INTERNATIONAL JOURNAL OF RESEARCH AND SCIENTIFIC INNOVATION (IJRSI)
ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XII Issue VI June 2025

Determinants of Cassava Farmers' Climate Risk Aversion in Anambra State, Nigeria

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DOI: https://doi.org/10.51244/IJRSI.2025.120600120

Received: 28 May 2025; Accepted: 31 May 2025; Published: 15 July 2025

ABSTRACT

Climate challenges can be very discouraging in contemporary agricultural business and stakeholders can only avoid associated risk for increasing output. Providing empirical evidence of the factors that account for farmers' climate change risk aversion in Anambra state, Nigeria for policy direction is imperative. Data were collected from 203 cassava based farmers in the state using a multi-stage sampling technique but only 141 of them were found useful for data analysis. Descriptive statistics and econometric tool like multinomial logit model (MLM) were used to analyze data collected. Result shows that majority (46.1%) of the farmers had formal education and above 11 years of experience (56.7%), which implied that farmers number of years and training can favourably enhance their understanding the variation in climate and adopt good climate smart agricultural practices for more production efficiency. Analysis of farmers' aversion level showed that majority (67.38%) of the farmers were mild risk seekers with only 5 Climate Smart Agricultural (CSA) practices and only 5.67% were high risk averse farmers who adopted more (16) of the CSA practices. Few (2.84%) high risk seekers adopted only 2 CSA practices implying that risk loving cassava farmers in the area are not climate smart friendly in the area. Risk aversion increases with factors like age (0.0035) farm-size (0.217) and previous production losses ($7.7X10^{-8}$) but decreases with economic size ($4.42X10^{-3}$), experience (0.071) and debt ratio (0.002). However, risk seeking increases with education (0.014), debt ratio (0.0002), economic size ($4.49X10^{-8}$) and decreases with previous production loss ($7.75X10^{-8}$). The study recommended that; there is need for policies directed towards CSA practices that will increase economic size of cassava production and also there is need for functional and effective extension services.

Keywords: Risk, Aversion, Cassava, farmers, Climate. Change and Agriculture

INTRODUCTION

Climate change is an observable phenomenon with the potential for disastrous effects and catastrophic impacts (Intergovernmental Panel on Climate Change (IPCC), 2007). Alterations in the average temperature and precipitation levels, coupled with an unpredictable or harsh environment, have the potential to impact not just the courses and levels of future development, but also today's yields, profits, health, and physical safety. Climate change affects crops and locations differently, but it increases the risk to global food security and increases the risk of under-nutrition in developing nations (Food and Agricultural Organisation (FAO), 2016). Climate change is expected to affect farmers and their livelihoods in the rainforest region of Nigeria where much of the population, especially the poor, rely on rain-fed agriculture, which are sensitive to climate variations. Disruptions of the existing food systems may have devastating implications on sustainable development and livelihoods. "In the absence of measures to reduce the vulnerability to, and the impacts of climate change, it can generate significant and negative impacts on food security" (FAO, 2010; Foresight, 2011).

The previous few decades have seen an incredible trend in the growth of agricultural output, which has significantly reduced poverty and food insecurity in many places (though regional variations remain significant). This was mostly brought about by investments in crop and livestock breeding programs as well as enhanced production systems (Babatunde *et al.*, 2011). Climate change threatens to exacerbate the existing challenges faced by agriculture, “It is expected to have generally negative effects on Nigeria’s agriculture, with concomitant implications for food security” (Onyeneke, 2010). A 2009 report by the Department for International Development (DFID) specifically mentioned Nigeria and calculated that between 6% and 30% of GDP could be lost due to climate change by 2050, amounting to an estimated US$ 100 billion to 460 billion. Should adaption measures not be taken, Nigeria's GDP may decline by 2-11% by 2020. Nigeria is a market economy with more profit motivated agricultural production system. With such profit maximization objective, farmers adjust resources (resource allocation) to produce at a maximum output or produce a particular quantity at a minimum possible cost. This farming attitude does not consider the input and technology used and the impact on the climate and environment. According to Osuji *et al. (*2023) farming activities overtime, had widely exacerbated climate change in diverse ways causing innumerable disruptions of agricultural activities.

