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Socioeconomic Determinants of Farmers' Vulnerability to Climate Variability and Extreme Events in Kitui County, Kenya

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Abstract

A field survey was carried out to model farmers' vulnerability to climate variability and extreme events in selected agroecological zones in Kitui County. The indicator approach was used to calculate the overall household vulnerability index, where Principal Component Analysis (PCA) was used to allocate weights to indicators of exposure, sensitivity and adaptive capacity. Multinomial logistic regression was run in Stata to model the influence of socioeconomic characteristics on farmers' vulnerability levels. The study established that different socioeconomic characteristics of households had a varying influence on the households' vulnerability levels. Proximity to the Market and the arid agroecological zone significantly reduced the probability of a household belonging to the low and moderate vulnerability categories. On the other hand, the education level and the semi-humid zone significantly increased the odds of a household belonging to the low vulnerability category. Further, access to credit facilities and the semi-humid agroecological zone significantly increased the odds of a household belonging to the moderate vulnerability category. The study thus recommends that policy interventions should target specific socioeconomic characteristics that influence households' vulnerability to climate variability and extreme events.

Keywords

Vulnerability Index, Principal Component Analysis, Multinomial Logistic Regression, Households

1. Introduction

Variations in the climate system reported in the recent decades have had significant impacts on both the natural and human systems across the globe. Changes in temperature and rainfall patterns coupled with the increase in CO_2 levels have caused significant impacts on agricultural productivity resulting from the occurrence of extreme weather events including droughts, floods and changes in distribution patterns of diseases and pests where projections indicate a reduction in yield of up to 50% as well as up to 90% reduction in revenue from crop farming by 2100 (IPCC, 2023; 2014). Empirical studies have shown that due to high dependence on sectors highly sensitive to climatic changes as the major drivers of its economy like agriculture and fisheries, Kenya is rated as one of the highly susceptible nations to variability and occurrence of extreme weather events in the African continent (Obwocha et al., 2022; Kalele et al., 2021; Kogo et al., 2021).

Being a key livelihood strategy for the majority of rural communities in Kenya, negative developments in agriculture will have adverse effects on livelihoods that are highly dependent on agricultural production (Lekarkar et al., 2024; Kogo et al., 2021; NDMA, 2017; Njoka et al., 2016). Rising temperatures and increased drought occurrences have exacerbated the fragility of farmers in the Arid and Semi-arid Lands (ASALs) whose livelihoods are dependent on agricultural production thus increasing incidences of food insecurity and malnutrition (Ondiko & Karanja, 2021; Ochieng et al., 2020). The cumulative effects of climate variability and extreme climate events in Kenya, therefore pose a significant threat to the attainment of the country's Vision 2030 as well as the implementation of the Sustainable Development Goals (UNCCS, 2017; UNECA, 2018).

Just like other farmers in ASALs, farmers in Kitui County are highly vulnerable to the effects of increased temperature, unreliable and erratic rainfall patterns and increased frequency of droughts (NDMA, 2017). Although the farmers in the county have implemented several adaptation options in efforts to reduce the associated agricultural losses they are still faced with several challenges in the implementation of adaptation strategies (Ndungu & Mwangi, 2023; Mutunga et al., 2018). In order to achieve effective adaptation to climate variability and extreme events, understanding the vulnerability of farmers to climate variability and extreme climate events would be paramount.

