RURAL HOUSEHOLDS AGROFORESTRY TECHNOLOGY ADOPTION IN ASSOSA DISTRICT, BENISHANGUL GUMUZ REGIONAL STATE, WESTERN ETHIOPIA

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ABSTRACT

Agroforestry technology is becoming increasingly important in regions where land is limited and population density is high. While it has the potential to enhance agricultural production, the sector is encountering several challenges. Farmers face various barriers in adopting agroforestry technologies, but research suggests that technology adoption plays a crucial role in overcoming these challenges and improving agricultural productivity. Thus, this study examined determinants of agroforestry technology adoption in the Assosa district, Benishangul Gumuz Regional State (BGRS), Western Ethiopia. The research used both primary and secondary data, and 173 household heads were selected using a multistage stratified random sampling technique. Descriptive statistics and inferential statistics, including ANOVA and chi-square tests, along with an ordered logit model, were employed for analysis. The findings revealed that most (61.7 %) households had a low level of agroforestry technology adoption, followed by medium (30 %) and high levels (8.3 %). Additionally, the study shows significant differences in terms of age, farm incomes and frequency of extension contact of rural households across these adoption categories at 1 % of significance level; but, livestock ownership exhibit significance difference at 10 % of significance level. The ordered logit model results indicated that factors such as the age and family size of the household head shows significant difference 10 % of significance level; off-farm income, total land holding, access to credit and extension contacts exhibit significant difference 5 % of significance level. Additionally, farm income of households significantly affects the extent of agroforestry technology adoption at 1 % of significance level. Notably, the study found that total land holding had a positive impact on agroforestry technology adoption. The implications of this study suggest the need for policies that enhance farmers' potential for adopting agroforestry technology, including improving extension services, increasing access to off-farm and non-farm opportunities, creating a favorable environment for livestock production, and enhancing the knowledge of elder farmers.

Keywords: Adoption, agroforestry, technology, rural household.

INTRODUCTION

Over the last few decades, the global community has been actively working on implementing policies to encourage more farmers to adopt sustainable agricultural practices. This is crucial in addressing worldwide poverty and hunger while also safeguarding the environment (Hák, 2016). Despite some progress, the world still grapples with the challenge of meeting the increasing demand for food amidst insufficient agricultural output, compounded by a growing population, changing climate patterns, and land degradation (Global Risks Report, 2022). Therefore, agroforestry plays a dual role, contributing to both the environment and socio-economic aspects wherever it is practiced. Its environmental benefits include promoting biodiversity, conserving soil, preventing soil erosion by wind and water, enhancing soil fertility through nitrogen fixation, and serving as windbreaks or shelterbelts. On the socio- economic front, agroforestry helps increase farmers' income, alleviate poverty, create job opportunities, provide fuel wood, fodder, and construction materials, as well as supply food and medicine (Hasan & Alam, 2006).

In Ethiopia, the integration of multipurpose trees with food crops and livestock has been a longstanding practice (Kindu, 2001). Various traditional agroforestry methods are found in different regions of the country, such as coffee shade-based systems, scattered trees on farmlands, home gardens, woodlots, farm boundary tree planting, and trees on grazing lands (Mesele, 2002; Zebene, 2003; Tesfaye, 2005; Azene, 2007). However, to enhance and optimize existing practices, it is essential to identify the key determinants. In accordance with Pattanayak *et al*. (2003), several factors may influence the adoption of agroforestry technology. These encompass household characteristics (such as age, education, gender, and family size), resource endowments (including livestock size, off-farm income, and farm size), institutional and policy factors (such as visits by development agents, technical support, training, land tenure, and market distance), and biophysical factors (like slope, soil fertility, and soil erosion). Sood & Mitchell (2004) highlighted the lack of empirical investigations into the influence of economic and farming aspects on the adoption of traditional agroforestry systems. They emphasized the tendency to focus on biophysical aspects and tree-based needs in the design of agroforestry technologies, neglecting the economic and farming aspects of households. In the Assosa district of the Benishangul Gumuz Regional State, agroforestry trees serves as a source of fuel wood, construction materials, and income generation. Therefore, it is crucial to identify and document the determinants of agroforestry technology adoption and their relative impacts for further expansion. The study's objectives include identifying the major factors affecting farmers' adoption of agroforestry technology and measuring the level of adoption in the study area.

METHODOLOGY

The study was carried out in the Assosa district, Assosa Zone, Benishangul Gumuz Regional State, Western Ethiopia. According to the Central Statistical Agency (CSA, 2020), Assosa district comprises 74 kebeles, with approximately 49 kebeles (66.22 %) engaging in agroforestry practices, while the remaining 25 kebeles (33.78 %) rely on daily labor, shifting cultivation, monoculture, trade, traditional mining, etc (Yasin *et al*., 2022).This area is well-known for its widespread home garden and parkland agroforestry practices and holds a wealth of indigenous knowledge regarding traditional plant uses (Kifle & Asfaw, 2016). The total population of the Benishangul Gumuz region stands at 460,459, resulting in a population density 9 persons/km^2. But, Assosa zone covers a total area of 1,519 km^2 and is home to a population of 28,970, with a population density 19.1 persons/km^2 (CSA, 2020).

The topography of the study area is characterized by undulating elevations that gradually decrease towards the western part, with an average altitude of 500 m along the Ethiopia-Sudanese border (Mosissa & Wakjira, 2020). The study area experiences a mono-modal rainfall pattern from the end of April to October, with an average annual rainfall of approximately 1291.2 mm (Kifle & Asfaw, 2016). The average yearly temperature in the region fluctuates, with a daily average of 22°C and 237 mm of precipitation recorded at the Assosa meteorological station (Mosissa & Reda, 2018). The soils in the area have very low organic carbon and nitrogen content, indicating poor fertility (Kifle & Asfaw, 2016). This is attributed to limited use of organic and inorganic fertilizers and nutrient loss through leaching (Kifle & Asfaw, 2016).

