Analysis of perception and adaptation of maize–based farming households to climate change in Nigeria

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The problem of climate change is becoming more threatening to sustainable economic development. The fact that climate has been changing in the past and will change in the future emphasises the need to understand how farmers perceive climate change and adapt to it in order to guide strategies for adaptation in the future. This study examines perception and adaptation to climate change of maize-based farmers in three agro–ecological zones of Nigeria using data from a cross sectional survey of 346 farming households selected through a multistage sampling technique. The study re-affirmed male dominance in maize production with about 90.8% of the farmers being male, while about 54.6% were between the productive ages of 41 – 60 years with a mean age of 45 years. About 47.4% of the farmers had no formal education, while the average number of years of formal education was 6.5. Results showed that 81.5% of the sampled maize farmers had perceived changes in climatic variables and 68.5% had employed adaptation measures. Econometric estimation of Heckman probit model revealed that the likelihood of farmers perceiving changes in climate was positively and significantly influenced by farming experience, access to extension agents, farm income and agro-ecological settings, while farming experience, distance to market centre, access to extension agents and farm income increase the probability of adapting to climate change. Policy focus should be awareness creation as well as improved farmers' knowledge through extension agents, social network and NGOs and strengthening of credit institutions.

Keywords: Perception, adaptation, climate change, maize, farmers, Heckman–probit model, Nigeria

Agriculture contributes about half of the global emissions of two of the most potent greenhouse gases: nitrous oxide and methane (World Bank 2008). Application of fertilizers, rearing of livestock and related land clearing are some agricultural activities that influence both levels of greenhouse gases in the atmosphere and the potential for carbon storage and sequestration (Mark et al. 2008). In Africa, estimates indicate that around 60 – 70% of the population is dependent on the agricultural sector for employment, and the sector contributes on average nearly 34% to gross domestic product (GDP) per country (Adams et al. 1993). In Nigeria, agriculture contributed 41.25% of GDP in 2005 (Central Bank of Nigeria 2005) and has been declining since then i.e 25.08% in 2017 and 25.13% in 2018 (National Bureau of Statistics 2018). The agricultural sector in Nigeria is highly sensitive to rainfall pattern especially in southern Nigeria where rain-fed agriculture is mainly practiced. It has been predicted that climate change will pose a serious threat to food security. Ayinde et al. (2010) opined that climatic fluctuation is putting Nigeria's agriculture system under serious threat and stress. Over 60% of the Nigerian populace depends on agriculturally related activities for sustenance and crop production is a significant aspect of these activities; crop production contributes more than 80% of agricultural GDP and more than 48% of total non–oil GDP in Nigeria (Central Bank of Nigeria 2011).

Many people and most households in Nigeria depend on cereals (especially, maize) as a contributing, if not principal, source of food and nutrition (Central Bank of Nigeria 2005). Maize has been in the diet of Nigerians for centuries. It started as a subsistence crop and has gradually become a more important crop. Maize is now a commercial crop on which many agro–based industries depend for raw materials (Iken and Amusa 2004). Increases in maize production in Nigeria have been achieved by expansion in area harvested

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rather than increases in yield. The area harvested increased from 2.8 million ha in 1986 to over 3 million ha in 2000 and over 6 million ha in 2011 (Olaniyan 2015). Despite its high yield potential, maize production is faced with numerous constraints. One of the major constraints is intermittent droughts during the growing season which significantly reduce maize yield (Ayanlade et al. 2007). Evidence of the devastating effect of climate change on Nigerian agriculture in the past included the drought of 1972 – 73, in the northeastern of Nigeria where about 300,000 animals, representing 13% of the livestock population of the north-eastern region, were reported to have died, while agricultural yield dropped to between 12% and 40% of the annual averages (Fagbemi 2002). The effects of drought in terms of reduced food production are believed to have been even more severe between 1982 and 1984 than in the 1972 – 73 period. In some parts of Borno state, nearly 100% crop losses were recorded (Enabor 1987). The poor households that are affected by drought and desertification do not have adequate resources to deal with food shortages leading to food insecurity and hunger that affect millions of people. Recent estimates suggest that, in the absence of adaptation, climate change could result in a loss of between 2 – 11% of Nigeria's GDP by 2020, further rising to between 6 – 30% by 2050. This loss is equivalent to between ₦15 trillion (US$75 billion) and ₦64 trillion (US$325 billion) (DFID/ERM 2009).

