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Research article

Effects of participatory forest management programs on Land use/ land cover change and its Determinants in Alle District, southwest Ethiopia

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ABSTRACT

In order to create sustainable conservation policies for biodiversity, it is imperative that participatory forest management (PFM) be assessed. Forests contribute to the sustainability of the planet by controlling soil erosion in agricultural areas and by moderating the effects of climate change. However, Ethiopia's forest resources have been under intense pressure because of the increased demand for wood products and agricultural conversion. As one of the potential solutions, the PFM programme was implemented in 1990. This study set out to investigate the effects of the PFM programme on land use and land cover (LULC) in the Alle district of southwest Ethiopia, as well as the variables influencing community involvement and the obstacles to PFM implementation and community involvement. Changes in forest cover were detected using Landsat images from 1992, 2012, and 2022 obtained from Thematic Mapper (TM), Enhanced Thematic Mapper (ETM+), and Operational Land Imager (OLI). Images were obtained during the dry season and were cloud-free. A total of 240 respondents were chosen by means of a straightforward random sampling technique, and survey data were collected using questionnaires, interviews, and field observations. Data were analyzed using ArcGIS 10.5, ERDAS Imagine 2015, SPSS version 20, and Excel 2010. The change in forest cover shows an increasing trend from 2012 to 2022. Again, grassland and wetland coverage in this study decreased rapidly. In the years 2012–2022, forest land increased from 462.7ha (74.8 %), to 569.8ha (92.1 %), while, the agricultural land, grassland, and wetland were reduced from 109.5ha (17.7 %) to 37.8ha (6.1 %), 31.9ha (5.2 %) to 0.0ha (0.0 %); 14.1 ha (2.3 %), to 10.8 ha (1.7 %) respectively. There have been beneficial developments in the forests over the last 30 years. The binary logistic regression model **disclose** that, land ownership had a negative impact on forest management participation, while other factors such as gender, education level, family size, TLU, access to credit, training, and law enforcement had a positive and significant ($p < 0.05$) effect on PFM practices. LULC change in study area causes rapid wetland ecosystem deterioration, which may result in the extinction of the most significant and ecologically valuable species and a loss of biodiversity in the environment. In this context, developing an integrated participatory approach requires rapid attention, and all farmers and stakeholders must be actively involved in PFM programs.

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1. Introduction

Forests are ecosystems with a high concentration of tree cover that sustain a diverse range of creatures [1]. They are also tracts of land with a high concentration of trees that are significant for infrastructure, the economy, society, and other reasons [2]. Forest composition and structure vary depending on climate, soil type, and topography [3]. Due to these variations, different types of forests each with unique characteristics and biodiversity are created, such as temperate forests, tropical rainforests, and boreal forests [4]. Forests provide a source of income for millions of people and help many countries develop their economies [5]. They are used for construction, tools, furniture, fuel, medicine, grass and herbage, foraging, and edible fruit production [6]. As the world's lung, forests store more carbon dioxide to reduce global warming by emitting oxygen and renewing the atmosphere, which is one of the world's most pressing problems [5]. They are utilized for building, tools, furniture, firewood, medicine, grass and herbage, foraging, and edible fruit production [6]. Forests, as the world's lung, store more carbon dioxide, reducing global warming by emitting oxygen and rejuvenating the atmosphere, which is one of the world's most important issues [5].

Globally, the critical problem of forest cover may be linked to unending population growth [7]. This is consistent with the rapid development of agriculture, the proliferation of personal residences and industrial communities, and the uncontrolled exploitation of resources that are renewable, such as forests [8,9]. As an illustration, the FAO [10] reported that around 420 million hectares of global forestland have been degraded, with 10 million hectares deforested annually during the 1990s. In Africa, the level and degree of extraction of natural resources have caused major changes in land features [11]. According to FAO [10], Ethiopia's forest cover in 2020 was around 16.7 million hectares, or 15.11 % of the country's total land area. Deforestation and forest degradation are major environmental issues in the nation [12]. Between 1990 and 2020, the country lost 3.78 million hectares of forest (or 18.46 % of their forests cover in 1990). Deforestation and forest degradation are hurting people's livelihoods, particularly in rural areas, by diminishing the ecological services that forests supply [13].

Ethiopian government and NGOs is making greater efforts to conserve and manage its forests sustainably, but the country's forest cover and quality are decreasing, this is mostly due to the conversion of forests to other land uses [14]. Although the Yami & Mekuria [15], has the most abundant forest resources in Ethiopia, little emphasis has been placed on managing and conserving these resources while raising local communities' standard of living in proximity to the forests. Since 1990, PFM has been introduced as a solution addressing the issue of unrestricted utilization of forest assets while also promoting long-term community participation [16]. In this regard, in accordance with government policy, non-governmental organizations sought to address the current PFM issues by introducing, adapting, and establishing PFM projects. For example, FARM Africa initiated pilot PFM projects in Chilimo, Borana, and Belete Gera forests, whereas the GTZ (*Gesellschaft fürTechnische Zusammenarbeit)* meaning "German Agency for Technical Cooperation" implemented a project in Adaba Dodolla PFM project [17]. According to Solomon et al. [12], PFM in Ilu Aba Bor was intended to be implemented by incorporating the four kebeles that have been chosen, with approximately 2576 ha of forest areas designated for PFM. As a result, the Walle & Nayak [18], state forest was transferred to this cooperative for sustainable management, beginning in 2012. This resulted in a legal status, allowing them to sue those who illegally harvested products in their designated forest areas [17]. Only the southern, southwestern, and southeastern highlands of the country retain many forest blocks IN Ethiopia [19].

PFM seeks to maintain forest-based benefits for rural livelihoods while preventing natural resource degradation [20]. Nonetheless, the effective implementation of PFM necessitates a better understanding of the role of forest resources in rural households' livelihoods and their contribution to poverty alleviation. Furthermore, most studies on PFM in Ethiopia have concentrated on the economic benefits of natural resources [16,21], local communities' perceptions and attitudes towards PFM [20], institutional aspects of management outcomes, and variables that explain variations in PFM cooperative performance [22]. Nonetheless, little attention has been paid to the relationship between PFM and the various livelihood assets that form the basis of sustainable livelihoods [20].

Numerous empirical studies have shown that, in recent decades, there has been a significant decrease in the global forest cover change [23–30]. Nevertheless, some studies have observed an increasing trend [31]. For example, the FAO Global Forest Resources Assessment (https://www.fao.org/forest-resources-assessment/en/) and Hansen et al. [32] found that temperate forest cover has increased while tropical forest cover declined. Tadesse et al. [33] found that forest cover grew in the Global North while decreasing drastically in the Global South. This shows that the study findings from various regions do not agree on the role of forest management programmes.

In Alle District, Southwest Ethiopia, the study data were processed and analyzed to investigate the impact of PFM programs on changes in LULC and the factors that influence these changes. Field surveys, interviews with local residents, and remote sensing techniques were employed to collect data. To identify changes over time, satellite images and GIS tools were used to analyze changes in LULC [34]. Through statistical analysis of the survey data and interviews, the drivers of these changes were identified, looking at things such as population increase, economic development, and governmental policies. The analysis was applied to evaluate how PFM programs affected changes in LULC type.

The Alle district in Southwest Ethiopia, which has not been extensively studied on the impact of PFM on dynamics in LULC, is the study's distinctive emphasis. This study aims to provide a more contextualized and localized understandings of the effectiveness of these interventions in focusing on this specific area, which will help to promote sustainable land, use practices and mitigate land degradation. Furthermore, the studies attempt to pinpoint the reasons for changes in land cover and usage in Alle district, shedding light on the particular issues that need to be resolved for the effective management of forest resources and the realization of regional sustainability. Through an analysis of the dynamics of LULC change in Alle district; this study aims to provide insights for more effective strategies and actions that support sustainable development and conservation efforts in the comparable region of Ethiopia. The findings of this study contribute to the existing body of knowledge on PFM programs and how they bring value to LULC, and they may be valuable to practitioners and policymakers interested in environmental conservation and natural resource management in Ethiopia and elsewhere. This study aims to address the following research questions: What changes were observed in LULC following the implementation of PFM in the study area? What problems are associated with PFM participation and implementation in the study area? What elements influence community engagement in PFM in the study area?