Subsistence agriculture is the primary economic activity, involving around 80 % of the population. The main agricultural products include cotton, soybeans, coffee, sesame, millet, sorghum, maize, and mango, primarily cultivated through rain-fed and some irrigated farming (Mosissa & Wakjira, 2020). The district's forest and woodland vegetation comprise both native and non-native tree species. Indigenous woody species consist of *Combretum molle, Croton macrostachyus del., Faidherbia albida, Ficus thunningii, Ficus vasta, Millettia ferruginea (Hochst.) Bak., Olea welwitschii, Syzyglum guineense (Willd.), Tamarindus indica L., Terminalia brownii Fresen.* and the exotics *Acacia saligna, Albizia lebek, Azandrica indica, Cassuarina equisetifolia, Cupressus lusitanica, Delonix regia, Eucalyptus camaldulensis Dehnh., Eucalyptus citrodora, Eucalyptus saligna, Gravellia robusta, Jacaranda mimosifola, Leucanea leucocephala, Melia azedarach L., Schinus molle,* and *Spatodia nilotica* (Kifle & Asfaw, 2016, Abera & Yasin, 2018; Yasin *et al*., 2022).

Types of data and data collection tools Primary data

In order to comprehensively explore the implementation of agroforestry technology, interviews were carried out with key representatives from the Agriculture and Rural Development Office, Kebele administration, and model farmers. The selection specifically consisted of two key informants from the Agriculture Office, one from the Kebele Administrative leaders, and two model farmers. Generally, five key informants from each kebele were deliberately chosen to gather a comprehensive understanding of agroforestry technology in the study area. The interviews were structured into two parts, with the first part focusing on the background of the respondents and traditional agroforestry technologies, while the second part addressed the main constraints and motivating factors for adopting agroforestry technologies. Prior to the interviews, four field assistants were trained in basic data-gathering techniques. Moreover, the selected focus groups engaged in detailed discussions to enhance the effectiveness of data collection. The researcher organized the participants into focus groups based on gender and age to ensure balanced participation and to address potential gender and age-related biases. This systematic approach was adopted to counteract the dominance of men in discussions and to provide an inclusive platform for women's opinions, as well as to account for the potential differences in attitudes and experiences based on age.

Focus group discussion (FGD)

The researcher engaged in focus group discussions to gather the community's perspectives on the factors influencing the adoption of agroforestry technologies. The participants were categorized into four groups based on age and gender, including older women, older men, young men, and young women, as well as village leaders, model farmers, and agricultural experts. Following initial meetings and the identification of participating farmers, the focus group interviews took place at the kebele level, with four individuals participating in each discussion. The conversations centered on research issues related to agroforestry technologies, their constraints, and the status of their implementation. The group discussions specifically involved selected model farmers from the study area.

Household survey

The kebele administrator leaders and development agents initially gathered lists of all household heads in the selected kebeles and used a random selection procedure to choose 173 households for interviews. Surveys were developed, adjusted, and translated into the local language with input from the initial survey and feedback from the pilot survey. One enumerator with diploma qualifications was assigned to each kebele to collect data, while the researcher conducted regular follow-ups. Structured and semi-structured questionnaires, including closed and open-ended questions, were used to gather socio-economic data from household heads about their agroforestry practices.

Personal observation

In this study, the researcher documented his observations of agroforestry technologies (AFT) on the farmland to describe current farming practices and compare reported data with actual occurrences in the study area (Obeng-Odoom, 2014). The researcher directly observed selected household farm fields under the general conditions of their agroforestry practices.

Selection of study area and sampling techniques

Sampled kebeles and household respondents were selected purposely and by using stratified random sampling procedures. The research was executed in a tripartite framework, employing stratified random sampling methodologies (Kothari, 2004). In the first stage, the Assosa district was purposely chosen among the districts in the Assosa zone because it had potential coverage and the existence of agroforestry technology. Next, 74 rural kebele administrative of Assosa district were stratified into two: natives (36 kebeles) and settlers (38 kebeles) (ADARDO, 2024). Then, a total of four (4) kebeles (two kebele from natives and two kebele from settlers) were randomly selected from both strata (Table 1). The study site selected a specific number of kebeles from each stratum, considering the presence of diverse agroforestry practices and the adequacy of agroforestry technologies in the district for representation. From the selected kebeles, the sample sizes were determined based on the proportion of household heads. Finally, a proportionate representative household selection of four selected kebeles was identified as par, according to Kothari (2004): "*If the population from which a sample is to be drawn does not constitute a homogeneous group, a stratified technique is generally applied to obtain a representative sample.*" This sampling procedure is useful when a sampling frame is in the form of a list. Household lists were obtained from each site's kebele manager. With the assistance of village leaders, two groups of farmers were identified as adopters and non-adopters of the agroforestry technology in each kebele. Thus, 173 HHs were randomly selected (Table 1).

Table 1: Household sample distribution in sampled kebeles of each stratum

Sampled rural Kebeles	Origin of households	Total HHs per Kebele	Number of sample HHs head (PSS = Ni/N*n)
Oura	Native	450	53
Tsetse	Native	380	44
Mengele-29	Settler	351	41
Selga-20	Settler	300	35
Total		1481	173

Sample size determination

The size of the sample is a critical factor in research, and it should be carefully determined to ensure it is neither too large nor too small (Kothari, 2004). For quantitative analysis, the sample size was calculated using a specific formula, while for qualitative research, the sample size selection is based on judgment rather than set guidelines (Cohen *et al*., 2000). The sample size was calculated as described by Kothari (2004).

$$\boldsymbol{n} = \frac{Z^2 * N * p * q}{e^2(N-1) + Z^2 * p * q} \quad \text{------------------------} \ (1)$$

Where n =sample size, N=total households in selected kebeles, e^2= acceptable error, z^2=standard variation at a given confidence level (1.96–95 %), p=0.5, q=0.5 and P=proportion of successes, q=proportion of failures. Using the above formula, the study's total sample was 173 households selected proportionally from 1,881 households in the study area.

