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Determinants of small-scale farmers' adaptation decision to climate variability and change in the North-West region of Cameroon

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Small-scale farmers' adaptation decision in the face of climate variability and change (CVC) depends largely on their ability to perceive the impacts of CVC as well as their degree of vulnerability to these impacts. This research looks at the factors that influence small-scale farmers' adaptation decision faced with climate variability and change, with particular focus on Mbengwi Central Sub-Division, North-West Region of Cameroon. The study made use of household surveys to identify the impacts, determine vulnerability and assess the factors influencing small-scale farmers' adaptation decision. Data obtained from household surveys was analyzed using descriptive statistics (bar charts, percentage indices) and inferential statistics (Mann-Whitney test, Chi-Square, and the Binomial Logistic (BNL) regression model). Data analysis was done on Microsoft Excel 2007 and the Statistical Package for Social Sciences (SPSS) 17.0. Results showed that, following small-scale farmers' perceptions, crop productivity decline was the main impact of CVC (96.7%) and poverty the principal cause of vulnerability to CVC (98.3%). Mann-Whitney test results revealed that there was a significant difference between farmers' adaptation decision and six hypothesized continuous explanatory variables (age, household size, farm size, number of farms, annual family income, farm experience) (p<0.01). Chi-square test results revealed that there was a significant difference between farmers adaptation decision and some hypothesized discontinuous explanatory variables (perception of extreme weather events, access to weather information, access to extension services, access to credit, membership in farming groups and distance to markets) (p<0.01). Results of the BNL regression model showed that the main determinants of small-scale farmers' adaptation decision in the study area were age of household head, farm size and access to weather information (p<0.05).

Key words: Climate variability and change, small-scale farmers, impacts, vulnerability, adaptation decision, North-West Region of Cameroon.

INTRODUCTION

Africa is already experiencing the devastating impacts of climate variability and change especially on its small-scale farmers' population which make up the largest proportion of the economically active population (FAO,

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2016). This situation is expected to worsen in the coming decades owing to even greater variability and change in climate across the continent with scanty and erratic rainfall coupled with high temperatures to take precedence (IPCC, 2001). Africa is predicted to experience temperature changes of between 0.2 to 0.5°C per decade with the interior regions of Africa to bear the brunt of adverse variations and changes in rainfall and temperature patterns (IPCC, 2007).

Sub-Saharan Africa in particular is expected to experience decreased precipitation and increased temperatures in future predicted climate scenarios which will cause production instability amongst small-scale farmers (Morton, 2007; Challinor and Wheeler, 2008). With rain-fed agriculture being the most practiced form of agriculture in sub-Saharan Africa, variations and changes in temperature and rainfall in particular will pose a serious problem to the mostly agriculture dependent economies of this region (World Bank, 2013). Smallholder farmers in sub-Saharan Africa are therefore highly vulnerable to the nefarious impacts of climate variability and change. According to the Inter-Governmental Panel on Climate Change (IPCC), vulnerability to climate variability and change is a function of exposure to extreme climate events, sensitivity to the events and adaptive capacity of the affected community (IPCC, 2007). The high vulnerability of these small-scale farmers completely wears away their resilience faced with an increasingly variable and changing climate (FAO, 2010).

Cameroon is a predominantly agriculture dependent economy with small-scale farmers constituting the bulk of the farming population (Molua and Lambi, 2007). These small-scale farmers live mainly in the rural areas where they practice farming as a means of livelihood. With the average temperature in Cameroon predicted to increase by 0.7 to 0.8°C by the 2020s as a result of global warming according to transient General Circulation Models (GCMs), small-scale farmers in particular are expected to bear the brunt of these predicted variations and changes owing to their limited adaptive capacity (Gordon et al., 2000; Johns et al., 2003; Tingem et al., 2007). Some studies carried out in Cameroon have already proven that extreme climate events like rising temperatures lead to production instability amongst small-scale farmers due to their economic impoverishment (Molua, 2006; Molua and Lambi, 2007; Tingem et al., 2008a, b, c; Ngondjeb, 2013).

