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Research article

Linking farmers' risk attitudes, livelihood diversification and adoption of climate smart agriculture technologies in the Nyando basin, South-Western Kenya

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ABSTRACT

Climate smart agriculture (CSA) technologies are innovations meant to reduce the risks in agricultural production among smallholder farmers. Among the factors that influence farmer adoption of agricultural technologies are farmers' risk attitudes and household livelihood diversification. This study, focused on determining how farmers' risk attitudes and household livelihood diversification influenced the adoption of CSA technologies in the Nyando basin. The study utilized primary data from 122 households from two administrative regions of Kisumu and Kericho counties in Kenya. The study employed the multivariate probit (MVP) and ordered probit (OP) models and descriptive statistics in data analysis using Stata 14.0. Results from the study indicated that farmers' risk attitudes had a significant negative influence in the adoption of terraces, ridges and bunds as well as the intensity of adoption of given CSA technologies. Household livelihood diversification had a significant negative influence in the adoption of stress tolerant livestock but did not have a significant effect on the intensity of adoption of given CSA technologies. The study recommends that relevant stakeholders should introduce an appropriate agricultural index insurance product to Nyando basin farmers to encourage the broader adoption of CSA technologies.

1. Introduction

One key challenge that agriculture faces is the effects of climate change at the production level (Lipper et al., 2014). In order to adapt to adverse climate change, farmers, governments and other relevant stakeholders need to promote and embrace climate smart agriculture (CSA). CSA is an approach to manage the necessary changes in agriculture with the aim of achieving food security in the face of climate change (Meybeck and Gitz, 2013). According to Meybeck and Gitz (2013) one such measure is for agriculture to adapt to climate change through the adoption of CSA technologies. There are three key CSA technologies classified as managerial, technological and institutional innovations (Zilberman et al., 2018). A key distinction of the three innovations is that institutional innovations are principally applicable at a macro-level requiring a farm systems approach while technological and managerial innovations are applicable at the micro-level, at the farm (Zilberman et al., 2018). One of the goals of CSA is to improve food security in a sustainable manner via increasing agricultural productivity and incomes (Palombi and Sessa, 2013). Mutenje et al. (2019) argued that CSA technologies are meant to enable farmers cope with climate risks in farming and increase farm level productivity in a sustainable way and thereby contribute to the realization of food security. CSA technologies are context specific and the appropriateness of CSA technologies may differ by gender, region, age and cultural dimensions (Mwongera et al., 2017).

Zilberman et al. (2018) stated that climate change would adversely affect the tropics as compared to temperate regions. The Climate Change Agriculture and Food Security (CCAFS) program identified key areas within the greater eastern Africa region to investigate the impacts of adverse climate change (Aggarwal et al., 2018). One such CCAFS identified region is the Nyando basin in South-western Kenya (Bernier et al., 2015). The Nyando basin has experienced reduced rainfall frequency and

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increased rainfall variability, flooding, strong winds and high frequency of storms, increase in average surface temperatures and high frequency of droughts in the last ten years as compared to 20–30 years ago (Thorlakson, 2011). These negative effects of climate change in the Nyando basin increase the risks in agricultural production faced by smallholder farmers.

Through the CCAFS program, a number of suitable climate smart agricultural technologies suitable for the Nyando basin were developed through the climate smart village (CSV) approach, though the consideration of all the CSA technologies was beyond the focus of this study (Bernier et al., 2015; Kinyangi et al., 2015). This study considered only four climate smart agricultural technologies: - stress tolerant livestock(S), terraces (T), ridges and bunds (R) and inorganic fertilizer (F).

Hurley (2010) pointed out that there is risk in agricultural production and that farmers' risk attitudes may influence how farmers use inputs in agricultural production. Hardaker et al. (2015) argued that farmers' risk attitudes influence the decision that farmers make in terms of whether to adopt given new agricultural technologies or fail to adopt. The risk in the adoption of farm-level technologies among smallholder famers is brought by the need for additional resources (Crentsil et al., 2018; Hardaker et al., 2015). Komarek et al. (2020) pointed out that the need for additional resources exposes smallholder farmers to financial risk mainly due to reliance on debt to finance the adoption of farm-level technologies. An understanding of how farmers' risk profiles influence the adoption of CSA technologies will potentially guide policy direction towards promoting resilient agricultural production in the face of climate change.

Other than farmers' risk profiles, livelihood diversification is another factor in literature found to influence the adoption of agricultural technologies. Teshager Abeje et al. (2019) emphasized that it is pivotal to explore the empirical relationship between household livelihood diversification and agricultural technology adoption among rural households. Diversification of livelihoods among smallholder famers in developing countries as used in this study refers to household access to sources of nonfarm and off-farm income to boost household income. Loison (2015) noted that diversification of livelihoods among smallholder farmers is geared at increasing household incomes. Increased household incomes may enable farmers overcome the financial constraints in the adoption of new agricultural technologies. Hailu et al. (2014) found that access to off-farm income increased the likelihood of Ethiopian households to adopt fertilizer by overcoming their financial constraints in fertilizer purchase.

Shikuku et al. (2017) found that farmers have varied attitudes to CSA technologies and that institutional and household socioeconomic characteristics influenced the adoption of CSA technologies among households in four CCAFS′ sites in East Africa that included Nyando basin. Bernier et al. (2015) found that there are gender differences in awareness of CSA technologies though gender did not significantly influence the adoption of CSA technologies among Nyando basin households. Bernier et al. (2015) further found that institutional, household head and household socioeconomic characteristics significantly influenced the adoption of CSA technologies among Nyando basin households. Bernier et al. (2015) recommended that future studies should analyse how risks influence the adoption of various CSA technologies in the Nyando basin. A review of past studies done among Nyando basin smallholder farmers showed that farmer' risk attitudes and household livelihood diversification as determinants of agricultural technology adoption have received little attention. Hardaker et al. (2015) pointed that farmers' risk preferences should be incorporated when analysing determinants of agricultural technology adoption among farming households. Bernier et al. (2015) explored the effect of off-farm income on piecemeal CSA technology adoption in the Nyando basin. This study explored the effect of both off-farm income and non-farm income on the intensity of adoption of CSA technologies.

Previous studies in Nyando basin have used univariate analysis to model the piecemeal adoption of CSA technologies. Bernier et al. (2015) used Heckman two-selection model and Shikuku et al. (2017) analyzed the piecemeal adoption of CSA technologies by Nyando basin households by using a binary probit model. Teklewold et al. (2013) argued that one is likely to generate biased estimates when analyzing the adoption of agricultural technologies in a piecemeal manner in univariate analysis. However, in multivariate analysis, one is able to analyze the joint adoption of CSA technologies and thereby explore any statistically significant cross-technology correlation effects (Aryal et al., 2018; Teklewold et al., 2013). This study was carried out with the aim of contributing knowledge to the identified knowledge gaps in literature.

The specific objective of this study was to determine how Nyando basin farmers' risk attitudes and livelihood diversification influence their adoption of CSA technologies. The particular null hypothesis tested in this study was that Nyando basin farmers' risk attitudes and household livelihood diversification do not significantly influence the adoption of CSA technologies. It is critical for policy makers to understand how farmers risk attitudes play a role in influencing the adoption of CSA technologies hence develop an appropriate insurance scheme. Diversification of livelihoods affects labor availability that can be allocated to the farm and the liquidity of a household. It is imperative for Nyando basin smallholder farmers to understand how their livelihood diversification affects their response to climate change in relation to adoption of CSA technologies.

2. Literature review

2.1. Risk management in agriculture

Risk and uncertainty are two related concepts that permeate everyday life. Hardaker et al. (2015) defined risk as uncertain consequences of what will happen after possible exposure to a given event while uncertainty is imperfect knowledge of whether a given event will occur. Komarek et al. (2020) identified five types of risks in agriculture, which include financial, production, market, personal and institutional risks. Ullah et al. (2015) pointed that production risk is a major risk in agriculture and Duong et al. (2019) noted that farmers have identified change in climate and weather as the major sources of risks to their farms. Production risks in agriculture stem from the fact that agriculture is depended on unpredictable weather and biological processes (Hardaker et al., 2015; Komarek et al., 2020). Girdžiūtė (2012) pointed out that the technology used by farmers is a source of production risk. Notably, adverse climate change in Sub-Saharan Africa exposes smallholder farmers to major production risks in agriculture (Hansen et al., 2019; Huet et al., 2020).