The sample size for the Kebele level was determined using Kothari's (2004) proportional allocation formula.

$$n_i = \frac{N_{i*n}}{N} \quad \text{------------------------}(2)$$

Where n_i= sample size taken from each stratum/sector, Ni= total number of population of each stratum/sector, n = total sample size of the study, N =total population size.

Based on the above formula, the proportional sample households for the study areas Oura, Tsetse, Mengele-29, and Selga-20 Kebele's were determined as 53, 44, 41, and 35 households, respectively, calculated among the total households (Table 1) in accordance with the sample size taken from each stratum and the total population of each stratum.

Data analysis

Descriptive and econometric analyses were conducted to examine the characteristics of sampled households and their adoption of agroforestry technology. The descriptive statistics, including means, percentages, standard deviations, and frequencies, were analyzed using SPSS. Additionally, inferential statistics such as the chi-square test and t-test were performed. ANOVA and chi-square tests were used to compare different levels of agroforestry technology adoption. It was noted that descriptive statistics alone were insufficient to predict the joint impacts of explanatory variables on the dependent variable, and therefore appropriate econometric models were employed. The study utilized an econometric model to forecast the effects of explanatory variables on the adoption of agroforestry technology and to investigate the main limiting factors in the study area. An ordered logit model was specifically used to analyze the factors influencing the adoption of agroforestry technologies.

Model specification

The study employed an ordered logit model to analyze the factors influencing farmers' decisions to adopt agroforestry technology. This model was selected to maintain the ordinal scales, utilizing Likert-scale questions with a range of 1 to 3 to gauge the extent of technology adoption. The dependent variable uses independent variables to compute the predicted probabilities for each of the three levels of the dependent variable. Regarding the specification of the model, consider a latent random variable $Y_n{}^*$ for individuals.

$$Y^*_n = \beta_n + \varepsilon_n \quad with \; \varepsilon_n = N(0, \sigma^2) \qquad \text{----------} \qquad (3)$$

That linearly depends on X_n. The random error ε_n is assumed to be logistically distributed. $Yn^* =$ is the underlying unobserved (latent) variable that indexes the extent of agroforestry technology adoption, X_n is a vector of explanatory variables describing farm, household and institutional characteristics, β' are parameters to be estimated and εn is the error term, assumed to follow a standard normal distribution. For an ordered model, we define $Y_n{}^* = j$ if, $a_{j-1} \leq Y_n{}^* \leq j$ where $a_0 = -\infty =$ and $a_m = \infty$. This will yield

$$(Y^*_n = j) = P(a_{j-1} \leq Y^*_n \leq \qquad \text{---------------------}(4)$$

$$= (a_{j-1} \leq \beta' X_n + \varepsilon_n \leq a_j) \qquad \text{----------------------}(5)$$

$$= (a_{j-1} - \beta' X_n \leq \varepsilon_n \leq a_j - \beta' X_n) \qquad \text{-----------------}(6)$$

$$= (a_{j-1} \leq \beta' X_n) - F(a_j - \beta' X_n) \qquad \text{-----------------}(7)$$

Where F is the CDF of ε_n The regression parameters, β', and the $m - 1$ threshold parameters, a_1 to a_{m-1} are obtained by maximizing the log-likelihood with ($Y_n{}^* = j$). Then the model (ordinal logistic regression mode**)** is specified as follows:

$$\text{logit}(P_1) = \log \frac{P_1}{1-P_1} = a_1 + \beta' X_n \qquad \text{----------------------}(8)$$

$$\text{logit}(P_1 + P_2) = \log \frac{P_1+P_2}{1-P_1-P_2} = a_2 + \beta' X_n \qquad \text{----------------------}(9)$$

$$\text{logit}(P_1 + P_2 + \cdots P_k) = \log \frac{P_1+P_2+\ldots+P_k}{1-P_1-P_2-P_k} = a_k + \beta' X_n \qquad \text{------}(10)$$

$$\text{And } P_1 + P_2 + \cdots + P_k = 1$$

The model, referred to as the proportional odds model, assumes that the dependent and explanatory variables are independent and that the odds ratio of the event is constant for all categories (Allen *et al.*, 2009).

Operational Definition of Variables

Dependent variable Agroforestry Technology Adoption

The level of adoption of introduced agroforestry technologies by farmers is measured as an ordinal variable, ranging from 1 for low adoption, 2 for moderate adoption, to 3 for high adoption. The assessment is based on the percentage of new technology implemented by the respondents, as described by Kulkarni & Sangle (1984). Accordingly, the scoring process will be made based on the following table.

Table 2: Description of Extents of agroforestry Technology Adoption Index computation

Percentage of Area under practice	Score
Up to 10%	1
Up to 20%	2
Up to 30%	3
Up to 40%	4
Up to 50%	5
Up to 60%	6
Up to 70%	7
Up to 80%	8
Up to 90%	9
Up to 100%	10

Source: Kulkarni & Sangle, 1984.

Thus, each practice has the potential to receive adoption scores between 0 and 10. In order to classify the practices, the mean adoption score for each practice will be calculated, and based on mean scores the practices will be categorized into 3 levels as follows.

Table 3: Extents of Agroforestry Technology Adoption Index

Category	The mean adoption score range
Low	1-3.33
Moderate	3.34-6.66
High	6.67-10

Independent variables

The factors represented by the independent variables (Xi) either positively (+) or negatively (-) influence the use of agroforestry practices.

