ISSN: 2634-9221
European Journal of Applied Sciences; Vol. 14 No. 05 (2026) (479-485)
https://doi.org/10.14738/ejas.1405.12260

Institutional Drivers of Climate-Smart Agriculture Adoption Among Smallholder Rice Farmers in Sierra Leone

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Abstract: This study examined factors associated with the likelihood and intensity of climate-smart agriculture adoption among 385 smallholder rice-farming households in Moyamba, Kambia, and Kenema districts of Sierra Leone. A cross-sectional mixed-methods design combined a household survey with focus group discussions and key informant interviews. Binary logistic regression estimated whether a household adopted any of 12 climate-smart practices, while negative binomial regression modelled the number of practices adopted. Training, group membership, credit access, frequent extension contact, secure land tenure, and strong climate concern were positively associated with adoption. Training showed the largest institutional association with adoption likelihood (odds ratio 2.50) and adoption intensity (incidence-rate ratio 1.49). Group membership was also influential (odds ratio 2.10; incidence-rate ratio 1.41). Robustness checks across count and linear specifications produced consistent directions and significance patterns. The findings indicate that adoption is shaped less by fixed household characteristics than by farmers access to knowledge, finance, organizations, and secure conditions for investment. Policies that combine training, extension, group-based delivery, credit, and tenure support are therefore more likely to deepen adoption portfolios than isolated technology promotion.

Keywords: climate-smart agriculture, adoption intensity, extension, agricultural training, rural credit, rice farmers, Sierra Leone

INTRODUCTION

Rice production in Sierra Leone faces increasingly variable rainfall, delayed season onset, shortening growing periods, soil fertility decline, and recurrent production risk. Climate-smart agriculture offers a portfolio of agronomic and resource-management practices intended to improve productivity, strengthen adaptation, and where feasible reduce emissions (Food and Agriculture Organization, 2013; Lipper et al., 2014). Yet awareness does not automatically translate into adoption, and adoption of one practice does not necessarily lead to a sufficiently broad portfolio to protect farm livelihoods.

Technology-adoption theory emphasizes expected benefits, compatibility, knowledge, risk, and communication channels, while livelihood and household models emphasize resource constraints and competing welfare objectives (Rogers, 2003; Singh et al., 1986). Empirical studies likewise identify extension, training, credit, farmer organizations, land rights, and climate perceptions as important, although their effects vary across contexts (Feder et al., 1985; Knowler & Bradshaw, 2007; Teklewold et al., 2013). Evidence specific to Sierra Leone's rice systems remains limited.

This article estimates the socioeconomic, farm, institutional, and perceptual correlates of both adoption likelihood and adoption intensity. It asks which factors

distinguish adopters from non-adopters and which factors help households assemble broader portfolios of climate-smart practices.

Study Contribution

The article contributes in three ways. First, it separates the decision to adopt at least one practice from the decision to deepen a portfolio, recognizing that entry and intensity may respond to different constraints. Second, it combines institutional access, tenure, and climate perceptions in one empirical framework rather than treating adoption as a purely demographic choice. Third, it tests whether the institutional results remain stable across alternative count and linear specifications and selected interaction terms. This combination provides a more policy-relevant account of adoption than a single binary model.

Conceptual Expectations

Adoption is expected to rise when farmers receive credible information, observe locally relevant results, and can obtain the complementary resources required for implementation. Extension and training reduce information asymmetry and uncertainty; credit relaxes liquidity constraints; and farmer organizations support peer learning, input access, collective marketing, and contact with service providers. Secure tenure strengthens incentives for practices whose benefits accumulate over several seasons. Climate concern can increase the perceived cost of inaction, although concern may not translate into adoption where institutional constraints remain binding.

These mechanisms imply that institutional variables should be positively associated with both entry and intensity. They also imply complementarity: training may be more effective when finance is available, while group membership may amplify the value of extension and market information. The analysis therefore evaluates direct institutional associations, selected interactions, and correlations among practice choices.

MATERIALS AND METHODS

The study used a cross-sectional convergent mixed-methods design in Moyamba, Kambia, and Kenema districts. Districts were selected to represent important rice-producing environments and contrasting institutional and agroecological conditions. Multistage sampling proceeded from districts to chiefdoms, villages, and rice-farming households. The analytical sample comprised 385 complete household records. The survey measured awareness and use of 12 climate-smart practices, household and farm characteristics, extension contact, training, group membership, credit access, tenure security, market access, information access, climate perceptions, and food-security indicators. Focus groups and key informant interviews were used to interpret institutional mechanisms and implementation conditions.

Adoption was defined as use of at least one of the 12 practices. Adoption intensity was the number of practices used, ranging from zero to 12. Binary logistic regression estimated adoption likelihood and results were reported as coefficients, odds ratios, and marginal effects. Because intensity was an over-dispersed count, negative binomial

regression was used for the principal intensity model and incidence-rate ratios were reported. Multivariate probit analysis examined complementarities among selected practices. Interaction terms tested whether selected institutional effects varied by gender, education, farm size, and group membership. Alternative Poisson and ordinary least squares specifications, exclusion of outliers, and district subsamples were used as robustness checks. Coefficients are interpreted as adjusted associations rather than experimental causal effects.