2. Materials and methods

2.1. Study area description

The study was carried out in Alle district, which is found within the Ilu Abba Bor zone of the Oromia regional state in southwestern Ethiopia [35]. The district is renowned for its rich cultural heritage, diverse landscapes, and agricultural activity. It is one of the 14 districts in the Ilu Abba Bor zone of the Oromia Regional State. It is situated astronomically between 7°56′40″-8°16′45″ N and 35°22′10″-35°52′40″ E (Fig. 1). The elevation ranges from 649 m to 2442 m above sea level, with an average annual rainfall of approximately 2000 mm [35]. The zone's annual average temperature ranges from 16 °C to 24 °C, and the climax vegetation is tropical montane rainforest. A Digital Elevation Model, or DEM, is a raster GIS layer that was employed in this investigation. They are raster grids of the Earth's surface related to the vertical datum, which is the surface of zero elevation to which scientists, insurers, and geodesists refer when measuring heights. At most scales and environments, a generic term like DEM can be used because the difference between bare soil and a surface object is negligible, with DEMs often having spatial resolutions of 20 m or more.

The predominant land use type in the study area is agricultural land with crops, which is followed by bare lands, grasslands, forestlands, shrub woodlands, and settlement. Because of its high production potential and tropical climate, the region is heavily populated and actively farmed, leading to overgrazing, forest cover degradation, and land fragmentation. The bulk of the economic activity is derived from small-scale subsistence mixed farming, which is highly dependent on seasonal rainfall. Nonetheless, some small-scale farmers earn a living through non-farm and off-farm pursuits, such as handcrafting, small-scale trading, and daily labour. Due to a combination of human and environmental factors, including climate, population pressure, relief, over cultivation, deforestation, and overgrazing, most of the region's land resources, particularly its soils, have been impaired.

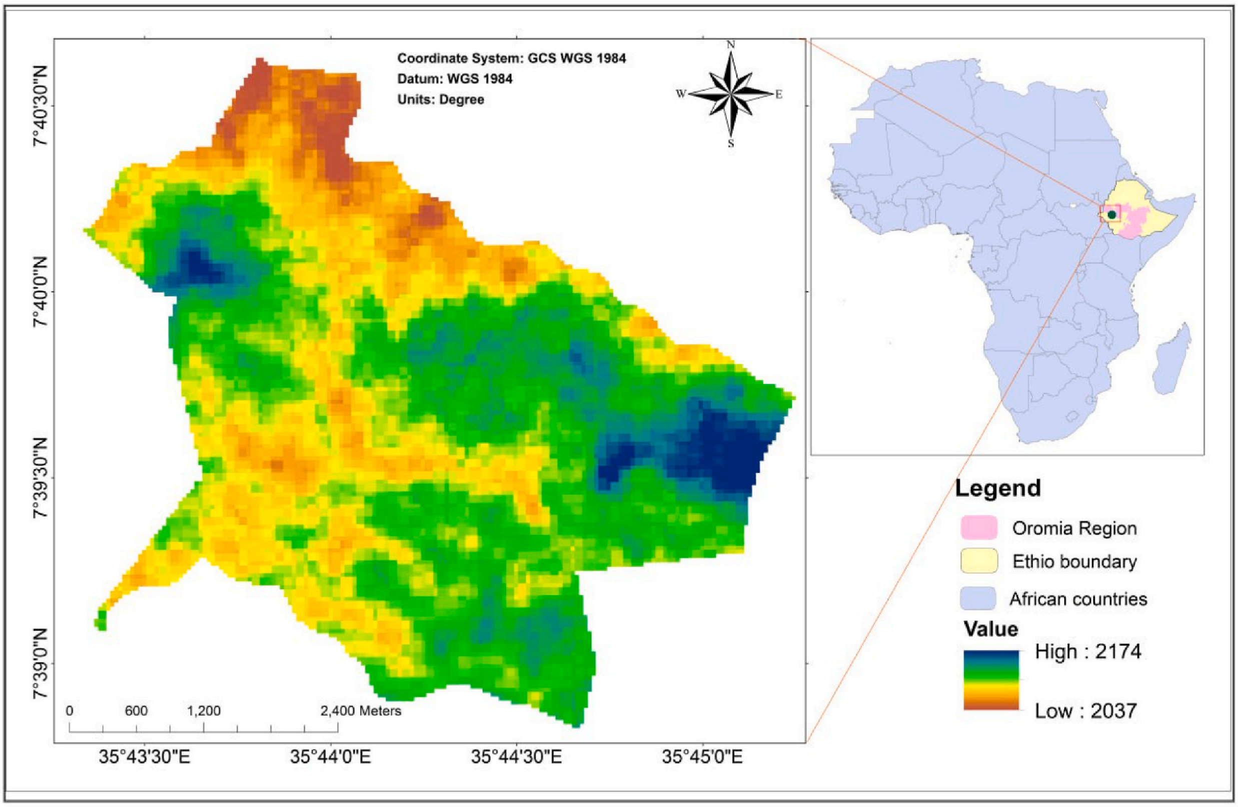

Fig. 1. Location map of Alle district.

2.2. Research design and approach

Due to the heterogeneous nature of the data and variables, two separate research strategies (longitudinal and cross-sectional) were used to meet the aims of this study. A longitudinal research design was used when data for a specific site or target group were collected over time [36]. The current study collected land cover data for the area at three different time intervals (1992, 2012, and 2022). Thus, a longitudinal design has been utilized to analyze forest cover dynamics during the last few decades. A cross-sectional survey was used to investigate the challenges of PFM participation and implementation, as well as factor affecting the participation. The motivation for using this survey methodology in the current study was that it is useful to gather data at a specific point in time and evaluate the pattern of connection between variables to detect causal effects. The target population consisted of heads of households living in the area.

2.3. Geospatial data collection and processing

2.3.1. Data acquisition

Landsat data were used over Sentinel data for this study because of its longer historical record and because it is more readily available in the study area. Landsat data are commonly utilized in land use/land cover change studies because of their high resolution, which allows them to capture terrain changes. Although Sentinel data provide greater spatial resolution, the study area is very small, and the benefits of Landsat's extended temporal coverage outweigh the possible geographical advantages of Sentinel data [36]. Furthermore, the researcher has greater experience and knowledge using Landsat data management, making it a more viable option for this specific topic. Finally, the decision to use Landsat data was made based on its fit to the study objectives as well as the unique features of the study area.

Landsat images were chosen over other available satellite images for a variety of reasons, including the fact that Landsat has been collecting images of the Earth's surface since the early 1970s, providing a valuable historical record of environmental changes over time [37,38]. The uniform design and calibration of Landsat satellites guarantees consistent and dependable data collection over an extended period of time [39]. The very high spatial resolution (30 m) of Landsat sensors makes it possible to analyses features and landscapes in great detail on the surface of the planet [40]. Because Landsat data is publicly available, it can be used for a wide range of applications by scholars, decision-makers, and members of the general public [41]. Numerous spectral bands are covered by data captured by Landsat sensors, which opens up a world of possibilities for mapping land cover, vegetation monitoring, and urban planning, among other uses [42]. All things considered, Landsat images are a popular option for researchers and analysts because they are an invaluable tool for researching and tracking Earth's natural and constructed surroundings.

The area's dry season was chosen for image capture because vegetation is typically less dense and there is less moisture in the air, making it easier to capture clear images with no clouds present. This makes it possible to see the ground below more clearly. Landsat 5 with Thematic Mapper (TM) sensor in 1992, Landsat 7 with ETM+ sensor in 2012, and Landsat 8 with OLI sensor in 2022 are the Landsat satellite series that were used to capture the images. The United States Geological Survey (USGS) provided the images without any cost at website, which may be accessed at https://earthexplorer.usgs.gov. These satellites orbit the Earth and take images of the land surface at regular intervals. These images were taken using advanced satellite technology, allowing for high-resolution and detailed views of various landscapes and geological features.

The images were taken during the dry season, which lasts from January to February and is characterized by low cloud cover in the region. This guarantees that the image's captured are of good quality with little influence from clouds. Landsat satellites collect images in several spectral bands, allowing for the examination of a variety of surface features such as vegetation health, land use, and land cover (Table 1). Scalene errors in Landsat ETM + images were addressed using a variety of methods, including manual pixel removal, data replacement with neighboring pixel values, and interpolation techniques to fill in missing information. In addition, a rigorous quality control process was implemented to guarantee the accuracy and dependability of processed geospatial data, with special emphasis on calibration procedures and validation techniques to mitigate any potential errors introduced during image processing.

