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Original Article

Impact of Agroforestry Adoption among Smallholder Farmers' Households in Zambia: An Expenditure Approach

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ABSTRACT

The environmental, economic, and social effects of climate change are expected to be profound for smallholder farmers, especially in developing countries like Zambia, whose way of life is largely dependent on the natural world. Many underdeveloped countries are finally realizing that agroforestry and other climate-smart farming practices offer solutions to current climate change-related issues. Tree plants are incorporated into farming systems through agroforestry technologies, which provide farmers with fruits and vegetables as well as animal and vegetable fodder, lessen soil erosion, and restore soil fertility. This study looked at how the implementation of agroforestry affected household expenditures and yields of crops among smallholder farmers in Zambia's Nyimba area. The variables motivating smallholder farmers in the research area to embrace agroforestry were also investigated. Data was collected from July to August of 2022 from 325 randomly selected smallholder farmers' households in four villages in the Nyimba district of Zambia. This study utilized a binary logistic regression model to identify the variables affecting smallholder farmers' adoption of agroforestry. The results revealed that smallholder farmers' household head education level, access to extension services, household size, access to credit, farming experience, farmland size, and distance to the nearest market had an influence on agroforestry adoption. The effects of agroforestry adoption on smallholder farmers' household expenditures and crop production were assessed using propensity score matching. The results revealed that smallholder farmers' household adopters had 1,929.040 kilograms of crop yield (*Zea mays L.*) higher than non-adopters by 817.43 kilograms. Household expenditure for smallholder farmers adopters was ZMW 8,873.47 higher than non-adopters by ZMW 5,617.91 in the study area. Based on the findings, agroforestry should be implemented by smallholder farmer households throughout time to enhance household well-being. The study concluded that initiatives should be coordinated to spread awareness of agroforestry choices and remove obstacles to adoption among smallholder farmers.

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INTRODUCTION

Zambia is a developing country that heavily relies on agriculture to support household incomes, particularly those of smallholder farmers. Smallholder farmers experience economic, ecological, and/or climatic difficulties that are related to the production of their agricultural crops and livestock (Branca *et al.,* 2019). As a result, these farmers produce their crops and livestock with low throughput, poor yields, and low income (Sileshi *et al*., 2014; Williams *et al.,* 2015; Garrett *et al.,* 2021). Agroforestry continues to be developed, promoted, and used by smallholder farmers as one of the sustainable agricultural practices to address the aforementioned problems (FAO, 2018; Santoro *et al*., 2020). According to Walter *et al*. (2015), FAO (2018), Chavula (2022), and Franzel *et al.* (n.d.), the implementation of agroforestry practices will improve household food security and income while reducing the consequences of climate change. Agroforestry promotion has been made one of the most crucial elements of agriculture extension and advisory rural service delivery by the Zambian government and non-governmental organizations as a result of its significance (Amadu *et al*., 2020; Miller *et al*., 2020, 2021).

Agroforestry's impact on smallholder farmers' livelihoods has been the subject of various research in Zambia (Ajayi *et al*., 2006; Katanga *et al.*, 2007; Jacobson *et al*., 2020). The majority of these research (Jama *et al.,* 2019; Nkhuwa *et al*., 2020) have concentrated on the impacts of agroforestry adoption on smallholder farmers' household income as a measure of adopters' household welfare. Nkhuwa *et al.* (2020) revealed that adopting improved fallows and green leaf manure agroforestry practices significantly increased the household income of smallholder farmers. According to Jama *et al.* (2019), smallholder cotton growers in Zambia who adopted agroforestry practices saw an increase in household income. An income-based measure of welfare has several restrictions, despite the fact that income is often regarded as a sufficient indication of household welfare (Praag & Frijters, 1999; Khor & Pencavel, 2008). For instance, using income as a welfare indicator may be misleading because some respondents may understate their household's income in order to obtain financial assistance (Attanasio *et al*., 2002; Curley, 2005; Dabla-Norris & Kochhar, n.d.). Additionally, income-based well-being indicators (Ringen, 1988; Ravallion & Lokshin, 1999; Attanasio *et al.,* 2002) only take into account current income and ignore wealth (such as savings or other liquid assets). The indicator also does not account for poverty-related inequality; it does not account for inequalities in consumption brought on by variations in credit availability among families (Cutler and Katz, 2012; Attanasio &

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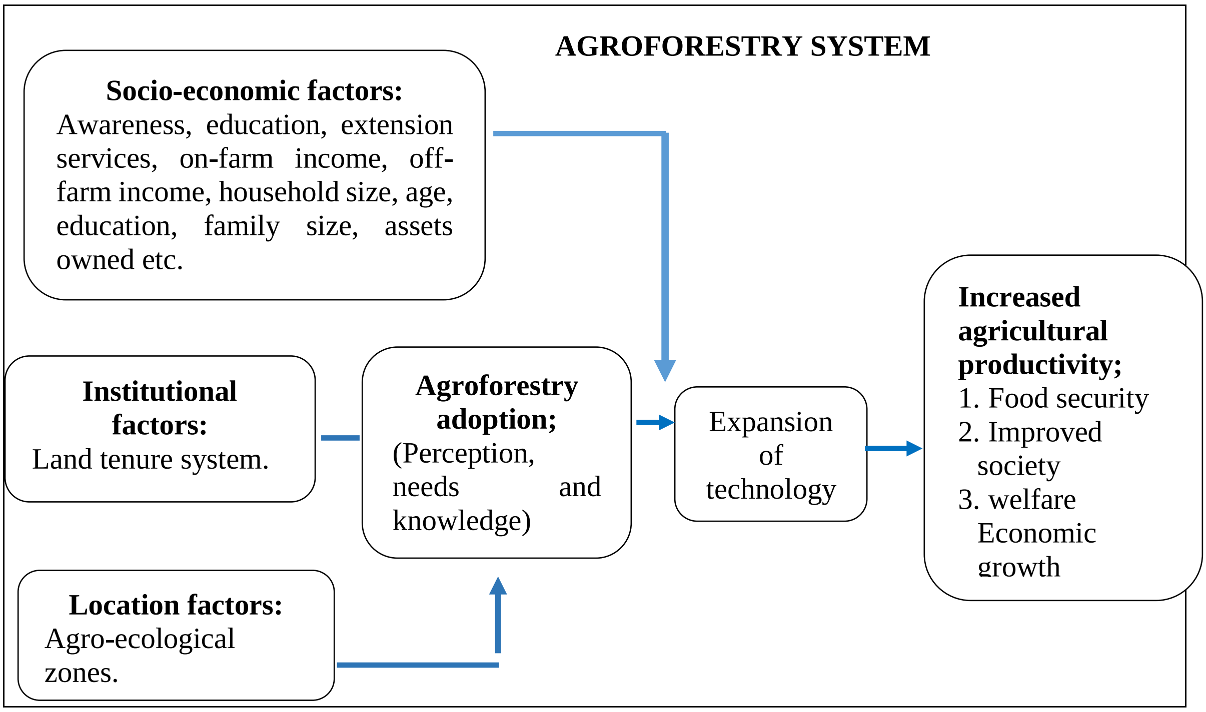
Pistaferri, 2016). The expenditure approach seems to be a reliable and comprehensive option among measurements of smallholder farmers' household welfare. Expenditure is a more direct indicator of quantifiable well-being, less subject to under-reporting bias, and more informative (Johnson *et al.*, 1993; Bruce *et al.*, 2003; Amendment, 2006). The effectiveness of new technology, changes in poverty, and household expenditures over time (such as short-, mid-, and long-term expenses) are all evaluated by expenditure (Bruce *et al*., 2003).