Risk management are the set of tools and practices that are used in order to mitigate and cope with losses emanating from varied risk sources (Schaffnit-Chatterjee et al., 2010). There are two main risk management strategies that farmers apply at the farm; they include ex-ante and ex-post strategies. Ex-post strategies are risk coping strategies applied after suffering a loss due to a specified risk while ex-ante strategies are risk-reducing strategies to mitigate against any potential loss brought by varied risk sources (Hansen et al., 2019; Ramaswami et al., 2008). Examples of ex-post strategies used by farm households include the liquidating of productive assets, selling stored produce, overusing natural resources, borrowing and even defaulting on loans, migrating to seek work and withdrawing children from school to engage in farm labor (Hansen et al., 2019; Ramaswami et al., 2008). Farm households can resort to the adoption of improved production technology that includes CSA technologies, investing in productive assets and avoiding borrowing as ex-ante strategies to manage risks in agriculture (Hansen et al., 2019; Ramaswami et al., 2008).

Taking up of appropriate agricultural insurance covers is an important risk management strategy among farmers in both developing and developed countries (Giampietri et al., 2020; Mahul and Stutley, 2010; Santeramo et al., 2016; Winsen et al., 2016). A novel agricultural insurance cover for developing countries is the use of index-based insurance, for instance agricultural weather index insurance that has been applied in different developing countries contexts (Chantarat et al., 2013; Jin et al., 2016; Mahul and Stutley, 2010). Although the demand for index-based agricultural insurance has been low (Carter et al., 2014; Magruder, 2018).

2.2. Farmer risk attitudes and risk management in agriculture

There are three distinct risk attitudes that individuals can fall into; they include risk-averse, risk-loving and risk-neutral attitudes (Binici et al., 2003; Hartog et al., 2000; Jianjun et al., 2015). Identification of these risk attitudes among individuals follows a risk elicitation exercise. The multiple price list (MPL) method, certainty equivalent method (CEM), ordered lottery selection (OLS), the balloon analogue risk task (BART), Gneezy and Potters method, `bomb' risk elicitation task (BRET) and use of questionnaires are some of the common risk elicitation techniques (Charness et al., 2013; Charness and Viceisza, 2016; Harrison and Rutström, 2008; Holzmeister and Stefan, 2020). The elicitation techniques can be either incentivized or non-incentivized and they vary from been simple to complex (Charness and Viceisza, 2016). The choice of elicitation technique a researcher uses depends on the objectives of the study although Holzmeister and Stefan (2020) noted that the choice of an elicitation technique may have a major effect on elicited risk preferences of individuals.

This study used the OLS technique to elicit the risk preferences of Nyando basin smallholder farmers. Harrison and Rutström (2008) noted that in the OLS technique subjects are presented with an ordered list of choices to pick a single preferred choice, one of the choices is a sure payoff, which is the safe option and the rest of the choices increase in average payoff from the sure payoff but with increasing standard deviation around the payoff. The OLS elicitation technique is a single choice list (SCL) method and it was pioneered by Binswanger (1980) among rural India subjects (Harrison and Rutström, 2008; Holzmeister and Stefan, 2020). This study used a variation of the six ordered choices as used by Dave et al. (2010). The six ordered lottery choices is a variation of the Eckel and Grossman (2002) method and is a simple technique that generates enough heterogeneity and is suitable for subjects with low numeracy skills (Charness et al., 2013; Dave et al., 2010).

Winsen et al. (2016) noted that the more risk averse a farmer was the less likely that the farmer would adopt ex-ante risk management strategies, opting to deal with farm risks ex-post while the more risk-seeking farmers were more likely to adopt ex-ante risk management strategies. Winsen et al. (2016) termed it as counterintuitive farmer behaviour after analysing how risk attitudes influenced the intention to implement risk management strategies among Belgium farmers. Hansen et al. (2019) argued that risk aversion leads to sub-optimal adoption and under-investment in better agricultural production technologies. Mao et al. (2017) noted that more risk averse famers were less likely to adopt new agricultural technologies and invest less in agricultural technologies. This shows that risk averse farmers are less likely to spend their scarce resources on risk mitigation strategies, which is a paradox. It is a paradox because mitigation strategies as ex-ante risk management strategies are meant to reduce the severity of a loss when a risk occurs or even prevent the possibility of suffering any loss from a potential risk. For instance, drought tolerant livestock is an important technology, which ensures that farmers' livestock is resilient during a period of prolonged drought. However, Jin et al. (2016) observed that risk averse farmers in China were more likely to adopt agricultural weather index insurance, which is an ex-ante risk management strategy. This shows that risk averse farmers can benefit from agricultural insurance in countries where it exists like China and a majority of developed countries but the availability of agricultural insurance is very low or non-existent in a majority of Sub-Saharan Africa countries (Mahul and Stutley, 2010). However, this study focused on analysing how Nyando basin farmers' risk attitudes influenced their adoption of CSA technologies as ex-ante risk mitigation strategies.

3. Study area, sampling and data collection methods

3.1. Study area

The study area is the Nyando basin, which traverses two counties in Kenya, part of Nyakach in Kisumu County and part of Soin in Kericho County. . Nyando experiences a humid to semi-humid climate with mean annual rainfall ranging between 900-2000 mm (Bernier et al., 2015). Kericho county records average annual temperature of 17 degrees Celsius although some drier areas do record mean temperatures slightly above 21 degrees Celsius (MoALF, 2017a). Kisumu county records average temperatures of about 20.9–22.3 degrees Celsius (MoALF, 2017b). . Mixed farming system, which includes rearing of various livestock breeds and planting of food crops, is the main source of livelihood for most of the households in the Nyando basin (Bernier et al., 2015; Kinyangi et al., 2015). Due to adverse climate change, Kericho County has started experiencing flashfloods around lower lying areas of Kipkelion and Soin and erratic rainfall throughout the year (MoALF, 2017a). Kisumu County has also recorded increased cases of floods within the Nyando basin and areas of lower Nyakach (MoALF, 2017b). Additionally, heat stress, vulnerability to droughts and unreliable rainfall has been experienced across the two counties within the contiguous Nyando basin region (MoALF, 2017a; 2017b). These undesired effects of climate change threaten the food security status of the region. Figure 1 is a map of the study area.

3.2. Sampling and data collection methods

Multistage sampling technique was used in obtaining the sample size for the study. In the first stage, Kisumu and Kericho counties were purposively chosen but within the contiguous Nyando basin, Nyakach – Soin administrative regions. In the second stage, households in both CSVs and non-CSVs were purposively selected. The study ensured that sampled households in CSVs and non-CSVs were very similar in observable characteristics; main agricultural activities; climate and soils. In the last stage, stratified random sampling was employed in selecting individual households. The different strata considered in the sampling included first, whether a household owns sheep and goats and if it owns; whether the owned sheep or goats are the improved breeds or the indigenous ones and second whether a household has high or low crop and land management technologies. The key reason for considering these strata is that the study focused on the upscaling of stress-tolerant livestock; sheep and goat breeds, and crop and land management technologies in the Nyando basin.

The sample size was determined using the following formula.

$$n = \frac{Z^2 p(1-p)}{e^2}$$

n is the sample size, p is the assumed proportion of residents with desired characteristics, in this study about 70 percent of the residents in the strata considered have the desired characteristics, Z abscissa of the normal curve at 1.96, and e is the allowed measurement error at 0.08.

$$n = \frac{1.96^2 0.7(1-0.7)}{0.08^2} = 126.0525 \approx 127$$

The actual number of duly completed questionnaires was 122; therefore, data from 122 households was used for data analysis. The recommended ratio of observations to independent variables is 10:1 but the bare minimum is 5:1 (Hair et al., 2018). The sample size for this study was at a ratio of 7:1, which is higher than the bare minimum but short of the recommended ratios of 10:1 and 20:1 (Hair et al., 2018). The key reason for settling on this sample size is that the expected proportion of respondents with desired characteristics was higher than 0.5 at 0.7. A proportion of 0.7 meant that there was not a maximum variability of