Although the market oriented nature of Nigerian affected the farming environment, it is a strong stimulant to its expanded production, organized around some practices such as uncontrolled use of fertilization, tillage operations, slash and burn practices, deforestation, livestock production (especially enteric fermentation of ruminants), and methane from rice farms, which trigger climate risk (Federal Ministry of Environment, 2023). Farmers ignorantly used these copping strategies without considering the environmental degradation and climate risk associated with them in Nigeria and Anambara State in particular. Climate change seriously threatened the area occasioned with flooding, erosion, higher temperatures and variations in precipitation patterns and pest and diseases incidence The risk of long term output losses and short term crop failure with low quality yields persist in the long run with these farmers attitude (Wouterse, 2017). According to Ifeanyi-Obi and Obasi, (2021), various approaches have been suggested for reducing the impacts of climate change on food crops production, but an important action sort to respond to negative impacts of climate change by crops farmers is climate smart agriculture practices.

Climate Smart Agriculture (CSA) practice is the use of farm technologies, methods, strategies, techniques or services to increase crop yield (net income) simultaneously and improve the climate (Onyeneke *et al.*, 2022). The benefits of a sustainable increase in agricultural productivity, the adaptation and construction of resilient agricultural and food security systems, which raises the carrying capacity of the farming environment and lowers greenhouse gas (GHG) emissions from agricultural activities, are all included in the usefulness of CSA practice (Food and Agricultural Organization (FAO), 2010). Climate Smart Agriculture (CSA) is therefore, an appropriate approach to reduce the climate change impact on crop production (Campbell, Corner – Dolloff, Girvetz and Rosen stock, 2015; Onyeneke *et al.*, 2018). The concept was originally put forth by Food and Agriculture Organization (FAO) after the Hague conference on agriculture, food security and climate change in 2009 (FAO, 2010) with an objective of resting agriculture to assure a “triple win of adaptation, mitigation and development (FAO, 2010).

The impact of climate change in agriculture can be addressed by climate smart agriculture practices through improving soil fertility, sequestering soil carbon, enhancing crop yields and income (Mahdu and Ellis, 2021). Nsikak–Abasi and Ndaeyo (2020) indicated that climate smart practices like combination of crop rotation, application of organic manure and crop diversification can deliver ecosystems services, including soil carbon sequestration, nitrogen fixation and breaking the life cycle of pests and improving weed suppression, increase crop yield and farmers income. Nsikak–Abasi and Ndaeyo (2020) further reported that combination of crop rotation, crop diversification; organic manure application and irrigation farming can also reduce the use of chemical fertilizers and pesticides and hence contribute to mitigation of climate change. It is therefore important to investigate the economics of climate smart agriculture practices by small-holder food crops farmers in Imo State, Nigeria.

One way to mitigate the risks connected with climate change is to reduce greenhouse gas emissions, or adapt to its repercussions. Mitigation lessens the effects of climate change by slowing down the rate and amount of global warming. This raises the likelihood that adaptations can be made to the remaining dangers. A system's capacity to adapt improves when it comes to handling the extreme occurrences and variability of a changing climate (Jones and Preston, 2006). Mitigation and adaptation attitude of the farmers are both climate smart agriculture practices that will not just sustain increased economic size in the production but also the environment and climate risk.

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Farmers’ risk aversion attitudes were addressed more often in recent decades. In contemporary agricultural economics, one of the primary study concerns is the issue of risk aversion (Cao et al., 2011). A true understanding of farmers' economic behavior depends on accurate assessment of their attitude toward risk. Bard and Barry (2001) stated that the propensity to risk affects the choice of appropriate agricultural policy tailored to the needs of the sector and the national economy. They stressed that understanding how farmers react to risk factors is important not only for the farmers themselves, but also for the extension services, the agri-food industry (both supplying farmers with production factors and food processing) and authorities. Most of the studies of farmers’ attitudes to risk concluded that the farmers are characterised by risk aversion (Organisation for Economic Co-operation and Development OECD, 2009). Most people are averse to risk and to uncertainty and ambiguity when making choices. More familiar options tend to be seen as less risky, all other things being equal, and thus more likely to be selected (Figner and Weber, 2011).

The research area's farming practices are not sustainable. A significant amount of the land is burned or removed for farming, exposing the delicate topsoil to erosion. The loss of ground cover makes the soil more prone to erosion. These unsustainable practices by farmers in the area have led to persistent crop failures, poor harvest and several climate change related problems which have resulted to questions on farmers’ awareness on climate change and their attitude towards climate change risk.

Generally, studies on farmers’ attitude towards risk and factors determining their attitudes have elicited significant research interest in Africa but carried out in several other regions like Poland but is low in Nigeria and especially in the South-East region. In one such study conducted in Poland, Piotr & Anna (2014) noted that farmers are the most risk averse when it comes to their personal health, and the least with respect to their farms. It was also noted that Polish farmers risk aversion hinge on their debt ratio, economic size, loss in production and financial independence. In line with the above observations, this study analysed the socio-economic characteristics of farmers in the area, cassava farmers’ level climate change risk aversion and factors determining Cassava farmers’ level of climate change risk aversion in the area.

