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Factors Affecting Adoption of Climate-Smart Agricultural Technologies: Evidence from Nandi County, Kenya

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ABSTRACT

Adoption of Climate Smart Agricultural Technologies (CSAT) such as Biogas production, silage making, agro-forestry and water conservation help in improving smallholder production. However, in rural areas of Nandi County of Kenya, adoption of CSAT amongst smallholder dairy farmers is low. In this study, we analyze factors affect adoption of CSAT using information drawn from 350 smallholder dairy farmers participating in East Africa Dairy Development programme. Using ordered Logit model, we find that the intensity of adoption of CSAT is partly affected by access to extension and credit services. Specifically, we showed that farmers who had access to extension services and credit lines were more likely to adopt drought resistant crops but not biogas production, agro-forestry and silage making. Moreover, our result showed that owning a stable tenure system allows farmers to adopt technologies which require more land and takes more time like biogas production, drought crops, agroforestry, water storage and silage making. Finally, we showed that distance between a farmer's home and farm is an important factor in adopting an agricultural technology. This effect is more pronounced amongst technologies that are heavy to transport like biogas production, water storage and conservation, zero grazing and silage making.

Key Words: Adoption, Climate Smart Agricultural Technologies, Extension, Agro-forestry, Biogas.

INTRODUCTION

Studies of the determinants of adoption are dispersed around the world. However, there are very few studies covering sub-Sahara Africa where agriculture contributes over 70 percent of Gross Domestic Product (GDP). In addition, most studies have neglected smallholder dairy production despite evidence that climate variability negatively affect yield levels and can even lead to death of dairy animals. Such a gap makes it difficult for policy making and development of dairy guidelines by stakeholders.

In Vietnam, Tran et al., 2020 analyzed the determinants of adoption of CSAT (water saving techniques and improved stress tolerant varieties) using multinomial endogenous switching regression framework. They showed that gender of head, age of head, family workers, farm characteristics, climatic factors, distance to markets, access to climatic information, access to extension, membership to an association and attitude towards risk are key determinants of the decision to adopt CSAT. In Bihar, India, Lopez-Ridaura et al., (2018) analyzed the effects of CSA on household food security and showed that adopter of conservation agriculture was determined by wealth status of a household. They also noted that farmers with alternative off-farm income sources are less likely to affect by environmental shocks.

In Mali, Quedraogo et al., (2019) analyzed the uptake of CSAT (in this case drought tolerant crop varieties, micro-dosing, organic agriculture, intercropping, farmer managed natural regeneration, agroforestry, contour farming, and climate information service). They found low observed adoption rate compared to actual adoption: 39-77 percent versus 55-81 percent, respectively. Important factors affecting adoption of CSAT to include education of head, family size, access to subsidies and training. In Zimbabwe, Mujeyi, Mudhara and Mutenje (2021) showed that adopting CSA was impacted by farmer and farm-related characteristics as well as market factors are important.

In Nandi County, smallholder dairy production is mainly practiced under rain-fed system. This implies large variation in productivity between wet and dry seasons. This has a direct implication on farm household’s income levels. In most instances, it’s not possible to sustain productivity due to negative environmental externalities like drought, floods and storms occasioned by resource intensive agricultural practices. In addition, the rising climatic variability has exerted additional pressure, requiring farmers to change their way of farming to cope up with new challenges (Easterling et al., 2000; Thornton et al., 2009).

Nandi County has agricultural rich land with over 80 percentage of its population being classified as smallholder, resource-poor farmers. In the region, farmers practice mixed farming with Friesian cows being the dominant breed species (Ngeno et al., 2013; 2014). According to Zagst, (2011) the project assisted dairy hubs to procure and install milk cooling plants. The EADD programme introduced the concept of CSAT to farmers through collaboration with MICCA in Nandi County. In addition, it incorporated production of fodder shrubs and herbaceous legumes to increase productivity of dairy cows, control soil erosion and finally, as a way of promoting zero-grazing units, which in turn facilitates installation of biogas units (Wambugu, 2011). The project also explored local solutions and mechanisms to promote adaptation and climate change mitigation.[4]

In enhancing adoption of technology, diffusion model emphasizes the importance of extension agents, community opinion leaders and mass media in promoting technology adoption. For instance, the laggards and late majority requires additional information and assurance from extension agents to allow them to adopt the technology. Agarwal (1983) emphasized the need for extension in promoting adoption of new technologies and this should be supported by mass media, demonstration, and farmer field days. In some instance, extension agents may apply informal communication channels or interpersonal communication channels to entice farmers especially illiterate to adopt a given technology.

The adoption of technologies has been shown to depend upon a myriad of factors including household and farm characteristics. These characteristics include age, gender, level of education, and head of household, asset endowment, farm size and farming experience. Other factors that influence decision about adoption comprise perception of the problem, characteristics of technologies, institutions, and the influence of the market (Jones et al., 2010; Rogers, 2003; Frank & Penrose, 2012). Assets and wealth endowment such as income, savings and access to credit, and insurance is considered to have significant influence on adoption of technologies by small scale farmers. This is because they act as ‘safety nets’ in time of crisis, thus enabling farmers to be innovative, and take risks. This in turn supports long-term sustainability of adaptation (Jones et al., 2010).