The North-West Region of Cameroon in particular is dominated by small-scale farmers who grow crops that are highly sensitive to variations and changes in temperature and precipitation. These crops have a narrow threshold for production success, such that variations and changes in temperature and rainfall that occur during key developmental phases of the crop can lead to production failure. Some of these highly sensitive crops are: cereals like beans, groundnuts, maize and soybeans; market gardening crops like tomatoes, condiments, cabbages, lettuce, huckleberry and carrots as well as tubers like yams, cocoyams and cassava. Hence the continuous dependence on rainfall in order to cultivate these highly sensitive crops makes smallholder farmers vulnerable to the negative impacts of climate variability and change. Studies conducted in the North-West Region of Cameroon have shown that climate variability and change is already impacting negatively on agriculture especially on small-scale farmers (Tingem et al., 2008a; Sunjo et al., 2012; Kimengsi et al., 2015).

With climate variability and change impacting nefariously on small-scale farmers, adaptation therefore becomes incumbent. From the foregoing, it is noticed adaptation to climate variability and change by small-scale farmers is not just straight forward as small-scale farmers' adaptation decisions vary. It is for this reason that this paper sought to provide answers to the following burning questions: what are the impacts of climate variability and change on small-scale farmers? What are the causes of small-scale farmers' vulnerability to the impacts of climate variability and change? What are the factors influencing small-scale farmers' adaptation decision to climate variability and change? The answers to the aforementioned questions aided in the attainment of the objectives of the study which were:

1. To identify the impacts of climate variability and change on smallholder farmers.
2. To identify the causes of smallholder farmers' vulnerability to the impacts of climate variability and change.
3. To analyze the factors affecting smallholder farmers' adaptation decision in the face of climate variability and change.

MATERIALS AND METHODS

Description of the study site

This study was carried out in the North-West Region of Cameroon, specifically in Mbengwi Central Sub-Division (Latitude 6° 02' N and Longitude 10° 01' E). It was conducted in four villages: Tugi (Lat. 6° 01' N; Long. 10° 02'E), Ngyen-Mbo (Lat. 6° 01' N; Long. 10° 02' E), Ku-Bome (Lat. 6° 00' N; Long. 10° 03' E) and Njah-Etu (Lat. 5° 87' N; Long.10° 20' E). The dry season which stretches from mid October to mid March and the rainy season which stretches from late March to late October constitute the two main distinct seasons of the area. The long-term average temperature in Mbengwi central sub-Division is 26°C and the long-term annual average rainfall is 1450 mm with major variability in the past three decades (Awazi, 2016). It is a very hilly area characterized by a rolling topography. The principal vegetation type is the savannah grassland. Agriculture predominates with small-scale farmers doing most of the farming. The main food crops grown are maize, groundnuts, okra, beans, cocoyams, yams, plantains and cassava. Cash crops cultivated include: coffee, oil palms, and banana. Market gardening crops grown include: tomatoes, cabbages, lettuce, carrots, huckleberry and watermelon. Fruits grown are: oranges, pineapples, avocado, guava, plums, paw-paw and mangoes. Animal husbandry is equally

Table 1. Description of hypothesized explanatory variables.

Variable	Description
Household size	Continuous
Sex	Dummy, takes the value of 1 if male and, 0 otherwise
Noticed extreme sunshine	Dummy, takes value of 1 if Yes and 0 otherwise
Age	Continuous
Number of farms	Continuous
Farm size in hectares	Continuous
Noticed high temperatures	Dummy, takes value of 1 if Yes and 0 otherwise
Annual family income	Continuous
Farm experience	Continuous
Access to weather information	Dummy, takes value of 1 if Yes and 0 otherwise
Noticed highly inconsistent rainfall	Dummy, takes value of 1 if Yes and 0 otherwise
Access to extension services	Dummy, takes value of 1 if Yes and 0 otherwise
Education	Dummy, takes value of 0 No education, 1 primary, 2 secondary, 3 tertiary
Access to credit	Dummy, takes value of 1 if Yes and 0 otherwise
Noticed reduced rainfall	Dummy, takes value of 1 if Yes and 0 otherwise
Distance to market	Dummy, takes value of 1 near, 2 moderate, 3 far
Land ownership	Dummy, takes value of 1 if owned, 0 otherwise
Noticed storms	Dummy, takes value of 1 if Yes and 0 otherwise
Membership in farming group	Dummy, takes value of 1 if Yes and, 0 otherwise

widespread (goats, pigs, sheep, poultry, and cattle).