The overall effect is possible rapid decline in food production in the face of rapid population growth in Nigeria. However, farmers are quite conscious of these challenges and are expected to put up diverse coping strategies. The effectiveness of these strategies goes a long way in determining the diversities and level of impact of climate change on the production of a notably strategic crop such as maize. Adaptation is an important component of climatic change impact and vulnerability assessment and is one of the policy options in response to climatic change impacts (Smith and Lenhort 1996, Fankhauser 1996). The awareness of climate problems and the potential benefits of taking action are important determinants of adoption of agricultural technologies (Hassan and Nhemachena 2008). Maddison (2006) argued that farmer awareness of change in climate attributes (temperature and precipitation) is important to adaptation decision making.

Studies have shown that the perception or awareness of climate change and taking adaptive measures (Maddison 2006, Hassan and Nhemachena 2008, Gbetibouo 2009) are influenced by different socio-economic and environmental factors.

Adaptation to climate change is a two-step process, which initially requires the perception that climate is changing and then responding to changes through adaptation (Maddison 2006). This two-step process of adaptation was addressed by Maddison (2006) at the regional level for Africa using Heckman probit model (Heckman 1976). However, results from that study are highly aggregated and hence have little relevance for addressing country-specific perception and adaptation to climate change. Similarly, this study adopted the Heckman-two step procedure but differed by conducting a farm level adaptation survey that is specific to agro-ecological zones in Nigeria. The major objective of this study was to analyse the perception and adaptation of maize–based farmers to climate change in three agro–ecological zones of Nigeria.

Materials and methods

Study area

The study area is Nigeria, one of the sub-Saharan African nations in the western part of Africa. It shares land borders with the Republic of Benin to the west, Chad and Cameroon to the east, Republic of Niger to the north, and its coast lies on the Gulf of Guinea. The total land area of Nigeria (923,766 km^2) is divided into seven broad ecological or land resource zones:

mangrove swampy forest, rainforest, montane forest/grassland, derived savanna, guinea savanna, sudan savanna, and sahel savanna. The categorization is based on the similarity of climate and vegetation cover as well as the type of crops that are adapted to each land area. With the exception of the montane region, both the length of wet season and temperature increase from the coast to the hitherland. In this categorization no state of the federation can boast of one ecological zone and a state may have up to three ecological zones. All zones support maize production.

Type and sources of data

The study employed both primary and secondary data. Primary data were collected with the aid of a structured questionnaire. Data were collected on different household and farm characteristics, infrastructure, and institutional factors that influence the use of adaptation methods by farmers. Household characteristics included age, education, farming experience, marital status, gender of the head of the household, farm income and non-farm income. Farm characteristics included farm size, distance to farm and yield. Institutional factors included access to extension services on crop production, information on climate, access to credit and social capital which include farmer-to-farmer extension services. Finally, data were collected on farmers' perceptions of short– and long-term climate change and their adaptation strategies in response to these. Secondary data on climate variables that is temperature and rainfall for 41 years (1970 – 2011) were employed in the study. Rainfall is the most important climatic measure in terms of meeting water requirements of agricultural crops. The metrological data were obtained from the Nigerian Metrological Agency in Oshodi, Lagos State. Averages of temperature and rainfall for the 41-year period were pooled to allow enough variation in the data set. Their averages for the two predominant seasons (dry and rainy) in the country were estimated for the 41-year period.

Sampling procedure

A multistage sampling technique was employed for this study. In the first stage, three major maize producing states were purposively selected to represent agro-ecological zones (Niger: guinea savanna; Taraba: montane savanna and Oyo: derived savanna). The second stage was the selection of four local government areas (LGAs) with the highest maize production in each of the states (2015 production). Thirdly, five villages were randomly selected from each LGA and lastly 400 maize-based farming households were randomly selected from the list of maize producing farmers obtained from the Agricultural Development Programme (ADP) of each zone in a proportionate sampling method. The sample size of respondents in each state was determined by probability proportional to size of farm families. The total sample size of respondents for the study was determined using (Bowley's 1977 quoted in Nzelibe 1999) proportionate sample formula assuming a 95% confidence interval as shown below:

$$S_{total} = \frac{N}{1 + N(e^2)} \quad \text{......... 1}$$

Where

S_{total}= Sought total sample size of all respondents

N = Total population of farming households in the three states (Oyo, Niger and Taraba)

e = level of significance (confidence interval i.e 0.95)

The sample sizes in each state, zone, and village were determined by probability proportional to size of farming households in each sampling unit respectively.