METHODOLOGY

This study was undertaken in Nandi County, Kenya. This county occupies 2,884.4 square Kilometers (KM^2). It has a population of 752,965 (as at Census 2019 data), with majority of residents are natives of Nandi speaking people. It is bordered to the West by Kisumu, East by Nakuru, South by Kericho and to North by Uasin-Gishu Counties. Its altitude ranges from 1,400-2,400m above sea level, average temperatures between 18 and 25°C while rainfall varies between 1,200-2,000mm above sea level per year. Out of the six sub-counties, Aldai sub-county was purposively selected to be EADD programme station. Aldai sub-county is located within latitudes 0°34″ North and longitudes 34°44″ and 35°25″ East. Majority of households in this sub-county are smallholder dairy farmers. We selected Kaptumo/Kaboi and Ndurio/Koyo wards because of the high number of smallholder dairy farmers (approximately 1600) who supply milk to Kaptumo Dairy Cooperative Society Limited.

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Figure 1: Map of Kaptumo area

Source: Adapted from Jönsson (2012)

In determining sampling size, we followed Cochran's (1963) formulation. Using this formula, a total of 385 smallholder dairy farmers who participated in EADD project was selected for interview. See Table 1 for distribution of stallholder dairy farmers within Aldai sub-county. The formula is shown below.

$$S = \frac{Z^2pq}{e^2},\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(Equation 1)}$$

Where; S is the required sample size; Z² is the table value of chi-square for one degree of freedom at the desired confidence level of 95 percent. At this confidence level, e (i.e., error term) is 0.05 and Z equals 1.96. This implies that Z^2 equals 3.841 (i.e., 1.96 *1.96=3.8416). p is the estimated variance in the population, expressed as a decimal while $q = 1 - p$. Due to variability in the population of smallholder dairy farmers, we will apply a conservative value of 50 percent. This means that our sample size will be calculated as.

$$S = \frac{1.96^2 * 0.5 * 0.5}{0.05^2} = 384 \text{ smallholder pumpkin farmers}$$

However, we dropped 34 respondents because of incomplete information. This leaves us with 350 farmers with complete information for analysis. We also undertook key informants' interview with 21 community opinion leaders, extension agents and non-governmental organization's officials working in the dairy sector.

Table 1: Distribution of farmers in seven sub-locations in Nandi County

Wards	Sub-location	Number of farmers interviewed	Key informants interviewed
Kaptumo/Kaboi	Chepkong'ony	53	3
	Mosombor	62	3
	Ibanja	54	3
Ndurio/Koyo	Kaboi	50	3
	Mugundoi	48	3
	Kapsoo	63	3
	Kamarich	54	3

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Total	**384**	**21**

We used both structured and semi-structured questionnaires, Focus Group Discussions, and key informant schedule in collecting data. The parameters of interest in the questionnaire were socio-economic, institutional and weather-related factors affecting adoption of CSAT in Aldai sub-county of Nandi County, Kenya. We first, undertake a pre-tested of questionnaire using trained numerators with 40 smallholder dairy farmers from Sameta sub-county, Kisii County. We found a Cronbach's alpha coefficient of 0.7 thus lending reliability for our questionnaire (Santos, 2013). To verify the validity of questions, we applied Content Valid Index (CVI) and found 56 percent- a value deemed valid for scientific research purposes.

MODELING ADOPTION OF CSAT

Adoption of a new technology or practice in agricultural setting is influenced by several factors: which can be classified into socio economic, farmer and institutional factors. For instance, a farmer can fail to adopt a technology, adopt partially, or adopt all components of a technology. In view of this, we categorized adoption levels into three levels: no intensity, low intensity, and high intensity. This means that our outcome variable is ordered from no intensity to high intensity. Analysis of ordered dependent variables can be done using either duration or ordered response models. In this study, we adopted an ordered logit model (Kockelman and Kweon 2002; Barua and Tay, 2010). The advantage of this model is that it yields estimates that are consistent and efficient. In addition, ordered model also capture the qualitative differences between adoption categories (Khattak and Council, 1998; O'Donnell and Connor, 1996).

The model we estimate can be written mathematically as;

$$y_i^* = X_I\beta + \varepsilon_I \quad \text{............................ (Equation 1)}$$

Where y_i^* is latent variable which is measuring the adoption of new agricultural technologies adopted by smallholder farmers ranging from $-\infty$ to ∞; X_I is a vector of independent variables that are likely to influence the intensity of adoption; β is unknown parameters to be estimated while ε_I is the white noise error term. The adoption intensity levels of climate smart agricultural technologies are recorded into different categories. In our case we have no, low, medium, and high intensity levels.[5] The latent value of adoption levels can therefore be mapped into the intensity levels as follows.

$$y = \begin{Bmatrix} 1\, if -\infty \le y^* < \tau_1 (nointensity) \\ 2\, if \tau_1 \le y^* < \tau_2 (lowntensity) \\ 3\, if \tau_2 \le y^* < \tau_3 (mediumintensity) \\ 4\, if \tau_3 \le y^* < \infty (highintensity) \end{Bmatrix} \quad \text{.............. (Equation 2)}$$

Where $\tau_1 \tau_2 \tau_3$ are thresholds separating the four categories of adoption intensity as reported by dairy farmers. This means that the estimated probability that farmer i adopt a given level (j) of climate smart agricultural technology $(j = 1,2,3,4)$ is equal to probability that the latent value takes a value within the appropriate range as shown below; give in form of equations,

$$\Pr(y_{i=1}|x_i) = \Phi\{\tau_1 \_ X_I\beta\} \quad \text{..................... (Equation 3)}$$

$$\Pr(y_{i=2}|x_i) = \Phi\{\tau_2 \_ X_I\beta\} - \Phi\{\tau_1 \_ X_I\beta\} \quad \text{...................... (Equation 4)}$$

$$\Pr(y_{i=3}|x_i) = \Phi\{\tau_3 \_ X_I\beta\} - \Phi\{\tau_2 \_ X_I\beta\} \quad \text{....................... (Equation 5)}$$

