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Determinants of Adoption Intensity of Climate Change Adaptation Strategies Among Sorghum Farming Households in Arid and Semi-Arid Lands of Embu and Tharaka-Nithi Counties, Kenya

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Climate variability and change is a major concern globally. Global warming has altered weather patterns turning extreme events of weather changes particularly drought and floods to be new normal experiences. This has contributed to declining productivity of sorghum among other cereal crops, intensified food insecurity, and threatened livelihoods of millions of people especially in developing countries. The effect of rapidly varying and changing climatic conditions in various agroecosystems is exacerbated by poor extension services and poor climate change adaptation (CCA) strategies. To gain full control of the impacts created by climate change, farmers must be well equipped with CCA strategies. The adoption of CCA strategies remains a challenge among farming households. The study used cross sectional survey research design, multi-stage and random sampling techniques to obtain a sample of 426 sorghum farming households in the Arid and Semi-Arid Lands (ASALs) of Embu and Tharaka-Nithi Counties. Ordered probit model was used to assess socioeconomic and institutional factors that influence adoption intensity of CCA strategies. The results revealed access to extension services, access to credit, hired labour, access to weather information and agro-advisories had positive statistically significant influence on adoption intensity of CCA strategies while marital status and age had negative correlation. The results revealed that sorghum farming households had medium adoption intensity of CCA strategies. Based on the findings, the policy and decision makers should devise strategies of improving delivery of extension services through capacity building, use of modern technologies and community engagement. National and County governments to enact policies that promote financial institutions to offer affordable credit to farmers. Weather institutions to offer timely and reliable information that would inform farmers and government's decisions both short as well as long term to adapt and mitigate to climate change. This will help create an efficient use of the CCA strategies in production of sorghum in the ASALs which will reduce the households' vulnerability and create resilience to the ever changing and unpredictable trend of climate change.

Keywords: Climate change and variability, climate change adaptation strategies, adoption, resilience, ordered probit model, arid and semi-arid lands, sorghum.

INTRODUCTION

Global climate changes, driven by anthropogenic activities particularly increasing use of fossil fuels and land use changes, have caused lasting shifts in weather patterns and rising temperatures, significantly impacting the planet as we strive for economic and social development (Mikhaylov, 2020). Furthermore, climate change has caused severe and sometimes irreversible impacts, including extreme precipitation events, wildfires, extreme temperatures, droughts, tropical cyclones, stronger hurricanes, and other devastating occurrences particularly in the ASALs (Clarke *et al.,* 2022). The devastating effects of climate change if not urgently addressed could overwhelm the adaptive capacity of

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the society and exacerbate vulnerabilities resulting to economic damage, and loss of both land and water resulting in food insecurity that triggers synchronous failures (Kemp *et al.,* 2022). Notably, the number of people experiencing drought could reach nearly 700 million by the year 2100 which is 3 times more as compared to the current situation (Valavanidis, 2023). By 2050, Intergovernmental Panel on Climate Change **(**IPCC) predicted that change in climate will lead to decline in the productivity of wheat, rice, and maize among cereal crops by 22%, 14% and 5% respectively. This will worsen food insecurity and increase poverty of the households that depend on agriculture (Change, 2018). Currently, there are 30 million people who live in extremely hot places primarily in the Sahara Desert and Gulf Coast. However, due to climate change, it is projected that this number will increase to 2 billion people by 2070 (Xu *et al*., 2020). Effects of change in climate have intensified in Sub-Saharan Africa (SSA) mainly due to overdependence on rainfed agriculture thus posing a threat to food production (Mairura *et al.,* 2021; Atube *et al.,* 2021). In Kenya, agriculture contributes 51% of the Gross Domestic Product (GDP), employing 60% of the people and 65% of the exports (World Bank, 2018). Despite of this, 98% of farmers in Kenya carry out rainfed agriculture therefore change in climate has a direct threat to food production sustainability among farmers including those growing sorghum in marginal areas (Gebre *et al.*, 2023).

It is postulated that households can overcome significant challenges associated with climate change and variability only by building their resilience through sustainable agricultural practices, boosting income, and reducing greenhouse gas emissions (Habib *et al.,* 2022). To achieve this, vulnerable households must be adequately equipped with CCA strategies, relevant knowledge, skills, development of strategic linkages with supportive organizations, climate and market information (Bakare *et al*., 2023). These CCA strategies help mitigate the destructive effects of climate change particularly in the agricultural sector (Raj and Garlapati, 2020). The CCA strategies are viewed in terms of superior crop varieties and cropping systems management, adjusting planting time, harvesting technologies; irrigation technologies and biotic environmental strategies (Eka *et al.*, 2022; Vincent and Balasubramanian, 2021). Most adopted strategies to climate change that are key in many SSA countries include planting drought-resistant crops like sorghum, diversifying crops and livestock, modifying crop varieties and planting schedules (Mutandwa *et al.*, 2019).

