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Drivers of adaptation to climate change in vulnerable farming communities: a micro analysis of rice farmers in Ndop, Cameroon

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Abstract

Farmers in developing economies often struggle to adapt to climate change and their decisions to adapt usually hinges on perception and prevailing socio-economic factors. This study examines factors controlling farmers' decision to adapt to climate change and evaluate the impact of such decisions on farm output. Using primary data from 138 rice farming households in Ndop-Cameroon, we employ the probit model with endogenous switching regression to investigate the impact of the farmers' adaptation decisions on output. The results indicate that access to credits, other incomes, farmers' age, extension services and farmer groupings form key factors that significantly affects farmers' decision to adapt to climate change. Strategic implementation of adaptive measures, significantly increased average output of adapters by 49 %. Building resilience against climate change and ensuring food security, therefore requires stakeholders to take into account existing management strategies and the underlying factors influencing these. This study suggests the crucial need for institutional advancement and policy changes towards credit accessibility for rice farmers. More local farmers' associations should be created and extension services improved to enhance effective adaptation and farmers' vulnerability.

Keywords: socio-economic factors, food security

1 Introduction

Feeding the world's growing population under climate uncertainties is a major challenge facing farmers in both developed and developing nations. Growing arguments firmly agree that climate change highly affects agricultural systems and areas of less developed countries will be hardest hit (Dube *et al.*, 2016; Jalloh *et al.*, 2013). Population growth together with climate change and myriads of other environmental constraint constitutes serious threats to food security in many parts of Cameroon, Africa and the world. Ensuring food security in the midst of climate change is increasingly becoming a complex scenario requiring urgent response from all sectors of the global economy (Kim *et al.*, 2017). While a significant body of research exist on the impacts of climate crises and adaptation (Chen *et al.*, 2014; Mendelsohn, 2012; Khanal *et al.*, 2018), adequate studies on adaptation putting farmers at the center of research is limited. A better understanding of vulnerability, adaptability, decision and impact on crop yield is essential in designing flexible-adaptive-coping strategies that integrally deal with climate hazards in Cameroon. As the world responds to COVID-19, stakeholders also have a chance to rebuild and modernise policies towards a more efficient and resilient food system, against environmental issues. By and large, household decisions and policies that constrain and ultimately reduce greenhouse gas emissions will mitigate potential impact of climate change.

According to IPCC (2014), adaptation to climate change refers to adjustments in natural or human systems in response to actual or expected climatic stimuli which moderates harm or exploits beneficial opportunities. Adaptation at farm level involves any change(s) in capital or behaviour made by actors (household, firm, government) to reduce harm or increase potential gains from climate change. It involves two stages; perceiving the change then deciding whether or not to adapt, and which strategy should be adopted. Given that there is no one-size-fits-all-solution to adaptation, identifying true measures that supports farm pro-

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ductivity remains a difficult problem. The "set of mechanisms that minimises marginal cost and maximises net benefits" are efficient for adaptation. Specific answers to particular questions such as; which action(s) need to change; where should change be effected; how and at what level of production should change take place are therefore critical for effective adaptation (Khanal *et al.*, 2018; Mendelsohn, 2012). Unfortunately, imperfect information and uncertainty remains the ultimate limitation to efficient adaptation particularly for less developed nations.

It is widely established that human activities are largely responsible for climate crises (IPCC, 2013). Climate change induces extreme weather events around the world, causing changes faster than vulnerable populations and farming systems can cope with. Empirical studies indicate that even moderate increases in temperatures and/or changes in rainfall patterns have negative impacts manifested through crop failure and yield loses for major cereal crops (Van Ittersum *et al.*, 2016). While these adverse conditions poses a big burden, some studies predict beneficial effects for some crops (e.g. sweetcorn in Denmark) if suitable adaptation measures are implemented (Ainsworth & McGrath, 2010). Ice melting at the poles will mean more agricultural land available for farming. However, this is compromised by loss of coastal land as sea level rises. Other studies predict impacts and trends that are highly uncertain at the spatial and temporal scales (Knox *et al.*, 2012). Despite these uncertainties, it is clear that the magnitude of projected changes require adaptation and transformation which typically depends on the complex interaction of bio-physical, social and economic conditions of the farmer (Smit *et al.*, 2006).

A number of studies have simulated the possible effects of climate change on rice production in Sub-Saharan Africa. Some indicate that rice yields in West and Central Africa would slightly decline and those of East and Southern Africa would slightly increase with climate change (Lobell *et al.*, 2008). Van Oort *et al.* (2018), predicts increase in irrigated rice yields thanks to favorable temperatures and CO2 fertilisation in East Africa, while that of West Africa will decrease. Cameroon based study predicted that net revenue for rice crop production will fall as temperatures or precipitation increase or decrease (Molua, 2007). The effects are still quite uncertain for many parts of Africa. However, whether the ultimate impacts are mild or severe, conscious farmers and stakeholders must be precautionary and prepare tactics that individually or collectively assist vulnerable communities to adapt to climate changes. Excellent progress has been made in China and other Asian countries particularly in identifying growth poles and relocation of major rice fields (Li *et al.*, 2015).

Agriculture in Cameroon is the backbone of the economy, employing over 70 % of the population and contributing about 76 % to GDP (MINADER, 2018). The country is sometimes known as the breadbasket of Central Africa. Agricultural production is mostly seasonal and highly dependent on rain-fed. It is characterised by low level input and capital investment following farmers' low purchasing power. The high reliance of the economy on weather sensitive activities like agriculture, makes Cameroon highly vulnerable to the effects of climate crises.