Although a total of 400 questionnaires were administered on the respondents, 54 of these were found unsuitable for analysis and consequently, data from 346 questionnaires were analyzed for the study.

Analytical tools

This study made use of descriptive and inferential statistics. The descriptive statistics included frequency distributions, means, percentages and standard deviations. These were used to profile socioeconomic variables, production practices, and information on climate change, perception indicators, adaptation methods and constraints to adaptation.

Heckman probit model

Adaptation to climate change involves a two–stage process: first perceiving change and then deciding whether or not to adapt by taking a particular measure. This leads to sample selectivity problem since only those who perceive climate change will adapt. Following Maddison (2006) and Gbetibouo (2009) Heckman's sample selectivity probit was selected which is based on the following two latent models:

$$Y_1 = \beta' X + \mu_i \qquad \text{.........2}$$

$$Y_2 = \propto' Z + \mu_2 \qquad \text{........3}$$

Where, X is a k– vector of regressors, Z is an m–vector of repressors; possibly including I's for the intercepts, and the error terms μ_i and μ_2 are jointly normally distributed, independently of X and Z, with zero expectations. Although, the primary interest is the first model, the latent variable Y_1 is only observed if $Y_2 > 0$. Thus, the actual dependent variable is:

$$Y = Y_1 \; if \; Y_2 > 0, Y \; is \; a \; missing \; value \; if \; Y_2 \leq 0 \text{.....4}$$

The latent variable Y_2 itself is not observable, only its sign. $Y_2 > 0$ if Y is observable, and $Y_2 <= 0$ if not. Consequently, one may without loss of generality normalize μ_2 such that its variance is equal to 1. If one ignores the sample selection problem and regress Y on X using the observed Y's only, then the OLS estimator of β will be biased, because:

$$E[Y_1 | \, Y_2 > 0, X, Z] = \beta' X + rsf(\propto' Z) | \, F(\propto' Z) \text{......5}$$

Where F is the cumulative distribution function of the standard normal distribution, f is the corresponding density, s^2 is the variance of μ_1, and r is the correlation between μ_1 and μ_2.

Hence:

$$E[Y_1 | \, Y_2 > 0, X] = \beta' X + rsE[f(\propto' Z) | \, F(\propto' Z) | X] \qquad \text{.........6}$$

The latter term causes sample selection bias if r is non–zero. In order to avoid the sample selection problem, and to get asymptotically efficient estimators, one has to estimate the model parameters by maximum likelihood.

Model variables

The first stage of the Heckman sample selection model is the perception to changes in climate and this is the selection model, while the second stage model is whether the farmer adapted to climate change, conditional on the first stage that he perceived a change in climate. This second stage is the outcome model.

Dependent variable for the selection equation

Y_1 = perceived climate change (1=yes, 0 otherwise)

Explanatory variables for the selection equation (perceptions model)

X_2 = age of household head (years)
X_4 = education of household head (years)
X_6 = farming experience (years)
X_{10} = access to extension agents (1= yes, 0 otherwise)
X_{11} = access to other source of climate information (1= yes, 0 otherwise)
X_{13} = farm income (Naira)
X_{14} = non–farm income (Naira)

Agro–ecological zone dummies

X_{16} = derived savanna (1 = yes, 0 otherwise)
X_{17} = guinea savanna (1= yes, 0 otherwise)
X_{18} = montane savanna (1= yes, 0 otherwise)

Dependent variable for the outcome equation

The dependent variable for the outcome equation is whether a farmer has adapted or not adapted to climate change.

Y_2 = *adapted to climate change (1=yes, 0 otherwise)*

Explanatory variables for the outcome equation (adaptation model)

The explanatory variables were selected based on Maddison (2006) and Gbetibouo (2009).