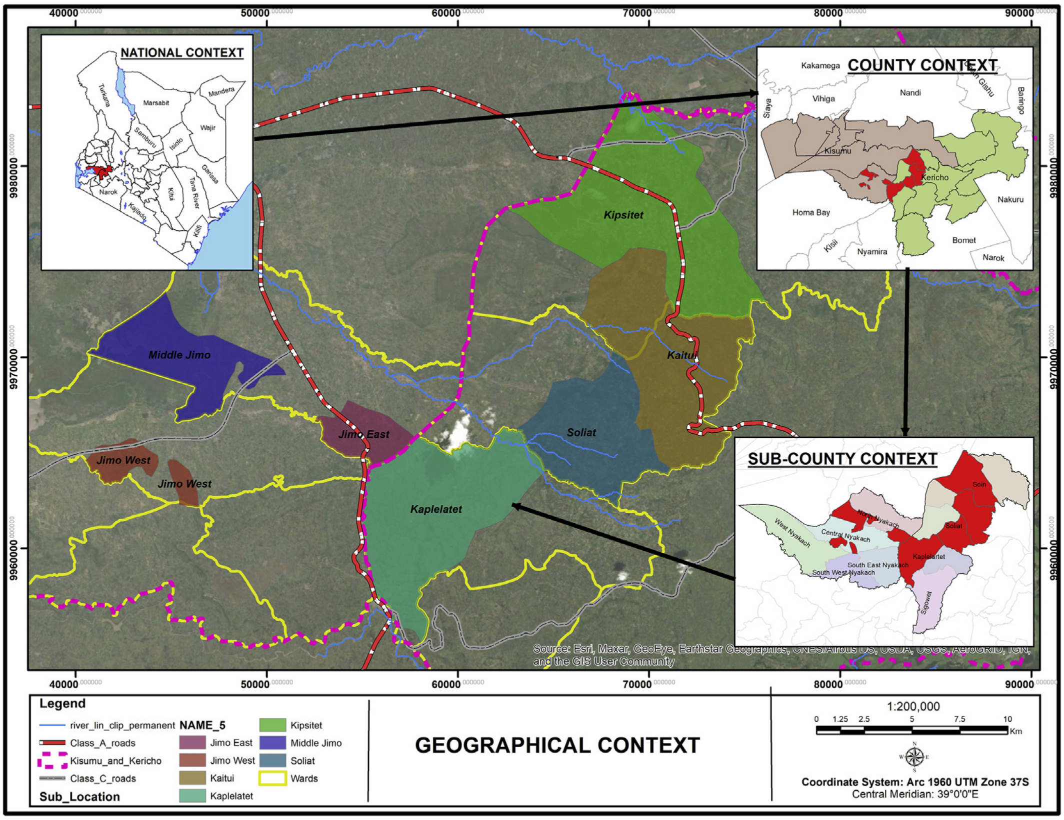

Figure 1. Map of the study area. Source: (IEBC, 2012).

observations expected, therefore a sample of 122 was deemed sufficient to avoid the possibility of committing type I error. Kline (2015) observed that large sample sizes can result in making any relationship statistically significant even when it is not supposed to be.

The data used came from a baseline survey of households conducted in the month of February 2019. The data was collected as a collaboration between University of Nairobi, VU University and International Livestock Research Institute (ILRI). The data consisted of household socioeconomic characteristics, results of a hypothetical risk experiment and type of CSA technologies adopted by Nyando basin households. The data was collected using a semi-structured questionnaire through computer aided personal interviewing (CAPI) by using an open data kit (ODK) tool.

4. Theoretical framework and empirical models

4.1. Theoretical framework

In this study, farmers are assumed to form preferences over the choices they face. Nyando basin farmers were assumed to form preferences over the types of agricultural technologies to adopt or not adopt. In economics, preferences can be modeled through the expected utility theory (Hardaker et al., 2015; Varian, 2010). The theoretical grounding of study is the expected utility theory. This theory holds that if choice x is preferred to choice y then, expected utility of x (U_x) is greater than the expected utility of y (U_y), that is, $U_x > U_y$ and the vice versa holds. Therefore, farmers in the Nyando basin will adopt given CSA practice (m) if the utility of adoption is greater than the utility from not adopting (Teklewold et al., 2013) as shown in Eq. (1).

$$Y^*_{im} = Um - Uo > 0 \tag{1}$$

Y* is a latent variable that captures the benefits to farmer (i) from adopting given CSA technology (m). *Um* is the expected utility from adopting while *Uo* is the expected utility from non-adoption.

4.2. Elicitation of risk attitudes

This study assumed that subjects' choices in the risk experiment were consistent with the assumptions of the expected utility theory. According to Jin et al. (2017) and Cotty et al. (2018), the utility function showing farmers risk aversion is as shown in Eq. (2).

$$U_{(w+x)} = \frac{(w+x)^{1-r}}{1-r} \tag{2}$$

where r stands for the coefficient of relative risk aversion, x is the expected payoff and w is the background endowment of wealth, which was assumed zero in this study. Trained enumerators presented to the subjects six ordered options to choose only one option as shown in Table 1. The trained enumerators showed the research subjects six decision cards and explained the instructions. The instructions of the experiment were as follows:-

I have six decision cards; each card has two options; Event A and Event B. The probability of either event occurring is 50 percent. Imagine

Table 1. Hypothetical risk experiment. [Read out and show the six decision cards, each event has a 50 % chance of occurring].

Gamble choice	Event A (high payoff) with probability, p	Event B (low pay off) with probability, (1-p)	Coefficient of relative risk aversion (CRRA) parameter (r) (Not visible to respondents)
1	20000	4000	$r < 0$
2	18000	6000	$0 < r < 0.5$
3	16000	7000	$0.5 < r < 0.71$
4	14000	8000	$0.71 < r < 1.16$
5	12000	9000	$1.16 < r < 3.46$
6	10000	10000	$3.46 < r$

the six decision cards as representing SIX different business ventures (either on-farm or off-farm business) with event A representing high payoff and event B representing a low payoff. Given the opportunity, which of the six options would you pick? I expect you to choose ONLY ONE option among the six decision cards. **Note: You can only choose one choice.**

The study relied on a hypothetical risk experiment to elicit the risk preferences of Nyando basin farmers. A hypothetical experiment was chosen for two key reasons. First, the research funds were limited to the extent that it was not possible to conduct a real risk experiment. Second, previous studies have shown that hypothetical risk experiments if carefully conducted can elicit risk preferences from farmers (Cotty et al., 2018; de Brauw and Eozenou, 2014; Hill, 2009; Shimamoto et al., 2018). In fact, Wik* et al. (2004) noted that there is insignificant difference in employing either incentivized or non-incentivized games in eliciting a subject's risk attitude. The figures in the risk experiment were designed to resemble possible gains from adopting CSA technologies, particularly drought tolerant sheep and goats, which is a key CSA technology in the Nyando basin. Galla goats and Red Maasai sheep can fetch market prices ranging from 4000 Kenya shillings to excess of 15000 Kenya depending on sex, market and age of the animal.

4.3. Econometric models

The net gain (Y^*_{im}) for adopting CSA technology m by farmer i is a latent variable influenced by farmer risk attitude, livelihood sources and other household specific and location characteristics (χ_i) and the unobserved factors captured in the error term (ε_i) (Aryal et al., 2018) as shown in Eq. (3).

$$Y^*_{im} = \chi_i \beta_m + \varepsilon_i \tag{3}$$

where (m = terraces (T), inorganic fertilizer (F), ridges and bunds (R), stress-tolerant livestock (S)) corresponding to the CSA technologies analyzed in this study.

The β is the estimated beta coefficients for each of the explanatory variables and ε is a normally distributed error term with a constant variance and zero mean (Ω, 0). It is the binary outcome for each decision to adopt technology m that is observed since the latent variable is unobserved as shown in Eq. (4) (Teklewold et al., 2013).

$$Yim = 1 \ if \ Y^*_{im} > 0 \ and \ 0 \ otherwise \tag{4}$$

4.4. Multivariate probit model

Smallholder farmers may need to address various felt needs in their decision to adopt CSA technologies. Farmers may need to adopt more than one technology while at the same time; the adoption of one technology may exclude the adoption of another. In order to capture this scenario, it is important to rely on multivariate modelling as opposed to univariate modelling. This study applied the multivariate probit (MVP) model, which allows for multivariate modelling. In the MVP model where the simultaneous adoption of multiple CSA technologies is possible, the errors terms will together follow a multivariate normal (MVN) distribution with zero conditional mean and variance normalized to unity; MVN(0,Ω) (Teklewold et al., 2013). The covariance matrix is as shown in Table 2 ρ is the correlation between the error terms. The necessary condition is that the values of the off-diagonal elements be non-zero which leads to Eq. (4) been a MVP model (Aryal et al., 2018).

Table 2. Covariance matrix of the error terms in the multivariate probit model.

1	ρTF	ρTR	ρTS
ρFT	1	ρFR	ρFS
ρRT	ρRF	1	ρRS
ρST	ρSF	ρSR	1

4.5. Ordered probit model

The MVP model has a weakness in that it does not inform on the number of CSA technologies adopted by any given farmer ((Aryal et al., 2018). To overcome this MVP model weakness, the study employed a model that accounted for the different intensity in adoption of the four CSA technologies among farming households. Kpadonou et al. (2017) noted that intensity of adoption is count data, which is still ordinal in nature, making the use of Poisson models inappropriate in modelling the intensity of adoption. Poisson models assume equal probability of adopting one or more technologies, which is not the case, because the adoption of the second or additional technology is conditional on the adoption of the previous technology (Maguza-Tembo* et al., 2017). Following Kpadonou et al. (2017), an ordered probit (OP) model was employed to account for the intensity of adoption of the four CSA technologies.