Since adaptation needs vary significantly between different locations, people, and sectors (IPCC, 2023; Eriksen et al., 2021; Zhou et al., 2022) effective and strategic adaptation planning should thus target the most vulnerable systems. Vulnerability assessment studies are therefore important in the planning phase of adaptation programs, in the identification of the impact of climate variation on farming systems and prioritization of adaptation strategies with regard to farmers' vulnerability levels (Eriksen et al., 2021; Fritzsche et al., 2014). According to the fifth assessment report (AR5) of the Intergovernmental Panel on Climate Change (IPCC), vulnerability to climate change is defined as the "degree to which biological, geophysical and socioeconomic systems are susceptible to and unable to cope with adverse impacts of climate change including variability and climate-related extremes" (IPCC, 2014). The IPCC further expresses vulnerability as a function of the character, magnitude, and rate of climate variation to which a system is exposed, its sensitivity, and its adaptive capacity (IPCC, 2007). According to de Sherbinin et al. (2015), similar regions and communities have different vulnerability patterns since the exposure to climatic stressors, the sensitivity of the populations to climatic stressors and capacities to adapt are spatially differentiated. Vulnerability assessments should therefore emphasize the local level context since even neighboring communities respond differently to the effects of climate variability and extreme climate events depending on their ability to adapt (Bobadoye et al., 2019; Herrera et al., 2018; Ludena & Yoon, 2015). Further, empirical studies have shown that the vulnerability of households to climate variability and extreme events is dependent on various household characteristics (Khan et al., 2022; Azumah et al., 2020; Ghosh & Ghosal, 2020). Modeling the influence of different socioeconomic characteristics of households on farmers' vulnerability is therefore important in informing policy interventions to target specific household characteristics based on their influence on households' vulnerability.

Although several climate variability and extreme climate events-related studies in Kitui County have been conducted in the recent past, their main focus has been on the effects of climate change on agricultural production and adaptation strategies adopted by farmers (Ndungu & Mwangi, 2023; Khisa, 2018; Mutunga et al., 2018), with little focus on farmers vulnerability to climate variability and extreme events. Thus, the present study sought to bridge the knowledge gap on how different socioeconomic characteristics of households influence farmers' vulnerability to climate variability and extreme events in Kitui County.

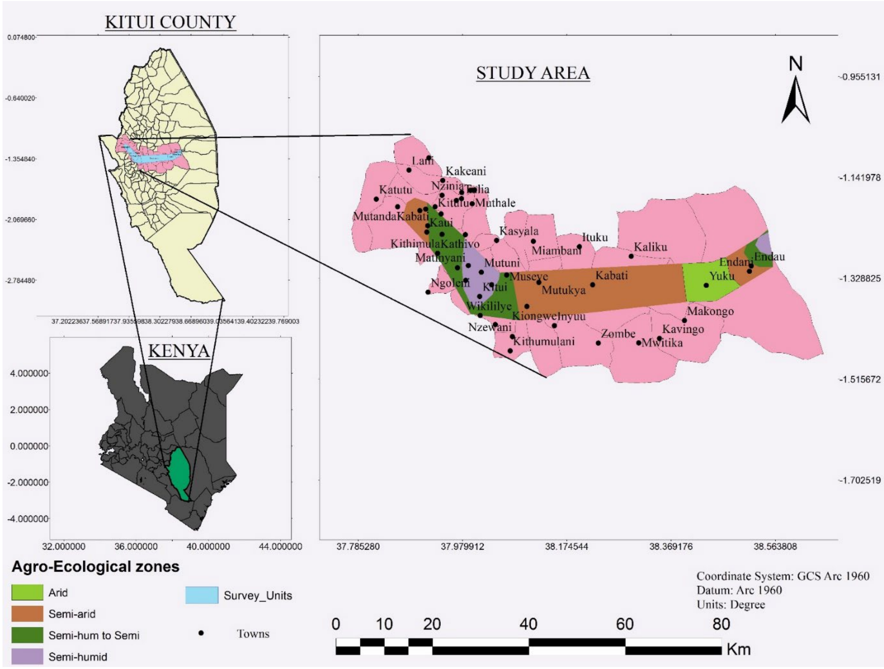
2. Materials and Methods

2.1. Profile of the Study Area; Topography and Climate

The study was carried out in four sub-locations selected along a transect line (in a buffer zone of a 5km radius on both sides of the line) in four agro-ecological zones; semi-humid, transitional semi-humid to semi-arid, semi-arid and arid zones in Kitui County. The study sites are shown in **Figure 1**.

2.2. General Topography and Climate of Kitui County

Kitui County is situated between 400 and 1,830 meters above sea level and typically slopes from west to east (KCIDP, 2018). The region has a semi-arid climate with extremely variable and unpredictable rainfall. Throughout the year, the region experiences hot, dry weather with minimum temperatures of 14˚C - 22˚C and maximum temperatures of 26˚C - 34˚C. The two warmest months of the year are February and September (KCIDP, 2018). Rainfall is distributed within two distinct seasons annually, with 500 - 1050 mm of rain, with about 40% reliability. Long rains occur between March and May, and short rains occur between October and December. Short rains are considered more reliable than long rains since they are the time during which farmers get their main food production opportunity (NDMA, 2017). The soil types range from red sandy soils, to clay black cotton soils which are generally low in fertility (KCIDP, 2018).