Education of the household head: The literacy status of farmers, measured in terms of completed years of schooling, is a crucial variable in the adoption of improved agroforestry technology. Our study hypothesized a positive correlation between agroforestry practices and this variable, as it plays a significant role in preparing individuals to embrace expected agroforestry practices (Akareem & Hossain. 2016; Jara-Rojas *et al*., 2020, Tega & Bojago, 2024).

Family size: It is a continuous variable, which is expected to have a positive impact on the adoption of agroforestry practices, as larger family sizes are typically associated with a higher endowment of labor, allowing households to engage in various agricultural activities over time. This study hypothesizes a positive relationship between the variable and the adoption of agroforestry practices (Kassie, 2018, Tega & Bojago, 2024).

Credit availability: The dummy variable represents whether the household has credit (1) or not (0). Credit availability influences farmers' decisions to adopt innovation (Tega & Bojago, 2024); and the lack of credit has been identified as a constraint to agroforestry technology adoption (Tesfaye & Melaku*,* 2017). Lack of initial capital particularly hinders resource-poor farmers from adopting technology. This study anticipated a positive relationship between receiving credit and technology adoption.

Off and/or non-farm income: The variable, which measures the off-farm and non-farm income of farmers in birr per year, has been found in empirical studies to potentially discourage investment in new farming technologies and therefore hinder their adoption if farming is not their primary source of income (Zemedu *et al*., 2024). As a result, it was hypothesized that this variable would have a negative impact on technology adoption.

Agroforestry practice experience: This is a continuous variable that counts every year. Rural households spend most of their time making their lives through different agricultural practice. The older the household head is, the more farming experience they are likely to have (Tega & Bojago, 2024). Consequently, it was anticipated that this variable would positively influence the adoption of agroforestry technologies by farmers.

Distance from the market center: The distance of farmers' fields from the nearest market, measured in kilometers, is a continuous variable. Proximity to the market presents an opportunity for farmers to sell agroforestry products, while improved market access is likely to encourage technology adoption. In remote areas with high physical access costs, adoption of new agricultural technologies is expected to be lower, indicating a negative influence on households' technology adoption (Barrett *et al*., 2001).

Sex of the household head: The dummy variable represents the gender of the household head, with a value of 1 for male and 0 for female, and is linked to differences in exposure to external information and adoption of new agricultural technology (Lakew *et al*., 2005; Neway & Zegeye, 2022). In this study, I hypothesize that there is a positive correlation with the adoption of agricultural practices.

Nature of settlement: The dummy variable in this study indicates the origin of households, with a value of 0 for native's and1 for settlers. According to the regional Bureau of Agriculture's report, natives are less open to new technologies compared to settlers. Therefore, this study proposes that the nature of settlement is likely to have a positive impact on the adoption of agroforestry technologies.

On-farm income: Farm income, a continuous variable measuring total earnings from farm activities, constitutes the annual earnings of a family from selling agricultural products like crops, livestock, and their products after meeting family needs (Rahmeto, 2007). This income is crucial for purchasing agricultural inputs, and households with higher farm income are more likely to invest in improved seeds and essential agricultural inputs, thereby adopting agricultural technologies (Rahmeto, 2007). This study hypothesized that higher farm income leads to increased technology adoption.

Farm size: The size of landholdings is a crucial factor in agroforestry practices, as farmers with large farms are less likely to adopt these practices compared to those with small landholdings (Iiyama *et al*., 2017; Rosati *et al*., 2021). When technologies require a significant amount of land, farmers with smaller acres are also less inclined to adopt agroforestry technologies. The impact of land change depends on various circumstances, including the type of agroforestry practice encouraged, and the variable was anticipated to have a positive effect on the extent of technology adoption.

Frequency of extension contact: The binary variable indicates whether the household receives extension services, with a value of '1' for yes and '0' for no. Adugna & Wegayehu (2012) showed that the frequent extension contact with extension services leads to greater exposure to new agricultural technologies for farmers, which in turn influences their decision to adopt or reject innovations. Consequently, it is expected that more frequent contact with extension services will have a positive impact on the adoption of agroforestry practices (Urgessa & Fekadu, 2021; Pinho *et al*., 2012). This study also hypothesizes that frequent extension visits will lead to increased adoption of agricultural technologies.

Livestock holding of household: The continual variable represents the overall quantity of animals in each surveyed household, measured in Tropical Livestock Units (TLU). Since the number of animals signifies wealth, it encourages risk-taking and the probability of farmers investing in new technology (Mahmoud, 2017). Households with more animals can access more income sources to buy food, particularly during food shortages (Thornton, 2010; Mutisya *et al*., 2016; Taruvinga *et al*., 2022). Therefore, income from livestock is anticipated to positively influence adoption.

Soil fertility: The study hypothesized that farmers' adoption of new agroforestry technologies is positively influenced by soil fertility, which is indicated by a dummy variable taking a value of 1 for fertile soil and 0 for infertile soil. Thus, this study hypothesized that soil fertility positively affects farmers' technology adoption status.

RESULTS AND DISCUSSION

Demographic and Socio-economic Characteristics of Households

In this study, primary data was used from 173 households. 80 % of the households were male- headed and 20 % were female-headed. I found that there are more male-headed households than female-headed ones. In terms of settlement, 55 % of the households were native, while 45 % were settler households. The average family size was 5.35 members, with a range from 3 to 9 members. The farmers in the study area engage in mixed farming, including staple food crop production and rearing of domestic animals (Table 4).

The average livestock holding was 4.23 tropical livestock units (TLU), with a range from 1.54 to 9.86 TLU. The main sources of income were on-farm activities, such as crop and livestock sales, and off-farm activities, including trading and handcraft. The average farm income was 45890 birr per annum, while the average off-farm income was 570.83 birr per annum (Table 4). The mean age of the households was 46.73 years, and the average years of formal education attended was 2.02. The average farmland size owned was 3.45 hectares, and 63.3 % of households perceived their soil as fertile. The average number of extension contacts was 2.85 visits, and 58.3 % of households had access to credit (Table 4).

