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Research Article

Socioeconomic Drivers of Land Use and Land Cover Change in Western Ethiopia

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A variety of socioeconomic and environmental drivers have contributed to changes in LULC around the world in recent years. This study examines the socioeconomic drivers that accelerated LULC in western Ethiopia. The data were generated from terrestrial satellite images primary and secondary sources. Primary data sources include household surveys, field observations, group discussions, interviews, key informants, and interpreting remote sensing data. Secondary data were reviewed mainly from relevant literature both published and unpublished materials. Landsat images were classified using the supervised classification technique and maximum likelihood classifier using arc GIS 10.3 to create LULC maps of the study area. Accuracy score and kappa coefficient were used to confirm the accuracy of the classified LULC, and agricultural land, settlement, bare land, forest land, and water body were the main LULC classes in the district. Forest cover in three decades (1990–2020) in the study area decreased from 12.1% in 1990 to 2.6% in 2020. The data were also analyzed using a descriptive model, Pearson correlation, and binary logistic regression. The independent variables (age and gender) show a Pearson's positive correlation with the drivers of LULC dynamics; that is, as these independent variables increase, the drivers of LULC dynamics also increase, whereas educational status and land holding size show a negative correlation. This shows that the drivers of the anthropogenic forces of LULC dynamics decreased as the number of educated populations and the size of land holdings increased, and vice versa. Then, the binary logistic regression model examined the relationship between the dependent and the major socioeconomic (independent) variables. Logistic regression was performed to determine how independent variables and the drivers of LULC (natural forces or anthropogenic forces) change and the model was statistically significant ($x^2 = 23.971$, df $= 5$, $P < 0.001$). The model explained 13.9% (Nagelkerke R^2) of the variance in the drivers of LULC dynamics and correctly classified 66.1% of the cases. The study found that age, gender, and educational status largely determine the drivers of LULC dynamics and have the greatest chance of determining the anthropogenic forces. Therefore, relevant stakeholders should take integrated measures to reduce the drivers of LULC dynamics through landscape restoration.

1. Introduction

The relationship between humans and nature has been explained and conceptualized in many ways throughout human history, and significant heterogeneity still exists across cultures [1–4]. The interaction between humans and nature has recently led to LULC changes worldwide [5, 6]. The impacts of land use/land cover change are determined by human activities [5]. LULC change is a dynamic and complex process that can be caused by many interacting processes, ranging from various natural to socioeconomic factors [7–9].

Drivers that accelerate LULC changes can be social, economic, or environmental and can have positive or negative impacts on the planetary system [10–12]. LUCC has been affected by a variety of important human endowments and biophysical phenomena [13, 14]. The relationship between LULC change and its drivers is complex and dynamic, as some of the previous studies suggest that demographic changes contribute more than any other causal factor to land use/land cover change [15–17]. LULC changes have led to global loss of native biodiversity and altered ecological processes and services in different ecosystems [18–20].

In developing countries, such as Africa, most of the populations are engaged in agriculture (both commercial and subsistence farming) and charcoal production as a source of income [21, 22]. In Ethiopia, the expansion of agriculture into forestland, logging, charcoal production, and fuel wood harvesting were the main drivers of LULC change [23, 24]. Drivers for land use/land cover dynamics are multiple and complex in space and time, requiring more investigation in Ethiopia [25, 26, 27]. Agricultural land expansion, increased demand for fuel wood and building materials, illegal forest settlement, and illegal logging are said to be the main drivers of LULC change in Ethiopia [28, 29].

In western Ethiopia, Wayu-Tuka district, where this study was conducted, human-induced changes in land use/ land cover are often observed [30, 31].

A recent study by Negassa et al. [23] near the current study area showed that agricultural land expansion is one of the main drivers of changes in LULC changes in the district. However, the LULC change detection proposed by Negassa et al. [23] focuses on forest LULC change. Therefore, this study analyzes the socioeconomic drivers of land use and land cover dynamic changes in the study area. Understanding these issues requires a rigorous investigation of ongoing LULC changes in research. Research findings contribute to the development of sound policy and management options for sustainable use and management of natural resources in the study area [30–32]. Therefore, this study aimed to analyze the socioeconomic drivers of land use and land cover change in Wayu-Tuka district, East Wollega Zone, western Ethiopia.

2. Materials and Research Methods

2.1. Description of the Study Area. The study area, Wayu-Tuka district, is located in the administrative zone of Oromia National Regional State of East Wollega, approximately 322 km west of Addis Ababa. The district is bordered by Sibu Sire district in the North and East, Leka Dulacha district in the South, and Guto Gida in the West. Specifically, the field of study is located between 8° 51′ 30″–9° 10′ 30″ north latitude and 36° 32′ 0″–36° 50′ 0″ east longitude (Figure 1). The area has peaks and slopes such as Komto, Gara-achani, and Tuka with elevations of 3350, 3140, and 2350 m.a.s.l, respectively. The area has a total area of 54,590.4 hectares and includes 12 Kebeles (i.e., Kebeles—the smallest administrative unit in Ethiopia), 10 villages, and 2 urban centers.

The district is divided into three agroecological divisions, of which 11% are upland, 49% are midland, and 40% are lowland [33]. The average annual rainfall in this area ranges from 1000 to 2551.4 mm, while the annual rainfall in the study area is about 2158 mm. The recorded climate data show that the annual rainfall in the study area in 1993 and 1998 was about 2525.3 mm and 2551.4 mm, respectively (Figure 2). Recorded climate data show that the average annual minimum and maximum temperatures in this area are about 12.5°c and 25.5°c [34].

The main vegetation types observed in the study area are Afromontane upland forest, interupland semideciduous forest, several forms of riparian forest, and plantation types. Southwestern Ethiopia hosts this moist evergreen montane forest, which is the native vegetation [35]. The soils of the study area are deep and belong to the orders Oxisols and Ultisols; of these, the main soil types and their spatial coverage in the district are 17,371.68 ha (60%) of clay loom soil, 10,133.49 ha (35%) of sandy soil, and 1,447.64 ha (5%) of clay soil (Figure 3), which are suitable for agriculture such as cereal cultivation: maize, sorghum, and teff production in the district [36].

Subsistence agriculture is the principal economic activity in the study area, crop cultivation and livestock rearing. According to the 2015 demographic and housing census, the population of Wayu-Tuka district was estimated to be 66,194 [37]. Of the 66,194 people, 32,391 were male and 33,803 were female (Figure 4).

2.2. LULC Change Data

2.2.1. Sources and Data Processing. The data used for Wayu-Tuka District LULC changes come from satellite images acquired in 1990 MSS, 2000 TM, 2010 ETM+, and 2020 OLI in four periods, downloaded free of charge from USGS: https://earthexplore.usgs.gov. LULC change classes such as bare land, settlements, agricultural land, forests, and information on changes in water bodies were obtained from Landsat images.

Landsat satellite images were obtained and processed of (path 170, raw 54) which contains an operational land imager (OLI), thematic mapper (TM), enhanced thematic mapper plus (ETM+), and multispectral scanner (MSS) used for LULC classification in the study area. Table 1 summarizes satellite data type, acquisition date, resolution, path and rows, and number of bands for the Landsat images used in this study (Table 1).

(1) Data Processing. In this study, the preprocessing of the images was georeferenced (UTM, WGS84) from the data downloaded. This image preprocessed corrects the image distortions and increases the quality of the image's data. Formerly, the Landsat images of each study year were independently classified with a supervised classification technique and maximum likelihood classifier (MLC) applied to classify the LULC types in arc GIS used for supervised classification. Lastly, the postclassification was employed using separately classified Landsat images made accuracy assessment pixel selection checked by using Google Earth for the LULC maps of 1990–2000, 2000–2010, and 2010–2020.

