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SCIENCE AND SOCIETY INSIGHTS
Sci Soc Insights (2025), 1(4): 195-202
Research Article

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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Article History: 25-303 Received: 08 Nov 2024 Revised: 08 Feb 2025 Accepted: 08 Feb 2025 Published Online: 2025

Citation: Komolafe JO, Okeke NK, Adejoh SO, Emeka AS, 2025. Determinants of snail farmers willingness to use climate-smart agricultural practices in Awka south local government area of Anambra state, Nigeria. Sci Soc Insights. 1(4): 195-202.

ABSTRACT

Climate change (CC) remains a global concern impacting food security and human health negatively. Climate smart agriculture. Climate-Smart Agriculture (CSA) has emerged as an important adaptation and mitigation strategy to counter the effects of CC, but the level of adoption has been low in Nigeria due supposedly Farmers' awareness and knowledge of CSA among others factors. Thus, this study was conducted to determine the willingness of snail farmers to use climate smart agriculture practices in Anambra State. Three-stage sampling technique was adopted. First stage witnessed the purposively election of Ogbaru, Anambra west, Ihiala, Awka South, Idemili North and Anaocha Local Government Areas (LGAs). Base on the degree of involvement in snail farming as documented by the Anambra State Agricultural Development Program. Second stage witnessed the selection of three (3) communities randomly from each LGA and in the third stage, random sampling was used to select ten (10) snail farmers per community. A total of thirty farmers were sampled per LGA, totaling a hundred and eighty (180) sampled farmers. Structured questionnaire was then used to collect data on farmers' Socio-economic characteristics, climate-smart practices by snail farmers; he willingness to use climate-smart practices by snail farmers and snail farmer's annual yield. Descriptive and inferential analysis: logit and ordinary least square regression. The result revealed that 65% of the respondents were males with mean age 39.05 years. Majority (60.0%) had secondary education and 70% of the respondents have household size of 1-5 persons. Adaptation method employed were water conservation adopted by (50.0%) Agroforestry Integration (27.5%), Waste Management (28.33%), Natural Pest Control (87.72%), Habitat Preservation (09). Training, farmers interest in CSA and past implemented of CSA significant at 1%. positively and significantly affect willingness to adopt CSA at 5% and 1% respectively while type of climate-smart agriculture adopted negatively impacted willingness to adopt CSA. Flock size. (P=0.000), water conservation, agroforestry integration, waste management and natural pest control (P=0.01) were all having, positive and statistically significant effect on the yield. The higher the number of snails used for production the high the yield. The study recommends training and water conservation as the min 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, which can occur due to natural processes such as solar cycles or volcanic eruptions, as well as from human activities like 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, fossil fuel burning 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 its productivity and profitability are influenced by socioeconomic, institutional, and technological factors.

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, farmers who are skilled, environmentally conscious, and 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 growing demand for snails as food, Snails are a nutrient-rich, protein-packed food source with increasing demand worldwide. Understanding how to produce snail sustainably and adapt to climate change can help meet this demand and support food security. For this reason, there is a need for farmers to understand the adaptation strategies in the science of Snail production especially in developing countries, due to 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 the impacts of climate change. Unfortunately, Climate-Smart Agricultural Practices, which could provide effective solutions, are not yet widely integrated into snail farming. Consequently, this study examine the determinants of snail farmer's willingness to use climate-smart agricultural practices with the specific objectives to:

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

MATERIALS AND METHODS

3.3 Population

The Population of the study comprised of farmers who are into snail farming production in the Anambra State, Awka, Nigeria.

3.4 Sampling procedure and sample size

Three stage sampling technique was adopted for this study. First stage witnessed the purposively selected Ogbaru, Anambra west, Ihiala, Awka South, Idemili North and Anaocha Local Government Areas (LGAs). Base on the degree of involvement in snail farming as documented on by the Anambra State Agricultural Development Program. Second stage witnessed the selection of three (3) communities randomly from each LGA and in the third stage, random sampling was used to select ten (10) snail farmers from each community. A total of thirty farmers were sampled per LGA, to sum up to a hundred and eighty (180) farmers that were sampled. Structured questionnaire was used to collect data on farmers' Socio-economic characteristics, climate-smart practices by snail farmers; he willingness to use climate-smart practices by snail farmers and snail farmer's annual yield

Model Specification

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

The logit model, or logistic regression, is commonly used to model dummy dependent variable with outcomes (e.g., yes/no, success/failure, etc.). It assumes that the log-odds of the outcome are a linear function of the explanatory variables. The logit model is model 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) = $e^{\beta x}$ …………………… (1)
1+$e^{\beta x}$

With the cumulative distribution function given by
F(βx)= 1 …………………… (2)
1+$e^{\beta x}$
Where β represents the vector of parameters associated with the factor x

Logit Model
Objective 3: was analyzed using the Logit Model. Logit Model models were used to model relationships 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, then the individual empirical models to be estimated may be specified as:

NSA=β_0 + $\beta_1 X_1$ +$\beta_2 X_2$ + ……… $\beta_n X_n$ + ε_i ………… (3)
SA=γ_0 + $\gamma_1 X_1$+ $\gamma_2 X_2$ + …………$\gamma_n X_n$ + ε_i …………(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 farmer's yield

Objective 3: Y= β_0+β_{i1} socioeconomic characteristics+ adaptation strategies+ mitigation strategies+ϵ_i
Y= Yield (kg) (dependent variable) socioeconomic characteristics, and CSA practiced (independent variables)

Ordinary least Squares (OLS)
Y =β_0 +$\beta_{1_{X_I}}$ +$\beta_{2_{X_2}}$ ……..+ε_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 result from Table 1 shows that 35% of the respondents are females while 65% are males. The results have shown that snail production is mostly carried out by males. 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.