2.3.2. Image preprocessing

Standard image processing methods were carried out in this investigation using the ERDAS Imagine 2015 programme. To make the image clear and easy to classify, several image preprocessing techniques were utilized, including; (I) Geometric correction (the process of reducing visual distortions induced by the sensor or the Earth's surface) performed using polynomial transformation [43]. (II) Topographic correction (this technique tries to diminish the impacts of terrain and topography on the image; the methods used for topographic correction in this study were C-corrections). This is because the C-correction method gave the best results [44]. (III) Haze reduction (this technique aims to remove atmospheric haze and improve the clarity of the image; the methods used for haze reduction include dark channel prior, atmospheric light estimation, and image dehazing algorithms [45]). (IV) Noise reduction (this technique aims to reduce the noise present in the image caused by sensor limitations or environmental factors. In this method, the only median

Table 1
Satellite image used to analyses LULC changes and their properties.

Satellite image	Sensor	Path/Row	Acquisition Date	Resolution (m)	Source
Landsat 8	OLI-TIRS	168/054	04/Jan/2022	30*30	USGS
Landsat7	ETM+	168/054	02/Feb/2012	30*30	USGS
Landsat 5	TM	168/054	02/Feb/1992	30*30	USGS

filtering method was used [46]). (VI) Sub-Setting (this technique involves selecting a specific region of interest from the image for further analysis or processing [47]). (VII) Resampling (this technique involves changing the resolution of an image by adding or removing pixels). Methods used for resampling include nearest neighbor, bilinear interpolation, and cubic convolution [48], and (VIII) Layer Stacking (this technique involves combining multiple image layers, such as different spectral bands or time periods, into a single multi-layered image for analysis, so image arithmetic, band math, and composite were used as layer stacking in this study [49].

Additionally, by combining the various land use/cover conversion matrix classes for the various land uses specifically, the ArcGIS 10.5, ERDAS Imagine 2015 was used to compute the manner in which dense forests are converted to other types of land use, and the rate at which the forest cover is changing was also identified using the following formula. Before image classification, a reconnaissance survey was conducted to gather preliminary information on forest cover changes.

The topographic correction equation was determined for how geography affects remote sensing data, particularly satellite images. This due to its potential to adjust the radiance values of the image's pixels based on the landscape's slope and aspect. The equation frequently includes variables such as the sun's zenith angle, the slope of the ground, and the aspect of the landscape which was used adequately. Again researcher used C-correction method, which is a typical topographic correction equation that accounts for the effects of landscape illumination on satellite images [50]. By using this algorithm, the algorithm calculates a correction factor based on the sun angle, slope, and aspect of the landscape, which is then applied to the pixel radiance values in the image [51]. The following topographic correction procedures and equations may be used depending on the needs of the study or analysis being conducted using the calculation outlined in Equation (1-3).

2.3.3. LULC classification

The study measured the rates and magnitudes of LULC changes in Alle district using GIS and Landsat data to classify four LULC classes throughout three periods (1992, 2012, and 2022). The flow chart in Fig. 2 depicts the overall procedure of these stages. The computation assessed the rate of LULC change between 1992 and 2012, 2012–2022, and 1992–2022. Equation was used to calculate the magnitude of change over specified intervals using the calculation outlined in Equation (4).

$$LULC\ change\ \left(hayr^{-1}\right) = \left(\frac{A_{fyr} - A_{iyr}}{T_{fyr-iyr}}\right) \tag{4}$$

Where A_{fyr} is the equivalent area (ha) to recent area of the land use and land cover $T_{fyr-iyr}$ is the number of years between final year and initial year, and A_{iyr} is the previous (initial) area of the land use and land cover in ha. Calculations were made to ascertain the extents (measured in hectares) and proportions of changes within LULC categories across the periods based on the investigations carried out by Tilahun et al. [52]. The researcher used the following formula to calculate changes between periods, the same method were used in pervious study by using the calculation outlined in Equation (5):

$$\text{Percentage of LULC} = \frac{\text{Area final year} - \text{Area initial year}}{\text{Area initial year}} \times 100 \tag{5}$$

Based on the survey results and the researcher's knowledge of the study area, four LUC categories were identified and defined. The LUC categories included agricultural land, forest area, grass, and wetlands (Table 2). A supervised classification strategy based on the maximum-likelihood algorithm was applied for both reference years. The image classification for 1992 and 2012 was supervised using training points obtained from topo sheet maps, high-resolution Google Earth® Pro images, and interviews with elderly farmers. Using its spectral feature analysis, this method determines which class a pixel belongs to with the highest probability. A signature for 2022 was created by utilizing the ground truth data acquired in the field via a handheld GPS.

2.3.4. Supervised classification

In this investigation, the Maximum Likelihood classifier in supervised classification proved to be the most effective method. In this classification method, all pixels with similar spectral values are automatically grouped into unique land use/cover classes or theme

Technique	Formulation	Correction Coefficient
Cosine	$\left[SR\left(\frac{Cos\ \theta_z}{Cos\ i}\right)\right]$	
C	$\left[SR\left(\frac{Cos\ \theta_z + C}{Cos\ i + C}\right]\right.$	$C = m \cos i + b \quad (1)$
Slop Match	$[SR + (SR_{max} - SR_{\min})]\ X\ \left(\frac{\cos i_{sa} - \cos i'}{\cos\ i_{sa}}\right)C_s$	$C_s = \left[\frac{(S1_a - N_{a)}}{(N1_a - N_a}\right] \quad (2)$
VECA	*SR X λ*	$\lambda = \left(\frac{SR_{mean}}{s\cos i + b}\right. \quad (3)$

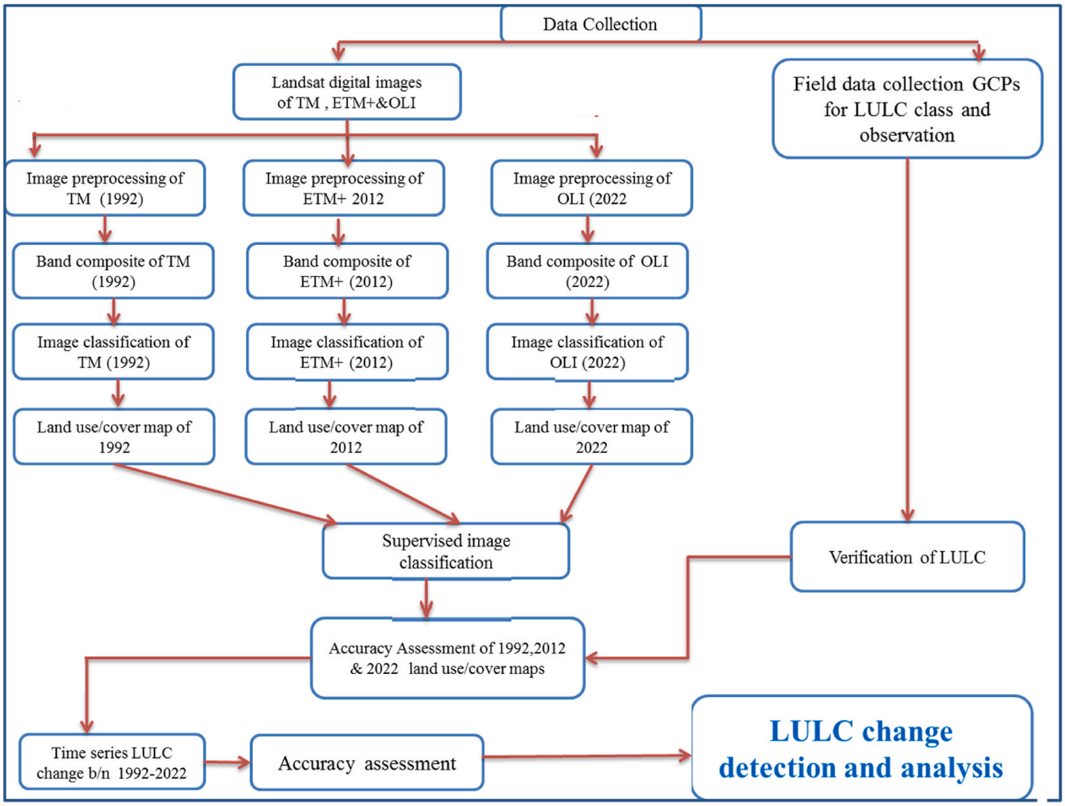

Fig. 2. Flow chart of LULC changes and analysis processes.