In Zambia, it appears as though there is little information on expenditure as a stand-in for well-being measures as an indicator among smallholder farmer households who utilize agroforestry and those who don't. As a result, this study used crop productivity as a welfare indicator and an expenditure technique to estimate the effects of agroforestry adoption among smallholder farmers in Zambia's Nyimba district.

CONCEPTUAL FRAMEWORK

Smallholder farmers' decisions to adopt sustainable agriculture practices, such as agroforestry, to mitigate the negative effects of climatic variability and change are influenced by a variety of factors, both directly and indirectly (Islam *et al.*, 2016, Kabwe *et al.*, 2016, Tiwari *et al.*, 2018, Jha *et al.*, 2021). However, by providing insight into the interactions between institutional, socioeconomic, and agro-ecological shocks, agroforestry practices can help adjust other practices to adapt to climate change and climate variability (UN DESA, 2012; Ranganathan, 2013; Ackerman *et al.*, 2014; Chavula, 2022). A variety of institutional factors (such as extension service, market distance, access to credit, and social group membership) and socio-economic factors (such as asset ownership, on- and off-farm income, gender, farming experience, and education level), and agro-ecological factors influence smallholder farmers' households to adopt agroforestry practices (Green *et al.*, 2005; Tiwari *et al.*, 2011; Eisler *et al.*, 2014). These factors have a significant impact on the adoption of agroforestry, which in turn affects the crop productivity and annual expenditure of smallholder farmer households. Regarding the welfare impact on smallholder farmers that embrace agroforestry, the elements have both an inverse and a direct link. However, as shown in *Figure 1*, the conceptual framework of this study is based on the idea that smallholder farmers' decisions to adopt agroforestry practices are influenced by a variety of factors.

Figure 1: Conceptual framework of the study.



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THEORETICAL FRAMEWORK

Theoretical Framework for Adoption of Agroforestry

A new technology can be viewed in one of two ways: either as an increase in the adopter's physical results or as an enhancement in their level of contentment. In order to compare the utility of non-adopters (the status quo) and adopters (the new state), utility theory based on production choice was utilized as the theoretical foundation for the adoption decision of the smallholder farmers' households in agroforestry practices. Although the utility is predicated on income, it also considers other aspects that have an impact on the farmer's household, such as socioeconomic, demographic, and institutional characteristics. Although profit is used to buy items and services that increase the firm's utility, the producer's goal is maximization.

Therefore, the utility function for the two states is as follows:

Utility for the status quo would be:

$$U_{oj} = u(Y_j, Z_j, q^o \varepsilon_{0j})$$

In addition, the utility for the final state would be:

$$U_{1j} = u(Y_j, Z_j q^1 \varepsilon_{1j})$$

Based on this model, respondent j adopts agroforestry practices if the utility of the adoption of agroforestry technology exceeds the utility of the status quo.

$$U_{1j}(Y_j, Z_j, q^1 \varepsilon_{1j}) > U_0(Y_j, Z_j, q^0, \varepsilon_{0j})$$

Where U_0 denotes the utility function from the status quo, U_1 denotes the utility from agroforestry adoption. Moreover, Y factors influencing adoption, q^0 and q^1 are the alternative levels of the good indexes with and without agroforestry practices, respectively, (with $q^1>q^0$, indicating that q^1 refers to the improved total output of the farmer after practicing), Z_j is a vector of individual characteristics.

Assuming that smallholder farmers maximize utility, the decision by the farmers' household j to adopt agroforestry practices (AFPs=1) or non-adoption of agroforestry practices (AFPs=0) is based on a comparison of expected utilities of both situations. Using the difference in expected utilities gives the following decision rule:

$$AFPs = \begin{cases} 1, \ andif \ E\left[U_j^i - U_j^0 \middle| Z_j\right] > 0 \\ 0, \ andif \ E\left[U_j^1 - U_j^0 \middle| Z_j\right] \leq 0 \end{cases}$$

Where E is the expectation operator, U_1 and U_0 are the same as mentioned above. Smallholder farmers' households differ in the way they form expectations on the utility levels of both choices. The vector Z_j accounts for the variables that are assumed to have an impact on the utilities of both choices and the way expectations are formed on these utilities.

The probability that farmer *i* will choose AF practice *j* among the set of AF practices *k* could be defined as follows:

$$Pr[i|AF] = Pr\left[U_j > U_k\right], \forall_j \in AF$$

$$= Pr\left[(V_j + \varepsilon_j) > (V_k + \ \varepsilon_k)\right]$$

$$= Pr\left[(V_j - V_k) > \mu\right]$$

Where AFPs are the complete choice set of available AF practices. To estimate the equation, assumptions must be made over the distributions of the error terms in the model. A typical assumption is that the errors are independently and identically distributed.

MATERIAL AND METHODS

Study Map and Description

Nyimba District is located in Zambia's Eastern Province, 334 kilometers from Lusaka, the country's capital. Its three main components are a fertile agricultural region bordered by rocky hills in the center, a deforested plateau bordering Mozambique in the south, and woodland that descends into the Luangwa Valley in the north. The district lies between latitude (13°30'1019" and 14⁰55'81426" South) and longitude (30° 48'5047" and 31⁰48'20252"East).

