

Article

Factors Affecting Adaptation to Climate Change through Agroforestry in Kenya

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Abstract: The environmental effects of climate change have significantly decreased agricultural productivity. Agroforestry technologies have been applied as a solution to promote sustainable agricultural systems. This study evaluates the factors influencing the adoption of agroforestry technology in Kenya. A multistage sampling technique was employed to collect data from 239 households in West Pokot County, Kenya. A Probit model and K-means algorithm were used to analyze the factors affecting farmers' agroforestry technology adoption decisions based on the sampled households' socio-economic, demographic, and farm characteristics. The study found that the total yield for maize crop, farm size, extension frequency, off-farm income, access to training, access to credit, access to transport facilities, group membership, access to market, gender, distance to nearest trading center, and household education level had significant effects on the adoption of agroforestry technologies. The findings of this study are important in informing policy formulation and implementation that promotes agroforestry technologies adoption.

Keywords: climate change; agroforestry-based technology; probit model; K-means

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1. Introduction

The economy of most sub-Saharan African (SSA) countries greatly depends on agricultural production. Agriculture accounts for about 15% of their total GDP and a source of employment to more than half of the entire labor force within the rural population [1,2]. The agricultural systems in SSA are characterized by smallholder farmers who highly depend on rain-fed agriculture and unsustainable farming practices, i.e., monoculture, burning, and clearing of natural vegetation [3]. However, a report by the FAO (2017) [2] on crop yields (wheat, maize, rice, and soybeans) under different climate change conditions reported a decline in cereal yields with climate change. Furthermore, Mulungu and Ng'ombe (2019) [4] also reported a gradual decline in agriculture production in the SSA regions in the last 50 years. With an annual population growth of 2.7% in the SSA region, combined with land pressure and climate variability, food insecurity problems are inevitable. Therefore, forcing farmers to take-up new agricultural practices in response to the altered environmental conditions [5].

Unsustainable human activities, such as deforestation, have led to increased drought frequency, floods, and heat stress, a manifestation of climate change [6]. Kovats et al. [7] defined climate change as a statistically significant variation in climate variability or the mean state for an extended period. About 30% of global land areas (three billion people)

have experienced considerable degradation. Additionally, between 1992 and 2014, the number of countries experiencing water scarcity and water stress increased from 30 to 50 countries [8]. Furthermore, Reppin et al. (2020) [9] highlighted the negative impacts of climate change as a decline in crop yields, increased cases of agricultural pests and diseases, and decreasing livestock pasture.

The main focus of the agricultural response to climate change is biophysical (rising temperatures, change in precipitation regimes, and increased atmospheric carbon dioxide) and socio-economic (yield and prices) factors [10]. Nevertheless, studies have shown that the biophysical effects will be positive in some agricultural systems while negative in others [10]. However, the affected areas would suffer from prolonged droughts, floods, landslides, and an increase in infectious diseases and pests, which would lead to food insecurity, poverty, and even loss of human life [11]. Several climate change mitigation approaches have been proposed, such as adopting renewable energy resources, sustainable transport systems, and advocating for more sustainable use of land and forests [12], to mention a few. In developing countries, climate change countermeasures are focused on land sustainability and forest use by implementing reforestation, forest protection, and agroforestry (AF) policies [13].

AF is a dynamic, ecologically based, natural resource management system that diversifies and sustains production for increased economic, social, and environmental benefits for land users [14]. AF is an old practice that consists of growing perennial trees and shrubs with crops, pastures and keeping livestock in the same field [15]. In Africa, efforts are already made to reduce tropical deforestation, even as the need to expand agricultural production to feed the continent's growing population increases [16]. Besides, Kenya has committed to restoring 5.1 million hectares through its national strategy to achieve and maintain over 10% tree cover by 2022 [17]. Generally, AF encourages afforestation and agricultural productivity, whereby the adoption of AF technology can increase farmers' resilience and strategically position them to adjust to climate change's adverse effects [18]. Studies have established that AF has several sustainable attributes, substantial assets for climate change adaptation, and agricultural productivity. Backed by previous studies in Kenya, AF has improved the environmental conditions by providing shade, controlling soil erosion, acting as windbreakers, and regulating the microclimate, as trees sequester atmospheric carbon [19,20].

Concerning agricultural productivity, AF creates considerable benefits in farm crop and livestock production in several mutually interdependent ways, e.g., the upbringing of water and nutrients from deep to the ground, building soil organic matter, and providing fodder and shelter for livestock [21]. Additionally, trees provide goods and services, such as food, fruits, timber, and fuel, generating income [17]. Therefore, through the adoption of AF, agricultural production can be increased to improve livelihoods to achieve Sustainable Development Goal 2 (SDG 2), which aims at ending hunger, ultimately achieving food security, improved nutrition, sustainable agriculture, eradication of poverty, and an appropriate response to climate change [2].

Agroforestry is widely purported to improve smallholder farmers' livelihoods, rehabilitate degraded landscapes, and enhance the provisioning of ecosystem services [5]. Agroforestry has emerged as a system for study as it recognizes the relationship between the human and environmental aspects of delivering livelihoods [22]. Trees on a farm and in the landscape provide income and wood fuel, while fodder shrubs reduce the cost of meeting dairy cows' protein requirements and a range of other ecological services [23]. For example, trees influence the hydrological cycles, and biodiversity drives nutrient recycling and water fluxes in agroecosystems [24]. Indeed, the environmental services provided by agroforestry mean that its adaptation potential extends well above the farm level [25].

