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Determinants of Snail Farmers Willingness to Use Climate-smart Agricultural Practices in Awka South Local Government Area of Anambra State, Nigeria

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ABSTRACT

Climate change (CC) remains a global concern, negatively impacting food security and human health—particularly through its impacts on climate-smart agriculture. Climate-Smart Agriculture (CSA) has emerged as an important adaptation and mitigation strategy to address the effects of CC, but its adoption has been low in Nigeria due to limited awareness and knowledge of CSA, among other factors. Thus, this study was conducted to determine snail farmers' willingness to adopt climate-smart agriculture practices in Anambra State. A multistage sampling technique was adopted. The first stage involved the purposive selection of Local Government Areas (LGAs), including Ogbaru, Anambra West, Ihiala, Awka South, Idemili North, and Anaocha. The selection was based on the degree of involvement in snail farming as documented by the Anambra State Agricultural Development Program. At the second stage, three communities were randomly selected from each LGA and in the third stage, random sampling was used to select ten snail farmers per community. A total of thirty farmers were sampled per LGA, totaling a hundred and eighty (180) sampled farmers. A structured questionnaire was then used to collect data on farmers' Socio-economic characteristics, the willingness to use climate-smart practices by snail farmers and snail farmer's annual yield. Descriptive and inferential analyses were used. The result revealed that 65% of the respondents were males with a mean age of 39 years. The majority (60.0%) had secondary education, and 70% of respondents had a household size of 1-5 persons. The adaptation methods employed were water conservation (50.0%), agroforestry integration (27.5%), waste management (28.33%) and natural pest control (87.72%). Training, farmers' interest in CSA, and past implementation of CSA are significant at the 1% level. positively and significantly affect willingness to adopt CSA at 5% and 1%, respectively, while the type of climate-smart agriculture adopted negatively affected willingness to adopt CSA—flock size. (P=0.000), water conservation, agroforestry integration, waste management, and natural pest control (P=0.01) had positive and statistically significant effects on yield. The higher the number of snails used for production, the higher the yield. The study recommends training and water conservation as the minimum variables to increase adoption of CSA and, consequently, increase yield.

***Keywords*:** Determinants, Snail farmers, Willingness to use, Climate-smart, Agriculture.

INTRODUCTION

Climate change refers to long-term shifts in global or regional climate patterns that can result from natural processes such as solar cycles and volcanic eruptions, as well as from human activities such as deforestation and industrialization (EPA, 2024; NASA, 2024). Natural causes of climate change include meteorite impacts, volcanic eruptions, forest fires, ocean currents, and fluctuations in sunspot and solar cycles (NOAA, 2024; UCL, 2024). For example, volcanic eruptions inject aerosols into the atmosphere that temporarily cool the Earth's surface, while solar variations can influence temperature over centuries. However, these natural changes cannot fully explain the rapid warming observed in recent decades (EPA, 2024; Royal Society, 2023). Human activities remain the dominant driver of climate change. Key contributors include land-use changes such as deforestation and agricultural expansion, along with emissions from fossil fuel combustion—coal, petroleum, and natural gas—which release large amounts of greenhouse gases (IPCC, 2023; NRDC, 2023). Deforestation in particular reduces natural carbon sinks, accounting for about 11% of global greenhouse gas emissions (Wikipedia, 2024). Additionally, burning fossil fuels has increased atmospheric CO_2 concentrations by more than 40% since the Industrial Revolution, a trend strongly linked to the current climate crisis (NASA, 2024; Royal Society, 2023). Recent assessments show that human activities have already caused about 1.0°C of global warming above pre-industrial levels. If this trajectory continues, global warming is likely to reach 1.5°C between 2030 and 2052 (United Nations, 2022).

Alongside these global concerns, agriculture and food systems are also adapting to climate change. Snail farming, also known as heliciculture, involves raising edible land snails primarily for human consumption. Snails are valued as a rich source of protein, minerals, and vitamins, and are considered a delicacy in many parts of the world. Beyond their nutritional benefits, snail farming is increasingly recognized for its sustainability and relatively low environmental footprint. According to Ojigbede et al. (2020), snail farming in Nigeria is predominantly practiced by small-scale farmers, and socio-economic, institutional, and technological factors influence its productivity and profitability.