Worth noting is that 80% of the Kenya land mass (582,646Km^2) is arid and semi-arid land (ASALs) and often experience adverse effect of climate change from moderate to severe (Macharia *et al*., 2020). This underscores the need of households adapting CCA strategies to mitigate against climate change and improve resilience. Results from a study done in six counties in Kenya by Gebre *et al.* (2023) showed that highly adopted strategies against climatic changes were; planting different varieties of crops resistant to drought, crop and livestock diversification, growing fast maturing crops and household sources of income diversification. In the upper eastern region of Kenya, the CCA strategies that are very common include intercropping, fast maturing crop varieties and terraces for soil and water conservation. The least adopted strategies include staggering planting dates, water harvesting strategies and trenches (Ngetich *et al.,* 2022). Moreover, households that have adopted diverse adaptive strategies are likely to have higher resilience to climate change than those that have not. In ASALs of Kenya, there is limited information on the socioeconomic and institutional factors that influence adoption of CCA strategies. Duffy *et al.* (2021) noted that households with better access to agricultural institutions and high income possess high likelihood of implementing adaptation measures due to institutional support. Timely acquisition of climate change adaptation information by the households helps mitigate risks caused by climate change through alerts on weather, pests and diseases (Njenga *et al.,* 2021; Onyango, 2021). A study by Partey *et al.* (2020) noted that farmers who use climate change adaptation information services (32.9%) had acquired high level of education hence high literacy levels and understand more about climate information to implement the advice than the non-users (27.4%). Muriithi *et al.* (2021) reported that education and gender had significant influences on adoption of adaptation strategies In Machakos, Yatta sub county one of the ASAL areas in Kenya, Kalele *et al.* (2021) revealed that the most adopted strategies to climatic changes are water conservation and water harvesting at 62.71% and 53.95% respectively. The other strategies were crop diversification (42.7%), drought resistant crops (37.6%) change in planting dates (48.3%) and early planting (35. 9%).Moreover, Okeyo and Wamugi (2018) noted that growing of crops that are generally indigenous such as millet, vegetables and sorghum is an adaptation strategy implemented by about 69% of the farmers in Embu County. Extension services access had a significant and statistical correlation to climate information at 10% indicating that it influences the adoption intensity of CCA strategies (Alidu *et al.* 2022). Extension services helped the farmers to understand the latest strategies hence minimise risks of drought thereby increasing resilience (Vincent and Balasubramani, 2021). Income of the household creates a high likelihood of adopting adaptation techniques. Income among smallholder farmers is positively correlated to CCA strategies and climate information services at 5 percent (Alidu *et al.,* 2022). The level of education, wealth, or farmer's resources, risk attitudes and market access significantly influence extension methods available to the farmers (Mwololo *et al.,* 2019). Age has a positive influence on experience, which was a determinant to access to information (Antwi-Agyei *et al.,* 2021). Access to advisory services and early warning systems were positively influenced by access to credit which increase the ability of the household in acquisition of necessary platforms which are mainly mobile phones, radios and TVs used as channels for accessing information (Ngigi and Muange, 2022). Moreover, large households had more access to information and were endowed with relatively big active members of between 14-64 years of age who provide labor which was crucial in adoption of adaptation strategies (Fikadu *et al.*, 2023; Sarker *et al.*, 2021). In Tharaka-Nithi County in Kenya, Kaua (2020) reported that an increase in income, experience, age and land size had a significant and positive correlation on adoption of indigenous strategies while the level of education had a negative influence. The determination of the adoption level of the strategies is crucial in addressing the devastating conditions of climate change as well as variability that result to low agricultural productivity and ultimately food insecurity. Furthermore, enhancement of adoption intensity of CCA strategies result to increased food productivity, income, and eradicated poverty levels increasing the resilience of farming households. This will create a positive effect in attaining the SDGs mainly SDG1(No poverty), SDG 2 (Zero hunger), SDG 3 (Good health and well- being) and SDG 15 (Life on land). As already discussed in the literature, climate change result to devastating consequences and households have adopted strategies to counteract its effects. There is scanty information about the adoption intensity of CCA strategies in the study area. The socio-economic and institutional factors influencing adoption intensity of CCA strategies among sorghum farming households in the study area has not been properly documented. This study sought to address this gap. The results are source of crucial information necessary in developing and implementing policies that will ensure enhancement of adoption intensity of the climate CCA strategies.

***Theoretical framework*:** This study was founded on the Diffusion of Innovation (DOI) and Random Utility (RU) theories. The DOI theory developed by Rogers (2004) focus on how an innovation diffuses through a population until it is ultimately adopted. Adoption in a social system is not an event rather a process that takes place at different rate to specific individuals. There are five categories of adopters depending on adoption rate. The innovators come first, then early adopters, early and late majority and finally laggards (Rogers, 2004). The adopter perceives an innovation as having a relative advantage over the current or previous technology/strategy. The DOI theory help to explain the extent of uptake of CCA strategies and assess the factors that influence their adoption. Key aspects explained through DOI include, innovation, adoption, communication channels, perceived attributes, social networks and innovation-decision process. The random utility (RU) theory postulates that utility is relative and farmers adopt a preferred strategy based on the utility derived from it. According to RU theory, a strategy that gives maximum utility has higher adoption intensity as compared to a strategy that gives low utility. A farmer's decision to increase the adoption intensity of a strategy is dependent on the utility that comes along with it. This theory was used by Faisal *et al*. (2021) to model the adaptation decisions by livestock herders. A farmer will adopt a strategy if the net benefits from adoption are positive. The farmer will therefore increase the intensity of adoption of the strategies that will reduce vulnerability to the impacts of climate change and hence increase the household resilience.

MATERIALS AND METHODS

***Description of the study area*:** The study was conducted in 5 Sub-Counties namely Mbeere North and Mbeere south in Embu County and Tharaka South, Chiakariga and Igambang'ombe in Tharaka Nithi Sub-county in the upper eastern regions of Kenya's drylands. The combined area of the two counties is 3,895 square kilometers, with Embu having a population of approximately 454,162 people and Tharaka-Nithi consisting of 121,796 households (KNBS, 2019). Embu County is located between 0° 8' and 0° 50' South and 37° 3' and 37° 9' East while Tharaka- Nithi County lies between 0° 07' and 0° 26' South and 37° 19' and 37° 46' East. The area receives low unreliable and poorly distributed rainfall of between 500 to 800 mm per annum which assumes a bimodal pattern of long rains between March to June and short rains expected between October and December. The lies within lower midland and inner lowland agro-ecological zone dominated by semi-arid agro climatic conditions with low production potential due to low poorly distributed rainfall and infertile soils (Ngetich *et al.*, 2022; Kiprotich *et al.*, 2024). The area is more suitable for drought resistant crops such as sorghum, green grams, cowpeas, pigeon peas, chick peas and livestock rearing (Kiboi *et al.*, 2019).

***Research design, sample size and Sampling procedure*:** The study used cross sectional survey design. This design was ideal for the reason that it allowed the researcher to collect data (both qualitative and quantitative) at one point in time, describe, analyze and interpret all the variables under investigation (Connelly, 2016).