[58]. To express the spectral signature of recognized features in the images, the point of interest areas must be manually distinguished as a reference or ground truth. Beyond the ERDAS imagine 2015, Arc GIS 10.5 software was also utilized for raster & vector data analysis and mapping purposes. The supervised classification and recoding process was followed by an evaluation of classification accuracy to make changes to the first LULC map classification based on on-the-ground confirmation of questionable areas.

In order to use the approach, 320 training sample data were gathered. Using a variety of tools, including Google Earth and high-resolution aerial image, training areas have been selected in order to produce a land cover and land use map with a respectable degree of accuracy. There is a high-resolution Google Earth image of the research region. Identifiable items from Google Earth image would have been digitalized, assigned an area of interest (AOI), and utilized for categorizing Landsat image.

2.3.5. Accuracy assessment

As a result, the same formulas used by previous researchers were used to calculate the kappa index, producer accuracy, user accuracy, and total accuracy [59,60]. Utilizing, the Kappa coefficient and overall accuracy were determined by using the calculation outlined in Equation (6) and (7).

$$\text{Overall accuracy} = \left(\frac{\textit{The number correctly classified values}}{\textit{The total number of values}}\right) \times 100 = \frac{\sum_{i=1}^{r} x_{ii}}{N} \times 100 \tag{6}$$

In this equation TS is the total number of samples i.e., 60 and TCS is the Total number of Correctly Identified Samples. Follow the formula and insert the values you have received from your table and calculate like the one conducted.

Table 2
Description of LULC categories considered in image classification.

LULC class	LULC Description
Agricultural land	Areas where crops are grown using rain and scattered rural communities that are typically connected to agricultural areas.
Forest	Densely vegetated areas with a mix of coniferous and Eucalyptus trees.
Grassland	Land with grasses and shrubs, as well as occasional small trees strewn throughout and newly planted areas.
Wetland	Area that is comparatively dry during the dry season and flooded or swampy during the wet season. regions where a river runs

Source: own summary based on literature [52–57].

$$\text{Kappa coefficient (T)} = \frac{(TS \times TCS) - \sum(Column\ Total \times Row\ Total)}{TS^2 - \sum(Column\ Total \times Row\ Total)} \times 100 = \frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r} x_{ii}\ (x_{i+} * _{x+i})}{N^2 - \sum_{i=1}^{r}\ ((x_{i+} * _{x+i})} \times 100 \tag{7}$$

The marginal totals of row i and column i are denoted by $xi+$ and $x+i$, respectively, and x_{ii} indicates the total number of properly categorized pixels in row i and column i, where r is the number of rows in the matrix.

The emphasis was on the effects of PFM on LULC change, which may have contributed to the lack of classification of residential land uses. Because residential areas are not considered forests, it is logical that they were excluded from this study. Furthermore, residential land use is typically differentiated by human settlement and infrastructure, as opposed to wild vegetation found in forests. The study's narrow emphasis on forests allows it to more effectively assess the environmental implications of PFM without the additional complexity of residential land use. The classification focused on the specific land cover classifications found in the study area, excluding aquatic bodies. The inclusion of protected forest cover and participatory forest management were important considerations in selecting these four classes for investigation (Table 2).

2.4. Sample size estimation and sampling design

Alle district was purposefully chosen as the primary site for the PFM program, with the district's woods managed using indigenous ways of forest conservation (Kobo management practices) and the remaining forests treated using conventional methods. A simple random sampling approach was employed to select sample households from a list of all dwellings in the chosen district. This strategy is thought to not influence the sample representation because each household head has an equal probability of being selected. The study district has a population of 2330 households. The sample size was determined based on a 95 % confidence level and a ±5 % margin of error. Using Kothari's [61] sample size determination formula, the necessary sample size was determined by using the calculation outlined in Equation (8),

$$n = \frac{z^2 * \mathrm{p} * \mathrm{q} * \mathrm{N}}{e^2(N-1) + z^2 * \mathrm{p} * \mathrm{q}}\ ; \tag{8}$$

where "n" is sample size "N" is population size in this case which is 2330, e is the accepted error or degree of confidence desired, usually at 0.05, z is standard variation (1.96), p is the standard deviation (0.11), q = 1-p. Consequently, 240 sample households were selected through simple random sampling technique explicitly.

$$n = \frac{z^2 * \mathrm{p} * \mathrm{q} * \mathrm{N}}{e^2(N-1) + z^2 * \mathrm{p} * \mathrm{q}} = n = \frac{(1.96)2\ * 0.11 * 0.89 * 2330)}{(0.05)2\ * (2330-1) + (1.96)2\ * 0.5 * 0.5} = 240$$

2.5. Sources of survey data and collection tools

To fulfill the study's objectives, data was gathered from both primary and secondary sources. Primary data (qualitative and quantitative) were acquired directly from informants who were intimately familiar with the problem and its solutions. Key informant interviews (KII), focus groups (FGD), field observations, and a survey questionnaire with both open- and closed-ended questions were used to collect all of the primary data for the study from farm households. Secondary data were gathered and organized from a variety of published and unpublished papers from the district's natural resources management office as well as district and zonal annual reports that are likely to be relevant to the study.

2.6. Data analyses techniques

The Statistical Package for Social Sciences (SPSS) version 20 was used to analyses the data. As a result, it was analyzed using descriptive and inferential statistics. Means, frequencies, and percentages were used as descriptive statistics, while t-tests and chi-squares were used for inference. A narrative format is used to highlight the qualitative information that was acquired through key informant interviews and focus group discussions.

2.6.1. Econometric model

A logistic model was regressed against institutional, social, economic, and biophysical explanatory variables, with participation as the dependent variable, to account for the observed fluctuations in involvement. The respondents' response on their involvement in PFM was examined as a binary-choice model, with a household decision as the outcome either participation or non-participation. The similar methodology was employed by the earlier researcher Jatana & Paulos [62] to identify the variables influencing the PFM participation performance of farmers in southern Ethiopia. The model permits the estimate of the joint distribution without placing parametric constraints on it by assuming independence between observable and unobservable [63].

Households make the decision whether or not to engage in PFM based on institutional, social, biological, and economic factors. Y_i represents the dependent variable participation in the logistic model, with 1 indicating that the respondent participated in PFM and 0 indicating that they did not. With X_i representing a variety of explanatory variables and β representing the predictor variable's coefficient that explains how a unit change in an explanatory variable affects the dependent variable, the probability of household participation in PFM, Pr (Y_i = 1), is a joint probability density function/likelihood function evaluated at $X_i\beta$. The likelihood that participants will have favorable opinions about participating in PFM P_r (Y_i = 1) can be estimated using the logistic transformation and represented Equation (9-11) as follows:

$$P_r\ (Y_i = 1) = \exp\ (X_i\ \beta) \tag{9}$$

1+exp (X_ip)

The above equation can be reduced to:

$$P_r\ (Y_i = 1) = \beta_0 + \beta\ _1X_1 + \beta\ _2X_2 + \ldots + \beta\ _iX_i \tag{10}$$

Where:

"P" denotes the probability of the occurrence of the attribute of interest, community engagement.

"B" is the coefficient of the predictor variables, which is produced from calibration data using the maximum likelihood method.

"X" is a host of explanatory variables (Table 3)

$$P(P) = \beta_0 + \beta_{1(SEXHH)} + \beta_{2(AGEHH)} + \beta_{3(EDULHH)} + \beta_{4(HHFSIZE)} + \beta_{5(LANDHH)} + \beta_{6(TLU)} + \beta_{7(OFFFARM)} + \beta_{8(TRAINAWR)} + \beta_{9(ACCREDIT)} + \beta_{10(DISTMAR)} + \beta_{11(DISFO)} + \beta_{12(ENLOW)} \tag{11}$$

3. Results and discussion

3.1. Types of land cover, their areas, and rates of change

Land use, coverage, and change maps provide essential information for a wide range of forest monitoring and spatial planning applications. The findings in Fig. 3 clearly illustrate that closed forests maintained the dominant land cover in Alle district forest throughout the study period. The land cover of the area, which consists primarily of agricultural land, forestland, grassland, and wetlands, is represented below. Agricultural land, grassland, and marsh were dramatically reduced in the study region due to growing forest management and protection (Fig. 3), while forestland improved significantly as a result of a community-based PFM program. The observed increase in vegetation cover can be attributed mostly to the rapid decline of grasslands and agricultural lands, which decreased by 8.2 and 4.5 ha/year from 1992 to 2022, respectively.