MATERIALS AND METHODS

The study was carried out in Anambra State which is located in Southeast Nigeria. It is located between longitudes 6^0 36^l and7^l 20^l E of the Greenwich Meridian and latitudes 6^0 45^l and 5^0 44^l of the Equator. Its borders are shared by Enugu State to the northeast and east, Kogi State to the north, Imo State to the south, and Delta State to the west. With 5,527,809 residents, Anambra State has a land area of 4,844 square kilometers (NPC, 2016). There are twenty-one Local Government Areas, three senatorial districts, and four agricultural zones in it.

Date and information were sourced from both primary and secondary sources. In-depth data for this study was gathered through interviews and questionnaires. The data gathered covers the farmers' socioeconomic characteristics as well as the many climate-smart strategies they have implemented. The study adopted a multistage sampling technique to draw its respondents. This is to ensure that all the farming segment of the state with different ecological status area represented in the study. The first stage was a purposive selection of two (2) Local Government Areas (LGAs) from each of the four Agricultural zones of the state. The LGAs selected were predominantly rural with farming activities across every household. A total of eight LGAs were used for the study. The second stage was a random selection of five communities from each of the selected LGAs. The list of these communities was drawn from each of the LGAs headquarters. A total of 40 communities were included in the study. From each of these communities, two villages were randomly selected in the third stage. This was done from the list of villages in different communities kept with the LGA councils. A total of 80 villages were used in this study. Across these villages was a list of 19,860 registered cassava crop farmers who were affected by at least one or more of climate change risk factors in cassava production in the state. There were unequal number of registered cassava crop farmers across the 80 villages; hence a proportion 7.0% of them was drawn from the list that served as the sample frame for this study using Slovian’s (1960) formula adopted by Marek *et. al.* (2013).

The Slovian model is expressed as: $$n = \frac{N}{(1+N)(e^2)} \qquad 1$$

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Where n = sample size

N = Population size (sample frame)

E = proportion of the sample to be drawn representing the margin of error.

1 = constant value

The Slovian model gave a total of 203 cassava based farmers which were drawn using a random sampling technique in the fourth stage. The study found only 141 cassava base farmers response very useful for the study after all collected data were cleaned through careful inspection of questionnaire.

Data Analysis

Data collected were analyzed using descriptive statistics and multinomial logistic model. Farmers' level of climate change risk aversion was achieved using descriptive and inferential statistics. The farmers were interviewed on some climate Smart Agricultural Practices (CSAP) and Good Agricultural practices (GAP), which they apply to their farms to avert climate change risk associated with cassava production. Farmers were asked to select from various climate smart practices some good agronomic practices (GAP) provided. Other good agricultural practices that are detrimental to climate were not considered in this study. Farmers were allowed to select among those enlisted, the practices they actually apply in the production of cassava in the area. The proportion of actual risk aversion measures applied by an ith farmer to the total cassava farming risk aversion practices multiplied by 100 gave the individual farmers percentage risk aversion in cassava production in the area.

The study described the level of climate change risk aversion using the mean and standard deviation of farmers based on their percentage risk aversion measures in the area. The mean cassava farming risk aversion index $\pm$ the standard deviation was used to categorize farmers into their various risk aversion categories in the area.

The mean of the selected practices was computed using the formula

$$\text{Mean} = \frac{\sum_{i=1}^{n} FX}{N} \qquad 2$$

While the standard deviation from the mean is computed using the formula

$$\text{SD} = \sqrt{\frac{\sum_{i=1}^{n} F(X-x)^2}{N}} \qquad 3$$

The mean $\pm$ standard deviation (i.e 1SD, 2SD and 3SD respectively) computed in both direction based on the number of categories in both direction, and the results grouped and ranked in the following order: highly risk seeking, risk seeking, mildly/slightly risk seeking, risk neutral, mildly/slightly risk averse, risk averse, highly risk averse (very high risk aversion).

Using a multinomial logit model, factors influencing cassava farmers' level of risk aversion was achieved/identified. The multinomial logit model is specified and estimated using the classification of farmers based on their degree of aversion. It conveys the probability of falling into a certain aversion group category in comparison to a base category. A polychotomous model known as a multinomial logit model is one that predicts the utility that a farmer would derive from a choice based on his level of aversion. If the benefit of falling into a particular category is represented as follows:

$$U_{ij} = \gamma_j N_{ij} + \varepsilon_{ij} \qquad 4$$

U_{ij} = Utility derived by ith farmer in being in jth category due to his aversion level.