Source: ILRIS GIS Database

Figure 1. Map of Kitui County showing the study area in four agroecological zones.

2.3. Population and Economy in Kitui County

Kitui County's population is approximated at 1,136,187 people, according to the population and housing census report of 2019 (GoK, 2019). The primary drivers of the local economy are crop and livestock farming, which account for almost three-quarters of household income (KCIDP, 2018). Cattle (beef and dairy), goats (meat and dairy), sheep, and poultry are the primary livestock types kept in the County (KCIDP, 2018).

While green grams, sweet potatoes, vegetables (such as tomatoes, kales, spinach, pawpaw, onions), and fruits (mangoes, bananas, watermelons) are grown for sale and household consumption, other crops (such as maize, beans, sorghum, pigeon peas, millet, and cassava) are primarily grown for subsistence (KCIDP, 2018; NDMA, 2017).

2.4. Study Design and Sampling Techniques

2.4.1. Study Design

The descriptive survey design was used. Agro-pastoral farmers in the study area were the study's target population. The household served as the unit of study, and the household heads were the respondents.

2.4.2. Sampling Techniques

The study sites were selected using the stratified sampling method to represent four distinct agroecological zones in the study area. Along a transect line, one sub-location in each agroecological zone was chosen at random (in a buffer zone of a 5 km radius on both sides of the line). Respondents within the chosen sub-location were then selected using the systematic random sampling technique, with a beginning point conveniently identified from the local shops and every tenth household interviewed.

2.4.3. Sample Size Determination

The sample size for the study was determined by calculating 10% of the number of households in the selected sub-location as shown in Table 1 below. According to Mugenda, a sample size of 10% provides an adequate representation of the target population in descriptive research.

Table 1. Sample size of the study.

Agroecological zone	Selected Sub-location	Number of Households	Sample Size
Arid	Yuku	390	39
Semi-arid	Kauwi	1600	160
Semi-arid to semi-humid	Kasaini	380	38
Semi-humid	Kaveta	1040	104
Total sample size			**341**

Source: GoK (2019); KCID (2018).

2.5. Data Collection

Primary data was collected through the administration of questionnaires to 341 respondents. Interviews with key informants were also conducted.

2.6. Data Analysis

Calculation of vulnerability indices

From the IPCC (2007) expression of vulnerability as a function of exposure, sensitivity and adaptive capacity, where the potential impact is represented by exposure and sensitivity while adaptive capacity denotes the extent to which the impact would be averted, the vulnerability of a farmer to climate variability and extreme climate events (V) can be defined mathematically as shown in Equation 1;

$$V = f\left(I - AC\right) \tag{1}$$

Where, V is vulnerability, I is potential impact and AC is adaptive capacity.

From the above equation, vulnerability indices for individual households were calculated from the selected vulnerability indicators. Since the indicators were in different units and scales, normalization was done using the formula in Equation 2;

$$x' = \left(x - \mu\right)/\sigma \tag{2}$$

Where, x' is normalized value, x is observed value, μ is mean and σ is standard deviation.

Weights for the various indicators were calculated using the Principal Component Analysis (PCA) where loadings of principle components (PC) which were highly correlated to the indicators were used as the weights for the indicators as described by Abson et al.(2012). Using Equation 3, the standardized variables were multiplied by the allocated weights to get the indices for exposure, sensitivity and adaptive capacity.

$$I_j = \sum_{i=1}^{k} b_i \left[\frac{a_{ji-x_i}}{si} \right] \tag{3}$$

Where, I = respective index value for the j^{th} household, b = weighted value for the i^{th} indicator, a_i = the i^{th} indicator value for j^{th} household, x = the mean value for the j^{th} indicator and s = the standard deviation for the i^{th} indicator value.

The overall vulnerability index for individual households was then computed using Equation 4;

$$V = E + S - AC \tag{4}$$

Where, V = the vulnerability index, E = the exposure index, S = the sensitivity index and AC = the adaptive capacity index for each household (IPCC, 2007).