In the 1st term of the year 1992–2012, as it has been observed from the in Table 4, agricultural land increased from 55.6 ha (9.0 %) to 109.5 ha (17.7 %), forest land 418.2 ha (67.6 %) to 462.7 ha (74.8 %), and wetland 12.2 ha (2.0 %) to 14.1 ha (2.3 %) while grassland were reduced from 132.4ha (21.4 %) to 31.90ha (5.2 %), respectively for the 1st last ten years. In the 1st term of the year interval from to 1992–2012, only grassland was reduced owing to the expansion of forest land and agricultural land (Fig. 4).

In the 2nd term year 2012–2022, forest land increased from 462.7ha (74.8 %), to 569.8ha (92.1 %), while, the agricultural land, grassland and wetland were reduced from 109.5ha (17.7 %) to 37.8ha (6.1 %); 31.90ha (5.2 %) to 0.0ha (0.0 %); 14.1 ha (2.3 %), to 10.8 ha (1.7 %) respectively for the 2nd last ten years. "*This rehabilitation of the forest attributed to improved community participation in PFM and increasing motivations for forest protection, as well as a good agro-ecological situation, shows an improvement in the forest ecosystem compared to the first period*," the FGD and key informant interviews conducted between 2012 and 2022 confirmed. The results amply illustrated the frequency of significant LULC transitions between land use classes.

During the study period, the wetlands fell swiftly and drastically from 14.1 ha (2.3 %), to 10.8 ha (1.7 %) in a decade, which may have a detrimental influence on carbon sequestration, carbon pool, and ecosystem biodiversity. LULC in the study area causes rapid wetland ecosystem deterioration, which may result in the extinction of the most significant and ecologically valuable species and a loss

Table 3
The summary of independent and dependent variables, types, measurements, and expected sign.

No	Variables	Type of variable	Unit of Measurement	Expected sign
Dependent Variables				
1	Participation on PFM	Dummy	0 and 1	
Independent Variables				
1	Gender of HH (SEXHH)	Dummy	0 and 1	+/−
2	Age of HH (AGEHH):	Continuous	Year	-
3	Educational levels (EDULHH)	Dummy	0 illiterate 1 literate	+
4	Household Family sizes (HHFSIZE)	Continuous	Adult equivalent	+
5	Landholding size (LANDHH)	Continuous	Hectare	+
6	Total livestock holding (TLU)	Continuous	TLU	+
7	Off Farm income (OFFFARM)	Dummy	0 and 1	+
8	Training and awareness (TRAINAWR)	Dummy	0 and 1	+
9	Access to credit (ACCREDIT)	Dummy	0 and 1	+
10	Distance from the market (DISTMAR)	Continuous	Kilometer	-
11	Distance from the forest (DISFO)	Continuous	Kilometer	-
12	Enforcement of laws (ENLOW)	Dummy	0 and 1	+

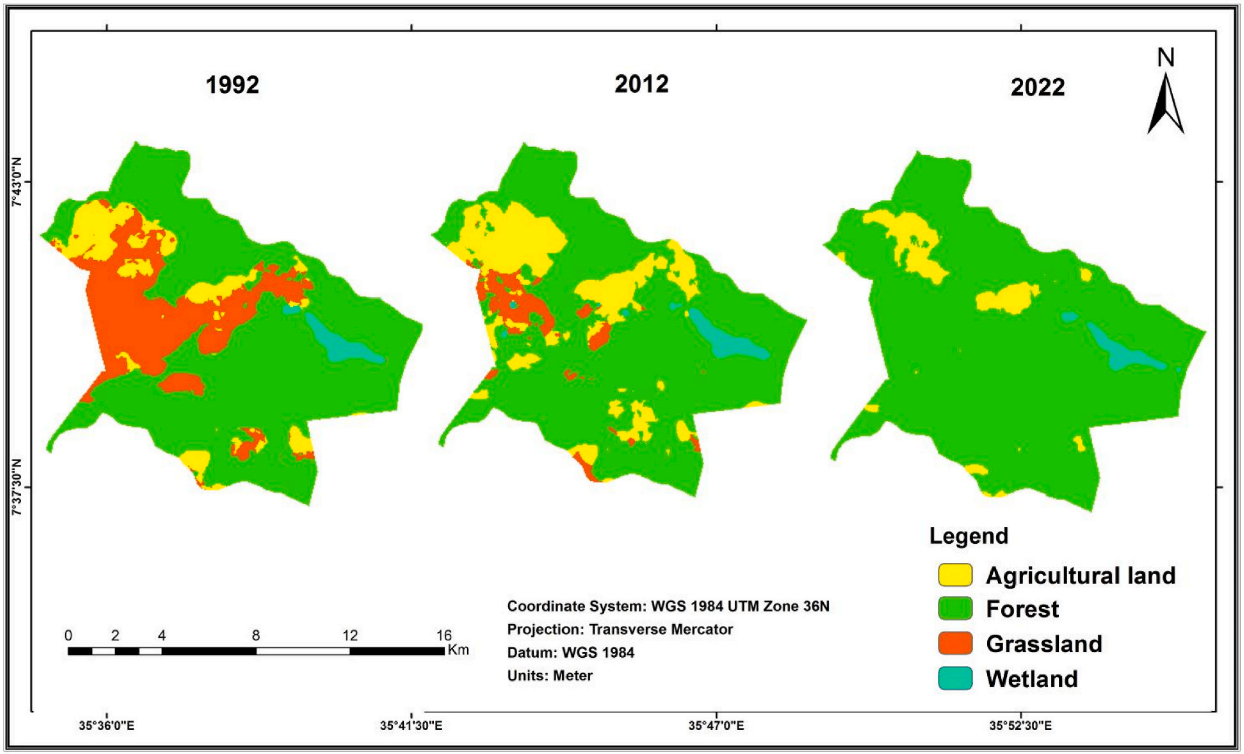

Fig. 3. LULC map of Alle district.

Table 4
Area coverage of each class of LULC change of study area.

LULC Class	1992		2012		2022		Rate of change ha/year		
	Ha	%	Ha	%	Ha	%	1992–2012	2012–2022	1992–2022
Agricultural	55.60	9.00	109.58	17.70	37.80	6.10	2.70	−7.20	−4.50
Forest	418.20	67.60	462.79	74.80	569.80	92.10	2.20	10.70	12.90
Grassland	132.40	21.40	31.90	5.20	0.00	0.00	−5.00	−3.20	−8.20
Wetland	12.20	2.00	14.13	2.30	10.80	1.70	0.10	−0.30	−0.20
Total	618.40	100	618.4	100	618.	100			

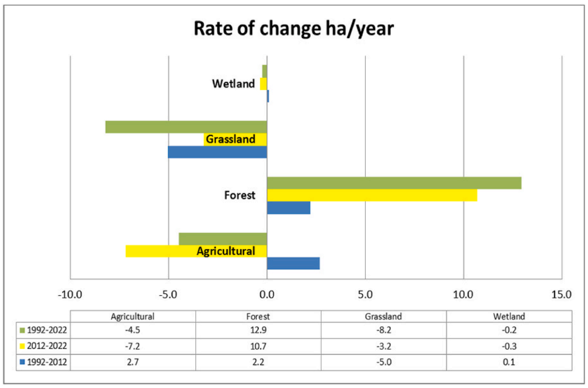

Fig. 4. Rate of LULC change Ha/year of Alle district.

of biodiversity in the environment. These include water scarcity, increased flooding and inundation, increased flooding and coastal erosion, lower capacity to control climate and pollution, decreased biodiversity, and the extinction of fisheries and agriculture. This finding was confirmed by Assefa et al. [64], who found that changes in LULC resulted in a continuous loss of almost all individual ecosystem services over the study period, with the majority of this drop explained by a decrease in wetland coverage, which leads to the loss of ecosystem services such as water management, waste treatment, and habitats for biodiversity conservation. In general, wetlands loss due to land use change can have a negative impact on ecological services, biodiversity, carbon dioxide sequestration, and cultural values. To ensure that these vital ecosystems survive, forest management partnerships must address wetland preservation and restoration.

