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Agricultural Land-Use Systems and Climate Change among small farmers in Sub-Saharan Africa: Relationship and Evidence of Adaptive Processes in Nigeria.

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Abstract
In most of sub-Saharan-Africa (SSA), agriculture land-use supports the livelihoods of the majority of people. Land use for agricultural-activity is an economic activity that is highly dependent upon weather and climate that produce food and fiber necessary to sustain human life. Hence, land-use for agriculture is expected to be vulnerable to climate variability and change. This paper deduced that Trans-logarithmic coefficients results of short-run sustainability-index (SRSI), land policy-intervention variables and household-sizes are dominance factors. Also, SRSI showed 0.69, suggesting that 69% of the farmers made unsustainable use of agricultural-land. Marginal Value Product (MVP) model was used as adaptation factors determinants and was tested for its appropriateness which gave a robust estimations. The estimated correlation coefficients among the various adaptation options are significant for 10 out of 19 combinations. Access to information on climate-change from extension or other public sources, farmer-to-farmer extension and knowledge on agro-ecology strengthen the likelihood of climate-change perception and adaptation. The study indicated a strong relationship between efficient use of agricultural land and adaptive processes to climate change. Hence, policies of promoting and motivating sustainable land-use management need to be entrenched, in addition to providing efficient climatic data intervention that will improve on adaptive processes of farmers.

Keywords: Climatic data, adaptive processes, agricultural livelihood, Short Run Sustainable Index, Association, Nigeria

Introduction

Literature revealed about 75% of farming households in sub-Saharan Africa (SSA) obtained livelihood from agricultural land-use (Akhter and Olaf 2017, Kennedy *et al*, 2018). In Nigeria, agriculture land-use supports the livelihoods of the majority of people by providing 80% of employment and outputs from agriculture contributes 43% to the gross domestic product (GDP) (Apata, 2011, Odafivwotu, 2015, Salami, 2017). Land use for agricultural activity is an economic activity that is highly dependent upon weather and climate in order to produce the food and fiber necessary to sustain human life (AGRA 2017). Hence, land-use for agriculture is expected to be vulnerable to climate variability and change (Virginia, 1997, Zahid *et al*, 2019). Climate change has been considered to have disastrous effects on human survival (Bouzid *et al* 2014, Xiaoxu *et al*, 2016, Muthee *et al*, 2017). It has become a major obstacle to developing economies, like Nigeria (Ayinde *et al*, 2011, Apata, 2011). Hence, increase in its vulnerabilities would further result in higher susceptibility of the poor and other communities who depend mainly on agriculture except there is an effective intervention.

Past studies have argued that some agricultural activities influenced climate vagaries through the creation of anthropogenic Greenhouse gases (GHG) emissions (UNEP 2016, Asare-Kyei *et al*, 2017, Kelvin *et* *al,* 2017). In Nigeria, these activities include large number of cattle that roams the road indiscriminately and excreta around disturbing the top soils and destroying food crops, unsustainable agricultural land-use, inadequate manure management, improper use of agro-chemicals among others (Salami, 2017). Among these activities unsustainable agricultural land-use have been dominant and have been argued to have generated at least 52% of GHG emissions (IPCC. 2014, Singh *et al*, 2016, Nyamwanza *et al*, 2017, Muchuru & Nhamo, 2017). Consequently, the study examined agricultural land-use management and its relationship to climate change. Also, how the people have been coping with the climate change vagaries.

Several studies in Nigeria have examined agricultural land-use and climate change (Ayinde *et al*, 2011, Audu *et al* 2013, Odafivwotu, 2015, Okpara *et al*, 2017). Most of these studies were conducted at the Local Government level or at the State level, and these studies are useful because they helped to identify the structure of agricultural land-use management at the local and state levels respectively. However, their application for policy formulation at the national level is limited due to small scope. This study however, uses national data, and will add to the already existing body of knowledge on agriculture and climate change.

Methodology

Area of study:

Nigeria comprises of a geographical area of 923,768 square kilometers with a projected population of around 140 million (2006 estimates) people. Nigeria lies exclusively within the tropics along the Gulf of Guinea on the western coast of Africa. The country has a favorably diversified agro ecological condition, which makes it possible for the production of a wide range of agricultural products. Less than 50% of the country's cultivable agricultural land is under cultivation. Even then, smallholder and traditional farmers who use rudimentary production techniques, with resultant low yields, cultivate most of these lands. The country is divided into a four major agro-ecological zones which is used as a base of analysis for this study.

Method of data collection

Both primary and secondary data were used. A cross-sectional data from 1200 farmers were collected through farm level rigorous cost route surveys, out of which 880 (73.33% response rate) data found useful. The 320 unused data contained incomplete data, questionnaire lost in transit and data that cannot properly be transcribed. Data were collected with the assistance of pre-tested, structured-questionnaire administered by sixteen-trained enumerators. However, the secondary data were obtained from the records of various Agricultural Developments Projects (ADPs), Land records department of various Federal and State Ministries respectively. Data collected include: socio-cultural/economic, agronomic, land use data, environmental, prices on input and output data among others.

Sampling Techniques and procedures

Multi-stage sampling technique was engaged in choosing the sample desirable for this study. Firstly, division of the country into four regions: Core North, North central, Southern part and South-south and from each region two States were selected based on data availability in actualization of the study stated objectives. Secondly, two locations in each state were identified through secondary sources information about the data on heterogeneity of land-use systems and high intensity of farming operations. In addition, poverty status as provided by secondary sources too inspired the choice of these locations. Thirdly, selection of the farm-households from sixteen identified communities/towns, where 55 data were provided from each household to give 220 per region and 880 overall (Table 2). Data collection were done through a modified form of simple random sampling called the random walk method. Also, field observation and complimentary key informant interviews surveys (KIIS) were held with reputable farmers to validate information. Also, assistance of competent scientists/researchers were sought for in the identification of certain land use system, degradation parameters and indices among others.