[5] For analysis purposes, we collapsed low and medium intensities to low intensity because few farmers reported medium level of adoption of CSAT. This means that we have three - low, medium, and high, adoption intensities. As a robustness check, we also run regressions where outcome variables are categorized into four levels of intensities (i.e., no, low, medium, and high) as reported in the questionnaire. However, our result does not seem to change significantly form what we present here. We do not present these results here for brevity but they available from the authors upon request.

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$$\Pr(y_{i=4}|x_i) = 1 - \Phi\{\tau_3 \_ X_I\beta\}$$ …………………… (Equation 6)

Where; Φ is the cumulative density function (CDF) of a normal distribution. However, one assumption is necessary if probability is to be positive, in that $0<\tau_1<\tau_2<\tau_3<\tau_4$. This model is estimated using maximum likelihood procedure. There are numerous explanatory variables likely to influence adoption levels. We classified these factors into two main classes: either socio-demographic or institutional factors. In Table 3, we provide the summary description of the main explanatory variables used in our regression. Following literature, we classify our variables into two broad categories: socio-demographic and institutional factors (Table 3).

Table 2: Description of variables used in the ordered logit regression and expected sign

Variables	Description	Value	Expected sign
Independent variables			
Socio-demographic characteristics			
Household size	What is the total number of people in your household?	Number of people eating from the same pot1=0-5:2=6-10:3=>=11	Positive (+)
Age of the respondent	What is your age?	Years1=15-29:2=30-39:3= 40-49:4=>=50	Positive (+) or Negative (-)
Education of household head	What is the respondent level of education?	1=literate (>=secondary education):0= otherwise	Positive (+) or Negative (-)
Marital status of the respondent	What is the gender of household head?	1=Male; 0=Female	Positive (+) or Negative (-)
Institutional factors			
Distance to the farm	What is the average distance to your farm in from your homestead?	Kilometres (Km) 1=0-05:2=0.6-1;3=1.1-2;4=>2	Negative (-)
Dairy farming systems	Which of these dairy farming systems did you practice	1=zero grazing 2= semi – intensive farming 3= tethering, 4 extension/ free range, 5=paddocking and 6=pastoralism	Positive or negative
Land tenure	What is the type of land ownership do you have?	1= Owned/inherited; 0= Leasehold	Positive (+)
Membership to farmer association	Do you belong to any civil, local and farm association?	1= Yes; 0=No	Positive (+)
Access to credit facilities	Do you have access to credit facilities?	1= Yes; 0=No	Positive (+)
Awareness of agricultural technologies	Are you aware of any agricultural technologies necessary to mitigate climate variability?	1= Yes; 0=No	Positive (+) or Negative (-)
Access to extension services	Do you have access to agricultural extension services?	1=Yes; 0=No	Positive (+)

Under socio-demographic characteristics, age of the respondent was measured as a categorical variable. Here (in Table 2), age of a respondent proxy farming experience that small holder dairy farmers hold in undertaking their farming activities. We expect the sign to be either positive or negative. If the sign is positive, this means that farmers with more experience are likely to adopt new technologies because of their financial status and trainings they might have been exposed to. If the sign is negative, this implies that experienced farmers might not adopt technologies because of their past bad experiences on using these technologies and therefore want the status quo to remain.

On the other hand, household size was captured in terms of the number of people eating from the same pot. The expected sign was

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positive. This implies that when there are many people, the probability that some of the member adopt the new technologies. Education was captured in terms of number of years in schooling and we believe that the expected sign will be positive. This means that the farmers who are educated are likely to adopt the new technologies than their counterpart who are not. Under family characteristics marital status was captured as dummy variable of which the expected sigh was either positive or negative. This means that the direction is not clear and therefore will depend on the perception one is looking at it. On positive side the probability that married people are likely to adopt the new technologies is high because are people who will work as labourer to implement them. On the hand those who are not married are likely to adopt simply because resources allocated to them are not likely not to be spent on other issues but new technologies adoptions.

Under institutional factors the distance from the farm was captured in kilometers and we expected the sign to be negative. This is because most farmers are old and therefore might not want to travel for long distance hence affecting adoption of new technologies. Also land tenure was another factor which was captured as land owned or inherited and leased variable and the expected sigh was anticipated to be positive. This means that farmers who own the land or inherited are likely to adopt the new technologies because there is continuity. On the other hand, if the land is leased then are less likely to adopt because of time leased may expired before achieving the target goal.

Membership to a farmer association was captured as a dummy variable and the expected sign might be positive. This implies that farmers who belong to association are likely to adopt the new agricultural technologies compared to those who are not members any association. In addition, another variable was the access to credit facilities which was captured as dummy variable and the expected sign was positive. This means that the farmers who can access the credit facilities have the high probability to adopt the new agricultural technologies than those who cannot access them. New technologies are expensive therefore requires money to implement them

Awareness of new agricultural technologies was captured as dummy variable and we expected the sigh to be either positive or negative. The implication here means the farmers who are aware are expected to adopt the new technologies than those who are not aware. On the other hand (Nm negative sign) those who are aware are also likely not to adopt simply because they understand the disadvantage of the new technologies hence may not adopt. The last institutional factor which captured as dummy variable is the access to extension services and the expected sign is positive. This means that the farmers who access extension services have the high chances of adopting new agricultural technologies than those who are not able to access the services.