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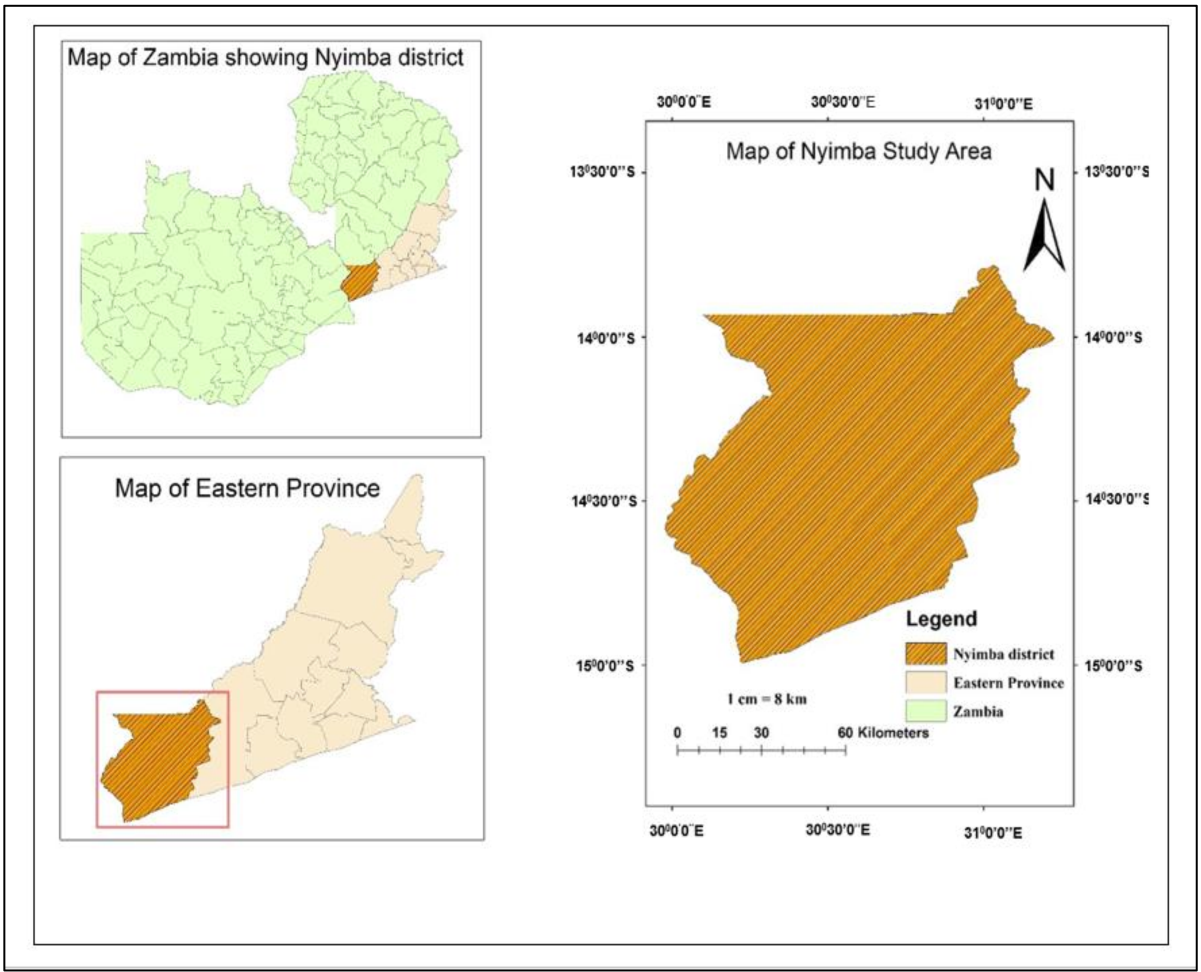
Figure 2: Map of the study area.



Source: Author's sketch using Arc GIS

Climate, Soil and Topography

There are three (3) agroecological zones in Zambia: Zone I, Zone II (IIa and IIb), and Zone III. Nyimba district is situated in Zone I of these zones. It penetrates parts of the Western and Southern provinces of Zambia in the south. The Zambezi and Luangwa River basins' Southern and Eastern rift valleys are located in agroecological zone I. The district experiences an average annual rainfall of 600 to 900 millimeters, with December to February being the wettest month and May to November being the driest. The daily temperature range is 10.3°C to 36.5°C, while the yearly mean temperature is 24.2°C. The district is composed of hills and plateaus with *Lithosol*-*Cambisol* soil types, while valleys have *Fluvisol*-*Vertisol* soil types, owing to its geography. The altitudes of the district's plateau in the middle, the mountain tops in the western part, and the valley floor of the Luangwa River are all between 450 and 1000 metres.

Land Use and Farming Systems

According to the population and housing census of 2010, the total land area of the Nyimba district is roughly 10,500 square kilometers. As a result, 82% of the district's population is rural, with an average household income. The majority of these rural households have mixed agriculture, with a focus on local practices. Smallholder farmers in the district, on the other hand, practice shifting agriculture and/or traditional agriculture practices. The main crops cultivated are banana *(Musa spp*.), haricot bean (*Phaseolus vulgaris*), cowpea (*Vigna unguiculata spp*.), finger millet (*Eleusine coracana*), peanut (*Arachis hypogaea*), and soybean (*Glycine max*). The agricultural households are typically located on gently to moderately steep slopes, which frequently

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encourages the employment of a multiple cropping method. The agricultural or agriculture pattern of the district differs from that of other districts due to the geography of the location. Smallholder farmers raise animals, goats, chicks, ducks, and doves in addition to crops. For household financial gain, smallholder farmer households also produce charcoal, lumber, and, collect firewood and non-timber forest products (NTFPs) from the miombo woodland in addition to agricultural activities.

Study Site Selection

Prior to collecting data from smallholder farmer households, a reconnaissance survey was conducted to acquire basic information about the research area. Distances between villages, the number of farming households in each village, contact information for lead farmers, agroforestry practice adopters' households, and farmland location.

Sample Size and Sampling Techniques

A multistage random selection method was used to choose the smallholder farmers' households for this study. This survey also included smallholder farmer households from agricultural camps. An agricultural camp is described by the Ministry of Agriculture of the Republic of Zambia as a stretch of land spanning communities that accommodates a set number of smallholder farmer households for easy access by agriculture extension employees. The study considered eight (8) agricultural camps, from the eight (8) agricultural camps in Nyimba District, four (4) agricultural camps were randomly selected (*i.e.*, Ndake, Central camp, Lwende, and Ofumaya). In the selected four (4) agricultural camps in Nyimba District, there are a total of 10,700 farmers. The sample size was calculated using Slovin's formula in the study. Furthermore, three (3) villages (Sikwenda, Sichipale, Mawanda, Elina, Katumbila, Sichalika, Malalo, Mwenecisango, Mulivi, Lengwe, Mofu, and Yona) were chosen at random from each camp. The study first determined a sample size of 386 people with a margin of error of 0.05. Considering such a small sample required a greater number of resources and time, the study used a margin of error of 0.1 and obtained a sample size of 99, as shown below.

Sample size formula: Slovin's (1960) formula.

$$n = \frac{N}{1+Ne^2}$$

$$n = 10700/(1 + 10700(0.1^2) = 99.07 = 99$$

The study picked a sample size of 325 participants to avoid oversampling, which falls between 99 (with a 0.1 margin of error) and 386 (with a 0.05 margin of error). Farmers' records from each village were used to generate a random selection of participants in an Excel spreadsheet with the assistance of agricultural camp officers.

Data Collection Techniques

The study collected data from the households of smallholder farmers by administering questionnaires with closed and open-ended questions. The questionnaires were pre-tested ten (10) times for appropriateness (e.g., clarity, adequacy, and question sequence) before being used in the household research, and then altered based on the results. Pretesting was done on smallholder farmer households that were not participating in the actual survey. The principal researcher trained and supervised seven (7) enumerators who collected household data from smallholder farmers. The data collected was reviewed, cleaned, and updated after each fieldwork day prior to being saved on the CSPRO temporal Cloud.

Data Analysis

Data from the household survey were analyzed using STATA 15MP to establish the characteristics of smallholder farmers' households. Mean, frequency, standard deviation, and percentage were determined as descriptive statistics. Propensity score matching was used to examine the impacts of agroforestry practices adoption on household adopters and non-adopters' annual expenditure and crop productivity among smallholder farmers. The study also used principal component analysis to estimate the household resilience of smallholder farmers in the study area to climate change shocks and hazards.

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Propensity Score Matching

In this study, the propensity score matching (PSM) method was used to compare the influence of agroforestry adoption on crop productivity (yield) and household expenditure among adopters and non-adopters. Estimation of the propensity scores used a binary logit model, choosing a matching algorithm, checking on common support condition and testing the matching quality of the treatment and/or participants (smallholder farmers' households).