Table 2. Distribution of sampled respondents in the study area

Region	State	Local government	Questionnaire distributed	Questionnaire used
Northern	Kano	Makoda	75	55
		Kura	75	55
	Jigawa	Guri	75	55
		Gumel	75	55
Northcentral	Adamawa	Maiga	75	55
		Mchika	75	55
	Kogi	Yagba east	75	55
		Okene	75	55
Southern	Abia	Abia South	75	55
		Ohafia	75	55
	Ondo	Akoko South	75	55
		Owo	75	55
South-south	Cross rivers	Yakurr	75	55
		Odukpani	75	55
	Rivers	Port-harcourt	75	55
		Ahoda west	75	55
Total			**1200**	**880**

Source: Field Survey (2016-2018).

Our analysis focuses on access to land use and management practices adopted at the household level and interactions with climate change. “Land access” refers to land which is under the household’s use rights, so long as it is regularly utilized, including rented land. This generally includes all cropped land, wood lots, fallow land, land under tree crops, gardens and rented land. Climate change interactions were captured through level of perceptions and adaptive processes used by the respondents.

Method of data analysis

The analytical tools employed in this study are developed to analyze the data in order to fulfill the stated objectives of this study. Therefore a combination of analytical tools including descriptive, statistical and econometric procedures were utilized.

Model estimation and interpretation

Multiple regression model based on the assumptions of the functional forms and also data availability was used to measure the indices of sustainable land use and management of the farmers in the area. Consider the production function of:

$$Y = h\ (X, L, V, M, \beta)\ \exp(U_i - V_i) \qquad (1)$$

Where Y = Output of crops consumed

X = Vector of physical inputs and indigenous status measured

L = Land quality variable measured as a Dummy variable

V= Vector of land use variables measured as index

M = Vector of land management practices assumed to have an impact on land quality Measured by ranking number and Dummy.

Ui = Components of error terms

Vi = Mis-specification of the model.

h ( ) = Suitable function to be adopted for the study.

i= 1,2,…,n

The parameters (βi) of eqn 1 and the density function of Ui and Vi will be estimated by maximizing the log-likelihood function given as:

$$Lhf = \frac{n}{2} Lh \left(\frac{2}{\pi}\right) - Kn\sigma + \sum_{i=1}^{n} Lh - F \left[\left(\frac{-\epsilon\lambda}{\sigma}\right)\right] - \frac{1}{2}\sigma^{-2} \sum_{i=1}^{n} \in i^2 \quad (2)$$

Where Lhf = log-likelihood function

n = number of observations (880 farming households)

σ = standard deviation error term

$\lambda = \sigma/\sigma x$

F = Standard distribution

$\in i$ = component error term

π= 3.145

Basic assumptions of the estimation procedure of the model adopted.

The validity of the model adopted was built on the following assumptions and this is line with the study of (Aigner *et al*, 1977, Hasan et *al*, 2012, The Global Commission, 2014)

1. A farmer essentially practices the similar type of land-use and management practices every cropping season.
2. Farmers are confronted with the even climatic factors and similar soil type.
3. Farmer practices can either enhance the productivity of the soil as well as core nutrient re-cycling or depreciate nutrient status of the soil.
4. The environmental analysis of employing and handling the agricultural land in the area is attained by farm specific land use and management index
5. Agronomic procedures used have clear carry-over consequence on the soil and in effects result in the estimated frontier; and
6. Farm specific output level is mutually regulated by input use and agronomic procedure adopted are assumed at the farm level.

Hence, these assumptions influences the structural model adopted. The theoretical framework routing most land use systems and management measures are presented in the works of Liu (2006). Past studies have indicated that the estimates of the trans-logarithms may be unacceptable because of the defilement of symmetry settings of intense sample values to the additions of the second-order terms, particularly in small sample (Mahesh & Meenakshi 2006, Gerber *et al*, 2014). Hence, this problem is somewhat resolved with very large sample size (N=880) with enhanced degree of freedom (Hasan et *al*, 2012). Moreover, the polynomial growth model exhibited considerable multicollinearity (Kalirajan & Shand, 1986). Thus, by means of a stepwise selection approach and consideration of likely interaction relationships between land-use quality and management practices, the model was constructed. Consequently, a full trans-logarithmic specification of land-quality use and management practices interaction on farm output was embraced.

$$LUM = a_0 + \sum_{i=1}^{n} a_i \, In \, X_{ij} + \frac{1}{2} \sum_{i-1}^{n} \sum_{j=1}^{n} b_{ij} \left(InX_{ij}X_{ij}\right) + \sum_{j=1}^{n} M_j L_{ij} + \sum_{i=1}^{n} L_i \, In \, Mij + \sum_{i=1}^{n} b_{ij} \, (In \, X_{ij})^2 + \frac{1}{2}\sum_{i=1}^{n} \sum_{j=1}^{p} h_{ij} \, \left(InX_{ij}Inb_{ij}\right) + \sum_{h=1}^{p} e_i \, In \, L_{ij} + \frac{1}{2}\sum_{i=1}^{n} \sum_{j=1}^{p} h_{ij} \, (InX_{ij} \, InM_{ij} + \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{p} h_{ij} \, \left(In \, X_{ij} InM_{ij}\right) + \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{p} L_{ij} \left(L_i L_{ij}\right) + \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{p} V_{ij} \left(InM_i L_{ij}\right) + \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{p} hij \, \left(InM_{ij} \, InL_{ij}\right) + V_i + U_i \quad (3)$$

Where LUM = Land-use and management practices on farm output.

i = 1,2,…,880, j=1,2,…p which are physical inputs.

