 to 2010 (ha)

	To	2010							
	Land uses	Built-up area	Bush land	Farmland	Forest land	Bare land	Water body	Total year1 (ha)	Loss in 1995
From 1995	Built-up	**204.29**	262.11	318.25	164.93	21.72	42.31	1013.61	809.32
	Bush land	3946.33	**19502.83**	12919.86	14639.08	253.6	598.9	51860.6	32357.77
	Farmland	8003.06	10883.32	**16608.59**	5846.09	705.47	237.89	42284.42	25675.83
	Forestland	12866.46	59817.65	38493.6	**49953.7**	861.08	1888.51	163881	113927.3
	Bare land	740.23	222.33	612.08	67.41	**160.43**	5.24	1807.72	1647.29
	Water body	601.87	2717.56	784.89	2976.36	7.64	**1091.13**	8179.45	7088.32
	Total area	26362.24	93405.8	69737.27	73647.57	2009.9	3863.98	269026.8	
	Gain (ha) in 2010	26157.95	73902.97	53128.68	23693.87	1849.5	2772.85		181505.83

During the period from 2010 to 2020, a substantial increase was observed in the built-up area, rising from 9.66% in 2010 to 12.65% in 2020, with an annual growth rate of 1,664.63 hectares (164.2%). Additionally, the period from 1995 to 2020 witnessed an average annual increase of 1,320.6 hectares of built-up area (Tables 4 and 5). The data reveals that between 2010 and 2020, the built-up area expanded by gaining land from various land cover types, including bush land (7,460.37 hectares), farmland (14,007.46 hectares), forestland (4,509.38 hectares), and bare land (849.79 hectares). This resulted in a total gain of 26,871.53 hectares (14.7%) in the built-up area (Table 8). The primary contributors to this gain were farmland (52.1%) and bush land (27.8%). Conversely, during the same period, conversions of 6,605.44 hectares, 5,786.03 hectares, and 6,382.35 hectares of the built-up area into bush land, farmland, and forestland were observed respectively. The transformation from built-up areas to other land cover types was driven by governmental efforts to consolidate scattered villages for the provision of essential infrastructure such as water supply, electricity, schools, markets, and access roads. The built-up area that remained unchanged during the study period amounted to 7,157.54 hectares.

The coverage of bush land exhibited a declining trend from 34.5% in 2010 to 22.77% in 2020, with an annual decrease of 3,155.69 hectares (Tables 4 and 5). From 2010 to 2020, bush land expanded at the expense of built-up areas (6,605.44 hectares), farmland (15,513.51 hectares), forestland (16,411.84 hectares), bare land (341.89 hectares), and water bodies (923.45 hectares). As shown in Table 8, the primary contributor to the gain in bush land was forestland (41.2%), followed by farmland (39%). Conversely, bush land was converted into built-up areas (7,460.38 hectares), farmland (16,429.65 hectares), forestland (47,109.81 hectares), and bare land (262 hectares). The most significant conversion of bush land occurred into forestland (66%), followed by farmland (23%). According to the respondents, the conversion of bush land into forestland has been largely attributed to management interventions by the district's agricultural and natural resources development office. An area of 21,469.01 hectares of bush land remained unchanged during the past 10 years.

Farmland area decreased from 25.95% in 2010 to 18.71% in 2020, with an annual reduction of 1,946.58 hectares (Tables 4 and 5). As indicated in Table 8, farmland underwent conversions into built-up areas (14,007.46 hectares), bush land (15,513.51 hectares), forestland (23,732.89 hectares), and bare land (1,231 hectares). Farmland gained a significant amount of land from bush land (46.9%), forestland (34.3%), and built-up areas (16.5%), resulting in a total gain of 35,035.78 hectares (19.1%). Conversely, a considerable amount of farmland was converted into forestland (43.5%), contributing to the increment in forestland in 2020. Meanwhile, during the period from 2010 to 2020, 15,308.59 hectares of farmland remained unchanged.