Model Specification

The Logit model was chosen for this study because of the consistency of parameter estimation linked with the assumption that the error factor in the equation has a logistic distribution. As a result, the logit model is used to evaluate the probability of smallholder farmers adopting agroforestry practices based on socioeconomic, agroecological, and institutional factors. A dependent variable was assigned a value of 1 for agroforestry practice adopters and 0 for non-adopters.

$$P_i = P(Y = 1|X) \qquad (1)$$

In line with Pindyck and Rubinfeld (1981), the cumulative logistic probability function is specified as follows;

$$P_i = F(Z_i) = F[a + \sum_{i=1}^{m} \beta_i X_i] = \left[\frac{1}{1+e^{-(a+\sum \beta_i X_i}}\right] \qquad (2)$$

Where e represents the base of natural logs, X_i represents the i^{th} explanatory variable, P_i the probability that a household adopted agroforestry practices, α and β_i are parameters to be estimated.

The interpretation of coefficients is simplified when the logistic model is expressed in terms of odds and log of odds. The odds ratio implies the ratio of the probability that an individual will be a participant (P_i) to the probability that he/she will not be a participant (1-P_i). The probability that he/she will not be a participant is defined by:

$$(1 - P_i) = \frac{1}{1+ e^{zi}} \qquad (3)$$

$$\left(\frac{P_i}{1+ P_i}\right) = \left[\frac{1+e^{zi}}{1+ e^{-zi}}\right] = e^{zi} \qquad (4)$$

Alternatively,

$$\left(\frac{P_i}{1+ P_i}\right) = \left[\frac{1+e^{zi}}{1+e^{-zi}}\right] = e^{[a+ \sum B_i X_i]} \qquad (5)$$

Taking the natural logarithms of equation (5) will give the logit model as indicated below.

$$Z_i = ln\left(\frac{P_i}{1-P_i}\right) = a + B_1 X_{1i} + B_2 X_{2i} + \cdots B_m X_{mi} \qquad (6)$$

If consider a disturbance term, μ_i, the logit model becomes

$$Z_i = a + \sum_{t=1}^{m} B_t X_{ti} + \mu_i$$

So, the binary logit will become:

$$Pr(pp) = f(X) \qquad (7)$$

Where *pp* is the adoption of agroforestry practices, *f(X)* is the dependent variable intervention participation, and *X* is a vector of observable household covariates. The dependent variable will be set to 1 for those who have adopted agroforestry and 0 for those who have not.

RESULTS AND DISCUSSION

Demographic Characteristics of Smallholder Farmers

The household survey comprised 325 smallholder farmer households chosen at random from the study area. Smallholder farmer households were interviewed about crop productivity, climate change perception, and the implementation of agroforestry practices. The study presents the findings of the household survey, beginning with the demographic characteristics of the participants' *Table 1*, crop production and productivity, cropping methods, CSA adoption, factors influencing agroforestry adoption, smallholder farmers' resilience to climate change, and the effects of agroforestry adoption on household expenditure.

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In accordance with the findings in *Table 1*, the mean age of the selected smallholder farmers was 42.21 years, with a standard deviation of 12.45. The majority of households (76.31%) were headed by males, and 57.85% (188) practiced agroforestry. The mean number of years of farming experience was 9.42, with a standard deviation of 7.99. The mean cultivated land area was determined to be 2.16 hectares, with a standard deviation of 2.58. In terms of farm size, the mean was 3.67 hectares, with a standard variation of 4.55. The average household size was 6.6 people, with a standard deviation of 3.04. The mean total annual expenditure was found to be ZMW 7,218.40 (USD 378.92) (K19.05 per 1 USD), and 12300.17 as the standard deviation. From the sampled smallholder farmer households 57.54% reported to own assorted livestock on their farms. Whilst 16.92% of the smallholder farmer households reported to access credit and 52.62% reported to access rural agriculture extension services. The land tenure system was entirely based on customary land (100%). The mean distance to the food market was 24.69 kilometers, with a standard deviation of 17.64 kilometers.

Table 1: Demographic characteristics of smallholder farmers

Variable	Mean	Standard Deviation
Agroforestry adoption	(Yes= 188) 57.85%	
Age household head	42.21	12.44906
Gender household head	(Male= 248) 76.31%	
Farming experience	9.42	7.993649
Cultivated land	2.16	2.575961
Farm size	3.67	4.548267
Household size	6.6	3.040874
Maize productivity	1658.66	2470.031
Annual expenditure	7218.40	12300.17
Livestock ownership	(Yes=187) 57.54 %	
Access to credit	(Yes= 55) 16.92 %	
Access to extension	(Yes=171) 52.62 %	
Distance to market	24.69	17.63977

Table 2: Demographic characteristics of agroforestry adopters and non-adopters

	Adopters		Non-adopters	
Variable	**Mean**	**Std.**	**Mean**	**Std.**
AF	(Yes= 188) 57.84%	13.06212	(No=137)42.16%	11.44569
Age HH	43.26	8.543211	40.77	6.902879
GenderHH	(Male= 143) 76.06%	3.119706	(Male= 105) 76.64%	1.391216
Farm. exp.	10.55	5.342544	7.86	2.89146
Cult. land	2.55	3.035024	1.63	3.058451
Farm size	4.39	2904.839	2.69	1540.846
Househ. size	6.65	15322.48	6.53	3181.578
Maize prod.	2071.26		1092.45	
Annual Exp.	10113.89		3245.02	
Livestck ow.	(Yes= 115) 61.17 %	17.06372	(Yes= 72) 52.55%	18.40272
Access to cre.	(Yes= 55) 16.92 %		(Yes= 17) 12.41%	
Acc ext.	(Yes= 38) 20.21 %		(Yes= 89) 64.96%	
Dist. market	25.52		23.55	

Source: Computed from survey data 2022, using STATA 15SE

Regarding cropping methods, the study observed that crop rotation was the most commonly used in the study region, as reported by 290 households (89.23% *Table 3*), followed by intercropping (69.23%) and multiple cropping (170 (52.31%). Smallholder farmer households reported 150 (46.15%), 124 (38.15%), and 103 (31.69%) cover cropping.

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Table 3: Cropping methods in the study area

Method	Freq.	Percentage
Monocropping	150	46.15%
Intercropping	225	69.23%
Crop rotation	290	89.23%
Strip cropping	103	31.69%
Cover cropping	124	38.15%
Multiple cropping	170	52.31%

From the results obtained, conservation farming basin was reported by 234 (72.00%), followed by agroforestry alley cropping reported by 188 (57.85%), conservation farming ripping implemented by 150 (46.15%) households. Conventional agriculture was reported by 137 (42.15%) households and integrated nutrient management by 137 (40.30%) *Table 4*. The results from the analysis clearly indicates the willingness of smallholder farmers in adoption and/or implementation of climate-smart agricultural practices in the study area.