X, L, V and M are as earlier described in Eqn. (1)

a_0 = parameters of intercepts.

a_i = parameters of physical inputs and indigenous status

b_{ij}= parameters for interactions across the ith and the jth physical inputs.

L_{ij}= parameters for dummy variables on land resources quality.
M_j= parameters for land management variables
h_{ij}= parameters for interactions between the ith physical inputs and land use variables.
X_{ij}= parameters for interactions among land use variables.
V_{ij}= parameters for interactions between the physical inputs and land management variables.
L_iL_{ij}= parameters for interactions between land management variables and land resource quality.
M_iL_{ij}= parameters for interactions between land management variables and land use variables.

It is specified that X_{ij} are the convectional inputs that are usually well-thought-out in transformation process, but L,V and M are conditioning variables whose additions into the model is to capture the consequences of land use and management procedures on the outputs from farm.

Measurement of Short-run Sustainability Index (SRSI).
This comprises of 2-step methodology, firstly, valuation of farm specific index of sustainable land use and management (FSM). Secondly, summing the index with farm specific inefficiency index (SII). FSM will be assessed in eqn. 3 with reverence to all the agronomic practices (i.e. land use and management practices) assessed at different level of input use and resource quality. Hence, this is stated as:

$$FSM = \sum_{i=1}^{n} L_i + \sum_{i=1}^{n} \in_i + \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{p} S_{ij} + \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{p} h_{ij}\left(InX_{ij}\right) + \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{p} V_{ij}\,(L_{ij}) \quad (4)$$

All symbols/notations are earlier defined in eqn. 3 and SII assesses the land use and management index.

Past studies have indicated that if the value of FSM is zero, then land use and management practices do not alter land quality, but if, it is positive, there has been enhancement in the use and management of the land. Also, if the value turn out negative, then, land use and management practices have unfavorable consequences on the land resources (Hasan et *al*, 2012). These studies stated that summation of the index of sustainable land use and management results to SRSI and this is stated as:

$$SRSI = 1 - \left[(X_iP)\left(X_{ij}P\right)^{-1}\right]\Big] + \sum_{i=1}^{n} d_i + \sum_{i=1}^{n} \in_i + \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{p} S_{ij} + \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{p} h_{ij}\left(InX_{ij}\right) + \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{p} V_{ij}\,(L_{ij})^2 \quad (5)$$

All symbols/notations are earlier defined in eqn. 3.
Literature have indicated that if SRSI is positive, it shows that the production process methods in terms of input use, land use and management the farmers adopted is sustainable, but if SRSI is negative then the production process not sustainable. This study used SRSI to capture and to reflect the status of the land use and management and its relationship to climate change effect and adaptation processes.

Estimation technique
Following 'land use system and agricultural production works, a farm household chooses a mixture of adaptation processes to maximize his/her predictable profit at the end of the production era. The probability that a farm household might choose an adaptation method hangs on how gainful that option is. Past studies argued that the selection of adaptation method is controlled by a mass of factors connected to socio-economic characteristics of the household contact to informal and formal institutions, and the quality of the climatic intense procedures. Supposing that the utility function is state autonomous, hence,

resolving this hitch would give an optimum mix of adaptation processes undertaken by the farm household, taking a cue from the study of Chandra and Venkatachalam (2013) and Di Falco *et al.*, (2012): empirical relationship stated thus:

$$A_{fh} = A\left(SRSI_{fh}, HH_{fh}, INFOR_{fh}, FOR_{fh}, \beta\right) + e_{fh} \quad (6)$$

Where, A_{fh} signifies adaptation strategies that farm household *fh* take up to survive against the climatic vagaries. Households' bias for adaptation methods hangs on a vector of the characteristics of the head of household (HH_{fh}), access to informal ($INFOR\ fh$) and formal (FOR_{fh}) institutions and strength of short-run sustainable index ($SRSI_{fh}$) . β is the vector of parameters to be assessed, and e_{fh} is the household definite random error term.

Past and similar studies have argued that the farm household would select a set of adaptation methods ' *m* ', over all other set *j* if, (Kurukulasuriya and Mendelsohn, 2007; Seo and Mendelsohn, 2008; Di Falco *et al.*, 2012),

$$E\ [U(A_m)] > E\left[U\left(A_j\right)\right]\ for\ \forall\ j \ldots m \quad (7)$$

Past and similar studies have argued that a suitable and appropriate model for adaptation measures that is not mutually exclusive is a multivariate probit model (MVP) The most regularly cited multivariate choice models in unordered choices are multinomial logit (MNL) and multinomial probit (MNP) models. Multivariate choice models have benefits over their equals of binomial logit and probit models in two aspects (Bahinipati & Patmik, 2015). First, they allow exploring both factors conditioning specific choices or combination of choices and second, they take care of self-selection and interactions between alternatives. (Nhemachena and Hassan, 2007; Piya *et al.*, 2013). These studies highlighted the merit of this model as it can simultaneously models the influence of the set of explanatory variables on each of the different adaptation apparatuses while consenting the unobserved and unmeasured factors (error term) to be easily correlated (Nhemachena and Hassan, 2007, Nalau *et al*, 2015). Consequently, MVP model adopted in this study is characterized by a set of *n* binary dependent variables Y_{fh}, such that,

$$\begin{aligned} Y_{fh} &= 1\ if\ X\beta_{fh} + \in_{fh} > 0 \\ &= 0\ if\ X\beta_{fh} + \in_{fh} \leq 0\ fh = 1,2,3,\ldots,n \end{aligned} \quad (8)$$