The target population were a total of 97,555 sorghum farming households the ASAL areas in Embu (Mbeere region) having 67,867 while Tharaka-Nithi Counties had 29,688 households. The minimum number of households sampled were obtained using the formula developed by Cochran (1977) as follows

$$n = \frac{z^2pq}{d^2} = \frac{1.96^2}{0.05}\frac{\times 0.5(0.5)}{0.05} = 384 \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots 1$$

Where; n represents the sample size, z is the t value from normal table, p gives the probability of success (0.5), while q is (1-p) probability of failure, while d is 5% level of significance (0.05). The size was increased to 426 from 384 to reduce the margin of error. A smaller margin of error is useful in research as it increases the precision and reliability of results. This was done proportionally as per the population in the sampled areas. Multi-stage sampling and random sampling techniques were used. Multi-stage sampling was appropriate because sampling was done from the sub-counties which are large administrative units to the wards, to the locations and down to the sub-locations which are smaller units. In each stage, random sampling was done to select the units and finally to identify the households sampled at the sub-location level. In the first stage, 2 sub-counties (Mbeere South and Mbeere North) out of 3 in the ASALs in Embu County were selected. In Tharaka-Nithi 3 sub-Counties (Tharaka south, Chiakariga and Igambang'ombe) were selected out of 4 in the ASALs. In the second stage, two wards were selected at random per Sub-County (except in Chiakariga and Igambang'ombe where each acted as the sub-county and still the ward) to give a total of 8 wards. In the third stage, two locations were selected in each ward at random to give a total of 16 locations. In the fourth stage, two sub-locations were selected randomly to make 32 sub-locations. The identification of the sampled households was done randomly at the sub-location level. The proportionate to size formula was used to determine the number of households sampled per each sub-location. In this formula, number of farmers in the selected sub-location in each ward was divided by total number of farmers in the thirty-two sub-locations and multiplied by sample size to get the sampled households (Table 1).

$$M = \frac{n}{m} x426 \quad \text{...} 2$$

Where, M = the total number of sorghum farming households interviewed in each sub- location, n = total number of sorghum farming households in each location and m = total number of sorghum farming households from the thirty two sub- locations.

Household distribution**:** Table 1 shows the distribution of the sampled households in each ward. Mbeere -South had the majority (88) while Ngondi had the least (20) households. This was according to the population of the sorghum households in each ward.

Table 1. Sampled households in the 8 wards.

County	Sub-County	Ward	No. of sampled households
EMBU	Mbeere south	Mbeti south	88
	Mbeere North	Mavuria	61
		Nthawa	60
THARAKA-NITHI	Tharaka south	Evurore	68
	Chiakariga Igambang'ombe	Marimanti	27
		Ngondi	20
		Chiakariga	26
		Igambang' ombe	76

Data collection**:** The semi-structured questionnaire was used to obtain the primary data from the respondents. Questionnaires help to gain more insight into the sample population (Bernard, 2017). The respondent was the household head and in his/her absence a senior family member was requested to respond. The questionnaire was developed by determining the objective of the survey, the target population (sorghum farming households), mode of survey (face to face interviews), the survey questions organized in a logical manner, pretesting. Some modifications of questions were made after pretesting to ensure content validity. Detailed information on socioeconomic factors, institutional factors, CCA strategies, and productivity were captured. Kobo Toolbox smartphone application was used by enumerators in data collection.

Pretesting of the research instruments: A pilot test was conducted Mumoni and Kyuso sub-counties in Kitui County due to their similar environmental conditions as the area of study. Thirty (30) questionnaires were administered which were within 1% to 10% of the sample size for a successful pilot study (Mugenda and Mugenda, 2003). The questionnaires were administered randomly to selected farmers (Moradhaseli *et al.,* 2021). The pretested questionnaires were used to show the reliability of the instruments. Split halve method was used to test for the reliability of each instrument. The correlation coefficient (r) of each instrument was obtained by use of the Pearson's product linear correlation formula.

$$r = N\sum Y\,[\sum(X)\,(\sum(Y)]/ \sqrt{[N\sum X^2 - (\sum(X^2)]\,[N\sum Y^2 - (\sum(Y^2)}} \qquad (3)$$

Where r = represents the correlation coefficient between halves\ X = odd scores; Y = even scores; $\sum(X)$ = the sum of X scores; $\sum(Y)$ = the sum of Y scores; $\sum(X^2)$ = the sum of squared of X scores; $\sum Y^2$ = the sum of squared Y scores; $\sum XY$ = the sum of the product of X and Y scores; N = the number of paired scores. The obtained r value was 0.8 which was the closer to 1, indicating that the instrument was reliable.

Data analysis

Adoption intensity**:** The strategies used by sorghum farming were identified from the records of the extension offices who had worked in the study area. The strategies were categorized as CCA strategies because they enable households adapt and mitigate against the effects of climate change without compromising productivity. Climate change adaptation strategies focus on adjusting systems, practices and behaviors to reduce the negative impacts of climate change. They are mainly climate resilient strategies that promote climate smart agriculture. Some of the strategies considered in this study were drought resistant crops, staggering planting dates, soil and water conservation (terracing, water harvesting, agroforestry) as well as integrated livestock and crop systems among others (Table 6). The intensity of adoption of CCA strategies for each household was measured using an adoption intensity index. The index was developed from 5 indicators shown in Table 2. The five indicators were the number of strategies adopted, the percentage proportion of land under

Table 2. Adoption intensity scores under the 5 categories.

Adoption intensity score	No. of strategies	% land under strategy	Years before adoption	Years after adoption	Changes after adoption
1	1 to 2	less than 20	More than 4	less than 1	Trailing
2	3 to 4	21 -40	3.1-4	1.1-2	Dis-adoption
3	5 to 6	41-60	2.1-3	2.1-3	Decrease
4	7 to 8	61-80	1.1-2	3.1-4	Constant
5	above 9	above 80	Less than 1	above 4	Increase

Table 3. Quantitative and qualitative variables on adoption intensity of CCA strategies and the expected effects.

Variable	Nature of variables	Variable definition and measurement	Expected effect
Gender	Categorical- Binary	0=female 1=male	+/-
Marital status	Categorical- Multinomial	1=married 2= widow 3=single 4=divorced 4= widower	+/-
Age	Continuous	Age of the household head in year	+/-
Education level	Categorical- Multinomial	1=primary 2= secondary 3= college 4= university 5= non-formal	+
Land size in acres	Continuous	Land size under sorghum production	+/-
Farm size in acres	Continuous	Total farm size owned in acres	+/-
Experience	Continuous	Number of years in sorghum farming	+
Occupation	Categorical- Multinomial	1=formal employment 2=informal employment 3=farming	+/-
Income	Categorical- Multinomial	1=one source 2=Two sources 3=More than two sources	+
Extension services	Categorical- Binary	1 access, 0 otherwise	+
Market information	Categorical- Binary	1 access, 0 otherwise	+
Weather information	Categorical- Binary	1 access, 0 otherwise	+
Access to credit	Categorical- Binary	1 access, 0 otherwise	+
Adoption intensity	Categorical- ordinal	1-verylow 2=low 3=medium 4=high 5=very high	+/-

the highest adopted strategy, the trial period before use of the strategy (number of years before adoption), the number of years after adoption of the strategy and the changes undergone after adoption (adoption pathways). A household with higher percentage of the land under the strategy is generally a better adopter and therefore has higher adoption scores. This is consistent with (Otara, 2022; Mwaura *et al*., 2021) who used land under a technology as a percentage of the total land area to determine extent of uptake and adoption intensity of the technologies. The household that has adopted many strategies is better in terms of adoption intensity than those that have adopted few. The more the number of strategies, the higher the adoption score (Kiconco *et al*., 2022).