Table 4: Improved agricultural practices adopted by smallholder farmers

Practice	Freq.	Percentage
AF Improved fallows	97	29.84%
Biomass transfer	56	17.23%
Alley cropping	188	57.85%
Organic farming	73	22.46%
Integrated nutrient management	131	40.30%
CF Ripping	150	46.15%
CF Basin	234	72.00%
Conventional agriculture	137	42.15%

Concerning the crops produced in the study area, maize was the most produced crop by 325 (100%) of the study area's smallholder farmers' households, followed by pumpkins 167 (51.38%), and soya beans 165 (50.77%), *Table 5*. Groundnuts were produced by 123 households (37.85%), cowpeas by 107 (32.92%), and sunflower by 103 (31.69%). According to the findings, smallholder farmers' households produced largely non-cash crops for household consumption, with excess sold to markets or the communities nearby.

Table 5: Crops grown by smallholder farmers

Type	Freq.	Percentage
Maize	325	100.00%
Sunflower	103	31.69%
Groundnuts	123	37.85%
Cotton	51	15.69%
Soya bean	165	50.77%
Cowpeas	107	32.92%
Pumpkins	167	51.38%
Millet	11	0.38%
Sorghum	23	7.07%

Factors Affecting Agroforestry Adoption among Smallholder Farmers

The logistic model was used in the study to assess the likelihood that the sampled smallholder farmer families will adopt agroforestry practices in the study area using the hypothesized independent variables. Agroforestry adoption was utilized as a dummy dependent variable in a logistic regression model, with 11 explanatory variables (4 dummy, 1 categorical, and 6 continuous). The study

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discovered that the education level of the household head positively influenced the adoption of agroforestry practices in the study area, with a p-value of 0.076 ($p<0.1$). According to Gebru *et al*. (2019), gender, family size, educational level, and farm size (landholding) significantly ($p<0.05$) influence farmers' households' role in agroforestry adoption practices in the study logistic regression model analysis. With a 0.004 p-value ($p<0.01$), access to extension services had a negative impact on agroforestry adoption. A comparable study by Jara-Rojas *et al*. (2020) discovered that access to and use of financing, location, and the livestock system implemented all influenced the decision to embrace agroforestry. The household size of smallholder farmers positively influenced the adoption of agroforestry practices, with a p-value of 0.063 ($p<0.1$). Pello *et al*. (1936) also found that farm size, frequency of extension services, off-farm income, access to training, access to credit, access to transport facilities, group membership, access to market, gender, distance to nearest trading centre, and household education level all had a major impact on agroforestry adoption.

Access to credit was found to have a favourable impact on agroforestry practice uptake at a p-value of 0.068 ($p<0.1$). According to Zerihun (2020), factors that influence the adoption of agroforestry innovations in the study area include increased availability of extension services, access to credit, access to extension, information sharing among farmers, trust in local institutions, active participation in social groups and organizations, and prior exposure to agricultural technologies. The farming experience of smallholder farmer households also had a significant influence on the adoption of agroforestry practices with a p-value of 0.082 ($p<0.1$). According to the findings of a similar study conducted by Nkamleu and Manyong (2005), farmer gender, household size, education level, experience, association membership, contact with research and extension, security of land tenure, agro-ecological zone, distance from nearest town, and livestock income, all influenced agroforestry adoption.

Farm size and/or landholding significantly influenced the adoption of agroforestry practices in the research area, with a 0.046 p-value ($p<0.1$). According to the findings of the Dhakal *et al.* (2015) study, farm size, irrigation water availability, household head education, agricultural labour force, frequency of extension worker visits, cost of farm input, household experience with agroforestry, and distance from home to government forest are all important factors to consider. The study also found that distance to food markets has a negative impact on smallholder farmers' households' adoption of agroforestry practices, with a p-value of 0.011 ($p<0.1$). Mesike and Okwu-Abolo (2022) discovered that characteristics such as farmers' average distance from rubber fields and markets, as well as off-farm income, had a negative impact on the adoption of rubber agroforestry practices at the 1% ($p<0.001$) and 10% ($p<0.1$) levels.

Impacts of Agroforestry on Smallholder Farmers’ Household Annual Expenditure and Maize Productivity

Distribution of propensity scores

Propensity score matching pairs each agroforestry adopter with non-agroforestry practise non-adopters based on an identical common distinguishing attribute. The distribution helps to identify the influence of agroforestry adoption on household welfare based on mean annual expenditure and yield of staple crops (*Zea mays L.*). The distribution of propensity scores and common support locations among adopters and non-adopters is depicted in *Figure 3*. The lower half of the histogram depicts the propensity score distribution of agroforestry practices among non-adopters, whereas the upper half depicts the propensity score distribution of agroforestry practices among adopter households. The green (treated on support) and red (untreated on support) colours indicate observations in the adopters' and non-adopters’ groups that have a suitable comparison, respectively, whereas the orange (treated off support) and blue (untreated off

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support) colours indicate observations in the adopters' and non-adopters' groups that do not have a suitable comparison, respectively. The frequency of the propensity score distribution is indicated by the x-axis.

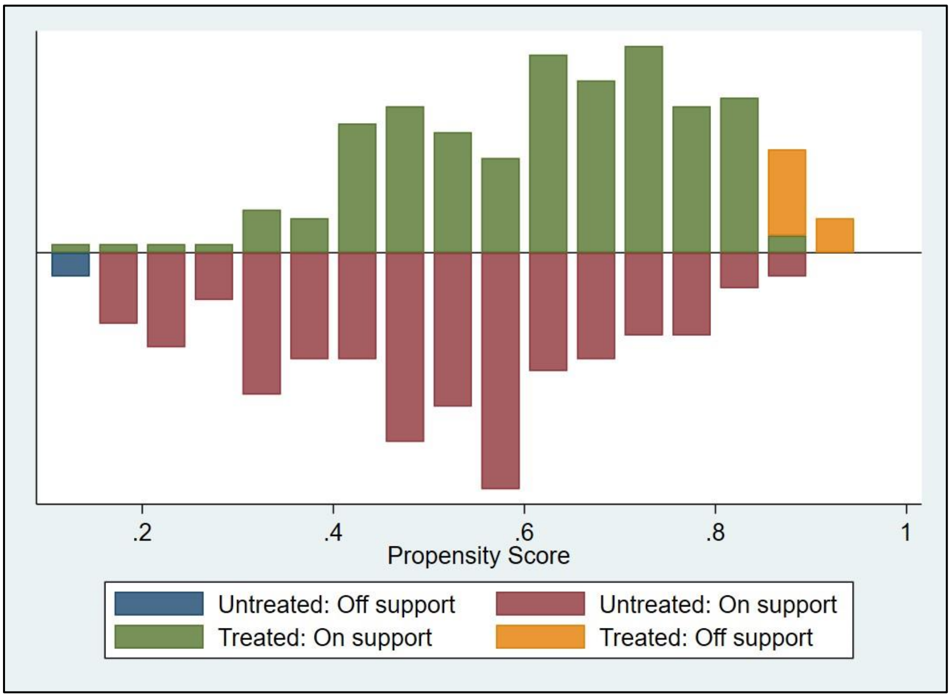
Table 6: Factors Affecting Agroforestry Adoption

Logistic regression
Number of Obs = 325, LR chi2(12) = 47.30, Prob > chi2 = 0.0000, Log likelihood = -197.60337, Pseudo R2 = 0.1069

