Analysis of household savings and adoption of climate smart agricultural technologies. Evidence from smallholder farmers in Nyando Basin, Kenya

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ABSTRACT
Investments in climate smart agriculture (CSA) are often hampered by inadequate finance. The risks of climate change further scare away private investors from this technology. However, household savings have been established as a key contributor to farm investment in rural households. This study sought to analyze the influence of household savings on adoption of CSA technologies. It utilized descriptive statistics, chi square, Poisson and ordered probit models on a sample of 122 households in its analysis. The findings showed that saving households adopted more CSA technologies compared to non-saving households with the chi square results indicating a statistically significant difference at 1%. In addition, household savings and interest earned on savings increased the likelihood of a household to adopt more than one CSA technology. Thus, increasing household savings is an important strategy for scaling CSA, and community groups through which households channel their savings need strengthening through regular trainings on group management and financial literacy.

1. Introduction

Sub-Saharan Africa (SSA) is mainly reliant on rain-fed agriculture and, therefore, vulnerable to the vagaries of weather and climatic change. In Kenya, for instance, agriculture is predominantly rained (Ochieng et al., 2016) and the effects of climate change and variability threaten to overturn productivity gains in the sector (World Bank 2016; Mekune et al., 2018). Climate smart agriculture (CSA) promises to transform and re-orient agricultural development towards meeting the challenges of climate change (Lipper et al., 2014). It simultaneously addresses the challenges of climate change while supporting economic growth in the agricultural sector.

In sub-Saharan Africa (SSA), policymakers and development practitioners have paid close attention to the adoption of CSA technologies in order to ensure that as many farmers as possible practice low-emission, climate-resilient agriculture while increasing agricultural productivity. The Consultative Group for International Agriculture Research (CGIAR) program on Climate Change Agriculture and Food Security (CCAFS) is among the organizations promoting various CSA technologies in regulated sites within some specific countries in Africa, Asia and South America. In East Africa, CCAFS is present in six sites in four countries, namely; Tanzania, Kenya, Uganda and Ethiopia Recha et al. (2017). Nyando Basin is a site in Kenya which CCAFS chose to work in mainly because it is a focal area representing similar places which are becoming increasingly vulnerable to extreme wet and dry weather conditions. Hence, an analysis of Nyando region produce results which can be applied and adapted in similar regions (Förch et al., 2013). About 40% of the landscape in Nyando Basin is degraded as a result of soil erosion and water run-off creates deep gullies (Bernier et al., 2015). Climate change is evident within the area which is characterized by frequent droughts, irregular and unreliable rainfall with extreme flooding during the rainy season (Macoloo et al., 2013). This leads to low agricultural production which increases the vulnerability of farmers to climate risks and negatively impacts on household food security and nutrition (Kinyagi et al., 2015). It is in this context that CCAFs identified agroforestry, greenhouse farming, improved breeds and water harvesting as the most suitable interventions in the area. The organization has since late 2011 partnered with other development agencies such as World Neighbors, Vi Agroforestry, Kenya Agriculture and Livestock Research Organization (KALRO), Kenya’s Ministry of Agriculture and Livestock Development in promotion

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of a portfolio of promising CSA interventions in Nyando (Ojango et al., 2015).

Despite the potential benefits of adaptation, mitigation and productivity of CSA interventions to small-scale farmers, their adoption requires farmers to acquire new knowledge, and to invest a considerable amount of their time, labour and cash in the process. Given the high levels of poverty among these farmers, the requirements slow down adoption of CSAs (Bernier et al., 2015). Apart from the investment costs, there is a time lag between investment and realization of benefits associated with a CSA technology. Therefore, there is need for support mechanisms to cushion farmers during this interim period.

Among the financial avenues utilized by small scale farmers to finance CSA practices is use of credit finance, remittances from relatives and accumulated household savings (Wattel et al., 2018). Credit finance is, however, a challenge to small-scale farmers due to their poor credit history and lack of collateral. Lenders find small-scale farmers unappealing as they entail high transaction costs that outweigh the small loan amounts that they require (Sadler et al., 2016). Basak (2017) adds that the ever-increasing climate change risks scare away private investors from CSAs. Statistics point out that two thirds of Kenya’s rural farmers cannot access sufficient financial services to improve their livelihoods (Poulton and Kanyinga, 2014). The few who have access to credit direct it to non-agricultural sectors. Some rural households are afraid of using their debt fund to invest in unpredictable farm enterprises for fear of losing their collateral (Hertz, 2009). Furthermore, the cost of accessing own-accumulated savings is cheaper than the cost of a loan (Abebe et al., 2018).