Data collection and analysis

This study made use of the stratified random sampling procedure wherein smallholder farmer household heads were stratified based on age. And then, only small-scale farmers whose ages were greater than 30 years were randomly selected for the survey. All this was done with the help of agricultural extension officers found in the different study villages. Mainly old small-scale farmers were surveyed in order to get more reliable information pertaining to the degree of variability and change in climate elements. Following sampling, household survey of small-scale farmer household heads was then conducted in the four villages under study (Tugi, Ku-Bome, Ngyen-Mbo and Njah-Etu). This was done through the administering of structured and semi-structured questionnaires. A total of 120 small-scale farmer household heads were interviewed during the survey with a 100% respondents' rate. Household surveys provided information on the impacts, vulnerability and adaptation to climate variability and change as perceived by small-scale farmers. The data collection method used for this study was similar to those of other related studies (Tabi et al., 2012; Harvey et al., 2014; Rurinda, 2014; Rurinda et al., 2014).

Variables of the study

This study made use of the explanatory or independent variables as shown in Table 1. Data analysis for this study was done using descriptive and inferential statistics on Microsoft Excel 2007 and SPSS 17.0. Famer identified impacts of and causes of vulnerability to climate variability and change were analyzed through descriptive statistics only (bar charts and percentage indices).

Meanwhile, factors influencing small-scale farmers' adaptation decision in the face of climate variability and change were analyzed through inferential statistics. In order to test whether there was a significant difference between farmers' adaptation decision and various hypothesized continuous and discontinuous explanatory variables (Table 1), the Mann-Whitney test (U-test) and Chi-Square test (X^2 test) were used respectively. A similar approach was followed by Temesgen et al. (2014). As a rule of thumb, the normality of the continuous variables was tested using: histogram with normal curve, PP and QQ plots and most importantly the one sample Kolmogorov-Smirnov test, before choosing the suitable statistical tool for the analysis. For non-normal categorical variables, non-parametric tests such as the U-test (Mann-Whitney test) and H-test (Kruskal-Wallis test) were used. The Kruskal-Wallis test (H-test) in particular was used to test whether smallholder farmers' adaptation decision differed significantly across the four villages studied.

The Binary Logistic (BNL) Regression model on its part was used to examine the causal relationship between farmers' adaptation decision (binomial dependent variable) and several hypothesized continuous and discontinuous explanatory variables (Table 1). The Binary Logistic (BNL) regression model (Equation 1) predicts the log odds of having made one decision (adaptation) or the other (non-adaptation). This model therefore permits the analysis of decisions across two categories (adaptation and non-adaptation). This model is expressed as:

$$\ln(\text{odds}) = \ln\left(\frac{\hat{Y}}{1-\hat{Y}}\right) = \propto\ + \beta X \quad (1)$$

Where
$\hat{Y}$ is the predicted probability of the event (adaptation);
$1-\hat{Y}$ is the predicted probability of the other decision (non-adaptation);
X is the independent variable.

In order to run the BNL model, the Box-Tidwell Test was carried out. The Box-Tidwell Test was used to test if the relationship between the continuous predictors and the logit (log odds) was linear before running the model. This assumption was tested by including in the model, interactions between the continuous predictors and their logs. The aforementioned assumption and the BNL regression proper were done on SPSS version 17.0. The Binary logistic regression (BNL) model has also been used by other authors in order to decipher the factors influencing farmers' adaptation in the face of climate variability and change (Di Falcao et al., 2011; Belay et al., 2017).

RESULTS AND DISCUSSION

Farmer identified impacts of climate variability and change

Smallholder farmers in the study area increasingly perceive the negative impacts of climate variability and change. As revealed by household surveys, smallholder farmers generally perceive more than one impact of climate variability and change which were all negative (Table 2).