2.2.2. Methods of Data Analysis. The socioeconomic drivers of LULC change classes were analyzed from the data that freely downloaded Landsat imagery from https://earthexplore.usgs.gov. The imagery data were processed

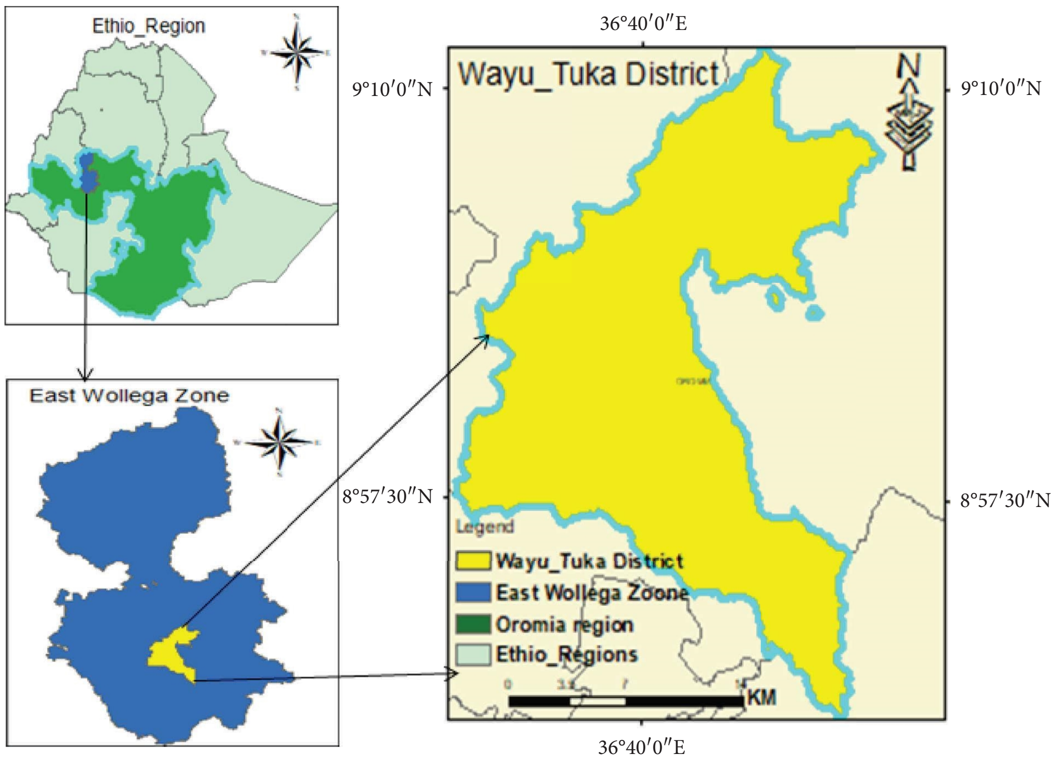


Figure 1: Site map of Wayu-Tuka district (source: self-designed based on Ethio-GIS database, 2023).

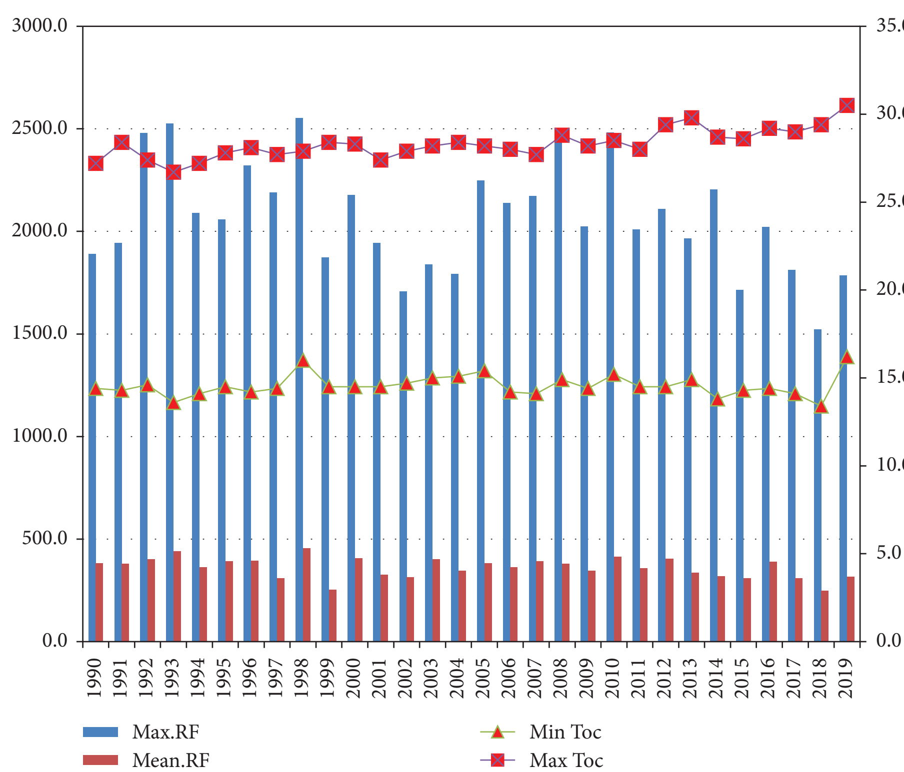


Figure 2: Max and mean RF and max and min T°c (1990–2019) in the Wayu-Tuka district (source: Nekemte meteorology station).

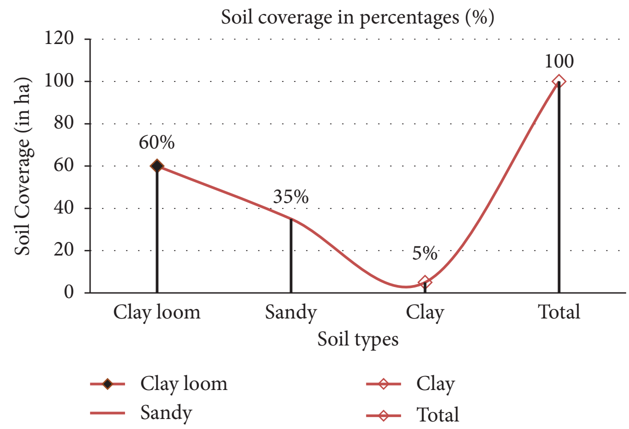


Figure 3: Main soil types in the study area.

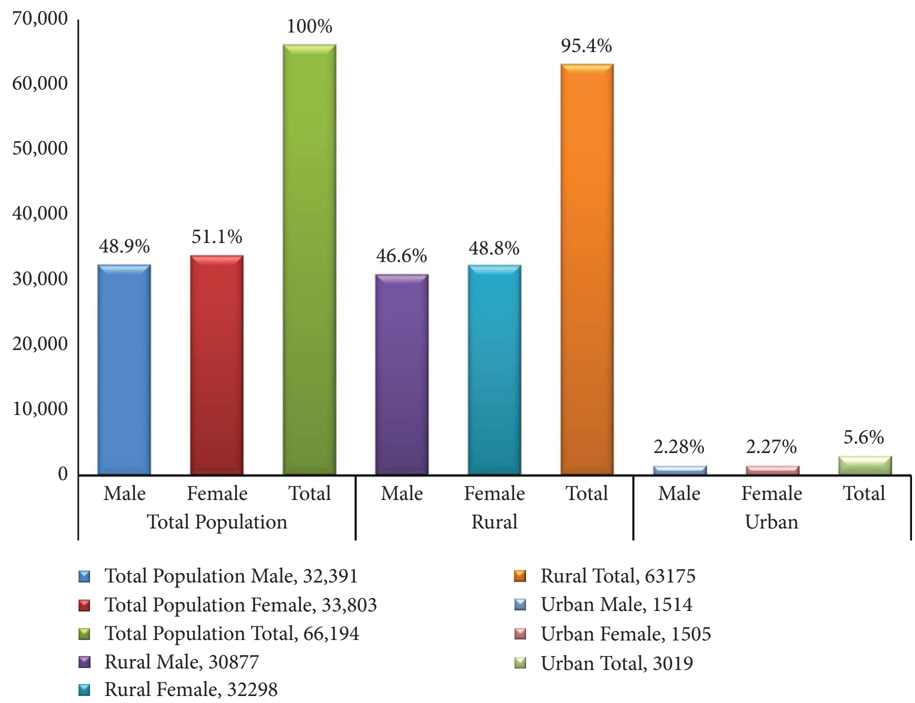


Figure 4: Population of Wayu-Tuka district (source: [37]).