Cameroon, like many other African countries is far from self-sufficiency in rice production; a situation which is projected to worsen following climate crises (Van Ittersum *et al.*, 2016). Malnutrition and food insecurity is still a major challenge in Cameroon. According to the Food and Agricultural Organisation, there is high prevalence of undernourishment in almost all sub-regions of Africa (FAO, 2019). This chronic crisis has been driven by a variety of factors including economic shocks, social and political conflicts and above all, climate change and land degradation. Rice is one of the main crops grown in Cameroon, and has become the most rapidly growing food source for millions of people. According to the Ministry of Agriculture and Rural Development (MINADER), domestic demand for rice in Cameroon is estimated at 576,949 tons on an average national production of 140,710 tons (MINADER, 2020). Despite great potentials, rice production in Cameroon is still far below demand leaving the country at the mercy of imports to meet domestic demand. With population growth, climate change and uncertainties, providing enough of this staple food is a serious issue challenging local producers. Keeping up with the growing population and per-capita rice consumption will require substantial yield gap closure and area expansion, or continues import dependency.

This study thus, examines the different factors that may control farmers' decision to adapt to climate change, and analyses the impact of such decisions on farm output. The study specifically examines the farmers' perception of climate change and measures put in place to mitigate impact on rice farming in the Ndop plain. This baseline information may serve as a knowledge platform designed to form effective collaborations between stakeholders and agriculture dependent communities, offering adaptation and development programs aimed at reducing agrarian vulnerability while improving the production and supply chain of local rice on the African continent. This study is therefore timely, contributing to the Cameroon's emerging economy plan by 2035, and advancing the realisation of Africa agenda 2063.

2 Materials and methods

2.1 Study area

This study was conducted in the Upper Noun Valley commonly known as Ndop Plain (Fig. 1). It is located in the Ngoketunjia Division, Northwest region of Cameroon and lies between 50 42' and 60 10' north of the equator and 100 11' and 100 40' East of the Prime Meridian (Wirmvem *et al.*, 2015). The Upper Noun Valley extensively covers 13 villages with a surface area of about 1,152 km2. These 13 villages are administratively divided into three subdivisions (i.e. Ndop central, Babessi and Balikumbat subdivisions) with headquarters in Ndop. The population is mostly agrarian with rice cultivation as the main activity.

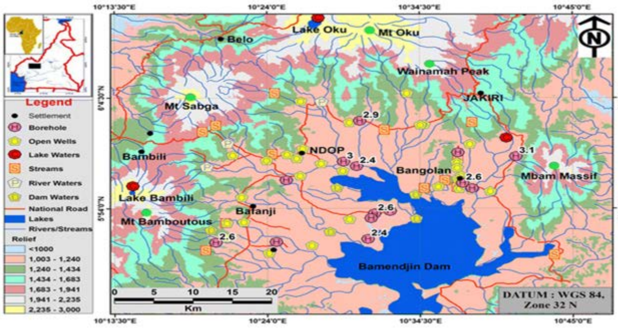

Fig. 1: *Map of Ndop plain showing relief and drainage (Source: Wirmven et al. (2015)*

The climate is humid tropical equatorial type with two distinctive seasons (rainy and dry season). The rainy season is extensive and last for approximately 8 months from mid-March to mid-November. Annual average rainfall varies between 1500 and 2000 mm, average temperatures rise above 21.3 °C with average maximum and minimum daily temperatures of 27.2 °C and 14.0 °C respectively (Wirmvem *et al.*, 2015). The plain is surrounded in the North and Northwest by the Bamenda Highlands and the Oku Mountain range, in the west by the Bamboutos and Lefo mountains and to the East and Southeast by the Mbam and Nkogam Massifs (Fig 1). The rock basement is basaltic lava and trachytes which gives rise to sandy clay soil type found in the plain. These geologic features are also made of volcanic rocks in the Oku Mountain range which largely account for the fertile alluvial volcanic deposits in the floodplain. Numerous tributaries from surrounding highlands unite to form the Noun River and floodplain with wetland characteristic suitable for swap rice cultivation. Following the low lying nature of the plain between the Oku mountain range (Fig. 1), flooding in Ndop plain is almost inevitable with the coming of the rains. Human activities including over grazing, subsistence and rudimentary farm practices (e.g. 'the slash and burn' system) have proliferated observed effects (Wotchoko *et al.*, 2016). Moreover, since the completion of the Bamendjim dam over the Noun River in 1975, the water table in the plain increased and about 25 % of the Ndop plain is now exposed to flood hazards. Potential land area for rice cultivation covers about 15,000 ha while area under cultivation covers only about 3,366.41 ha (UNVDA, 2019). A huge gap thus exists with vast unexploited potentials which can be harnessed to enhance food security in the region.