RESULTS AND DISCUSSION

Characteristics of dairy farmers in Aldai sub-county, Kenya

The characteristics of dairy farmers in Aldai sub-county, Kenya can be grouped into two: those related to households and institutional factors. Household characteristics of interest in this study include household size, age of household head or respondent, marital status, gender of household and education level. On the other hand, institutional factors include aspects that may influence farmers such as membership to association, dairy farming system practiced, land tenure system, access to extension service and access to formal credit facility. A summary of these characteristics are provided in Table 3 below.

Table 3: Socio-Economic, Institutional and Farm-Specific Characteristics of Dairy farmers in Aldai sub-county, Nandi County, Kenya

Variables	N (1)	Mean (2)	S.D. (3)	Min (4)	Max (5)
Household size (Continuous)	350	1.491	0.523	1.000	3.000
Membership to association (Dummy, 1= Yes)	350	0.291	0.455	0.000	1.000
Dairy farming systems	350	2.869	1.211	1.000	6.000
Age of household head (Years)	350	2.814	0.827	1.000	4.000
Marital status (Dummy, 1=Married)	350	0.874	0.332	0.000	1.000
Gender of the household (Dummy, 1=Male)	350	0.709	0.455	0.000	1.000
Education level of the respondent	350	2.731	0.588	1.000	4.000
Land tenure (Dummy, 1=Secure)	350	0.929	0.258	0.000	1.000
Access to extension services (Dummy, 1=Yes)	350	0.537	0.499	0.000	1.000

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Access to credit facilities (Dummy, 1=Yes)	350	0.303	0.460	0.000	1.000

Notes: N are the 350 smallholder dairy farmers who completed our questionnaires and their information used in the analysis; SD is the standard deviation; Min captures the minimum value of an explanatory variables; Max captures the maximum value of a variable; Dairy farming system clasification:1=zero grazing; 2=semi-intensive; 3=Tethering; 4=Extensive/free-range; 5=Paddocking; 6=Pastoralism; Highest education level of the respondent; 1=Never attended school; 2=Attended primary school; 3=Attended secondary school; 4=Attended post-secondary school.

Our findings indicate that each farm household are made up of about 2 members eating from the same pot (Table 3). This low household size can be attributed to; first the small land sizes caused by increasing human population leading to land sub-division and, two, the burden of accessing food and other social amenities. The high expenditure (or cost of living) of maintaining large families is likely to encourage farmers to use modern family planning methods. The mean household land holdings cultivated are small ranging from 1-2 hectares. This is consistent with the fact that most land holdings in Nandi County where the study area took place are mainly under large scale tea farming by multi-national companies. Results show that about 29.1 percentage of dairy farmers belonged to farmer associations. This number is low considering that small scale dairy farming in the study area is practiced by most small-scale farmers. This low membership to farmer associations may be explained by several factors. First, farmers might have joined these associations expecting some windfall in form of cash bonuses which never happened. Therefore, most of them may have left and joined other association for which we do not have information about. Secondly, this low membership to farmer associations might be attributed to the low levels of education of most dairy farmers (in Table 1 above). The low literacy limits farmers from participating in the activities organized by the association and any benefit that may accrue to them as a result of participation from the associations.

We found that tethering system, a traditional form of livestock farming was dominant in the study area. Interestingly, this farming system has low returns compared to other modern and more effective systems like zero grazing. The high number of farmers using this method can be attributed to the lack of sensitization, awareness, knowledge of new farming system and lack of capital to start the zero grazing unit due poverty levels. Most respondents (45.1 percentage) were aged between 40 and 50 years old (Table 3). This implies that few young people (those aged below 40 years) were engaged in dairy farming in the study area, despite high returns from dairy farming and high unemployment rate of youths (15-24 years) in Kenya (estimate at above 7.27 percentage, as at 2020) (ILO, 2020). This further means that young people who are able to grow the dairy sector are not involved. These results are in congruence with the findings of Murage et al. (2013), who found out that there were more elderly farmers (aged 60years and above) in Kenya, compared to Tanzania and Ethiopia. Similar findings were established by Wemali (2014) and Mironga, (2005) in Kenya. These results affirmed United Nations Development Program (UNDP) position that Kenya’s farming population is aging because agriculture remains unattractive to youths (UNDP, 2011). Over 87.4 percentage of the respondents were married. This high percentage can be explained by the fact that married people have more responsibilities to carry such as paying school fee for the children, providing for the family in terms of food, clothing and shelter. This therefore made them to work hard to meet these household responsibilities.

Both male and female were actively involved in dairy farming in the study area although male dominated (70.1 percentage) compared to their female counterparts (Table 3). This has implications for gender equality and therefore calls for mainstreaming of women in agriculture. Interestingly, it is the female household heads that constitute the bulk of agricultural workforce in Kenya. These findings agree with Okuthe et al., (2013), who reported an existing bias in extension service provision where it was mainly offered to males compared to female farmers. Despite the skewness in gender involvement in dairy farming, it remains the main source of livelihood to about 80 percentage of the rural dwellers in the study area (GoK, 2009).