Multinomial logistic regression model was then used to predict farmers' vulnerability to climate variability and extreme climate events in the study area. The model was expressed as follows (Dragoş & Vereş, 2007; Nkondze et al., 2013);

$$p(y_i = j) = p_{ij} = \frac{\exp(x_i \beta_j)}{\Sigma \exp(x_i \beta_k)} \quad Where\, 0 < p_{ij} < 1 \tag{5}$$

$$p(y_i = j) = p_{ij}(\beta_0 + \beta_1 x_1 + \cdots \beta_k x_k) = p_{ij}(\beta_0 + x\beta) \tag{6}$$

Where: p_{ij} is the probability of a household i to be moderate or highly vulnerable with respect to, x_i is low vulnerability vector of the independent variables associated with household i and β_j is the vector of parameters associated with the alternative j.

For this study, the dependent variable consisted of the three vulnerability quartiles which were classified according to FANRPAN (2011) categorization of the Household Vulnerability Index (HVI) as shown in **Table 2**. Socioeconomic characteristics of the farmers were used as the explanatory variables for the model as described in **Table 3**.

Variance inflation factor (VIF) was used to test for multicollinearity among the explanatory variables as described by Yoo et al. (2015) in Equation 7.

$$VIF = {}^{1}\!\big/_{1 - R_j^2} \tag{7}$$

where $R^2{}_j$ is the R^2 value obtained by regressing the j^{th} predictor on the remaining predictors.

Table 2. Household vulnerability categorization.

Vulnerability Category	Quartile Range	Description
Low Vulnerability	0 - 33.3	The household is in a vulnerable situation, but still able to cope
Moderate Vulnerability	33.4 - 66.7	Household has been hit so hard that it needs urgent but temporary assistance for it to recover
High Vulnerability	66.8 - 100	Household is in a situation of almost a point of no return but could be resuscitated only with the best possible expertise. Emergency response required

Source: Modified from FANRPAN (2011).

Table 3. Description and summary statistics of explanatory variables used in the multinomial logistic regression model.

Variable	Description	Mean	SD	Expected sign
X_1	Gender of household head (1 = male; 0 = female)	1.29	0.46	+/−
X_2	Age of the household head (number of years of the household head)	55.86	15.11	+/−
X_3	Household size (number of family members in the household)	5.88	2.64	+/−
X_4	Highest education level attained in the household (number of schooling years)	12.43	4.41	−
X_5	Access to credit (1 = yes; 0 = otherwise)	0.35	0.48	−
X_6	Access to extension services (1 = yes; 0= otherwise)	0.16	0.37	−
X_7	Distance from the Market (how far the household is from the Market in Km)	2.79	3.24	+
X_8	Land size (number of acres owned by the household)	5.82	8.07	+/−
X_9	Agroecological zone (Arid)	0.10	0.84	+
X_{10}	Agroecological zone (Semi-humid)	0.30	0.84	−

Source: Modified from Bobadoye et al. (2019); Nkondze et al. (2013); Notenbaert et al. (2013); Opiyo et al. (2014).

3. Results and Discussion

Table 4 shows the results of the multinomial logistic regression analysis. As indicated in **Table 5**, the variance inflation factor (VIF) values for all explanatory variables were between 1 and 3, indicating that multicollinearity was not a concern. Multicollinearity concerns develop when the VIF value is larger than 10 (Yoo et al., 2015). The results showed that the household head's age ($p < 0.001$), proximity to the Market ($p < 0.001$), and arid agroecological zone ($p = 0.05$) significantly reduced the odds of a household belonging to the low vulnerability category relative to the high vulnerability category. On the other hand, the highest level of education in the household and the semi-humid zone significantly ($p < 0.001$) increased the probability of a household belonging to the low vulnerability category relative to the high vulnerability category.