Where X is a vector of explanatory variables, fh is a vector of parameters to be valued, $\in_{fh}$ is a random error term which is dispersed as multivariate normal distribution with zero mean and unitary variance, and *n* X *n* contemporaneous correlation matrix CM [$\grave{И}_{fhm}$] with density $\emptyset$ $[\in_1, \in_2, \ldots., \in_n\ CM)$. hence, the likelihood influence for an inspection is the n-variate standard normal probability

$$\Pr[Y_1, Y_2, \ldots\ Y_n/X] = \int_{-\infty}^{(2\gamma_1-1)(X^\wedge\beta_1)} \int_{-\infty}^{(2\gamma_2-1)(X^\wedge\beta_2)} \emptyset\ (\in_1, \in_2, \ldots \in_n Z^\wedge CMZ) d_{e1}, \ldots d_{e2}\, d_{e1} \quad (9)$$

Where $Z = diag\ [2y_i - 1, \ldots 2y_n - 1]$

Past studies contended that the appropriate techniques to adopt is the Maximum-likelihood estimation (MLE). MLE is used in equation 9 in maximizing the sample likelihood function of the product of probabilities through sample observations. Taking a cue from the studies of Cappellari and Jenkins (2003) and Chandra and Venkatachalam (2013), the study execute the MVP model using the method of simulated maximum likelihood. Also, the problem multicollinearity and heteroscedasticity were taken care of using variance inflation factor (VIF) for each of the explanatory variables. Also, a robust standard error was calculated to address the possibility of heteroskedasticity (Wooldridge, 2002). Consequently, the estimation process of the VIF value for each of the independent variables is between 2.05 to 4.81. Literatures deduced that any VIF value of independent variable below 10 indicated none presence of multicollinearity. Consequently, the study recorded no presence of multicollinearity.

Results and Discussions

Many characteristics concerning rural households in Nigeria can be drawn from Table 3 below. Table 3 indicated the poverty status of respondents in the study areas, where about 66.4% were categorized poor out of which 23.2% were extremely poor. Moreover, 92% of those in the category of extremely poor respondents seek their agricultural land ownership structure by rentage, while farmland with titled documents constitute 78.6% of the non-poor (Table 3). However, the poor category (39.5%) households depend mainly on agricultural livelihoods, whereas, for non-poor 26.7% augment farm income with non-farm income (Table 3). In contrast, the poorer have less education, higher families, greater dependency (children and old members), and are more attached to communal and family land.

Table 3. Land ownership structures, characteristics of households and production constructs across different Poverty Status

Particulars	Extreme poor*	Poor	Not poor	Total
Number of households (proportion of total %)	205 (23.2)	380 (43.2)	295 (33.6)	880 (100)
Region				
Northern (core) (%)	51	85	84	220
North central (%)	59	94	67	220
Southern (%)	48	116	56	220
South-south (%)	47	85	88	220
Land ownership structure				
Rented (%)	103	7	2	112
Ownership of land with Titled documents (%)	4	15	70	89
Ownership of land with NO Titled documents (%)	23	38	96	157
Family land (%)	52	136	26	214
Communal land (%)	19	170	21	210
Government land (%)	4	14	80	98
Household characteristics				
Sex Male Head	95	168	135	398
Female Head	110	212	160	482
Marital Status Single	12	23	23	28
Married	180	338	249	767
Separated	03	09	12	24
Widowed	10	10	11	31
Mean education title achieved****	1.9	3.8	2.1	1.7
Household members (1-4)	1	5	4	10
(5-8)	125	318	287	731
(9-12)	66	48	4	118
(13-30)	13	8	0	21
Age in years (15-25)	2	5	2	9
(26-45)	63	137	104	304
(46-60)	134	228	179	541
(61-100)	6	10	10	26
Indigenous head (%)	166	370	275	811
Dwelling structure: Rented	116	53	26	195
Family house	36	179	60	275
Owned + Titled Doc.	15	42	137	194
Owned No Titled Doc.	38	106	72	216
Production characteristics				
Farm size (acres) (0.5-2.0)	202	63	7	272
(2.1-3.5)	03	313	254	570
(3.51-5.0)	0	04	29	33
(5.1-10.0)	0	0	05	05
Farming experience (years) (1-5)	13	34	18	65

(6-10)	36	66	58	160
(11-1)	23	52	27	102
(16-100)	133	228	192	553
Farm specific resource-use index (0.000-0.01)	1	6	8	15
(0.011-0.25)	149	42	8	197
(0.26 -0.50)	49	240	7	274
(0.51 1.00)	6	92	274	372
Short-run Sustainability Index (-1.93- -0.01)	174	42	0	216
(0.0-0.99)	28	315	16	359
(1.0 – 2.50)	3	23	215	241
(2.51-6.0)	0	0	64	64
Livelihood: Agriculture only	186	209	60	455
Agriculture + Non agriculture	19	171	235	325
Welfare indicator (₦) (30,000-65,000)	127	21	0	148
(65,001-90,000)	75	212	11	298
(90,001 – 125,000)	3	140	76	219
(125,001-1,000,000)	0	7	208	215
Perceived Climate Change and Adapt (No)	137	138	8	343
(Yes)	8	242	287	537
Adaptation Choices Adapted by Respondents				
Planting of Trees	0	7	37	44
Mixed Farming	0	17	53	70
Mixed Cropping	0	28	80	108
Soil Conservation	2	35	8	45
Intercropping	1	36	10	47
Mulching	0	27	46	73
Zero Tillage	1	15	21	37
Making Ridges	1	13	7	21
Irrigation	2	20	13	35
Early or Late Planting Operations	1	43	13	57
No Adaptation	197	139	7	343