Table 1: Landsat images and their characteristics used in this study.

Satellite data type	Sensor type	Acquisition date	Resolution (m)	Path and row	Number of bands	Cloud cover (%)
Landsat 5	MSS	March, 1990	30	170/54	7	Below 10
Landsat 7	TM	April, 2000	30	170/54	7	Below 10
Landsat 7	ETM+	March, 2010	30	170/54	8	Below 10
Landsat 8	OLI	April, 2020	30	170/54	11	Below 10

Sources: https://earthexplore.usg.gov.

using ArcGIS10.8 software. First, images were converted into Universal Transfer Mercator and georeferenced to a datum in which Ethiopia was selected by WGS-84. To improve the image quality, histogram equalizations were used. Currently, the satellite images were georeferenced first; at that time, supervised and unsupervised classifications are applied to indicate the type and area of different land use/ land cover classes of study area for each of the period measured.

2.2.3. Accuracy Assessment Results. The evaluation of the accuracy of the LULC classes showed that the large values of the accuracy evaluation are useful to assess the level of results obtained with Landsat images depending on the classification of the LULC types of the study area in the period 1990, 2000, 2010, and 2020 to be considered independently. The goal of the accuracy assessment was to quantitatively evaluate how effectively the pixel was classified into the correct LULC classes. Additionally, the selection of pixels for accuracy assessment focused on areas that could be clearly identified in high-resolution Landsat imagery, Google Earth, and Google Maps. Therefore, evaluating the accuracy of classified images plays a great role in evaluating the reliability of information extracted from classification [38].

For these images, user accuracy, producer accuracy, overall accuracy, and the kappa coefficient were evaluated for each image in the LULC class in four periods 1990, 2000, 2010, and 2020 (Table 2).

Producer accuracy and user accuracy were calculated to verify the accuracy of land use/land cover change classification types.

As shown in Table 3, the estimated accuracy values showed differences between the five land use and use classes within the same time period, and the accuracy values of each land use and use class also showed differences from period to period in the three decades considered in the study (1990–2020). For example, for the Wayu-Tuka district in 1990 LULC classes, producer accuracy was 72.7%, user accuracy was 100% for farmland, user accuracy was 67.7%, and producer accuracy was 66.7% for forest, and UA (67.7%) of settlements and the AP of agricultural land (72.7%) were considered somewhat low. However, the levels of settlement of UA levels (66.6%) and (75%) of water bodies in 2000 were also relatively low. The UA settlement level (62.5%) in 2010 was considered the lowest of all values for the five LULC classifications across all four study periods. The maximum level of accuracy for all five land use categories was 100% (Table 2).

The overall accuracy levels for the LULC category for all four periods were 83.3% in 1990, 86.6% in 2000, 80% in 2010, and 83.3% in 2020 (Table 2) and above, which met the minimum requirements for Landsat imagery accuracy based on the classified land use and land cover classes of the study area [39, 40].

The kappa coefficients for the classified land use/land cover categories were 0.795 (79.5%) in 1990, 0.826 (82.6%) in 2000, 0.746 (74.6%) in 2010, and 0.788 (78.8%) in 2020 (Table 2).

2.3. Socioeconomic Drivers of LULC Change in the Study Area

2.3.1. Sources and Data Collection Method. The data necessary for the study was generated through primary and secondary sources. The primary sources of data include household surveys, field observations, group discussions, and key informant interviews. Secondary data mainly come from relevant literature of published and unpublished materials, i.e., reviews using published and unpublished relevant literature.

Socioeconomic data were collected from communities through questionnaires, key informant interviews, focus group discussions, and field observations. Survey tools were rational and used to collect information on household characteristics and drivers of LULC change. To meet the requirements of the main drivers of land use and land cover change, socioeconomic data should be integrated [41, 42]. This study also employs a combination of techniques to analyze socioeconomic variables that drive land use and land cover change.

2.3.2. Household Survey Data. For the socioeconomic survey, sample households were drawn from the total population of villages (1340 HHs). Three villages, Dalo Komto, Gara Hudha, and Kich, were selected based on their distance from the forest area (geographic location), and a questionnaire survey was conducted among the households.

The formula used to determine sample size is [43] using the sample size formula. Finally, the sample size was calculated using the sample size determination correction formula, which is commonly used for sample size determination in most social science research when the target population is less than 10,000. The sample size formula [44] is as follows:

$$\begin{aligned} \text{no} &= \frac{\mathbf{t^{2*}\,(p)\,(q)}}{\mathbf{d^2}}\,\frac{\mathbf{(1.96)^2\,(0.5)\,(0.5)}}{\mathbf{(0.5)^2}} \\ &= 0.38416\text{x}100 \sim\ 384. \end{aligned} \tag{1}$$

Therefore, for a population of 1,340, the required sample size is 384. However, since this sample size exceeds 5% of the population ($520 * 0.05 = 26$) [43], a formula for correction should be used to calculate the final sample size. These calculations are as follows:

l = (**no**/(**1** + (**no/population**))) **n1** = **384**/(**1** + (**384**/**520**)) = 221. Therefore, the final sample size is 221.

Where

no = sample size required when the population is greater than 10,000,

$n1$ = limited population correction coefficient when the population is less than 10,000,

t = normal standard deviation (95% confidence level is 1.96),

Where t = the value of the chosen alpha level of 0.025 for each tail = 1.96 (an alpha level of 0.05 represents the level of risk the researcher is willing to take that the true margin of error may exceed the margin of acceptable error),

n = sample size,

where (p) (q) = variance estimate = 0.25.

Table 2: Accuracy assessment for 1990, 2000, 2010, and 2020.

LULC classes	Bare land	Farmland	Forest	Settlement	Water body	Total user	User's accuracy (%)
Accuracy assessment in 1990							
Bare land	**4**	0	0	0	0	**4**	**100**
Farmland	0	**8**	0	0	0	**8**	**100**
Forest	0	2	**4**	0	0	**6**	**67.7**
Settlement	0	1	2	**6**	0	**9**	**67.7**
Water body	0	0	0	0	**3**	**3**	**100**
Total producer	**4**	**11**	**6**	**6**	**3**	**30**	
Producer accuracy (%)	**100**	**72.7**	**66.7**	**100**	**100**		
Accuracy assessment in 2000							
Bare land	**4**	0	0	0	0	**4**	**100**
Farmland	0	**7**	0	1	0	**8**	**87.5**
Forest	0	0	**7**	0	0	**7**	**100**
Settlement	0	1	1	**6**	0	**8**	**75**
Water body	1	0	0	0	**2**	**3**	**66.6**
Total producer	**5**	**8**	**8**	**7**	**2**	**30**	
Producer accuracy (%)	**80**	**87.5**	**87.5**	**85.7**	**100**		
Accuracy assessment in 2010							
Bare land	**4**	0	0	0	0	**4**	**100**
Farmland	0	**6**	1	0	0	**7**	**85.7**
Forest	1	1	**6**	0	1	**8**	**75**
Settlement	1	1	1	**5**	0	**8**	**62.5**
Water body	0	0	0	0	**3**	**3**	**100**
Total producer	**5**	**8**	**8**	**5**	**4**	**30**	
Producer accuracy (%)	**80**	**75**	**75**	**100**	**75**		
Accuracy assessment in 2020							
Bare land	**3**	0	0	0	1	**4**	**75**
Farmland	0	**7**	0	0	0	**7**	**100**
Forest	0	1	**6**	0	0	**7**	**85.7**
Settlement	0	2	0	**6**	0	**8**	**75**
Water body	1	0	0	0	**3**	**4**	**75**
Total producer	**10**	**10**	**6**	**6**	**4**	**30**	
Producer accuracy (%)	**75**	**70**	**100**	**100**	**75**		
Overall accuracy	**For 1990 = 83.3**		**For 2000 = 86.6**		**For 2010 = 80**		**For 2020 = 83.3**
Overall kappa statistics	**0.795 (79.5%)**		**0.826 (82.6%)**		**0.746 (74.6%)**		**0.788 (78.8%)**

Sources: own summary of Landsat image results analysis via Arc GIS 10.3 (2023). The diagonal bold values show that the areas correctly classified for each year (1990–2020), the bold values of the last two rows for each year (1990–2020) represent total producer and producer accuracy (%), where as the last two columns for each year bold number represent total user and user's accuracy (%), and finally, the last two rows bold values indicate that to focuses overall accuracy and overall kappa statistics.