The second model results indicated that distance from the Market ($p < 0.001$) and the arid agroecological zone ($p = 0.04$) significantly reduced the odds of the households belonging to the moderate vulnerability category relative to the high vulnerability category by a factor of 0.28 and 1.36, respectively. Access to credit facilities ($p = 0.02$) and the semi-humid agroecological zone ($p < 0.001$) on the other hand significantly increased the odds of a household belonging to the moderate vulnerability category relative to the high vulnerability category by a factor of 0.81 and 2.51, respectively. Further, the results revealed that the household head's gender and the highest level of education attained increased the probability of a household belonging to the moderate vulnerability category relative to the high vulnerability category by 20% and 6%, respectively. Additionally, access to extension services and household size increased the odds of a household belonging to the moderate vulnerability category relative to the high vulnerability category by a factor of 0.81 and 0.04, respectively. Moreover, the results indicated that household head's age and land size reduced the odds of a household belonging to the moderate vulnerability category relative to the high vulnerability category by 1%. The influence of household head's gender, the highest level of education attained, access to extension services, household head's age, size of the household and land size on the moderate vulnerability category was however not significant at 5% significant level.

Table 4. Coefficient estimates of multinomial logistic regression model results on determinants of farmers' vulnerability to climate variability and extreme climate events in the study area.

Explanatory Variables	Dependent Variable	
	Low Vulnerability	Moderate Vulnerability
Age	−0.05 (0.01)***	−0.01 (0.01)
Gender	0.06 (0.40)	0.20 (0.36)
Household size	−0.05 (0.07)	0.04 (0.06)
Market distance	−0.45 (0.10) ***	−0.28 (0.08) ***
Highest education level	0.20 (0.05) ***	0.06 (0.04)
Land size	−0.07 (0.04)	−0.01 (0.02)
Access to extension services	0.01 (0.48)	0.50 (0.48)**
Access to credit facilities	0.04 (0.37)	0.81 (0.35)**
Agroecological zone (Arid)	−0.35 (1.18) **	−0.36 (0.66) **
Agroecological zone (Semi-humid)	2.93 (0.37) ***	2.51 (0.63) ***

Note: Figures in parentheses are standard errors; ***, ** significant at 99% and 95% confidence levels, respectively.

Table 5. Multicollinearity test for explanatory variables used in the study.

Variables	VIF
Agroecological zone	1.169
Gender of the household head	1.128
Age of the household head	2.085
House hold size	1.146
Membership to farmers group	1.425
Years involved in farming in this piece of land	1.989
Access to credit when free of debt	1.082
Acess to extension services	1.372
Access to Early warning information	1.064
Distance in Km to the nearest Market	1.109
Highest education level in the HH (Number of schooling years)	1.095
Size of your land	1.271

Further scrutiny of the results indicated that a unit increase in household head's age and distance from the nearest Market significantly decreased the odds of a household belonging to the low vulnerability category relative to the high vulnerability category by 5% and 45%, respectively, while a unit increase in the number of schooling years increased the odds of a household belonging to the low vulnerability category by a factor of 0.20. The results implied that household head's age had a significant negative influence on a household belonging to the low vulnerability category compared to those with younger household heads probably because households with elderly heads are highly vulnerable in comparison with younger household heads since the elderly do not have the energy to engage in diversified livelihood options and thus have lower adaptive capacity compared to younger households. Additionally, younger households have a higher probability of adopting different adaptation measures since they are innovative and have the energy to implement new techniques aimed at improving agricultural production compared to older households. The findings are in consonance with those by Ncube et al. (2016) which indicated that a unit increase in household head's age increased the chances of the household being classified as moderately or highly vulnerable in Lambani and Alice Provinces in South Africa. Similarly, Opiyo et al. (2014) while assessing households' vulnerability to climatic shocks in Kenya's pastoral rangelands, found out that the household heads' age significantly increased households' vulnerability in Turkana County.

Regarding proximity to the Market, the results implied that increasing market distance increased households' vulnerability to climate variability, thereby reducing the probability of belonging to the low and moderate vulnerability categories. The probable reason could be that increasing market distances reduce access to social and financial assets which are crucial in enhancing households' adaptive capacity. The current trend of findings is concurrent with findings from a similar study by Ghosh and Ghosal (2020) which indicated that decreasing distance to the Market reduced households' vulnerability to climatic stressors in the Himalayan foothills of West Bengal, India. Similarly, Marie et al. (2020) found that accessibility to the Market increased farmers' probability of adopting various adaptation techniques thereby reducing their sensitivity to climate change.