According to de Oca Munguia *et al*. (2021) the household that take more number of years before adoption after being aware of the strategy are the sluggards hence awarded the least score. Notably, households that have adopted a strategy for many years were awarded a higher score due to the experience and certainty in the use of the strategy. On changes undergone after adoption, some households remain undecided on whether to adopt a strategy or not and remain in this state (trailing) which make them indecisive decision makers and attain the minimum adoption score. The household that adopted then dis-adopt are better compared to indecisive decision makers hence awarded a higher score. The household that adopts then decreases adoption is better than those who are trailing and those who adopt and dis-adopt. The households that remain constant after adoption are better than the first three under this category. The households that increases the scale of adoption are awarded the highest score. The adoption index determines the adoption level of each household (de Oca Munguia *et al*., 2021; Kiconco *et al*., 2022). Each indicator was awarded a score ranging from 1 to 5.

In determining the adoption intensity, the scores from each of the five categories were added together to give the total score. The total score range from 1 to 25 in the overall adoption intensity score. To determine the adoption index, the overall adoption scores were categorized into five levels of adoption intensities. Scores between 1-5 were categorized as 1, 6-10 as 2, 11-15 as 3,16-20 as, 20 to 25 as 5. The adoption intensity indices 1,2,3, 4 and 5 represent very low, low, medium, high and very high adoption intensities for the CCA strategies (Table 7). The dependent variable is bound by the adoption level of (1-5) interval.

Model specification: The dependent variable was the adoption intensity that was a categorical variable having five adoption intensity categories from 1 to 5 (Table 8). The independent variables were the socio-economic and institutional factors (Table 4 and 5). After attaining the adoption intensity of each household, Ordered Probit Regression model was employed to determine the socio-economic factors that influence the adoption intensity of CCA strategies. An ordered probit regression statistical technique examines the relationship that exists between one or more of the independent factors and an ordinal dependent variable. The Ordered Probit Regression model uses the values of the independent variables to calculate the probability of each level of the dependent variable. The Ordered Probit model specification is as below

$y_i^*=X_i'\beta + U_i$ ……………………………………4

Where y* represents an underlying and unobserved measure of the households' adoption intensity whereas B is a vector of the predictor variable, U_i stands for the random error term distributed generally with unit variance. For a certain jth household where normalization is that the regressors x (CCA strategies) do not include an intercept, for a low y*, adoption intensity is low, for y* > 1 the adoption intensity increases, for y* > 2, adoption intensity increases more and this trend continues further. For certain categories m, the following is a standard ordered probability model, where the probability of observing outcome i corresponds to the following:

$pr\ (outcome_j = i) = pr(K_{i-1} < X'_I\beta + u_i \ \leq \alpha_I$….. 5

where u_i is assumed to be normally distributed with a standard normal cumulative distribution function. Notably, the coefficients $\beta_1 \ldots \beta_k$ are jointly estimated with the cut points α_1, α_2 …α_{k-1} where k represents the number of possible outcomes. The model was used by Oyetunde (2021); Alhassan (2020).

RESULTS

***Socioeconomic characteristics of sorghum farming households*:** The study gathered both quantitative and qualitative data from sorghum farming households, which constituted the 426 households sampled. The specific socio-economic and institutional factors considered included the quantitative variables such as age, experience, household size, land size and farm size (Table 4). The qualitative data included gender, marital status, education level of household head and occupation besides training, extension services and credit access as well as market information among others (Table 5).

***Quantitative variables*:** Table 4 shows the sample mean and 95% confidence interval for the mean of the population. The statistics give a comprehensive overview of the continuous variables associated with the level of resilience of the sorghum farming households. The mean for age was 50.065 years with a range of 20 to 90 years suggesting that both the youth and elderly household heads are involved in sorghum production. The average sorghum farming experience is 15.1 years with a range of 1 to 60 years implying that some farmers are venturing into the sorghum growing sector while others have been there for as long as 60 years. The mean household size was 6 persons implying that the households in the study area are relatively medium sized. The mean land size under sorghum and farm size are 0.897 acres and 2.862 acres respectively an indication that majority of the sorghum growing households in the study area own relatively small parcels of land of which about a third (31.3%) is used for sorghum growing. The small parcels of land may be due to subdivision of the land as inheritance to children and siblings, a factor that may reduce available land for cropping and serious investment. The 95% confidence interval for the population mean was computed using the mean and the margin of error.

***Qualitative variables*:** Table 5 shows the sample proportions and 95% confidence interval for the categorical variables. Gender distribution indicated that majority (79.34 %) were males suggesting that they more available to respond on the sorghum production. Marital status showed that the married were predominant at 76.76% while widows and singles comprised of 12.91% and 6.81% respectively, an indication that the farmers here highly regard marriage as a unit of society. On education, the household's heads who attained primary level were the largest group at 64.32 %, while those who had acquired secondary level formed a proportion of 20.66% showing a trend of decline in numbers involved in sorghum production beyond primary education level. Majority of the household heads (82.86 %) engaged in farming as an occupation and a smaller group (12.21%) were in informal employment while those in formal employment formed a partly (4.93%) of the sorghum farmers. This suggests that s farming as an occupation has an association with growing of sorghum. The findings showed that the majority of the households (73.47%) do not receive extension services suggesting that they may not be up to date with the strategies that create a positive impact in farming. A majority (63.62%) of the sorghum farmers have only one source of income while slightly above a third (35.45%) have two sources while a partly (0.94%) have more than two sources. This suggests of limited access to financial resources which are very crucial in acquisition of sorghum seeds and other inputs necessary for sorghum farming. A very high

Table 4. Sample means and 95% confidence intervals for quantitative variables.