* For illustrative purposes extreme poverty line is set at ₦360. 00 (US$1) per capita and day of total monetary income. Poverty line is set at ₦720.00 (US$2).
* For each household member 1= foundation 2=primary 3=basic 4=diversified 5=university 6=postgraduate
Source: Field Survey 2016-2018

Table 3 indicated that majority derived livelihood in farming while income received from agricultural production is somewhat insignificant. The non-poor category involved more in non-farm livelihood activities and possesses moderate farm-size. Moreover, farming-households with less than 2 ha of agricultural land are poorer (30.1%) and on family/communal land for farming purposes. Moreover, analysis of land-use policy and role of government and NGO-intervention policies to improve agricultural production revealed a significant role. Moreover, evidence indicated that government-policy intervention programme on land use for agricultural purposes constitutes 8.8% but focus more on farmers that uses government land (57.2%) for farming purposes. Likewise, NGO-local intervention (36.9%) emphasis more on family/communal land (28.6%). Whereas, for government and NGO (local and international) intervention (6.3%) focuses more on households that owned land (3.0%).

Literature on access to land and climate change revealed a decisive links. Studies by Winters (2009), DaMatta *et al*, (2010) and Davis *et al*, (2017) deduce that government intervention/program should be able to select only those households with practically zero opportunity costs. This study contended an average subsidy of one daily ₦360 (1US$) per capita would influenced majority (cumulative of 106 ha) of the poor landed farmers (table 3). However, result from this study would still be far from being able to recommend any form of intervention/program on effective land-use system for farming purposes in Nigeria. The disparities in productivity between poor and non-poor farmers discerned in table 3 was influenced either by differing incentives or lack of capital. The study argued that non-poor farmers have access to productive inputs, climatic information and non-farm livelihood activities more than poor farmers as this access enhanced investments and income.

The poor do not believe much in adaptation as 31.3% perceived that there is Climate Change but do not act. Moreover, many of the poor farmers do not take advantage of the various adaptation methods (Table 3). Similarly, out of the 61% of the respondents that perceived there is Climate Change and adapt, 54% are non-poor. Mixed cropping is the dominant adaptation choices (12.3%) among respondents, out of which 74.1% were non-poor (Table 3). This findings tend to suggest that the poor do not take advantage of the various adaptation methods available. Hence efforts should be gear towards enlighten the poor farmers on the benefits inherent in adaptation to mitigate the effects of climate change.

Result of analysis of the model adopted.

The trans-logarithmic specification model was estimated using Maximum Likelihood Estimation (MLE) method and the Diagnosis Statistics[1] result generated revealed large estimate of sigma-square which is statistically significant and different from zero. Thus, an indication of a good fit and the correctness of the specified distributional assumptions of the composite error-term. In addition, the variance ratio had a high estimate of 91.04%, signifying that systematic effects that are unexplained by the production function are the leading sources of random errors. In other word, the existence of technical inefficiency among the sample of farm explains 91% variation in the output level on land use systems. The coefficients generated from eqn. 3 were then used to interpret the elasticities of output with respect to the inputs. These results were generated from the outputs of the likelihood parameter estimates of equation 3. Hence, this production elasticities are computed and hereby presented in the table below.

Table 4: Distribution of Production Elasticities among the Variables

Set of Variables	**Estimated Value**	**Remark**
Physical input and indigenous status	0.4102	SR-Decreasing Return to Scale
Land use and management	0.0712	SR-Decreasing Return to Scale
Interaction terms	0.149	SR-Decreasing Return to Scale
Overall	**0.417**	SR-Decreasing Return to Scale

Source: Computed from MLE of Equation 3.

Table 4 revealed the sum of the elasticities of output with respect to the physical inputs and the indigenous status that generates an estimated scale elasticity, hence, this indicates the presence of short-run decreasing return to scale (SRD). Past study has indicated that SRD depict a case in which each additional unit of output yield smaller increase in product than in the previous unit (Hasan *et al*, 2012). These production elasticities computed are of interest in explaining the interactions and the variability in farmer's farm outputs. The estimated elasticities of the set of variables and output with respect to the conditioning variables are of particular interest to the computation of short-run sustainability index (SRSI). Hence, interaction between land use variable and management variable generated a coefficient of joint action index of 0.417, which is statistically significant at $\alpha = 0.05$ and is positively related to output level. This result indicated that management employed on land use influenced farm output.

Computation of Short-run sustainability index (SRSI)

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[1] Quasi-function coefficient = 0.870, Ln (likelihood) 135. 601 Sigma-square $\delta^2 = 0.762$* (0.041)

Gamma (Y) = 0.9026* (028) Mu (μ) -1.621* Asterisk indicate significance *1%, **5% ***10% variance ratio $\gamma = \frac{\delta u^2}{\{\delta u^2 + \delta v^2\}} = 91.04$

Computation of SRSI takes 2-step methodology, firstly, valuation of farm-specific index of sustainable land use and management (FSM) using eqn. 4. Secondly, summing the index with farm specific inefficiency index (SII) using eqn. 5. The distribution of the indices were presented in Table 3. The distribution of farms based on FSM indicates that 46% (mean values = 0.458) of the farmers adopted land use and management practices that reduced land quality. Hence, 54% of them adopted practices that improved land quality. Further analysis revealed that 16% of the lower group adopted sustainable land management practices while a higher median were found mostly on non-poor group (Table 3). However, FSM projected in this study may be limited because pertinent management practices that enhanced land quality have not been built-in in the analysis. Hence, within the context of the assumptions used for analysis, the indices used to a large extent captured the effect of land use management practices for farming purposes.