As shown on Table 2, the most recurrent negative impacts perceived by smallholder farmers were crop productivity decline (96.7%), increased poverty (80.8%), food insecurity (67.5%) and shortage of water (52.5%) while the least recurrent negative impacts perceived by farmers were death of animals (18.3%), increase in bushfires (13.3%) and "No Impact category" with 0%. Studies conducted by Molua and Lambi (2007) in Cameroon; IPCC (2007); Morton (2007); Mary and Majule (2009) in the Singida Region of Tanzania; Herrero et al. (2010) in Kenya; FAO (2011); Tabi et al. (2012) in the Volta Region of Ghana; Mbilinyi et al. (2013) in Tanzania; Ngondjeb (2013) in the Sudano-Sahelian Area of Cameroon; FAO (2016); The Global Risks Report (2016); Shumetie and Alemayehu (2017) in the Western Hararghe Zone of Ethiopia; and Fadina and Barjolle (2018) in the Zou Department of South Benin, showed that the impacts of climate variability and change on smallholder farmers are essentially negative and farmers always perceive a combination of several negative impacts. Hence CVC generally impacts negatively on smallholder farmers in MCSD.

Direct observations through transect walks vindicated farmers' perception that there has been an increase in crop diseases which reduces crop productivity.

Farmer identified causes or sources of vulnerability

Smallholder farmers in the study area are increasingly conscious of the sources or causes of their vulnerability in the face of climate variability and change. Household surveys conducted in the study area showed that smallholder farmers often perceived varied causes of vulnerability (Table 3).

Farmers identified a combination of causes from the twelve causes of vulnerability cited by smallholder farmers in the study area (Table 3). Hence the most recurrent sources or causes of vulnerability identified by farmers were poverty (98.3%), inadequate rainfall (85.8%), limited weather information (55.8%), and biased land tenure system (55%) while the least recurrent causes of vulnerability perceived by farmers were limited access to credit facilities (20.8%) and soil infertility (15.8%). Similar studies conducted by Tabi et al. (2012) in the Volta Region of Ghana; Lema et al. (2014) in the Hai District, Kilimanjaro Region, Tanzania; Rurinda (2014); Rurinda et al. (2014) in the smallholder farming systems of Zimbabwe; Harvey et al. (2014) in Madagascar and the FAO (2016) showed that there are several causes of smallholder farmers' vulnerability and small-scale farmers themselves always cite a combination of factors responsible for their vulnerability in the face of climate variability and change.

Factors influencing smallholder farmers' adaptation decision

Even though climate variability and change is a reality in the study area, some farmers are adapting while others do not. This study found out that smallholder farmers' adaptation or non-adaptation is influenced by several socio-economic, institutional and environmental factors (Tables 4 and 5).

Mann-Whitney test (U-test)

The U-test was used to test if there was a significant difference between farmers' adaptation decision and various hypothesized continuous variables and the following results were found (Table 4).

Age of household head: Many studies have shown that age of household head has a positive effect on farmers' adaptation decision (Temesgen et al., 2014; Belay et al., 2017). In this study, the ages of the sampled household heads ranged from 30 to 65 years with an average of 43.98 and a standard deviation of 8.89. A U-test was conducted to see if there is a difference between farmers' adaptation decision with respect to age of household head was statistically significant. The test results revealed that there was a significant difference between farmers' adaptation decision with respect to age ($Z=-7.598$, $p<0.01$). This means that the older the household head, the greater the propensity to adapt to climate variability and change in the study area.

Household size: Several studies have also shown that household size has a significant influence on farmers' adaptation decision (Temesgen et al., 2014; Belay et al., 2017). In this study, the household size of the sampled households ranged from 1 to 12 persons with an average of 5.86 and a standard deviation of 2.22. The U-test was conducted order to see if the difference between farmers' adaptation decision with respect to household size was

Table 2. Impacts of climate variability and change**.**

Impact	Number of respondents	%
Crop productivity decline	116	96.7
Increased poverty	97	80.8
Food insecurity	81	67.5
Shortage of water	63	52.5
Surge in crop and livestock diseases	48	40
Surge in farmer-grazier conflicts	36	30
Surge/resurgence of new pests	31	25.8
Surge in disease attack on farmers	27	22.5
Death of animals	22	18.3
Increase in bushfires	16	13.3
No impact	0	0

n = 120.
Source: Own Survey (2015).

Table 3. Causes or sources of vulnerability (farmers perceived a combination of causes).