Variable	Mean	Std. Dev.	Margin of error	95% confidence interval	
Age (years)	50.065	14.196	1.327	48.738	51.392
Household size (No.)	5.727	2.218	0.209	5.518	5.936
Experience (years)	15.185	13.923	1.320	13.865	16.505
Land size (acres)	0.897	0.988	0.094	0.803	0.991
Farm size (acres)	2.862	2.126	0.202	2.660	3.064

Source: Field data, 2024

percentage (97.89%) of the farmers do not access to credit suggesting limited access to the quality inputs like certified seeds, fertilizers and agrochemicals crucial in production. Weather information is received by a large majority (92.49%) which is an indication of existence of effective channels such as radio's and phones messages that relay information. Market information is received by less than half (46.71%) of the farmers suggesting of majority of the them selling their produce without prior knowledge of the best prices that exist in different markets.

***Adaptation strategies adopted by sorghum farming households*:** Table 6 gives the strategies and the 95% confidence interval for the population mean. There are 13 strategies that farmers use to counteract the effects of the change in climate. Notably, some of the farmers had more than one strategy used in combination to create an effective outcome. Mixed farming is the most adopted strategy (29.42%) in the study area that involves farmers combining the production of crops and livestock, implying the farmers diversify farming enterprises as a guard against effects that may lead to loss of the produce. Growing of drought resistant crops is the second most adopted strategy at 17.86 % showing farmers are aware that the climate of the area is characterized with low rainfall and prolonged droughts. Drought resistant crops such as sorghum, green grams, millet, pigeon peas and cowpeas are grown by 17.86% of the households in the study area. The third and fourth most adopted strategies are growing of fast maturing crops and early planting at 8.34% and 7.08 % respectively. This ensures optimal utilization of precipitation and completion of the growing cycle within the small window of available moisture. There is only one farmer (0.097%) who has adopted water harvesting used for irrigating sorghum. This was an outgoing farmer who had invested against water scarcity in the area. Irrigation and fertilizer application are second and third least adopted strategies at 0.97% and 1.06% respectively. This may mean farmers are resource poor and

Table 5. Sample proportions and 95% confidence intervals for the categorical variables.

Variable	Frequency	Percentage	Standard error	95% Confidence interval	
Gender					
Female	88	20.66	0.020	0.171	0.248
Male	338	79.34	0.020	0.752	0.849
Marital status					
married	327	76.76	0.020	0.725	0.805
Widow	55	12.91	0.016	0.100	0.165
Single	29	6.81	0.012	0.048	0.095
Divorced	13	3.05	0.008	0.018	0.052
Widower	2	0.47	0.003	0.001	0.019
Education level					
Primary	274	64.34	0.203	0.596	0.687
Secondary	88	20.66	0.020	0.171	0.248
College	31	7.28	0.013	0.062	0.102
University	7	1.64	0.006	0.008	0.102
Non formal	26	6.1	0.012	0.042	0.088
Occupation					
Formal	21	4.93	0.010	0.032	0.075
Informal	52	12.21	0.016	0.094	0.157
Farming	353	82.86	0.018	0.790	0.862
Income					
One source	271	63.62	0.023	0.589	0.681
Two sources	151	35.45	0.023	0.310	0.401
More than two	4	0.94	0.005	0.004	0.025
Extension services					
No	313	73.47	0.021	0.691	0.775
Yes	113	26.53	0.021	0.225	0.310
Market information					
No	227	53.29	0.024	0.485	0.580
Yes	199	46.71	0.024	0.420	0.515
Access to credit					
No	417	97.89	0.007	0.960	0.989
Yes	9	2.11	0.024	0.011	0.040
Weather information					
No	32	7.51	0.013	0.054	0.104
Yes	394	92.49	0.013	0.896	0.946

Source: Authors analysis from field data 2024

Table 6. Adaptation strategies adopted by the sorghum farming households.

Strategy	Frequency	Percentage	Standard error	95% Confidence interval	
Early planting	73	7.08738	0.008000	0.056694	0.088268
Fast maturing crops	86	8.34951	0.008624	0.068058	0.102051
Drought resistant c	184	17.86408	0.011941	0.156398	0.203285
Diversification	12	1.16505	0.003345	0.006622	0.020420
Fert.application	11	1.06796	0.003204	0.005918	0.019198
Soil &water Con.	29	0.02816	0.005157	0.019622	0.040247
Water harvesting	1	0.09709	0.000971	0.000136	0.006881
Intercropping	15	1.45631	0.003735	0.008791	0.024034
Agroforestry	12	1.16505	0.003345	0.006622	0.020420
Irrigation	10	0.97087	0.003057	0.005226	0.017967
Mixed farming	303	29.41748	0.014205	0.267090	0.322797
Staggering p. dates	150	14.56311	0.010996	0.125351	0.168560
Proper grain storage	144	13.98058	0.010811	0.119908	0.162396

Table 7. The scores for the five indicators of adoption.

	Score	Frequency	Percentage	Standard deviation	95%cofidence interval	
Strategies (No.)						
1 to 2	1	11	2.580	0.00769	0.01432	0.0461
3 to 4	2	196	46.010	0.02418	0.41308	0.5078
5 to 6	3	174	40.850	0.02384	0.36254	0.4560
7 to 8	4	44	10.329	0.01476	0.07766	0.1361
9 to 10	5	1	0.002	0.00235	0.00033	0.0166
Land area (%)						
< 20	1	240	56.338	0.02406	0.51566	0.6100
21 to 40	2	102	23.944	0.02070	0.20114	0.2825
41 to 60	3	61	14.319	0.01670	0.11292	0.1799
61 to 80	4	11	2.582	0.00770	0.01432	0.0461
>80	5	12	2.817	0.00802	0.01602	0.0491
Years before adoption						
4.1<	1	66	15.490	0.01755	0.12347	0.1926
3.1 to 4	2	147	34.510	0.02306	0.30125	0.3917
2.1 to 3	3	124	29.110	0.02203	0.24973	0.3362
1.1 to 2	4	60	14.080	0.01687	0.11082	0.1774
<1	5	29	6.810	0.01222	0.04764	0.0964
Years after adoption						
<1	1	10	2.350	0.00734	0.01264	0.0432
1.1 to 2	2	220	51.640	0.02424	0.46878	0.5638
2.1 to 3	3	6	1.410	0.00572	0.00632	0.0311
3.1 to 4	4	2	0.470	0.00332	0.00117	0.0187
>4	5	188	44.130	0.02409	0.39464	0.4891
Changes after adoption						
Trailing	1	190	44.600	0.02411	0.39924	0.4938
Dis-adopted	2	18	42.250	0.00976	0.02673	0.0662
Decreased	3	10	2.350	0.00734	0.01264	0.0432
Constant	4	51	11.970	0.01575	0.09205	0.1543
Increased	5	157	36.850	0.02340	0.32386	0.4156

Source: Authors computation from field data,2024

that the risk of heavy investment in an area of unpredictable weather patterns is not a ready option for them.