5. Independent and dependent variables

A review of literature showed a number of factors that do influence the decision of farmers to adopt varied farm-level technologies. The independent variables considered in this study include farmer risk attitudes, livelihood diversification, distance to market, social capital, credit access, education level, farmer training, age, family size, gender, land size, livestock ownership, climate risks (floods and drought), asset ownership and location dummy (Ahmed, 2015; Bernier et al., 2015; Cotty et al., 2018; Crentsil et al., 2018; Kurgat et al., 2018; Rajendran et al., 2016; Vieider et al., 2014). The dependent variables are the dummies on whether a farm household adopts terraces, ridges and bunds, inorganic fertilizer or stress tolerant livestock. Table 3 shows the

Table 3. Description of independent variables used in the study.

Variable	Description and measurement of variable	Expected sign
Risk attitude	Continuous, CRRA parameter	+/-
Livelihood diversification	Dummy, 1 = has access to off-farm or non-farm income sources 0 = otherwise	+/-
Land size	Continuous, Total size of land owned by household in acres	+
Social capital	Dummy, 1 = if household head is member of community based groups, including agricultural related groups, 0 = otherwise	+
Distance to market	Continuous, Number of kilometers to nearest market	-
Credit access	Dummy, 1 = household received credit in past one year, 0 = otherwise	+
Location	Dummy, 1 = located in Kisumu county, 0 = otherwise	+/-
Literacy of household head	Dummy, 1 = household head has attained secondary education, 0 = otherwise	+
Farmer training	Dummy, 1 = household head has received agricultural related training, 0 = otherwise	+
Age	Continuous, Years of the household head	-
Family size	Continuous, Number of household members in adult equivalents (14 ≤ 64 years)	+
Gender	Dummy, 1 = household head is male, 0 = otherwise	+/-
Livestock ownership	Continuous, Tropical livestock units	+
Asset ownership	Continuous, An asset index generated from value of non-land and non-livestock assets owned by a household	+
Climate risks (floods or drought)	Dummy, 1 = experienced climates risks, 0 = otherwise	+

hypothesized expected effect of each factor on the decision to adopt given CSA technologies considered in this study. Where (+) shows that the variable increases the probability of adoption while (-) shows that the variable reduces probability of adoption of given CSA technology and (+/-) show that the variable can either increase or decrease the probability of adoption.

6. Model diagnostics

6.1. Multicollinearity

Wooldridge (2016) recommends that in estimating regression results, there should be less correlation between explanatory variables and suggests the use of variance inflation factors (VIFs) to test for presence of multicollinearity, where a VIF below 10 is recommended. VIFs were obtained for all of the explanatory variables. The mean VIF for the explanatory variables used in the MVP and OP models was 1.465.

6.2. Heteroscedasticity

Following Wooldridge (2016) a test to determine whether there was constant variance across the error terms was done using Breusch-Pagan test for heteroscedasticity (BP test). The BP test was run for the MVP and the OP models in Stata 14. The BP test for the MVP and OP models failed to reject the null hypothesis that there was constant variance across the error terms with a chi-square value of 1.10 and p-value of 0.2942.

7. Ethical consideration

The study dealt with human subjects; therefore, considerable effort was made in ensuring that respondents were treated with human dignity. Senior lecturers at the University of Nairobi approved the survey questionnaire before deployment. Additionally, ILRI Institutional Research Ethics Committee (IREC) reviewed the survey questionnaire to ensure compliance with approved standards given by Kenya's government and international ethical standards. During data collection, enumerators obtained the informed consents from respondents, which were obtained voluntarily.

8. Results and discussion

8.1. Socioeconomic characteristics of Nyando basin smallholder farmers

Table 4 shows summary statistics of independent and dependent variables used in the study differentiated between Kisumu and Kericho counties.

There is a significant difference in the average age of the household heads between Kisumu and Kericho smallholder famers. The mean age of the Kericho household heads is significantly lower than that of the mean age of the Kisumu household heads at five percent level of significance. Kericho households have significantly larger plot sizes in acres than Kisumu households at 10 percent level of significance. This is a reflection of the high population density in Kisumu as compared to Kericho county (KNBS, 2019). High population density favors the subdivision of land, which leads to small plot sizes per capita. Kisumu households have a significantly higher asset index as compared to their Kericho counterparts at one percent level of significance. This difference could be explained by difference in value of non-land and non-livestock assets owned by households across the two counties. Kericho residents walk a significantly longer distance to reach their local market centers than Kisumu residents do at five percent level of significance. This difference in distance to market centers could be because of larger farm sizes in Kericho and low population density, which favors a slow development of market centers.

A significantly larger percentage of Kisumu households reported flooding as a major climate risk as compared to Kericho households at one percent level of significance. Nyando area on the side of Kisumu is a lowland area where water from the neighboring hilly Kericho county

Table 4. Socio-economic variables of households by county.

Independent variables	Description of variables	Kericho (51) Mean	Kisumu (71) Mean	Pooled sample mean (122)	t_value	P_value
Age	Years of household head	49.922	56.986	54.033	-2.4	.0175**
Family size	Number of household members in adult equivalents (between 14 and 64 years)	3.039	3.352	3.221	-.85	0.260
Livestock ownership	Tropical livestock units (TLUs)	4.677	3.336	3.896	1.5	.137
Land size	Total size of land owned by household in acres	6.084	3.207	4.409	1.9	.057*
Assets	An asset index generated in a principal component analysis from value of non-land and non-livestock assets owned by a household using Stata 14	2.294	3.479	2.984	-4.95	0.000***
Distance	Number of kilometers to nearest market	3.737	2.55	3.046	2.4	.0175 **
Gender	Dummy, 1 = household head is male, 0 = otherwise	0.843	0.788	0.811	0.75	0.453
Literacy	Dummy, 1 = household head has completed secondary school education, 0 = otherwise	0.196	0.254	0.230	-0.75	0.461
Social capital	Dummy 1 = if household head is member of community based groups, including agricultural related groups, 0 = otherwise	0.529	0. 493	0.508	0.4	0.696
Credit access	Dummy 1 = household received credit in past one year, 0 = otherwise	0.431	0.451	0.443	-.2	0.834
Livelihood diversification	Dummy, 1 = if household has diversified its livelihood sources to off-farm or non-farm income 0 = otherwise	0.569	0.549	0.557	0.2	0.834
Floods	Dummy, 1 = if household experienced floods in the past five years, 0 = otherwise	0.138	0.352	0.262	-2.7	0.007***
Drought	Dummy, 1 = if household experienced droughts in the past five years, 0 = otherwise	0.51	0.648	0.59	-1.55	0.128
Training	Dummy 1 = household head has received agricultural related training in the last five years, 0 = otherwise	0.451	0.648	0.566	-2.2	0.03**
Dependent variables						
Terraces (T)	Dummy 1 = if adopted terraces, 0 = otherwise	.687	.592	.631	1.05	.288
Inorganic fertilizer(F)	Dummy 1 = if adopted fertilizer, 0 = otherwise	.647	.408	.508	2.65	.009***
Ridges and bunds (R)	Dummy, 1 = if adopted ridges and bunds, 0 = otherwise	.509	.352	.418	1.75	.083*
Stress tolerant livestock (S)	Dummy 1 = if adopted stress tolerant livestock, 0 = otherwise	.255	.352	.311	-1.15	.257

drains (Owuor et al., 2012). A significantly larger percentage of Kisumu households received farmer training as compared to Kericho households. Kericho households significantly adopted more of fertilizer and ridges and bunds than Kisumu households at one percent and 10 percent level of significance respectively.

8.2. Nyando basin farmers' risk attitudes profile

Table 5 shows the summary of the responses from the risk experiment. The risk experiment was designed so that respondents with risk-neutral and risk loving attitudes would choose gamble choices two (2) and one (1) respectively. Otherwise, individuals choosing gamble choices three to six are the ones with a risk-averse attitude to risk. Dave et al. (2010) and Holzmeister and Stefan (2020) pointed out that someone with a risk-seeking attitude chooses gamble choice one (1) and someone with a risk neutral attitude chooses gamble choice two (2). Gamble choices three (3) to six (6) represent varying degrees of a risk averse attitude (Dave et al., 2010).

The midpoints of the coefficient of relative risk aversion intervals for gamble choices corresponding to captured responses were used to find the mean risk aversion level among Nyando basin farmers. The study used the lower bound of gamble choice six and upper bound of gamble choice one for analysis purposes.

