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Modeling the Adoption and Intensity of Climate-smart Maize Varieties in Embu County, Kenya: Double Hurdle Approach

John K. Wanjira [a*], John I. Mburu [a], Felister M. Nzuve [b], Stella Makokha [c], Rosemary A. Emongor [c] and Catheline Taracha [d]

[a] Department of Agricultural Economics, University of Nairobi, P.O Box 29053-00625, Nairobi, Kenya.
[b] Department of Crop Protection, University of Nairobi, P.O Box 29053-00625, Nairobi, Kenya.
[c] Department of Socio-Economist, Kenya Agricultural and Livestock Research Organization (KALRO), P.O Box 57811-00200, Nairobi, Kenya.
[d] Department of Biotechnology, Kenya Agricultural and Livestock Research Organization (KALRO), P.O Box 57811-00200, Nairobi, Kenya.

Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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ABSTRACT

This paper examines the determinants of adoption and intensity of climate-smart maize varieties (CSMVs) in Embu county of Kenya using primary data. A total sample of 550 respondents were sampled through a multistage and systematic random sampling techniques. Data were analyzed using descriptive statistics and a double hurdle model. The results indicated that the level of awareness was 86 percent while the adoption rate was 63 percent. The results further indicated that land size, land ownership, size of the family, contact to extension officer, and previous yield had a significant influence on the intensity of adoption. Thus the results justifies the need for promotion of not only awareness but also widespread adoption of climate-smart maize varieties both locally and nationally. It is therefore recommended that, adequate policies and development programs for promoting use of climate-smart maize varieties in Kenya should be directed towards input and output delivery, land under climate-smart maize varieties, extension service provision, affordable credit, education and age mechanism that are more effective and youth oriented initiatives.

**Corresponding author: E-mail: kinyuajohn9@gmail.com;*

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1. INTRODUCTION

Despite the rapid economic growth over last decade, Sub-Sahara Africa (SSA) has the highest prevalence of undernourishment. Out of every nine people, one is chronically hungry [1]. Therefore, reducing poverty and food insecurity in SSA requires sustainable agricultural production [2]. In Kenya, 43% of the country's population is food insecure, and about 46% live below the poverty line [3].

Kenyan population is projected to increase from 47.5 million people to 95 million people by 2050, if the current growth rate in population continues (KNBS, 2019) [4]. This growth will lead to increase in food demand, particularly for maize since maize is a primary staple food in Kenya. Maize account for 68% of daily per capita cereal consumption and 42% of dietary energy intake [5]. Over the last decades, annual average maize production is about 2.9 million tons [6]. Consumption of maize is far higher than production at 3.9 million tons annually, leaving a shortfall that is mostly met by importation and food aid.

Improved maize varieties suited to climatic change, together with soil management improvement, can be used as a strategy to enhance maize productivity, especially in Kenya, where soils are depleted of crucial nutrients. Breeding of maize varieties which are stress tolerant such as drought-tolerant maize could help farmers respond to the adverse impact of climate variability in Africa [7,8]. Climate-smart maize varieties, especially drought-tolerant maize types, have been regarded as part of the answer to sustaining production of maize especially under small scale production systems [9]. Drought-tolerant maize varieties are estimated to produce 30% of their potential yield after suffering water stress for six weeks before and during flowering and grain-filling [10]. The three climate-smart maize varieties propagated by CIMMTY and KALRO are (DUMA 43, DH0, and KDV) [11]. Climate-smart maize varieties, especially drought-tolerant maize, offer insurance to small-scale farmers over dry spells and ensures an excellent maize yield under trivial drought environments (CIMMTY, 2013).

Despite the perceived benefits of climate-smart maize varieties and considerable efforts to encourage farmers to invest in them, the rate of adoption among small scale farmers in Kenya is still low [12]. The low adoption rate of improved climate-smart maize is evidenced by continued constraint to improving maize production among small scale farmers who are majority producers of maize in Kenya, amounting to 75 % of total maize produced [13]. Therefore, to increase maize production it is necessary to design auspicious pro-poor strategies promising to stimulate their adoption. Designing these strategies requires understanding the limitations that condition farmers' behavior regarding the adoption of these varieties and related practices. Therefore, this paper try to understand what are the factors influencing farmers decision to adopt and the extent of land to dedicate climate smart maize varieties.