Household savings present an opportunity where smallholder farmers can overcome credit limitation by building adequate capital to invest in CSA technologies. It has been found to be an important budget item in rural households (Kibet et al., 2009). Iyoha et al. (2003) and Rutherford (1999) observe that savings enhance household wellbeing by supporting and expanding rural enterprises while cushioning and insulating them during times of shock. Saving in itself is a form of risk management approach as well as an indicator of credit repayment ability. Saving not only helps to cover investment costs but also influences a farmer’s risk behavior by providing a mechanism for coping with risk and income variation. This may be a motivation to farmers to invest in CSA technologies (Wattel et al., 2018). According to Kenya’s Financial Sector Deepening (FSD, 2016a), most farmers self-finance their farm activities using savings. Wattel et al. (2018) found saving to be the most important strategy for coping with risk in the rural households of Nyando. Despite the fact, a general review of studies focusing on determinants of CSA adoption (Abegunde et al., 2019; Kurkat et al., 2020; Pagliacci et al., 2019; Awuni et al., 2018; Makate et al., 2018 and Aryal et al., 2018) reveals that inadequate attention has been paid to household saving in its contribution to farm investment in rural households. Abegunde et al. (2019) urges researchers to examine more indicators as they study farm investments. In light of this, the study sought to assess if household saving has any influence on adoption of CSA technologies in the study area.

2. Materials and methods

2.1. Study area

This research was conducted in Nyando Basin within the counties of Kericho and Kisumu in Kenya. The basin covers a 10 x 10 km block located between coordinates (013 30’S - 024 00’S, 34 5400’E - 35 4300’E) comprising of seven villages, namely; Kamango, Obiiero, Obinju, Kamuama, Chemlilagay, Kapsorok and Tabet B. The site is characterized by dense population of over 400 persons per square km, scant vegetation and deep gullies caused by run-off water. About 40% of the landscape is degraded by erosion (Bernier et al., 2015). Nyando Basin is also characterized by frequent droughts and irregular rainfall (Macoloo et al., 2013). Floods and droughts undermine agricultural production in the area and render households vulnerable to malnutrition, hunger, among other shocks (Kinyagi et al., 2015). With agriculture as the main economic activity in the region, the community has to adapt to climate change (Kinyagi et al., 2015). Among the adaptation strategies is adoption of climate smart agriculture (CSA).

The Consultative Group for International Agricultural Research (CGIAR) program on Climate Change Agriculture and Food Security (CCAFS) has been promoting a range of promising CSA practices in Nyando. They include agroforestry, greenhouse farming, small livestock breeds improvement and water harvesting. Since late 2011, CCAFS has been partnering with other development agencies in promoting these interventions that also close the nutrition cycle.

2.2. Sampling and data collection

CCAFS had been operating in Nyando Basin since 2011. In 2017, CCAFS conducted an endline survey of 216 households within Climate Smart Villages (CSVs) and 217 in non-CSVs. The randomly selected households shared similar characteristics in terms of climate, farm soil conditions and agricultural practices. The project leading to this paper utilized this sample and used stratified random sampling technique where 12 strata were created based on three criteria: Location (Household is located in CSV or Household is not located in CSV), ownership of sheep/goat (no sheep or goat, indigenous breed, improved breed), crop and land management practice by household (low/high). A household was considered to practice low crop management if it did not use improved seeds, fertilizer, pesticides; and to have high crop management if otherwise. Low land-management households had not introduced ridges, terraces, hedges, intercropping, or planted a bare minimum number of trees per acre for the past 10 years. High land-management households practiced otherwise.

A total of 123 households were sampled for survey, but one household later dropped out. The data was collected through a structured questionnaire using face-to-face interviews. Table 1 presents the selection criteria and the number of households interviewed from each stratum.

| Stratum number | Location | Ownership of goats/sheep | Crop/land management | Sample frequency |
|----------------|----------|--------------------------|----------------------|-----------------|
| 1              | GSV      | None                     | Low                  | 6               |
| 2              | GSV      | None                     | High                 | 11              |
| 3              | GSV      | Indigenous               | Low                  | 11              |
| 4              | GSV      | Indigenous               | High                 | 10              |
| 5              | GSV      | Improved                 | Low                  | 17              |
| 6              | GSV      | Improved                 | High                 | 36              |
| 7              | Non-GSV  | None                     | Low                  | 6               |
| 8              | Non-GSV  | None                     | High                 | 4               |
| 9              | Non-GSV  | Indigenous               | Low                  | 9               |
| 10             | Non-GSV  | Indigenous               | High                 | 5               |
| 11             | Non-GSV  | Improved                 | Low                  | 4               |
| 12             | Non-GSV  | Improved                 | High                 | 4               |