In Kenya, about 80% of the total landmass is arid and semi-arid lands (ASAL), based on the country's relatively low annual rainfall. Agricultural practices are predominantly performed by poor smallholder farmers who are constrained mainly by land degradation

[26]. Historic climatic data of West Pokot shows that the region experiences a moderately warm and moist climate throughout the year. The average annual temperature ranges between 15 °C in the southern to above 25 °C in the northern regions and has an average precipitation of 500–1000 mm annually throughout the county [27]. The variation in temperature and precipitation, flooding, dry spells, and heat stress contributes to the county's agricultural risk [28]. Furthermore, studies have projected extreme precipitation and prolonged moisture stress in the future [29]. Therefore, AF can be applied in this region as a survival technique to mitigate environmental degradation and other climate change-related problems. Remote sensing data show that, in 2010, 43% of the global agricultural land had 10% tree cover [30]. Even though AF's benefits are well known, and farmers have implemented various innovations throughout the tropics, widespread adoption has not occurred in the SSA regions.

Furthermore, from empirical studies on agricultural technology adoption, socio-cultural factors, such as gender, farmers' age, education level, and family size, influence the adoption rate of new farm technologies among farmers [31]. Deressa et al. (2009) [32] expressed that livestock ownership, local temperatures, and the amount of precipitation influence the decision to adopt new technologies. Additionally, Nhemachena and Hassan (2007) [33] pointed out that market access, electricity, technology availability, land ownership, and gender of the household head influence household decisions to adopt new agricultural technologies. Furthermore, Thangata and Alavalapati (2003) [34] indicated other factors, such as risk and uncertainty, household preferences, resource endowments, land tenure, market constraints, inadequate extension work, and policy constraints, affect the adoption rate of new farm technologies. Moreover, Noordin et al. (2001) [35] reported that development organizations have a significant role in scaling AF from a study based in Western Kenya. Most of these studies have lamented that the adoption and diffusion of AF technologies are still lagging. Hence, reducing the potential impacts of AF technologies for climate change adaptation [36]. This raises concerns for further scientific research to establish the determinants of AF technologies' adoption for climate change. Therefore, this study will assess the factors affecting the adoption of AF-based technologies among smallholder maize farmers in West Pokot County in Kenya.

Studies have already been performed to understand the biophysical and socio-economic factors related to farmers' decisions to adopt and promote AF practices [9,13,18,19,37–40]. However, most of these studies aimed to understand the impacts of the technology on crop production and less on the factors that influence the adaptation strategies. Although AF projects may fail due to several reasons, one common factor is the inadequate attention given to socio-economics factors in developing systems and projects [41]. Therefore, many AF institutions are now calling for increased socio-economic research as a solution [42]. This calls for more investigation, as most 21st-century agricultural projects require knowledge of how households would adopt new technologies with climate variation.

Langyintuo and Mekuria (2008) [42] used a Tobit model to analyze the household characteristics' effects on adopting improved varieties among Mozambican farmers. They found a significant contribution of social networks to technology adoption. They suggested that the government should invest in farmers' associations to facilitate high technology adoption. Similarly, Deressa et al. (2009) [32] found that household size and gender, credit availability, and temperature positively influence household adaptation to climate change in Ethiopia, based on the Heckman model. Further, Nhemachena and Hassan (2007) [33] argued that female-headed households are more likely to take up climate change adaptation options when exposed to information.

Since the findings on factors that influence the adoption of AF technologies vary between studies, it is necessary to evaluate the adoption process further to identify what factors influence AF technologies' adoption. These would be fundamental in promoting AF technologies. Most studies have proposed specific techniques to address climate change impacts and household adaptation in particular locations. Additionally, these

studies suggest that successful adoption depends on the convergence of the socio-economic, institutional and technical, factors [43,44]. However, little research has been performed to assess the factors that determine the decision to adopt AF technologies at the household level in the face of climate change in West Pokot County, Kenya. Furthermore, climate variability in West Pokot County, with the increases in the frequency of prolonged droughts, landslides during flood events, and changes in river patterns, call for research to mitigate these problems [45]. Therefore, it is against this framework that this study sought to explore the main drivers of adopting AF technologies in this region. This study introduced a bivariate analysis to model factors that influence the household decision to adopt AF using a probit model. However, the vital research gap to date is the lack of understanding of how each factor affects adoption of AF technologies by smallholder farmers. To address this, the study further employed *K*-means clustering analysis to establish the strengths of the different factors with the adoption of these technologies. This study would contribute to the current debate on climate change mitigation strategies. Furthermore, it would be valuable to the relevant stakeholders to provide a basis for the formulation of policies geared towards sustainable development.

2. Materials and Methods

2.1. Study Area

Kenya covers 580,728 km², and as already mentioned, 80% of this land is arid and semi-arid (ASAL). These regions account for 70% of the livestock production and 30% of the national population (Government of Kenya, 2013). West Pokot County is partially arid and semi-arid, with rainfall amounts that range between 700 mm to 1600 mm per year. The highlands climates are sub-humid, while the lowland climate is arid [27]. West Pokot is located in the North Rift along Kenya's Western boundary with Uganda, as shown in Figure 1. It borders Turkana County to the north and northeast, Trans Nzoia County to the south, and Elgeyo Marakwet County and Baringo County to the southeast and east.