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N_{ij} = Set of determinants which is constant across alternative categories

N_1 = age, N_2 = level of formal education, N_3 = soil quality/suitability, N_4 = economic size, N_5 = Farm size, N_6 = debt ratio, N_7 = previous production loss, N_8 = Number of workers, N_9 = financial independence/strength, N_{10} = level of experience, N_{11} = famers' perception, ε_{ij} = The random. This model is built on *'j'* possible categories, as *'j' = 1,2,3...,J.* – that are exclusive and exhaustive (Cramer, 1991). In this analysis, the seven (7) categories considered are: Highly risk averse, slightly risk averse, risk averse, risk neutral, risk seeking, slightly risk seeking and highly risk seeking.

The multinomial logit assigns probabilities $P_{ij}(1,2,...5)$ to the likelihood of an ith farmer belonging to any of the 7 aversion categories. The multinomial logit model as designed by Greene (2003) is giving by

$$P_{ij} = \frac{\exp^{\gamma_j N_i}}{1 + \sum_{J=I}^{5} \exp^{\gamma_j N_i}} \quad j = 1,2,...,5 \qquad 5$$

P_{ij} is the probability of being in each of the groups 1,2,…,7

$$P_{i0} = \frac{1}{1 + \exp^{\gamma_j N_i}} \quad j = 0 \qquad 6$$

P_{i0} is the probability of being in the reference group

Modelling the probability of the multinomial logistic model for this study is as given by Onyeneke (2010):

$$P(y = j / X) = \frac{\exp(x\beta_j)}{1 + \sum_{k=1}^{J} \exp(x\beta_k)} \quad j = 1,..., J$$

Where β_j is K × 1, j = 1……., J 7

Where; P = Probability of being risk adverse or in any category

Y = Risk aversion level (obtained from various CSAPs and GAPs adopted)

Where CSAP= Climate Smart Agricultural practices and GAP are Good Agronomic Practices

X_i = (Regressors) X_1, X_2, X_3…X_{11}

X_1 = Farmer's Age

X_2 = Farmer's level of education (in years)

X_3 = Soil quality/suitability (scale: 0: theoretical minimum; 1: theoretical maximum)

X_4 = Economic size (in terms of output in ₦)

X_5 = Farm size (ha in terms of crop)

X_6 = Debt ratio (value of debt divided by value of assets)

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X_7 = Previous production loss [(expected output-actual output) *unit price]

X_8 = Number of workers (labour) (including household)

X_9 =Financial independence/strength (off farm income)

X_{10} = Level of experience in years.

X_{11} = Famers' perception (using perception index derived)

e = Error term

B_j = β_0, β_1, β_2, β_3, β_4, β_5, β_6, β_7, β_8, β_9, β_{10} and β_{11} are the parameter estimates of the independent variables.

According to Greene (2003), in practice, the reference category is usually normalized to zero. This is because the probability for belonging to all aversion level is summed up to unity. Hence, for J choices, only J_{7-1} distinct parameters can be estimated and identified.

In this study, the estimation of the multinomial logistic model was undertaken by normalizing level of risk aversion based on number of SAP/GAP adopted, which is normally referred to as the "base option". For this analysis, risk neutral was chosen as the base option.

RESULTS AND DISCUSSION

Socioeconomic Characteristics of Cassava Farmers

Table: Distribution of Respondents according to Socioeconomic Characteristics

Characteristics	Categories	Frequency	Percentage (%)
Age	15- 24	7	4.97
	25 - 34	31	21.99
	35 - 44	36	25.53
	45 - 54	41	29.09
	55 - 64	26	18.44
	Mean 39 yrs		
Gender	Male	88	62.41
	Female	53	37.59
Farming experience (years)	1 – 5	20	14.18
	6 – 10	64	45.39
	11 – 15	16	11.35
	16 - 20	26	18.44
	21 - 25	15	10.64

	Mean 11.3 years		
Educational Level	0 (No formal Education)	21.42	15.19
	1-6	21	14.89
	7-12	53	37.55
	13-18	65	46.10
	Mean 11 yrs		
Household Size	1 – 5	56	39.72
	6 - 10	72	51.06
	11 - 15	13	9.22
	Mean 6 persons		

Source: Field Survey Data, 2019

The data presented in the table indicates that majority of respondents or 54.62%, were in the age range of 35 - 54 with the mean age of 39 years. Due to the indication that majority of them are in their prime age and consequent economically active, the cassava farmers were well-off. These farmers could become more productive if they are provided with the needed resources.