2.2 Data source

Five major rice producing villages including, Bamunka, Bamali, Babungo, Babessi and Bambalang in the study area were strategically selected for this study. Selection was based on the high prevalence of rice cultivation and high vulnerability to extreme weather events (UNVDA, 2019; Cordelia, 2019). Data was collected in two phases between June and July 2019 (rice planting season). Phase one, was a quality recognition phase where semi structured interviews and focus group discussions were used to collect information regarding the peculiarities and general characteristics of the villages under survey. Interviews and discussions involved community elites, leaders of Common Initiative Group (C.I.G) and field experts from Upper Noun Valley Development Authority (UNVDA) – a state owned cooperative in charge of rice production in Ndop plain. These discussions were guided by three contingent questions included in the questionnaire. First, "*do you perceive any changes in the local climatic condition in the last decade?*" If yes, "*what are these?*" Secondly,"*what has been the impact of such changes on rice production?*' ' this was particularly designed to capture the farmer's knowledge and understanding of climate change and to ensure that the adaptation measures undertaken are a consequence of climate change. Lastly, "*what have you done to deal with such changes?*" designed to identify the adjustments taken by farmers to cope with the changes. The identified adaptation practices were then included in the survey questionnaire to examine the actual adaptations adopted by the sample population. Prior to administering the questionnaire, a pre-testing with a non-sample household was carried out to test the applicability of the questionnaire. Inputs from pre-testing and discussions were then incorporated into the questionnaire and finalised into three sections following our objectives.

The second phase focused on a random selection, distribution and collection of data using a survey questionnaire. A list of 413 farmers registered in the five villages with farming experience over 15 years, was obtained from UNVDA. From this list, farmers were randomly selected with no bias to gender, socio-cultural or religious affiliations and contacted for their availability and willingness to participate in the survey exercise. In total 138 responses were obtained (Bamunka = 38, Bamali = 16, Babungo = 27, Babessi = 32, Bambalang = 22 and 3 from extension service agents) from household decision makers, ranging between the ages of 30 and 70 years. Survey was done with the help of trained research personnel who were able to communicate with respondents face to face in the language best understood by them. This sample was considered adequate given that, the population of this area is relatively homogenous (Kongnso *et al.*, 2020; Cordelia, 2019). There is thus a high probability that results of a larger sample size would have no significant difference in the overall results.

2.3 Modelling adaptation and its impact on farmers' output

We model adaptation to climate change under the Random Utility Theory (RUT) which specifies that farmers will choose between adaptation and non-adaptation based on the utility they receive. It is assumed that farmers are risk neutral, and their decision to employ adaptation is influenced by the utility they will derive from adaptation. Farmers therefore rationally select amongst management options that maximise net benefits of their action (Abdulai & Huffman, 2014). The farmers' decision is driven not only by rational choices but also by socio-economic and cultural norms. In the context of Cameroon, many of such factors interact to influence farmer's decision towards adaptation to climate change. A high dependency on rain-fed agriculture equally makes weather conditions (rainfall and temperature) to have pivotal control over farmers' adaptation decision. We therefore hypothesise that the socio-economic condition of farming households including, farmers' age, education, household size and income, credit access, seed variety, farmers' association, extension service, droughts and floods, have a significant influence on farmers' decision to adapt to climate change and that adaptation has significant positive influence on farmers' output.

Assuming Y_{Ai} is the utility (yield) a farmer derives from adaptation and Y_{Ni} the utility farmers derive from non-adaptation, farmers typically implement adaptation if $\mathrm{Y}_{Ai} > \mathrm{Y}_{Ni}$. Following the example of Abdulai *et al.* (2014), we present the farmers' adaptation decision by a latent variable (Ai^*) which captures the expected benefits derived from farmers' adaptation decision.

$$A_i^* = \alpha_i Z_i + \eta_i \tag{1}$$

$$A_i = \begin{cases} 1 & A_i^* > 0 \\ 0 & \text{otherwise} \end{cases}$$

A_i^* is a latent variable equal to 1 for all farming household i that choose to implement any form of adaptation and 0 otherwise. α_i is the parameter to be measured and Z_i, a vector of household characteristics. In this stage, we employ the probit model which is widely used in economic literature to estimate binary variables. The model is estimated by Full Information Maximum Likelihood (FIML), and restricts the probability between 0 and 1, contrary to the linear probability model which fails to impose such restrictions. Thus, violating the homoskedasticity and normality of errors. As climate changes, famers experience either productivity increases or decreases, so perceived changes pushes them towards varying inputs and farming techniques. In this study, we build a second model on the impact of adaptation using the following production function, specified in log.

$$Y_i = \beta_i X_i + \mu_i \tag{2}$$

Y_i is the quantity of rice produced per hectare; X_i is a set of farm characteristics including farmers' decision to adapt. β is a vector of parameters to be estimated and μµ is the error term. With adaptation as a dummy variable, two econometric challenges may arise when estimating the impact of adaptation on rice yield. An endogeneity problem could occur given that adaptation is assumed to be exogenous to rice output, meanwhile it is potentially endogenous. Secondly, a sample selection bias may occur given that, farmers who adapt may have systematically different characteristics from those who do not adapt. Empirically, selection bias occurs when the unobservable factors influence both the error terms of the adaptation (η) and the outcome equation (μ), resulting in a correlation between η and μ (Abdulai & Huffman, 2014). Unobservable household characteristics may equally affect both the household's decision to adapt and their output (Di Falco *et al.*, 2011). We therefore employ the Endogenous Switching Regression model (ESR) developed by Lee and Trost (1978) to account for the endogeneity and selection bias challenge. This model identifies the impact of adjusting farm management practices on the mean output of farmers who adapt. To improve the identification of the model, we use 'extension service and farm group' variables as selection instruments, assuming that these variables may directly influence farmers' adaptation decisions but not output. Given the households decision to apply adaptation measures, a separate outcome function can be specified for farmers who adapt and those who do not adapt; - 'Adapters' and 'Non-Adapters'.