Moreover, farm specific index of short-run sustainability is a product of indices of farm specific inefficiency index (SII) and farm specific index of sustainable land use and management (FSM). The distribution of SRSI were presented on Table 3. The results of these analyses revealed that 69% (mean value of 0.6895) of the farmers made unsustainable use of agricultural land coupled with practices of resource-use inefficiency. Although, 31% of the farmers improved their land productively as indicated by the net balance of the resource-use inefficiency and agricultural land and management practices consequence. Hence, only 31% of the farmers undertook sustainable production process. Further analysis clearly shown that majority (76%) of the non-poor practices sustainable production processes (Table 3).The assumption that both the FSM and SII were influenced by different factors such as socio-cultural/economic and environmental hold. Moreover, the trend of the relationship between these indices were examined using simple-linear correlation coefficient stating their degree of association. The result revealed the $r = 0.207$, that is the Null hypothesis of no correlation amid the two indices in the farms was consented at $\alpha = 0.05$ level. Hence, each of the indices influences sustainability index differently and at diverse magnitude. SRSI were thus used as independent variables in equation 9 above.

Interactions between agricultural land-use and climate change

Literature have argued that emissions of greenhouse gases (GHG) that emanated from agricultural activities influences climate change, while climate variability affects the productivity of land (Mendelsohn, and Dinar 2009 and Tom *et al*, 2014). In other words land-use management play a key role in climate change. Thus, effective sustainability of agricultural land-use and sound adaptive processes can have positive influence in the reduction of greenhouse gas emissions. Hence, this study examines SRSI as proxy for agricultural land-use and the interactions of climate vagaries using perceptional index, adaptation choices and determinants of such choices. Results of this analysis is presented from Figures 2-3.

Fig. 2 revealed Farmers' perception of long-term temperature, rainfall and precipitation changes indicated that 39% perceive that adopting mixed cropping can influences reduction on the effects of climate change. Moreover, Low rainfall (13%) is the dominant ecological problems farmers faced in the study area. Other mains ecological problems are Temperature increase (11.1%), Precipitation decrease (11%), Precipitation increase (10.8%). The effect of agricultural land-use and climate change was captured by SRSI (Fig. 3). Farmers that had a positive SRSI had a dominant perception of low rainfall (12.5%) out of which 38% had positive SRSI. Evidence from Table 3 indicated that these categories of farmers had access to productive factors and climatic information. Also, they have designed a coping mechanism. Several adaptive methods were imbibed by farmers in Nigeria to cope with the vagaries of climate change as stated in Fig. 2. Mixed cropping is the dominant method as 12% of such farmers were found in this category (Fig. 2).

Figure 2: Agricultural Land-Use and Adaptation Processes

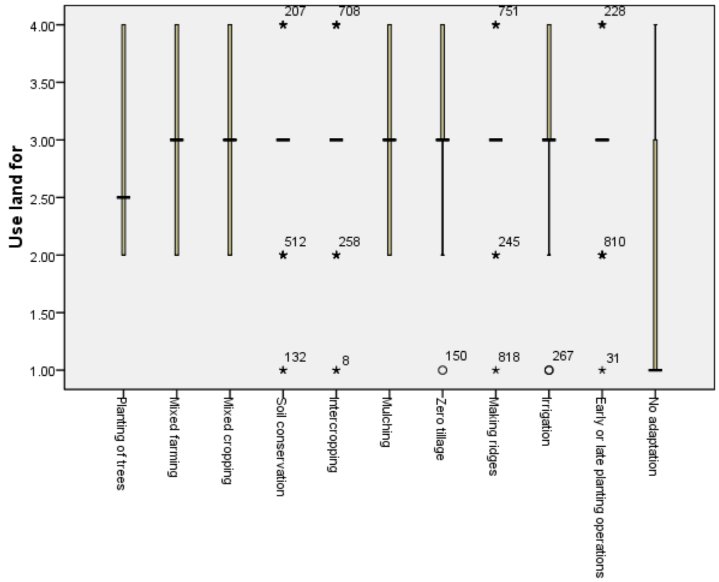
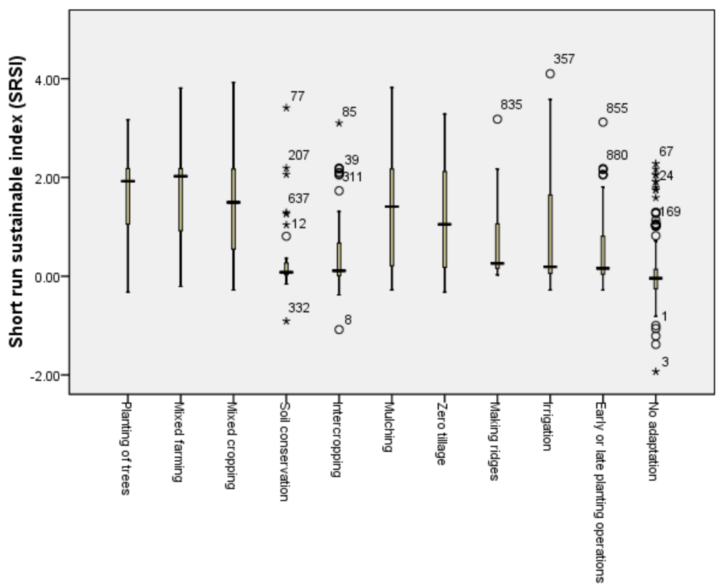


Figure 3: SRSI and Adaptation Processes



Description of variables used in the Agricultural land-use of the MVP model

Description of variables used in the Agricultural land-use response to climate of the MVP model were presented from Table 5. The dependent variable is whether a farmer has perceived that there is climate change or not. Does this perception leads to adaptation and what are the factors influencing choice of adaptation. These factors are those natural, socio-economic, institutional and physical factors as argued by past studies (Hassan and Nhemachena (2007), Deressa *et al*. (2011), Table 5 provide a description of variables used in the Agricultural land-use of the MVP model