Education, measured in years of normal schooling of household head is a proxy for managerial input (Maddison, 2006). According to theory, higher level of education diminishes the probability of adoption of new technologies as respondents are able to distinguish between the benefits and costs of adopting a given technology. Our results in Table 1) shows that majority of the respondents had secondary level of education. This is the minimum level of education as prescribed by the government of Kenya. This shows that most of the farmers in study area had sufficient basic skills to understand and apply farming principles, and therefore capable of adopting CSAT. In addition, a large percentage of respondents (93 percentage) reported owning land or were in possession of inherited land in in the study area. This is important because land is an important asset in technology adoption because without it, a farmer cannot adopt technologies requiring longer period of time like 5 years.

Access to extension service refers to the number of contacts that a farmer has been with extension agents each year. This is

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important in that it increases the farmer's knowledge, skills, and awareness towards new agricultural technologies, which in turn influences adoption of technology. Our result (Table 3) shows that majority of respondents (54 percentage) had access agricultural extension services. This finding is consistent with previous studies showing that smallholder farmers (especially smallholder dairy farmer) depend on Agricultural extension as source of farming information and advice. This can be attributed to the fact that extension service in Kenya is free of charge or is subsidized by the government. This shows that most of the farmers in study area had sufficient basic skills to understand and apply farming principles, and therefore capable of adopting CSAT. The quality of interaction between extension officers, farmers determine the effectiveness in extension service delivery (Howley et al., 2012; Millar, 2010). There is a positive relationship between extension contact and farmer's adoption decision (Maponya and Mpandeli 2013; Obayelu et al., 2014; Shongwe et.al, 2014). In addition, these households were visited at least once every 3 months by an extension officer. This indicates possibility that extension officers are effective in reaching many rural farmers.

Access to credit is vital in supplementing the meager resources of the farmers (Jones et al., 2013). With limited credit access, farmers are constrained in terms of investing in technologies such as CSAT. Our results showed that about 70 percentage of dairy farmers in the study area did not have access to credit facilities. Our findings contradict the reported access to credit services in Kisii County where only 16 percentage of households had access to credit services from formal financial institution (ASDSP, 2014). The low access to credit can be attributed to lack of formal financial institutions in the location. In Kaptumo ward, farmers have to travel to either Kapsabet or Nandi hills towns to access banking services. Given that most dairy farmers are of old age, they are not likely to have frequent visits to these institutions. Secondly, given the fact that most dairy farmers are old, they do not have required collateral to allow them access credit from financial institutions. In some instances, farmers lack knowledge about existing credit facilities within the financial sector. Finally, most financial institutions do not have agricultural loans product that can meet the demand of farmers. In instances where they have such products, interest rates are high, and requirements are strict. This means that farmers have to rely on local cooperative societies with low capital base for financial support.

Socio-demographic and institutional factors affecting intensity of adoption of CSAT

In Table 4, we provide a summary of independent variables likely to affect the intensity of adoption of climate smart agricultural technologies. Household reported low or no intensity of adoption (i.e., with membership below 5) compared to high intensity adopters. For high level adopters, firs, we demonstrate that they consist of large household sizes, those ranging from 6 – 10 members compared to no and low intensity adopters. The large family sizes found among high intensity adopters indicates the high labour required in implementing climate smart agricultural technologies. Secondly, we show that almost all farmers (those who reported no, low, and high intensity of adoption) were not members of associations except for adoption of drought resistant fodder crops by high intensity adopters. Thirdly, most adopters of technologies were middle aged (i.e., 40 – 49 years), married and mostly are male headed households. Moreover, farmers who reported no and low intensity levels of adoption lived far away from their farms i.e., between 0.6 to 1 Km. However, high intensity level adopters lived closer to or on their farms, about 0.5 Km. Finally, most farmers (those that recorded no, low, and high intensity level of adoption) are literate.

Table 4: Summary statistics of explanatory variables used in the regression

Variable	No intensity	Low intensity	High intensity
	Mean (SD)	Mean (SD)	Mean (SD)
Biogas Production			
Household size	1.43(0.50)	1.49 (0.51)	1.50(0.53)
Association	0.33(0.48)	0.47 (0.50)	0.26(0.44)
Age	2.57(0.82)	2.53 (0.88)	2.89(0.81)
Distance	1.43(0.68)	1.77 (0.87)	1.43(0.70)
Marital status	0.90(0.31)	0.89 (0.31)	0.87(0.34)
Dairy farming systems	3.17 (1.44)	3.28 (1.28)	2.77(1.16)
Land tenure	0.80(0.41)	0.94 (0.25)	0.94(0.24)
Gender	0.77 (0.43)	0.74 (0.44)	0.70(0.46)
Education	0.80(0.41)	0.83 (0.38)	0.63(0.48)
Access to credit	0.57(0.50)	0.57 (0.50)	0.23(0.42)
Awareness level	0.17(0.38)	0.23 (0.43)	0.16(0.37)
Access to extension	0.30(0.47)	0.32 (0.47)	0.60(0.49)