The table's result also reveals that the study area's sampled cassava farmers had a range of educational backgrounds. Eleven years was the average amount of schooling. Just 15.19% of people have never attended school. This suggests that the majority of the farmers in the region are literate and have a good understanding of how climate change affects agricultural productivity. They should also be able to respond to the need to develop human capacity. Education contributes to the development of a positive mentality. A positive mental attitude which is cultivated through education, is beneficial for the adoption of innovations and management-intensive procedures.

The sample of cassava farmers' sex distribution reveals that, with a margin percentage of 24.82, 62.41% of the respondents were men and 37.59% were women. This suggests that the area's cassava production is dominated by men.

The results also indicate that, with a mean farming experience of 11.3 years, the majority of cassava crop producers (45.39%) had between 6 and 10 years of experience, while 10.64% had more than 21 years. Considering that the farmers' mean age is 39, this indicates that they have dedicated a respectable amount of their life to farming. Experience is crucial because it provides greater understanding of the dynamics of climate change and the threat it poses to the production of cassava. Because of the years of experience and information gained, it suggests a favorable impact on production efficiency.

The majority of respondents (51.06%) reported having a mean household size of six (6) people and a size range of six to ten. Greater household sizes meant that more of family labour was engaged by farmers than hired labor. This makes it possible for them to allocate more funds and resources to other household and production requirements. More members of a household, particularly those with a low dependence ratio, are more advantageous since traditional farming requires a lot of manual labour and more hands to help with other farming tasks and activities (Henri-Ukoha et al., 2015).

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Cassava Farmers Climate Change Risk Aversion

Table 2: Distribution of Farmers according to their Climate Change Risk Aversion

Aversion Level	Class Boundaries	Average No of Smart Agricultural Practices	Frequency	Percentage (%)
Highly Risk Averse	14.81 and Above	16	8	5.67
Risk Averse	14.80 – 11.67	14	3	2.13
Mildly risk Adverse	11.66 – 8.53	11	8	5.67
Risk Neutral	8.52 – 5.38	8	22	15.60
Mildly Risk Seeking	5.37 – 2.24	5	95	67.38
Risk Seeking	2.23 – 0.01	2	4	2.84
Highly Risk Seeking	0	0	1	0.71
Total			**141**	**100**

Mean Aversion Level: 5.38   Standard Deviation (SD): 3.14

Source: Field Survey Data, 2019

Table 4.10 shows the risk aversion level of cassava farmers interviewed as it concerns farms and farming methods. The mean and standard deviation were obtained and used to categorize the farmers into different levels of aversion based on the deviation from the mean in both directions. The result shows that majority of the respondents (67.38%) were mildly risk seeking, adopting an average of 5 Smart Agricultural practices and good agronomic practices out of the total number, 2.84% were risk seeking adopting an average of 2 while 0.71% were highly risk seeking. On the other 5.67% were both mildly risk averse and highly risk averse respectively while 2.13% were risk averse. This result shows that majority of cassava farmers are risk seekers and are below risk neutral adopting less Smart Agricultural Practices and Good Agronomic Practices while few farmers are risk averse in general and are above neutral adopting more Climate Smart Agricultural Practices (CSAP) and Good Agronomic Practices (GAP) compared to the risk seekers. This might be due to the fact that farmers in this area do not have a good understanding or perception of the effect of Climate Change on their crop or they do not have an understanding of the positive effect of the SAPs or GAPs. Some cassava farmers may not be able to differentiate between each of the practices and might not be able to tell the effect of one practice from the other. This goes to explain further that more farmers in this area are exposed and more vulnerable to climate change risk and as such should be educated more on the effect of climate change on their crop production and advised to adopt good practices.