Table 4: Demographic and socio-economic characteristics of the sample households (N=173)

Explanatory Variables	Mean	SD	Min	Max
Sex of HH head (Male)	0.8			
Nature of settlement (Settler)	0.45			
Education of HH head (Years)	2.02	2.626409	0	8
Age of the HH head (Years)	46.73	9.411257	29	67
Family size(Number)	5.35	1.470904	3	9
Total land holding (Hectare)	3.45	0.9419597	2	5
Livestock ownership (TLU)	4.23	1.651674	1.54	9.86
Farm income (Birr)	25685.12	8547.192	3210	45890
Off & non-farm income(Birr)	570.83	557.4071	0	2000
Frequency of extension contact (Number)	2.85	2.023799	0	8
Distance from the market (Km)	5.32	1.214205	2	7
Access to credit (yes)	0.67			
Perception of soil fertility status (Fertile)	0.63			

Source: Own survey result, 2024

Households Extent of Technology Adoption

The study area's households exhibit varying levels of technology adoption, as indicated by the study's findings. The majority of surveyed households (61.7 %) are classified as low-level adopters, while 30 % fall into the medium adopter category, and 8 % are categorized as high- level adopters (Table 5).

Table 5: Summary of sampled household's extent of technology adoption (N= 173)

The extent (level) of household technology adoption	Frequency (N)	Percent (%)
Low	107	61.7
Medium	52	30
High	14	8.3
Total	**173**	**100**

Comparison of Households Whith Regard to Extent of Technology Adoption

The study utilized ANOVA (F-test) and chi-square test to compare households at different levels of agroforestry technology adoption based on various socio-economic characteristics. Significant differences were found in the mean values of continuous variables across the three levels of technology adoption. For instance, age of household head, total annual cash income from on farm, livestock owned and frequency of extension contacts (Table 6).

Accordingly, the mean ages of sampled farmers were 44.84, 47.28 and 58.8 for low-level, medium level and higher-level agroforestry technology adopters, respectively. The study showed that the ages of farmers who were low-level of agroforestry technology adopters are relatively younger or smaller than those medium and higher levels of agricultural technology adopters. In addition, the mean values of total livestock (in TLU) owned by rural farmers were 3.85, 4.71 and 5.26 for lower-level, medium level and higher-level adopters, respectively. This implies that higher-level technology adopters own larger livestock than lower-level and medium-level adopters (Table 6).

Generally, the mean age of farmers increased with higher levels of technology adoption, and higher-level adopters had larger livestock and better incomes compared to lower and medium adopters. Additionally, households with higher levels of agroforestry technology adoption had more frequent extension contacts compared to lower and medium levels. Furthermore, the mean value of total farm income earned by households falling in low level, medium level and higher level was Birr 21,800, 36,000, and 37,000, respectively. This result suggests that farmers with higher-level agroforestry technology adoption had better incomes compared to lower and medium adopters. The mean value of extension contact received by households falling in lower, medium and higher levels of agroforestry technology adoption was 2.14, 3.22, and 6.80 contacts, respectively. It also indicated that those households with higher levels of agroforestry technology adopters had more frequency of contact than the rest levels (Table 6).

Table 6: Summary of ANOVA results for continuous explanatory variables (N=173).

Independent variable	Households extent of technology adoption status			Total	F-value
	Y=1	Y=2	Y=3		
	Mean(SD)	Mean(SD)	Mean(SD)	Mean(SD)	
Education of HH head	2.35(2.66)	1.89(2.74)	.00(.00)	2.02(2.63)	1.85
Age of HH head	44.84(8.71)	47.28(9.47)	58.8(5.07)	46.73(9.41)	5.66***
Family size	5.22(1.27)	5.44(1.76)	6.0(1.87)	5.35(1.47)	0.67
Total land holding	3.42(0.79)	3.33(1.19)	4.10(0.89)	3.45(0.94)	1.36
Livestock ownership	3.85 (1.32)	4.71(2.09)	5.26(1.52)	4.22(1.65)	2.91*
Farm income	21800(7121.63)	36000 (6782.7)	37000(3709.61)	25685.12(8547.19)	17.63***
Off & non-farm income	531.08(532.98)	572.22(546.44)	860.0(798.75)	570.83 (557.407)	0.76
Extension contact	2.14 (1.68)	3.22(1.396)	6.80(1.304)	2.85(2.02)	19.92***
Distance from market	5.27(1.24)	5.39(1.15)	5.40(1.52)	5.32(1.22)	0.07

N.B:- ***, **, and * indicates significant at 1 %, 5 %, and 10 % probability level respectively. Y=1, Y=2, and Y=3 represent a low adopter, medium adopter, and a higher level adopter respectively.

A chi-square test was performed to compare households with varying levels of technology adoption in relation to discrete explanatory variables. The findings suggest that there was no notable distinction between households at different technology adoption levels in terms of discrete explanatory variables (Table 7).

Table 7: Summary of Chi-square test for dummy explanatory variables (N=173)

Independent variables	Response	The extent of technology adoption status of Households (%)			Total (%)	χ2 value
		Y=1	Y=2	Y=3		
Sex of HH	Male	50	23.3	6.7	80	0.083
Head	Female	11.7	6.6	1.7	20	
Access to Credit	Yes	40	18.3	0	58.3	2.804
	No	21.7	11.7	8.3	41.7	
Soil fertility	Fertile	38.3	21.7	3.3	63.3	1.807
Status	Not	23.3	8.3	5	36.7	
Nature of	Settler	30	11.7	3.3	45	0.521
settlement	Native	31.7	18.3	5	55	

N.B:-Y=1, Y=2, and Y=3 represent low-level, medium-level, and higher-level of agroforestry technology adopters, respectively.