AF		Odds Ratio	Std. Err.	z	P>|z|	[95% Conf. Interval]	
GenderHH		.9662171	.2802581	-0.12	0.906	.5472398	1.705972
Education	2	.6908965	.215857	-1.18	0.237	3745173	1.274542
	3.	.5388902*	.1876261	-1.78	0.076	.2723557	1.066263
Access_ext		-.4729356**	.1222191	-2.90	0.004	.2849896	.7848289
Household_size		1.001873*	.0406388	1.05	0.063	.9253064	1.084775
Accesstocredit		1.871779*	.6433142	1.82	0.068	.9543421	3.671176
Lnfarming_exp		1.366785*	.245395	1.74	0.082	.9613337	1.94324
Lnfarm_size		1.493472*	.2997475	2.00	0.046	1.007758	2.213286
Lnculti_land		1.140677	.2568831	0.58	0.559	.7336181	1.773598
Lndistance		-1.509655*	.2441586	2.55	0.011	1.099541	2.072734
Livestockown		1.038615	.2789301	0.14	0.888	.613559	1.758138
LnageHH		.9323438	.4188892	-0.16	0.876	.3864942	2.249102
_cons		.3687925	.6066747	-0.61	0.544	.0146734	9.269024

Source: Computed from own survey data 2022, using STATA 15SE.

Figure 3: Distribution of propensity scores



Source: Computed from own survey data, 2022.

Identifying Common Support region

The estimated values of propensity scores for the sampled households range from 0.1031488 to 0.9432406 with a mean score of 0.5784615 *Table 7*. The propensity scores for smallholder farmer households to adopt agroforestry range from 0.145249 to 0.9432406 with a mean score of 0.6362691. Similarly, the non-adopter propensity scores for smallholder farmer households vary from 0.1031488 to 0.8601569, with a mean score of 0.4991344 (*Table 7*). Matching smallholder farmer households' non-adopters with adopters of

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agroforestry practices was done based on anticipated propensity scores to find the common support region. The primary criterion for establishing the common support region is to eliminate all observations whose propensity score is less than the minimum propensity score of an intervention for non-adopters and more than the maximum of adopters.

The overlap region or common support region for both the control (non-adopters) and treated (adopters) groups was found to be between 0.145249 and 0.8601569. The region of common support/overlap indicates that the two comparison groups can be matched. This means that observations with propensity scores ranging from 0.145249 to 0.8601569 were excluded from the impact analysis. As a result, 17 observations (15 from adopters and 2 from non-adopters) were excluded from the impact analysis, and 325 sampled households were identified throughout the impact assessment approach.

Table 7: Distribution of estimated propensity scores for sample households

Group	Obs	Mean	Std. dev.	Min	Max	Cast off
Adopters	188	.6362691	.1649606	.145249	.9432406	15
Non-adopters	137	.4991344	.1792387	.1031488	.8601569	2
Total households	325	.5784615	.1838226	.1031488	.9432406	17

Source: Computed from survey data, 2022

Choosing the Best Matching Algorithm

To determine the shared support zone between adopters and non-adopter's smallholder farmer households, four matching methods (nearest neighbour matching, radius calliper matching, calliper matching, and kernel bandwidth matching) were utilized. After matching, an equal mean test recommends a matching estimator that balances all explanatory factors (resulting in insignificant mean differences between the treated 'adopters' and control groups 'non-adopters'). Second, the pseudo-R^2 value shown in the logistic model shows the significance of the independent variable or covariate of the study; the high value indicates high significance and the small value indicates low significance. Hence, considering the pseudo-R^2 value (*Table 8*), the smallest value is preferable because a low value shows small signs of covariates between non agroforestry adopters and adopters. The third is a matching estimator in which the average treatment effects on the treated (ATT) result with the largest number of matched sample sizes is preferred. The fourth insignificant likelihood ratio test is preferred. The implication is a matching estimator that balances all explanatory variables, the lowest pseudo-R^2 value, and produces a large matched sample size, and an insignificant LR chi-square is preferable. Therefore, among the matching algorithm techniques, radius caliper matching with a bandwidth of 0.1 was used to estimate the ATT.

Table 8: Comparisons of total annual expenditure and maize productivity

Performance Criteria	Matching Algorithm	Pseudo R^2	Matched sample size	Balancing test	β*
Radius Caliper	0.01	0.012	295	30	26.0*
	0.1	**0.005**	**308**	**17**	**16.9***
	0.25	0.019	308	17	33.1*
Caliper	0.01	0.026	295	30	38.3*
	0.1	0.026	308	17	38.5*
	0.25	0.026	308	17	38.5*
Nearest Neighbor	1	0.027	325	0	38.8*
	2	0.022	325	0	35.2*
	3	0.029	325	0	40.3*
Kernel Bandwidth	0.01	0.013	295	30	26.9*
	0.1	0.006	308	17	17.5*
	0.25	0.010	308	17	23.5*

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Matching Quality

After selecting the best-performing matching algorithm with a radius calliper of 0.1, the following step was to ensure that the propensity score and variables were balanced. The mean absolute standardised bias technique proposed by Rosenbaum and Rubin (1983), in which the standardised difference must be less than 20% to demonstrate success in the matching procedure, is the most commonly used criterion for balancing the test. The main purpose is to see if there are any changes in the propensity score of non-adopters and adopters before and after matching conditioning.

As shown in *Table 9*, the t-value revealed that 11 variables were statistically significant before matching but became statistically insignificant after matching. Furthermore, the findings demonstrated that the mean standardised bias for all covariates prior to matching was higher, ranging from 0.4% to 44.6% in absolute value. However, following matching, the mean standardised bias for all covariates dropped and ranged from 0.6% to 7.1% in absolute value, which is less than the 20% indicated by Rosenbaum and Rubin (1983). This suggests that the matching method has a good matching quality. As a result, the covariates in the treatment and control groups were highly balanced and fit to be employed in the ATT estimation.

Table 9: Balancing test for covariates

	Before matching				After matching			
Variables	**Treated**	**Control**	**%bias**	**t-test**	**Treated**	**Control**	**%bias**	**t-test**
GenderHH	.76064	.76642	-1.4	-0.12	.76301	.79404	-7.3	-0.69
Education	.51596	.47445	8.3	0.74	.53179	.52719	0.9	0.09
Education	.21277	.32117	-24.6	-2.21	.21965	.25071	-7.1	-0.68
Access_ext	.43617	.64964	-43.7	-3.88	.47399	.48286	-1.8	-0.16
Household_size	6.6543	6.5255	4.2	0.38	6.6127	6.7262	-3.7	-0.36
Accesstocredit	.20213	.12409	21.2	1.86	.17919	.16619	3.5	0.32
Lnfarming_exp	2.0212	1.714	35.6	3.17	1.9877	1.981	0.8	0.07
Lnfarm_size	1.079	.63883	52.7	4.66	.96549	.91582	5.9	0.60
Lnculti_land	57578	.22952	44.6	3.93	.48627	.46404	2.9	0.28
Lndistance	3.0225	2.8016	27.4	2.50	2.9891	3.032	-5.3	-0.51
Livestockown	.6117	.52555	17.4	1.55	.60116	.57254	5.8	0.54
LnageHH	3.7205	3.6686	17.5	1.55	3.7173	3.7191	-0.6	-0.06

Source: Computed from own survey data, 2022

As indicated in *Table 10*, the joint significance test revealed that the low pseudo-R^2 (0.005) and the insignificant likelihood ratio tests support the hypothesis that both groups have the same distribution in covariates after matching. The mean bias of the covariates was minimized from 25.6% to 4.1%. The Beta was also reduced to 19.9%, or less than 25%. The results clearly show that the matching technique can balance the features of the treatment (adopters) and control (non-adopters) groups. As a result, it was utilized to compare observed treatment outcomes with those of a comparison group that shared common support in order to assess the impact of agroforestry adoption on smallholder farmers' household expenditure and crop yield (Zea mays L.) with similar observed characteristics.