***Adoption intensity of the strategies*:** Table 7 gives the adoption scores used to determine the adoption intensity. The adoption intensity was determined by awarding a score to each of the five categories (Refer to process of data analysis). On awarding a score based on the number of strategies, the farmers identified the number of strategies they had adopted and given a score based on the criteria shown in table 7. The scores ranged from 1 to 5 in each category. The total score scores ranged from 1 to 25 that were used to categorize the households

Table 8 represents the adoption intensity level for the households. The adoption intensity level was determined by grouping the adoption index 1-5 to give adoption intensity level 1, 6-10 to give adoption intensity 2, 11-15 to give

Table 8. Adoption intensity of the households.

Category	Adoption intensity	Frequency	Percentage	Standard error	95% Confidence interval	
1- Very low	1.0-5.0	8	1.8779	0.0065846	0.009392	0.037195
2- Low	5.1-10.0	170	39.9061	0.0237542	0.353412	0.446534
3- Medium	10.1-15.0	43	10.0939	0.0146127	0.075625	0.133502
4- High	15.1- 20.0	200	46.9484	0.0242083	0.422319	0.517120
5-Very high	20.1-25.0	5	1.1737	0.0052242	0.004876	0.027979

adoption intensity 3, 16-20 to give adoption intensity 4 while 21-15 gave adoption intensity level 5. The numbers 1,2,3,4 and 5 represents very low adoption, low, medium, high and very high adoption intensities respectively. and very high. The results indicate that 200 households (46.94%) attained level 4 which represent high adoption intensity. The second largest group comprising of 170 households (39.9061%) attained low. The two groups make more than 86% of the households in the study area. A relatively small group (1.17 %) attained very high adoption intensity. The adoption intensity score for the sample was 3.056 with a standard deviation of 0.9948667 representing medium adoption intensity for the CCA strategies. The reasons would be due to the fact that the resource poor farmers find themselves in an environment that is harsh for crop production, lowering their ability and will to invest more on the mitigation strategies.

DISCUSSION

***Determinants of adoption intensity of climate change adaptation strategies*:** The findings of the factors that influence the adoption of climate change strategies are presented in Table 9. The results of the ordered probit model revealed that marital status, age, extension services, access to credit, hired labour, weather information and early warnings (advisories) were statistically significant variables to the adoption intensity of the strategies in the study area.

Marital status of the household head was found to have a negative statistical relationship with intensity of adoption of the CCA strategies. This indicates that marriage commitments had a negative correlation to the adoption intensity. The p-value for marital status has a p-value of 0.075 indicating that marital status has a significant influence on adoption intensity of CCA strategies at 10%, however there is a weak correlation between the variables. The coefficient is -.1313641suggesting that increase in the number of married people reduces the probability of increasing the adoption intensity of CCA strategies. This negative influence of marital status on adoption intensity may arise from marital commitments. The most probable reason being that married individuals do not allocate adequate resources and time towards increasing the use of strategies as a result of other competing family responsibilities. Married farmers may have higher investment in off farm activities to sustain their livelihoods than in the farm. The other probable reason is that marriage comes along with additional family responsibilities particularly for ladies who are the main supplier of agricultural labour with such responsibilities being reproduction. The results are in agreement with Mthethwa *et al*. (2022) and Ojo *et al*. (2021) who found marital status to negatively influence the adoption of climate smart agricultural practices as well as soil and water conservation strategies respectively. However, the results contrast those of Fikire and Emeru (2022), who reported a significant positive relationship between marital

Table 9. Ordered probit regression model results .

Adoption intensity	Coef.	St.Err.	z-value	p-value	[95% Conf	Interval]	Sig
Marital status	-0.13136	0.07379	-1.78	0.075	-0.27599	0.01326	*
Age	-0.00731	0.00414	-1.77	0.077	-0.01543	0.00080	*
Income	0.03460	0.12339	0.28	0.779	-0.20724	0.27644	
Education level	-0.03195	0.05375	-0.59	0.552	-0.13729	0.07339	
Occupation	-0.17125	0.13132	-1.30	0.192	-0.42864	0.08614	
Average income	0.03453	0.08874	0.39	0.697	-0.13939	0.20845	
Extension service	0.30700	0.13659	2.25	0.025	0.03930	0.57471	**
Access to credit	1.07233	0.44881	2.39	0.017	0.19267	1.95199	**
Market inform.	-0.18437	0.11918	-1.55	0.122	-0.41796	0.04922	
Weather inform.	0.43683	0.23142	1.89	0.059	-0.89039	0.01674	*
Hired labour	0.39252	0.12813	3.06	0.002	0.14138	0.64366	***
Advisories	0.79577	0.13795	5.77	0.000	0.52538	1.06616	***
cut2	0.08100	0.49600	.b	.b	-0.89000	1.05200	
cut3	1.99000	0.51500	.b	.b	0.98100	2.99900	
Pseudo r-squared	0.0987				Number of obs.	426	
Chi-square	90.85				Prob > chi²	0.000	

**** p<.01, ** p<.05, * p<.1*

status and adoption of modern technologies in agriculture such as use of seeds that are improved, herbicides and row planting among others. The setting of the different areas as well as prevailing information gaps may be the cause of these inconsistent findings.