2. METHODOLOGY

2.1 Theoretical Framework

The decision making process in the technology adoption can be modelled using discrete choice models. The models are based on two distinct theories namely random utility theory (RUT) and expected utility theory (EUT). Both theories assumes that given set of alternatives, a farmer will always make choice on the alternative that yields the maximum utility [14]. The RUT is therefore applicable when preferences of the outcome are revealed and outcome decision are made in environment with no uncertainties. The EUT on the other hand is used when the preferences are stated and the choices are made in presences of uncertainties [15]. This implies that a farmer can only expect the outcome since the choices are made on unknown outcomes. The technology adoption process of Climate-Smart maize varieties (CSMVs) are based on stated preferences since the outcome of the choices made are not known.

Therefore, farmers' decision on adoption of CSMVs are assumed to be based upon the theory of expected utility maximization. Following Adesina and Zinnah, [16], the technology type denoted by p represents $p=1$ for CSMVs and $p=0$ for other varieties. The unobservable utility function of the i^{th} farmer preferences ranking is therefore presented by U (W_{pi}, D_{pi}). Where the technology type depends on W representing the demographic characteristics of the adopters and D representing technology specific attributes.

Since utility is unobserved, therefore utility derived from p^{th} technology is assumed to be a function of the demographic characteristics (such as age, gender, land size, extension, credit access) and the technology specific attributes (such as high yielding, early maturity, pest and diseases resistance and drought resistance) and a disturbance term assumed to be normally distributed with zero mean and constant variance.

$$U_{pi} = \beta_p F_i(W_i, D_i) + \mu_i \quad p = 1,2, \; i = 1,2, \dots n.. \; (1)$$

Furthermore, utilities being random and the F function not being restricted to be linear in equation (1), the i^{th} farmer therefore chooses climate-smart maize variety if the utility expected from adopting is higher than that of the alternative varieties or non-adoption as *p=1* if $U_{1i} > U_{0i}$ or when the unobservable random variable is $y^* = U_{1i} - U_{0i} > 0$. The likelihood that $Y_i=1$ (for instance the farmer adopts Climate-smart maize variety) is a function of explanatory variables as follows;

$$\begin{aligned} P_i &= \Pr(Y_i=1) = \Pr(U_{1i} > U_{0i}) \\ &= \Pr[\beta_1 F_i(W_i, D_i) + \mu_{1i} > \beta_0 F_i(W_i, D_i) + \mu_{0i}] \\ &= \Pr[\mu_{1i} - \mu_{0i} > F_i(W_i, D_i)\,(\beta_0 - \beta_1)] \\ &= \Pr[\varepsilon_i > -F_i(W_i, D_i)\alpha] \\ &= F_i(X_i\alpha) \; \dots\dots\dots\dots\dots\dots \quad (2) \end{aligned}$$

Where Pr is the probability function, X_i is the independent variables, α parameter to be estimated, ε_i random error term, F(Xα) is the cumulative distribution function for ε_i estimated at $X_i\alpha$. Hence, the likelihood that a farmer adopts climate-smart maize variety is a function of independent variables, unknown parameters and random error term.

2.2 Study Area

The study was carried out in Embu County which is located at the eastern parts of Kenya. The county altitude ranges from 515m at the basin of river Tana to 5199m above sea level Southwest at the top of Mt. Kenya [17]. Embu County has a population of about 608,599 according to 2019 census (KNBS, 2019). The County temperature ranges from 9^{o}C to 28^o C and receives a considerable rainfall of 1206mm yearly due to its proximity to Mt Kenya [18].

2.3 Data Collection Techniques

The study employed both primary and secondary data where primary data was collected using semi-structured questionnaires which were administered face to face. The study used face-to-face interviews because it's considered resilient since it allows immediate follow-up and clarification [19].The primary data collected from the farmers was supplemente with the secondary data.