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Observations	**30**	**47**	**273**
Drought resistant fodder crops			
Household size	1.39(0.50)	1.50 (0.53)	1.52(0.51)
Association	0.28 (0.48)	0.27 (0.45)	0.57(0.51)
Age	2.83(0.92)	2.83 (0.82)	2.65(0.88)
Distance	1.56(0.78)	1.45 (0.71)	1.83(0.94)
Marital status	0.83(0.38)	0.87 (0.33)	0.91(0.29)
Dairy farming systems	2.94(1.51)	2.83(1.17)	3.30(1.46)
Land tenure	0.72(0.46)	0.94 (0.24)	0.96(0.21)
Gender	0.67 (0.49)	0.71 (0.45)	0.70(0.47)
Education	0.61(0.50)	0.66 (0.47)	0.83(0.39)
Access to credit	0.33(0.49)	0.28 (0.45)	0.65(0.49)
Awareness level	0.17(0.38)	0.16 (0.37)	0.35(0.49)
Access to extension	0.33(0.49)	0.54 (0.50)	0.61(0.50)
Observations	**18**	**309**	**23**
Tree planting			
Household size	1.56(0.51)	1.46 (0.52)	1.50(0.53)
Association	0.17 (0.38)	0.26 (0.44)	0.32(0.47)
Age	2.61(0.98)	2.76 (0.81)	2.86(0.82)
Distance	1.50(0.79)	1.52 (0.79)	1.45(0.70)
Marital status	0.83(0.38)	0.87 (0.33)	0.88(0.33)
Dairy farming systems	2.56(1.25)	2.86(1.25)	2.90(1.19)
Land tenure	0.56(0.51)	0.97 (0.18)	0.94(0.24)
Gender	0.56 (0.51)	0.75 (0.44)	0.70(0.46)
Education	0.61(0.50)	0.35 (0.48)	0.64(0.48)
Access to credit	0.28(0.46)	0.28 (0.45)	0.28(0.45)
Awareness level	0.11(0.32)	0.13 (0.33)	0.20(0.40)
Access to extension	0.17(0.38)	0.47 (0.50)	0.61(0.49)
Observations	**18**	**127**	**205**
Water conservation			
Household size	1.47(0.51)	1.47 (0.52)	1.50(0.53)
Association	0.06 (0.24)	0.32 (0.47)	0.30(0.46)
Age	2.41(1.12)	2.80 (0.78)	2.85(0.82)
Distance	1.65(0.93)	1.56 (0.77)	1.44(0.70)
Marital status	0.71(0.47)	0.88 (0.33)	0.88(0.32)
Dairy farming systems	2.71(1.21)	2.94(1.24)	2.85(1.20)
Land tenure	0.65(0.49)	0.93 (0.25)	0.95(0.23)
Gender	0.47 (0.51)	0.74 (0.44)	0.71(0.45)
Education	0.71(0.47)	0.71 (0.46)	0.65(0.48)
Access to credit	0.24(0.44)	0.37 (0.48)	0.28(0.45)
Awareness level	0.06(0.24)	0.18 (0.38)	0.18(0.38)
Access to extension	0.18(0.39)	0.47 (0.50)	0.59(0.49)
Observations	**17**	**90**	**243**
Zero grazing units			
Household size	1.38(0.49)	1.51 (0.53)	1.49(0.51)
Association	0.09 (0.30)	0.29 (0.46)	0.41(0.50)
Age	2.50(0.95)	2.86 (0.80)	2.80(0.87)
Distance	1.78(1.01)	1.44 (0.69)	1.49(0.71)
Marital status	0.84(0.37)	0.87 (0.34)	0.92(0.28)
Dairy farming systems	2.91(1.33)	2.88(1.20)	2.80(1.19)
Land tenure	0.78(0.42)	0.96 (0.21)	0.88(0.33)
Gender	0.69 (0.47)	0.70 (0.46)	0.78(0.42)
Education	0.72(0.46)	0.68 (0.47)	0.59(0.50)
Access to credit	0.25(0.44)	0.31 (0.46)	0.29(0.46)
Awareness level	0.09(0.30)	0.16 (0.37)	0.29(0.46)

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Access to extension	0.25(0.44)	0.55 (0.50)	0.63(0.49)
Observations	**32**	**269**	**49**
Silage making			
Household size	1.55(0.51)	1.44 (0.51)	1.52(0.53)
Association	0.25 (0.44)	0.35(0.48)	0.26(0.44)
Age	2.50(1.00)	2.80 (0.82)	2.86(0.81
Distance	1.70(0.98)	1.53 (0.80)	1.41(0.64)
Marital status	0.90(0.31)	0.83 (0.38)	0.90(0.30)
Dairy farming systems	2.45(1.05)	3.07(1.29)	2.76(1.14)
Land tenure	0.70(0.47)	0.94 (0.24)	0.95(0.23)
Gender	0.70 (0.47)	0.70 (0.46)	0.72(0.45)
Education	0.55(0.51)	0.76 (0.43)	0.61(0.49)
Access to credit	0.30(0.47)	0.42 (0.49)	0.22(0.41)
Awareness level	0.10(0.31)	0.18 (0.38)	0.18(0.38)
Access to extension	0.25(0.44)	0.46 (0.50)	0.62(0.49)
Observations	**20**	**142**	**188**

Dairy farmers who reported no, low and high intensity adoption of agricultural technologies normally practice mainly semi-intensive form of dairy farming system. This is against modern dairy farming systems (i.e., zero grazing, and paddocking) available in the study area. The adoption of sem-intensive form of dairy system can be attributed to the most common land tenure in the area. In fact, most farmers hold secured land tenure system which they can use as collateral in accessing credit. Third, most dairy farmers are not able to access credit from formal financial institutions. Fourth, most small holder dairy farmers did not have or have limited access to information about climate smart agricultural technologies practices. Finally, we show that farmers who indicated no and low intensity levels of adoption did not have access to extension services. Compared to other farmers, high intensity adopters of technology did have excellent access to information about CSAT from extension services.