Table 3: Classes of LULC for Wayu-Tuka district (1990–2020).

No	Classes of LULC	1990		2000		2010		2020	
		Area (km^2)	(%)	Area (km^2)	(%)	Area (km^2)	(%)	Area (km^2)	(%)
1	Bare land	113.0	28.1	43.0	10.7	39.0	9.0	3.727	1
2	Farmland	147.0	36.6	216.0	53.4	209.0	51.0	227.0	56.0
3	Forest	49.0	12.1	33.0	8.2	16.0	4.0	10.0	2.6
4	Settlement	90.0	22.3	104.0	25.7	138.0	34.0	148.00	36.0
5	Water body	2.0	0.6	8.0	2	1.0	0.3	15.0	3.0
6	Total	**404.209**	**100**	**404.209**	**100**	**404.209**	**100**	**404.209**	**100**

Source: analysis via Arc GIS 10.3, 2023. The bold values show the total area (in skewer kilometer) and total (%).

According to the sample size determination formula above, 221 houses were randomly selected from 3 villages, 79 houses in Dalo Komto, 63 houses in Gara Hudha, and 79 houses in Kich.

The district was chosen purposively because of the presence of forested areas in the area. Likewise, the sample/study villages were selected using a purposive sampling method based on the presence of nearby forests. Therefore, out of the 10 district villages, three villages were selected namely Dalo Komto, Gara Hudha, and Kich. Then, in twelve questions, six were closed-ended that required a "YES" or "NO" answer (Tables 4–7), four were multiple-choice questions, and the remaining two were

Table 4: Are socioeconomic variables age factors in LULC dynamics?

		Respondents' age											
		20–30	(%)	31–40	(%)	41–50	(%)	51–60	(%)	61–70	(%)	Total	(%)
Is socioeconomic variable age is driving force for LULC dynamics?	No	13	5.9	32	14.5	25	11.3	10	4.5	5	2.3	85	38
	Yes	22	10	57	25.8	30	13.6	20	9	7	3.2	136	62
Total		45	15.9	89	40.3	55	24.9	30	13.5	12	5.5	221	100

Source: survey questions analyzed using SPSS, 2023. *Age of respondents cross-tabulation.

Table 5: Are socioeconomic variables gender factors in LULC dynamics?

		Respondents' gender					
		Male	(%)	Female	(%)	Total	(%)
Is socioeconomic variables are driving forces for LULC dynamics?	No	72	32.6	15	6.8	87	39.4
	Yes	106	48	28	12.7	134	60.6
Total		178	80.5	43	19.5	221	100

Source: survey questions analyzed using SPSS, 2023. *Gender of respondent cross-tabulation.

open-ended which were structured into two sections. The first section was the socio-demographic structure which contains the details of the respondents (i.e., age, gender, educational status, and land holding size), and the second structure was households' perception of drivers of LULC change.

2.3.3. Method of Data Analysis. The driving forces of LULC dynamics were analyzed using data generated from both primary and secondary sources. Quantitative and qualitative data were analyzed in this study. The quantitative data obtained from the household survey were coded and entered into statistical software version 20 (SPSS 20) for descriptive statistical analysis. The results were summarized and presented in percentages, tables, and figures. The analytical data were useful in determining and quantifying the driving factors of the land use/land cover change in the study area.

In addition, Pearson's chi-square test and logistic regression analysis were performed. Descriptive statistics using simple frequency analysis were used to describe the socioeconomic characteristics of households and to examine their responses and the classification of land use/land cover change dynamics [45]. The drivers of LULC dynamics were analyzed using nonparametric tests, specifically the Pearson chi-square test [46]. In addition, quantitative binary logistic regression analysis was employed at the household level to identify the main socioeconomic determinants of observed land use changes and the drivers of land use dynamics [47]. Logistic regression analysis is a statistical procedure suitable for examining the relationship between a variable (dependent) and several socioeconomic variables (independent) [48].

This is an efficient analysis technique when the dependent variable is binary [4] that estimates the LULC driving force of the independent (explanatory) variable on the dependent (response) variable:

$$\mathbf{Logit}\,(\mathbf{Y}) = \boldsymbol{\alpha} + \beta_1 \mathbf{x_1} + \beta_2 \mathbf{x}_{2+} \beta_3 \mathbf{x_3}, \ldots, +\beta_\mathbf{n} \mathbf{x_n}, \quad (2)$$

where Y = dependent variable representing the probability of $Y = 1$, α = intercept, $\beta_1 \ldots \beta_n$ = coefficients of related independent variables, and $X_1 \ldots X_n$ = independent variables.

A logistic regression model was used to analyze the relationship between demographic data and socioeconomic conditions [49]. In this study, the outcome variable (forest dependence) was taken from selected explanatory variables: age, sex, education, and property size were used as proxies for socioeconomic variables.

Figure 5 shows the framework and methodology flowchart used to create the LULC and socioeconomic drivers for LULC change (Figure 5).

3. Results and Discussion

3.1. Changes in Land Use/Cover in Wayu-Tuka Since 1990–2020. Five major LULC categories, namely bare land, farmland, forest, settlement, and water body, were analyzed based on Landsat imagery during 1990–2020 (Table 3).

The year 1990 was the decade when the farmland in the study area accounted for approximately 36.6% (147.0 km^2) of the total area of the district, of which bare land, settlements, forest coverage, and water bodies each accounted for 28.1% (113.678 km^2), 12.1% (49.0 km^2), 22.3% (90.0 km^2), and 0.6% (2.0 km^2) about more than two-third 66.1% of the area of Wayu-Tuka district in the same period in 1990. The potion of water body (0.6%) is insignificant in 1990 indicating that within the total area of the study area (Table 3).

In 2000, the district's farm land accounted for the largest proportion of the total area at approximately 53.4% (216.0 km2), while the rest bare land 10.7% (43.0 km2), forest cover 8.2% (33 .09 km2), settlement for 25.7% (104.0 km2) and 2% of the water body (8.0 km2), respectively, accounted in 2000 and indicating a decline since the early 1990s. In fact, 2000 was also a period when bare land and forest coverage were 10.7% (43.0 km^2) and 8.2% (33.0 km^2), respectively, indicating a significant decrease compared with the area of 1990. On the other hand, the area percentage for farmland 53.4% (216.0 km^2) and water body 2% (8.0 km^2) of the study area increased in the year 2000 (Table 3).

Except the settlement of the district, the rest of LULC classes decreased compared with the previous period (2000). In 2010, the area of bare land 9.7% (39.0 km^2), farmland 51.7% (209.0 km^2), forest cover (16.0 km^2), and water body 0.3% (1.0 km^2) included in this research area.

Finally, in 2020, the Landsat images depending on the analysis showed that farmland with about 56.2% (227.0 km^2) was the LULC type which accounted the largest area share of the study site, and this accounted the largest from the periods of 1990, 2000, and 2010. The settlement land was 36.0% (148.0 km^2) in the last period accounted for the district. Water body, forest cover, and bare land constituted about 3.7% (15.0 km^2), 2.6% (10.0 km^2), and 1% (3.0 km^2) in the study area, respectively (Table 3).

Figure 6 shows the LULC classification of four maps for five (5) classification types in 1990–2020 from left to right. The first map shows the LULC classification of the TM in the 1990 image. Among them, most areas include 36.0% farmland, 28.1% bare land, 22.3% settlement areas, 12.1% forest coverage, and 0.6% water bodies. For the TM 2000 image, the LULC classification results show that most of the various types of land use/land cover flow to farmland and settlement areas, accounted for 53.4% and 25.7% of the

Table 6: Is socioeconomic educational status is driving force for LULC dynamics?