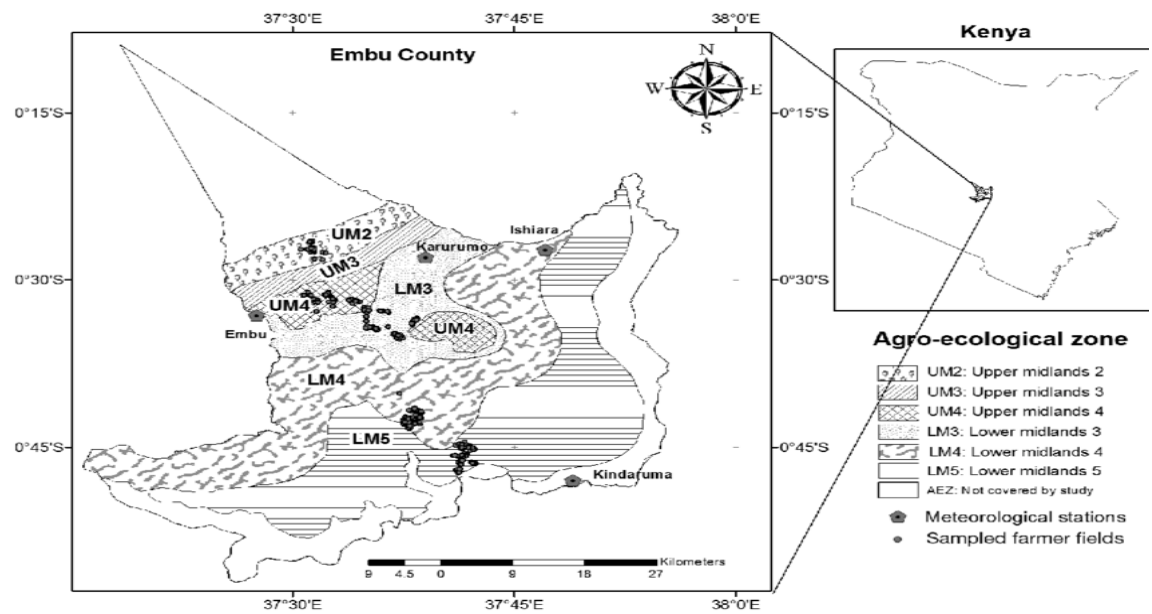

Fig. 1. The study area
Source: The County Government of Embu (2013-2017)

2.4 Sampling Procedure and Sample Size

The study embrace the use of survey design in natural research setting .The adopted design enabled the study of different groups of the population concentrated in different sub-locations forming three Agro-ecological zones. The study used multistage sampling procedure where in the first stage Embu county was purposively selected. It was selected because it has different agro-ecological zones that give room for growing different maize varieties ranging from hybrid maize, open-pollinated varieties (OPVs), and local varieties. In the second stage, the stratification of sub-locations of Kyeni south ward was done forming three strata on the basis of similar characteristics and participation in CSMVs. Stratified random sampling of sub-location formed sampling frame. Lastly, systematic random sampling was used to sample 550 households comprising 346 adopters and 204 non- adopters. Kreycia and Morgan [20] 384, whereas the sample size used by the study was 550 .The sample size was increased to gain more power to avoid presence of heteroscedasticity and multicollinearity in the analyses and allow the researcher to have conclusive data to be used in the analysis.

2.5 Empirical Framework

In the literature, the outcome of technology choice on agricultural technology adoption is classified in two ways [21]. The outcome takes the value of zero if no land is dedicated to climate-smart maize varieties and one if any area is dedicated to climate-smart maize varieties. The other one is the intensity of adoption. In this study, adoption intensity is expressed as the proportion of the total land where climate-smart maize variety is planted. Thus, an empirical model was used to examine the determinants of maize farmers to adopt climate-smart maize varieties and the area over which they have planted them. The intensity of adoption was measured as the proportion of the area under which climate-smart maize variety was dedicated then used ration formula to linearize it to be a continues variable.

A double hurdle model proposed initially by Cragg [22] was employed to analyze factors which affect the probability and intensity of the use of climate-smart maize varieties. The fundamental assumption in the double hurdle approach is that, farmers make two decisions. The first choice is decision to assign climate-smart maize variety an actual amount of land. The other one is the proportion of the area to allocate, which is a conditional on the decision made at first. The possibility of a different set of variables to affect the two decisions are permitted by double hurdle model [23].

The double-hurdle model is a generalized parametric of the Tobit model [24] where, two discrete stochastic procedures define the adoption decision and the adoption level of the technology. The adoption decision of the climate-smart maize is modelled as a binary function which is Probit, and the latent variable of a given household decision to use climate-smart maize varieties CSA_i^* is specified as;

$$CSA_i^* = \beta X_i + \mu_i \qquad (1)$$

The Probit was estimated on the observed outcome as

$$\left.\begin{array}{l} CSA_i = 1 \text{ if } CSA_i^* > 0 \text{ and} \\ CSA_i = 0 \text{ if } CSA_i^* \leq 0 \end{array}\right\} \qquad (2)$$

In the above equation CSA_i^* is a latent variable taking the value of 1 if the farmer decided to adopt climate-smart maize varieties and 0 if otherwise, X is a vector of explanatory variables that influenced farmers' adoption decision, a vector of parameters to be predicted is denoted by β while µ is normally distributed error term with mean zero and constant variance. CSA_i is observed when the farmer makes a decision to adopt climate-smart maize varieties.