$$\mathit{Regime}\ 1:$$

$$Y_{Ai} = \beta_A X_{Ai} + \mu_{Ai}, \quad if \quad A_i = 1 \tag{3}$$

$$Regime\ 2:$$

$$Y_{Ni} = \beta_N X_{Ni} + \mu_{Ni},\ \ if\ \ A_i = 0 \tag{4}$$

Where; Y_{Ai} and Y_{Ni} are rice output produced per hectare and specified in log for adapters and non-adapters respectively. The vector β_A and β_N are parameters to be estimated. The error terms η, μ_{Ai} and μ_{Ni} are assumed to have a trivariate normal distribution with zero mean and the following covariance matrix:

$$Cov(\eta,\ \mu_A\ \&\ \mu_N) = \sum = \begin{pmatrix} \sigma_\eta^2 & \sigma_{\eta A} & \sigma_{\eta N} \\ \sigma_{A\eta} & \sigma_A^2 & \sigma_{AN} \\ \sigma_{N\eta} & \sigma_{NA} & \sigma_N^2 \end{pmatrix}$$

Where:

$$Var(\eta) = \sigma_\eta^2 \text{ and } Var(\mu_A) = \sigma_A^2,\ \ Var(\mu_N) = \sigma_N^2$$

$$Cov(\mu_A, \mu_N) = \sigma_{AN},\ \ Cov(\mu_A, \eta) \text{ and } Cov(\mu_N, \eta) = \sigma_{N\eta}$$

The sample selection bias may lead to non-zero covariance between the error term of the selection equation and the outcome equations (Maddala, 1983). Since YAi and YNi are not observed simultaneously, the covariance between µAi and µNi is not defined. According to Lee & Trost (1978), the expected values of the error terms µAi and µNi conditional on the sample selection are given as follows:

$$E[\mu_{Ai}|\,A_i = 1] = \sigma_{A\eta}\frac{\varphi\left(\frac{Z_i\alpha}{\sigma}\right)}{\Phi\left(\frac{Z_i\alpha}{\sigma}\right)} = \sigma_{A\eta}\lambda_{Ai} \tag{5}$$

and

$$E[\mu_{Ni}|\,A_i = 0] = \sigma_{N\eta}\frac{\varphi\left(\frac{Z_i\alpha}{\sigma}\right)}{\Phi\left(\frac{Z_i\alpha}{\sigma}\right)} = \sigma_{N\eta}\lambda_{Ni} \tag{6}$$

$\varphi(.)$ and $\Phi(.)$ are the standard normal probability density function and cumulative distribution function respectively. The term λ_A and λ_N refer to the inverse Mills ratio evaluated at $Z_{i\alpha}$ and are incorporated in the outcome equations to account for selection bias. This approach is limited by the fact that it generates heteroskedastic residuals, which cannot be used without complex adjustments to obtain consistent standard errors (Lokshin and Sajaia 2004). In an attempt to investigate how adaptation decisions may impact rice output amongst the different categories of farmers, this study accesses the treatment and heterogeneity effect on farmers' output. The impact can be examine by first specifying the potential outcome mean, calculated respectively for adapters and non-adapters as follows.

$$E[Y_{Ai}|A_i = 1] = X_{Ai}\beta_A + \sigma_{A\eta}\lambda_{Ai} \tag{7}$$

$$E[Y_{Ni}|A_i = 0] = X_{Ni}\beta_N + \sigma_{N\eta}\lambda_{Ni} \tag{8}$$

In the same way, the expected outcome of the same adapter, had this person chosen not to employ adaptation mechanisms and the same non-adapter had this person chosen to adapt is given as follows:

$$E[Y_{Ni}|A_i = 1] = X_{Ai}\beta_N + \sigma_{NA\eta}\lambda_{Ai} \tag{9}$$

$$E[Y_{Ai}|A_i = 0] = X_{Ni}\beta_A + \sigma_{A\eta}\lambda_{Ni} \tag{10}$$

Change in outcome owing to application of innovative farm management options can then be specified as the difference between implementation and non-implementation otherwise known as the average treatment effect on the treated (ATT). Thus the ATT is the difference between equation (7) and (9) given as follows:

$$\begin{aligned} ATT &= E[Y_{Ai}|A_i = 1] - E[Y_{Ni}|A_i = 1] \\ &= X_{Ai}(\beta_A - \beta_N) + (\sigma_{A\eta} - \sigma_{N\eta})\lambda_{Ai} \end{aligned} \tag{11}$$

Similarly, we can calculate the average treatment effect on the untreated (ATU) i.e. farmers who did not adapt. This is given by the difference between equations (8) and (10)

$$\begin{aligned} ATU &= E[Y_{Ni}|A_i = 0] - E[Y_{Ai}|A_i = 0] \\ &= X_{Ai}(\beta_N - \beta_A) + (\sigma_{N\eta} - \sigma_{A\eta})\lambda_{Ni} \end{aligned} \tag{12}$$

Since sample selection is taken into account through λ_{Ai} and λ_{Ni} in equation (11) and (12), ATT and ATU generate unbiased estimates of the impact of adaptation on rice yield. Regardless of adaptation decisions, farming households that adapted may have produced more than those who did not adapt based on unobserved characteristics. Following Di Falco *et al.* (2011), this heterogeneity effect can be measured by the difference between the expected yield function described in equation (7) and (10):

$$\begin{aligned} H_A &= E[Y_{Ai}|A_i = 1] - E[Y_{Ai}|A_i = 0] \\ &= (X_{Ai} - X_{Ni})(\beta_{Ai} + (\lambda_{Ai} - \lambda_{Ni})\sigma_{A\eta} \end{aligned} \tag{13}$$

Likewise, the heterogeneity for households that decided not to adapt is given by the difference between equations (8) and (9):

$$\begin{aligned} H_N &= E[Y_{Ni}|A_i = 1] - E[Y_{NAi}|A_i = 0] \\ &= (X_{Ai} - X_{Ni})(\beta_{Ni} + (\lambda_{Ai} - \lambda_{Ni})\sigma_{N\eta} \end{aligned} \tag{14}$$

We employ the 'movestay' command in STATA 14 to estimate parameters of the ESR model (Lokshin & Sajaia 2004).