Sources or causes of vulnerability	Number of respondents	%
Poverty	118	98.3
Inadequate rainfall	103	85.8
Limited or no weather information	67	55.8
Limited access to land	66	55
Limited off-farm jobs	53	44.2
Limited or no advice from extension agents	48	40
Low prices of farm products	43	35.8
Rolling topography	41	34.2
Distant markets	33	27.5
Limited or no credit facilities	31	25.8
Limited farm-to-market roads	27	22.5
Soil infertility	19	15.8

n = 120.
Source: Own Survey (2015).

Table 4. Descriptive statistics and U-test results for continuous variables.

Variable	Unit	Min.	Max.	Mean	Std. Dev	*Z (U-test)*	P-level
Age	Years	30	65	43.98	8.89	-7.598	0.000***
Household size	Number	1	12	5.86	2.22	-6.563	0.000***
Farm size	Hectare	0.2	6	1.29	1.08	-7.721	0.000***
N^o of farms	Number	2	17	7.09	3.21	-7.454	0.000***
Ann. family income	FCFA$^+$	30000	700000	184291.7	118400.2	-6.761	0.000***
Farm experience	Years	7	45	23.43	8.81	-6.807	0.000***

$^+$ 1 US$= 580 FCFA, *** Significant at 1% (df=2; p< 0.01).

statistically significant. The U-test result showed that there was a significant mean difference between farmers' adaptation decision with respect to household size (Z= -6.568, p<0.01). This implies that larger households have a higher propensity to adapt in the face of climate variability and change than smaller households.

Table 5. Summary of Chi-square test results for discontinuous explanatory variables.

Variable	Description	Frequency (N)		%		Chi-Square	p-level
		Adapted	Not adapted	Adapted	Not adapted		
Education	No formal education	10	5	8.3	4.2	1.085	0.781NS
	Primary	65	25	54.2	20.8		
	Secondary	7	5	5.8	4.2		
	Higher	2	1	1.7	0.8		
Noticed extreme sunshine	No	3	25	2.5	20.8	61.127	0.000***
	Yes	81	11	67.5	9.2		
Access weather information	No	8	28	6.7	23.3	55.903	0.000***
	Yes	76	8	63.3	6.7		
Noticed high temperature	No	0	25	0	20.8	73.684	0.000***
	Yes	84	11	70	9.2		
Access extension services	No	9	24	7.5	20	39.570	0.000***
	Yes	75	12	62.5	10		
Sex of HH head	Male	41	13	34.2	10.8	1.642	0.200NS
	Female	43	23	35.8	19.2		
Access to credit	No	8	23	6.7	19.2	38.873	0.000***
	Yes	76	13	63.3	10.8		
Noticed highly inconsistent rainfall	No	3	24	2.5	20	57.532	0.000***
	Yes	81	12	67.5	10		
Land ownership	No	46	23	38.3	19.2	0.859	0.354NS
	Yes	38	13	31.6	10.8		
Noticed decrease rainfall	No	1	21	0.8	17.5	54.959	0.000***
	Yes	83	15	69.2	12.5		
Membership in farming group	No	2	23	1.7	19.2	57.805	0.000***
	Yes	82	13	68.3	10.8		
Distance to market	Near	32	2	26.7	1.7	40.990	0.000***
	Moderate	39	7	32.5	5.8		
	Far	13	27	10.8	22.5		
Noticed storms	No	2	20	1.7	16.7	47.591	0.000***
	Yes	82	16	68.3	13.3		

Source: Own Survey (2015); *** Significant at 1% (df=1, p<0.01); NS= Not significant.

Farm size: The U-test was conducted to see if there is a significant difference between farmers' adaptation decision with respect to farm size. In this study the farm size ranged from 0.2 to 6 ha with an average of 1.29 and a standard deviation of 1.08. The U-test result showed that there is a significant mean difference between farmers' adaptation decision with respect to farm size (Z= -7.721, p<0.01). This implies that farmers with larger farm sizes have a higher ability to adapt than those with smaller farms.

Number of farms: In this study the number of farms ranged from 2 to 17 farms with an average of 7.09 and a standard deviation of 3.21. The U-test was conducted to see if there was a significant difference between farmers' adaptation decision with respect to number of farms. The U-test result showed that there was a very significant mean difference between farmers' adaptation decision with respect to number of farms (Z= -7.454, p<0.01). This implies that smallholder farmers with many farms have a higher propensity to adapt than those with few farms.