ORDERED LOGISTIC REGRESSION RESULTS

In Table 5, we provide results and discussion of our ordered logit model. In each column, we provide estimates of each independent variable likely to influence intensity of adoption of agricultural technology. These technologies include biogas production, adoption of drought resistant crops, tree planting, water harvesting, zero grazing and silage making. The model we estimate seem to fit our data well; in that F-statistics are above rule of thumb (i.e., F=10) and the chi square statistics are also significant at conventional levels. Importantly, we retain all variables in the model and present their estimate in Table 5 below. Our confidence interval is maintained at 95 percent interval levels, similar to other previous studies.

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Table 5: Parameter estimates from ordered logistic regression of intensity of adoption of agricultural technologies

Variables	Biogas production	Drought resistant crops	Agro -forestry	Water storage	Zero grazing	Silage making
Household size	0.091	0.120	-0.076	0.006	0.062	0.156
	(0.304)	(0.352)	(0.226)	(0.245)	(0.260)	(0.226)
Association	-0.090	0.535	0.525*	0.349	0.883***	-0.147
	(0.348)	(0.420)	(0.279)	(0.298)	(0.313)	(0.271)
Age	0.429**	-0.421*	0.010	0.015	-0.089	0.057
	(0.207)	(0.247)	(0.160)	(0.173)	(0.184)	(0.161)
Distance to farm	-0.243	0.215	-0.178	-0.340**	-0.376**	-0.301**
	(0.184)	(0.235)	(0.151)	(0.161)	(0.183)	(0.152)
Marital status	-0.358	0.306	0.187	0.472	0.446	0.507
	(0.509)	(0.567)	(0.367)	(0.383)	(0.427)	(0.364)
Farming systems	-0.251**	0.093	0.115	-0.015	0.004	-0.073
	(0.116)	(0.140)	(0.095)	(0.100)	(0.107)	(0.091)
Land tenure	0.940*	1.741***	0.963**	1.147**	0.600	0.961**
	(0.490)	(0.608)	(0.472)	(0.452)	(0.536)	(0.459)
Gender	-0.156	-0.351	-0.282	-0.050	0.019	-0.033
	(0.363)	(0.423)	(0.280)	(0.297)	(0.321)	(0.279)
Education	-0.587	0.314	-0.288	-0.337	-0.542*	-0.429*
	(0.371)	(0.389)	(0.253)	(0.274)	(0.288)	(0.255)
Access to credit	-1.736***	0.893**	-0.439*	-0.322	-0.184	-0.786***
	(0.343)	(0.404)	(0.259)	(0.276)	(0.297)	(0.257)
Awareness	-0.434	0.435	0.396	-0.022	0.307	0.154
	(0.434)	(0.491)	(0.356)	(0.371)	(0.374)	(0.337)
Extension	1.440***	0.579	0.776***	0.733***	0.719**	0.800***
	(0.369)	(0.409)	(0.259)	(0.280)	(0.309)	(0.259)
Thresholds						
/cut1	-2.632***	-1.014	-1.915**	-2.000**	-1.916**	-2.113***
	(0.915)	(1.050)	(0.766)	(0.782)	(0.859)	(0.765)
/cut2	-1.247	5.183***	0.795	0.260	2.532***	0.776
	(0.895)	(1.123)	(0.750)	(0.763)	(0.867)	(0.749)
Summary statistics						

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Variables	Biogas production	Drought resistant crops	Agro -forestry	Water storage	Zero grazing	Silage making
Log likelihood	-192.981	-140.671	-277.347	-249.830	-230.019	-280.409
F-test	85.830	27.720	28.950	24.970	27.36	43.55
Pseudo R squared	0.182	0.009	0.050	0.050	0.056	0.072
Prob>chi2	0.000	0.000	0.050	0.050	0.001	0.000

Notes: Standard errors in parentheses; Significance level *** p<0.01, ** p<0.05, * p<0.1; N=350

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BIOGAS PRODUCTION

Our results (Table 5) indicate that adoption of Biogas is affected by both socio–demographic and institutional factors. Age of respondents significantly (p-value = 0.021) and positively 0.429 influenced the level of adoption of climate smart technology biogas. This is because older people are likely to adopt the technologies because they reside mostly in rural areas where main raw material (animal waste) necessary in making biogas is mainly found. Moreover, old people are not likely to move to other locations and Biogas production being technology that requires time and labour; they are likely to adopt such technologies. Unlikely young people who want to enjoy live and therefore move between towns depending on the posting for those who are working class. Secondly, the type of farming system that a farmer adopts influences his level of adoption of climate smart technology like biogas production. As most of dairy farmer in the study area adopted tethering as a farming system, it is very difficult for them to collect animal waste from the field for biogas production. In line with this argument, we find that adopting tethering method lowers farmer's level of adoption of technology by about 0.25 percent or what. This result is statistically significant at conventional levels and in line with our earlier hypothesis. Thirdly, access to credit negatively was statistically significant ($p> 0.01$) and influenced adoption of biogas production technology by about 1.7 times. This is because most people who are financially stable are likely to buy clean sources of energy such as electricity and solar since they can afford. This can lead to a negative influence on the adoption of biogas production as a climate smart agricultural technology. Finally, access to extension services is more likely to be positively influence the level of adoption to biogas production by about 1.4 times (See Table 14). This result is statistically significant at conventional levels (i.e., $P<0.1$). This can partly be explained by the fact that biogas production requires skill and knowledge which only extension agents are able to provide.