4.1 Section A: Socioeconomic Characteristics of Snail Farmers

Variables	Frequency	Percentage	Mean			
Sex						
Male	117	65.00				
Female	63	35.00				
Age						
30	63	35.00	39.05 years			
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		3-4	18	10.00
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	11years			
7-12	108	60.00				
>12	38	20.00				
Extension contacts						
	153	85.00				
	27	15.00				

2. Age

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

3. Educational qualification

The educational level of respondents plays an important role in the snail production. According to Oladejo (2010), education is important in achieving high level of management capabilities. Finding from the result shows that 60% have secondary education, 20% have tertiary education, and 20% have primary education only. In the general, majority had one form of education or the other which is a good for the adoption of innovation. It implies that all the respondents have formal education which is a factor that will likely contribute to high returns to their production level. Also, the snail farmers in the study area should be able to adopt new production technologies.

4. Marital Status

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. The result conforms with Adewale & Belewu (2022) that Most (86.7 %) of farmers were married with large family sizes (mean household size of 4.12). The predominance of married farmers is most likely born out of the necessity to fend for their household.

5. Household size

The study reveals that 30% of the respondents have household size of 1-5 persons and 70% of the respondents have household size of 6-10 persons. The implication is that family labor can substitute for paid labor. The result conforms with Adewale & Belewu (2022) that Most (86.7 %) of farmers were married with large family sizes (mean household size of 4.12). The predominance of married farmers is most likely born out of the necessity to fend for their household.

6. Major occupation

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

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

The study objective of profiling the climate smart practices used by snail farmers reveals that the percentage of users of water conversation is 50% which is equal to the level of the non-users. The percentage of non-users for Agroforestry Integration and waste management which shows 72% is greater than the level of users which shows 27% and could be as a result of lack of knowledge of these climate smart practices. The percentage of non-users of Energy Efficiency and Habitat preservation 95% and shows 5% of users, probably due to a very low knowledge and technical know-how on how to apply them. The table also shows that there are greater users of natural Pest control as well as Natural Feeding which shows 87% and 100% of users respectively and 12.50% and 0% of non-users respectively.

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

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

Age

Coefficient of age: 0.043 (P=0.142) This indicates that age has a small positive effect on the outcome of age, meaning we cannot conclude that age is a significant predictor of willingness to use climate smart practices by 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 to adopt CSA practices than women. 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 show 1% level of significance. This show that training in climate-smart agriculture has positively on willingness to adopt climate-smart agriculture. The marginal effect has a ($p < 0.0001$), this showed that 1% increase in climate-smart agriculture training will lead to 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 and (P=0.008) Interest in climate-smart agriculture has a significant positive effect on the outcome. p value showed 5% level of significance. This show that interest in climate-smart agriculture has positively influence on willingness to adopt climate-smart agriculture. The marginal effect has a ($p < 0.001$), this showed that 5% increase in climate-smart agriculture training will lead to 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 and (P=0.098) Weather variability faced— This variable has a positive effect that approaches statistical significance of 5% (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 showed a greater willingness to use 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 1% significance, 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 had a strong influence on 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 and (P=0.006). Implemented climate smart agriculture has a significant positive effect on the outcome. p value showed 5% level of significance. This show that implemented climate-smart agriculture has positive influence on willingness to adopt climate-smart agriculture. The marginal effect has a (P=0.001) — The marginal effect is negative and statistically significant, suggesting that the actual implementation may slightly decrease the likelihood of further adoption if the process is too complex or tasking for farmers.

Effect of Climate Smart Agricultural Practices on Farmer's 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 thus; Prob>F=0.0000, R-squared= 0.6757, and Adj R-squared=0.5665 meaning 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 the yield. The higher the number of snails used for production the high the yield. This is in line with the work of (Garr et al., 2011; 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; 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

Thus, this study was conducted to determine the willingness of snail farmers to use climate smart agriculture practices in Anambra State. Three-stage sampling technique was adopted. A total of thirty farmers were sampled per LGA, totaling a hundred and eighty (180) farmers. Structured questionnaire was used to collect data on farmers' Socio-economic characteristics, climate-smart practices by snail farmers; he willingness to use climate-smart practices by snail farmers and snail farmer's annual yield. Descriptive and inferential analysis was adopted for the study: logit and ordinary least square regression. The result revealed. Training, farmers interest in CSA and past implementation of CSA significant positively and significantly affect willingness to adopt CSA while type of climate-smart agriculture adopted in the past negatively impacted willingness to adopt CSA. Flock size, water conservation, agroforestry integration, waste management and natural pest control were all having positive and statistically significant effect on the 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 encouragemed
4. Guidance on optimal stocking densities to balance aggregate yield with per-animal growth and welfare should be provide.

Funding

This study did not get any financial support from any organization.

Acknowledgement

The authors declare no conflict of interest.

Data Availability

Not applicable

Ethics Statement

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 did significant contributions to improving the final version of the manuscript.

Generative AI Statements

The authors confirm that no generative-AI tools (including DeepSeek) were used in the writing or preparation of this manuscript.

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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 did significant contributions to improving the final version of the manuscript.

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