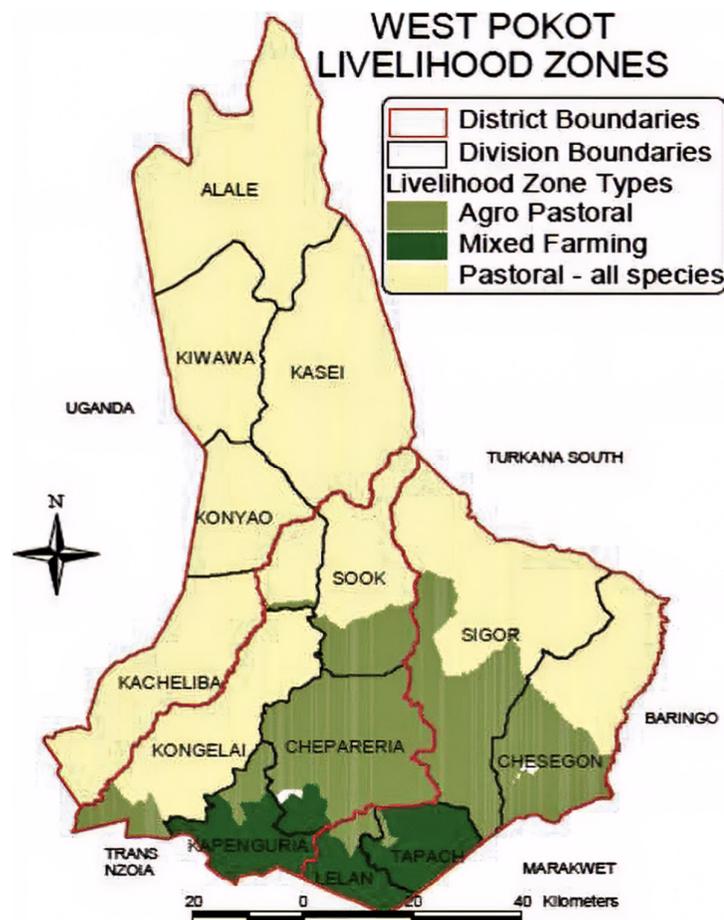


Figure 1. Map of West Pokot, Kenya, indicating the West Pokot County Livelihood Zones. Source: Adapted from the National Drought Management Authority (NDMA) (NDMA, 2014).

Historically, the land use in West Pokot was divided based on the soil composition. The high, mountainous areas, which receive a higher amount of rain, are the most fertile and productive. However, its characterized by steep slopes. The conventional crops produced include maize, finger millet, potatoes, beans, onions, sweet potatoes, peas, mangoes, oranges, bananas, green grams, coffee, and pyrethrum. Maize is the leading food crop in the county and is grown in West Pokot Sub-County. Pyrethrum and potatoes are grown in South Pokot Sub-County. The Kapenguria and Pokot South Sub-Counties keep improved dairy cows, such as Ayrshire and Friesian. The lower side, Pokot Central, and Pokot North Sub-Counties are drylands that pastoralists use in grazing livestock, with Zebu cattle being the common breed used for meat production [29,46,47].

AF has been intensified in Kenya under the Kenya Agriculture Carbon Project (under the Ministry of Agriculture), promoting carbon sequestration through the uptake of sustainable agricultural land management practices. The project enables smallholder farmers to access the carbon market and increase yield and productivity and enhance resilience to climate variability and change [48]. Additionally, AF has been supported by several organizations in the area, including World Agroforestry (ICRAF) and VI Agroforestry [49]. These organizations have partnered with extension workers from the government and lead farmers to reach a large number of farmers and encourage them to incorporate these practices (sustainable agricultural land management) into their production system. The operation of the organizations in West Pokot entails free tree seedlings, training, and advice on AF practices, including the cultivation of trees, crops, fruit, and vegetables. The participation of farmers is voluntary at the village level, and most participating farmers

expect to benefit from the technology. Figure 2 below describes the factors that affect farmers' adoption decisions, e.g., socio-economic characteristics, institutional characteristics, non-governmental organizations (NGOs), government extension agents, farmers groups, community-based organizations (CBOs), and the lead farmers, forming part of the intermediate variables that contribute to adoption decisions.

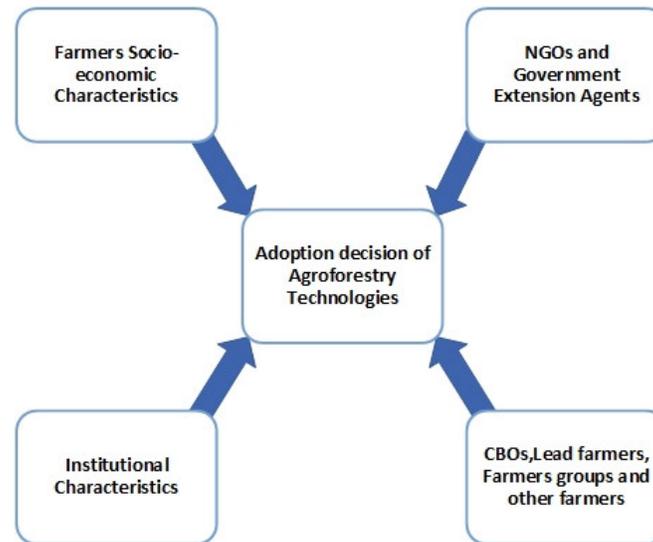


Figure 2. Factors affecting a farmer's adoption decision.