Variables		Educational status of respondents								Total	(%)
		Illiterate	(%)	High school	(%)	Some colleges	(%)	Undergraduate	(%)		
Is socioeconomic variables are driving forces for LULC dynamics?	No	44	19.9	29	13.1	10	4.5	4	1.8	87	39.4
	Yes	49	22.2	50	22.6	18	8.1	17	7.7	134	60.6
Total		93	42	79	35.7	28	12.7	21	9.5	221	100

Source: survey question analyzed using SPSS, 2023. *Educational status of respondents' cross-tabulation.

Table 7: Are socioeconomic variables land holding size driving forces for LULC dynamics?

Variable		Land-holding size of the respondents					
		No land	(%)	Own land	(%)	Total	(%)
Is socioeconomic variables are driving forces for LULC dynamics?	No	63	28	48	21	111	50
	Yes	64	28	46	20	110	50
Total		127	46	94	41	221	100

Source: survey questions analyzed using SPSS, 2023. *Size of respondent's land holdings cross-tabulation.

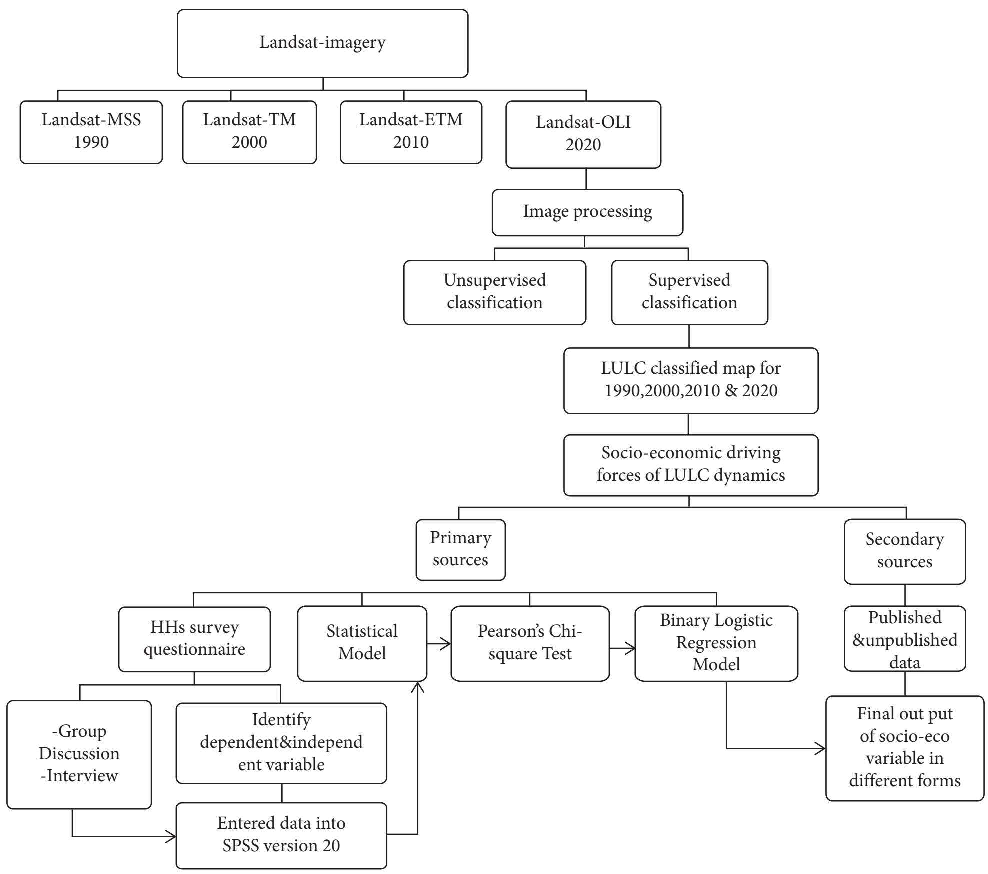


Figure 5: Framework of this article (source: own design, 2023).

total area, respectively. Bare land, forest coverage, and water body coverage are 10.7%, 8.2%, and 2%, respectively. The minimum area is covered by water bodies, accounting for 2% of the total category of the study area. The LULC classification results of the ETM 2010 images show that most of the LULC of all categories flow to farmland and settled areas, covering 51.7% and 34.3%, respectively. Bare land and forest land cover 9.7% and 4%, respectively. Water bodies cover the smallest area, accounted for 0.3% of the total area of the district. Finally, the LULC results for the 2020 OLI images were also similar, showing that the majority of LULC for all categories of drivers flowed toward farmland and settlement areas, covering 56.0% and 36.0% of the total area of the study area, respectively. The water body and forest land coverage rates are 3.7% and 2.6%, respectively. During this period, the area of bare land was the smallest, accounted for 1% of the total area of all types in the district (Figure 6).

3.2. Area Change of LULC in 1990–2020. From the Landsat image analyzed, the area change of LULC classes was analyzed for the periods (1990–2020) by using Arc GIS 10.3. LULC area changes of 1990–2000, 2000–2010, 2010–2020, and 1990–2020 were structured in km^2 as shown in Figure 7.

From 1990 to 2000, the change results of LULC area of bare land and forest coverage showed positive changes, while the changes of cultivated land, settlement areas, and water body areas showed negative changes of km^2. However, the LULC category type of area change subsidence showed negative changes from 2000 to 2010, indicating that settlement increased through area change.

Figure 7 also indicated that the area change results (2010–2020 km^2) of bare land, farm land, forest land, settlement areas and water bodies are 35.537 km^2, −17.9951, 5.457 km^2, −9.2042 km^2, and −13.788 km^2, respectively. Finally, the area changes during 1990–2020 show that the largest area change during the same period was farmland

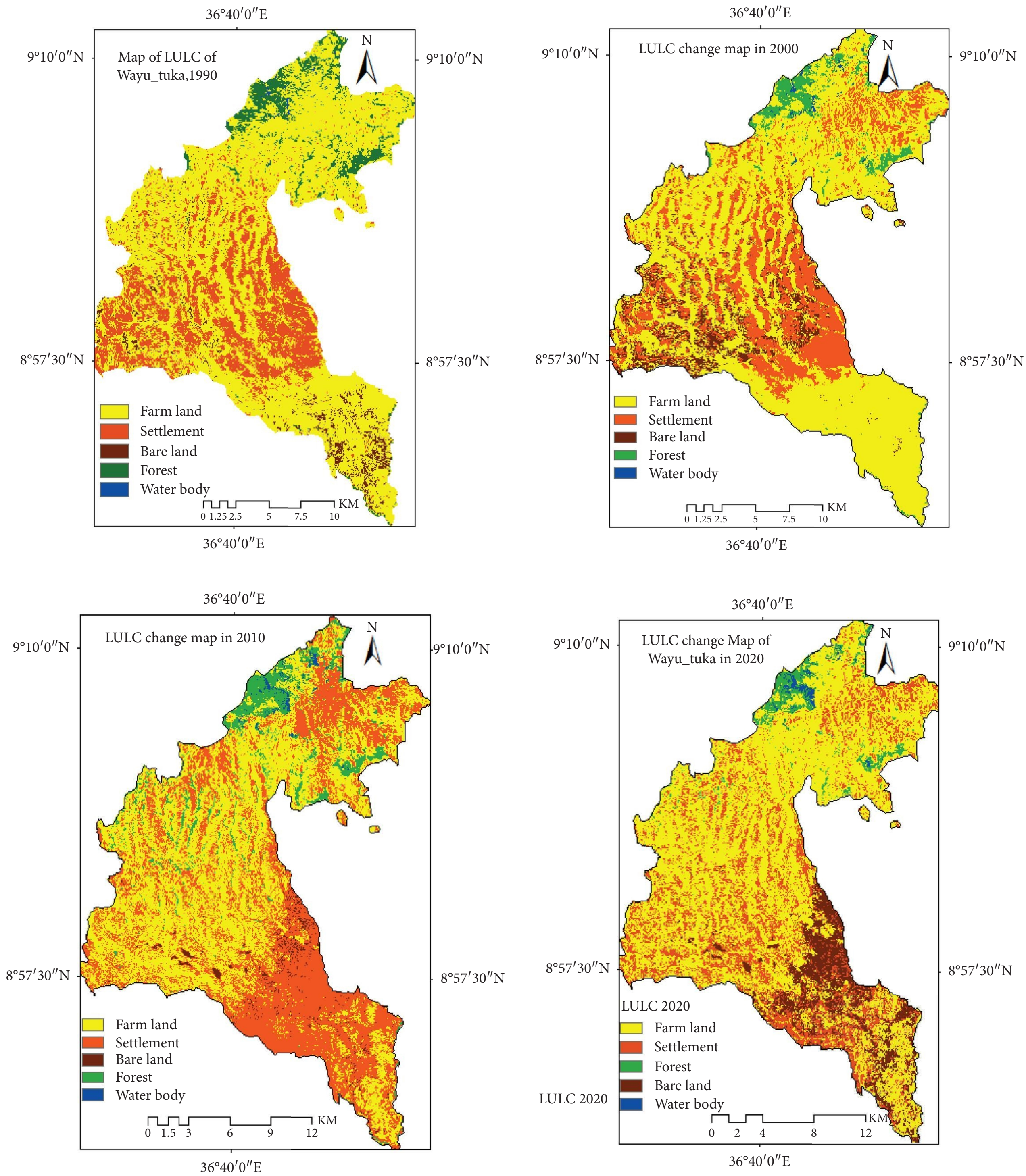
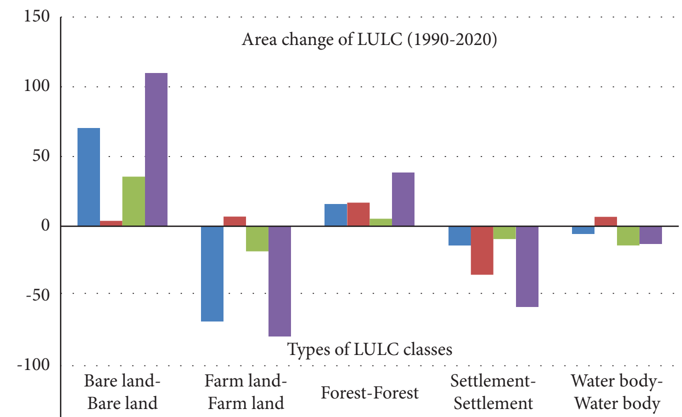