The unobserved latent value of the desired area planted to climate-smart maize varieties or latent variable of adoption intensity is A_i^* which can be specified as;

$$A_i^* = \acute{\alpha} Z_i + v_i \qquad (3)$$

The study worked with an observed area that is A_i since A_i^* is a latent variable where;

$$\left.\begin{array}{l} A_i = A_i^* = \alpha Z_i + v_i \quad \text{if} \quad A_i^* > 0 \text{ and } CSA_i^* > 0 \\ A_i = 0 \text{ otherwise} \end{array}\right\} \qquad (4)$$

Where A_i was the observed share of land area where climate-smart maize varieties are planted (signifying the intensity or extent to adopt), Z is hypothesized to be the vector of explanatory variables affecting the extent use of climate-smart maize varieties, ά, was a vector of the parameter to be evaluated. The error term is v_i.

v_i and μ_i are the error terms and are assumed to be independent of each other and are normally distributed with constant variance and mean which is zero which is distributed as;

$$\left.\begin{array}{l} \mu_i \sim N(0, 1) \\ \\ v_i \sim N(0,1) \end{array}\right\} \quad (5)$$

Log-likelihood function of the double hurdle model is expressed as;

$$LogL = \sum_0 \ln\left\{1 - \emptyset(\beta_i X_i)\left(\frac{\alpha Z_i}{\sigma}\right)\right\} + \ln \emptyset BiXi1\sigma\emptyset Ai{-}\alpha Zi\sigma \quad (6)$$

The model is equal to a univariate Probit model: equations 1, 2, and the truncated regression model: equations 3, 4 combined under the independence assumption between the error terms U_i and Vi [25]. Therefore, the sum of the Probit model and truncated regression is the log-likelihood of a double hurdle. A double hurdle hypothesis test was done against the Tobit model. Using the log-likelihood ratio test, a trial was done by estimating three regression models independently, which are; Tobit model, the Probit model, and the truncated regression. Tobit was used to measure how well our model fits by comparing the observed values in the dataset and predicted values based on the Tobit model [26]. The study used truncated regression to assess which of the observation not to include in the value of the dependent variable analysis [27]. Probit was used to test whether the model fits by producing a variety of fit statistics [28]. Greene, [29] formula was used to compute LR statistic.

$$\acute{r} = -2\{\ln L_T - (\ln L_p + \ln L_{TR})\} \sim x^2{}_k \quad (7)$$

Where in both equations the number of independent variables is denoted by k, the Probit model likelihood is L_p, Tobit model likelihood is $L_{T,}$ and the truncated regression model likelihood is L_{TR}.

The hypothesis test was written as; Ho: $\lambda = \frac{\beta}{\sigma}$ and H_1: $\lambda \neq \frac{\beta}{\sigma}$

Thus study rejected the H_o on pre-specified significance level if $\acute{r} > x^2{}_k$

2.6 Empirical Model Specification

In this study the model specifying the adoption was expressed as;

$$Y_1 = B_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \ldots\ldots\ldots\ldots\ldots + \beta_{14} X_{14} + \mu \quad (8)$$

Y_1= (decision to adopt and intensity of adoption) ,X_i defined as X_1 =The age of household head (years), X_2 = household head level of schooling (years), X_3 = Farming capability (years), X_4 = Size of the household (numbers), X_5 =off-farm income, X_6 = Size of the farm (Ha), X_7 = Credit access (1 if access, 0 otherwise), X_8 = access to extension services, X_9 = Distance to market , X_{10} = association into a group(1 if yes ,0 otherwise), X_{11} = Early maturity(3 – 4 months),X_{12} Drought resistance, , X_{13}= high yielding(1 if yes, 0 otherwise), X_{14} = pest and disease resistance(1 if yes, 0 otherwise), X_{14} = Taste (1 if yes, 0 otherwise) ,μ= error term

3. RESULTS AND DISCUSSION

3.1 Socio-demographic Characteristics of Farmers' Respondents

Table 1 shows characteristics of farmer respondents' in terms of adoption intensity. The study involved maize farmers, who have adopted CSMVs and those who have not adopted. The average pooled age of the respondents was 58 which indicates that maize farming is mostly carried out by aging farmers who are constrained by labor for managing maize farming. There was a significant difference in the average age between adopters and non-adopters where non-adopters were older on average compared to adopters. Old age is associated with risk- averse hence not readily adopting new technologies [29].