The results further indicated that the highest education level attained in the household positively influenced a household's likelihood of belonging to the low and moderate vulnerability categories. This implies that households with members who had attained higher education levels were less vulnerable in comparison with their counterparts with low academic qualifications. The positive influence of education on low and moderate vulnerability categories could be because high education levels increase opportunities for formal employment and engagement in diversified income-generating activities which intensify a household's human capital thereby enhancing its adaptive capacity (Asrat & Simane, 2018; Fagariba et al., 2018). Further, farmers with high education levels have higher chances of perceiving climatic variations and the associated risks and have awareness and skills to implement new technologies thus a higher probability of implementing various adaptation measures compared to those with low to no academic qualifications (Belay et al., 2017; Deressa et al., 2008). In a similar study, Azumah et al. (2020) noted that higher academic qualifications increased the likelihood of a household becoming less vulnerable to climate change in Ghana's South Tongu and Zabzugu districts. Similarly, Ghosh and Ghosal (2020) found that access to higher secondary education reduced households' vulnerability to climatic variations in the Himalayan foothills of West Bengal, India. Further, the results corroborate the findings by Matsalabi et al. (2018) which showed that a unit increase in the number of educated members decreased the probability of a household being vulnerable by 11.5% in the Aguie district of Niger.

A close examination of the results revealed that the arid agroecological zone reduced the probability of a household belonging to the low vulnerability category relative to the high vulnerability category by a factor of 0.35 while the semi-humid agroecological zone reduced the probability of household belonging to the low vulnerability category by a factor of 2.93. The results imply that households in the arid agroecological zone are highly susceptible to climatic stressors as opposed to their counterparts in the semi-humid zone. The negative influence of the arid agroecological zone on households belonging to the low and moderate vulnerability categories could be explained by the harsh climatic conditions coupled with high exposures to climatic variability and natural disasters which increase the vulnerability of households in the arid zone. Similarly, low adaptive capacity owing to the marginalization of the zone also increases the vulnerability index of households in the arid zone. The positive influence of the semi-humid zone on households belonging to the low and moderate vulnerability categories on the other hand could be attributable to the low exposure and sensitivity levels in the zone owing to its relatively wetter climatic conditions and higher adaptive capacity due to its proximity to the County headquarters. The results align with findings by Owusu et al. (2021), which indicated that agroecological zones strongly influenced households' vulnerability in Ghana where while 58.8% of the households in the highly vulnerable category were from the Guinea Savannah agroecological zone, only 11.8% of the households in that category were from the Moist Semi-Deciduous Forest agroecological zone. Similarly, Chauhan et al. (2020) reported a varying influence of biogeographical zones on social and ecological vulnerability indices of agricultural communities in Himachal Pradesh, India.

Further examination of the results indicated that the gender of the household heads, access to extension services as well as access to credit facilities increased the odds of a household belonging to the low vulnerability category by 6%, 1% and 4%, respectively, while household size and land size reduced the probability of a household belonging to the low vulnerability category by 5% and 7%, respectively. The influence of the gender of the household head, access to extension services, access to credit facilities, household size and land size on households belonging to the low vulnerability category was however not significant at a 5% significance level.

The positive relationship between household heads' gender and the probability of a household belonging to the low vulnerability category implies that households headed by men had a higher likelihood of being less vulnerable in comparison with those headed by women. The possible reason could be that men have better access to services that enhance their adaptive capacities such as education and employment opportunities as well as the ability to be involved in labor-intensive off-farm livelihood strategies compared to women. In addition, households headed by men have a higher probability of adopting diverse adaptation strategies since they have better access to and ability to adopt new techniques to boost agricultural productivity in comparison with their female counterparts. The positive influence of the gender of the household head on the probability of households being less vulnerable was also highlighted by Opiyo et al. (2014) while working on households' vulnerability to climate-induced stresses in Kenya's pastoral rangelands in Turkana County. Concurrent findings have also been reported by other researchers (Asrat & Simane, 2018; Belay et al., 2017; Mihiretu et al., 2019).

Regarding access to extension services, the findings showed that households with access to extension services had a higher probability of falling in the low vulnerability category compared to those without probably because extension services increase awareness of climatic changes and related risks as well as providing households with knowledge and skills to implement relevant adaptation strategies to avert the risks thus enhancing households' adaptive capacity. The current trend of results concurs with findings from similar studies (Belay et al., 2017; Fagariba et al., 2018; Nhemachena et al., 2014; Teklewold et al., 2019).