Climate-Smart Agriculture (CSA) has emerged as an important adaptation and mitigation strategy to counter the effects of climate change (Partey et al., 2018). Farmers' awareness and knowledge of CSA, access to credit, and extension services are significant drivers of CSA adoption (Bah et al., 2022). Moreover, skilled, environmentally conscious farmers who are open to innovation tend to adopt CSA practices more readily. On the other hand, barriers such as limited awareness, inadequate capacity, weak innovation, negative attitudes, and risk aversion hinder adoption (Beatles, 2023). Similarly, Onodu et al. (2022) emphasize that while farmers' awareness, perceived benefits, and social support encourage CSA adoption, challenges such as lack of credit access and high startup costs significantly reduce their willingness to adopt these practices.

There is a growing demand for snails as food. Snails are a nutrient-rich, protein-packed food source with increasing demand worldwide. Understanding how to produce snails sustainably and adapt to climate change can help meet this demand and support food security. For this reason, farmers need to understand adaptation strategies in the science of Snail production, especially in developing countries, given their vulnerability to climate change. Adoption of climate-smart snail farming practices can improve their resilience and food security.

Snail farming plays an important role in rural livelihoods, offering a source of iron, calcium, vitamin A, and other essential nutrients. Despite these benefits, snail production in Nigeria remains relatively low. Farmers face unique challenges, particularly those linked to climate change. Unfortunately, Climate-Smart Agricultural Practices, which could provide effective solutions, are not yet widely integrated into snail farming. Consequently, this study examines the determinants of snail farmers' willingness to use climate-smart agricultural practices with the specific objectives to:

1. To describe the Socio-economic characteristics of snail farmers, 2. To profile the climate-smart practices used by snail farmers, 3. To determine the willingness of snail farmers to use climate-smart practices and 4. To find out the effect of climate-smart agricultural practices on farmers' yield.

MATERIALS AND METHODS

The Population of the study comprised farmers engaged in snail farming in Anambra State, Awka, Nigeria. A multistage sampling technique was adopted for this study. The first stage involved the purposive selection of Local Government Areas (LGAs), including Ogbaru, Anambra West, Ihiala, Awka South, Idemili North, and Anaocha. The selection was done based on the degree of involvement in snail farming as documented by the Anambra State Agricultural Development Program. The second stage was the selection of three communities randomly from each LGA and in the third stage, random sampling was used to select 10 snail farmers from each community. A total of thirty farmers were sampled per LGA for a total of one hundred and eighty (180) farmers. A structured questionnaire was used to collect data on farmers' Socio-economic characteristics, climate-smart practices by snail farmers, snail farmers' willingness to adopt climate-smart practices, and snail farmers' annual yield. Data analysis was conducted using descriptive and inferential statistics in SPSS.

Model Specification

Objective 3: Determinants of the willingness of snail farmers to use climate-smart:

The logit model, or logistic regression, is commonly used to model a dummy dependent variable with outcomes (e.g., yes/no, success/failure). It assumes that the log-odds of the outcome are a linear function of the explanatory variables. The logit model models the probability of an event occurring as a function of a set of explanatory variables (Tilmann Gneiting and Roger Kühn 2019). The logit equation is written as (Greene, 1993)

$$P_r(Y=1) = \frac{e^{\beta x}}{1+e^{\beta x}} \quad \text{……………………. (1)}$$

With the cumulative distribution function given by

$$F(\beta x) = \frac{1}{1+e^{\beta x}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

Where β represents the vector of parameters associated with the factor x

Logit Model

Objective 3: was analyzed using the Logit Model. A logit model was used to model the relationship between a dichotomous response variable and a set of regressor variables.

Assuming the probability that farmer n will choose to produce snail using a particular technology -non- smart agriculture (NSA) or (smart agriculture (SA) is equal to proportion of maize farmers using that technology. The individual empirical models to be estimated may be specified as:

$$NSA = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots\ldots\ldots \beta_n X_n + \varepsilon_i \ldots\ldots\ldots\ldots (3)$$
$$SA = \gamma_0 + \gamma_1 X_1 + \gamma_2 X_2 + \ldots\ldots\ldots\ldots \gamma_n X_n + \varepsilon_i \ldots\ldots\ldots\ldots (4)$$

Where NSA= -non- smart agriculture

SA= - smart agriculture

βandγ are vectors of respective parameters to be estimated.

X_i= vectors of explanatory variables.