Data Quality and Model Assessment

Questionnaires were pre-tested, enumerators were trained, completed instruments were checked in the field, and data were screened for missing values, coding inconsistencies, and implausible ranges. Composite scales demonstrated acceptable internal consistency, with Cronbach alpha values ranging from 0.71 to 0.88. Model assessment used likelihood-based fit statistics, dispersion tests, multicollinearity checks, and comparison of coefficient stability across alternative specifications. Analytical denominators were tied to complete cases for the variables used in each model.

Table 1: Composite indicators used in the analysis

Index	Description	Mean	SD	Min	Max	Cronbach's α
CSA awareness index	Number of practices aware of (0–12)	7.24	2.68	0	12	0.84
CSA adoption index	Number of practices adopted (0–12)	3.82	2.51	0	9	0.79
Institutional access score	Access to extension, training, credit, information (0–5)	2.94	1.82	0	5	0.71
Constraint index	Sum of constraint severity scores (16–80)	47.8	12.4	22	76	0.88
Food security index	Composite of 5 indicators (standardized)	0.00	1.00	-2.34	2.86	0.82
Socioeconomic status	Asset based index (standardized)	0.00	1.00	-1.92	3.12	0.76

Source: Household survey, 2026.

RESULTS

Average awareness covered 7.24 practices, whereas average adoption covered 3.82 practices. Institutional access averaged 2.94 on a five-point scale. Nearly half of respondents had never received an extension visit, indicating that the information and support environment remained thin despite farmers exposure to climate risk.

Table 2: Binary logistic regression of adoption likelihood

Variable	Coefficient	SE	Z	P	Odds Ratio	Marginal effect
Socio-economic characteristics						
Age	-0.008	0.007	-1.14	0.254	0.992	-0.002
Gender (female)	0.152	0.185	0.82	0.412	1.164	0.030
Education level	0.212	0.095	2.23	0.026	1.236	0.042
Household size	-0.042	0.032	-1.31	0.190	0.959	-0.008
Farm size	0.124	0.068	1.82	0.069	1.132	0.025
Institutional factors						
Extension (rarely)	0.182	0.198	0.92	0.358	1.200	0.036
Extension (occasionally)	0.412	0.215	1.92	0.055	1.510	0.082
Extension (frequently)	0.678	0.301	2.25	0.024	1.970	0.134
CSA training	0.915	0.241	3.80	<0.001	2.497	0.182
Credit access	0.587	0.198	2.96	0.003	1.799	0.117
Farmer group member	0.742	0.181	4.10	<0.001	2.100	0.148

Tenure and assets						
Secure tenure	0.422	0.162	2.60	0.009	1.525	0.084
Livestock ownership	0.184	0.158	1.16	0.246	1.202	0.037
Climate perceptions						
Climate concerned	0.312	0.168	1.86	0.063	1.366	0.062
Climate perception (ref: positive)						
- Neutral	0.156	0.242	0.64	0.522	1.169	0.031
- Negative	0.412	0.218	1.89	0.059	1.510	0.082
- Very negative	0.648	0.242	2.68	0.007	1.912	0.129
District (ref: Moyamba)						
Kambia	-0.188	0.215	-0.87	0.384	0.829	-0.037
Kenema	0.105	0.208	0.50	0.617	1.111	0.021
Constant	-1.845	0.421	-4.38	<0.001	0.158	–
Model fit						
Log likelihood	-189.1					
McFadden R^2	0.124					
AIC	406.2					
Percent correctly predicted	74.8%					

Source: Household survey, 2026.

The logistic results show that institutional variables were the most consistent predictors. Training increased the odds of adoption by approximately 150 percent, group membership by 110 percent, and credit access by 80 percent. Frequent extension contact, secure tenure, and strong climate concern were also positively associated with adoption. Age and sex did not show statistically significant net associations after the model controlled for institutional access and farm characteristics.

Table 3: Negative binomial regression of adoption intensity

Variable	Coefficient	SE	Z	p	IRR
Socio-economic characteristics					
Age	-0.003	0.003	-1.00	0.317	0.997
Gender (female)	0.041	0.073	0.56	0.575	1.042
Education level	0.076	0.036	2.11	0.035	1.079
Household size	-0.018	0.012	-1.50	0.134	0.982
Farm size	0.052	0.026	2.00	0.046	1.053
Institutional factors					
Extension (rarely)	0.071	0.076	0.93	0.352	1.074
Extension (occasionally)	0.158	0.081	1.95	0.051	1.171
Extension (frequently)	0.262	0.107	2.45	0.014	1.300
CSA training	0.401	0.090	4.46	<0.001	1.493
Credit access	0.233	0.078	2.99	0.003	1.262
Farmer group member	0.345	0.071	4.86	<0.001	1.412
Tenure and assets					
Secure tenure	0.152	0.062	2.45	0.014	1.164
Livestock ownership	0.068	0.061	1.11	0.267	1.070
Climate perceptions					
Climate concerned	0.108	0.066	1.64	0.101	1.114
Climate perception (ref: positive)					
- Neutral	0.042	0.094	0.45	0.653	1.043
- Negative	0.152	0.086	1.77	0.077	1.164
- Very negative	0.242	0.094	2.57	0.010	1.274
District (ref: Moyamba)					
Kambia	-0.082	0.081	-1.01	0.313	0.921
Kenema	0.015	0.078	0.19	0.849	1.015
Constant	0.842	0.152	5.54	<0.001	2.322
Model fit					