According to satellite images from 1992, 2012, and 2022, grassland and wetland coverage declined with time. Recent statistics from 2022 show that, the grassland and wetland coverage in this study is rapidly decreasing. The coverage of forestland increased, and other LULC changes were detected. There have been beneficial developments in the forests over the last 30 years. Furthermore, field observations revealed that native trees in natural forests are rapidly recuperating as a result of recent PFM in the study area, which remains forest limited to high altitudes.

The primary causes of the accelerated LULC change observed in the study area over the past 30 years have been reported. Based on change detection, the data indicate the transition of LULC types. The reference periods exhibit varying transformation rates. The first period of reference (1992–2012) demonstrated a significant increase in agricultural and forest areas, loss of grassland, and an increase in wetlands. Agricultural land area has doubled as cultivated fields have been expanded into increasingly marginal and vulnerable habitats, such as tropical forests, grasslands, and boreal forests. The demand to locate new land for agriculture led to changes in land cover and conversion from one category to another [65,66]. The increase of cereal-covered land was therefore the primary driver of total cultivated area growth [67]. Overall, population increase, government policies, infrastructural development, climate change, and land use changes may have led to the doubling of agricultural land in Ethiopia's Alle district between 1992 and 2012.

The implementation and effectiveness of PFM programs may have contributed to the notable increase in wetlands, loss of grassland, and increase in agricultural and forest areas in Alle district of Southwest Ethiopia during the first period of reference (1992–2012). The observed rise in these land cover categories may have resulted from the programmers' encouragement of communities to develop their agricultural and forest areas through sustainable land-use practices. The programs may also have contributed to the conversion of grassland into agricultural or wooded areas, which would have resulted in their loss, while the promotion of better water management techniques might have led to the growth of wetlands. Overall, the results indicated a beneficial effect of PFMPs on changes in land cover and usage in the study area. During the second period (2012–2022), forestland expanded rapidly, whereas marsh areas decreased. There was a noticeable decline in the growth of grasslands and in agriculture. Such conversions from wetlands, grasslands, and agricultural lands to forests have a significant effect on ecosystems. Third-period reference intense grassland loss, agricultural and wetland habitat simplification, and positive changes in forest resources were observed between 1992 and 2022. This suggests that the application of PPM in the study region contributed positively and significantly to the restoration of the forest ecosystems.

The effectiveness of the PFM program, implemented in regions that controlled unrestricted access to forest resources, may be responsible for this type of forest regeneration. The PFM conceptual also helped to organize communities and gave inhabitants the option to participate in forest development projects. This study is consistent with Winberg's [68] found that, informal farmer interactions may benefit local communities and frequently result in farmers replicating strategies used in PFM zones, such as producing spices in their home gardens for income. PFM was initially brought to Ethiopia 13 years ago, but the methodology is spreading to encompass an increasing number of hectares of forest around the nation. PFM is used in Ethiopian forests, which have several important ecological and cultural characteristics. A few of these characteristics are among the justifications for bringing PFM to a region; the others, while insufficient in and of themselves, have great potential or are clearly valuable to communities or ecosystem functions (such as ecosystem services, tourism potential, or significance to long-standing local customs).

3.2. Satellite image classification accuracy

The classification accuracy was evaluated using error matrix analysis, which included both overall accuracy and kappa analysis. As a result, the overall classification accuracy for the three year classes was 91.18, 94.83, and 88.81 %, with kappa values of 0.89, 0.92, and 0.93 %, respectively (Table 5). Both the kappa coefficient and total accuracy demonstrated a high level of agreement for each of the four detected photos, with an increasing tendency from the oldest (1992) to the most recent (2022). According to Congalton and

Table 5
Data pertaining to the accuracy evaluations for each year 1992, 2012 and 2022.

Class name	1992		2012		2022	
	Producers Accuracy (%)	Users Accuracy (%)	Producers Accuracy (%)	Users Accuracy (%)	Producers Accuracy (%)	Users Accuracy (%)
Agricultural land	86.82	93.00	100.00	90.00	93.75	88.24
Forest	89.00	91.91	100.00	90.91	80.00	100.0
Grassland	92.00	86.71	93.86	92.86	90.00	94.44
Wetland	90.00	100.00	91.00	100.00	84.00	80.00
Overall accuracy assessment	91.18		94.83		88.81	
Overall Kappa Statistics	0.89		0.92		0.93	

Green [69], an overall accuracy level of 85 % was utilized to differentiate between acceptable and poor image categorization results. This indicated a strong level of consistency in image classification over time.

3.3. Change matrix

The change matrix shows a shift in area coverage. The change matrix depicts the changes in area coverage by hectares and percentage over three time periods: 1992, 2012, and 2022. This study found a significant LULC variations during the reference years 1992, 2012, and 2022. The satellite imagery results showed growing and decreasing variations in each of the four probable land use types in the study area. This study also demonstrates that a significant amount of one type of LULC change was converted into another in the study area. This finding indicates that there has been a change in land cover and use, with woodlands and grasslands replacing agricultural land. Tables 6 and 7 indicate that, from 2012 to 2022, only 74.1 ha of agricultural land in the satellite image were covered by forests. There has been a transition in land cover from forest to grassland and there has been a significant amount of PFM in the study region. This finding is congruent with that of Kedir et al. [34], who reported that the rate of forestland conversion to other land uses reduced following the introduction of PFM using satellite image analysis. Significant forest regeneration occurred throughout the PFM programmer's execution (1992–2012), resulting in the conversion of substantial sections of shrub lands to forestland (Fig. 5).

The effectiveness of the PFM program, implemented in regions that control unrestricted access to forest resources, may be responsible for this type of forest regeneration. The PFM strategy also helped to organize the neighborhood and gave locals the ability to participate in forest development projects. This outcome was consistent with Gobeze et al. [16] findings, which indicated that in Bonga forest priority regions; forests under PFM exhibited superior regeneration than nearby non-PFM forests. According to an analysis conducted by Lemenih et al. [70] based on satellite images, PFM intervention enhanced forest cover and stopped deforestation in the Chillimo forest. According to study conducted in Tanzania by Kajembe et al. [71], and Central Rift Valley, Ethiopia by Girma et al. [72], the PFM may be the best option for sustainably managing forest resources in developing nations. Deforestation in Kenya's Lembus Forest decreased from 11.2 % in the first period (pre-PFM intervention) to 8.2 % in the second period (post-PFM intervention) [73].

Prior to the implementation of the PFM (1992–2012), there was a rapid increase in the area used for agriculture, with approximately 65 ha of forest land being converted to grassland and other land uses. Studies conducted in several regions of Ethiopia [74–77] have also demonstrated the frequency with which forestland was converted in the 1990s to alternative land uses. This appears to have been made possible by restricted access and community-led forest development.

3.4. Challenges that affect PFM implementation and community participation

PFM faces various challenges that limit its effective implementation. The primary causes of forest resource degradation, such as rapid population growth, deforestation, overgrazing, soil erosion, and soil nutrient depletion, affect PFM implementation and participation. The consumption of wood and non-wood forest products is one of the difficulties in adopting PFM. Furthermore, people who live near woods and woodlands usually continue to progressively extend their farms, which, like human-caused forest fires, is a factor in the study area. The interviews and discussions of the respondents' responses are shown in Fig. 6.

The percentage of respondents who recognized the different issues affecting PFM implementation and involvement are shown in Fig. 6. Concerns about population growth were raised by 24.8 % of participants and 23.7 % of non-participants in both groups. This could be due, in part, to the fact that population growth frequently increases the demand for natural resources, such as forests, which can strain existing forest management initiatives. To satisfy the demands of both the present and the future generations, there might be a growing need for efficient and sustainable management of forest resources as the population grows. This concern may have influenced both participants and non-participants in PFM programs.

However, participants' dependence on forest resources increased more significantly (13.9 %) than that of the non-participants (12.4 %). The need for forest goods (19 %) was the least critical challenge, followed by insufficient law enforcement (11.5 %), rising demand for forest goods (19.6 %) and increased reliance on forest resources (12.4 %). The high population increase and increasing demand for forest goods suggest that forest resources are under intense pressure, necessitating more effective and equitable management. The expansion of agriculture and human-caused forest fires imply a risk of deforestation and ecosystem damage. The increased reliance on forest resources indicates that local communities rely largely on forests for their survival and well-being. Inadequate execution of the law implies a lack of institutional support and regulation for PFM programs.

To solve these issues, the local population understands of and engagement in PFM programs should be increased by providing them

Table 6
LULC change matrix from 1992 to 2012 (before PFM establishment).