Table 1: *Summary and descriptive statistics of the sample distribution*

Variable	*Description*	*Mean*	*Std. Dev.*
Age	Farmer's age	50.43	8.95
Gender	Dummy (1= male; 0 otherwise)	0.51	0.5
Adaptation	Dummy (1= adapted to climate change; 0 otherwise)	0.63	0.48
Climate belief	Dummy (1= belief climate change; 0 otherwise)	0.89	0.31
Family-size	Dummy (1= household >5; 0 otherwise)	0.8	0.39
Education	Dummy (1= attended Primary education; 0 otherwise)	0.82	0.38
Extension	Dummy (1= receive extension service; 0 otherwise)	0.39	0.48
Income level	Annual income (000 XAF)	655.14	257.87
Other income	Dummy (1= income from off-farm activities; 0 otherwise)	0.54	0.49
Farm-size	Household farm size (hectares)	1.33	0.54
Seed variety	Dummy (1= access improved seed variety; 0 otherwise)	0.59	0.49
Experience	Years of rice production.	11.19	3.76
Input	Amount on farm inputs (000 XAF)	51.84	7.45
Output	Quantity of rice produced (kg ha-1)	2385.51	846.94
Credit	Dummy (1= access to credit; 0 otherwise)	0.42	0.49
Farm group	Dummy (1= farmer's group member; 0 otherwise)	0.67	0.47
Droughts	Dummy (1= affected by drought; 0 otherwise)	0.6	0.49
Floods	Dummy (1= affected by floods; 0 otherwise)	0.79	0.41

3 Results

3.1 *Farmers' perception on climate change*

The summary statistics is presented in table 1. About 89 % of the sample population belief in climate change and about 63 % consciously employ one or two adaptation mechanism to cope with actual or expected effects of climate change.

A sub-sample of farmers who belief in climate change was obtained and observed that about 72 % of households perceive increasing temperatures and about 46 % perceive decreasing rainfall over the years. Others perceive increasing extreme events of floods and droughts which are commonplace in the plain. Almost every household in the sample perceived increasing flood occurrences (Table 2).

Table 3 presents the different characteristics of adapters and non-adapters. The average output for adapters is 1172.2 kg ha^{-1} higher than that of non-adapters. It is also evident that adapters have greater access to credit, receive higher extension service and improved seed varieties.

3.2 *Adaptation measures*

The adaptation strategies commonly employed by farmers are shown in Fig. 2. Construction and maintenance of waterways is the most common practice. Adjusting planting dates is also common, while others plant improved seed varieties. The use of soil conservation techniques is least adopted by farmers in the plain.

Table 2: *Farmers' perception on climate variability (n=123).*

Climate variable	*Trend*	*Percentage*
Temperature	Increasing	72.36
	Decreasing	5.69
	No change	21.95
Rainfall	Increasing	12.2
	Decreasing	46.46
	No change	41.46
Drought	Increasing	57.72
	Decreasing	4.88
	No change	37.4
Floods	Increasing	80.49
	Decreasing	2.44
	No change	17.07

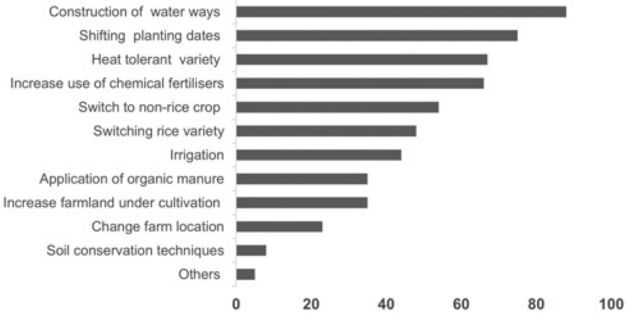

Fig. 2: *Adaptation strategies adopted by farmers in Ndop plain*

Table 3: *Farm and household characteristics for adapters (A; n=88) and non-adapters (NA; n=50).*

		Adapters		Non-Adapters		
Variable	*Description*	*Mean*	*SD*	*Mean*	*SD*	*MD A/NA*
Adaptation	1= adapted; 0= otherwise	1	0	0	0	
Gender	1= male; 0= female	0.43	0.5	0.64	0.5	-0.21^{*}
climate belief	1= belief climate change; 0= otherwise	0.99	0.1	0.72	0.5	0.27^{***}
Age	farmers' age (year)	46.2	6.8	57.8	7.4	-11.59^{***}
Household-size	1= household >5; 0 otherwise	0.93	0.3	0.58	0.5	0.35^{***}
Education	1= attended primary education; 0 otherwise	0.91	0.3	0.52	0.5	0.39^{***}
Extension service	1= receive extension service; 0 otherwise	0.6	0.5	0.02	0.1	0.46^{***}
Income level	Annual income (000 XAF)	757	251	476	151	280.61^{***}
Other income	1= income from off-farm activities; 0 otherwise	0.75	0.4	0.18	0.4	0.57^{***}
Farm-size	Household farm size	1.44	0.6	1.14	0.5	0.30^{**}
Seed variety	1= access improved seed variety; 0 otherwise	0.83	0.4	0.18	0.4	0.65^{***}
Farm experience	Years of rice production	9.7	3.1	13.8	3.5	-4.12^{***}
Input	Amount on farm inputs	51.9	7.3	51.8	7.7	0.075
Output	rice produced	2810	738	1638	380	1172.23^{***}
Credit access	1= access to credit; 0 otherwise	0.61	0.5	0.08	0.3	0.53^{***}
Farm group	1= farmer's group member; 0 otherwise	0.87	0.3	0.3	0.5	0.57^{***}
Drought	1= affected by drought; 0 otherwise	0.75	0.4	0.34	0.5	0.41^{***}
Floods	1= affected by floods; 0 otherwise	0.89	0.3	0.6	0.5	0.29^{***}