Farm experience: Farm experience generally increases with age and this has been identified by various studies and found to have significant influence on farmers' adaptation decision (Temesgen et al., 2014; Belay et al., 2017). In this study, farm experience ranged from 7 to 45 years with a mean of 23.43 and a standard deviation of 8.81. The U-test was used to see if there was a significant difference between farmers' adaptation decision with respect to farm experience. The U-test result showed that there was a significant mean difference between farmers' adaptation decision with respect to number of farms (Z= -6.807, p<0.01). This

Table 6. Logistic regression predicting adaptation decision from explanatory variables.

Predictor variable	Coefficients	Wald X^2	p-level	Odds Ratio (Exp B)	95% C.I. for Exp (B)	
					Lower	Upper
Intercept	−27.611	7.749	0.005	0.000		
Age of Household head	0.367**	5.564	0.018	1.443	1.064	1.957
Number of farms	0.710	2.128	0.145	2.035	0.783	5.285
Household size	−0.619	1.167	0.280	0.538	0.175	1.656
Annual family income	0.000	1.290	0.256	1.000	1.000	1.000
Farm size	8.678*	3.161	0.075	5871.514	0.411	8.383E7
Access_weather_ infos	4.958**	4.098	0.043	142.372	1.171	17313.038
Number of observations	120					
-2 Log Likelihood	146.664					
Likelihood Ratio X^2	123.716***					
Nagelkerke R Square	0.912					

*, **, *** Significant at 10, 5 and 1% probability levels respectively.

implies that the greater the experience of the farmer, the more likely the farmer will adapt in the face of climate variability and change.

Annual family income: Studies have equally found out that annual family income has a significant influence on smallholder farmers' adaptation decision (Temesgen et al., 2014; Belay et al., 2017). In this study, annual family income of the smallholder farmer households censored ranged from 30 000 FCFA (US$ 52) to 700 000FCFA (US$ 1 207) with an average of 184 291.67FCFA (US$ 323.5) and a standard deviation of 118 400.218FCFA (US$ 201.63). The U-test was used to test if there was a significant difference between farmers' adaptation decision with respect to annual family income. The U-test result showed that there was a significant difference between farmers' adaptation decision with respect to annual family income (Z= -6.761, p<0.01). This implies that adaptation is highly affected by the income of the household and households with higher family income have a greater likelihood to adapt.

Chi-Square test result

In order to test whether there was a significant difference between farmers' adaptation decision and several hypothesized qualitative explanatory variables, the chi-square test was used. The chi-square test results showed that there was a significant difference between farmers' adaptation decision with respect to perception of extreme sunshine, access to weather information, perception of high temperature, access to extension services, access to credit, perception of highly inconsistent rainfall, membership in farming groups, perception of decreased rainfall, distance to markets and perception of storms (p<0.01) with Chi-square values of 61.127, 55.90, 73.68, 39.57, 38.87, 57.53, 57.81, 54.96, 40.99, and 47.59 respectively (Table 5). This implies that the more farmers have better access to weather information, good extension services and credit facilities as well as belonging to farming groups and having easy accessibility to markets as well as perceiving extreme climatic events, the higher their likelihood to adapt to climate variability and change. With the p-levels being very statistically significant (p<0.01), it implied that there was a 99.99% probability that these events did not occur by chance.

However, the chi-square test did not show any high statistical significance between farmers' adaptation decision and educational status, sex, and land ownership. This implies that these variables have no significant influence on smallholder farmers' adaptation decision.

Binary logistic regression model

In order to determine the causal relationship between farmers' adaptation decision and various hypothesized explanatory variables, the binary logistic regression model was used and the following results were found (Table 6).

This regression model was run to ascertain the effects of six predictors namely; age of household head, number of farms, household size, annual family income, farm size, and access to weather information on smallholder farmers' adaptation decision in the face of climate variability and change. Several other predictor variables were dropped either because of high levels of multicollinearity with other predictor variables or because they were redundant and did not contribute significantly when added to the model. The model was statistically significant, Likelihood Ratio X^2 (6, n = 120) = 123.72, p<0.01. The likelihood ratio statistics from the BNL model therefore indicated that X^2 statistics was highly significant

Table 7. Classification table for predictor variables.