ε_i=error terms

The Explanatory Variables include

Farmers Characteristics

X_1=Training in climate-smart agriculture

X_2=Interest in climate-smart agriculture

X_3=Effect of climate change before

X_4=Weather variability experience

X_5=Type of climate-smart agriculture adopted

X_6 =Implemented climate-smart agriculture

Objective 4: Effect of climate-smart agricultural practices on farmers' yield

Objective 3: Y= β_0+β_{i1} socioeconomic characteristics+ adaptation strategies+ mitigation strategies+ϵ_i

Y= Yield (kg) (dependent variable), socio-economic characteristics, and CSA practiced (independent variables)

Ordinary Least Squares (OLS)

$$Y = \beta_0 + \beta_{1_{X_I}} + \beta_{2_{X_2}} \ldots\ldots\ldots + \varepsilon_I$$

Y is the yield of maize

β=parameters to be estimated

x_i= sets of explanatory variables

ε_I= Error term

M_1= Age of farmers (years)

M_7=Gender (Male=1 female=0)

M_2=Farming experience (years)

M_3=Years of formal Education (years).

M_4=Flock size

M_5=Labour (Man-days)

M_6=Water conservation

M_7=Agroforestry integration)

M_8=Waste management

M_9=Natural Pest control

RESULTS AND DISCUSSIONS

Socio-economic characteristics of the respondents

1. Gender

The results from Table 1 show that 35% of respondents are female, while 65% are male. The results have shown that males mostly carry out snail production. The result agrees with the findings of Adewale & Belewu (2022), who showed that the majority (92.5 %) were males, indicating the strength of men in the snail production sector of farming.

Table 1: Socio-economic Characteristics of Snail Farmers

Variables	Frequency	Percentage			
Sex					
Male	117	65.00			
Female	63	35.00			
Age					
30	63	35.00	31-40	41	22.77
41-50	36	20.00			
51-60	22	12.22			
>60	18	10.00			
Marital Status					
Single	72	40.00			
Married	108	60.00			
Household Size					
1-2	38	20.00			
5-6	72	40.00			
7-8	54	30.00			
Major Occupation					
Farming	54	30.00			
Civil Service	50	27.77			
Trading/ Artisanship	76	42.22			
Years in school					
1-6	38	20.00	7-12	108	60.00
>12	38	20.00			
Extension contacts					
	153	85.00			
	27	15.00			

Age

Age is very important in agricultural production, as it determines an individual's physical strength. Young people tend to withstand stress and put more time into various agricultural operations, which can result in increased output. The results from Table 1 indicate that 22.50% of the snail farmers are within the 31-40 years age bracket, 12.50% are within the 51-60 years age bracket, and 21-30 years are within the 39.05% bracket. The mean age of the respondents is 36.9years. This indicates that the majority of respondents are relatively young people actively engaged in agricultural operations. The result agrees with Adewale & Belewu (2022), who stated that most (39.2%) of the respondents' ages fall in the range of 41–50 years, with a mean of 41.58. Aiyeloja & Ogunjinmi (2010) also revealed the predominance of men (90 %) in snail production.

Educational qualification

Respondents' educational level plays an important role in snail production. According to Oladejo (2010), education is important in achieving a high level of management capabilities. The findings show that 60% of respondents have secondary education, 20% have tertiary education, and 20% have only primary education. It implies that all the respondents have formal education, which is likely contribute to high returns to their production level.

Marital Status and Household Size

The marital status indicates that 60% of the respondents are married, and 40% are single. The implication is that family labor can substitute for paid labor. Table 1 further reveals that 30% of respondents have a household size of 1-5 persons, and 70% have a household size of 6-10 persons. The implication is that family labor can substitute for paid labor. The result aligns with Adewale & Belewu (2022), who found that Most (86.7%) of the farmers were married and had large family sizes (mean household size of 4.12).

Major occupation

The majority of the respondents are practicing solely in business (42%), while 30% are into farming and 27.50% are civil servants

Table 2 presents the climate-smart practices used by snail farmers and reveals that 50% of users adopt water conservation, which is equal to the level among non-users. The percentage of respondents adopting Agroforestry Integration and waste management is 72%, which is greater than the level of users at 27%, and could be a result of a lack of knowledge of these climate-smart practices. The percentage of non-users of Energy Efficiency and Habitat preservation is 95%, with 5% of users, probably due to very low knowledge and technical know-how on how to apply them. The table also shows that more users use natural Pest control and natural feeding, with 87% and 100% of users, respectively, and 12.50% and 0% of non-users, respectively.

Table 4.3 shows the results of a logistic regression model. The log-likelihood of -60.70 is significant at the 1% level (Prob>chi2=0.000), indicating that the model is statistically significant. The LR chi2 (8) = 67.79 and Pseudo R2 = 0.41 also affirm that the model as a whole is statistically significant.