3.3 *Drivers of adaptation to climate change*

The factors controlling farmers' adaptation decision and its impact on farmers' output are estimated by FIML and presented in Table 4. The results show that access to credit and farmers' age significantly influences farmers' decision to adapt to climate change with $p < 0.01$. However, access to credit positively influence farmers' decision to adapt, while farmers' age is negatively related. Other incomes received by the farmer, extension service, and farmers' grouping also positively influences farmers' decision to adapt at $p < 0.05$ level of significance. Extreme weather events also positively influence farmers' decisions. The incidence of drought significantly influence adaptation at $p < 0.05$ while floods considerably controls farmers' decision at $p < 0.01$.

3.4 *Impact of adaptation on farm output*

The correlation coefficient (ρ_A and ρ_{NA}) are both negative for adapters and non-adapters but statistically significant for adapters with $p = 0.024$. Only farm size significantly explain higher yields for both adapters and non-adapters while farmer's age and credit access have differential impact on rice yield (table 4).

Table 5 presents a linear regression of farmers' output and adaptation. Here, output significantly depend on adaptation with $p < 0.001$. The causal effect of adaptation on rice yields is presented in table 6. The table presents estimates for the average treatment effect (ATT), the average treatment effect on the untreated (ATU) and the heterogeneity effect (HE).

4 Discussion

Ndop plain is exposed to climate hazards. As established in table 2, farmers in the plain perceive climate change through increasing temperatures and increasing extreme events of floods and droughts. This is confirmed by meteorological evaluations of Cordelia (2019). This study observed that many farmers were conscious of climatic changes and had undertaken one or two measures to cope with such changes. Maintenance of drainage patterns is widely practiced by farmers in the plain to control floods and irrigate rice fields during dry periods (Fig. 2). This agrees with the work of (Kongnso *et al.*, 2020). Most farmers equally shift planting dates following the onset of the rains, while many others plant improved seed variety such as NERICA (New Rice for Africa). Increase use of chemical fertilisers is also seen amongst farmers.

Table 4: *Farmers' perception on climate variability (n=123).*

Explanatory variables	*Adapt. (Y)*	*Rice output (log)* A (Y)	*Rice output (log)* NA (Y)
_Cons	-12.1	5.684^{***}	4.222^{***}
	(8.409)	(0.668)	(0.796)
inputs	2.67	0.377^{**}	0.706^{***}
	(1.88)	(0.157)	(0.173)
Age	-0.116^{***}	0.00987^{***}	0.000935
	(0.045)	(0.003)	(0.004)
Education	-0.0817	0.0177	0.0364
	(0.675)	(0.085)	(0.06)
Household-size	-0.908	-0.0245	-0.0184
	(0.861)	(0.095)	(0.061)
Credit access	2.844^{***}	0.181^{***}	-0.116
	(0.942)	(0.047)	(0.105)
Other income	1.747^{**}	0.0401	0.0662
	(0.715)	(0.048)	(0.073)
Farm-size	1.445	0.136^{***}	0.188^{***}
	(0.965)	(0.041)	(0.061)
Seed variety	0.604	0.0704	0.0678
	(0.745)	(0.069)	(0.076)
Drought	1.253^{**}	-0.0047	-0.0519
	(0.592)	(0.049)	(0.057)
Floods	3.517^{***}	-0.0763	0.119^{**}
	(1.327)	(0.073)	(0.059)
Farm group	1.799^{**}		
	(0.705)		
Extension service	2.360**		
	(0.969)		
σ_A		-1.613^{***} (0.081)	
σ_{NA}			-1.699^{***} (0.107)
ρ_A		-0.672^{**} (0.297)	
ρ_{NA}			-0.287 (0.365)

Adapt. = Adaptation; A = Adapters; NA = Non-Adapters
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$ (significant at 10 %, 5 % & 1 %); Standard Error in parenthesis

Table 5: *Linear regression for farmers' output.*

Variable	Coefficients	*Std.Err.*
_Cons	-108.85	419.96
Adaptation	701.91^{***}	170.35
Age	20.99^{**}	6.63
Education	139.16	131.78
Household size	-58.78	142.27
Credit	363.86^{**}	113.57
Other income	103.91	110.48
Farm group	44.36	120.62
Farm size	349.28^{***}	90.59
Seed variety	70.88	133.19
Extension	428.64^{***}	122.15
Drought	-20.80	102.84
Floods	34.83	125.30
R^2	0.66	
F-stat	20.07	
N	138	

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$ (significant at 10 %, 5 % & 1 %); Standard Error in parenthesis.