The observed mean constant relative risk aversion parameter among Nyando smallholder farmers was 1.291. Results of an independent t-test showed that 1.291 was significantly different from zero at one percent level of significance. Since it is a positive risk parameter, it shows that Nyando basin farmers are risk averse confirming findings in literature that smallholder farmers in developing countries are generally risk averse (Crentsil et al., 2018; Jin et al., 2016).

8.3. Multivariate probit results

The likelihood ratio test of the chi-square (χ^2) (6) = 24.4289 of the independence of the error terms is rejected at one percent level of significance, which means that the adoptions of CSA technologies is not mutually independent and it supports the use of the MVP model. Table 6 shows that Nyando households adopt given CSA technologies as complements and substitutes. The adoption of terraces and inorganic fertilizer, ridges and inorganic fertilizer has a significant positive correlation, which means that farmers adopted the technologies as complements. The adoption of ridges and stress tolerant livestock has a significant negative correlation, which means that farmers adopted the two technologies as substitutes.

Table 7 shows the results of the MVP model on household technology adoption decisions. The Wald test (χ^2 (64) = 286.47 Prob > χ^2 = 0.0000) of the hypothesis that regression coefficients in all the equations are jointly equal to zero is rejected.

Family size had a significant positive influence on the decision of a household to adopt ridges and bunds. Erecting of ridges and bunds is a labor-intensive exercise, which necessitates households to take advantage of available family labor. Gender of the household head had a significant positive influence on the decision of a household to adopt stress tolerant livestock. Male-headed households (MHHs) have a higher likelihood of adopting stress tolerant livestock as compared to female-headed households (FHHs). Obisesan (2014) found similar results where MHHs are more likely to adopt agricultural technologies than FHHs, the study attributed the difference to gendered access to resources and appropriate information.

Table 5. Summary of the Risk Profiles of Nyando rural households.

Gamble choice	Coefficient of relative risk aversion interval	Frequency	Percent	Cumulative percentage
1	0 > r	39	31.97	31.97
2	0 < r < 0.5	7	5.74	37.70
3	0.5 < r < 0.71	9	7.38	45.08
4	0.71 < r < 1.16	15	12.30	57.38
5	1.16 < r < 3.46	38	31.15	88.52
6	3.46 < r	14	11.48	100.00

Table 6. Covariance Matrix of the Error terms: Substitutability and Complementarities of CSA technologies.

CSA technologies	Terraces	Inorganic fertilizer	Ridges and bunds	Stress-tolerant livestock
Terraces	1			
Inorganic fertilizer	0.518 (0.139)***	1		
Ridges and bunds	0.187 (0.162)	0.299 (0.136)**	1	
Stress-tolerant livestock	-0.037 (0.185)	0.322 (0.202)	-0.470 (0.208)**	1

Likelihood ratio test of interdependence of the regression: Chi-square (χ^2) (6) = 24.4289 $Prob > \chi^2$ = 0.0004.

Table 7. MVP results of households' technology adoption decisions.

Dependent variables/ explanatory variables	Terraces	Fertilizer	Ridges and bunds	Stress tolerant livestock
Family size	-0.039 (0.069)	-0.062 (0.077)	**0.108 (0.065)***	-0.050 (0.088)
Gender of household head	0.261 (0.330)	0.492 (0.349)	-0.148 (0.361)	**1.420 (0.589)****
Age of household head	0.008 (0.009)	-0.003 (0.009)	0.008 (0.009)	-0.012 (0.015)
Literacy of household head	0.070 (0.331)	-0.192 (0.344)	0.314 (0.347)	0.835 (0.525)
Land size in acres	**0.167 (0.069)****	**0.182 (0.074)****	-0.028 (0.020)	**0.224 (0.060)*****
Asset index	0.114 (0.112)	0.127 (0.123)	0.073 (0.109)	**0.267 (0.145)***
Livelihood diversification	0.137 (0.291)	0.066 (0.290)	-0.153 (0.277)	**-0.561 (0.339)***
Tropical livestock units	0.044 (0.055)	-0.073 (0.049)	0.031 (0.036)	-0.031 (0.061)
Risk attitude	**-0.191 (0.111)***	0.024 (0.109)	**-0.343 (0.114)*****	-0.134 (0.136)
Access to loans	0.068 (0.260)	0.384 (0.281)	0.057 (0.264)	**0.824 (0.335)****
Distance to market	0.046 (0.055)	**0.179 (0.054)*****	0.076 (0.049)	**-0.193 (0.068)*****
Social capital	0.188 (0.292)	0.281 (0.285)	0.208 (0.280)	0.445 (0.336)
Floods	0.019 (0.286)	**0.672 (0.320)****	-0.103 (0.297)	**0.962 (0.347)****
Drought	-0.070 (0.280)	0.091 (0.274)	**0.745 (0.281)*****	0.337 (0.347)
Training	**0.464 (0.280)***	-0.237 (0.267)	-0.151 (0.273)	**1.707 (0.413)*****
Kisumu	-0.365 (0.285)	**-0.600 (0.308)***	**-0.625 (0.290)****	-0.574 (0.369)
_cons	**-1.326 (0.757)***	**-1.399 (0.777)***	-1.005 (0.778)	**-3.691 (0.985)*****

Note: Standard errors in parenthesis, statistical significance ***p < 0.01, **p < 0.05, *p < 0.1.
N = 122 (Number of draws = 10) Log likelihood = -230.96552 Wald (χ^2) (64) = 286.47***.
TLU conversion factor: 1 head of cattle = 0.7 TLU, 1 sheep or goat (small stock) = 0.1 TLU, 1 donkey = 0.5 TLU, poultry = 0.01 TLU (Source Hailemichael et al., (2016); Mkonyi et al. (2017).

Land size had a significant positive influence on the decision of a household to adopt stress tolerant livestock, terraces and fertilizer use. In addition, asset index had a significant positive influence on the decision of a household to adopt stress tolerant livestock. Asset index and land size are measures of the wealth of a household. A wealthier household is more likely to adopt stress tolerant livestock, fertilizer and terraces. Wealthy households are able to deal with any risks that come with the adoption of various agricultural technologies (Teklewold et al., 2013). Access to off-farm or non-farm income negatively influenced the probability of a household adopting stress tolerant livestock. Ahmed (2015) found similar results where access to off-farm or non-farm income had a significant negative influence on technology adoption. Ahmed (2015) attributed the negative influence to some technologies been labor intensive and households may not have labor allocated for the same. Similarly, the adoption of stress tolerant livestock may require allocation of labor for its safe caring and thus households that have diversified may not have available labor to allocate towards caring of stress tolerant livestock.

Risk attitude had a significant negative influence on whether a household adopts terraces and ridges and bunds. Ambali et al. (2019) found similar results, whereby farmers who avoided taking risks were less likely to adopt agricultural technology. Erecting of terraces, ridges and bunds may require cash outlay in paying for required labor and purchase of appropriate tools. Risk averse farmers may be unwilling to spend their limited cash reserves on the same. Adoption of CSA technology can be thought of as an ex-ante risk management tool. Winsen et al. (2016) noted that more risk averse farmers were less likely to adopt ex-ante risk management strategies when faced with risks. Access to loans had a positive significant influence on the decision of a household to adopt stress tolerant livestock. Adoption of stress tolerant livestock requires cash outlays and loans provide the needed cash. Loans provide farmers with access to cash if they are not able to self-finance (Jerop et al., 2018; Teklewold et al., 2013).

Distance to the market had a significant negative influence on the probability of a household adopting stress tolerant livestock. The reason could be transaction costs that increase as distance to the market increases (Teklewold et al., 2013). Alternatively, distance to the market had a significant positive influence on the decision of a household to adopt fertilizer. The probable reason is that households in the Nyando basin collaborate with a local non-governmental organization that brings them farm inputs at their doorstep without requiring them to go the market. Teklewold et al. (2013) had similar results where distance to the market had a significant positive effect on the adoption of agricultural technology.

Floods had a significant positive influence on the decision of a household to adopt stress tolerant livestock and fertilizer. Households have faith that stress tolerant livestock are able to cope well during flooding episodes. At the same time, farmers hope to improve farmland productivity by applying fertilizer since floods reduce the farmland productivity of their farms as noted by Thorlakson (2011). Droughts had a significant positive influence on the decision of a household to erect ridges and bunds. Ridges reduce the speed of surface run-off (Bernier et al., 2015). It is from this reduced surface run-off that ridges and bunds aid in soil moisture retention, which farmers can utilize in periods of dry-spells to plant early maturing crops like vegetables (Wolka et al., 2018).