X_1 = gender of household head (1= male, 0 otherwise)
X_2 = age of household head (years)
X_3 = household size (number)
X_4 = education of household head (years)
X_5 = farm size (ha)
X_6 = farming experience (years)
X_7 = distance to output market (km)
X_8 = distance to input market (km)
X_9 = livestock ownership (1=yes, 0 otherwise)
X_{10} = access to extension agents (1= yes, 0 otherwise)
X_{11} = access to other source of climate information (1= yes, 0 otherwise)
X_{12} = access to credit (1=yes, 0 otherwise)
X_{13} = farm income (Naira)
X_{14} = non–farm income (Naira)
X_{15} = land tenure (1= land ownership, 0 borrowed land)

Agro–ecological zone dummies

X_{16} = derived savanna (1 = yes, 0 otherwise)
X_{17} = guinea savanna (1= yes, 0 otherwise)
X_{18} = montane savanna (1= yes, 0 otherwise)

Climate variables

X_{19} = mean monthly temperature (^{o}C)
X_{20} = mean monthly rainfall (mm)

Results and discussion

Farm and farm household characteristics

The results (Table 1) indicate that 81.5% of the sampled maize farmers claimed to have observed a change in temperature and rainfall over the years; 68.5% of those who claimed to have observed changes in climate said they have adopted adaptive measures. Results showed an overall male dominance of 90.8%. Male dominance has severally been attributed to the laborious nature of peasant farming due to high dependence on manual labour. Also limited access to production incentives by women has also made men the major actors. This is mostly the case in developing countries agriculture where the farming system is predominantly patriarchal in nature with both males and females contributing their labour input, but males playing dominant roles due to their greater access to farm resources (Okoruwa et al. 2009). The average age of the maize farmer was 45 years. This depicts an active and productive population of maize crop farmers in the study area with greater possibility for the supply of physical strength and mental alertness which is capable of increasing the potential for improved productivity. The mean years of farming experience was 25.56 ± 12.69. This indicates that most of the farming households have been practising farming for a long time and implies that they are expected to have more knowledge and information about climate change and other agronomic practices that they can use in response to climate change. According to Maddison (2006) and Hassan and Nhemachena (2007), experience in farming increases the probability of uptake of adaptation measures to climate change. The years of educational attainment was found to be low with mean years of schooling of 6.5. The low level of education depicts a scenario which is capable of undermining the potential for improved productivity. Sampled households had an average size of eight persons and farm size of

3.31 ha. The average maize yield was estimated at 3.01 t/ha which is lower than the expected yield of 5 – 6 t/ha depending on the maize hybrid (CGIAR 2010). The average distances of product and output market places to the farms were 7.90 and 7.45 km respectively. About 58.5% of the respondents had access to extension services and 55% had access to other sources of climate change information. According to Maddision (2006) access to information on climate change through extension agents or other sources creates awareness and favourable conditions for adoption of farming practices that are suitable under climate change. Access to credit was available to 52% of the maize farmers and 31% owned livestock which they used as an alternative source of farm income to cushion the adverse effect of climate change. Average annual farm income was ₦262,720.81 (US$1,318.58) and annual non–farm income was ₦97,913.70 (US$491.42). This implies that sampled farmers engaged in non–farming work to cushion the adverse effect of climate change on maize production. The average annual rainfall for the 41 years (1970 – 2011) was 1035.2 mm, while average annual temperature for the same period was 32.2 ^{0}C.

Table 1: Summary statistics of the samples

Dependent variable (1)	Farmers perceived changes in temp/rainfall	Farmers not perceived changes in temp/rainfall
	(%) 81.5	(%) 17.5
Dependent variable (2)	Farmers adapted	Farmers not adapted
	%	%
Adaptation to climate change	68.5	31.5
Independent variables	mean	Standard deviation
Age of household head (years)	45.14	10.45
Farming experience (years)	25.56	12.69
Education of household head (year)	6.46	4.40
Household size (number)	8.33	4.28
Farm size (ha)	3.31	2.52
Maize yield (t/ha)	3.01	2.64
Distance to output market (km)	7.90	3.39
Distance to input market (km)	7.45	2.59
Farm income (Naira)	262,720.81	80,747.68
Non –farm income (naira)	97,913.70	34,304.82
Mean annual rainfall (mm)	1035.2	214.2
Mean annual temperature (^{o}C)	32.2	2.05
Aggregate measures	**%**	
Gender (male headed)	90.8	
Livestock ownership (dummy)	31	
Access to extension agents (dummy)	58.4	
Other sources of information on CC (dummy)	56.4	
Access to credit (dummy)	52	

Perception of climate change by agro–ecological zones

Table 2 presents the farmers' perceptions of long term climate change by agro–ecological zones. Results indicate that significant number of farmers in the three agro–ecological zones; derived savanna (48.1%), guinea savanna (65.2%) and montane savanna (75.9%), said that the temperature had increased over the years. By contrast, 15.8%, 10.6% and 7.6% of farmers in derived, guinea and montane savanna respectively said that temperature had decreased. Farmers in montane savanna recorded the lowest percentage in terms of decreased temperature (7.6%), altered temperature change (3.8%) and no change in temperature (2.5%) than their counterparts in other agro–ecological zones.