Additionally, the results indicated that access to credit facilities positively influenced the probability of a household belonging to the low and moderate vulnerability category, implying that access to credit facilities reduced households' vulnerability to climate variability. The positive influence of access to credit facilities on reducing households' vulnerability could be attributed to its contribution to adaptive capacity by providing the financial ability to households to aid in the adoption of capital-intense adaptation strategies and technologies as well as investing in off-farm income generation activities which help farmers diversify their livelihood options. The results are in agreement with the findings by Azumah et al. (2020) who while assessing farm households' perceived climate change impacts, vulnerability and resilience in Ghana reported that access to credit facilities increased the likelihood of households being in the low vulnerability category. Further, Arun and Yeo (2020) found a positive association between access to credit facilities and the adoption of changing cropping date, crop type, crop variety and investment in irrigation among households in Nepal. Similarly, Tesso et al. (2012) noted that the accessibility of financial services increased the resilience of households by 16.6% due to its importance in influencing the adoption of adaptation options like planting hybrid seeds which would otherwise be limited by financial constraints.

Household size on the other hand reduced the odds of a household belonging to the low vulnerability category implying that households with more family members had higher chances of being in the high vulnerability category as opposed to the low category. A possible explanation could be that bigger households have a higher demand for resources, where household income is directed to meet the household's basic needs, with little left for investment in education and diversified off-farm generation activities that enhance a household's adaptive capacity. The results corroborate a similar study by Matsalabi et al. (2018) which indicated a highly significant and positive influence of family size on households' vulnerability where a unit increase in household size increased the vulnerability by 48.1% in farming households in the Aguie district of Niger. Additionally, Opiyo et al. (2014) also reported a positive influence of household size on vulnerability among pastoral households in Turkana County. Regarding the moderate vulnerability category, the findings however showed a positive effect of the size of the household on the probability of households being in the moderate vulnerability category compared to the high vulnerability category which could be because a larger household size provides an opportunity to improve productivity where productive members could be utilized as a human resource for both farm and off-farm income-generating activities thereby enhancing the households' financial capital. In addition, a larger household size provides family labor for the adoption of labor-intensive adaptation strategies. A positive association between household size and low vulnerability was also reported by Nkondze et al. (2013). Similar studies also reported a positive relationship between the adoption of labor-intensive adaptation techniques and the number of members in a household (Asrat & Simane, 2018; Belay et al., 2017; Jiri et al., 2015).

Contrary to the expectation, land size was negatively associated with the probability of a household belonging to the low and moderate vulnerability categories implying that bigger land sizes increased the vulnerability of households which could be because larger land sizes were recorded in the arid zone which has high exposure to climate-related natural disasters and thus higher agricultural sensitivity.

Additionally, households in the arid zone recorded low financial capital thus limiting their ability to invest in technologies that increase their land productivity. Similar findings by Boori and Voženílek (2014) indicated that areas with undeveloped or less developed land in Olomouc, Czech Republic were vulnerable to environmental changes but improvement of agricultural force to turn it into a developed area would increase its adaptive capacity and resilience. The results however contradict findings by Ghosh and Ghosal (2020) who while examining the determinants of households' vulnerability to climatic changes in the Himalayan foothills of West Bengal in India, noted that agricultural land size positively influenced the low vulnerability of households in the study area.

4. Conclusion and Recommendations

The study deduced that different socioeconomic characteristics of households had varying influences on the households' vulnerability levels. Variables such as the highest level of education, access to credit facilities, access to extension services and decreasing distance to markets increased the probability of a household belonging to the low and moderate vulnerability categories. The study therefore concludes that increasing opportunities for access to education, markets, weather information, extension services and credit facilities would be critical in enhancing households' adaptive capacity thereby reducing their vulnerability to climate variability and extreme climate events. The study recommends that policies, programs and projects by government and non-governmental agencies aimed at helping enhance households' resilience to climate variability and extreme events should target specific socioeconomic characteristics of households that influence their vulnerability to climate variability and extreme events.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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