Source: Project document 2019-1.
in decision-making, and that they choose alternatives which yield maximum utility. A farmer’s decision to save and invest in a modern technology is based on the expected utility of adopting a technology. Let’s consider the ith farming household (i = 1, 2, … n) that must decide on either to adopt or not adopt available Mk CSA technologies (M = greenhouse farming, agroforestry, water harvesting, improved animal breeds. k = number of adopted technologies from M). Let ηik represent the associated benefits of adopting k CSA technologies, and η0 to represent the utility derived from not adopting either technology (i.e., k = 0). The farmer will adopt k number of CSA technologies if the net benefit (Btik) of adopting is greater than from not adopting i.e.,

\[ Bt_{ik} = \eta_{ik} - \eta_0 > 0 \] (1)

The net utility (Btik) from adopting a technology is a latent variable. However, there are some farmer specific attributes which could be associated with the decision of a farmer to either adopt or not adopt any number of CSA technologies. These attributes include the socio-economic characteristics of a farmer, farm and institutional characteristics. The net benefits of adopting could therefore be rewritten as;

\[ Bt_{ik} = \beta_t X_i + \epsilon_i \] (2)

where \( X_i \) = vector of farmer specific attributes.
\( \beta_t \) = vector of coefficients
\( k \) is as earlier defined
\( \epsilon_i \) = error term.

2.3.2. Econometric modeling

Agricultural technology adoption involves a two-stage decision making process whereby a farmer decides whether or not to adopt a CSA practice, and if the decision is to adopt, the next decision is on the number of technologies to adopt. In the first stage the dependent variable is a binary choice of adopting or not adopting. In the current study however, only two households in the total sample who had not adopted any CSA technology. The study therefore dealt with the second stage of analyzing intensity of adoption.

The study considered the four CSA technologies which are being promoted in the region by CCAFS and have proven to be beneficial to the farmers, namely; improved breeds, agroforestry, water harvesting and greenhouse farming. When analyzing factors which influence intensity of adoption of agricultural technologies, count data models such as Poisson may be utilized. The model assumes that the dependent variable, yi, takes non-negative integer values and has a Poisson distribution. According to Greene (2003) the probability density function of the model can be specified as follows

\[ \text{Prob}(Y = y_i | x_i) = \frac{e^{-\beta^T x_i} \beta^T x_i^y_i}{y_i!}, y_i = 0, 1, 2, \ldots \] (3)

Y is a random variable that represents the number of CSA technologies adopted, yi is a specific count value for the ith farmer, \( x_i \) represents independent variables that influence the number of CSA technologies adopted by the ith farmer and \( \beta \) is a parameter to be estimated.

While the results of the Poisson model give the likelihood of adopting CSA technologies without considering the different adoption levels, it is important to consider the fact that adoption of subsequent technologies is conditioned by adoption of the first technology given that farmers adopt subsequent technologies once they have been exposed to the benefits and information regarding the technologies as noted by Justin et al. (2017).

In this regard, an ordered probit model would be appropriate as it helps in analyzing the factors influencing adoption of CSA practices at specific intensity levels. The model shows the factors which would encourage or discourage a farmer from adopting one CSA technology, two technologies, three technologies and so on. The dependent variable in the model therefore takes the values of 1, 2, … representing the number of technologies adopted. Following the expected utility framework, a farmer chooses to adopt a number of CSA technologies in order to technology function represented in Eq. (2).

The following model was fitted in the data;

\[ Y_i = \beta_0 + \beta_1 \text{hsaving} + \beta_2 \text{svninterest} + \beta_3 \text{spousesvn} + \beta_4 \text{agehh} + \beta_5 \text{agessq} + \beta_6 \text{sexHH} + \beta_7 \text{eduHH} + \beta_8 \text{tpdents} + \beta_9 \text{landsz} + \beta_{10} \text{TLU} + \beta_{11} \text{crdtacc} + \beta_{12} \text{discatmrkt} + \beta_{13} \text{training} + \beta_{14} \text{noofgroup} + \beta_{15} \text{stfdmrtkt} + \beta_{16} \text{tfoodshck} + \epsilon_i \] where Yi = No. of CSA technologies adopted by a farmer (1, 2, 3, or 4), \( \beta_0 \ldots \beta_{16} \) = coefficients to be estimated, hsaving = whether a household saves or not, svninterest = whether the spouse saves or not, agehh = age of the household head, agessq = age of the household head squared, sexHH = sex of the household head, educHH = whether household head has formal education, tpdents = total dependants in the household (number of people below 14 years and above 65 years), landsz = land size in acres, TLU = total livestock units, crdtacc = credit access, foodshck = food shock, training = agricultural training, noofgroups = the number of groups the household head belongs to, distfdmrtkt = distance to food market, discatmrkt = distance to cattle market.