Age had a significant negative statistical relationship with the adoption intensity of the CCA strategies. The p-value is 0.077 indicating that age has significant negative influence to adoption intensity at 10 % level of significance suggesting of a weak correlation between the two variables. The coefficient is -.007313 implying that increase in age by one year decreases the probability of moving to a higher adoption category. The standard error is small (.0041415) indicating that there is certainty in the population estimates. In sorghum farming, increase in age decrease the likelihood of high adoption intensity which may arise from reduced physical activity of the older farmers considering that sorghum farming require labour in land preparation, planting, weeding, pest control and harvesting which they may struggle to accomplish. Increase in age may make farmers reluctant to adopting improved seed varieties and new farming techniques which decline the adoption intensity. These results are consistent with Marie *et al*. (2020) who noted that age has negative influence on mixed farming. The results are in contrast with the study by Ngaiwi *et al*. (2023) which revealed that age had significant and positive influence on adoption of diverse practices such as cover cropping, agroforestry and zero tillage.

Notably, for weather information, the p-value was 0.059 indicating that it was statistically significant at 10% indicating a positive correlation between the two variables, however, it was not highly significant**.** The coefficient was 0.4368264 suggesting that increase in access to weather information increases the likelihood of farmers attaining a higher adoption category. Households that have more access to weather information have higher likelihood of utilizing the strategies resulting to high adoption intensity. The results are in concurrence with the study by Marie *et al*. (2020) which indicated that access to climate information is a significant variable in determining adoption of climate change adaptation strategies by farmers.

The early warnings (advisories) had a p-value of 0.000 indicating that it was highly significant at 1% which implies that there exists a strong correlation between the two variables. Since the coefficient is positive (.7957706) it suggests that there was a positive statistical relationship between the variables. This implies that was that increase in weather advisories increase the likelihood of attaining higher adoption category of CCA strategies. The standard error was 0.1379547 as compared to the coefficient (.7957706) suggesting of high precision in the population estimates. Increase in the access to weather advisories makes the households appropriately geared towards counteracting the effects of climate change hence increasing the adoption intensity of CCA strategies. The results are in concurrence with Djido *et al*. (2021) who reported that use of weather and climate information services significantly increases the adoption of water management and cropping practices by 6.8% and 5.6% respectively.

Provision of extension services had a p-value of 0.025 which indicate that it was highly significant at 5%. The coefficient of (.3070045) indicate of a positive statistical relationship between the variables implying that increase in extension services increases the adoption intensity of the strategies. Extension services provide the farmers with more information on the best way to utilize the strategies which increases their use to boost productivity. As a result of farmers frequent interactions with extension agents who are linked to research organizations, farmers benefit by receiving latest information about the new and existing strategies. Increase in extension services leads to increased creation of awareness about diverse strategies that improve farm productivity. The results concur with Kiprotich *et al*. (2024); Rodthong *et al*. (2020) and Ngaiwi *et al*. (2023) which indicated that extension services had significant influence on the household decision to adopt farming practices, technologies and strategies.

The results of the current study revealed that credit access had a p-value of 0.017 indicating that it was highly significant at 5%. The coefficient of 1.072327 indicates of a positive correlation between the two variables meaning that increase in access to credit increases the likelihood of attaining a higher adoption intensity of CCA strategies. Farmers who access credit have a high likelihood of increasing the adoption intensity of the strategies. Adoption of some strategies require capital hence access to credit provide the necessary resources for initiating the use of such strategies. If a household is able to access formal credit it becomes better placed in increasing adoption intensity of the agricultural strategies. The results are consistent with Girma (2022); Cholo *et al*. (2023) and Ullah *et al*. (2024) who found credit as being a significant factor in overcoming financial hindrances associated with adoption of technologies. Ogunleye *et al*. (2024) reported that farmers who are constrained in accessing credit are unable to adopt agricultural technologies and implement necessary measures to counteract the consequences of change in climate

The study revealed of a statistical significant positive correlation between hired labour and the adoption intensity. The p-value for hired labour was 0.002 meaning that it was highly significant at 1%. This implies a strong correlation between hired labor and adoption intensity. The coefficient is positive (.3925207), it implies that hired labour was positively correlated to the adoption intensity of CCA strategies. This means that increasing the use of hired labour increases the adoption intensity of the strategies. Use of the strategies require labour of which the family labour may not be adequate to implement the strategies hence the need for hired labour. The results are consistent with those of Fernandez (2017) who indicated that permanent hired labour positively influenced the likelihood of adopting practices used in management of irrigation projects. Similarly, Sarker *et al*. (2021) found that adoption of the newly released technologies in agriculture is influenced positively by the proportion of hired labour engaged in the farm

Conclusion**:** The objective of this study was to assess the socioeconomic and institutional factors influencing the adoption intensity of CCA strategies among sorghum farming households in the ASALs of Embu and Tharaka -Nithi Counties. The results based on the ordered probit model revealed that seven variables out of the twelve that were analyzed had a significant statistical influence on adoption intensity of CCA strategies. Access to extension services, access to credit, weather information, hired labor and weather advisories had a significant positive statistical correlation on adoption intensity of CCA strategies. Marital status and age showed significant negative correlation with adoption intensity of CCA strategies. The results showed a medium adoption intensity to the CCA strategies among the households. According to the finding, there is need to enhance delivery of extension services to increase the level of adoption intensity of CCA strategies among the sorghum farming households. The policy makers and decision makers can achieve this through capacity building of extension agents, use of modern technologies, community engagement and proper utilization of available resources to create awareness on the effective CCA strategies to enhance their adoption intensity. Agriculture being a devolved function in Kenya, the County Governments should offer affordable credit accessible to the farmers with the aim of improving their income to improve on adoption intensity of CCA strategies with the requisite inputs. The government can consider to subsidize farm inputs while lending institutions can offer credit inform of inputs to enhance adoption intensity. Weather stations to be provide forecasts that are accurate and timely to ensure implementation of the appropriate CCA strategies to counteract the devastating effects of climate change.