The average years of schooling for both adopters and non-adopters was 8 years which implied a low levels of education among the farmers. There was a significant difference on average years of farming experience between adopters and those who did not adopt. Non-adopter had more experience on maize farming hence most farmers were used to their old maize varieties hence not easily convinced to uptake new varieties. The mean household size was found to be significantly different between those who adopted and non-adopters. Adopters had a bigger a household size compared to non-adopters in study area. The bigger the number of household members, the more people to feed, therefore a household will adopt new technologies which has more yield especially in current climatic conditions. There is a statistical significant difference in off-farm income between those who adopted and those who did not adopt, where it is high among adopters. This difference signifies that high off-farm income made it possible for the adopters to be inquisitive and try new technologies.

Even though on average, farmers' access or contact to extension services was low at 38%, there was a significant difference between the two groups where the adopters had more access to extension facilities. Extension services access or being in contact with extension officers during the production period of a given crop is a proxy of awareness and subsequent adoption of new technology in our case climate-smart maize varieties [30]. In respect to group membership, it was deduced that there was a statistical significant difference between those who adopted and non-adopters, where most adopters were under a given association. Group membership is seen as a way to build social capital, which improves information and resource sharing and sometimes can act as a source of subsidizing credit for members [31].

There was a significant difference in access to credit services between the two groups, where those who adopted had more access to credit services. Those farmers who can access credit have a high likelihood of adopting new technologies since they will have resources to purchase the required agricultural practices.

Table 1. Socio-economic characteristics of households

Continuous Variables	**Pooled mean(Std Dev)**	**Adopters mean (n=346)**	**Non-adopters mean(n=204)**	**t-value**
Age of household head (years)	58.4 (14.19)	57.3(14.52)	60.36(16.10)	2.3825*
Years of schooling	8.0(3.69)	8.2(3.53)	7.6(3.92)	-1.8262
Number of years farmer farmed maize	26.9(16.00)	25.9(15.43)	28.43(16.85)	1.7701*
Number of household in the house in 2019	4.1(1.82)	4.3(1.80)	4.0(1.80)	-1.8814*
Distance to nearest input market in KMs	3.8(0.30)	3.8(0.44)	3.66(0.30)	-0.2494
Log of off-farm income	7.2(0.23)	7.6(0.28)	6.6(0.38)	-2.0800**
Dummy Variables	**Percentage of farmers value**			**א ²–**
The household head gender	(Male)= 72	62.9	37.1	-3.1205***
	(Female)= 28	63	37	-4.9701***
Access to extension services(% Yes)	37.5	76.7	23.3	-6.0273***
Farmers belonging to a group(% Yes)	59.3	65	35	-5.1977***
Access to any form of credit (% Yes)	25.8	83.1	16.9	-6.5780***

Note: statistical significance levels, *** =1%, ** = 5%, * = 10%.
Source: Survey Data(2019)

Table 2. Farmers awareness and rate of adoption of climate-smart maize varieties

Climate-smart varieties	% of the farmers aware of the varieties (n=550)	% of the farmers growing the varieties(Adopted) (n=550)
Duma43, Decalp and Dk 8031	86.4	62.9
Source: Survey Data(2019)		

3.2 Farmers' Awareness and Adoption of Climate-smart Maize Varieties

Table 2 shows farmers' awareness and adoption level of climate-smart maize varieties in our study area. The results show that besides the awareness of the climate-smart maize varieties being high at 86%, the adoption rate is 63%. These results show that even though farmers are aware of these improved climate-smart maize varieties, some percentage of the farmers don't adopt them. The study carried out by Ogada *et al*., [32] also confirm these finding where they found out that the rate of adoption of improved maize varieties was at 65% in the midlands ecological zones in the year 2007.