The analysis presented in Table 4 indicates that forest cover declined from 60.92% in 1995 to 27.4% in 2010. However, it experienced an increase from 27.4% in 2010 to 44.31% in 2020, with an annual growth rate of 4,551.2 hectares (Table 5). In agreement with this study, Alemayehu et al. (2019) reported that in the Komodo watershed in southwestern Ethiopia, forestland increased by 3.2% between 2005 and 2017. The improvement in forestland can be attributed to several factors including the blocking or column system of investment lands, the area closure of degraded lands, the designation of a new protected park (Godebie Park) in the recent past, and the issuance of land holding certificates to local farmers. The primary contributors to the increment in forestland were bush land (59.7%), farmland (30%), and built-up areas (8%), resulting in a total gain of 78,915.75 hectares (43.5%). As shown in Table 8, during the period from 2010 to 2020, forestland was converted into built-up areas (4,509.38 hectares), bush land (16,411.84 hectares), farmland (12,020.26 hectares), bare land (251 hectares), and water bodies (211.47 hectares). The insights from the focus group discussions, key informants, and group discussants highlight the contributions of the blocking or column system of investment lands, area closure of degraded lands, the designation of a new protected park (Godebie Park; 18,987 hectares), and the issuance of land holding certificates to local farmers to the improvement of forest cover in the study area.

Table 8: Land Use/Land Cover conversion matrix from 2010 to 2020 (Hectares)

	To	2020							
	Land uses	Built-up area	Bush land	Farm land	Forest land	Bare land	Water body	Total year2	loss in2010
From 2010	Built-up	**7157.5**	6605.44	5786.0	6382.35	50	1.66	25983.0	18825.5
	Bush land	7460.4	**21469.1**	16429.7	47109.8	262.03	91.2	92822.1	71353.1
	Farmland	14007.5	15513.51	**15308.6**	23732.9	1230.5	17.24	69810.2	54501.6
	Forestland	4509.4	16411.8	12020.2	**40306.5**	251	211.47	73710.5	33404.0
	Bare land	849.8	341.89	370.84	387.34	**979.55**	0.83	2930.24	1950.69
	Water body	44.53	923.45	429	1303.36	665.2	**405.26**	3770.8	3365.54
	Total area	34029.1	61265.14	50344.4	119222.3	3438.3	727.66	269026.8	
	Gain (ha) in 2020	26871.5	39796.13	35035.8	78915.8	2458.7	322.4		183400.33

3.4. Perception of the local people on the land use and land cover change and its implication on their Livelihood

Large-scale land-based investments are often justified through development narratives that highlight the potential for new employment opportunities, increased agricultural productivity, and improved infrastructure (German et al., 2016). However, the adverse impacts most commonly associated with such investments are the loss of land access and natural resources, which significantly affect rural livelihoods (Oberlack, 2022). The intervention of large-scale investments often leads to the loss of indigenous tree species that are vital to local communities for various socio-economic purposes. As reported by 86% of respondents, the recent expansion of large-scale land-based investments is the primary driver of land use and land cover changes in the study area, resulting in a scarcity of forest products that local communities rely on for their livelihoods. Additionally, 31% of respondents identified illegal encroachment as a contributing factor to these observed changes. Focus group discussions (FGDs) and key informants revealed that prior to the commencement of large-scale farming, more than half of the study area was covered by forests, but these forests were later cleared for mechanized agriculture.

The majority of respondents (69%) believe that large-scale land-based investments account for the largest proportion of the causes of land use and land cover changes, followed by illegal encroachment, the demand for fuel and construction materials, and local farming practices (Table 9). According to key informants, the changes in land use and land cover have had detrimental effects on the ecosystem, such as increased temperatures resulting from the removal of native trees, as well as on the livelihoods of neighboring communities in the study area. One key informant stated, "Due to the expansion of large farms and the cutting of trees for firewood and charcoal, indigenous trees were cleared about eight years ago. However, now the Kebele leaders, together with community leaders, have initiated discussions to establish forest protection committees in each Kebele administration, aiming to safeguard the forests from clearance by large-scale farms, community members, and illegal encroachers from neighboring districts." He further highlighted significant improvements in forestland cover in the area. Other surveyed households (65%) expressed concerns that, as the area serves as a green buffer zone protecting against the expansion of desertification, future investments and the clearing of forestland may have adverse impacts on the region as a whole and on the livelihoods of the local community in particular.