The coefficients of an ordered probit model are not easy to interpret directly. The marginal effects were thus calculated to determine the magnitude with which each independent variable alters the likelihood of each of the four categories of the response variable.

In addition to estimating the Poisson and the Ordered probit models, the study also utilized the chi square estimate in order to show if there was a difference in adoption of specific CSA technologies and the intensity of adoption between the saving and non-saving households and if the difference was statistically significant.

2.4. Model diagnostics

2.4.1. Multicollinearity

Multicollinearity refers to a situation where there is presence of linear relationship among the independent variables (Koutsoyannis, 1973). This leads to one type error due to wide confidence intervals (Woolridge, 2009). It becomes impossible to assess the impact of each explanatory variable on the dependent variable. The presence of multicollinearity in the data was assessed using the Variance Inflation Factor (VIF) technique. As a rule of the thumb, if the VIF value of a variable exceeds 10, it indicates presence of multicollinearity (Gujarati and Sangeetha, 2007). Such a variable could be excluded from the model. The assessment indicated absence of multicollinearity since the VIF values of all the variables were less than ten as shown in Table 2.

2.4.2. Heteroscedasticity

Heteroscedasticity exists when the variance of the error term varies across data (Gujarati, 2004). It results in biased and inconsistent OLS estimates which then fail the criterion of best linear unbiased estimator (BLUE), (Wooldridge, 2015). Its presence in the Poisson and ordered probit models was tested using the Breusch Pagan Test. Breusch Pagan tests the null hypothesis that the variance of the error term is constant across observations versus the alternative that the error term variance is not constant across observations. The chi-square of 0.0002 for the two models was statistically significant leading to the rejection of the null hypothesis of homoscedasticity and heteroscedasticity could not be ruled out in the data. Robust standard errors were therefore utilized to correct for this problem in the estimations.

Breusch-Pagan/Cook-Weisberg test for heteroscedasticity in the Poisson & ordered probit models

Ho: Constant variance
Variables: fitted values of number of CSA adopted.
\[ \text{chi2} (1) = 14.19 \]
\[ \text{Prob} > \text{chi2} = 0.0002 \]
Table 2. VIF values for variables used in Poisson and ordered probit models.

| Variable           | VIF  | 1/VIF |
|--------------------|------|-------|
| Spouse saving      | 2.35 | 0.424863 |
| Household saving   | 2.23 | 0.447459 |
| Log of land size   | 1.75 | 0.570107 |
| Age                | 1.69 | 0.591015 |
| Sex                | 1.62 | 0.616315 |
| Head's education   | 1.59 | 0.628607 |
| TLU                | 1.55 | 0.647049 |
| Number of groups   | 1.44 | 0.693795 |
| Credit access      | 1.39 | 0.720802 |
| Training           | 1.36 | 0.733251 |
| Distance to the cattle market | 1.33 | 0.752630 |
| Interest rate pa   | 1.28 | 0.780177 |
| Total dependents   | 1.23 | 0.811709 |
| Distance to food market | 1.23 | 0.814241 |
| Flood shock        | 1.22 | 0.820819 |
| Mean VIF           | 1.55 |       |

2.5. Ethical considerations

The questionnaire was reviewed and approved by CCAFS ethics committee headed by John Recha (Participatory Action Research Specialist, CCAFS East Africa, j.recha@cgiar.org) and Maren Radeny (Science Officer, CCAFS East Africa, m.radeny@cgiar.org). Furthermore, on the front page of the survey questionnaires, there was a statement explaining what the research was all about and the confidentiality of the responses given. The statement further sought acceptance/rejection of the respondent to be interviewed. The data was collected under CCAFS which has a standing agreement with the four community-based organizations (CBOs) in Nyando whose members were the subjects during the interviews, and under the watch of the respective village elders and administrators. Thus, voluntary and informed consent was obtained from each respondent to the interview.

3. Results and discussions

Tables 3 and 4 presents summary statistics of the variables used in the analysis of the influence of household savings on intensity of adopting CSA technologies in the Nyando basin of western Kenya.