Factors influencing cassava farmers' level of risk aversion

Table 3: Determinants of Farmers Level of Risk Aversion

Variables /t-value/	**Highly Risk Averse**	**Risk Averse**	**Mildly Risk Averse**	**Mildly Risk seeking**	**Risk Seeking**	**Highly Risk Seeking**						
	Coefficient	**Mar Eff**	**Coefficient**	**Mar Eff**	**Coefficient**	**Mar Eff**	**Coefficient**	**Mar Eff**	**Coefficient**	**Mar Eff**	**Coefficient**	**Mar Eff**
Age	0.013	0.0035*	-0.113	-0.002	-0.095	-0.004	-0.118	-0.009	-0.095	-0.004	-0.037	-0.005

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			**	9	**	9	**	2**	**	*		
t-value	0.420	2.08	3.33	1.69	3.37	1.52	4.29	2.97	3.18	1.33	1.29	1.63
Education	-0.098	-0.0029	-0.118*	-0.0044	0.072	0.0231**	-0.184**	-0.0248**	0.032	0.013**	0.150**	0.014**
t-value	1.67	1.00	2.09	1.51	1.44	3.87	3.69	4.04	0.62	2.50	2.92	2.76
Soil Quality	-1.841**	-0.0898**	-0.980*	-0.0381	0.151	0.1036*	0.441	0.1584**	-1.422**	-0.164	-0.726	-0.0469
t-value	4.39	3.50	2.24	1.58	0.41	2.40	1.13	3.49	3.76	4.20	1.91	1.26
Economic size	-1.90×10^{-6}**	-4.92×10^{-8}	-3.34×10^{-6}**	-1.48×10^{-7}**	-1.52×10^{-6}**	-7.66×10^{-8}	-6.42×10^{-7}	8.80×10^{-8}	-1.58×10^{-6}**	-7.53×10^{-8}	7.73×10^{-7}	4.96×10^{-8}
t-value	2.72	1.34	4.47	3.46	2.73	1.08	1.31	1.43	2.59	1.09	1.42	0.87
Farm Size	0.217**	0.0044	0.174**	0.0018	0.188**	0.0078	0.154**	0.0014	0.254**	0.017**	0.114*	-0.0048
t-value	3.25	1.30	2.92	0.61	3.68	1.39	2.97	0.25	4.39	2.96	2.01	0.88
Debt Ratio	-0.030**	-0.0012**	-0.006	0.0002	-0.004	0.0011**	0.021**	0.0020**	0.012**	0.0003	0.009*	0.0002
t-value	3.40	2.86	1.73	1.14	1.86	2.79	4.03	2.81	2.67	0.48	2.23	0.43
Previous prod. loss	1.34×10^{-6}**	7.07×10^{-8}**	3.76×10^{-7}	1.13×10^{-8}	6.05×10^{-9}	-3.71×10^{-8}	-4.09×10^{-8}	-4.61×10^{-8}	9.20×10^{-7}**	1.15×10^{-7}**	-3.08×10^{-7}	-7.51×10^{-8}
t-value	3.07	2.70	0.63	0.32	0.02	0.69	0.12	1.05	2.46	2.62	0.75	1.65
Employed Labour	0.183**	0.0046	0.193**	0.0055	0.141**	0.0059	0.184**	0.0139	0.087	-0.0037	0.074	-0.0053
t-value	2.82	1.44	3.04	1.75	2.62	0.93	3.45	2.26	1.51	0.60	1.25	0.87
Off farm Income	-6.29×10^{-6}**	-2.51×10^{-7}**	4.07×10^{-7}	1.78×10^{-7}**	-3.34×10^{-6}**	-1.98×10^{-7}	-9.96×10^{-7}	-2.40×10^{-7}*	-3.97×10^{-6}**	-2.74×10^{-7}*	-3.15×10^{-6}*	-1.28×10^{-7}

t-value	3.51	3.12	0.33	2.89	3.07	1.58	0.99	2.12	3.29	2.14	2.55	1.02
Farming Experience	-0.071*	-0.0010	-0.228**	-0.0094**	0.089**	0.0006	0.070*	-0.0030	0.118**	0.0052	0.121**	0.0051
t-value	1.96	0.56	5.01	4.16	2.63	0.14	1.98	0.71	3.48	1.50	3.64	1.62
Perception	0.137	0.0104*	0.199*	0.0152**	-0.245**	-0.0401**	-0.042	-0.0023	-0.077	-0.0076	0.098	0.0187*
t-value	1.69	2.38	2.50	3.47	3.22	4.36	0.64	0.28	1.04	0.93	1.35	2.52
Constant	-1.177	-	-0.594	-	1.271	-	3.255	-	0.865	-	0.553	-
t-value	0.80	-	0.41	-	1.03	-	2.80	-	0.66	-	0.43	-
Chi Square value 384.06 Log Likelihood Ratio -927.16 Psuedo R2 0.272 Observation 141												