3.3 Determinants of Adoption and Intensity of Adoption of Climate Smart Maize Varieties

The results from the double hurdle model show the Probit model for the adoption decision and the truncated regression model for intensity of use of climate-smart maize varieties in the study area. In the second hurdle truncated regression model was used. All the zero values (those who did not adopt the climate-smart maize varieties (CSMVs)) from the selection model (first hurdle) were truncated, and only the positive values (proportion of land allocated for CSMVs) were included in the regression model. Table 3 presents the estimated coefficients' of Probit model and truncated regression model.

3.3.1 Factors influencing adoption of climate smart maize varieties

The results from Table 3 show that the household head's age was statistically significant at a 5% significant level with a negative relationship to adoption decision.

Hence, the negative relationship signified that, as the farmer's age increased, the adoption probability reduced. The results showed that when years of the respondent age increases, the probability of adoption of climate-smart maize varieties reduces by 0.7%. This result infers that the older the respondents become, the lower the likelihood of adopting climate-smart maize varieties since they become risk-averse on new technologies introduced to them. The results are consistent with preceding studies such as Ghimire et al., [33]. They found out that age had a negative effect on the adoption of improved maize varieties, which was the case with Akinbode and Bamire [34].

The size of the land was negatively influencing the probability of adopting climate-smart maize varieties at a 10 % significant level. The results indicate that an increase in land size with one unit decreased the likelihood of adopting the climate-smart maize varieties by 13.5%. This result might be because most of the respondents had a small landholding, with an average of 1 hectare divided according to the enterprises the farmer had. Similar results were reported by [35,36].

Land ownership had positive effect on the likelihood of adopting climate-smart maize varieties at 1% significant level. The land ownership was a dummy variable where if a respondent owned land with title, it was 1 and 0 if otherwise. The results in this study indicate that if a farmer-owned land with title, it increased the farmer's probability of adopting the climate-smart maize varieties by 10.4% since, ownership of land emboldens the adoption of agricultural technology. This is because land ownership can safeguard flow of cash over time and enable liquidation of asset given transferable rights of land. It can also boost resources access such as credit, which can incentivize the decision to adopt technologies that require investments. These results were in line with other studies [37,38,39].

Off-farm income had a positive effect on the farmers' adoption decisions at a 5% significant level. The result implies that farming household who were undertaking off-farm activities were more probable to adopt climate-smart maize varieties. The results indicate that an increase in the off-farm income in one unit increases the possibility of adoption of climate-smart maize varieties by 0.6%. Farm liquidity is enriched by off-farm income as it provides an alternative source of financing agricultural activities such as the purchase of farm inputs and meets labor costs involved in the cultivation of these climate-smart maize varieties. These results were consistent with other studies such as Muzari *et al*., [40].

Source of seeds was one of the factors where we enquired if the farmers were sourcing the certified seeds, which are recommended by the seed sector of Kenya and KEPHIS. According to the study, it is worth noting that the source of seed was positively influencing the probability of a farmer to adopt at 1% significant level. Sources of seed was a dummy variable where 1 represented sourcing seeds from the certified agro vet dealer while 0 was other sources. The results indicated that if a farmer sourced their seeds from an agro vet, it increased their decision to adopt climate-smart maize variety by 62.3%. This result explains that purchasing the certified seeds was perceived to increase production since farming households in remote areas hardly get reliable sources of improved certified seeds, magnifying the importance of the availability of seed in the local area. The outcome was consistent with that of Ghimire *et al*., [33].

Annual contact with the extension agent was positively significant at 1% and associated with the likelihood of adopting climate-smart maize varieties. The availability of extension services signified an increase in the adoption rate of climate-smart maize varieties among farming households. The extension officers popularize the innovation by providing the necessary information, knowledge, and appropriate special skills required for a given technology to enable farmers to apply the technology. The results were consistence with the finding of Maina et al., [41], Wekesa et al., [42], and Beshir et al., [43].

The results show that being a member of a farmer group was significant at 1% and positively associated with the likelihood of adopting climate-smart maize varieties. Farmer belonging to a farmer group increased the likelihood of adopting the climate-smart maize variety by 17.6%. Being in a social group it provided farmer with a linkage to access facilities such as extension services and credit facilities, which are important ingredients of adopting new technology. Belonging to a social group enriches social capital that allow trust, ideas, and information exchange [23].