Determinants of Extent Agroforestry Technology Adoption

The ordered logistic regression model was used to analyze the factors influencing technology adoption. The results indicated that the model is statistically significant at a 1 % level, with 7 out of 13 explanatory variables being significant. Only variables with coefficients statistically significant at or below a 10% probability level were discussed in this study. The significant determinants of technology adoption status for rural households included the age of the household head, family size, off-farm/non-farm income, farm income, land size, livestock ownership, and extension contact (Table 8).

Age of household head: The study's model indicates that the age of the household head significantly and positively impacts the household's technology adoption at a 10 % significance level. When other factors remain constant, for every increase of one year in the age of household heads, the odds ratio favoring technology adoption increases by a factor of 1.13 (Table 8). This positive correlation could be attributed to older household heads dedicating more time to farming compared to younger individuals, who often spend more time in urban areas. As elder farmers rely on farming, they increasingly leverage technology to enhance their livelihoods. Moreover, as individuals' age, they tend to accumulate a wealth of knowledge and experiential insight, thus improving their ability to leverage these experiences. This finding is consistent with finding of Turner (2016).

Off and/or non-farm income: The study yielded unexpected results, as off and/or non-farm income was found to have a positive and significant impact on households' technology adoption levels at a 5 % significance level. According to the model's findings, keeping other factors constant, a one birr increase in off and/or non-farm income raises the odds ratio favoring technology adoption by a factor of 1.002 (Table 8). The model's outcome suggests that off/non-farm income contributes to the adoption of agroforestry technology, as it enables farmers to easily afford the cost of purchasing various inputs like fertilizers and improved seeds. This finding is consistent with the finding of Gebrie (2021).

Table 8: Ordered logit model output for determinants of the extent of agricultural technology adoption (N=173)

Explanatory Variables	Coefficients	Std. Err.	p>[z]	Odds Ratio
Sex of HH head	-1..35293	.2635623	0.185	.2584819
Education of HH head	-.2768284	.1431306	0.143	.7581846
Age of HH head	.1203762*	.0717996	0.059	1.127921*
Family size	-.695414	.1849016	0.061	.4988679*
Nature of settlement	.5420304	.523069	0.547	.5815662
Total land holding	-1.137107**	.1677904	0.030	.3207457**
Perception of soil fertility	-.2211738	.8344203	0.832	.8015773
Livestock ownership	.1047957	.3241676	0.720	1.110484
Farm income	.0002907***	.000083	0.000	1.000291***
Off & non-farm income	.0020045**	.0009781	0.040	1.002117**
Frequency of Extension contact	.6573212**	.5809237	0.029	1.929616**
Access to credit	2.398072**	12.60708	0.036	11.00194**
Distance from the market center	.0007804	.3604284	0.998	1.000781
/cut1	9.498865	4.32272		9.498865
/cut 2	14.26227	4.801135		14.26227
Number of observations		**173**		
LR chi^2		**55.96**		
Log-likelihood		**-24.002**		
Prob > chi^2		**0.000**		
Pseudo R^2		**0.5383**		

Source: Own survey result, 2024.
N.B:- ***, **, *indicates significant at 1, 5, and 10 % significance level, respectively.

Farm income: The study found that an increase in farm income has a significant positive impact on the adoption of agroforestry technology (Table 8), likely due to increased investment capacity for purchasing technologies and inputs, as well as the tendency for farmers to invest in improved seed varieties and other new agricultural technologies to enhance productivity. This aligns with the findings of Kinyangi (2014).

Family size: Family size was found to have a significant impact on households' technology adoption levels in the study area, contrary to expectations (Table 8). The model results revealed that an additional person in the household decreased the odds ratio of higher technology adoption by a factor of 0.498. This was attributed to larger families, particularly those with non-productive age children, experiencing lower adoption due to higher dependency ratios and lower incomes, aligning with previous research by Feder & Slade (1984).

Total landholding: The research revealed that at a 5 % significance level, there is a negative and significant impact on the adoption of technology as farm size increases

(Table 8). This suggests that larger farm sizes are associated with lower technology adoption. Specifically, for each additional hectare of farmland, the odds ratio for higher technology adoption decreases by a factor of 0.32. This may be attributed to the tendency for larger farmers to prioritize food production, while smaller landholders focus on intensive farming to mitigate food insecurity, a finding supported by Berihun (2014).

Access to credit: Access to credit has a significant positive effect on the extent of technology adoption in households, increasing the odds in favor of technology adoption by a factor of 11.002, as it provides a solution to the financial problems of households, enabling them to purchase various farm inputs and consequently enhance their production and productivity in farming activities (Table 8).

Frequency of extension contact: The variable shows a strong positive impact on technology adoption at a 1 % significance level, with the odds in favor of adoption increasing by 1.93 for each additional extension contact (Table 8). This is attributed to the availability of improved agricultural information, aiding farmers in making informed decisions and adapting to technology adoption. These results align with Adugna and Wegayehu's findings in 2012.

CONCLUSIONS AND RECOMMENDATION

Conclusions

The decision to implement agroforestry practices on farmlands is essential for managing natural resources, but the farming sector has been encountering challenges due to various influences from household conditions and the farm environment. Achieving agricultural productivity growth hinges on the development and dissemination of yield-increasing technologies and their application by farm households. Therefore, it's crucial to enhance agroforestry technologies to boost agricultural productivity, alleviate poverty, and meet food demands without causing irreversible degradation of natural resources. This study focused on assessing the extent of technology adoption and its determinants among rural households in the Assosa district, utilizing data from 173 sampled household heads. Descriptive and inferential statistics revealed that the majority of households were categorized as low adopters, followed by medium and high adopters. The study also employed an ordered logit model to identify determinants of household technology adoption, with factors such as age of household head, family size, off-farm income, livestock ownership, extension contacts, and access to credit found to be significant. The study's results provide valuable insights for Policy makers and extension workers to enhance technology adoption and promote agricultural production, ultimately contributing to improved wellbeing and economic development.