Farmer training had a significant positive effect on the decision of a household to adopt stress tolerant livestock and terraces. Training offers farmers with the appropriate knowledge and equips them with skills to successfully adopt terraces and stress tolerant livestock for their benefit. Previous studies have found that farmer training favors the adoption of agricultural technologies (Aryal et al., 2018; Jerop et al., 2018; Maguza-Tembo* et al., 2017; Yirga et al., 2015). Lastly, households in Kisumu were less likely to adopt fertilizer, ridges, and bunds as climate smart technologies. The probable reason could be due to differences in resources used to erect ridges and bunds. Kericho residents are able to use surface rocks, which are plenty, to erect ridges and stone bunds in their farms, which Kisumu residents' lack. The difference in adoption of fertilizer between Kisumu and Kericho farmers may be due to varied access to farm inputs including fertilizer.

8.4. Ordered probit estimation results

Table 8 shows the number of CSA technologies adopted by Nyando basin households. Barely 15 percent of the farmers have adopted zero CSA technologies addressed in this study while about seven percent representing eight farmers have adopted all the four technologies and more than three quarters of the sampled households have adopted one to three technologies.

The OP model fits well with a *Prob* $>$ *chi-square* $(\chi^2) = 0.000$ and pseudo r-squared of 0.12. Table 9 shows the factors influencing the level of adoption of the given CSA technologies by the Nyando basin smallholder farmers. Gender of the household head had a significant negative influence on a household adopting one CSA technology but had a significant positive influence on the probability of a household adopting three and four technologies. MHHs are more likely to adopt three and four technologies and less likely to adopt one technology at 13.1, 2.7 and 8.5 percent respectively. This could be because MHHs have more resources as compared to their FHHs counterparts. Household asset index had a significant negative influence on the probability of a household adopting only one CSA technology and not adopting any practice at 3.6 and 3.1 percent respectively. However, asset index had a significant positive influence on the probability of a household adopting three CSA technologies at 5.1 percent. This shows that wealthier households were more likely to adopt more than one site-specific CSA technologies and less likely to adopt one or not adopt at all any CSA technology.

Risk attitude had a significant effect on the probability of a household adopting none, one, three and four CSA technologies. Risk attitude positively influenced the probability of a household adopting none and one CSA technology at 3.1 and 3.6 percent respectively. This means that Nyando basin farmers are able to deal with the risk of adopting one CSA technology. Alternatively, risk attitude negatively influenced the probability of a household adopting three and four CSA technologies at 5.1 and 1.3 percent respectively. This means that Nyando basin farmers perceive risk in the adoption of more than one CSA technology and thus are less likely to adopt many agricultural technologies.

Distance to the market significantly influenced the probability of Nyando farmers adopting none, one or three CSA technologies. Distance to the market negatively influenced the probability of adopting one practice by 1.5 percent and not adopting by 1.4 percent. At the same time, distance to the market positively influenced the probability of adopting of three technologies by 2.2 percent. The probable reason is that farmers may face inhibitive transaction costs in adopting one practice but not so with adopting more than one CSA technology. Floods had a significant negative effect on the probability of a household not adopting any CSA technology. Farmers who had experienced floods were less likely not to adopt any CSA technology at 5.9 percent, which means that floods encouraged the adoption of site-specific climate smart agricultural technologies by Nyando basin farmers.

Kisumu households were significantly more likely to adopt one or fail to adopt any CSA technology at 12.6 and 10.6 percent respectively.

Table 8. Level of adoption of CSA technologies by Nyando households.

CSA technologies adopted	Number of farmers	Percent	Cumulative percent
0	18	14.75	14.75
1	29	23.77	38.52
2	34	27.87	66.39
3	33	27.05	93.44
4	8	6.56	100.00

Table 9. Marginal effects of ordered probit estimation results.

Variable	Coeff.	Prob (Y = 0/X)	Prob (Y = 1/X)	Prob (Y = 2/X)	Prob (Y = 3/X)	Prob (Y = 4/X)
Family size	0.024 (0.056)	-0.004 (0.010)	-0.005 (0.011)	0.000 (0.001)	0.007 (0.016)	0.002 (0.004)
Gender of household head*	0.484 (0.285)	-0.102 (0.072)	**-0.085 (0.045)***	0.030 (0.033)	**0.131 (0.073)***	**0.027 (0.016)***
Age of household head	0.004 (0.007)	-0.001 (0.001)	-0.001 (0.001)	0.000 (0.000)	0.001 (0.002)	0.000 (0.001)
Literacy of household head*	0.009 (0.270)	-0.002 (0.047)	-0.002 (0.054)	0. 000 (0.005)	0.003 (0.077)	0.001 (0.020)
Land size in acres	0.028 (0.020)	-0.005 (0.004)	-0.006 (0.004)	0.001 (0.001)	0.008 (0.006)	0.002 (0.002)
Asset index	0.179 (0.092)	**-0.031 (0.017)***	**-0.036 (0.020)***	0.003 (0.006)	**0.051 (0.027)***	0.013 (0.008)
Livelihood diversification*	-0.220 (0.224)	0.038 (0.039)	0.044 (0.045)	-0.003 (0.008)	-0.062 (0.064)	-0.016 (0.018)
Tropical livestock units	0.014 (0.038)	-0.002 (0.007)	-0.003 (0.008)	0.000 (0.001)	0.004 (0.011)	0.001 (0.003)
Risk attitude	-0.178 (0.086)	**0.031 (0.016)***	**0.036 (0.018)***	-0.003 (0.006)	**-0.051 (0.026)****	**-0.013 (0.007)***
Access to loans*	0.304 (0.211)	-0.052 (0.037)	-0.061 (0.043)	0.004 (0.010)	0.086 (0.060)	0.023 (0.018)
Distance to market	0.077 (0.040)	**-0.014 (0.007)***	**-0.015 (0.009)***	0.001 (0.003)	**0.022 (0.012)***	0.006 (0.004)
Social capital*	0.237 (0.218)	-0.042 (0.039)	-0.047 (0.044)	0.005 (0.009)	0.067 (0.062)	0.017 (0.017)
Floods*	0.380 (0.247)	**-0.059 (0.036)***	-0.077 (0.052)	-0.003 (0.015)	0.108 (0.071)	0.033 (0.027)
Drought*	0.326 (0.220)	-0.060 (0.043)	-0.064 (0.044)	0.009 (0.013)	0.092 (0.061)	0.022 (0.017)
Training*	0.253 (0.218)	-0.045 (0.041)	-0.050 (0.043)	0.006 (0.010)	0.072 (0.062)	0.018 (0.016)
Kisumu*	-0.641 (0.239)	**0.106 (0.041)*****	**0.126 (0.051)****	-0.002 (0.020)	**-0.178 (0.067)*****	**-0.053 (0.029)***
Constant	0.342 (0.623)					
Constant	1.272 (0.629)					
Constant	2.100 (0.635)					
Constant	3.475 (0.679)					

Note: Standard errors in parenthesis, statistical significance ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.
N = 122 Log likelihood = -162.35133 LR (χ^2) (16) = 44.29*** Pseudo. $\mathscr{R}^2$ = 12.0%.

Alternatively, Kisumu farmers are significantly less likely to adopt three and four technologies at 17.8 and 5.3 percent respectively. This could be a reflection of disparity in access to information, resources and skills required for adoption of more than one site-specific CSA technologies between Kisumu and Kericho farmers.

9. Conclusion and policy recommendations

Results of the study rejected the null hypothesis that Nyando basin farmers' risk attitudes and household livelihood diversification do not significantly influence the adoption of CSA technologies. Results of the MVP model showed that risk attitudes had a significant negative influence on the adoption of terraces and ridges and bunds. The results of the OP model showed that risk attitudes had a significant negative influence as the intensity of adoption of given CSA technologies increased. The results of the MVP model showed that livelihood diversification had a significant negative influence in the adoption of stress tolerant livestock. Risk adverse individuals are the targets of insurance covers and risk averse farmers are not an exception. This study recommends an introduction of an agricultural weather index based insurance product in Nyando to encourage the adoption of CSA technologies. The rolling out of such insurance product will require timely and appropriate policy regulatory framework favorable to smallholder farmers in the Nyando basin. A similar insurance product has been rolled out in other parts of Kenya, particularly, the index based livestock insurance (IBLI) among pastoralists in Northern Kenya. Results of the study showed that farmers adopted some technologies as substitutes and others as complements. This shows that there are potential tradeoffs in the adoption of varied CSA technologies. Since farmer training had a significant influence on technology adoption; there is need for a policy to guide farmer training on the best mix of CSA technologies that farmers can optimally adopt. Gender had a significant influence in the adoption of one of the CSA technologies. The local county governments of Kisumu and Kericho should promote a policy that aims at empowering especially female household heads' ability to adopt varied CSA technologies. This study considered the risk profiles of subjects over gains only, future research can go further by considering the risk profiles of subjects over both gains and losses.