Land use class		2012				
		Agricultural	Forest	Grassland	Wetland	Total
1992	Agricultural land	**46.30**	18.10	45.00	0.00	109.40
	Forest	7.00	**397.70**	57.20	0.70	462.70
	Grassland	2.20	0.70	**29.00**	0.00	31.90
	Wetland	0.00	1.60	1.00	**11.50**	14.10
	Total	55.50	418.10	132.20	12.20	**618.10**

Table 7
LULC change matrix from 2012 to 2022 (After PFM establishment).

LULC class		2022			
		Agricultural land	Forest	Wetland	Total
2012	Agricultural land	**35.30**	74.10	0.00	109.50
	Forest	1.70	**460.10**	0.80	462.60
	Grassland	0.70	31.20	**0.00**	31.90
	Wetland	0.00	4.10	10.00	**14.10**
	Total	37.70	569.60	10.80	618.10

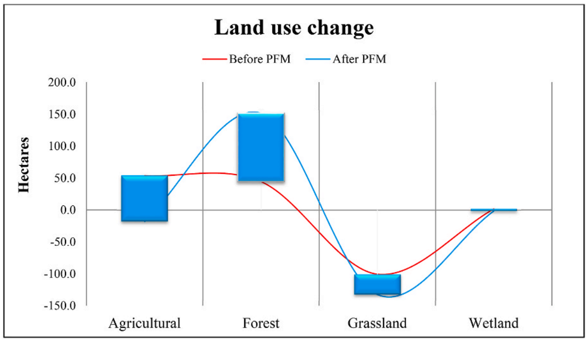

Fig. 5. Change in land use land cover before and after implementation PFM in study area.

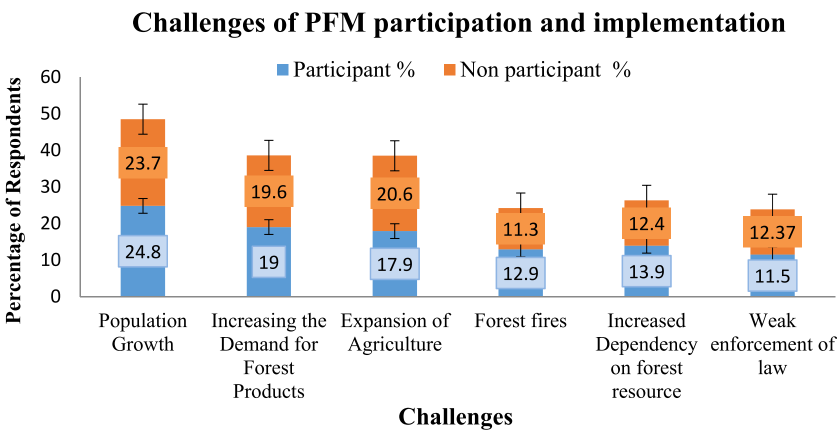

Fig. 6. Challenges of PFM participation and implementation in study area.

with information, training, and incentives. Diversifying and improving local communities' lives by providing them with alternative and complementary revenue sources such as off-farm activities, value-added goods, and eco-tourism. Increase collaboration and co-ordination among stakeholders, including the government, NGOs, and corporate sector, to offer technical, financial, and legal support for the PFM program. Monitoring and analyzing the impacts of the PFM program on forest conditions, biodiversity, and socioeconomic well-being in local communities is strongly advised in this study area. This approach is consistent with Treue et al. [78] and Zande and Mzuza [79], who argued that PFM woodlands are large and close enough to village settlements to make sustainable usage economically viable. Furthermore, the study emphasized the need to include local populations in forest management decision-making processes to ensure the long-term effectiveness of PFM programmers. It also emphasizes the importance of the continuous examination and adaptation of policies to handle changing environmental and social factors. Population expansion necessitates land for settlement and cultivation. Efforts to address the basic necessities in such settings are feasible, leading to the loss of existing forests without involvement in forest resource management.

3.5. Factors affecting community participation in PFM

3.5.1. Explanation of significant explanatory variables in binary logistic model analysis

A binary logistic regression model was used to investigate the characteristics that influenced community engagement in the PFM.

Table 8
Binary logistic result of independent variable.

Variable	β	S.E.	Wald	Sig.	**Exp(β)**
GENDERHH	**1.184*****	0.402	8.685	0.003	3.267
AGEHH	−0.205	0.329	0.389	0.533	0.815
EDUHH	**0.320****	0.153	4.380	0.036	0.726
FAMILSIZ	**0.244****	0.123	3.947	0.047	1.784
TOTLAND	**−0.916****	0.444	4.253	0.039	1.400
TLU	**0.656****	0.180	6.443	0.011	1.434
OFFFARM	−0.433	0.321	1.818	0.178	0.649
ACESSCRIDT	**1.746****	0.373	4.004	0.045	3.474
DISTFOREST	−0.419	0.222	3.559	0.059	0.658
DISMARK	−0.301	0.189	2.534	0.111	0.740
TRAING	**1.074*****	0.376	8.150	0.004	2.927
ENFORCELOW	**0.6628****	0.328	4.085	0.043	1.940

Pearson- χ^2 value = 0.260; -2Log Likelihood = 0.304a; Nagel kerke = 0.357; correctly predicted overall sample = 90.4; Overall prediction for non-users = 93.2; Overall prediction for users = 84.3; and Sample size = 270: *** Significant at 1 %, ** 5 % probability level.

Table 8 shows that eight of the 12 factors employed in the model were significant in terms of PFM involvement at various probability levels. Sex and training were significant at the 1 % significance level. Education, family size, TLU, access to credit, and law enforcement are statistically significant at the 5 % level of confidence, but household landholding is negatively significant, while the remaining four explanatory variables–age, distance from the forest, and distance from the market–do not show the significance of community participation.

Gender of household Head: Household head sex was found to have a significant impact on participation in PFM activities and membership. The researcher's hypothesis proposes that male-headed families are more likely to participate in forest management than female-headed households because of the biological and social restrictions that women suffer, limiting their active participation in all stages of PFM. It is well recognized that men dominate talks and decision-making processes in community-based development initiatives. Recognizing women's poor engagement in many development programs, PFM strategy supports their inclusion. The odds ratio obtained showed that when all other factors were equal, male participation in PFM was 3.267 times more likely than female participation. This positive correlation between sex and participation shows that being male increases the likelihood of engaging in forest management activities under PFM. It is worth noting that other studies, such as Gashu and Aminu [80] and Musyoki et al. [81] found a substantial association between gender and participation in forest conservation, with males showing higher levels of active involvement than females. This could be related to the high social weight that women bear, which limits their ability to participate fully.

Household educational level: Participation in PFM activities was favorably associated with educational level and the relationship was statistically significant at the 1 % level. According to the coefficient, for every year of higher educational attainment, the likelihood of a household participating in PFM activities increases by 0.726 when compared to families with one year of schooling. This suggests that households with higher educational levels are more likely to participate in PFM activities. One possible explanation for this tendency is that households with formal education have greater access to information, expertise, and resources, allowing them to comprehend and value the benefits of forests. They are better at communicating, reading literature, and using the media, which may lead to increased involvement in PFM activities. This finding is similar to that of Savari et al. [82] and Hussain et al. [83], who found the value of education in encouraging local community participation in rural development and natural resource conservation activities.

Furthermore, education appears to have a positive influence on people's attitudes towards forest conservation management techniques. This finding is reinforced by Pour et al. [84], who found that education programs as well as increasing the profitability of cultural services are suggested for forest ecosystem services. Higher education levels are associated with more positive attitudes towards the necessity and effectiveness of forest conservation efforts. These findings emphasize the importance of education as a vehicle for increasing community participation in various rural development and environmental conservation activities including forest management.

Household member size: The study revealed that there was a positive and statistically significant correlation between household size and the likelihood of participating in forest management activities. Previous hypotheses expected and validated this finding. Households with more family members are more likely to participate in forest management. Furthermore, the odds ratio showed that for every one-unit increase in the household labour force, the chance of using forest management approaches increased by 1.784 times. This is a result of the labor-intensive nature of forest management tasks like creating nurseries, preparing pits, planting, and fighting fires, which demand a substantial amount of physical labour. Larger families are therefore more likely to have the manpower needed to engage in these activities. This finding is similar to prior research undertaken in Nepal, particularly by Chhetri et al. [85] and Solomon et al. [86], who found that, households with larger families were more active participants in community forest management activities than those with smaller families.