The average age of the household heads was 54 years with a range of 25–94 years. The statistics were relatively the same between saving and non-saving households. Saving households belonged to more groups compared to non-saving households, and the result was significant at 1%. The distance to market was used as a proxy for market access. Households closer to markets were expected to have better returns on their produce due to reduced transaction costs, and therefore higher savings. This was confirmed in the study since households with savings were found to be closer to food and cattle markets. The result was statistically significant at 1% level. Majority of the household heads had obtained formal education with only 8% reporting to have no formal education. There was however some difference in education levels between the saving and non-saving groups. Saving households had more formal education compared to non-saving households. Majority of households with savings had higher access to credit compared to non-saving households, a result which was statistically significant at 1%. This can be attributed to the fact that majority of those who had saved were in groups whose main activity was saving and credit issuance. Additionally, more of the saving households had agricultural training and only a few of them had experienced flood shocks compared to non-saving households. These differences were statistically significant at 1% and 5% levels, respectively.

Among the saving households, spouses had a slightly higher tendency to save than the household heads as shown in Figure 1 above. This could be because the majority of homes in the research area were headed by males, and more women than men belong to community groups where they save. Interestingly, only in about 6% of the households did men save jointly with their wives.

The major saving avenue for saving households in the area was community groups, with a few saving in banks. A small percentage (5%) kept their savings at home as shown in Figure 2. This finding was in

Table 3. Variable mean, standard deviation and range.

| Variable                                    | Pooled Sample n = 122 | Group differences | P value |
|---------------------------------------------|-----------------------|-------------------|--------|
|                                            | Mean | Std dev | Min | max | Savers N = 79 | Mean | Std dev | Non-savers N = 43 | Mean | Std dev | Mean difference |
| Age                                         | 54.35 | 16.06 | 25 | 94 | 53.13 | 14.35 | 56.58 | 18.79 | 3.44 | 0.26 |
| Number of dependents                        | 2.8 | 1.61 | 0 | 8 | 2.76 | 1.63 | 2.89 | 1.6 | 0.1 | 0.74 |
| The number of groups a household belongs to  | 1.75 | 1.22 | 0 | 6 | 2.02 | 1.10 | 2.16 | 1.29 | 0.77 | 0.00*** |
| Land size in Acres                          | 4.41 | 8.26 | 5 | 70 | 4.46 | 7.91 | 4.32 | 8.95 | 0.41 | 0.93 |
| TLU                                         | 5.69 | 6.8 | 0 | 63 | 5.95 | 7.58 | 5.2 | 5.11 | 0.75 | 0.56 |
| Distance to food market in KMs              | 3.05 | 2.73 | 0 | 12 | 2.36 | 2.27 | 4.31 | 3.07 | 1.95 | 0.00*** |
| Distance to cattle market in KMs             | 8.84 | 3.72 | 2 | 20 | 8.34 | 0.41 | 9.76 | 0.57 | 1.43 | 0.04** |

Source: Survey data, 2019.

Table 4. Variables percentage within Households.

| Variable                                         | Pooled Sample n = 122 | Saving Households n = 79 | Non-Saving Households n = 43 | Chi Square |
|--------------------------------------------------|-----------------------|--------------------------|----------------------------|-----------|
| Whether household saves (yes = 1)                | 65                    |                          |                            |           |
| Whether spouse saves (yes = 1)                   | 40                    |                          |                            |           |
| Sex of household head (male = 1)                 | 81.15                 | 83.54                    | 76.74                      | 0.359     |
| Whether household head has formal education (yes = 1) | 91.80                 | 96.20                    | 83.72                      | 0.016**   |
| Whether households accessed credit past one year (yes = 1) | 66.39                 | 79.75                    | 41.86                      | 0.000***   |
| Whether household head has agricultural training (yes = 1) | 63.11                 | 74.68                    | 41.86                      | 0.000***   |
| Whether household experienced flood shock last 1 year (yes = 1) | 26.45                 | 19.23                    | 39.53                      | 0.015**   |

Source: Survey data, 2019.
consonance with Nwibo and Mbam (2013) who observed that farmers prefer mobilizing their savings through community groups because they are able to access loans which may not be possible in formal financial institutions that demand collateral.

3.1. Household savings and adoption of CSA technologies in Nyando

Out of the four CSA technologies considered in the study, agroforestry was the most adopted at 70% among the sampled farmers (see Table 5). This was followed by improved breeds (41%), water harvesting (30%) and greenhouse farming (8%). Greenhouse farming was closely associated with household savings. Households without savings did not adopt this technology. Improved breeds and agroforestry were practiced by savers and non-savers with a higher percentage of savers practicing agroforestry (52%) compared to (19%) among the non-savers. Among the households that had adopted improved breeds, 33% were savers while 8% were non-savers. Water harvesting was adopted by 16% of saving households and by 13% of the non-savers. Thus, household savings were positively associated with CSA adoption in Nyando as more saving households adopted greenhouse farming, improved breeds and agroforestry, and the results were statistically significant at 5%, 1% and 1%, respectively.