Table 2: Climate-smart agricultural practices used by snail farmers

Adaptation strategies	frequency	percentage	cumulative
Water Conservation			
Non-users	90	50.00	50.00
Users	90	50.00	100.00
Agroforestry Integration			
Non-users	130	72.22	72.50
Users	50	27.50	100.00
Energy/Feed Efficiency			
Non-users	171	95.00	95.00
Users	09	5.00	100.00
Waste Management			
Non-users	129	71.67	72.50
Users	51	28.33	100.00
Natural Pest Control			
Non-users	23	12.77	12.50
Users	157	87.72	100.00
Habitat Preservation			
Non-users	171	95.00.	95.00
Users	09	5.00	100.00

Field survey, 2024.

Table 3: Determinants of willingness to use climate-smart practices by snail farmers

Result			Marginal effect	
Variables	Coefficient	P>|z|	Coefficient	P>|z|
Age	0.043	0.142	0.10 1	0.142
Sex	0. 606	0.001	0.0452*	0.041
Trained in CSA	2.90	0.000	0.65***	0.000
Interest in c CSA	0.17	0.008	0.42**	0.007
Weather variability experience in the past	1.26	0.09	0.30*	0.098
Type of climate-smart agriculture adopted in the past	1.15***	0.000	-0.49***	0.000
Implementation of climate-smart agriculture	0.037**	0.006	-0.02**	0.001
Constant	-2.07	0.05		
Log likelihood=-60.70; Prob>chi2=0.000; LR chi2 (8)=67.79; Pseudo R2=0.41; No of obs=180				

Field survey, 2024.

Age

The coefficient for age (0.043; P=0.142) indicates that age has a small positive effect on age, suggesting that age is not a significant predictor of willingness to use climate-smart practices among snail farmers. Marginal effect: 0.10 (P=0.142) — The marginal effect of age is small and not significant, reinforcing that age does not have a meaningful impact on willingness to use climate-smart practices. (Kassa, 2022; Nazifi, 2024), consistent with your logistic result, where age was not a significant predictor.

Sex

Coefficient: 0.606 (P=0.001) — Sex is a significant predictor ($p < 0.05$) and has a strong positive effect on the outcome. Marginal effect: 0.0452 (P=0.041) — The marginal effect is smaller but still significant, indicating sex affects the likelihood of the outcome. Men are significantly more likely than women to adopt CSA practices. This could be due to differences in access to resources, decision-making power, or exposure to agricultural innovations. Gender-sensitive policies may be needed to close this gap (Abegunde et al., 2020).

Training in climate-smart agriculture

The coefficient is 2.90, and the p-value shows a 1% level of significance. This shows that training in climate-smart agriculture has a positive effect on the willingness to adopt it. The marginal effect is significant ($p < 0.0001$), indicating that a 1% increase in climate-smart agriculture training will lead to a 65% increase in willingness to. adopt climate-smart agriculture. Farmers who received training in climate-smart agriculture were far more likely to adopt these practices. Training boosts awareness, confidence, and technical know-how—making it a powerful tool for change (Shittu et al., 2021). Strong positive effect of training on willingness to adopt CSA replicates a common and robust finding: training/extension is among the strongest levers to increase CSA uptake (Shittu, 2021; Barasa, 2021)

Interest in climate-smart agriculture

The coefficient is 0.17 (P=0.008), indicating that interest in climate-smart agriculture has a significant positive effect on the outcome. The p-value showed a 5% level of significance. This shows that interest in climate-smart agriculture has a positive influence on willingness to adopt it. The marginal effect is significant ($p < 0.001$), indicating that a 5% increase in climate-smart agriculture training will lead to a 42% increase in willingness to. adopt climate-smart agriculture. Farmers who expressed interest in CSA even before training were more willing to adopt it. This highlights the importance of motivation and personal engagement. Outreach efforts that spark curiosity and enthusiasm could be highly effective (Tiamiu et al., 2018).

Weather variability experience in the past

The Coefficient is 1.26 (P=0.098). Weather variability faced—This variable has a positive effect that approaches statistical significance at the 5% level (P=0.053), suggesting that weather variability might impact the likelihood of adoption. The marginal effect (P=0.022) This is negative and statistically significant, meaning that while weather variability might initially seem positive, in practice, it may reduce the likelihood of adopting climate-smart agriculture. Farmers who had previously experienced the effects of climate change were more willing to adopt CSA. While not statistically strong, this trend suggests that personal exposure to climate risks can drive behavioral change (Lobell et al., 2011).