2.2. Sampling Procedure and Data Collection

This study was conducted in Chepareria, an ASAL area in West Pokot County, Kenya, targeting smallholder farmers between 8 July and 25 July 2020. A multistage sampling procedure was applied in this study. Firstly, the Chepareria Sub-County was purposively selected due to its potentiality in crop production. Secondly, stratified random sampling was applied to divide the farmers' population into two, i.e., AF-based technology adopters and non-adopters, based on [50]. The study target population comprised 594 (sampling frame) smallholder crop farmers (source; Department of Agriculture, West Pokot Sub-County). The Yamane (1967) [51] formula was used to calculate the sample size, as given in Equation (1). This approach has been adopted by several studies, including Osewe et al. (2020) [52] and Kiprop et al. (2020) [53], in the computation of sample size.

$$n = \frac{N}{1 + N(e)^2} \quad (1)$$

where n is the sample size, N is the size of the target population, and e is the confidence level at 95%; in this study, $N = 594$. According to Equation (1), a sample size of 239 respondents was selected from AF adopters and non-adopters. A simple random technique was used to give each member an equal chance of being selected into the sample. AF adopters and non-adopters were calculated in proportion to the population. There were 121 adopter and 473 non-adopter households. The sampling into these two categories was proportionate to the total smallholder maize crop farmers, as follows: adopters of AF (121) as $\frac{121}{594} * 239 = 48$, and non-adopters of AF (473) as $\frac{473}{594} * 239 = 190$.

This study utilized qualitative and quantitative analysis in pursuit of the study objectives. Primary data were sourced through interviews using a semi-structured questionnaire for households and focus group discussions (FGDs). Data were collected on socio-economic, demographic, and agricultural production indicators. Site visits and observation were also employed to determine the topography of the land. Secondary data on the

list of farming households were collected from the County agricultural offices. The household-level questionnaire was administered to 239 households. This survey achieved a response rate of 91.6% after receiving 219 (39 adopters and 180 non-adopters) well-filled questionnaires. The survey was conducted during the outbreak of COVID-19, making some respondents unwilling to participate due to fear of being infected.

2.3. Analysis Methodology

2.3.1. Research Design

This study applied a descriptive, cross-sectional research design to identify the factors influencing farmers' decisions to adopt AF technologies in West Pokot County, Kenya.

2.3.2. Variable Description

This study evaluated the factors determining AF technologies adoption among smallholder maize farmers in West Pokot County. A farmer's adoption status was the dependent variable, while the independent variables were household socioeconomic characteristics, economic characteristics, farm characteristics, and institutional characteristics. The household socioeconomic variables included age of household head, gender of the household head, household size, household education level, access to storage, access to transport services, and market access. Economic characteristics include off-farm income. The farm characteristics included the total yield from a previous maize harvest in kilograms (kgs), the topography of the land, distance to the nearest trading center, and land size. Lastly, the institutional characteristics included membership to agricultural groups, credit services, and extension services. Table 1 below presents the description of the dependent and independent variables applied in this study.

Table 1. Description of the dependent and independent variables used in the analysis.

Variable	Description	Measurement	Sign
	Dependent variable		
Agroforestry adoption	Type of household (adopters/non-adopters)	Dummy 1 = adopters, 0 = non-adopters	+/-
	Independent variables		
Gender	Sex of the household head	1 = male, 0 = female	+/-
Household Size	Number of household members	1~3 = 1	+/-
		4~7 = 2	
		8~10 = 3	
		Above 10 = 4	
Age	Age of the household head	18~24 = 1	+/-
		25~35 = 2	
		36~45 = 3	
		Above 45 = 4	
Education level	The education level of the household head	Years of education (continuous)	+
Topography of land	The topography of land	flat = 1, gentle slope = 2, steep slope = 3	+/-
Farm Size	Total land owned by household	Acres	+/-
Access to climate information	Farmers access to climate information	Dummy, 1 = yes, 0 = no	+
Group membership	Farmer belonging to a particular group	Dummy 1 = yes, 0 = no	+/-
Access to Training	Farmers access to training services	Dummy. 1 = yes, 0 = no	+/-
Extension frequency	The number of times farmers receive extension services	Continuous (number of extension meetings)	+
Access to transport facilities	If farmers have access to transport facilities	Dummy 1 = yes, 0 = no	+/-
Access to market	Farmers access to market	Dummy 1 = yes, 0 = no	+/-
Access to credit	Farmers access to credit services	Dummy 1 = yes, 0 = no	+/-
Distance to the trading center	Distance from farmers home to the nearest trading center	Distance in kilometers	+/-
Off-farm income	Income from other sources from farming	Income in shillings	+/-
Total yield	Total yield farmer obtains from maize crop	Yield in kilograms	+/-

2.3.3. Estimating Strategies

Descriptive statistics, the probit model, and *K*-means clustering were applied to determine the factors affecting the adoption of AF-based technologies in West Pokot County. The descriptive statistics were presented in terms of means, percentages, ratios, and standard deviation (SD) to compare the socio-economic, farm characteristics, and demographical factors for the sampled households. The data were processed and analyzed using the SPSS statistical package for social sciences (SPSS 26.0) and STATA version 16 software.