Figure 6: Map of LULC change in Wayu-Tuka district 1990–202 (source: Landsat images).

($-79.118\,km^2$), and the second largest area change was settlements ($-57.9901\,km^2$). The changes in bare land, forest coverage area, and water body area were $109.951\,km^2$, $38.457\,km^2$, and $-12.547\,km^2$, respectively.

3.3. Driving Forces of Land Use/Land Cover Dynamics. For the first analysis of the relationship between dependent variables (land use and drivers of land use) and socioeconomic variables (age, sex, educational status, and size of land



	Bare land-Bare land	Farm land-Farm land	Forest-Forest	Settlement-Settlement	Water body-Water body
Area change (1990-2000) in Km2	70.472	-68.1225	15.997	-13.9989	-5.594
Area change (2000-2010) in Km2	3.942	6.9996	17.003	-34.787	6.835
Area change (2010-2020) in Km2	35.537	-17.9951	5.457	-9.2042	-13.788
Area change (1990-2020) in Km2	109.951	-79.118	38.457	-57.9901	-12.547

Figure 7: Land use/land cover changes (1990–2020) (source: GIS 10.3 (2023) analysis).

Table 8: Correlation coefficient values between SEV and LULC driving force.

		Ir/nsv sdrs	Age	Genders	Edust	Lndsz
Is rscvLULC dynamics?	Pearson correlation	1				
Age	Pearson correlation	0.008	1			
Genders	Pearson correlation	0.020	−0.039	1		
Educational status	Pearson correlation	−0.016	−0.030	−0.136*	1	
Land-holding size	Person correlation	−0.14	0.771**	−0.053	−0.079	1

* correlation is significant at the 0.05 level (2-tailed). ** correlation is significant at the 0.01 level (2-tailed). Sedrs = socioeconomic drivers, Is scv = Is there r/n ship between socioeconomic drivers variables and LULC dynamics, SEV = socioeconomic variables, and Edust = educational status.

ownership), correlation analysis was applied before modeling continued (Table 8).

Major socioeconomic variables (i.e., age, gender, educational status, and land-holding size) were analyzed to determine the relationship with LULC changes or not. According to Chen et al. [50], before conducting modeling analysis, Pearson correlation analysis can be used to explain the correlation between the dependent variable and the independent socioeconomic variables. Similarly, the Pearson correlation coefficient indicates positive and negative correlations. A positive correlation indicates that the dependent variable (in this case, the main socioeconomic variable that LULC dynamics) increases with the value of the independent socioeconomic variable, while a negative correlation indicates that the dependent variable increases with the value of the independent socioeconomic variable decreases as the value increases the values of socioeconomic independent variables that are the main drivers of LULC dynamics. The independent variables (i.e., age and gender) have positive Pearson correlations with the drivers of LULC dynamics; this means that when these independent variables increase, the drivers of land use and land cover dynamics also increase. However, when the independent variable of education status is negatively correlated with the status of land holding and the number of educated population increases, the driving force of LULC cover dynamics, especially anthropogenic driving force, decreases, while the status of land holding increases, the driving forces of land use and land use dynamics decline. The figurative number one (1) correlation shows that the value of one variable can be accurately determined by knowing the value of the other variable, which is a perfect correlation (Table 8).

3.4. Analyzing Dependent Model. Correlations with drivers of land use/land cover dynamics become important after identifying the main socioeconomic determinants using Pearson's chi-square. The relationship between the (dependent) variable and various socioeconomic (independent) variables was examined according to [49] binary logistic regression model, which estimates the LULC of the independent (explanatory) variable on the dependent (response) variable driving force.

3.4.1. Independent Classification Encoding and Baseline Used in the Model. The independent categorical variable coded for education status in the model is divided into illiterate coded 0, high school coded 1, some college coded 0, and respondents who have completed a basic degree are recorded as 1, while respondent gender is coded for male as 0 and female as 1, and finally, for land holding size, respondents no land are coded as 1, and respondents own land are coded as 0 (Table 9).

The following part of the result, i.e., the baseline model of the drivers of LULC dynamics, is the result of the analysis without using any of the model's independent variables (i.e.,

Table 9: Coding of categorical independent variables.

Independent variables		Frequency	Parameter coding		
			(1)	(2)	(3)
Educational status	Illiterate	93	0.000	0.000	0.000
	High school	79	1.000	0.000	0.000
	Some colleges	28	0.000	1.000	0.000
	Undergraduate	21	0.000	0.000	1.000
Gender	Male	189	0.000		
	Female	32	1.000		
Land-holding size	No land	127	1.000		
	Own land	94	0.000		

Source: analysis via SPSS version 20 (2023).

socioeconomic variables age, gender, education level, and property size) in Block 0 (i.e., baseline model). The expected outcome of the main driving force of LULC for socioeconomic variables would be selected as natural forces, coded as 0, while for variables for which anthropogenic forces are selected, the driving force of LULC dynamics is classified as 1.

The baseline model would be used as a benchmark to compare the model to the results including the predictor variables. The following classification tables[a,b] show that the overall accuracy is 59.3% (Table 10).

3.4.2. Model Goodness-of-Fit Statistics. Goodness-of-fit statistics showed that the study was designed to determine whether the model is suitable to describe the data. The model is significant, and the likelihood ratio chi-square test revealed that the full model represents a significant improvement in fit over a null model and represents a significant improvement in fit over a null model, x^2 (23.971), $P < 0.001$. The Hosmer and Lemeshow test statistic indicates a poor fit if the significance value is less than 0.05 [51]. In this test, the Hosmer and Lemeshow model has a good fit, as the chi-square value is 4.450, $P = 0.814$, which is greater than 0.05.

According to Table 11 of the Hosmer and Lemeshow test contingency table, the test indicated that the model adequately fits the data. As anyone can see, there is no difference between what is observed and what is predicted models. This means that both values are almost the same.