Table 6: *Farmers' perception on climate variability (n=123).*

Sample group	*Adaptation statue* A	*Adaptation statue* NA	*Treatment effect*
A HHs	2707.598	1866.424	$TT=841.174^{***}$
	(26.72)	(14.05)	(1.791)
NA HHs	2526.97	1783.662	$TU=743.308^{***}$
	(12.21)	(21.51)	(1.19)
Het. eff.	180.628^{***}	82.762^{***}*	
	(0.299)	(0.169)	

A HHs = Adapting households; NA HHs = Non-Adapting households; Het. eff. = Heterogeneity effects
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$ (significant at 10 %, 5 % & 1 %); Standard Error in parenthesis.

4.1 Drivers of adaptation to climate change

Farmers' decision to undertake adaptation is significantly controlled by access to credit. The positive significance of this factor indicates that farmers with access to credit are more likely to employ adaptation measures. This significant result is in line with Ateka *et al.* (2021), and underlines the role of finance and credit in the adaptation process of climate change. Adaptation often requires huge capital investment. Financial exclusion of the local population negatively affects sustainable rice production and exacerbate the level of poverty (Abraham & William 2018; Ofeh & Thalut, 2018). Financial systems should be more concern with climate crises given that clients may one day be hit by climate change and may be unable to pay their bank loans. Central bankers need to creatively employ the enormous powers at their disposal and use its monetary policies to promote activities that help prevent climate change (Dikau & Volz, 2021). Improved mechanisms towards financial inclusion of farmers will be a beneficial process by which financial services are made easy and available to rice farmers. In the same way, farmers involved in off-farm activities were more likely to undertake adaptation, perhaps due to supplementary incomes from other sources. This agrees with Abdulai & Huffman (2014). Oppong & Bannor (2018), also argue that off-farm job participation is one of the main climate change adaptation strategy for small-scale, rain-fed dependent rice farmers in Upper Volter Ghana. Farmers should therefore be given training to available off-farm job opportunities to reduce the adverse impact of climate change on their livelihood (Ofeh & Thalut, 2018).

The positive and significant relationship between extension services and adaptation also imply that, farmers with reliable extension service contacts were more likely to implement adaptation strategies to cope with climate change than farmers with no access to extension services. This perhaps, is closely linked to the role of access to information and other resources that empower the farmer to adopt some climate risk coping strategies (Belay *et al.*, 2017). This is also in line with Maponya & Mpandeli (2013), who observed that, the odds of being affected by climate change is higher for farmers who receive information from extension service in South Africa than those who do not. Extension service involves monitoring and evaluating the performance of farmers. Participatory extension approach opens farmers to research and development on the one hand and places them at the center of research on the other (Deressa *et al.*, 2009; Kongnso *et al.*, 2020).

This study also advance that, a unit increase in membership of farm group is more likely to increase the probability of adaptation. This is possibly due to the farmers' open access to shared information and innovations (Brown & Denis, 2015; Junior & Wander, 2021). Local farmers' groups commonly bring together members with the goal of enhancing their strength and ability through capacity building programs that break down technicalities involved in adaptation mechanisms. Moreover, commitment with farmers' organisations generally encourages collective thinking, farmer-to-farmer communication and corporate adaptation practices which reduce the heavy burden of adaptation by an individual farmer (Karim & Thiel, 2017). Strengthening local farm organisation consequently increases the probability of adaptation.

The climate related variable (drought and floods) also indicate strong positive influence on farmers' adaptation decision in the study area. The significance of these variables is evident that the adaptation measures implemented by farmers are correlated with climate change. The positive significance of droughts and adaptation suggests that farmers affected by drought are more likely to implement adaptation measures on their farms following dryer conditions. The incidence of drought pushes affected households to adjust their farm management processes in respond to such eventualities (Chen *et al.*, 2014). Similarly, farmers affected by floods over the years were even more likely to develop adaptation mechanisms that can reduce effects of flood hazard. Recurrent flooding in the plain often caused severe damages on crops as many hectares are washed away, leading to lower output. The recurrent flood occurrence along with severe damages significantly shapes farmers' decision to implement innovative technologies that inherently deal with present and future flooding events. These findings are in line with Huang *et al.* (2015) in their China based study and Khanal *et al.* (2018) in Nepal, who suggested that farming households affected by drought and floods were more likely to employ climate change adaptation strategies on their farms. Alauddin & Sarker (2014) reported that, the greater the severity of drought, the greater the likelihood of farmers adopting supplementary irrigation and switching to water saving non-rice and horticultural crops.

The age of the farmers in this study had a significant inverse relationship with farmers' adaptation decision. This implies that the probability of adaptation significantly decreases with age of the farmer. This is consistent with khanal *et al.* (2018). It can be predicted that older farmers lack the incentive or interest to adopt climate change adaptation measures. Most of them may simply lack the ability to engage into adaptation practices that sometimes require physical strength. Moreover, older farmers may be more attached to traditional farming methods familiar to them than adopting modern techniques which are resistant to climate change (Kim *et al.*, 2017; Ateka *et al.*, 2021).