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REFERENCES

Alhassan, H. (2020). Farm households' flood adaptation practices, resilience, and food security in the Upper East Region, Ghana. *Heliyon, 6*(6), e04167. https://doi.org/10.1016/j.heliyon.2020.e04167

Alidu, A. F., Man, N., Ramli, N. N., Haris, N. B. M., & Alhassan, A. (2022). Smallholder farmers' access to climate information and climate-smart adaptation practices in the Northern Region of Ghana. *Heliyon, 8*(6), e09513. https://doi.org/10.1016/j.heliyon.2022.e09513

Antwi-Agyei, P., Dougill, A. J., Doku-Marfo, J., & Abaidoo, R. C. (2021). Understanding climate services for enhancing resilient agricultural systems in Anglophone West Africa: The case of Ghana. *Climate Services, 22*, 100218. https://doi.org/10.1016/j.cliser.2021.100218

Atube, F., Malinga, G. M., Nyeko, M., Okello, D. M., Alarakol, S. P., & Okello-Uma, I. (2021). Determinants of smallholder farmers' adaptation strategies to the effects of climate change: Evidence from Northern Uganda. *Agriculture & Food Security*, *10*(1), 1-14. https://doi.org/10.1186/s40066-021-00298-8

Bakare, A. Y., Ogunleye, A. S., & Kehinde, A. D. (2023). Impacts of microcredit access on climate change adaptation strategies adoption and rice yield in Kwara State, Nigeria. *World Development Sustainability, 2*, 100047. https://doi.org/10.1016/j.wds.2023.100047

Bernard, H. R. (2017). *Research methods in anthropology: Qualitative and quantitative approaches* (6th ed.). Rowman & Littlefield.

Change, P. C. (2018). *Global warming of 1.5°C*. World Meteorological Organization. https://www.ipcc.ch/sr15/

Cholo, M., Marisennayya, S., Bojago, E., Leja, D., & Divya, R. K. (2023). Determinants of adoption and intensity of improved haricot bean (*Phaseolus vulgaris* L.) varieties: A socio-agronomic study from Southern Ethiopia. *Journal of Agriculture and Food Research*, *13*, 100656. https://doi.org/10.1016/j.jafr.2023.100656

Clarke, B., Otto, F., Stuart-Smith, R., & Harrington, L. (2022). Extreme weather impacts of climate change: An attribution perspective. *Environmental Research: Climate*, *1*(1), 012001. https://doi.org/10.1088/2752-5295/ac6e7d

Cochran, W. G. (1977). *Sampling techniques* (3rd ed.). John Wiley & Sons.

Connelly, L. M. (2016). Cross-sectional survey research. *MEDSURG Nursing, 25*(5), 369-370. https://pubmed.ncbi.nlm.nih.gov/30086082/

de Oca Munguia, O. M., Pannell, D. J., Llewellyn, R., & Stahlmann-Brown, P. (2021). Adoption pathway analysis: Representing the dynamics and diversity of adoption for agricultural practices. *Agricultural Systems*, *191*, 103173. https://doi.org/10.1016/j.agsy.2021.103173

Djido, A., Zougmoré, R. B., Houessionon, P., Ouédraogo, M., Ouédraogo, I., & Diouf, N. S. (2021). To what extent do weather and climate information services drive the adoption of climate-smart agriculture practices in Ghana? *Climate Risk Management, 32*, 100309. https://doi.org/10.1016/j.crm.2021.100309

Duffy, C., Pede, V., Toth, G., Kilcline, K., O'Donoghue, C., Ryan, M., & Spillane, C. (2021). Drivers of household and agricultural adaptation to climate change in Vietnam. *Climate and Development*, *13*(3), 242-255. https://doi.org/10.1080/17565529.2020.1770898

Eka Suranny, L., Gravitiani, E., & Rahardjo, M. (2022). Impact of climate change on the agriculture sector and its adaptation strategies. *IOP Conference Series: Earth and Environmental Science, 1016*, 012038. https://doi.org/10.1088/1755-1315/1016/1/012038

Faisal, M., Abbas, A., Xia, C., Raza, M. H., Akhtar, S., Ajmal, M. A., & Cai, Y. (2021). Assessing small livestock herders' adaptation to climate variability and its impact on livestock losses and poverty. *Climate Risk Management*, *34*, 100358. https://doi.org/10.1016/j.crm.2021.100358

Fernandez, M. A. (2017). Adoption of erosion management practices in New Zealand. *Land Use Policy*, *63*, 236-245. https://doi.org/10.1016/j.landusepol.2017.01.018

Fikadu, T., Damene, S., & Teklu, A. (2024). Determinants of climate information service access and use among smallholder farmers in Bereh Woreda, Ethiopia. *Integrated Environmental Assessment and Management, 20*(3), 794-804. https://doi.org/10.1002/ieam.4824

Fikire, A. H., & Emeru, G. M. (2022). Determinants of modern agricultural technology adoption for teff production: The case of Minjar Shenkora Woreda, Ethiopia. *Advances in Agriculture*, *2022*, 2384345. https://doi.org/10.1155/2022/2384345

Gebre, G. G., Amekawa, Y., & Fikadu, A. A. (2023). Farmers' use of climate change adaptation strategies and their impacts on food security in Kenya. *Climate Risk Management*, *40*, 100495. https://doi.org/10.1016/j.crm.2023.100495

Girma, Y. (2022). Credit access and agricultural technology adoption nexus in Ethiopia: A systematic review and meta-analysis. *Journal of Agriculture and Food Research, 10*, 100362. https://doi.org/10.1016/j.jafr.2022.100362

Habib-ur-Rahman, M., Ahmad, A., Raza, A., Hasnain, M. U., Alharby, H. F., Alzahrani, Y. M., & El Sabagh, A. (2022). Impact of climate change on agricultural production: Issues, challenges, and opportunities in Asia. *Frontiers in Plant*

Science, *13*, 925548.
https://doi.org/10.3389/fpls.2022.925548

Kalele, D. N., Ogara, W. O., Oludhe, C., & Onono, J. O. (2021). Climate change impacts and relevance of smallholder farmers' responses in arid and semi-arid lands in Kenya. *Scientific African*, *12*, e00814.
https://doi.org/10.1016/j.sciaf.2021.e00814

Kemp, L., Xu, C., Depledge, J., Ebi, K. L., Gibbins, G., Kohler, T. A., & Lenton, T. M. (2022). Climate endgame: Exploring catastrophic climate change scenarios. *Proceedings of the National Academy of Sciences*, *119*(34), e2108146119.
https://doi.org/10.1073/pnas.2108146119

Xu, C., Kohler, T. A., Lenton, T. M., Svenning, J. C., & Scheffer, M. (2020). Future of the human climate niche. *Proceedings of the National Academy of Sciences*, *117*(21), 11350-11355.
https://doi.org/10.1073/pnas.1910114117