Among the varietal attributes, all of them were significant and had a positive effect on decision to adopt. The results show that if variety was perceived to be high yielding it positively influenced farmers' probability of adopting it at 5% significant level. If a farmer perceives that yield attribute to be reasonable concerning a given variety, it increased the likelihood of farmer adopting said variety by 13.3 %. This result suggests that farmers prefer those varieties which are high yielding to be more productive at minimum input cost possible to generate a market surplus and increase their returns from maize production. This result was consistent with the finding of Rahman and Chima [44]; Odhiambo et al., [30].

According to the results, the early maturity attribute of a given variety was significant at 1% and positively influenced farmers' adoption decision of climate-smart maize varieties. The results show that if farmers perceive that a given climate-smart maize variety will mature early than other varieties, it increased their probability of adopting that variety by 15.4 %. The reason for farmers to select these varieties, which are early maturing, it's because of the many short rainy seasons nowadays than the expected time due to climatic change, which causes acute crop failure. These findings were consistent with that of Odhiambo et al., [30].

Pest and disease resistance attribute was positively significant at 1% and associated with the possibility of adopting the climate-smart maize varieties. Any variety expected to be resistant to pests and diseases increased the likelihood of such variety being taken up by the farmer by 23.4 %. This attribute was essential to the farmers since it will reduce farmers' cost spent on purchasing chemicals to fight the menace brought by increased pests and diseases such as fall armyworm.

The drought tolerance attribute was significant at 5%, and it positively influenced farmers' decision to adopt the climate-smart maize varieties. The drought tolerance attribute was found to increase the likelihood of using the climate-smart maize varieties by 10.5%. This attribute was essential to the farmers since it would caution them of extreme drought stress due to climatic change over time, causing crop failure. This finding was consistent with Fisher et al. [45]. From the results it is evident that gender, household size, access to credit and yield of household in previous season no longer play role in adoption decision of new technologies.

Table 3. Determinants of adoption and intensity of adoption of climate-smart maize varieties

Model specification Variables	**Double- hurdle**						
	Probit Coefficient	**Robust Std. Err.**	**Marginal effects**	**P-values**	**Truncated Coefficient**	**p-values**	**Robust Std. Err.**
Socio-economic factors							
Gender	-0.128	0.147	-0.051	0.386	-0.011	0.945	0.166
Age respondent	-0.009	0.005	-0.008 **	0.055	-0.013 **	0.028	0.006
Household size	-0.00009	0.036	0.03	0.998	0.090 **	0.048	0.046
Land size	-0.051	0.029	-0.135 *	0.078	0.464 ***	0.000	0.099
Land ownership	0.154	0.060	0.104***	0.009	0.137 **	0.084	0.079
Logoff-farm income	0.027	0.013	0.006 **	0.038	-0.026	0.160	0.019
Seed source	1.702	0.158	0.623***	0.000			
Previous yield	0.015	0.012	0.016	0.205	0.030 ***	0.008	0.011
Institutional factors							
Credit access	-0.108	0.233	-0.042	0.642	-0.002	0.990	0.196
Extension serv.	0.574	0.147	0.320***	0.000	0.309 **	0.043	0.152
Group membership	0.422	0.135	0.176**	0.002	0.050	0.743	0.153
Perceived attributes							
High yielding	0.346	0.148	0.134 **	0.020			
Early maturity	0.403	0.138	0.154 ***	0.004			
Pestdis.resistance	0.590	0.190	0.234 ***	0.002			
Drought tolerance	0.277	0.140	0.105 **	0.048			
Constant	-2.395	0.463		0.000	-0.700	0.196	0.541
Model summary							
Log pseudo likelihood		-543.121					
Prob. > chi^2		0.0000					
Wald $chi^2(10)$		41.66					
Pseudo R^2		0.289					
Number of observations		550			346		

*Note: * , ** and * ** represents the significant levels at 10%, 5% and 1% levels respectively*
Source : Survey Data (2019)

3.3.2 Determinants of the intensity of climate-smart maize varieties

From the results in Table 3, the truncated regression represents the results of the level of adopting climate-smart maize varieties in the second step of the double hurdle model. The results show that the household size, land size, land ownership, extension services, and previous maize yield are significant and positively influencing the intensity of adoption. While, the household head age is significant and negatively influencing the extent of adopting climate-smart maize varieties. The results further show that gender of the household head, off-farm income of the farming household, access to credit, and being in a group or association had no significant influence on extent of adoption.