Table 10: Tests for joint significance

Sample	Ps R^2	LR chi^2	p>chi^2	Mean Bias	Med Bias	B
Unmatched	0.108	47.78	0.000	25.6	24.6	80.1*
Matched	0.005	2.48	0.996	4.1	3.7	19.9

Source: Computed from survey data, 2022

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Estimation of the Average Treatment Effect on the Treated (ATT)

To estimate the average treatment effect (ATT) on the treated, the study used propensity score matching to verify that both non-adopters and adopters of agroforestry practices smallholder farmers had the same features. ATT examines the average difference in total annual expenditure and crop productivity (maize) per hectare of families in the research area between adopters and non-adopters of agroforestry practices. Total annually household expenditure and crop productivity (maize) as an outcome measure of smallholder farmers' household welfare in the research area were used to assess the average treatment effect on the treated (*Tables 11 and 12*). The radius calliper matching estimates demonstrated that agroforestry adoption has a favourable and significant influence on household expenditure and crop productivity (maize) per hectare among smallholder farmers in the research area. Based on the study analysis results, impact analysis indicates that smallholder farmer households' agroforestry adopters' total annual expenditure was higher than for non-adopters that is **ZMW 8,873.47** (USD 465.80) and **ZMW 3,255.57** (USD 170.90) with **ZMW 5,617.91** (USD 294.90) (*Table 11*). The results indicate that, on average, the adoption of agroforestry practices by smallholder farmers increased household total annual expenditure by **ZMW 5,617.91** (USD 294.90) (K19.05 per 1 USD). In terms of household total annual expenditure, the results likewise revealed a significant difference between smallholder farmers adopters and non-adopters at less than 1% significance level. This implies that smallholder farmers' adoption of agroforestry has a favourable influence on household expenditure from both agricultural (cereals, livestock, and vegetable production) and non-agricultural (off/non-farm activity) activities in Nyimba district, Zambia.

Table 11: ATT estimation with Radius Caliper at 0.1.

Outcome indicators	Sample	Treated	Controls	Difference	S.E.	T-stat
Total expenditure (ZMK)	Unmatched	10113.89	3245.0219	6868.87	1330.01	5.16
	ATT	8873.47	3255.57	5617.91	922.462	6.09
	ATU	3275.32	7384.42	4109.1		
	ATE			4956.58		

ATE: Average Treatment Effects, ATT: Average Treatment on the Treated, ATU: Average Treatment Effects on the Untreated

Source: Computed from survey data, 2023

With regards to maize productivity the study analysis results *Table 12*, impact analysis indicate that agroforestry smallholder farmers adopters' maize yields were higher **1929.040 kilograms**, whilst **1111.61 kilograms** for non-adopters' households. Therefore, the difference between adopters and non-adopters on maize productivity per hectare was **817.43 kilograms**. The results indicate that, on average, the adoption of agroforestry practices by smallholder farmers increased household crop productivity.

Table 12: ATT estimation with Radius Caliper at 0.1.

Outcome indicators	Sample	Treated	Controls	Difference	S.E.	T-stat
Maize Productivity (Kg)	Unmatched	2071.26	1092.455	978.814	272.502892	3.59
	ATT	1929.040	1111.61	817.43	216.074883	3.78
	ATU	1100.8592	1961.836	860.97		
	ATE			836.52		

ATE: Average Treatment Effects, ATT: Average Treatment on the Treated, ATU: Average Treatment Effects on the Untreated

Source: Computed from survey data, 2023

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Sensitivity Analysis

Sensitivity analysis was performed to examine how the unobservable bias affected the outcome, and it aids in testing the robustness of the results (estimated ATT) and determining whether or not the unobserved confounders have an effect on the estimated ATT. In *Table 13*, the values that correspond to each row of the significant outcome variables are p- critical values (or the upper bound of Wilcox on significance level Sig+) at different critical values of gamma. The findings show that farmers' total expenditure and crop production of families are insensitive to unobserved selection bias, even up to γ =7, which is a very high number. As a result, the results demonstrate that the predicted average treatment effects on total expenditure and crop productivity were exceptionally resistant (insensitive) to the presence of unobserved factors.

Table 13: Sensitivity analysis using the Rosenbaum R-bounds approach

Outcome variables	**e^{γ} =1**	**e^{γ} =2**	**e^{γ} =3**	**e^{γ} =4**	**e^{γ} =5**	**e^{γ} =6**	**e^{γ} =7**
Total income	0.000	0.000	0.000	$2.8e^{-15}$	$1.4e^{-12}$	$8.8e^{-11}$	$1.7e^{-09}$

Note: e^{γ} (gamma) = log odds of differential due to unobserved factors

Smallholder Farmers' Households Resilience to Climate Change

The resilience index was calculated for each farming household in the study area using principal component analysis, which was then normalized/standardized using factor analysis (Elhaik, 2022). The findings were utilized to identify individual populations as well as relationships between variables of interest regarding the resilience of smallholder farmers' households to climate change.

However, the resilience capacity index can be successfully written as RCI = 0.1935* Comp.1 + 0.3171* Comp.2 + 0.4320* Comp.3. The principal component analysis based on the resilience blocs produced three probable components on the scree plot (*Figure 4*) with a cumulative variance of 43.20% using an eigenvalue cut off of 1.0 (*Table 14*). Based on *Table 14*, all of the indicators in Comp.1 were positive and strongly related to the resilience of smallholder farmers' households to climate change. Except for the amount of education of the household head, gender and years of agricultural experience were positively connected to climate change resilience in Comp.2. This suggests that education level, gender, agricultural experience, and age of household head all had a detrimental impact on household resistance to climate change.

In Comp.3, head of household years of farming experience, access to credit, and household head age were all positively connected with climate change resilience. Household head level of education, gender, farm size (landholding), and size of cultivated land were all adversely connected with climate change resilience in Comp. 3. This also implies that household resistance to climate change was influenced by education level, gender, farm size (landholding), and size of cultivated land. However, the most important factor contributing to smallholder farmers' household resistance to climate change in the research area was discovered to be the head of the household's agricultural experience, access to financing, and age. Furthermore, household resilience estimation cannot be one-dimensional, and the result displays the primary component while taking three components into account. The eigenvalues reveal a significant difference between distinct components of household resilience at the ($p<0.01$) probability level.