Table 5. Description of models variables used for the outcome of the Agricultural land-use of the MVP model

Dependent variable **Description**	Farmers that have Perceived change (%)	Farmers that haven't Perceived change (%)
Perceived climate change (takes the value of one if perceived and zero otherwise)	67.3	32.7
Perceived and adapt to climate change		

(takes the value of one if adapted and zero otherwise)	61.0	39.0
Regional perception		
(takes the value of one if perceived and zero otherwise)		
Northern (core)	16.3	8.8
North central	15.9	9.3
Southern	16.7	8.3
South south	18.6	6.4
Regional perception and adapt		
(takes the value of one if adapted and zero otherwise)		
Northern (core)	13.9	10.9
North central	14.6	10.5
Southern	15.3	9.7
South south	17.3	7.7
Independent variables		
Description	Mean	Standard deviation
Household size (continuous)	7.0	1.9
Gender (takes the value of 1 if male and 0 otherwise)	0.45	0.55
Education of household head in years (continuous)	11.2	5.2
Farm income in Nigerian currency (₦) (continuous)	107590	59703
Non-farm income in Nigerian currency (₦) (continuous)	133480	66348
Ratio of number of consumers to number of labors in the farm household	3.2	1.9
Credit access (takes the value of 1 if access and 0 otherwise)	0.62	0.26
Farming experience in years (continuous)	17.6	9.1
Age of household head in years (continuous)	48	9
Access to information on climate (takes the value of 1 if access and 0 otherwise)	0.7	0.3
Farmer-to-farmer extension (takes the value of 1 if access and 0 otherwise)	0.6	0.2
Knowledge on local agro-ecology (takes the value of 1 if knowledgeable and 0 otherwise)	0.8	0.3
Short run sustainability index (SRSI)	0.69	1.05
Access to adaptation measures (takes the value of 1 if access and 0 otherwise)	0.61	0.49
Livestock ownership (takes the value of 1 if owned and 0 otherwise)	0.32	0.68
Access to extension work (takes the value of 1 if access and 0 otherwise)	0.69	0.32
Distance to output market in kilometers (continuous)	4.2	3.1
Temperature in degree centigrade (continuous: annual average during the survey period)	18.3	9.1
Annual rainfall (continuous: annual average during the survey period)	94.27	53.6

Past studies have established that farmers that have access to information on climate, extension services, local agro-ecology influences adaptive behaviour (Patt *et al.*, 2005; Deressa *et al.*, 2009; Di Falco *et al.*, 2012). Moreover, education, agricultural and non-agricultural livelihood motivate farmers to adapt (Jodha,1981; Hassan and Nhemachena, 2008; Deressa *et al.*, 2009; Bryan *et al.*, 2009; Di Falco *et al.*, 2011; Bahinipati,2014). Results indicated that household, farm and non-farm incomes, and agro-ecological locales are variables influencing the consciousness of farmers adapt to climate change. Studies specified that educated farmers have a higher probability of perceiving climate change (Maddison, 2007; Ishaya and Abaje, 2008, Deressa *et al.*, 2009). Thus, the study hypothesize that older, experienced and educated farmers have a higher likelihood of perceiving climate change. In addition, access to information on climate change through extension agents or other sources creates awareness and favorable condition for adoption of farming practices that are suitable under climate change (Maddison, 2007). Thus, it is hypothesized that farmers' contact with extension agents or any other sources is a likelihood of access to information on climate variables and adaptive processes.

Zahid *et al* (2019) and Apata (2011) revealed that non-poor farmers that have access to productive factors and agroecology information are likely to notice impacts of climate change and developed mechanism to cope. Past studies have argued that the procedure of undertaking adaptation involves two stages, i.e., first, realizing the impact of climate change and then making an attempt to respond (Deressa *et al.*, 2009, Panda *et al.*2013, Bahinipati 2014). Hence, this study forestalls that non-poor farmers with positive SRSI is likely to notice the influences of changes in temperature, rainfall and precipitation, and then undertake various adaptation measures.

In the running of the MVP model specific procedures were taken and tested for its appropriateness over other similar models. The consequence of this procedure revealed robust results. Hence, validating the use of the MVP with significant Log Pseudo Likelihood (-616.004 P< 0.0000) revealing a strong explanatory power of the model. Furthermore, results show that most of the explanatory variables and their marginal values are statistically significant at 10% or less and the signs on most variables are as expected, except for a few (Table 6). The correlation coefficients of the error terms are significant (based on the t-test statistics) for any pairs of equations which specifies that there are complementarities (positive correlation) and substitutability (negative correlation) among different adaptation options. 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.

Table 6. Results of the farm-level Adaptation processes

Independent variables Description	**Adaptation Model Regression**	
	Coefficient	***P*-value**
Household size	0.007*	0.032
Gender	0.268	0.187
Education of household head in years	0.517*	0.004
Farm income	0.013*	0.029
Non-farm income	1.103***	0.000
Ratio of number of consumers to number of labors in the farm household	0.007	0.258
Credit access	0.258	0.413
Farming experience	0.705	0.122
Age of household head	-0.368*	0.017
Access to information on climate	0.518***	0.029
Farmer-to-farmer extension	0.103*	0.042
Knowledge on local agro-ecology	1.703***	0.003
Short run sustainability index (SRSI)	2.051***	0.014
Livestock ownership	0.217	0.082
Access to extension work	1.052*	0.081
Distance to output market in kilometers	0.138	0.108
Temperature	-0.068	0.318
Annual Rainfall	2.718	1.873
Constant	-3.101***	2.013
$\dot{\rho}_1$	0.308***	
$\dot{\rho}_2$	0.219***	
$\dot{\rho}_3$	-0.283***	
$\dot{\rho}_4$	-0.417***	
$\dot{\rho}_5$	0.528**	
$\dot{\rho}_6$	-0.026	
$\chi^2(18)$	102.28	0.000
Draws	64	
Number of Observations	880	
Log Pseudo Likelihood.	-616.004	
$p_f\ (y_{fh} = 1\ for\ all\ fh = 1,2,\ldots,6$	0.036	
$p_f\ (y_{fh} = 0\ for\ all\ fh = 1,2,\ldots,6$	0.017	