2.3.4. Probit Model

Probit models are preferred to logit models for most adoption studies [54]. Farmers' decision to adopt AF technologies in the study was considered a two-level ordinate response to adopting the AF practices: adopters and non-adopters (yes/no). The adopters and non-adopters served as a binary dependent variable to calculate the effect of farmers' household, socio-economic, demographic, and farm characteristics (independent variables) on farmers' decision to adopt AF technologies. The AF adoption decision function was defined according to Equation (2).

$$Y^* = \beta'x + \varepsilon \quad (2)$$

where Y^* is the unobserved propensity variable, β is the vector of the estimated parameters, x is the vector for independent variables, and ε is the randomly distributed error term (assumed to be normally distributed with zero mean and unit variance). The probit model was expressed according to Equation (3), based on the observed ordinal AF technologies adoption participation data.

$$Y = \begin{cases} 0 & Y^* \leq 0 \\ 1 & Y^* > 0 \end{cases} \quad (3)$$

Equations (4) and (5) were used to compute the probability of AF technology adoption for a given period, provided that it is normally distributed with a zero mean and unit variance.

$$\Pr(Y = 0|X) = \Phi(-\beta'X) \quad (4)$$

$$\Pr(y = 1|X) = 1 - \phi(-\beta'X) \quad (5)$$

where $\phi(\cdot)$ denotes the standard normal cumulative distribution function, $Y = 0$ indicates no (non-adopters), and $(y = 1|X)$ indicates yes (adoption of AF technologies). Table 1 presents a description of the variables used in this study.

2.3.5. K-Means Clustering Analysis

The *K*-means cluster analysis method was employed to determine the influence of the independent variables on the farmers adopting or not adopting AF technologies. Cluster analysis is often performed to group data based on information within the data that describes the variables and their relationships. Cluster analysis helps to account for heterogeneity within the sample by clustering respondents into groups. These groupings are internally homogenous while being externally heterogeneous from one another [55].

K-means is the most commonly used method for data clustering due to its easy implementation and empirical evidence of its effectiveness. Additionally, *K*-means is superior to the hierarchical methods when the outcome is dichotomous. In *K*-means clustering, the number of clusters is pre-specified, and k is the number of groups (for this study $k = 2$). The aim is to determine each independent variable's distance from these clusters' centers (the significance of each variable in each grouping).

3. Results

3.1. Descriptive Statistics

Farmers' decisions to adopt AF technologies are determined by several socio-economic, demographical, farm characteristics, and institutional factors, i.e., gender, household size, age, marital status, education, topography of land, farm size, access to climate information, access to training, credit access, extension frequency, off-farm income, and access to the market.

Table 2 presents the descriptive statistics of the adopters and the non-adopters of AF technologies. Continuous variables are expressed in the form of the mean and standard deviation while categorical variables are expressed in percentages. It was established that female farmers are more adopters of AF technologies compared to males. Additionally, adopters had a mean age of 45 years compared to the non-adopters' mean age of 44 years. Adopters had a mean household size of 2.4 while that of the non-adopters was 2.6. Hence, there was not much variation between adopters and non-adopters regarding age and household size. The majority of adopter farmers (59.0%) had access to training, and a higher extension visits mean (4.5), thus showing that access to training and the frequency of extension service visits influences the implementation of AF technology by farmers. The adoption of AF technologies was also affected by the topography of the land, whereby most non-adopters (71.8%) occurred on flat terrain, while all farmers in steep slope (1.7%) adopted the AF technologies. Adopters had higher access to the market (82.1%) compared to non-adopters (58.3%). Additionally, it was established that adopters had a bigger piece of land at a mean of 1.0 acres compared to non-adopters at 0.9 acres. Furthermore, the majority of adopters (70%) had access to climate information compared to non-adopters (64.2%). Non-adopters spent more time in school at a mean of 7.3 years compared to adopters at a mean of 6.7 years. Adopter farmers had a higher income from off-farm activities compared to their non-adopter counterparts.

Table 2. The descriptive statistics of the adopters and non-adopters.

Variables		Adopters of AF			Non-Adopters of AF		
		Column N%	Mean	SD	Column N%	Mean	SD
Gender	Female	61.5			34.4		
	Male	38.5			65.6		
Household size		100	2.4	0.7	100	2.6	0.9
Age		100	45.0	12.0	100	44.0	11.0
Education level		100	6.7	2.8	100	7.3	3.3
Topography of land	Flat	65.0			71.8		
	Gentle	33.3			28.2		
	steep	1.7			0.0		
Farm size		100	1.0	0.4	100	0.9	0.5
Extension frequency		100	4.5	3	100	2.5	2
Access to climate information	Yes	70			64.1		
	No	30			35.9		
Access to training	Yes	59.0			45.6		
	No	41.0			54.4		
Access to credit	Yes	35.9			27.7		
	No	64.1			72.3		
Access to market	Yes	82.1			58.3		
	No	17.9			41.7		
Access to transport	Yes	95.6			74.3		
	No	4.4			25.6		
Group membership	Yes	35.3			34.2		
	No	64.7			65.8		
Distance to the nearest trading center (km)		100	2.8	2.0	100	4.2	3.3
Off-farm income (KSh)		100	171,864	224,753.3	100	152,168	358,022.3
Total yield		100	519.7	306.1	100%	493.6	311.5