** = significant @ 1.0%; * =significant at 5.0%; Reference category = Risk Neutral

Source: Field Survey 2019

There are variations in Farmers' behaviour and attitude towards climate change risk as observed in their use of some technologies/practices to avert these climate change challenges on cassava production as shown in Table 3. The included factors influencing the use of these technologies that averts climate change risk on cassava production as presented in Table 3. It showed a consistent slope parameters with the coefficients and the marginal effect. Their signs and features showed that the coefficients may have collapsed to the marginal effect. Marginal effects were employed in the interpretation because multinomial logistic model parameter values only provide the direction, not the actual probability. The derivation techniques of marginal effects

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XII Issue VI June 2025

implicitly suggest that the sign and magnitude of the effects do not necessarily correspond to the sign of the coefficients used to obtain them. The purpose of marginal effects is to measure the change in dependent variable resulting from a unit change in independent variables (Rhaji & Fakayode, 2009).

It showed the influence of the socio-economic characteristics and other factors on the farmers' categories of risk aversion such as; highly risk averse, risk averse, mildly risk averse, risk neutral, mildly risk seeking, risk seeking and highly risk seeking. Though, multinomial logit regression is a polychotomous choice model with mutually exclusive categories of dependent variable, the study collapsed risk neutral as a desirable reference category relative to other categories. Risk neutral, which became the default (base) category to compare other choices, the effects of the included explanatory variables on risk aversion index of farmers to climate change risk in cassava production in the area.

The functional parameters such as log likelihood ratio and Chi Square value of -927.16 and 384.06 which are both significant at $P \leq 0.01$ implying that the model has a good fit and it is significantly different from zero. The included explanatory variables jointly explain the probabilities of farmers risk aversion to climate risk factors in the area. Ehirim (2014) further explained that such result implies that the model has a good explanatory power. Again, the Pseudo R^2 value is 0.272 and this value was considered high enough for providing sufficient explanation about the model. It could be deduced from this result that 27.2% variations in farmers' risk aversion level to climate change risk using some available cassava production technologies can be explained by the included explanatory variables such as age, education level, soil quality, value of output, farm size, debt ratio, previous production loss, hired labour, off farm income, farming experience and farmers' perception to climate change. The Pseudo R^2 value with significant variance may give a good impression regarding the model's goodness of fit. According to Rahji and Fakayode (2009) pseudo R^2 values of 0.25 and 0.3145 represents a relatively good-fit for a multinomial logit model. Hence, the pseudo R^2 value of 0.272 in this study is indicative of good fit and the correctness of the estimated model.

The slope parameters are consistent with the marginal effects obtained from the probabilities of farmers' risk aversion levels relative to the base category. Rahji & Fakayode (2009), state that the positive sign indicates that if these explanatory variables rise, there will be a marginal change in the probability of a farmer choosing other categories relative to the reference group, which in this case is risk neutral. Stated otherwise, a positive value for the parameter(s) increases the marginal shift in the chance of a farmer belonging to a different aversion level than the reference group. The likelihood of picking the reference group is higher than the marginal change in probability of being in the other option categories, as indicated by the negative parameter.

From the Highly Risk Averse model, the result shows that the coefficient of debt ratio was significant ($p<0.01$) and negatively signed. The implication is that as the marginal change in debt ratio increases the farmer becomes less risk averse. There is a 0.12%marginal decrease in the probability of the farmers being risk averse for every unit increase in debt ratio relative to the base category. This may be ascribed to the farmers' desperate need to undertake in various income yielding ventures that could assist him in offsetting the mounting debt. Some of the ventures or enterprises may be highly risky but that notwithstanding they embark in them to ensure they make enough income to sustain themselves and offset income. This finding is consistent with Piotr and Anna (2014) that debt ratio (value of debt divided by value of assets) affects farmers level of risk aversion. This on the other hand reduces the financial power of the farmers in adopting some of these good cassava production technologies and practices that can help him avert climate change risk or challenges.

In a similar manner, it could be seen from the result that previous production loss is significant ($p<0.01$) and positively signed. The implication is that as the production loss increases the farmer becomes more risk averse. There is a 7.07x10-6% decrease in the probability of the farmers being risk adverse for every unit decrease in previous production loss relative to risk neutral (base category). This conform to *a priori* expectation as the farmers are expected to adopt more technologies in other to combat climate change challenges which will increase his aversion level and invariably increase production. Perception is also seen from the result to be significant ($p<0.05$) and positively signed. This implies that the probability of the farmers becoming highly risk averse increases by about 1.04% for every unit increase in farmers perception of climate change risk relative to the base category. According to Chidiebere-Mark *et al*., (2014), a farmer with good perception and

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XII Issue VI June 2025

understanding of climate change risk and ways to combat them by adopting good technologies and practices will adopt more and invariable increase his aversion level.