Recommendations

An urgent action by all stakeholders is required to address the technology adoption of rural households, as well as to mitigate the impact of various shocks in the study area. This action may involve the following steps:

- ✓ Improving access to water, feed supply, veterinary services, management systems, and livestock breeds can help rural households expand their capacity for owning livestock.
- ✓ Enhancing the access of households to various non-farm and off-farm employment options can increase their income and enable them to effectively utilize agroforestry technologies.
- ✓ Improving farmers' access to extension services for agroforestry production can

assist them in producing market-focused goods, ultimately boosting their income from farming. If there's anything else you need, feel free to ask!

- ✓ Farming households should receive education on adopting agroforestry to help with labor-intensive work, and younger farmers should be informed about the importance of agroforestry technology by the regional government to encourage their involvement in farming activities.
- ✓ To enhance technology adoption at the household level, intervention is needed to boost cash crop productivity. This includes providing improved crop varieties (drought-tolerant and early-maturing), enhancing production systems, developing irrigation facilities, and improving infrastructure for the farming community in the study area.
- ✓ Enhancing access to credit for households from various sources has a positive impact on the adoption of technology.
- ✓ I suggest conducting further studies on agroforestry technology adoption to delve into factors such as resistance to improved seed variety with climate change, rural development, socio-economic problems of households, and household income. The success of interventions to improve agroforestry technology adoption will depend on collaborative efforts of various development actors, including the government, NGOs, and private investors. Enhancing networks and information exchanges among these
- ✓ actors may help in the planning and implementation of appropriate development activities, preventing wastage of resources and ensuring necessary attention to constraints.

CONFLICT OF INTEREST

The authors state that they have no conflicts of interest.

REFERENCES

Abera, Y. and Yasin, A. (2018). Diversity and Abundance of Woody Plant Species of Assosa Forest Field Gene Bank, Benishangul Gumuz Regional State, *Western Ethiopia*.8(23), pp.1-5.

Adugna, E. and Wegayehu, B, (2012). Determinants of livelihood strategies in Wolaita, Southern Ethiopia. *Agricultural Research and Reviews vol.1 (5), pp.153-161.*

Akareem, H., S. and Hossain, S., S. (2016). Determinants of education quality: what makes students' perception different? *Open Rev Educ Res* 3(1):52–67. https://doi.org/10.1080/23265507.2016.1155167

Allen, C.S., Chen, Q., Willson, V.L. and Hughes, J.N., (2009). Quality of research design moderates effects of grade retention on achievement: A meta-analytic, multilevel analysis. *Educational evaluation and policy analysis*, *31*(4), 480-499.

Assosa District Agriculture and Rural Development Office (ADARDO), (2024). *District Annual Report of Benishangul Gumuz Regional State*, Ethiopia 2024.

Azene, B. (2007). *Profitable agroforestry innovation for eastern Africa: Experience from 10 agroclimatic zones of Ethiopia*, India, Kenya, Tanzania and Uganda. World Agroforestry Center. 2007; 353.

Berihun, K., (2014). *Assessment of Factors Affecting Agricultural Production: Evidence from Smallholder Farmers of Southern Tigray, Northern Ethiopia*. Doctoral dissertation, the

Institute of Development Studies and partner organizations.

Central Statistics Agency (CSA) (2020). *Population and Housing Census of Assosa Branch:* Unpublished Annual Report; Central Statistical Agency: Assosa, Ethiopia; pp.24.

Cohen, M., A., Eliashberg, J., and Ho, T., H. (2000). An analysis of several new product performance metrics. *Manuf Serv Oper Manag* 2(4):337–349. https://doi.org/10.1287/ msom.2.4. 337.12341.

Feder, G. and Slade, R. (1984). "The Acquisition of Information and Adoption of New Technology," *American Journal of Agricultural Economics*, 66.

Gebrie, A., (2021). *Farmers participation in non-farm income activities in Enebsie Sar Mider Woreda, Southwest Amhara, Ethiopia* (Doctoral dissertation).

Hák, T., Janoušková, S. and Moldan, B. (2016). Sustainable Development Goals: A need for relevant indicators. *Ecol. Indic. 60*, 565–573. [CrossRef]

Hasan, M., K. and Alam, K., M. (2006). *Land degradation situation in Bangladesh and the role of agroforestry on-farm research division*, Bangladesh Agricultural Research Institute, Gazipur, Bangladesh School of Agriculture and Rural Development, Bangladesh Open University, Gazipur, Bangladesh.

Iiyama, M., Derero, A., Kelemu, K., Muthuri, C., Kinuthia, R., and Ayenkulu, E. (2017). Understanding patterns of tree adoption on farms in semi-arid and sub-humid Ethiopia. *Agrofor Syst* 91(2):271–293. https://doi.org/10.1007/ s10457-016-9926-y

Jara-Rojas, R., Russy, S., Roco, L., Fleming-Muñoz, D. and Engler, A. (2020). Factors affecting the adoption of agroforestry practices: insights from silvopastoral systems of Colombia. *Forests* 11(6):648. https://doi.org/10.3390/f11060648.

Kassie, G., W. (2018). Agroforestry and farm income diversification: synergy or trade-off? The case of Ethiopia. *Environ Syst Res* 6(1):1–14. https://doi.org/10.1186/s40068-017-0085-6.

Kifle, E., T. and Asfaw, Z. (2016). Woody Species Richness, Use Diversity and Management in Agroforestry Practices: The Case of Assosa District Benishangul Gumuz Region, Ethiopia. *J Biodivers Manage Forestry* 5: 4. *Of*, *7*; 2.

Kindu, M. (2001). Practices, constraints and agroforestry interventions in Yekuwatershed, northeastern Ethiopia. *Ethiopian Journal of Natural Resources*. 3(1):161-178.