The study also revealed that the government's weak enforcement of environmental laws and regulations contributes to extensive deforestation. Although environmental laws stipulate that investors must prepare Environmental Impact Assessment (EIA) documents before initiating their projects to mitigate adverse environmental impacts, nearly all investors have commenced their projects without obtaining endorsed EIA documents from the relevant agency. Furthermore, the lack of well-structured monitoring and evaluation mechanisms for assessing the performance of agricultural investments by responsible entities has exacerbated the extent of land degradation, particularly in forested areas. Despite the acknowledgement that large-scale land-based investments have resulted in environmental harm and increased competition for land required for grazing and crop cultivation among local farmers, key informants and participants in the focus group discussions emphasized that these investments have provided them with opportunities to access new technologies such as tractors, improved seeds, and employment prospects.

Table 9: Perceptions of respondents on the causes of LULC change

Causes of land use/cover change	Frequency	Percent	Level of contribution
Expansion of large-scale land-based investment	295	86	69%
Illegal encroachment	105	31	17.9%
Demand for fuel and construction materials	83	24.2	22.7%
Local farmers’ farming practices (shifting cultivation)	41	12	12.5%

4. Conclusion and Recommendations

The primary objective of this study was to investigate the impact of large-scale land-based investments on land use, land cover change, and the livelihood of the local community in the Western Armachiho district between 1995 and 2020, utilizing remote sensing and household surveys. The results of the study reveal changes in land use and land cover types over the past twenty-five years. However, these changes exhibit both increasing and decreasing trends.

During the initial period, there was a drastic decline in woody vegetation cover, indicating a failure of government authorities to effectively guide and monitor the activities of agricultural investors during their land preparation. The investors' reluctance to adhere to the Environmental Impact Assessment (EIA) report for their commercial farm enterprises, coupled with illegal encroachments into areas not designated for investment, aggravated the observed land use and land cover change between 1995 and 2010.

Conversely, positive changes, particularly in woody vegetation cover, were observed after 2010. This reflects the concerted development interventions of the land administration institution, which have influenced the local communities to carry out their farming practices on the land certified to them and the agricultural investors to fulfill their duties as per the contractual agreement. While the study indicated that agricultural investment provided some benefits to the local communities, the overall situation highlighted weak integration and interaction between the local community and the investors. As land that was once freely used by the local community is now largely cultivated by investors, its implications on land use systems and local livelihood activities will be serious unless a win-win situation is created for both parties.

The findings also imply that plans by the government to expand large-scale land-based agricultural investments should not solely focus on short-term economic advantages but should also consider the long-term sustainability of the environment and the livelihoods of the surrounding communities. Therefore, it is recommended that efforts to promote large-scale land-based agricultural investments be based on comprehensive baseline information about traditional land use, with due emphasis on social and environmental variables. This approach will ensure that the objectives of agricultural investment align with improvements in local community livelihoods and environmental sustainability.

Competing interests

The authors have no competing interests directly or indirectly related to the work submitted for publication in this journal.

Informed consent

Prior to conducting a face-to-face interview and questionnaire survey, the researcher obtained informed consent from respondents for their voluntary participation. In addition, the researcher preserved the respondent's privacy and confidentiality. The researcher also held the view that no parties harmed in any way during any stage of the research process.

Acknowledgements

The authors wish to thank the Mirab Armachiho District Agriculture and Environment Office, farmer respondents, the five kebeles leaders, and kebele development agents for their support. We are also grateful for all individuals and institutions who took part in the study, particularly, the Institute of Land Administration, Bahir Dar university. Special thanks go to Dr. Gebeyehu Belay (Bahir Dar University) and Dr. Wubneh Belete (University of Nevada) for their technical support.