Observed		Predicted		
		Decision		Percentage correct
		No adaptation	Adaptation	
Decision	**No adaptation**	33	3	91.7
	Adaptation	2	82	97.6
Overall percentage				95.8

(X^2 = 123.72, $p<0.01$) signifying that the model has a strong explanatory power. The model explained 91.2% (Nagelkerke R^2 or Pseudo R^2 = 0.912) of the variance in farmers' adaptation decision and correctly classified 95.8% of the cases. Pseudo R^2 (0.912) therefore showed that the weighted combination of predictor variables was jointly significant in explaining smallholder farmers' adaptation to CVC.

The model results showed that age of household head ($p<0.05$), farm size ($p<0.10$), and access to weather information ($p<0.05$) added significantly to the model/prediction, meanwhile number of farms, household size and annual family income ($p>0.10$) did not add significantly to the model. This indicated that the older the farmer, the greater the likelihood to adapt to climate variability and change. Similarly, the bigger the farm size, as well as easy access to weather information the greater the likelihood of the farmer to adapt to climate variability and change. However, number of farms, household size and annual family income did not contribute significantly in influencing smallholder farmers' adaptation decision ($p>0.10$). Household size in particular had a negative influence on adaptation which is unprecedented because most studies have shown that the bigger the household size, the greater the capacity to adapt to climate variability and change. This could be due to the presence of a high dependent population (infants and very old people) or sheer laziness and lukewarm attitude towards farming activities. The BNL regression model has also been followed by Di Falcao et al. (2011) and Belay et al. (2017) whose studies found that access to credit, extension services and information are the main drivers of farmers' adaptation decision in the face of climate variability and change.

The classification table of this model (Table 7) portrayed the sensitivity (% of occurrences correctly predicted); specificity (% of non-occurrences correctly predicted); false positive rate (% of predicted occurrences which are incorrect); false negative rate (% of predicted non-occurrences which are incorrect) and the overall success rate of the model.

Cut value is 0.5

The sensitivity of the prediction was 82/84 = 97.6%; the specificity of the prediction was 33/36 = 91.7%; the false positive rate was 3/85 = 3.53%; the false negative rate was 2/35 = 5.7%. Overall, the predictions were correct 115 out of 120 times, with an overall success rate of 115/120 = 95.8%.

The Kruskal-Wallis test (H-test) which sought to portray the degree of variation in smallholder farmers' likelihood to adapt to CVC across the four villages studied (Tugi, Ngyen-Mbo, Ku-Bome, and Njah-Etu) revealed that farmers' adaptation to CVC did not vary across the four villages [X^2 (1, n= 120) = 0.031, p> 0.10]. This therefore means that adaptation decision amongst smallholder farmers across the four villages were the same.

Conclusions

The study found that all the small-scale farmers interviewed, perceived the impacts of climate variability and change but some adapted while others did not. Farmers generally perceived a combination of impacts which were all negative. The most recurrent negative impacts identified by farmers were crop productivity decline (96.7%), increased poverty (80.8%), food insecurity (67.5%) and shortage of water (52.5%), while the least recurrent negative impacts perceived were death of animals (18.3%) and increase in bushfires (13.3%). The "No Impact category" had 0% meaning all the respondents perceived the negative impacts of climate variability and change. Pertaining to the causes of vulnerability, farmers perceived a combination of causes or sources of vulnerability with the most recurrent ones being poverty (98.3%), inadequate rainfall (85.8%), limited weather forecast (55.8%), and biased land tenure system (55%) while the least recurrent causes of vulnerability perceived by farmers were limited access to credit facilities (20.8%) and soil infertility (15.8%). BNL regression analysis revealed that age of household head, access to weather information and farm size ($p<0.05$) significantly influenced small-scale farmers' adaptation decision while household size, annual family income and number of farms ($p>0.10$) had limited influence on smallholder farmers' adaptation decision. Thus, more small-scale farmers will take to adaptation if younger farmers get advice from their older counterparts, if weather information is made accessible, and if more land is made available to farmers through better land tenure systems.

CONFLICT OF INTERESTS

The authors have not declared any conflict of interests.

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