Theta	2.84	0.31			
Log likelihood	-745.3				
AIC	1520.6				
LR test vs. Poisson	124.8***				

Source: Household survey, 2026.

The intensity model reinforced the central institutional finding. Training was associated with a 49 percent higher expected count of practices, group membership with a 41 percent higher count, and credit access with a 26 percent higher count, holding other variables constant. Complementarity among improved varieties, crop rotation, organic manure, and mulching suggests that farmers assemble practice portfolios rather than make entirely independent decisions.

Table 4: Robustness checks for key institutional predictors

Specification	Training coefficient	Group coefficient	Credit coefficient	Model fit
Base negative binomial	0.401***	0.345***	0.233***	AIC=1520.6
Poisson model	0.408***	0.352***	0.238***	AIC=1645.2
OLS (linear)	0.421***	0.368***	0.242***	R^2=0.342
Zero inflated negative binomial	0.392***	0.338***	0.228***	AIC=1518.4
With district fixed effects	0.398***	0.342***	0.231***	AIC=1522.1
Excluding outliers	0.388***	0.336***	0.224***	AIC=1486.3
Using adoption index (weighted)	0.412***	0.354***	0.238***	AIC=1532.8

Source: Household survey, 2026.

DISCUSSION

The dominance of training and extension is consistent with diffusion theory: farmers require opportunities to observe, understand, adapt, and evaluate practices before committing scarce resources (Rogers, 2003). Training may also reduce uncertainty about practice combinations and timing. The result aligns with evidence that agricultural training and information access improve uptake of climate-smart practices in other African settings (Martey et al., 2021; Waaswa et al., 2024).

Group membership appears to lower information and transaction costs, strengthen peer learning, and improve access to collective services. Similar mechanisms have been reported for cooperatives and collective action (Abebaw & Haile, 2013; Wollni et al., 2010). Credit access matters because several practices require purchased inputs, hired labour, equipment, or delayed returns. Tenure security similarly supports longer-horizon investments by strengthening farmers confidence that they will capture future benefits (Besley, 1995; Deininger & Jin, 2006).

The findings support bundled delivery. Training without credit may increase knowledge while leaving liquidity barriers intact; credit without technical guidance may expose farmers to poorly chosen investments; and both may have limited reach when extension contact is infrequent. Farmer groups offer a practical platform for integrating these services, including gender-responsive outreach.

The weak net association of sex with adoption after institutional controls should not be read as evidence that gender is irrelevant. Gender inequalities may operate through land rights, extension access, control over income, group participation, and credit rather than

through a direct coefficient. Policy should therefore monitor whether women receive the same quality and frequency of institutional support, not only whether a gender dummy is statistically significant.

District effects were modest after controlling for household and institutional characteristics, suggesting that service access explains part of the geographic variation. Even so, local adaptation remains necessary because water control, soil conditions, market distance, and rainfall exposure affect the feasibility and expected return of specific practice combinations. National policy can define a service bundle, while district extension teams tailor the technical portfolio.

LIMITATIONS

The results are based on cross-sectional household data and cannot establish temporal ordering or causal effects. Adoption and institutional access were self-reported, creating possible recall and social-desirability error. Unobserved farmer ability, motivation, local programme placement, and plot quality may influence both service access and adoption. The binary adoption threshold also groups together trial use and sustained use, although the separate intensity analysis partly addresses that limitation. The three districts cover important rice systems but do not represent every production environment in Sierra Leone.

CONCLUSION AND IMPLICATIONS

Climate-smart agriculture adoption among smallholder rice farmers in Sierra Leone is strongly associated with modifiable institutional conditions. Training, farmer organizations, credit, extension contact, and secure tenure are more actionable than fixed demographic characteristics and should form the core of adoption policy. District programmes should use farmer organizations as delivery platforms, increase the regularity of extension contact, link training to seasonal finance, and support documentation of land-use rights. Longitudinal or experimental studies are needed to determine how these institutional packages affect adoption trajectories over time.

RESEARCH ETHICS AND DATA AVAILABILITY

Consent and confidentiality: Respondents received information about the study purpose, voluntary participation, and the right to withdraw. Written consent was obtained; where literacy was limited, the information was read aloud and verbal consent was documented. Identifying information was removed from analytical data and was not reported in the study.

Data availability: Access to the underlying dataset is subject to the consent, confidentiality, and institutional requirements governing the doctoral study.

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