To further clarify, there is not much difference between the observed and expected drivers of LULC dynamics for natural forces and anthropogenic forces from the contingency test for Hosmer and Lemeshow, so the model adequately fits the data displayed clearly with the line graph (Figure 8).

3.4.3. Variables in the Model Equation. As shown in Table 5, the classification table[a] provides an indication of the model's ability to predict the correct class when predictors are added to the study. The percentages in the first two lines, that is, whether socioeconomic variables are drivers of land use/ land cover change and whether natural and anthropogenic forces are selected, provide information about the specificity and sensitivity of the model in predicting group membership of the dependent variable. Anyone can compare this classification table shown for Block 0 Table 10 to see how much improvement there is when the predictor variables are involved and these tables classifications are used for comparing with the result of observed and predictor variables included in the model. In this result, there was variation between Block 0 Table 10 classification Table[a,b] and Table 5 classification Table[a]. The model correctly classified a total of 66.1% of cases. This is the rate correct classification if the researcher always predicts that a respondent would choose anthropogenic forces.

Specificity which is called the true negative rate is the percentage of observed cases that fall into the nontarget (or reference) category [52]. The model correctly predicted 47.8% of respondents choosing natural forces as the driving force for LULC dynamics. In another word, the classification predicts that respondents would have chosen anthropogenic forces.

Specifically, it represents information about the degree to which observed results are predicted by the model used.

Sensitivity, also known as true positive rate, is the percentage of observed cases that belong to the target group, i.e., $Y = 1$, in which case the anthropogenic forces are chosen and the model correctly predicts that those who belong to this group (predict the chosen) anthropogenic forces model with a sensitivity of 78.6%. Generally, the accuracy is very high at 66.1%, as the overall percentage of correctly classifying the socioeconomic variables selected by respondents is the driver of the model-based LULC variation (Table 12).

3.4.4. Variables in Model Equations. Table 13 provides the regression coefficients (B), Wald statistics (for testing statistical significance), and the most important odds ratios (Exp (B) for each variable category) and also shows the relationship between the predictor variables and the outcome. The result for educational status is highly significant (Wald = 16.287, $\mathrm{df} = 3$, $p < 0.000$), and B (Beta) is the predicted change in log odds for a unit change in the ratio between the odds (Table 13).

So, the Exp (b) of the variable "Gender" is 0.869, and the researcher can state that the probability of a respondent choosing the anthropic forces that provide

Table 10: Classification Table[a,b] of dependent variables of LULC dynamic driving force.

Observed			Predicted: Driving forces for LULC dynamics — Natural forces	Predicted: Driving forces for LULC dynamics — Anthropogenic forces	Percentage correct
Step 0	Driving forces for LULC dynamics	Natural forces	0	90	0.0
		Anthropogenic forces	0	131	100.0
	Overall percentage				59.3

[a]Constant is included in the model. [b]The cut value is .500.

Table 11: Contingency table for Hosmer and Lemeshow test.

		Driving forces for LULC dynamics = natural forces		Driving forces for LULC dynamics = anthropogenic forces		Total
		Observed	Expected	Observed	Expected	
Step 1	1	15	15.311	9	8.689	24
	2	12	13.985	11	9.015	23
	3	16	13.147	8	10.853	24
	4	9	9.912	13	12.088	22
	5	8	8.365	13	13.635	21
	6	10	8.989	14	15.011	24
	7	8	8.398	17	16.602	25
	8	6	6.052	17	16.948	23
	9	6	4.587	18	19.143	24
	10	0	1.254	11	9.746	11

Sources: collected data analyzed using SPSS version 20 (2023).

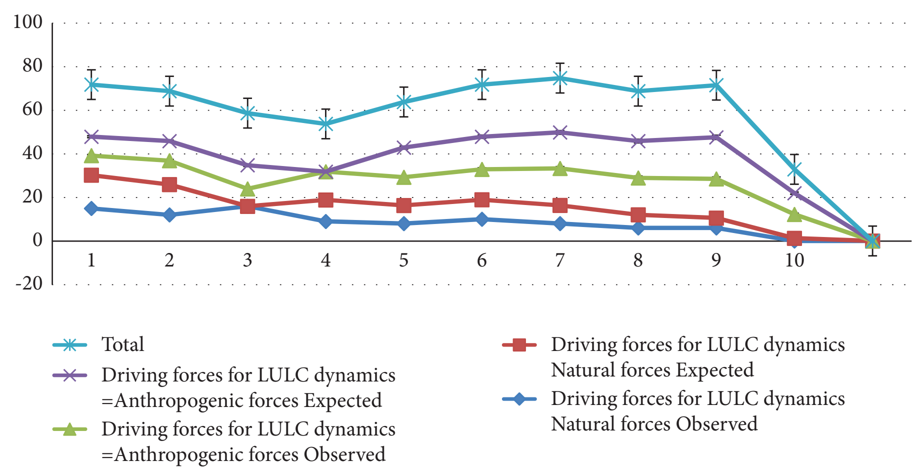


Figure 8: Comparison of observed and expected drivers of LULC dynamics (2023).

“Gender” is 0.869 times greater than that of the person who chooses “Gender,” i.e., the person who chooses “anthropogenic forces” 86.9% higher than those who chose “natural force.”

The variable educational status (1) has an Exp (b) of 2.596 and exp (b) of 2.596 times more likely than an uneducated person. People with a high school education have a 259.6% higher chance of choosing anthropogenic forces to participate in LULC dynamics than those without a high school education. For exp (b) educational status (2), the categorical variable is 2.610.

People with some college education have a 261% higher chance of choosing anthropogenic forces for LULC dynamics than people without some college education. In the case of exp (b), educational status (3) is 7.867. Those with a college education had a 786.7% higher chance of choosing anthropogenic forces for LULC dynamics than those without a college education and not providing natural forces, with a 95% CI of 2.146 to 28.843. The Exp (b) for the continuous variable age is 1.032. The Exp (b) for the continuous variable age is 1.032. The authors of [53] indicated results suggest that the aging of the study area is driving the observed changes (from the point of view of human activity), based solely on the basis of statistical models that provide adequate predictions of changes and comparisons of socioeconomic variables. The poor predictive performance highlights the problem of using aggregated socioeconomic variables; i.e., more selective socioeconomic variables are available.

Table 12: Classification Table[a] for step 1.

Observed		Predicted: Drivers of LULC dynamics — Natural forces	Predicted: Drivers of LULC dynamics — Anthropogenic force	Percentage correct
Drivers of LULC dynamics	Natural forces	43	47	47.8
	Anthropogenic force	28	103	78.6
Overall percentage				66.1

[a]The cut value is 0.500.

In this study, the coefficient of the value of the continuous independent variable exp (b) is almost equal to 1, which indicates that subjects who present higher values of the variable have the same probability of success as subjects who present lower values of the variable (i.e., the independent variable has no significant effect on the response variable) (Table 11).

3.5. Socioeconomic Drivers of LULC Changes. Socioeconomic data derived from distribution of survey questions to households, focus group discussions, key informant interviews, and observed field data were analyzed. The approach is comprehensive and strives to quantitatively and qualitatively characterize land use and the ongoing classification of the main drivers of land use change by combining many different data sources.

The following survey questions were asked for the selected sample households in the study area. Distributed and collected from a sample of households selected in the study area, this question is "Is socioeconomic variables (age, sex, educational status, and size of land ownership) affect land use and the drivers (natural or anthropogenic) of land use dynamics?

In this study, researchers analyzed the socioeconomic variables that drivers of LULC change in the study area. Therefore, the socioeconomic variables for LULC change drivers in the study area are age, gender, educational status, and landholding size. These independent variables were analyzed one by one below.

The question was asked to the selected respondents: "Is the socioeconomic variable of age influence the driving forces of land use and land use dynamics in your village?" For this survey question, almost more than 60% of the respondents (i.e. 62%) answered that age is the driving force of LULC dynamics in their village, of which 25.8% fall under 31–40 age group and the rest 0.3.2%, 9%, 10%, and finally, 13.6% were found 61–70, 51–60, 20–30, 41–50 under the age group, respectively (Table 4).