3.2. Factors Influencing Farmers' Adoption of Agroforestry Technologies

3.2.1. Probit Model

The study used a probit model in analyzing the factors that influence farmers' adoption of AF technology. From Table 3 below it is observed that the log-likelihood ratio statistics, as presented by chi2, are statistically significant ($p < 0.0000$). This ascertains that all the parameter models in the study were jointly significant in describing the dependent variable. Furthermore, the model's Pseudo R2 was (0.4451), which indicates that the independent variables jointly explain about 44% of the variation in the dependent variable. The results showed that farmers' AF technology adoption is significantly influenced by the gender of the household head, farm size, extension frequency, access to market, transport access, and total yield.

Table 3. Factors that influence farmers' adoption of agroforestry technologies.

Variables	Probit Model				K-Means Clustering	
	Coefficient	Std Error	z	$p > z $	F-Values	Sig
Gender	-1.564 ***	0.405	-3.86	0.000	8.356 **	0.004
Household size	-0.345	0.189	-1.82	0.068	0.821	0.366
Age	0.205	0.192	1.07	0.286	0.912	0.341
Education level	0.051	0.0624	0.81	0.416	3.799	0.053
Topography of land	0.077	0.329	0.23	0.816	1.080	0.300
Farm size	1.987 **	0.596	3.33	0.001	96.432 **	0.000
Extension frequency	0.233 **	0.070	3.30	0.001	33.827 **	0.000
Access to climate information	0.459	0.322	1.43	0.154	1.933	0.166
Access to training	0.452	0.329	1.37	0.170	25.849 **	0.000
Access to credit	0.335	0.338	0.99	0.323	12.136 **	0.001
Access to market	-1.052 **	0.398	-2.65	0.008	8.696 **	0.004
Access to transport	-1.837 **	0.491	-3.74	0.000	10.872 **	0.001
Group membership	0.016	0.341	0.04	0.965	8.988 **	0.003
Distance to nearest trading center (km)	-0.124	0.070	-1.78	0.075	8.143 **	0.005
Off-farm income (KSh)	0.219	0.323	0.68	0.499	29.597 **	0.000
Total yield	-0.003 **	0.001	-3.30	0.001	101.106 **	0.000
Constant	-0.060	1.370	-0.04	0.965		
Number of observations	189					
LR chi2(14)	79.280					
Log-likelihood	-49.421					
Prob > chi2	0.0000					
Pseudo R2	0.4451					

*** Significant at 1%; ** significant at 5%. Source: Survey (2020).

3.2.2. K-Means Analysis

The effects of each socio-economic, demographic, and household characteristic on the choice to adopt or not to adopt AF technologies were analyzed by cluster analysis based on the distance of the variable from the cluster center, as presented in Figures 3 and 4 and the F-value, as shown in Table 3.

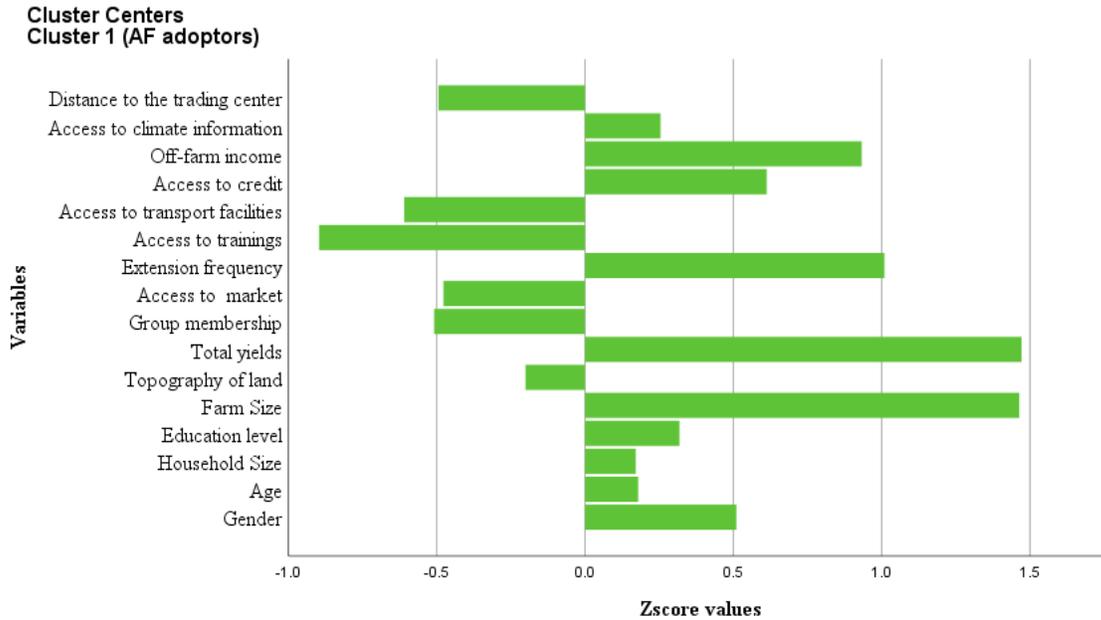


Figure 3. The variables’ distance from the agroforestry (AF) adopters’ cluster center.