From the Risk Averse model, the result shows that for the farmers who are risk averse the coefficient of output value was significant ($p<0.01$) and negatively signed. This implies that the probability of the farmers becoming risk averse decreases by about 1.48x10-5% for every unit increase in farm output value of the farmers relative to the base category. This relationship may be ascribed to the fact that the more the output of the farmers the less his interest of adopting new technologies or less he is ready to venture into risky investments or accept and adopt new innovations.. This is because he is already earning income from his farm firm. A farmer with increased output flow is less likely to be risk averse. The result also shows that off farm income is significant ($p<0.01$) and positively signed. This implies that the probability of the farmers becoming risk averse decreases by about 1.78x10-5% for every decrease in off farm income. A farmer with increase income flow has more finance to adopt new technologies and is more likely to be risk averse.

From the Mildly Risk Averse model, the coefficient of education is significant ($p<0.01$) and positively signed which implies that the probability of the farmers being mildly risk averse increases by 2.31% for every unit increase in the farmers education level. This suggests that the likelihood of a farmer being somewhat risk averse increases with the number of years of formal education. This outcome demonstrates the value of formal education in increasing an individual's awareness of the effects of climate change, the threats it poses to the production of his cassava crop and his means of subsistence, and the potential solutions to these problems. A more educated farmer would be better informed about practices that could also mitigate the effects of risks proceeding from climate change on his farm and on the adoption of these technologies.

From the Mildly Risk Seeking model, age is significant ($p<0.01$) and negatively signed implying that the probability of the farmers being mildly risk seeking decreases by 0.92% for a unit increase in farmers age relative to the base category. Farmer’s age has a lot to tell on risk seeking/taking to climate change challenges, hence older farmers are mild in taking risk and must therefore adopt cassava production technologies that can reduce climate change challenges. Hired labour is also significant ($p<0.05$) and positively implying a direct relationship between being mildly risk seeking and labored employed in the farm relative to the base category.

From the Risk Seeking model, the coefficient farm size was significant ($p<0.05$) and positively signed. This implies that for the risk seeking farmers, the probability of becoming risk seeking increased at about 1.7% for a unit increase in farm size.

This result does not conform to *apriori* but may be attributed to the farmers being contented with the scale of operation on the farm or not his having the capacity, ability and knowledge to manage a larger farm firm and the risk therein. Again, farmers age is significant ($p<0.01$) and negatively signed. This implies that the marginal change in probability of the farmers becoming risk seekers decreases by about 0.4% for every unit increase in age. This is in conformity with *a priori* expectations and may be due to the fact that older farmers irrespective of their wild experience will not be more ready to adopt new improved practices. Hence adopting risky new innovation may be difficult. This finding is consistent with Ehirim (2014) that older farmers depend more on their experience rather than venturing into technologies that will avers climate change risk when making decisions concerning the farm firm.

From the Highly Risk Seeking model, the coefficient of education is significant ($p<0.01$) and negatively signed which implies that the probability of the farmers being highly risk seeking increases by 1.4% for every unit decrease in the farmers education level. This discussion is in line with the above assertion and this implies that the more years of formal education the farmer has, the lower the probability of him being highly risk seeking. This result illustrates the role formal education plays in equipping the farmers towards the adoption of improved and good agricultural practices in other to combat and avert climate change challenges. A more educated farmer would be better informed about practices that could also mitigate the effects of risks proceeding from climate change on his farm and on the adoption of these technologies.

CONCLUSION

Climate change increase the problem of risk and with time general farm management will have to focus mostly on risk aversion as an important tool of risk management. The surveyed cassava farmers adopted effective and efficient technologies which is a good step towards ameliorating climate change. The farmers were observed to be risk seeking adopting less good and improved climate smart agricultural practices as a means of overcoming climate change effects.

RECOMMENDATION

The following recommendations are made based on the findings of the study:

The threat posed by the occurrence of climate change risk factors to cassava crop production should be made known to farmers as the can affect their aversion to climate change risk.

Farmers' aversion to climate change risk was found to be significantly influenced by a number of factors, particularly socioeconomic factors. The study area will benefit greatly from the provision of efficient extension services, as well as environments and policies that will improve farmers' socioeconomic welfare and help manage climate change risk.

Since most climate change risk can be managed and controlled, farmers should be educated on the need of adopting different Smart Agricultural Practices and Good Agricultural Practices as it will help them reduce high rate of uncertainty of agricultural production and invariably increase their profit.

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