Source: Computer results. Note: *** $P < 0.01$, ** $P < 0.05$, * $P < 0.10$

The estimated correlation coefficients among the various adaptation options are significant for 10 out of 19 combinations (Table 6). The results from the MVP model indicated variables that are positively and significantly impact adaptation to climate change. These include household size, education, farm income, non-farm income, and age, access to information on climate change, farmer-to-farmer extension, and knowledge on agro-ecological, SRSI and access to extension. Though, results indicated that many of the explanatory variables affected the probability of adaptation as expected, except age and temperature. While age and temperature are negatively related. The inferences of this result is that higher likelihood of perceiving climate change with increasing age is related with experience which allow farmers notice changes over time and associate such changes with present climatic conditions.

Access to information on climate change from extension or other public, sources, farmer-to-farmer extension and knowledge on agro-ecology strengthen the likelihood of climate change perception as they play an important role in the availability and flow of information. Also, adaptation to climate change increases with increasing temperature. Hence, agrees with the notion that increasing temperature is damaging to African agriculture. Farmers respond to this through the adoption of different adaptation methods (Kurukulasuriya and Mendelsohn, 2006; Deressa *et al*., 2009 and Apata 2011). Evidence from Table 6 indicated a large household size (7). Hence, It can be inferred that the larger the size of the household, the better the chance of adopting these measures.

Further, it is found that education of the head of the household influences the probability of adaptation. Because, there is a higher probability that an educated farmer has knowledge about climate change mitigation processes. Educated farmers have more knowledge, avenues for knowledge sharing and farmer-to-farmer interactions can lead to the increase in the use of various adaptation measures (Nhemachena and Hassan 2007, Chandra and Venkatachalam, 2013). Also, Farm and non-farm income increases the probability of farmers adopting mixed cropping and farming as evidenced in this paper and other past studies (Chandra and Venkatachalam 2013, Panda *et al.* 2013) (Table 6). Farmers who have extension contacts are more aware about various agricultural production and management practices, which they can use to adapt to climate change as evidenced in the work of Piya *et al. (*2013) and Wood *et al.* (2014). Moreover, the coefficients of SRSI are positively associated to high adaptation processes. In order to minimize risk involved in agriculture, farmers are into growing multiple cropping-system and mixed farming even livelihood diversification. This study point to direct association of these identified variables to adaptive process. This underlines the fact that the government should promote various developmental based activities in the rural areas, especially related to agriculture, in order to increase farm-level adaptation measures.

Conclusions and Policy Implications

The theoretical basis of this study focused on defining the level and strength of agricultural land use and management and climate change and relationship in between. The study revealed that agricultural land use and management practices induces climate change which in turn influences economic (poverty) status of farmers. Results indicated that farm level analysis of land use and management raised doubt as to how sustainable the system could be considering the signs and magnitudes of the estimated indices. A perspective analysis was carried out on how certain agricultural land-use and management practices could improve land resource use efficiency through effective adaptive processes. Although the poor do not believe much in adaptive measures, while the non-poor tend to take this advantage. Hence efforts should be gear towards enlighten the poor farmers on the benefits inherent in adaptation to mitigate the effects of climate change.

MVP model was used as adaptation factors determinants and was tested for its appropriateness which gave a robust estimations. The estimated correlation coefficients among the various adaptation options are significant for 10 out of 19 combinations. Though, results indicated that many of the explanatory variables affected the probability of adaptation as expected, except age and temperature. While age and temperatures are negatively related. Access to information on climate change from extension or other public, sources, farmer-to-farmer extension and knowledge on agro-ecology strengthen the likelihood of climate change perception. This play an important role in the availability and flow of information.

Sustainable and positive SRSI, education, extension access and access to agro-ecology information were found to promote adaptation. This implies that education to improve awareness of potential benefits of adaptation is an important policy measure. Hence, the paper suggest that government policies and investments must promote these determinants in order to enhance the adaptive capacity of the rural farmers. Hence, essential to restructure the current intervention programme on climate by embracing climate specific response measures, e.g., distribution of high yielding and tolerant seeds, inculcating good agricultural practices (GAP) and improving on the level of responsiveness among the farmers regarding climatic risks so that farmers can lessen against an expansive range of risk and shocks.

Moreover, policy should focus more on effective and reliable access to information such as mass media and extension on locale-specific climate change and adaptation processes such as mixed cropping and mixed farming. In this regards government policy should provide necessary machineries that will facilitate timely response. In addition, empowerment is crucial in enhancing farmers' awareness. This is vital for adaptation decision making and planning. Combining access to extension and modest income ensures that farmers have the information for decision making and the means to take up relevant adaptation measures. Moreover, encouraging informal social networks and importing adaptive technologies from other SSA countries with similar socio-economic and environmental settings could enhance the adaptive capacity of Nigerian farmers. The study indicated a strong relationship existed between efficient use of agricultural land-use and adaptive processes to climate change. Hence, policies of promoting and motivating sustainable land-use management for better and positive SRSI need to be implemented and providing efficient climatic intervention that will improve on adaptive processes of farmers.

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