The result for rainfall (Table 2) shows a similar pattern across the three agro–ecological zones. The majority of the farmers in the three agro–ecological zones; derived savanna (59.4%), guinea savanna (68.6%) and montane savanna (77.1%) said that rainfall had decreased over the years. By contrast 5.3% and 1.7% of the farmers perceived increase in rainfall for derived and guinea savannas respectively, while none of the sampled farmers in montane savanna said that rainfall had increased. A change in timing of the rains was the perception of 25.6% of the farmers in derived savanna, 22.5% of farmers in guinea savanna, while only 10.1% of the respondents in the montane savanna said the same. In addition, 11.7%, 8.2% and 13.9% of the farmers in derived, guinea and montane respectively said they had lived through a change in the frequency of droughts, while 11.7%, 8.2% and 1.3% of farmers in derived, guinea and montane respectively said that there is no change in rainfall pattern. From the above it suggests that farmers have perceived change in climate which is a basic precondition for adaptation.

Table 2: Perception of climate change by agro–ecological zones (% of respondents)

Perception	Derived	Guinea	Montane
Increased temperature	48.1	65.2	75.9
Decreased temperature	16.8	10.6	7.6
Altered temperature change	12.8	15.0	3.8
No change in temperature	8.5	9.2	2.5
Increased rainfall	5.3	1.7	0.0
Decreased rainfall	59.4	68.6	77.1
Change in timing of rains	25.6	22.5	10.1
Change in frequency of drought	11.7	8.2	13.9
No change in rainfall	11.7	3.5	1.3

Where temperature change responses do not add to 100% some respondents did not answer or did not know

Determinants of perception and adaptation of maize farmers to climate change

Results in Table 1 showed that the majority (81.5%) of the maize farmers interviewed claimed that they had perceived at least one change in climatic attributes, 31.5% of these farmers did not respond by taking adaptation measures. However, it is argued that farmers who perceived climate change but did not adapt had some common characteristics. Examining these characteristics could improve our understanding of the reasons underlying their failure to respond to perceived climate changes, based on the results of the Heckman probit model. Principal component analysis was used to generate a perception index from among the perception indicators. The model was checked for the problem of multicollinearity among the independent variables. All 20 variables included in the model were checked for multicollinearity using variance inflation factors (VIF); A VIF value greater than 10 may need further investigation. A tolerance (I/VIF) value lower than 0.1 is comparable to a VIF of 10 which means that the variable could be considered as a linear combination of other independent variables. The results showed that VIF for all variables were less than 10 (1.22 – 8.27) and tolerance values were higher than 0.1. This indicated that multicollinearity is not a serious problem in the model estimation. The model was also tested for the presence of heteroscedasticity using White's test (White 1980) and the Breusch–Pagan test (Breusch and Pagan 1979). Both test the null hypothesis that the variance of the residuals is homogenous. Results showed that P values on both tests are higher than the threshold (P >0.05). Thus, the null hypothesis of homogeneity of variance is rejected. These tests are very sensitive to model assumption, such as the assumption of normality (see Appendix 1).

The likelihood function of the Heckman model was significant (Wald $\chi^2 = 63.45$, $P \leq 0.001$) indicating the strong explanatory power of the model. Rho was significantly different from zero (Wald $\chi^2 = 10.06$, $P \leq 0.001$) indicating the presence of a sample selection problem, thus justifying the use of the Heckman probit model. Most of the explanatory variables and their marginal values were statistically significant ($P \leq 0.01$), ($P \leq 0.05$) and ($P \leq 0.1$). The calculated marginal effects measure the expected changes in the probability of both perception of climate change and adaptation with respect to a unit change in an independent variable.