Declarations

Author contribution statement

Mumo Elijah Musyoki: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

John Ronoh Busienei, John Kamau Gathiaka, George Njomo Karuku: Conceived and designed the experiments; Wrote the paper.

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References

Aggarwal, P.K., Jarvis, A., Campbell, B.M., Zougmoré, R.B., Khatri-Chhetri, A., Vermeulen, S.J., Loboguerrero, A.M., Sebastian, L.S., Kinyangi, J., Bonilla-Findji, O., Radeny, M., Recha, J., Martinez-Baron, D., Ramirez-Villegas, J., Huyer, S., Thornton, P., Wollenberg, E., Hansen, J., Alvarez-Toro, P., Yen, B.T., 2018. The climate-smart village approach: framework of an integrative strategy for scaling up adaptation options in agriculture. Ecol. Soc. 23 (1), art14.

Ahmed, M.H., 2015. Adoption of multiple agricultural technologies in maize production of the Central Rift Valley of Ethiopia. Stud. Agri. Econ. 117, 162–168 (1316-2016–102848).

Ambali, O.I., Areal, F.J., Geogantzis, N., 2019. Risk Preference as an Endogenous Determinant of Improved Rice Technology Adoption Decisions: Evidence from Nigeria (No. 289678; 93rd Annual Conference, April 15-17, 2019, Warwick University. Agricultural Economics Society - AES, Coventry, UK. https://ideas.repec.org/p/ags/aesc19/289678.html.

Aryal, J.P., Jat, M.L., Sapkota, T.B., Khatri-Chhetri, A., Kassie, M., Rahut, D.B., Maharjan, S., 2018. Adoption of multiple climate-smart agricultural practices in the Gangetic plains of Bihar, India. Int. J. Clim. Change Strat. Manag. 10 (3), 407–427.

Bernier, Q., Meinzen-Dick, R.S., Kristjanson, P.M., Haglund, E., Kovarik, C., Bryan, E., Ringler, C., Silvestri, S., 2015. Gender and institutional aspects of climate-smart agricultural practices: evidence from Kenya. In: CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS) [Working Paper]. https://cgspace.cgiar.org/handle/10568/65680.

Binswanger, H.P., 1980. Attitudes toward risk: experimental measurement in rural India. Am. J. Agric. Econ. 62 (3), 395–407.

Binici, T., Koç, A.A., Zulauf, C.R., Bayaner, A., 2003. Risk attitudes of farmers in terms of risk aversion: a case study of lower seyhan plain farmers in adana province, Turkey. Turk. J. Agric. For. 27 (5), 305–312.

Carter, M., De Janvry, A., Sadoulet, E., Sarris, A., 2014. Index-based weather insurance for developing countries: a review of evidence and a set of propositions for up-scaling. Develop. Pol. Work. Paper 111.

Chantarat, S., Mude, A.G., Barrett, C.B., Carter, M.R., 2013. Designing index-based livestock insurance for managing asset risk in northern Kenya. J. Risk Insur. 80 (1), 205–237.

Charness, G., Viceisza, A., 2016. Three risk-elicitation methods in the field: evidence from rural Senegal. Rev. Behav. Econ. 3 (2), 145–171.

Charness, G., Gneezy, U., Imas, A., 2013. Experimental methods: eliciting risk preferences. J. Econ. Behav. Organ. 87, 43–51.

Cotty, T.L., d'Hôtel, E.M., Soubeyran, R., Subervie, J., 2018. Linking risk aversion, time preference and fertiliser use in Burkina Faso. J. Dev. Stud. 54 (11), 1991–2006.

Crentsil, C., Gschwandtner, A., Wahhaj, Z., 2018. The effects of risk and ambiguity aversion on technology adoption: evidence from aquaculture in Ghana. AgEcon Search. Article 2229-2019–1877.

Dave, C., Eckel, C.C., Johnson, C.A., Rojas, C., 2010. Eliciting risk preferences: when is simple better? J. Risk Uncertain. 41 (3), 219–243.

de Brauw, A., Eozenou, P., 2014. Measuring risk attitudes among Mozambican farmers. J. Dev. Econ. 111, 61–74.

Duong, T.T., Brewer, T., Luck, J., Zander, K., 2019. A global review of farmers' perceptions of agricultural risks and risk management strategies. Agriculture 9 (1), 10.

Eckel, C.C., Grossman, P.J., 2002. Sex differences and statistical stereotyping in attitudes toward financial risk. Evol. Hum. Behav. 23 (4), 281–295.

The role of trust and perceived barriers on farmer's intention to adopt risk management tools. In: Giampietri, E., Yu, X., Trestini, S. (Eds.), Bio-Based Appl. Econ. J. 9.

Girdžiūtė, L., 2012. Risks in agriculture and opportunities of their integrated evaluation. Proc. - Soc. Behav. Sci. 62, 783–790.

Hailemichael, A., Gebremedhin, B., Gizaw, S., Tegegne, A., 2016. Analysis of Village Poultry Value Chain in Ethiopia: Implications for Action Research and Development. International Livestock Research Institute.

Hailu, B.K., Abrha, B.K., Weldegiorgis, K.A., 2014. Adoption and impact of agricultural technologies on farm income: evidence from southern tigray, northern Ethiopia. Int. J. Food Agric. Econ. 2 (4), 91–106.

Hair Jr., J.F., Black, W.C., Babin, B.J., Anderson, R.E., 2018. Multivariate Data Analysis, Eighth. Annabel Ainscow.

Hansen, J., Hellin, J., Rosenstock, T., Fisher, E., Cairns, J., Stirling, C., Lamanna, C., van Etten, J., Rose, A., Campbell, B., 2019. Climate risk management and rural poverty reduction. Agric. Syst. 172, 28–46.

Hardaker, J.B., Lien, G., Anderson, J.R., Huirne, R.B.M., 2015. Coping with Risk in Agriculture, third ed. Applied Decision Analysis. CABI.

Harrison, G.W., Rutström, E.E., 2008. Risk aversion in the laboratory. Res. Exp. Econ. 12, pp. 41–196). Emerald (MCB UP).

Hartog, J., Ferrer-i-Carbonell, A., Jonker, N., 2000. On a simple survey measure of individual risk aversion. Available at SSRN 260938.

Hill, R.V., 2009. Using stated preferences and beliefs to identify the impact of risk on poor households. J. Dev. Stud. 45 (2), 151–171.

Holzmeister, F., Stefan, M., 2020. The risk elicitation puzzle revisited: across-methods (in)consistency? Exp. Econ. 1–24.

Huet, E.K., Adam, M., Giller, K.E., Descheemaeker, K., 2020. Diversity in perception and management of farming risks in southern Mali. Agric. Syst. 184, 102905.

Hurley, T.M., 2010. A review of agricultural production risk in the developing world. In: Working Papers (No. 188476; Working Papers). HarvestChoice. https://ideas.repec.org/p/ags/hcwpum/188476.html.

Independent Electoral and Boundaries Commission (IEBC), 2012. Preliminary Report on the First Review Relating to the Delimitation of Boundaries of Constituencies and Wards. Nairobi, Kenya.

Jerop, R., Dannenberg, P., George Owuor, G., Mshenga, P., 2018. Factors affecting the adoption of agricultural innovations on underutilized cereals: the case of finger millet among smallholder farmers in Kenya. Afr. J. Agric. Res. 13 (36), 1888–1900.

Jianjun, J., Yiwei, G., Xiaomin, W., Nam, P.K., 2015. Farmers' risk preferences and their climate change adaptation strategies in the Yongqiao District, China. Land Use Pol. 47, 365–372.

Jin, J., Wang, W., Wang, X., 2016. Farmers' risk preferences and agricultural weather index insurance uptake in rural China. Int. J. Disa. Risk Sci. 7 (4), 366–373.

Jin, J., He, R., Gong, H., Xu, X., He, C., 2017. Farmers' risk preferences in rural China: measurements and determinants. Int. J. Environ. Res. Publ. Health 14 (7), 713.

Kenya National Bureau of Statistics, 2019. 2019 Kenya Population and Housing Census Volume I: Population by County and Sub-county. KNBS Nairobi.

Kinyangi, J., Recha, J., Kimeli, P., Atakos, V., 2015. Climate-smart Villages and the hope of Food Secure Households. https://ccafs.cgiar.org/publications/climate-smart-villages-and-hope-food-secure-households.

Kline, R.B., 2015. Principles and Practice of Structural Equation Modeling. Guilford Publications.

Komarek, A.M., De Pinto, A., Smith, V.H., 2020. A review of types of risks in agriculture: what we know and what we need to know. Agric. Syst. 178, 102738.