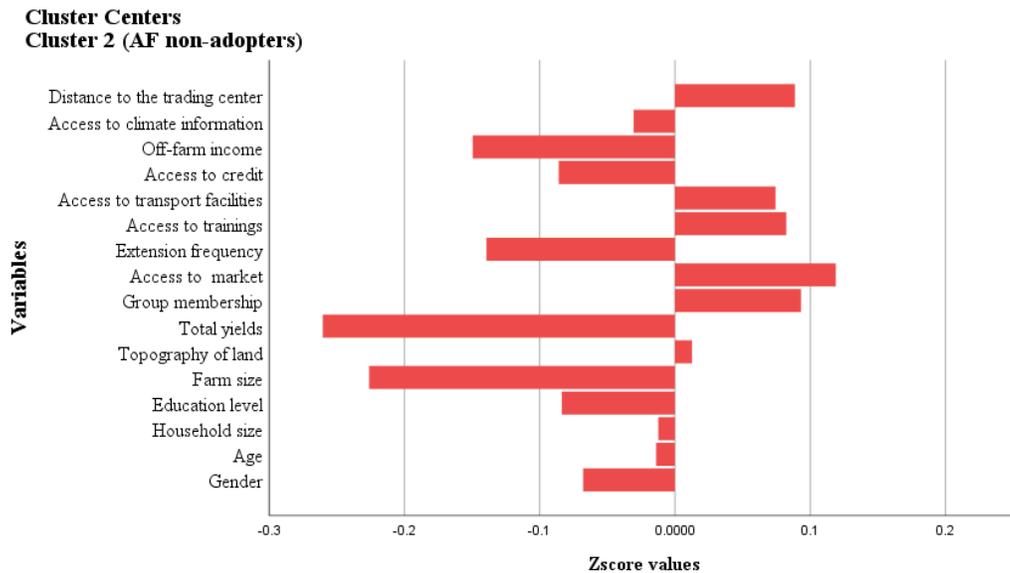


Figure 4. The variables’ distance from the AF non-adopters’ cluster center.

From the standardized values (equal amplitude) of the factors, as given in Figure 3, it can be observed that gender, age, household size, education, size of land, total yield, frequency of visits to extension services, access to credit, income from off-farm activities, and access to climate information are highest in Cluster 1 (adopters). In contrast, figure 4 group or organization, access to market, access to training, access to transport, and distance to the nearest extension services are highest in Cluster 2 (non-adopters).

From Table 3 above, the F-value indicates the impact of each variable in determining the cluster membership. The factor with the most significant effect on the adoption or non-adoption of AF technologies has the largest F-value. It can be observed that the ranking

order was total yield, farm size, extension visit frequency, off-farm income, access to training, access to credit, access to transport facilities, group membership, access to market, gender, distance to nearest trading center, and household education level—all having significant effects on the adoption of AF technologies.

4. Discussions

4.1. Probit Model Analysis

The gender of the household head has a significant influence on the adoption of AF, with female-headed households being more likely to adopt AF technologies than male-headed households. This is due to male-headed households using agriculture as a secondary form of income while the family head is employed in other formal jobs as the main source of income. Similar findings were presented by [33], who reported that female-headed households are more likely to take up climate change adaptation options when exposed to information. Additionally, Opaluwa et al. (2011) [56] reported that, in Nigeria, women were more likely to adopt AF technologies than men.

Farm size was found to positively and significantly affect the adoption of AF technologies. This implies that AF adoption increases with an increase in farm size owned by farmers. This is because AF technologies are scale-dependent. Hence, farmers with a larger land piece can devote part of their land to try the technology, unlike those with a small piece. Additionally, farm size is an incentive for diversification, which allows farmers to try on new technologies. These findings concur with those of [57], who reported that an increase in farmers' farm size led to a rise in the adoption of AF among contact farmers in Imo State, Nigeria. Additionally, Mwase et al. (2015) [58] presented that limited land availability is a significant factor, limiting the adoption of AF-based technologies and evergreen agriculture in southern Africa. Furthermore, the study noted that small land sizes limit the type of technology to adopt.

The frequency of visits to extension service centers positively and significantly affects the adoption of AF technology. Farmers with a higher number of contacts with extension agents had a higher probability of adopting AF technologies than farmers with fewer extension contacts. This is because visits to extension service centers increase farmers' knowledge through demonstration plots on farm fields, enhancing their understanding of the technology and improving adoption rates [58].

Access to markets had a significant effect on AF adoption decisions. Marketing aspects are essential, i.e., farmers sell their products and generate income [38]. However, there was a negative coefficient because farm households far from markets and roads impede them from accessing market information; hence, reducing their extent adoption [59]. Likewise, access to transport facilities had a significant negative effect on farmers' decision to adopt AF technology. It shows that with high access to transportation facilities, the intensity of adopting AF technology decreases. This could be due to the mode of locally available transport, such as motorbikes and bicycles (boda-bodas), which is inefficient in carrying output to the market. This concurs with [60], who established that having private transport (bullock-cart) to carry timber and fuelwood to the proximate market centers decreases farmers' willingness to adopt AF technologies.