References

Abate, A., and Lemenih, M. (2014). Detecting and quantifying land use/land cover dynamics in Nadda Asendabo Watershed, South Western Ethiopia. *International Journal of Environmental Sciences*, *3*(1): 45-50.

Adedeji, O. H., Tope-Ajayi, O. O., & Abegunde, O. L. (2015). Assessing and predicting changes in the status of Gambari forest reserve, Nigeria using remote sensing and GIS techniques. *Journal of Geographic information system*, *7*(03).

Agegnehu, A.W., and Dadi, T.T. (2020). Agricultural Investment Land Acquisition in Times of Emergency in Ethiopia: The Case of Land Delivery to Respond to COVID-19 in Amhara Region. *Bahir Dar University, Journal of law* , *11*(1): 97-126.

Alawamy, J. S., Balasundram, S. K., Mohd. Hanif, A. H., and Boon Sung, C. T. (2020). Detecting and analyzing land use and land cover changes in the region of Al-Jabal Al-Akhdar, Libya using time-series landsat data from 1985 to 2017. *Sustainability*, *12*(11). doi:10.3390/su12114490

Alemayehu, F., Tolera, M., and Tesfaye, G. (2019). Land use land cover change trend and its drivers in Somodo watershed south western, Ethiopia. *African Journal of Agricultural Research*, 14 (2): 102-117.

Alemu, B., Garedew, E., Eshetu, Z., and Kassa, H. (2015). "Land use and land cover changes and associated driving forces in north western lowlands of Ethiopia." . *International research journal of agricultural science and soil science* , *5*(1): 28-44.

Alufohai, G. O., and Oyoboh, D. (2013). Environmental impacts of commercial agriculture in Nigeria. *A review*. Paper presented at the 4th International Conference of the African Association of Agricultural Economists, September 22-25, 2013, Hammamet, Tunisi*a*

Ariti, A. T., van Vliet, J., and Verburg, P. H. (2015). Land-use and land-cover changes in the Central Rift Valley of Ethiopia: Assessment of perception and adaptation of stakeholders.. *Applied Geography, 65:* 28-37.

Azanaw, A., Fininsa, C., Sahile, S. O., and Terefe, G. (2018). Assessment of Sesame Bacterial Blight (Xanthomonas Campestris Pv. Sesami) on Sesame (Sesamum indicum L.) in North Gondar, Ethiopia. *ABC Journal of Advanced Research, 7*(2): 81-94.

Birhane, E., Ashfare, H., Fenta, A. A., Hishe, H., Gebremedhin, M. A., & Solomon, N. (2019). Land use land cover changes along topographic gradients in Hugumburda national forest priority area, Northern Ethiopia. Remote Sensing Applications. *Society and Environment, 13*: 61-68.

BoLAU. (2020). *Amhara National Regional State annual report on investor's profile* . Bahir Dar, Ethiopia: Bureau of Land Administration and Use.

Bufebo, B., and Elias, E. (2021). Land use/land cover change and its driving forces in Shenkolla watershed, south Central Ethiopia. *The Scientific World Journal*, vol. 2021, Article ID 9470918, 13 pages, https://doi.org/10.1155/2021/9470918

Buraka, T., Elias, E., and Lelago, A. (2021). Analysis and Prediction of Land Use/land Cover Changes and Driving Forces by Using GIS and Remote Sensing in the Coka Watershed, Southern Ethiopia. *Indian Journal Of Agricultural Research*.

Congalton, R. G. (1991). A review of assessing the accuracy of classifications of remotely sensed data. *Remote sensing of environment, 37*(1): 35-46.

Congalton, R. G., & Green, K. (2009). Assessing the accuracy of remotely sensed data: principles and practices. *CRC press. Taylor & Francis Group. Boca Raton London New Yor*.

Creswell, J. W., and Creswell, J. D. (2022). *Qualitative, quantitative and mixed methods approach, 5th edition.* Sage publication. Inc., USA.

CSA. (2013). *Population projection of Ethiopia for all regions at wereda level from 2014-2017*. Federal Democratic Republic of Ethiopia Central Statistical Agency, Addis Ababa, Ethiopia .