The results showed that the age of household head was statistically significant at a 1% significant level and negatively influenced the hectares of land under which climate-smart maize variety is cultivated. The result implies that as the respondent advance in years, the area allocated for climate-smart maize varieties become smaller; hence the respondent age increase with one year reduced the use intensity of climate-smart maize varieties. The old farmers have experience of different enterprises, especially in the study area such as mango, macadamia, and banana farming. Thus they dedicated a large piece of land to other enterprises compared to climate-smart maize varieties. Older farmers have a conservative attitude towards the fast adoption of new technologies. Akinbode and Bamire [34] attested to this finding when they observed that the age of the household head had a negative and significant influence on the intensity of adopting improved maize varieties in Nigeria.

The size of the family, which is an indicator of household labor availability, was statistically significant at 1% level and positively influenced the use intensity of climate-smart maize varieties. The effect of household size on the intensity indicates that as the respondent's household size increases with one member, the land size in hectares planted with climate-smart maize varieties increased. The size of the household is seen as a proxy of available cheap labor, thus more land cultivated with climate-smart maize varieties since cheap labor to take care of the crops will be available. This study also posits that the larger the household, the higher the consumption and demand for food hence more pressure to ensure food security. When faced with food insecurity, large households will likely cultivate more hectares of land with climate-smart maize varieties since they perceive them to have more yields. These findings are consistence with other studies [30,33,46].

The farm size of the respondent was significant at 1% and positively influencing the area allocated to climate-smart maize variety. This result implies that the larger the size of the farm of the respondent, the more area is allocated to climate-smart maize varieties. Hence, if the farm size of the respondent's increases with one unit it leads to an increase in the area planted with climate-smart maize varieties. As land size increases, it increases the household opportunity to utilize climate-smart maize variety. Ghimire *et al*., [30] found out that in Nepal, maize production increased as the land allocated to improved varieties of maize increased. This finding was also consistence with that of [34,47].

Land ownership had a positive influence on the area under climate-smart maize varieties and statistical significant at 5%. The result indicates that if a respondent has a secure land tenure, the more land area in hectares they will dedicate to climate-smart maize varieties. Thus if a respondent owned land with tittle, this led to an increase in the area planted with climate-smart maize varieties. Land ownership is considered as an indicator of wealth and proxy for social status, which can improve resource access such as credit, which can incentivize and influence the intensity of use of climate-smart maize varieties. The result is consistence with that of [385,39].

Access to extension services was statistically significant at 5% and had a positive effect on the intensity of adoption of climate-smart maize varieties. The result implies that as contact with an extension agent increased, it increased the intensity of the use of climate-smart maize variety. The household that had contact with extension agents was considered more enlightened about planting material and agronomic requirements of the new varieties hence appreciating the benefit of the new technology more than others. The frequent contact with extension agents shows there is the availability of reliable information sources, which will enhance the communication process and improve the intensity of use of improved technologies. Mignouna et al., [23] found that extension service is one of the most agreed situations for creating awareness and building the necessary knowledge for using the new technology following the approach, which is most convenient for farmers.

4. CONCLUSION AND POLICY RECOMMENDATION

Maize production is important for improving food security among small scale farmers. The decision to adopt new varieties is pegged on social, economic and institutional factors in the environment where different maize actors operates. The finding shows that awareness of CSMVs was high compared to adoption rate. Therefore, more resources should be directed towards enabling the adoption of Climate-smart maize varieties besides creating awareness. Young farmers were more likely to adopt new technologies hence policy intervention is needed to make maize enterprise more attractive to youths by making it easy to access the production factors such as land.

Access to extension services contributes to adoption, and therefore there is a need to strengthen support in the provision of extension services. The study recommends the county government and private sectors to come up with more innovative ways to disseminate information to farmers. This outreach could be through incorporating Information Communication Technologies (ICTs) such as mobile phones, televisions, or radio, in the dissemination of agricultural information, which can contribute greatly to increasing farmers' access to information.

The finding shows that land is significant in deciding to adopt and the extent of the area to dedicate adopted variety. The findings show that the land's size has been decreasing over the years in the region due to population pressure on arable land. Thus, multi-stakeholders need to invest in capacity building on production of intensification measures such as use of fertilizers, crop protection, and use of high yielding varieties to increase output per unit area since it's not possible to increase the land size among farmers. Finally, there is need for policies that will be directed at improving the adoption of climate-smart maize varieties amongst the non-adopters through the provision of more competent and effective extension services, addressing land tenure system and price of related agronomic practice.

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COMPETING INTERESTS

Authors have declared that no competing interests exist.

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