Total yield had a significant negative effect on farmers' decision to adopt AF technology. Thus, with an increase in yield, the adoption intensity decreases. This is because AF technologies are incorporated to improve the soil's quality, which in turn increases yields produced once the technology has been applied, and the objective realized there could be no more intensification of the technology because some trees stay longer on the farm [58]. Kassie et al. (2015) [59], in their study on AF and land productivity in rural Ethiopia, found a negative effect on land conservation and food production. Additionally, some farmers fail to adopt AF technologies because their yield levels are not affected.

4.2. K-Means Analysis

Total yield, farm size, extension frequency, access to transport, access to market, distance to the nearest trading center, and gender had significant effects, as explained above in the probit model. Distance to the nearest trading center negatively and significantly affects the farmers' decision to adopt AF technologies. Thus, farmers' decision to adopt AF technologies decreases with an increase in distance to trading centers. This could be due to the poor road network in the area, where farmers have to walk long stretches to access the market for their produce [58]. Off-farm income has a significant impact; households with an off-farm income had a higher chance of adopting AF technology compared to households without off-farm income. Similar results were found by [61], noting that the adoption of AF technologies increases with wealth levels because households with low incomes will not acquire the inputs required for substantial crop production, let alone for managing AF projects.

The significant effect of training corresponds to a study by Keil et al. (2005) [61] on improved tree fallows in smallholder maize production in Zambia, who found that farmers who benefited from various extension interventions in the form of on-farm experimentation of AF technologies were likely to adopt than those who did not benefit. Our results also noted that access to credit influences the decision to adopt AF technology. Idrisa et al. (2012) [31] infer that access to financial support or cash resources influences agricultural technology's adoption rate among farmers. Belonging to farmers' groups had a significant effect on adopting AF technologies. Osewe et al. (2020) [52] found that membership in a social group enhances social trust, information flow, capital, and idea exchange. In the same breadth, Deressa et al. (2009) [32], studying determinants of farmers' choice of adaptation methods to climate change in Ethiopia's Nile basin, found a significant influence on group membership to farmers' choice of climate change adaptation.

Farmers face several challenges in adoption of AF technologies on their farms; most of the positive effects of AF are dependent on the proper management and use of suitable tree species [16]. If done correctly, AF increases agricultural yields and improves the food and nutrition security of farmers living in poverty, while helping them adapt to more variable and extreme weather [62]. However, farmers are facing challenges when practicing AF; there are few value chains developed for AF products and for connecting them to consumers and the market and some are poorly developed [63]. Furthermore, the long return on investment in AF is also problematic, as many farmers do not have access to capital, credit, or secure tenure for their land [64]. Unclear land and tenure rights also discourages farmers from long-term investment in AF. Inputs used in AF systems, such as certified seeds and high-quality seedlings, is difficult to get hold of, especially for indigenous tree species [36].

5. Conclusions

This study's objective was to assess the factors that affect farmers' decisions to adopt AF technology, using survey data of 219 households in West Pokot County, Kenya. The study employed the probit model and K-Means clustering analysis to analyze smallholder crop farmers' AF technology adoption decisions. The results indicated that total yield, farm size, extension frequency, off-farm income, access to training, access to credit, access to transport facilities, group membership, access to market, gender, distance to nearest trading center, and household education level had significant effects on the adoption of AF technologies.

The results indicate that farmers are gradually adjusting to AF to mitigate the effects of climate change. AF technology is essential to the environment by generating significant contributions, such as biodiversity, watershed protection, and carbon sequestration. We found that the majority of the farmers in the area were small-scale farmers. Furthermore, female farmers are more likely to adopt AF technologies compared to their male counter-

parts. In addition to that, most of the adopter farmers had access to training, market information, and climate information, which shows that access to such information by farmers increases the adoption of AF technologies.

Based on the established results, this study recommends the following: the quality and the number of times extension services should be increased since this will lead to interpersonal contacts with extension providers and ensure closer collaboration with the farmers in improving the identification of suitable AF technologies on a case-by-case basis, to guarantee wide-scale adoption. Smallholder farmers should also be encouraged to form and participate in formal groups to enhance AF-based technology adoption despite their gender and age. Moreover, smallholder farmer groups should promote social networking, sharing farming ideas, advice, and experiences that improve agricultural production. It is also crucial that the government improve infrastructure facilities, such as roads, to ease farmers' mobility and so get farm produce to the market. Further, governments should scale up their involvement in enacting policies tailored to improving AF technology adoption and provide more generous incentives, such as issuing free seedlings to farmers.

The study based its findings on primary data; moreover, our methodology was only able to analyze the factors that influence AF technologies' adoption. Therefore, future research should consider using time series data to produce robust results in analyzing AF-based technologies' adoption and introduce a bivariate model that can analyze the impact of adoption on crop productivity among smallholder maize crop farmers. This research should also be extended to other counties with similar agroecological and climatic conditions. Future analysis should be carried out to quantify AF's contribution to household incomes, food security, and household welfare in general.

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