Growing drought resistant fodder crops

Our results revealed that growing of drought resistant crop is influenced by age of the respondent, type of land tenure system and access to credit services. First, we find that older farmers are less likely to adopt growing drought resistant crops as a technology. Our result suggests that being old reduces the likelihood of adopting drought resistant crops by about 0.42 percent (Table 5). This can be explained by the fact that growing drought resistant crops is a labour intensive and costly exercise which older respondents are not able to do or do not have resources to practice. Secondly, we find that adoption of drought resistant crops is statistically significant ($p>0.1$) and positively (1.74) related to the type of land tenure in use by farmers, an indication that farmers who own secure tenure are likely to adopt growing drought resistant crops. Finally, adoption of drought resistant crops is positively associated with farmer's access to credit resources. This means that if farmers are able to access credit, they are 0.93 percent likely to adopt drought resistant crops. This is possible for three reasons: drought resistant crops require inputs like seeds and fertilizer which are costly to farmers. These crops are labour intensive implying that farmers need to have enough capital and finally, the knowledge required is different from other technologies. This means that farmers have to pay extension services to be able to adopt these crops.

Agro - forestry

Adoption of tree planting as agricultural technology is influenced by only institutional factors like being members of an association, type of land tenure, access to credit and extension services (Table 5). Being a member of an association is likely to increase adoption of tree planting by about 0.53. As a member of a group, farmers are able to get sensitized and trained by extension persons on new tree varieties, type of fertilizer and general tree handling and management. On the other hand, we demonstrated that access to extension services significantly increased the likelihood of adoption of tree planting by about 0.78 percent (Table 5). Further, our results indicate that adoption of a technology is influenced by the type of land tenure system that farmers possess. For instance, secure land tenure is likely to increase adoption of tree planting by about 0.96 percent. Finally, adoption of tree planting as a technology requires resources for inputs acquisition. Our result shows that credit significantly and negatively influences adoption of tree planting as a technology. This is plausible because when farmers have more money, they are likely to move to other high return ventures that are common in the study area.

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Water conservation and harvesting technologies

Adoption of water conservation and harvesting technologies is important in rural areas in that they can help animals or be used for irrigation. We find that, adoption of these technologies is positively associated with the type of tenure system in use. Having secure land tenure increase the likelihood of adopting water conservation and harvesting by about 1.15 percent (Table 5). This is true as water conservation and harvesting technologies are long term investment and thus might take longer time before farmer get their returns on investment. Extension services significantly and positively (by about 0.73 percent) influence adoption of water conservation and harvesting technologies. This is because, designing of most water conservation and harvesting technologies requires in depth knowledge which can be provided by trained extension agents. Finally, we find that adoption of water conservation and harvesting technologies are negatively influenced by the distance from farm and homestead. Farmers residing far away from the farm are less likely to adopt any technologies. For instance, in constructing a dam for watering animals, it is costly to adopt such technologies given the high cost of transportation of materials. Even in adoption of the rainwater harvesting technologies, farmers must be sure that security of their property is in order before undertaking such investment. In all instances, distance from homestead plays a key role in facilitating adoption of such technologies

Zero grazing units

The adoption of zero grazing unit as a CSAT can be influenced by farmers being members of group association. When farmers are in group, it becomes easy for them to be trained and or invite extension service providers to come and train them on modern units unlike the individual farmers. On the other hand, the distance from the homestead negative influences the adoption of zero grazing units. From our priori hypothesis, educational level of a respondent is expected to increase levels of adoption of a technology (in this case a zero-grazing unit). This is because education increases the level of awareness about the benefits of a technology. This awareness may encourage a respondent or a farmer to adoption a technology. This is contrary to our findings in this study. We show that (in Table 5) that having high education negatively influences adoption of zero grazing unit. This implies that more educated farmers can understand and identify problems related to zero grazing units more easily.

Access to extension service by a farmer may influence adoption of zero grazing units. This is because, access to an extension service enables a farmer to get new knowledge from other farmers and this is expected to increase adoption of a technology. Our result showed that (in Table 5) farmers who had access to extension service increased their level of adoption of zero grazing units by about 72 percentage points. This result is statistically significant at 5 per cent levels.

CONCLUSION AND RECOMMENDATION

The paper was analyzed to determine the adoption of climate-smart agricultural technologies in Aldai sub-county, Nandi County of Kenya. First, the findings reveled that, smallholder dairy farmers had high level of awareness about climate smart technologies. Most households reported low, or no intensity of adoption compared to those who we call high intensity adopters. For high level adopters, we demonstrate that they have of large household sizes- those with members ranging between 6 and 10 members compared to no or low intensity adopters. The large family sizes found among high intensity adopters indicates the high labour required in implementing climate smart agricultural technologies. Secondly, most adopters of CSA technologies were of middle age (i.e., those in the age bracket of 40 and 49 years), married and mostly are male headed households. Moreover, farmers who reported either no or low intensity of adoption lived far away from their farms i.e., at an average distance of about 0.6 to 1 Km. However, high intensity level adopters lived closer to or on their farms, a distance of about 0.5 kilometres. Finally, most farmers (those that recorded no, low and high intensity level of adoption) are literate.

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