The results from the selection model (Table 3) which analyses the factors affecting the perception of maize farmers to climate change shows that farming experience, access to extension agents, farm income and the agro-ecological zones in which farmers are located influence the likelihood of perceiving climate change. As farmer's experience in farming increases by a year, the ability of the farmer to notice change in climate increases by 0.018 units. This indicates that the more experienced farmers would be better at distinguishing climate change from inter-annual variation. This result agreed with the findings of Maddison (2006), who reported that farmers best placed to pronounce on whether climate change has occurred are those who have the most experience of farming. Extension agents' information on climate change increases the perception to changes in climate. This is in line with Maddison (2006) and Deressa et al. 2009 that information on climate change through extension or other public sources increases the likelihood of climate change perception as they play an important role in the availability and flow of information. The result shows that farm income has a positive and significant relationship with farmers' perception of changes in climate; however, the relationship is weak. The local agro-ecological zones of the maize farmers positively influence their perception of climate change. However, there are marked differences in the abilities of the maize farmers from different agro-ecological zones to perceive climate change but this may be because climate change is itself a regional phenomenon. Maize farmers living in the montane savanna agro-ecological zone were 0.367 units more likely to perceive changes in climate than farmers living in derived savanna. Similarly, maize farmers living in guinea savanna were 0.305 units more likely to perceive changes in climate, than farmers living in derived savanna. This finding is similar to the studies conducted by Diggs (1991), Maddison (2006) and Hassan and Nhemachena (2007).

Results from the outcome model (Table 3) show that farming experience, distance to input market, access to extension agents, other source of climate information, farm income and temperature positively and significantly influence the probability of adapting to climate change while age of the household head, distance to output market and rainfall are negatively related to adaptation. A year increase in the age of the household head reduces the probability of adapting to climate change by 0.006 units. The possible reason could be that ageing farmers do not want to take risk in agricultural adaptation while the more productive and energetic young farmer would be more receptive in risk taking by adopting new innovative techniques to reduce the adverse effect of climate change. This result is in agreement with the findings of Shiferaw and Holden (1998), who found a negative relationship between age and adoption of improved soil conservation.

A year increase in farming experience increases the probability of adapting to climate change by 0.007 units. This result corroborates the findings by Maddison (2006), Hassan and Nhemachena (2007), Gbetibouo (2009) and Deressa et al. (2009), that experiences in farming increase the probability of uptake of adaptation measures to climate change.

If the farm distance is far from the output markets the probability of maize farmers' adapting to climate change decreases by 0.022 units whereas the nearer the distance of the farm to input markets increases the probability of adapting to climate change by 0.026 units. Proximity to market is an important determinant of adaptation because the market serves as a means of exchanging information with other farmers (Maddison 2006). As the farmers gain access to climate information from other farmers in the market, it enhances their predictive ability and response actions.

Increased access to extension services on climate change being public extension and private extension, increases the probability of the farmers adapting to climate change by 0.128 and 0.147 units respectively. This emphasizes the importance of social capital in the availability and flow of information in increasing the likelihood of climate change perception and adaptation. This result agreed with the findings of Deressa et al. (2009) and Maddision (2006). Increase in farm income of maize farmers increases the probability of adaptation measures to climate change. This implies that a farmer who earned reasonable income would be in better position to adopt different adaptation strategies. According to Knowler and Bradshaw (2007), adoption of agricultural technologies requires sufficient financial well–being. Thus, if a farmer earned higher income, He/she may be less risk averse and have more access to information and a longer time planning horizon (CIMMYT 1993).

Results further revealed a positive relationship between change in temperature and adaptation by famers. It was found that farmers who noticed a rise in temperature were more likely to adapt, compared to those who did not noticed any rise in temperature. This is because increased temperature on a marginal land or drier agro–ecological zones will compel farmers to adapt to whatever changes in climate they witness. According to Kurukulasuriya and Mendelsohn (2006) adaptation to climate change increases with increasing temperature that is damaging to African agriculture and farmers respond to this through adoption of different adaptation methods. This study found a negative relationship between change in rainfall and farmers' adaptation. This implies that farmers who observed a rise in rainfall were less likely to adapt compared to farmers who noticed a decline in rainfall. Gbetibouo (2009) made a similar observation in her study conducted among smallholder farmers in Southern Africa.