CSA. (2021). *Large and medium scale commercial farms sample survey 2020/21 results at country and regional level Vol.3. Statistical Bulletin.* . Addis Ababa.

Degife, A. W., and Mauser, W. (2017). Socio-economic and environmental impacts of large-scale agricultural investment in Gambella Region, Ethiopia. *Journal of US-China Public Administration, 14*(4): 183-197.

Emelie, C., and Anders, E. (2013). *Ethiopia environmental and climate change policy brief. Sida's Helpdesk for Environment and Climate Change www.sidaenvironment helpdesk.* Sida's Helpdesk.

FAO. (2016). *The state of food and agriculture climate change, agriculture and food security.* . Rome, Italy: Food and Agriculture Organization of the United Nations.

Fawagreh, K., Gaber, M. M., and Elyan, E. (2014). Random forests: from early developments to recent advancements. Systems Science & Control Engineering. *An Open Access Journal, 2*(1): 602-609.

Fung, T., and LeDrew, E. (1988). The determination of optimal threshold levels for change detection using various accuracy indices. . *Photogrametric Engineering and Remote Sensing , 54:* 1449-1454.

Gebresilase, Y., and Amede, T. (2014). Investing in land and water management practices in the Ethiopian highlands. Springer International Publishing Switzerland.

German, L., Cavane, E., Sitoe, A., and Braga, C. (2016). Private investment as an engine of rural development: A confrontation of theory and practice for the case of Mozambique. *Land Use Policy, 52*: 1-14.

Guyalo, A. K., Alemu, E. A., and Degaga, D. T. (2021). Impact of large-scale agricultural investment on the livelihood assets of local community in Gambella region, Ethiopia. . *International Journal of Social Economics, 48*(3): 363-383.

Hassen, E. E., and Assen, M. (2018). Land use/cover dynamics and its drivers in Gelda catchment, Lake Tana watershed, Ethiopia. . *Environmental Systems Research*, *6*(1): 1-13.

Jensen, J. R. (1996). Introductory digital image processing: a remote sensing perspective (2 ed.). Prentice-Hall Inc. ISBN-13: 978-03132058407

Kareem, O. I. (2018). The determinants of large-scale land investments in Africa. *Land Use Policy*, 75: 180-190.

Kebede, D., Tesfay, G., and Emana, B. (2021). Impact of land acquisition for large-scale agricultural investments on income and asset possession of displaced households in Ethiopia, *Heliyon*, *7*(12).

Khan, R., and Jhariya, D. C. (2018). Assessment of land-use and land-cover change and its impact on groundwater quality using remote sensing and GIS techniques in Raipur City, Chhattisgarh, India, *Journal of the Geological Society of India*, *92*(1), 59-66.

Kulkarni, A. D., and Lowe, B. (2016). Random forest algorithm for land cover classification.

Lambin, E. F., Geist, H. J., and Lepers, E. (2003). Dynamics of land-use and land-cover change in tropical regions. . *Annual review of environment and resources*, *28*(1): 205-241.

Lillesand, T. M., Kiefer, R. W., and Chipman, J. W. (2008). Digital image interpretation and analysis. *Remote sensing and image interpretation, 6:* 545-581.

MADoA. (2022). *West Armachiho District office of Agriculture annual report* . Abrehajira: West Armachiho District office of Agriculture.

Mariye, M., Jianhua, L., and Maryo, M. (2022). Land use and land cover change, and analysis of its drivers in Ojoje watershed, Southern Ethiopia. *Heliyon*, *8*(4): e09267.

Messerli, P., Giger, M., Dwyer, M. B., Breu, T., and Eckert, S. (2014). The geography of large-scale land acquisitions: Analysing socio-ecological patterns of target contexts in the global South. . *Applied Geography* , *53*: 449-459.