Kinyangi, A.A., (2014). *Factors influencing the adoption of agricultural technology among smallholder farmers in Kakamega north sub-county, Kenya* (Doctoral dissertation, University of Nairobi).

Kothari, C.,R. (2004). *Research methodology: methods and techniques*. New Age International, New Delhi.

Kulkarni, R., R. and Sangle, G., K. (1984). Analysis of technological gap in tribal farming system.

Lakew, D., Carucci, v., Asrat, W. and Yitayew, A. (eds) (2005). *Community-Based Participatory Watershed development: Addis Ababa*, Ministry of Agriculture and Rural Development of Ethiopia.

Mesele, N. (2002). *Socioeconomic aspects of farmer's eucalyptus planting practice in the enset- coffee based agroforestry system of Sidama, Ethiopia*: The case of Awassa and Shebedino district. M.Sc Thesis. 82. ISSN 1402-201X.

Mosissa, D. and Reda, D., (2018). American Journal of Life Science Researches. *American Journal of Life Science Researches*, *6*(3), pp.139-158.

Mosissa, D. and Wakjira, D. (2020). Large scale agricultural investment and a fragile soil paradox in Benishangul Gumuz regional state: Organic carbon stock of broadleaf and deciduous forests of Combretum–Terminalia woodlands of Benishangul Gumuz Regional State, Western and northwestern Ethiopia. *J Agric Sci Bot. 2020; 4 (3); 1-13. J Agric Sci Bot. Volume 4 Issue*, *3*.

Mutisya, M., Ngware, M., W., Kabiru, C., W. and Kandala, N., B. (2016). The effect of education on household food security in two informal urban settlements in Kenya: a longitudinal analysis. *Food Secur* 8(4):743–756. https://doi.org/ 10.1007/s12571-016-0589-3.

Neway, M., M. and Zegeye, M., B. (2022). Gender differences in the adoption of agricultural technology in North Shewa Zone, Amhara Regional State, Ethiopia. *Cogent Soc Sci* 8(1):2069209. https://doi.org/10.1080/23311886.2022.2069209.

Obeng-Odoom, F. (2014). Urban land policies in Ghana: a case of the emperor's new clothes? *Rev Black Polit Econ* 41(2):119–143. https://doi.org/10.1007/s12114-013-9175-5.

Pattanayak, S., K., Mercer, D., E., Sills, E., O., J., Yang, C. and Cassingham, K. (2003). Taking stock of agroforestry adoption studies. *Agroforestry Systems*.57:173–186.

Pinho, R., C., Miller, R., P. and Alafia, S., S. (2012). *Agroforestry and the improvement of soil fertility: a view from Amazonia*. Apple Environ Soil Sci. https://doi.org/10.1155/2012/ 616383

Rahmeto, N., (2007). *Determinants of adoption of improved haricot bean production package in Alaba Special Wored*a, Southern Ethiopia. An M. Sc Thesis, Haramaya University, Ethiopia.

Rosati, A., Borek, R., and Canali, S. (2021). Agroforestry and organic agriculture. *Agrofor Syst* 95(5):805–821. https://doi.org/10.1007/s10457-020-00559-6.

Sood, K., K and Mitchell, C., P. (2004). Do Socio-psychological factors matter in agroforestry planning? Lessons from smallholder traditional agroforestry systems. *Small-scale Forest Economics, Management and Policy*. 3(2):239-255.

Taruvinga, A., Kambanje, A., Mushunje, A. and Mukarumbwa, P. (2022). Determinants of livestock species ownership at household level: evidence from rural OR Tambo District Municipality, South Africa. *Pastoralism* 12(1):1–11. https://doi.org/10.1186/s13570-021-00220-6.

Tega, M. and Bojago, E. (2024). Determinants of smallholder farmers' adoption of agroforestry practices: Sodo Zuriya District, southern Ethiopia. *Agroforestry Systems*, *98*(1), 1- 20.

Tesfaye, A. (2005). *Diversity in home garden agroforestry systems of southern Ethiopia.* Ph.D Thesis. Wageningen University and Research Center. The Netherlands. 2005; 143.

Tesfaye, M. and Melaku, T. (2017). Determinants of adoption of improved highland forage type: evidence from Dendi District, West Shoa Zone, Ethiopia. *Journal of Experimental Agriculture International*, *15*(1), pp.1-8.

The Global Risks Report (2022). The_Global_Risks_Report_2022. Retrieved September 25, 2022, from https://www3.weforum.org/docs/WEF_ The_Global_Risks_ Report_2022.pdf.

Thornton, P., K. (2010). Livestock production: recent trends, future prospects. *Philos Trans R Soc B Biol Sci* 365(1554):2853–2867. https://doi.org/10.1098/rstb.2010. 0134.

Turner, D.M., (2016). *Knowledge Management Strategies: A Success Framework for the Changing Age Demographic of the United States Federal Workforce*. University of

Maryland University College.

Urgessa Waktola, T. and Fekadu, K., (2021). Adoption of coffee shade agroforestry technology and shade tree management in gobu seyo district, east Wollega, Oromia. *Advances in Agriculture*, *2021*(1), p.8574214.

Yasin, A., Ashine, T. and Asfaw, Z. (2022). Woody Species Diversity and Farmers' Preference of Parkland Agroforestry System in Benishangul Gumuz, Western Ethiopia. *Int J Plant Biol Res* 10(1): 1131.

Zebene, A. (2003). *Tree species diversity, topsoil condition and arbuscular mycorrhizal association in the Sidama traditional agroforestry land use, Southern Ethiopia*. PhD Thesis. Department of Forest Management and Products, SLU. Acta Universitatis Agriculture Sueciae, Silverstria. p. 263.

Zemedu, L., Abiy, S. and Nigussie, A., (2024). Contribution of Youth in Rural Household's Livelihood in Central Ethiopia. *Results of Agricultural Economics Research*.