Regarding the gender of the respondents, the question asked to the selected respondents was "Is the socioeconomic variable gender a driver of LULC dynamics in your village?" For this survey question, more than 80% of the respondents (i.e., 80.5%) answered that gender, especially men, is the driving force of LULC dynamics in their villages, while 19.5% were women and were the driving force of LULC dynamics in their villages. Finally, 39.4% of the respondents responded that LULC change is driven by natural forces, not gender, they answered "no," while a majority of respondents around sixty percent answered that gender is a socioeconomic variable, with driving forces that LULC change (Table 5).

Relating to the educational status of the respondents, the question asked for selected respondents was "Is the socioeconomic variable educational status a driver of land use/land dynamics in your village?" For this survey question, 19.5% of respondents answered that educational status is not a driver of LULC dynamics. Finally, 39.4% of respondents answered that LULC dynamics are driven by natural forces rather than educational levels, choosing "no," while the majority of respondents of similar gender, about 60% of respondents, answered that educational status is a socioeconomic factor (Table 6).

In the case of landholding size, as the number of landless respondents increases, the drivers of land use/land cover dynamics increase, while as the number of landless respondents decreases, the drivers of land use/land cover dynamics also decreases (Table 7).

3.6. Discussion. According to the respondent's explanations, household age groups play an important role in driving land use/land cover dynamics, especially for developing countries, because when their age groups reach 20 years and above; households want to increase their land holdings during illegal segregation, which leads to an alarming increase in land use rates or land use changes. This result is almost similar to the work of [10, 54, 55] titled "Socioeconomic Drivers of Land Use/Cover Dynamics and Their Impacts in Walecha Watershed, Southern Ethiopia." Table 7 also improves the ones shown under each item percentage of reasons by age group.

Some educated households responded separately that 1.8% undergraduate, 4.5% undergraduate, and 13.1% educational status were also not a driver of land use/land cover dynamics in their village. However, among the respondents, 7.7% of undergraduate students, 8.1% of partial college students, 22.6% of high school students, and 22.2% of illiterate students, respectively, responded that educational status is the driving force of land use and land use dynamics in their villages. This aspect is consistent with other works in Ethiopia [56] on the title "Drivers and Impacts of Land Use and Land Cover Change in the Central Highlands of Ethiopia," which mentioned that based on the socioeconomic characteristics of the households surveyed, 23% of the respondents were an illiterate person (see Table 6).

Table 13: Variable in the equation.

	Socioeconomic independent	B	S.E	Wald	df	Sig	Exp (B)	95% C.I. for EXP (B)	
								Lower	Upper
Step 1[a]	Age	0.031	0.014	4.945	1	0.026	1.032	1.004	1.060
	Gender (1)	−0.141	0.410	0.118	1	0.732	0.869	0.389	1.939
	Educational_.status			16.287	3	0.001			
	Educational_.status (1)	0.954	0.322	8.760	1	0.003	2.596	1.380	4.881
	Educational_.status (2)	0.959	0.462	4.314	1	0.038	2.610	1.055	6.452
	Educational_.status (3)	2.063	0.663	9.684	1	0.002	7.867	2.146	28.843
	Landholding size	−0.139	0.261	−0.036	1	0.000	0.654	0.530	0.377
	Constant	−1.357	0.560	5.869	1	0.015	0.257		

[a]Variables entered in step 1: age, gender, educational status, and landholding size.

Land use/land cover changes are the result of human impacts, biophysical drivers, and natural processes [57–59].

Focus group discussions were conducted among selected household heads and local people regardless of their social status.

According to the ideas raised during the focus group discussion on “Is socioeconomic variable gender is a driving force for LULC dynamics?” There is a huge change and urgent decline of land use/land use dynamics in the study area as stated by household heads and local people. The main reason for the decline is the independent variable of gender, especially women; men are responsible for the conversion of land cover from forests to agriculture and settlements. The results from focus group discussions indicated that past LULCCs were prioritized based on ideas presented by men.

The last question was posed for the informal discussion (interview): “Is the socioeconomic variable education level is a driver of LULC dynamics in your village?” In response to these joint analysis questions, key informant interviews were conducted with older adults who know and have lived in the study area for a long time to obtain more reliable information on the changes and drivers of LULC change in the study area. The results of the informal discussions (interviews) were almost similar to the focused discussions, indicating that the key solution to changes in the past and current situation of LULCC is to increase the number of educated populations, especially in developing countries [60–62]. According to these selected interviewers, the level of educational status is directly related to the drivers of LULC dynamics, suggesting that as educational status increases, the drivers behind forest decline (a specific recent trend) are, increased agricultural production overwhelms forests through a variety of mechanisms decreased. Educational status, then, is the most important socioeconomic independent variable in LULC change drivers.

4. Conclusions

This study analyzes the main socioeconomic variables of LULC drivers of land use dynamics in the Wayu-Tuka district. This study analyzes the main socioeconomic variables of land use/land use drivers of the Wayu-Tuka district. Data were obtained from Landsat imagery classified through Arc GIS used to develop the LULC map of the Wayu-Tuka district. Accuracy assessment and Kappa coefficient are used to confirm the accuracy of the LULC classification of farm land, settlement areas, bare land, forest land, and water bodies, which are the main land use/land cover changes in the district. The forest coverage in the study area over the past thirty years (1990–2020) decreased from 12.1% in 1990 to 2.6% in 2020. For socioeconomic data, research questions were distributed to households and focus group discussions, and key informant interviews and field data collection were analyzed. Pearson correlation was used to determine the relationship between the main socioeconomic determinants of the independent variables and the driving forces of land use/land cover dynamics in the selected district. The result of the study showed that the independent variables (i.e., age and gender) have a positive Pearson correlation with the driving forces of LULC dynamics; this implied that as these independent variables increase, the driving forces of LULC change also increase, whereas education status has a negative correlation, showing that as the number of an educated population increases, the driving forces of anthropogenic forces for LULC dynamics decreased and vice versa. The binary logistic regression model examined the relationship between the (dependent) and the main socioeconomic (independent) variables. Logistic regression was performed to determine how variables such as age, gender, educational status, and landholding size are the driving forces for LULC change (natural forces or anthropogenic forces). The logistic regression model was statistically significant ($x^2 = 23.971$, df = 5, $P < 0.001$). The model explained 13.9% (Nagelkerke R^2) of the variance in driving forces for LULC dynamics and correctly classified 66.1% of cases. Age, gender, and educational status largely determine the driving forces for LULC dynamics. The driving force for LULC dynamics has the greatest chance of selecting the anthropogenic forces. The survey question was asked for selected sample HHs of the study area and almost more than sixty percent of the respondents responded to this survey question, i.e., H. 62% that age is the driving force for the LULC dynamics in their village: 25.8% are under 31–40 years age group, and the rest (0.3.2%, 9%, 10%, and 13.6%) were 61–70, 51–60, 20–30 and 41–50 among the age group, respectively. Finally, the result of this study also showed that 39.4% of the respondents had answered that natural forces are the driving forces of LULC dynamics not at the educational level and they chose "No", while the majority of the respondents were similar in gender, about sixty percent of respondents responded that educational status was a socioeconomic variable that facilitated the driving forces of LULC dynamics. Therefore, concerned bodies should minimize the driving forces of LULC dynamics, especially anthropogenic forces, to rehabilitate and restore the landscape in the Wayu-Tuka district, western Ethiopia.

Data Availability

The data supporting the current study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Authors' Contributions

Jembere Bekere Kenea, Professor Fayera Senbeta Wakjira, and Dr. Abren Gelaw Mokonen share contributions to this manuscript. Jembere Bekere Kenea collected the data, analyzed the data, interpreted the data, and wrote the manuscript. Professor Fayera Senbeta Wakjira edited, conceived, and designed the manuscript. Finally, Dr. Abren Gelaw Mokonen also analyzed and interpreted the data. Both Professor Fayera Senbeta Wakjira and Dr. Abren Gelaw Mokonen supervised the article.

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