Mosisa, G. M. (2016). Large Scale Commercial Farming and Its Implications for Environmental Sustainability In Ethiopia: The Case of Gambella Regional State. *Journal of Agricultural Development, 6(2).*

Musa, M. K., and Odera, P. A. (2015). Land use land cover changes and their effects on agricultural land a case study of Kiambu County Kenya. *Kabarak Journal of Research & Innovation*, 3 (1):74-86

Nath, B., Niu, Z., and Singh, R. P. (2018). Land Use and Land Cover changes, and environment and risk evaluation of Dujiangyan city (SW China) using remote sensing and GIS techniques. *Sustainability*, *10*(2): 4631.

Nitze, I., Schulthess, U., and Asche, H. (2012). Comparison of machine learning algorithms random forest, artificial neural network and support vector machine to maximum likelihood for supervised crop type classification. Rio de Janeiro, Brazil: Proceedings of the 4th GEOBIA.

Noi, P., and Kappas, M. (2017). Comparison of random forest, k-nearest neighbor, and support vector machine classifiers for land cover classification using sentinel-2 imagery. *Sensors*, 18(1). https://www.mdpi.com/1424-8220/18/1/18#

Oberlack, C., Giger, M., Anseeuw, W., Adelle, C., Bourblanc, M., Burnod, P., and Messerli, P. (2021). Why do large-scale agricultural investments induce different socio-economic, food security, and environmental impacts? Evidence from Kenya, Madagascar,and Mozambique. *Ecology and Society*, *26*(4): 18.

Olay, K. O., and Okumo, O. (2017). The effect of large agricultural investment projects on the local people in Ethiopia: the case of Gambella Region. *Imperial Journal of interdisciplinary research* , *3*(6).

Oumer, H. A. (2009). Land use and land cover change, drivers and its impact: a comparative study from Kuhar Michael and Lenche Dima of Blue Nile and Awash basins of Ethiopia Doctoral dissertation. Cornell University, USA.

Pandian, M., Rajagopal, N., Sakthivel, G., and Amrutha, D. (2014). Land use and land cover change detection using remote sensing and GIS in parts of Coimbatore and Tiruppur districts, Tamil Nadu, India. *International Journal of Remote Sensing and Geoscience*, 3 (1).

Quintero-Gallego, M. E., Quintero-Angel, M., and Vila-Ortega, J. J. (2018). Exploring land use/land cover change and drivers in Andean mountains in Colombia: A case in rural Quindío. *Science of the Total Environment*, *634:* 1288-1299.

Reis, S. (2008). Analyzing land use/land cover changes using remote sensing and GIS in Rize, North-East Turkey. . *Sensors, 8*(10), 6188-6202.

Shiferaw, A., and Singh, K. L. (2011). Evaluating the land use and land cover dynamics in Borena Woreda South Wollo Highlands, Ethiopia. . *The Ethiopian Journal of Business and Economics, 2*(1).

Slovin, E. (1960). Slovin's formula for sampling technique, www.statology.org/slovins-formula-calculator/ Retrieved May 23, 2021.

Tewabe, D., and Fentahun, T. (2020). Assessing land use and land cover change detection using remote sensing in the Lake Tana Basin, Northwest Ethiopia. *Cogent Environmental Science, 6*(1).

Valero, M., A., J., and Alzate, A. (2019). Comparison of maximum likelihood, support vector machines, and random forest techniques in satellite images classification. *Tecnura, 23*(59): 3-10.

Wang, S. W., Gebru, B. M., Lamchin, M., Kayastha, R. B., and Lee, W. K. (2020). Land use and land cover change detection and prediction in the Kathmandu district of Nepal using remote sensing and GIS. *Sustainability, 12*(9): 3925.

Wendimu, M. A. (2015). Large-Scale Agriculture and Outgrower Schemes in Ethiopia: Land Acquisition, Productivity, Labour Markets and Welfare Effects (Doctoral dissertation, . Copenhagen: University of Copenhagen, Faculty of Science, Department of Food and Resource Econ.

Wenedem, A. (2021). Local Land Rights and Large-scale Farm Investments in Ethiopia: The Need for Inclusive and Responsible Governance (Dissertation), Bahir Dar University, Bahir Dar: Ethiopia.