Land holding size: Landholding size was found to be inversely linked to forest management engagement, validating the hypothesis at the 5 % significance level. An odds ratio of 1.400 means that for every one-unit increase in landholding, the chance of involvement falls by a factor of 1.400. The negative beta (β) coefficient of −0.916 confirms the fact that involvement diminishes with increasing landholdings.

The researchers found that, both participants and non-participants in forest management with substantial landholdings were less inclined to engage in forest management techniques and decision-making. This could be linked to their increased interest in growing crops on their farms as well as their ease of access to feed, grass, firewood, and construction materials from their land. On the other hand, farmers with small landholdings had limited access to resources and relied heavily on community forests for fodder, non-timber products, and income generation. Overall, these findings indicate a negative relationship between landholding size and engagement in forest management. People with larger landholdings are less likely to participate than those with smaller landholdings are. This finding is consistent with those of Kerse [87] and Gashu and Aminu [80], who found that households with sufficient grazing land had lower levels of participation in forest management activities.

The number of livestock: The number of animals in a tropical livestock unit (TLU) was positively correlated with participation in PFM. This association is statistically significant at the 5 % level. The probability ratio of 1.434 suggests that for every unit increase in TLU, the probability of engaging in PFM increases 1.434 times, assuming that all the other variables remain constant. These data indicate that having more TLUs increases the likelihood of participating in forest management activities. In other words, individuals with more TLUs were more likely to participate in PFM. Musyoki et al. [81] and Oli and Treue [88] found a similar favorable association in their Nepal investigations. To further on this association, the findings suggest that higher levels of TLUs correlate with higher levels of engagement in PFM. This suggests that those with more TLUs not only have a higher possibility of participating in PFM but also actively participate in management activities.

Our analysis revealed a strong positive association between TLUs and PFM involvement. Higher TLU levels are linked to increased participation in forest management activities. A study conducted in Nepal by Mbeche et al. [89] yielded similar results, indicating that respondents with more cattle participated in PFM activities more intensely and frequently.

Credit access: The availability of credit access had a considerable and favorable impact on involvement in PFM, according to a statistical study performed at a 5 % significance level. When other variables are controlled for, the odds ratio indicates that those with credit access are 3.474 times more likely to participate in PFM than are those without credit access. The beta (β) figure implies that every unit increase in credit access leads to a proportional increase of 1.746 units in PFM participation, holding all the other parameters equal. The results of the household survey provided additional support for this finding. Of the households with access to financing, 73 % exhibited increased participation in forest management activities. These households were able to minimize their dependency on forest products by acquiring agricultural inputs such as improved seeds and fertilizers, as well as cattle for resale after fattening. They also used loans to purchase equipment such as solar panels and wood-burning cooking stoves to reduce their reliance on fuel.

These findings are consistent with those of Mbeche et al. [89], who indicate that credit access promotes PFM involvement. Similarly, Liu et al. [90] found that access to financing increases participation in forest management and private forest investment. In summary, credit availability has a major impact on PFM involvement, with higher levels of credit access being related to greater engagement. This study emphasizes the necessity of improving financial access to encourage active participation in forest management projects.

Access to training and awareness: According to our findings, the availability of training and awareness has a significant impact on families' decisions to participate in forest management activities. Our findings showed a robust positive connection between training and involvement, with statistical significance at the 1 % level. This indicates that holding all other variables equal, people with higher degrees of training and awareness were approximately three times more likely to engage than those with lower levels.

Furthermore, the regression analysis revealed an odds ratio of 2.927, indicating a higher likelihood of engagement among those with more training and awareness. The beta (β) value indicates that increasing the training and awareness variables resulted in a 1.074 unit increase in the log chances of participation. This finding is consistent with Negashe and Addisie [91], who found that involvement in forest management is influenced by knowledge and awareness of management goals. Similarly, Bakala et al. [92] stated that access to a variety of training and experience exchange opportunities increases the likelihood of deciding to participate in forest management activities. This study found a significant and statistically significant beneficial link between training and involvement, with a significance level of 1 %.

Enforcement of law: Our study's findings indicate that implementing the law has a considerable positive influence on families' decisions to participate in forest management activities. The data indicate that inadequate enforcement has a positive and significant connection with engagement at the 5 % level of significance. An odds ratio of 1.940 indicated that participants living in areas with better enforcement of forest rules were 1.940 times more likely to participate in community forest management activities than those living in areas with poor enforcement.

The results of survey interviews and focus groups indicated that ineffective management of forest resources and a lack of legal system were detrimental to long-term economic expansion, fair social advancement, and environmental preservation. Inappropriate management of forests, as well as the prevalence of illegal forest operations, has resulted in considerable losses of forest resources and ecological value. Communities are more likely to engage in PFM when forest laws, rules, and regulations are appropriately implemented. The community's adherence to established forest management standards was valued and promoted. According to Noor et al. [93], lowering forest-related crimes in society improves community engagement through the PFM strategy, ultimately increasing income from livelihood activities. Similarly, our findings are congruent with those of Nugroho et al. [94], who found that communities coping with issues such as illegal logging, encroachment, forest fires, and other difficulties are less inclined to participate in forest management activities.

3.6. Policy implication

Overall, this study found that PFM approaches improved effective forest management, stopped deforestation, reduced the negative effects of climate change, and improved rural livelihoods. This suggests that there is a need to safeguard forest resources by implementing a PFM programme in the area, involving the local community, and collaborating with NGOs to achieve successful progress through long- and short-term training, which must be provided to all farmers on a sustainable basis. In this context, developing an integrated participatory approach requires rapid attention, and all farmers and stakeholders must be actively involved in the PFM program.

3.6.1. Study limitations

It's critical to recognize a number of study limitations when evaluating the findings since they might affect the validity and generalizability of the conclusions. First off, the study's findings might not apply to other parts of Ethiopia because it just examined the Alle area in the southwest of the nation specifically focusing on the PFM program implemented. Furthermore, the precision of the results may be impacted by the resolution and accuracy limits associated with using Landsat images to detect changes in land cover. In addition, response bias and social desirability bias may be present in the utilization of survey data gathered through questionnaires and interviews, which might have an impact on the data's dependability. Furthermore, there might be sampling bias because the 240 responders in the sample may not be entirely representative of the population. Lastly, the study's failure to assess the PFM program's long-term viability and how it affects forest conservation makes it more difficult to make generalizations about the program's influence on sustainable development. Subsequent investigations need to endeavor to tackle these constraints and provide a more all-encompassing comprehension of the correlation between PFM initiatives and the preservation of Ethiopian forests.

4. Conclusion

Forests play a vital role in environmental sustainability by acting as carbon sinks, absorbing and storing large amounts of carbon dioxide from the atmosphere. They also provide habitats for countless species of plants and animals, helping to maintain biodiversity and ecological balance. PFM is increasingly being used to maintain Ethiopian forests. Still, there are problems with financial viability and leakage. This study found that the PFM can act as a stepping stone for carbon financing systems to reduce greenhouse gas emissions and increase carbon sinks through forest resources. The results clearly show an increase in forest cover in both the second period and after implementation. Although household members have actively participated in reforestation programs, other equally crucial duties have yet to be properly executed due to the community's lack of commitment to forest management. The change in forest cover showed an increasing trend from 2012 to 2022. Again, the grassland and wetland coverage in this study decreased rapidly. In the years 2012–2022, forest land increased from 462.7ha (74.8 %), to 569.8ha (92.1 %), while, the agricultural land, grassland, and wetland were reduced from 109.5ha (17.7 %) to 37.8ha (6.1 %), 31.9ha (5.2 %) to 0.0ha (0.0 %); 14.1 ha (2.3 %) to 10.8 ha (1.7 %) respectively. Furthermore, the study area has implementation obstacles for PFM in study area. A binary logistic regression analysis revealed that total landholding had a negative effect on forest management engagement. Gender, educational level, family size, TLU, loan availability, training, and legal enforcement have a positive and significant impact on PFM practices. For the researcher should focus on the key limitations stated under the discussion section.

Data and materials availability

In the article body, all data output are available that were generated and examined during this investigation.

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Mamush Masha: Writing – review & editing, Visualization, Validation, Supervision, Software, Resources, Methodology, Investigation, Conceptualization. **Elias Bojago:** Writing – review & editing, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Gemechu Tadila:** Writing – original draft, Resources, Investigation, Formal analysis. **Mengie Belayneh:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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