Type of climate-smart agriculture adopted

The coefficient is 1.15 ($p < 0.001$). The type of climate-smart agriculture adopted in the past has a strong, highly significant positive effect at the 1% significance level, meaning certain types of climate-smart agriculture practices are much more likely to be adopted. The marginal effect ($p < 0.001$). Despite the positive coefficient, the marginal effect is negative and highly significant, suggesting that the specific types adopted may have a complex relationship with overall adoption rates. The specific CSA practices adopted strongly influenced willingness. Some methods may be more practical or appealing than others. Tailoring CSA options to local contexts is essential (Abegunde et al., 2020).

Implemented climate-smart agriculture

The Coefficient is 0.037 (P=0.006). Implementing climate-smart agriculture has a significant positive effect on outcomes; the p-value is 5%. This shows that implementing climate-smart agriculture has a positive influence on willingness to adopt it. The marginal effect is negative and statistically significant (P=0.001), suggesting that the actual implementation may slightly decrease the likelihood of further adoption if the process is too complex or taxing for farmers.

Table 4: Effect of Climate Smart Agricultural Practices on Farmers' Yield

Result		Marginal effect		
Variables	Coefficient	P>|z|	Coefficient	P>|z|
Sex	493.1141		0.101	
Experience	4025.975*		0.017	
education	733.1342*		0.013	
Flock size	65.11998***		0.000	
labour	15.41381		0.140	
Water conservation	1.982276 *		0.041	
Agroforestry integration	0.3678827 **		0.0736	
Waste management	0.6161437**		0.0562	
Natural Pest control	0. 6891083		0.481	
Number of obs = 180				
Prob>F = 0.0000	R-squared = 0.6757		Adj R-squared= 0.5665	

Field survey, 2024.

Table 4.4 presents the results of a logistic regression model analyzing the impact of several variables on an outcome, along with their marginal effects. A detailed interpretation shows that Prob>F=0.0000, R-squared=0.6757, and Adj R-squared=0.5665, indicating that the predictors, as a group, significantly explain the outcome. Adj R-squared=0.5665 — The pseudo-R-squared value indicates that about 51.00% of the variation in the outcome is explained by the model, which is an average.

Flock size

Coefficient: 65.11998*** (0.000) has a large positive and statistically significant effect on yield. The higher the number of snails used for production, the higher the yield. This is in line with the work of Garr et al. (2011) and Posch et al. (2012).

Water conservation

Coefficient: 1.982 (P=0.041) — Water conservation has a large positive and statistically significant effect on the outcome, meaning that implementing water conservation measures strongly increases the yield. This positive coefficient is consistent with these findings (Rockström et al., 2008)

Agroforestry integration

Coefficient: 0.368 (P=0.074) — This variable has a positive but not statistically significant effect (P>0.05), suggesting that agroforestry integration could increase the likelihood of the outcome, but the evidence is not conclusive. The finding is supported by the work of Baier et al. (2023) and Visscher et al. (2024).

Waste management

The coefficient: 0.616 (P=0.056) — Waste management showed a moderately positive effect on yield with statistical significance (P=0.056). Waste management improvements consistently show soil and yield benefits (Kebede et al., 2023; Ho et al., 2022).

Natural pest control

Coefficient: 0.689 (P=0.481) — Natural pest control has a positive but statistically insignificant effect (P>0.05), meaning there is no strong evidence that this variable significantly influences the yield.

Conclusions and recommendations

The study concluded that training, farmers' interest in CSA, and past CSA implementation significantly positively affect willingness to adopt CSA. In contrast, the type of climate-smart agriculture previously adopted negatively affects willingness to adopt CSA. Flock size, water conservation, agroforestry integration, waste management, and natural pest control all had positive, statistically significant effects on yield.

1. Farmers trained on the use of Climate Smart Agricultural practices in snail farming by Extension agents should be prioritized.
2. Design gender-sensitive interventions to address resource gaps that limit women's adoption
3. Cost-effective water conservation and waste management practices should be encouraged
4. Guidance on optimal stocking densities to balance aggregate yield with per-animal growth and welfare should be provided.

Declaration

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Conflict of Interests

The authors declare no conflict of interest.

Data Availability

Not applicable

Author's Contribution

JOK, NKO, and SOA conceptualized and designed the study, developed the research instruments, and supervised data collection. ASE drafted the manuscript. All authors contributed significantly to the final version of the manuscript.

Generative AI Statements

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