Various factors have been attributed to why farmers prefer a given technology compared to another technology. Cassim et al. (2017) found most households to have adopted soil and water conservation technologies compared to other technologies and attributed this to extension

### Table 5. Chi square estimates of the association between household saving and adoption of individual CSA technologies in Nyando Basin, Kenya.

| CSA Technologies     | Percentage Save (%) | Percentage Non-Save (%) | Chi Square |
|----------------------|---------------------|-------------------------|------------|
| Greenhouse farming   | 8.20                | 0.00                    | 0.015**    |
| Water harvesting     | 29.51               | 13.11                   | 0.169      |
| Improved breeds      | 40.98               | 8.20                    | 0.003***   |
| Agroforestry         | 70.49               | 18.85                   | 0.002***   |

Statistical significance at *p < 0.1, **p < 0.05, ***p < 0.01.
information focusing more on these practices. On the other hand, Ojoko et al. (2017) noted that farmers’ perceived climate change impact on their farms influence their choice of CSA practices. The current study shows that household saving also has an influence on the choice and level of adopting CSA technologies. Encouraging rural household saving could be an important policy strategy to enhance increased uptake of CSAs.

The results in Table 6 indicate that adoption rates of CSA technologies differ across the saving and non-saving households. Most of the households adopted one technology. However, more of saving households adopted two CSA technologies, and none of the non-saving households adopted more than two technologies. The chi-Square estimate indicated a significant difference at 1% on the intensity of CSA technology adoption between the saving and non-saving households. This underlines the potential of rural household savings as an important policy strategy that can enhance increased uptake of CSAs in an effort to make smallholder farmers climate-change resilient.

3.2. Determinants of intensity of CSAs adoption in Nyando

The farmers in the study area adopted different numbers of CSA technologies. The results of the Poisson model as presented in Table 7 point out that the main factors accounting for intensity of adoption of CSA technologies in Nyando include whether a household saves or not, and the annual interest rates earned. Other determinants include age of the household head, sex of the household head, level of household head’s formal education, whether a household had received any agricultural training, number of groups that a household ascribed to, land size, TLU and distance from a household to a food or cattle market. The Poisson model assumes no hierarchy in the number of CSA technologies adopted while an ordered probit model analyses factors influencing adoption at specific intensity levels thus considering the hierarchy of number of practices adopted (which is an important consideration). The study, therefore, estimated a Poisson model alongside an ordered probit model in order to determine the factors influencing adoption of CSA technologies at different intensity levels.

3.3. Ordered probit results of determinants of number of CSA technologies adopted by households in Nyando, Kenya

Table 8 shows the results of an ordered probit estimation of intensity of adoption of CSA practices in Nyando. The study considered four CSA technologies hence the outcome variable takes the values 1,2,3,4 of intensity levels. The chi square statistic (57.53 with 16 degrees of freedom) was statistically significant at 1% level.

Holding all the other factors constant, household savings and interest rate earned increased the likelihood of adopting more CSA practices. Saving households were less likely to adopt only one CSA practice. One percentage increase in savings increased their likelihood to adopt two practices by 20%. Households earning interest on savings were also less likely to adopt only one CSA practice, but more likely to adopt two or three practices. 1% increase on interest earnings increased the likelihood of adopting two practices by 1.3%, and adopting three practices by 0.2%.

The findings are consistent with those of Hohfeld and Waibel (2013) who found that savings positively influenced the amount invested in agriculture. This is explained in a study by Twumasi et al. (2019), who reported that an increase in savings increases the probability of a smallholder farmer access to credit as well as the amount one can borrow. Farmers not only use savings as a source of collateral, but also reflect their net worth in the credit market (Akudugu, 2016; Twumasi et al., 2019).

Having a male household head increased the probability of adopting only one CSA technology by 27.6%, but reduced the probability of adopting two CSA technologies by 21.5%. This stands in contradiction with available literature (Abdul-hanan et al., 2014; Awuni et al., 2018) that shows male-headed households to be more likely to implement many technologies as they have comparatively more resources (e.g., land) to allocate among various agricultural activities. Nevertheless, Nhemaacha & Hassan (2007) find that female headed households are more likely to take up climate change adaptation measures and argue that in Africa, more females than males live in rural areas where most agricultural practices are done. From this perspective, women gain more farming experience and information on climate conditions and how to adapt to such conditions. But Ndumgani and Watanabe (2016) show that women have more domestic responsibilities and less control over financial resources, hence they are less able to diversify their income sources by say, adopting more CSA practices. The likely effect of the sex of household head on intensity of adoption of agricultural technologies needs further research.