Table 14: Principal Components of the Study Data

Principal components/covariance			Number of obs. = 325			
			Number of components = 6			
			Trace = 11			
Rotation: (un-rotated = principal)			Rho = 0.4320			
Component	**Eigenvalue**	**Difference**	**Proportion**	**Cum**	**Chi-square**	**prob>Chi**
Comp.1	2.12809	.767976	0.1935	0.1935	155.725	<.0001
Comp.2	1.36011	.0965197	0.1236	0.3171	39.078	<.0001
Comp.3	1.26359	.156892	0.1149	0.4320	16.732	<.0001
Comp.4	1.1067	.0784496	0.1006	0.5326	11.091	0.0079
Comp.5	1.02825	.0233273	0.0935	0.6261	10.128	0.0052
Comp.6	1.00493	.161566	0.0914	0.7174	Comp.6	

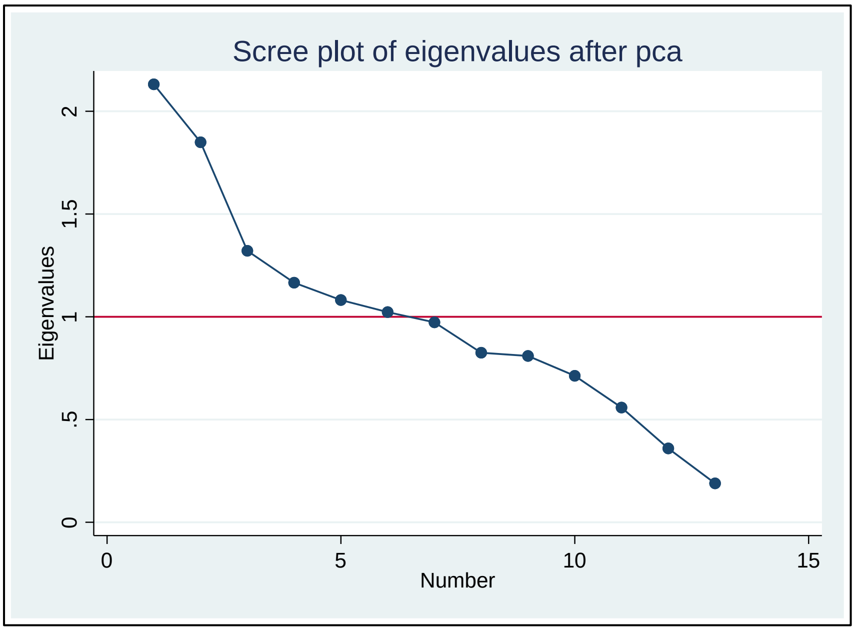
Adopters of smallholder farmer households outperformed non-adopters on all resilience measures, including access to credit, farming experience, cultivated land, farmland size, gender of household head, and education level (*Table 15*). However, it may be argued that the level of resilience of smallholder farmers is a function of all resilience characteristics. *Figures 4 and Figure 5* show that adopters of agroforestry practices are more robust in all resilience components than non-adopters, particularly in terms of the adoption of excellent agricultural practices. Furthermore, non-adopters have the lowest level of resilience in terms of implementing good agricultural practices.

Table 15: Principal components (eigenvectors)

Variable	Comp. 1	Comp. 2	Comp. 3	Unexplained
Education HH	0.0343	-0.0010	-0.0032	.1574
GenderHH	0.0480	-0.2763	-0.1306	.1698
Farming exp. HH	0.3407	-0.1110	0.5506	.3022
Farm size	0.5600	0.2934	-0.2403	.1336
Cult. Land	0.5774	0.2399	-0.2366	.1221
Access to credit	0.0425	0.0589	0.2918	.2712
AgeHH	0.2523	-0.0065	0.5907	.243

Source: Computed from own survey data, 2022

Figure 4: Principal component analysis scree plot



Source: Own sketch from survey data, 2022

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Smallholder farmer households Level of Resilience

Smallholder farmer households were classed as having low, moderate, or high resilience. As indicated in *Figure 5*, 32.15% (104) of the studied households were very robust, 49.35% (160) were moderately resilient, and 18.50% (61) were lowly resilient.

Figure 5: Smallholder farmers household resilience

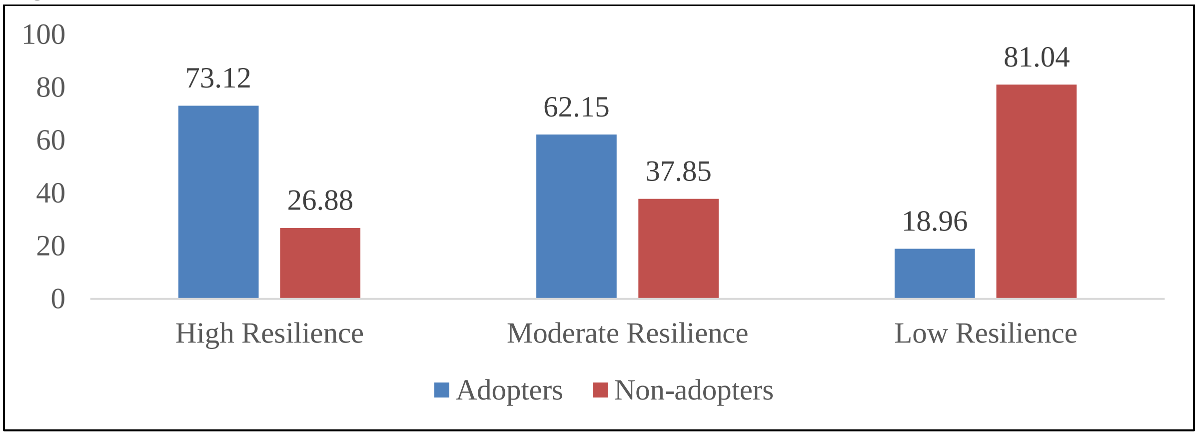

Figure 5 depicts the percentages of smallholder farmer households with high resilience (*i.e.*, 73.12% adopters and 26.88% non-adopters smallholder farmer households), and 160 with moderate resilience (*i.e.*, 62.15% adopters and 37.85% non-adopters smallholder farmer households). *Figure 5* depicts smallholder farmer households that have adopted agroforestry practices to increase their resilience to climate change shocks and risks in Zambia's Nyimba area. Additionally, highly and moderately resilient smallholder farmer households are likely to seek improved agricultural practices to increase farm output through the adoption of agroforestry practices and other sustainable agricultural practices.

The findings also show that 61 smallholder farmer households have limited resilience to climate change shocks and hazards (*i.e.*, 18.96% adopters and 81.04% non-adopters). The findings clearly reveal that non-adopter smallholder farmer households are less resilient to climate change shocks and hazards than adopters. Climate change shocks and hazards had a negative impact on the households of less resilient smallholder farmers in the research area.

CONCLUSION

The study objectives were attained in the study area Nyimba district Zambia among sampled smallholder farmers' households. Therefore, agroforestry as a sustainable agricultural practice has proved a point in increasing smallholder farmers' resilience to climate change. Among the adopters 'smallholder farmers' households, the practice has increased household expenditure and crop productivity per hectare, hence, improving household welfare in the study area. Therefore, agroforestry practices adoption must be stimulated among smallholder farmers' households in the study area and Zambia including other sub-Sahara African countries.

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