Contrary to our expectation, farmers' education, availability of improved seed variety, farm and household size were statistically insignificant in the model. In certain ways, these results are surprising in the light of the rhetoric and theory surrounding their use as a development instrument in the general case of climate change adaptation strategies (Kanburi *et al.*, 2019; Deressa *et al.*, 2009). Turning towards a deeper look at the literature surrounding these variables, we can theorise that, increasing knowledge does not change social behaviour of many people. Many are aware of environmental issues better than before, yet continue to act in unsustainable ways. Many farmers are reluctant to change. They remain attached to indigenous knowledge with little or no consideration of adaptation. These behaviours agree with Kahneman (2002 Nobel Memorial Prize winner), who argues that rationality is impossible with finite minds (Kahneman, 2003). Following Kollmuss & Agyeman (2002), other factors such as perceived barriers to change, personal relevance and social norms are more important predictors to behaviour than knowledge. Household-size may also be insignificant following population dynamics and climate change. Population growth weakens the capacity of poor communities to adapt to climate change. Moreover, mass migration owing to climate change may significantly reduce available labour required for adaptation (Stephenson *et al.*, 2010). Further research with a larger sample may however present different results. Nonetheless, the positive relationship with adaptation reveals that adaptation increases with a unite change in household size.

4.2 *Impact of adaptation on rice output*

A simple independent-sample t-test was applied to check the impact of adaptation on rice yield for each group of adapters and Non-adapters. The statistics indicate that households who adapted significantly produce on average 1172 kg ha-1 more than household who did not adapt (table 3). This significant difference may be meaningful but not reliable to measure the effective impact of adaptation on rice yield (Abdulai *et al.*, 2014). We also estimate a linear regression on production including adaptation as a dummy variable. The results show a positive and significant impact of adaptation on rice yield, showing that farmers' output is highly dependent on adaptation (table 5). However, this simple approach is limited by its assumption that adaptation is exogenously determined, meanwhile it is potentially endogenous. Results may be misleading as the differences might have been caused by unobserved characteristics of the farmer (Di Falco & Veronesi, 2013).

We therefore employ the endogenous switching regression model with FIML which simultaneously estimate the selection equation and the outcome equation to yield consistent standard errors as mentioned above. According to the results presented in table 4, columns 3 and 4 respectively for adapters and non-adapters, ρ_A is statistically significant for adapters, indicating self-selection in adaptation. Thus, adaptation may not have the same effect on non-adapters if they choose to implement adaptation (Kanburi *et al.*, 2019). The negative sign indicate positive bias, suggesting that farmers who choose to implement adaptation measures have higher yields than a random individual from the sample would have. Farmers with output greater than average, therefore have a higher probability of implementing adaptation (Abdulai & Huffman, 2014). The insignificance of the covariance term for non-adapters suggest that in the absence of adaptation, there will be no significant difference in the average output of the two categories of farmers caused by unobservable factors. The difference between the coefficients of the rice yield equation and the outcome equations indicate the presence of heterogeneity. $\rho_A < \rho_{NA}$ showing that adaptation increases farmer's output greater than they would without adaptation (Khanal *et al.*, 2018).

The estimation of the treatment effect presented in table 6, indicate that the expected rice output produced by the group of farmers who adapted to climate change is approximately 2707.5 kg ha^{-1}. On the other hand, the expected output produced by households who did not adapt is about 1783.6 kg ha^{-1}. This implies that adapting households produced averagely 923 kg ha^{-1} (49 %) more than non-adapters. Unlike the mean difference presented in table 3 which may confound the impact of adaptation decision on rice yield with the influence of other farm/household characteristics, the treatment effect account for selection bias stemming from the fact that adapters and non-adapters may be systematically diverse. The adapting households would have produced only about 1866.4 kg ha^{-1} on average if they decided not to adapt. Similarly, if the non-adapting households had decided otherwise i.e. adapted, the expected outcome of their production would increase to about 2526.97 kg ha^{-1}. The treatment effect therefore indicates that farming households who actually adapted increased output by 841 kg ha^{-1}(45 %) and households who actually did not adapt would have increased output by 743 kg ha^{-1} (41 %) if they had implemented adaptation. The heterogeneity effect indicates that there exist some source of diversity amongst farmers which make adapting households better producers than non-adapting households. This finding is consistent with (Kanburi *et al.*, 2019; Huang *et al.*, 2015) and submit that employing resilient adaptation measures against climate change significantly increase rice output in the region. This is evident with the increasing output reported by UNVDA, from 3,565 tons in 1995 to 20,000 tons in 2017.

5 Conclusion and recommendation

Farming systems around the world have been facing increasing adverse effects on farm productivity owing to environmental constraints like climate change. This study uses farm level information to investigate the driving forces behind farmer's decision to adapt to climate change and the impact on farm productivity. Adaptation to climate changes in the Ndop plain significantly increases farmers' output. Thus, farmers can increase rice supply by systematically employing strategic adaptation measures on their farms. Building strong climate resilience amongst rice farmers in Ndop plain requires new level of consensus and a call for action amongst stakeholders to improve rice productivity in Cameroon. Specifically:

- Financial service towards credit accessibility should be improved with flexible policies developed to include local rice farmers. Meanwhile farmers should create local farming groups, otherwise known as the focal points for adaptation providing easy access to credits, communication and technology transfer.

- Extension service that promote information flow between research development and farmers should be developed to include technical systems transmitting reliable information to farmers. By the same token, local authorities should map out constructive plans towards water management with farmers actively involved in decision making.
- Young farmers should be given the incentive to engage into rice farming, implement innovative ideas and develop new rice fields with upland farming to reduce the risk of flood disasters.

While adopting a single or combination of these adaptation strategies reduces vulnerability amongst farmers, government's intervention in planning adaptation taking into account, controlling factors is crucial for the development of rice production and the enhancement of food security in Cameroon. While this study cuts across farmers' adaptation decisions and controlling factors, further research is encouraged using a multinomial logit model to investigate how adaptation of each strategy may affect adaptation, taking into account other strategies.

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Conflict of interest

The authors declare that they have no conflict of interest.

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