| Table 6. Chi square estimates of association between household saving and intensity of adoption of CSA technologies in Nyando Basin, Kenya. |
|---|---|---|---|
| Pool sample | Number of Technologies | Number of Adaptors | Saving difference |
| | | | Savers | Non-savers | chi square |
| | | | Adopters | Adopters |
| 1 | 72 | 36 | 36 |
| 2 | 35 | 28 | 7 |
| 3 | 9 | 9 | 0 |
| 4 | 5 | 5 | 0 |
| Total | 121 | 78 | 43 | 0.001*** |

| Table 7. Poisson regression results of determinants of intensity of adoption of CSA technologies in Nyando Basin, Kenya. |
|---|---|---|
| Variable | Coefficient | t-value |
| Household saving patterns | | |
| Household saving (yes - 1) | 0.205*** (0.096) | 2.13 |
| Saving interest rates p.a. | 0.011***(0.004) | 2.59 |
| Whether spouse saves (yes - 1) | -0.073 (0.101) | -0.72 |
| Demographic variables | | |
| Age of household head | -0.011* (0.007) | -1.67 |
| Age of the household head square | 0.00008 (0.00006) | 1.33 |
| Credit access (yes - 1) | 0.005 (0.085) | 0.06 |
| Experienced floods in the past one year (yes - 1) | -0.069 (0.083) | -0.83 |
| Institutional factors | | |
| Agricultural training (yes - 1) | 0.401*** (0.081) | 4.97 |
| Number of groups | 0.141*** (0.030) | 4.70 |
| Distance to food market (km) | -0.242***(0.078) | -3.99 |
| Distance to cattle market (km) | 0.025***(0.009) | 2.69 |
| Observations | 121 |
| Wald chi2(16) | 172.03 |
| Prob > chi2 | 0.0000 |
| Log likelihood | -149.46036 |
| lnalpaha | -26.51942 |
| Alpha | 3.04e-12 |

Note: Robust standard errors are in parenthesis, Statistical significance at *P <0.1, **P <0.05, ***P <0.01. Source: Survey Data (2019).
A household head with formal education had 37.3% probability of adopting only one CSA technology, but was unlikely to adopt a second technology at 26.1%. Aryal et al. (2018) finds formal education to have a positive influence on technology adoption. However, Wekesa et al. (2018) argue that attainment of more formal education offers alternative livelihood strategies and may discourage agricultural engagements.

An increase in household land size by 1% decreased the probability of a household adopting only one CSA technology by 22.6%, but increased the probability of the household adopting two and three CSA technologies by 19.4% and 2.9%, respectively. Similar findings are reported by Wekesa et al. (2018) and Kpadonou et al. (2017). On the contrary Awuni et al. (2018) argue that as land size decreases due to population pressure, farmers adopt more improved technologies probably to increase production.

An increase in the number of total livestock units (TLU) increased the probability of adopting only one CSA technology by 1.4%, but decreased the probability of adopting two CSA technologies by 1.4%. Livestock farming is labor-intensive and takes more land space, and this can easily overshadow other agricultural activities.

Agricultural training reduced the likelihood of adopting only one CSA practice by 50.9%, and increased the likelihood of adopting two or three practices by 42.8% and 7.2%, respectively. Training increases the knowledge, awareness and skills to handle a technology and this can shape a farmer’s intensification decision. This finding concurs with that of Theophilus et al. (2019), Maumbe and Swinton (2000) and Justin et al. (2017).

An increase in the number of community groups that a household belonged to decreased the probability of adopting only one CSA technology by 22.6%, but increased the likelihood of adopting two and three CSA technologies by 31.8% and 4.8%, respectively. This means that the further away a household is from the food market, the less is the number of CSA technologies it is likely to adopt. Nkonya et al. (2004), Katungi et al. (2007) and Ghimire and Huang (2015) report similar findings and attribute their findings to increased transaction cost. On the contrary, distance to cattle market increased the probability of adopting more CSA technologies implying that households who sold their cattle to more distant markets adopted more CSA technologies than those who sold to nearby markets. This could be explained by price differentials where distant markets fetch higher prices compared to nearby markets, which may be characterized by open air markets with middlemen who exploit farmers through low prices. Higher returns favor technology adoption by increasing the purchasing power of households.

Note that once a farmer had adopted say three practices, adoption of additional practices was a matter of course depending on the benefits reaped from the first three. Thus, none of the variables on its own had any likelihood of influencing adoption of the fourth CSA technology.