Table 3: Results of the Heckman probit model

	Coefficient	Marginal effects
Selection model (Perception)		
Age household head (X_2)	0.006	0.004
Years of schooling (X_4)	–0.040	–0.003
Farming experience (X_6)	0.018**	0.001**
Access to extension agents (X_{10})	0.463*	0.040*
Other sources of extension information (X_{11})	0.254	0.025
Farm income (X_{13})	0.0002*	0.0001*
Non– farm income (X_{14})	–0.716	–0.057
Guinea savanna (X_{17})	0.305*	0.114*
Montane savanna (X_{18})	0.367*	0.239*
Constant	–1.935	
Outcome model (adaptation)		
Gender of household head (X_1)	– 0.012	–0.017
Age of household head (X_2)	– 0.006**	–0.005**
Household size (X_3)	0.001	0.001
Years of schooling (X_4)	– 0.001	–0.003
Farm size (X_5)	– 0.004	–0.004
Farming experience (X_6)	0.007**	0.006**
Distance to output market (X_7)	– 0.022***	–0.021***
Distance to input market (X_8)	0.026***	0.025***
Livestock ownership (X_9)	–0.034	–0.033
Access to extension agents(X_{10})	0.128*	0.123*
Other sources of extension information (X_{11})	0.147**	0.153**
Access to credit (X_{12})	–0.040	–0.038
Farm income (X_{13})	0.172**	0.228**
Non– farm income (X_{14})	– 0.051	–0.082
Land tenure (X_{15})	–0.143	–0.138
Guinea savanna (X_{17})*	–0.154	– 0.149
Montane savanna (X_{18})*	0.171**	0.165**
Mean monthly rainfall (X_{19})	–0.007***	–0.007***
Mean monthly temperature (X_{20})	0.144***	0.139***
Constant	–5.440***	

***Derived savannah (X_{16}) was the reference category**

Diagnostic statistics	
athrho	0.135
rho	0.134
Number of observations	343
Censured observations	23
Uncensored observations	320
Wald χ^2 (18)	63.45
Prob > χ^2	0.0000
Wald χ^2(independent equation)	10.06
Prob > χ^2	0.001

*** Significant at 1%, ** Significant at 5%, *Significant at 10%

Conclusion

Evidence from the study showed that the majority of the maize farmers believed that climate had change over the course of their farming lives. Many who felt that climate had changed had adjusted their farming practices to counter the effect of climatic change. The analysis of perception of farmers to climate change revealed that farming experience, access to extension agents, farm income and agro–ecological settings significantly influenced farmers' perception of climate change, while farming experience, distance to inputs market centre, access to extension agents, farm income and temperature all had positive and significant impacts on adaptation to climate change.

Recommendations

- Climate change information is a necessary prerequisite for adapting to climate change. Meteorological agencies should be strengthened to provide farmers with early warning signals through extension agents to enable them to make informed decisions and allow them to better prepare for adverse weather conditions.
- Credit institutions should be encouraged and strengthened to provide adequate loans at low interest rates that will enable the farmers to embark on effective adaptation strategies.
- Adult literacy programmes should be given priority as this will increase farmers' knowledge and enable them to take advantage of appropriate adaptation strategies that suit their local environments.

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Appendix 1

Variance inflation factors

Variable	VIF	I/VIF
Guinea savanna*	8.27	0.1209
Distance to output market	4.61	0.2171
Distance to input market	4.21	0.2374
Montane savanna*	4.16	0.2405
Rainfall	4.14	0.2414
Temperature	3.76	0.2843
Farming experience	3.52	0.3767
Age	2.65	0.3767
Farm size	1.77	0.5637
Household size	1.73	0.5794
Farm income	1.70	0.5874
Extension contact	1.52	0.6563
Non–farm income	1.46	0.6848
Years of schooling	1.42	0.7065
Livestock ownership	1.41	0.7074
Access to credit	1.37	0.7274
Land ownership	1.31	0.7613
Gender	1.26	0.7939
Other source of information	1.22	0.8222
Mean VIF	2.71	

Derived savannah (X_{16}) was the reference category

Brensch – Pagan test for heteroskedasticity

H_o: constant variance	
Variables: fitted values of adaptation method	
χ^2 (1)	0.02
Prob > χ^2	0.8924

White's test for H_o: homoscedasticity

against H_a: unrestricted heteroskedasticity

χ^2 (192)	= 199.28
Prob > χ^2	= 0.3448

Note:

1 US$ = ₦199.25 (year 2015 conversion rate)