Kpadonou, R.A.B., Owiyo, T., Barbier, B., Denton, F., Rutabingwa, F., Kiema, A., 2017. Advancing climate-smart-agriculture in developing drylands: joint analysis of the adoption of multiple on-farm soil and water conservation technologies in West African Sahel. Land Use Pol. 61, 196–207.

Kurgat, B.K., Ngenoh, E., Bett, H.K., Stöber, S., Mwonga, S., Lotze-Campen, H., Rosenstock, T.S., 2018. Drivers of sustainable intensification in Kenyan rural and peri-urban vegetable production. Int. J. Agric. Sustain. 16 (4–5), 385–398.

Lipper, L., Thornton, P., Campbell, B.M., Baedeker, T., Braimoh, A., Bwalya, M., Caron, P., Cattaneo, A., Garrity, D., Henry, K., Hottle, R., Jackson, L., Jarvis, A., Kossam, F., Mann, W., McCarthy, N., Meybeck, A., Neufeldt, H., Remington, T., Torquebiau, E.F., 2014. Climate-smart agriculture for food security. Nat. Clim. Change 4 (12), 1068–1072.

Loison, S.A., 2015. Rural livelihood diversification in sub-saharan Africa: a literature review. J. Dev. Stud. 51 (9), 1125–1138.

Magruder, J.R., 2018. An assessment of experimental evidence on agricultural technology adoption in developing countries. Ann. Rev. Res. Econ. 10 (1), 299–316.

Maguza-Tembo*, F., Mangison, J., Edris, A.K., Kenamu, E., 2017. Determinants of adoption of multiple climate change adaptation strategies in Southern Malawi: an ordered probit analysis. J. Dev. Agric. Econ. 9 (1), 1–7.

Mahul, O., Stutley, C.J., 2010. Government Support to Agricultural Insurance: Challenges and Options for Developing Countries. World Bank Publications.

Mao, H., Zhou, L., Ifft, J., 2017. Risk preferences, contracts and technology adoption by broiler farmers in China. In: 2017 Annual Meeting, July 30-August 1, Chicago, Illinois No. 257248. Agricultural and Applied Economics Association. https://econpapers.repec.org/paper/agsaaea17/257248.htm.

Meybeck, A., Gitz, V., 2013. Module 1: why cliMate-Smart agriculture, forestry and fisheries Overview. In: Climate-smart Agriculture Sourcebook. Food and Agriculture Organization of the United Nations, pp. p2–40.

Mkonyi, F.J., Estes, A.B., Msuha, M.J., Lichtenfeld, L.L., Durant, S.M., 2017. Socio-economic correlates and management implications of livestock depredation by large carnivores in the Tarangire ecosystem, northern Tanzania. Int. J. Biodiver. Sci. Ecosys. Serv. Manag. 13 (1), 248–263.

MoALF, 2017a. Climate Risk Profile for Kericho County. Kenya County Climate Risk Profile Series. The Ministry of Agriculture, Livestock and Fisheries (MoALF), Nairobi, Kenya. https://ccafs.cgiar.org/publications/climate-risk-profile-kericho-county-kenya-county-climate-risk-profile-series#.XuNL8edRXIU.

MoALF, 2017b. Climate Risk Profile Kisumu County: Kenya County Climate Risk Profile Series. The Ministry of Agriculture, Livestock and Fisheries (MoALF), Nairobi, Kenya. https://ccafs.cgiar.org/publications/climate-risk-profile-kisumu-county-kenya-county-climate-risk-profile-series#.XuNH6-dRXIU.

Mutenje, M.J., Farnworth, C.R., Stirling, C., Thierfelder, C., Mupangwa, W., Nyagumbo, I., 2019. A cost-benefit analysis of climate-smart agriculture options in Southern Africa: balancing gender and technology. Ecol. Econ. 163, 126–137.

Mwongera, C., Shikuku, K.M., Twyman, J., Läderach, P., Ampaire, E., Van Asten, P., Twomlow, S., Winowiecki, L.A., 2017. Climate smart agriculture rapid appraisal (CSA-RA): a tool for prioritizing context-specific climate smart agriculture technologies. Agric. Syst. 151, 192–203.

Obisesan, A., 2014. Gender Differences in Technology Adoption and Welfare Impact Among Nigerian Farming Households.

Owuor, J.B., Raburu, P.O., Kwena, F., 2012. Community Based Approach to the Management of Nyando Wetland, Lake Victoria Basin, Kenya. Mcpowl Media Ltd.

Palombi, L., Sessa, R., 2013. Climate-smart Agriculture: Sourcebook. Food and Agriculture Organization of the United Nations (FAO). https://www.cabdirect.org/cabdirect/abstract/20153237305.

Rajendran, N., Tey, Y.S., Brindal, M., Ahmad Sidique, S.F., Shamsudin, M.N., Radam, A., 1Abdul Hadi, A.H.I., 2016. Factors influencing the adoption of bundled sustainable agricultural practices: a systematic literature review. Int. Food Res. J. 23 (5).

Ramaswami, R., Ravi, S., Chopra, S., 2008. Risk Management in Agriculture. Discussion Papers, 03–08, 03–08.

Santeramo, F.G., Goodwin, B.K., Adinolfi, F., Capitanio, F., 2016. Farmer participation, entry and exit decisions in the Italian crop insurance programme. J. Agric. Econ. 67 (3), 639–657.

Schaffnit-Chatterjee, C., Schneider, S., Peter, M., Mayer, T., 2010. Risk Management in Agriculture. Deutsche Bank Reseach, Sept.

Shikuku, K.M., Winowiecki, L., Twyman, J., Eitzinger, A., Perez, J.G., Mwongera, C., Läderach, P., 2017. Smallholder farmers' attitudes and determinants of adaptation to climate risks in East Africa. Clim. Risk Manag. 16, 234–245.

Shimamoto, D., Yamada, H., Wakano, A., 2018. The effects of risk preferences on the adoption of post-harvest technology: evidence from rural Cambodia. J. Dev. Stud. 54 (10), 1819–1837.
Teklewold, H., Kassie, M., Shiferaw, B., 2013. Adoption of multiple sustainable agricultural practices in rural Ethiopia. J. Agric. Econ. 64 (3), 597–623.
Teshager Abeje, M., Tsunekawa, A., Adgo, E., Haregeweyn, N., Nigussie, Z., Ayalew, Z., Elias, A., Molla, D., Berihun, D., 2019. Exploring drivers of livelihood diversification and its effect on adoption of sustainable land management practices in the Upper Blue Nile Basin, Ethiopia. Sustainability 11 (10), 2991.
Thorlakson, T., 2011. Reducing Subsistence Farmers' Vulnerability to Climate Change: the Potential Contributions of Agroforestry in Western Kenya, p. 108.
Ullah, R., Jourdain, D., Shivakoti, G.P., Dhakal, S., 2015. Managing catastrophic risks in agriculture: simultaneous adoption of diversification and precautionary savings. Int. J. Disaster Risk Reduc. 12, 268–277.
Varian, H.R., 2010. Intermediate Microeconomics: A Modern Approach, eighth ed. W.W. Norton & Co.
Vieider, F.M., Beyene, A., Bluffstone, R., Dissanayake, S., Gebreegziabher, Z., Martinsson, P., Mekonnen, A., 2014. Measuring Risk Preferences in Rural Ethiopia: Risk Tolerance and Exogenous Income Proxies. The World Bank, pp. 1–37. No. WPS7137. http://documents.worldbank.org/curated/en/114411468036888842/Measuring-risk-preferences-in-rural-Ethiopia-risk-tolerance-and-exogenous-income-proxies.
Wik*, M., Aragie Kebede, T., Bergland, O., Holden, S.T., 2004. On the measurement of risk aversion from experimental data. Appl. Econ. 36 (21), 2443–2451.
Winsen, F., de Mey, Y., Lauwers, L., Van Passel, S., Vancauteren, M., Wauters, E., 2016. Determinants of risk behaviour: effects of perceived risks and risk attitude on farmer's adoption of risk management strategies. J. Risk Res. 19 (1), 56–78.
Wolka, K., Mulder, J., Biazin, B., 2018. Effects of soil and water conservation techniques on crop yield, runoff and soil loss in Sub-Saharan Africa: a review. Agric. Water Manag. 207, 67–79.
Wooldridge, J.M., 2016. Introductory Econometrics: A Modern Approach. Nelson Education.
Yirga, C., Atnafe, Y., AwHassan, A., 2015. A multivariate analysis of factors affecting adoption of improved varieties of multiple crops: a case study from Ethiopian highlands. Ethiop. J. Agricult. Sci. 25 (2), 29–45.
Zilberman, D., Lipper, L., McCarthy, N., Gordon, B., 2018. Innovation in response to climate change. In: Climate Smart Agriculture Building Resilience to Climate Change. Springer Nature, pp. 49–74.