4. Conclusions and policy implications

Adoption of CSA technologies is not an option but a necessity for agricultural sector to be climate resilient and for the achievement of food security. Financial constraints have been a setback to adoption of CSA technologies. Household savings present an opportunity where farmers can accumulate capital and invest in CSA technologies. The results of this study have shown that household saving and the annual interest earned on savings has the potential to increase the intensity of adopting CSA technologies. In order to encourage more households to save, there is need to strengthen the local community groups where most farmers put their savings. Government as well as non-governmental actors could lend their expertise on financial literacy and group management. Additionally, the impact and sustainability of the community groups can be enhanced by prioritizing them in government interventions such as Uwezo fund in Kenya. In agricultural trainings and seminars, the importance of saving for agricultural investment should be emphasized.

Table 8. Ordered probit results of determinants of number of CSA technologies adopted by households in Nyando Basin, Kenya.

| Variables               | Coefficients | Prob(Y = 1|X) dy/dx | Prob(Y = 2|X) dy/dx | Prob(Y = 3|X) dy/dx | Prob(Y = 4|X) dy/dx |
|-------------------------|--------------|------------|------------|------------|------------|
| Household saving position |              |            |            |            |            |
| HHsave                  | 0.687** (0.394) | -0.230** (0.118) | 0.200* (0.106) | 0.027 (0.018) | 0.003 (0.003) |
| interest                | 0.044*** (0.015) | -0.016*** (0.005) | 0.013*** (0.005) | 0.002** (0.001) | 0.0002 (0.0002) |
| spouse_save             | -0.435 (0.364) | 0.152 (0.123) | -0.131 (0.106) | -0.019 (0.018) | -0.002 (0.003) |
| Demographic factors     |              |            |            |            |            |
| ageHH                   | -0.035 (0.034) | 0.012 (0.012) | -0.011 (0.011) | -0.002 (0.002) | -0.0001984 (0.0002) |
| ageHH square            | 0.0003 (0.0003) | -0.0001 (0.0001) | 0.00009 (0.00009) | 0.000001 (0.000002) | 1.64e-06 (0.00000) |
| sexHH                   | -0.726* (0.429) | 0.276* (0.164) | -0.215* (0.119) | -0.052 (0.045) | -0.009 (0.010) |
| educHH                  | -0.973* (0.573) | 0.373* (0.207) | -0.261* (0.109) | -0.091 (0.087) | -0.020 (0.029) |
| dependents              | 0.021 (0.071) | -0.006 (0.025) | 0.007 (0.022) | 0.001 (0.003) | 0.0001 (0.0004) |
| Socio-economic factors  |              |            |            |            |            |
| Log land_size           | 0.632*** (0.219) | -0.226*** (0.076) | 0.194*** (0.071) | 0.029** (0.015) | 0.004 (0.003) |
| TLU                     | -0.044* (0.023) | 0.016** (0.008) | -0.014* (0.007) | -0.002 (0.001) | -0.0003 (0.0002) |
| credit                  | 0.037 (0.318) | -0.013 (0.113) | 0.011 (0.097) | 0.002 (0.014) | 0.0002 (0.0002) |
| flood_shock             | -0.338 (0.275) | 0.116 (0.090) | -0.101 (0.080) | -0.013 (0.012) | -0.002 (0.002) |
| agric_training          | 1.732*** (0.410) | -0.509*** (0.078) | 0.428*** (0.073) | 0.072** (0.031) | 0.012 (0.008) |
| grpmbship               | 0.475*** (0.109) | -0.170*** (0.039) | 0.145*** (0.037) | 0.022** (0.011) | 0.003 (0.003) |
| Community factors       |              |            |            |            |            |
| distdmrkt               | -1.037*** (0.376) | 0.371*** (0.135) | -0.318*** (0.118) | -0.048* (0.028) | -0.006 (0.006) |
| distcamrkt              | 0.101*** (0.033) | -0.030*** (0.011) | 0.031*** (0.010) | 0.005* (0.003) | 0.0006 (0.0005) |

No. of observations = 121, Wald chi2(16) = 57.53, prob > chi2 = 0.0000, log likelihood = -85.696217, pseudo r2 = 0.3167.
Note: robust standard errors in parenth, statistical significance at *p < 0.1, **p < 0.05, ***p < 0.01.
Institutions that assist rural poor farmers develop strong social capital such as cooperative societies are needed. This would greatly increase market access and return on investments leading to accumulation of savings and consequently investments in more CSA practices. Finally, other control variables such as agricultural training, number of groups, land size and distance to the cattle market significantly influence the adoption of CSA technologies. Such factors should also be considered when designing policies to promote adoption of CSA technologies by small-scale farmers.

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Author contribution statement

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The authors do not have permission to share data.

Declaration of interests statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

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