

Impact of Adaptive Climate-Smart Agricultural Practices on Rice Profitability in Kwara State

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Abstract—Climate-smart agricultural (CSA) practices are promoted to raise productivity and strengthen resilience, yet evidence on their economic returns among Nigerian rice farmers remains limited. This study examined the profitability of rice farming, the impact of CSA adoption on rice productivity and profitability, and the barriers to adoption among smallholder rice farmers in Kwara State, Nigeria. Data from 250 farmers selected through multi-stage sampling were analysed using profitability measures, a composite adoption index derived from principal component analysis (PCA), logit and probit regression, an independent samples t-test, propensity score matching (PSM) and Likert-scale barrier analysis. Rice farming was highly profitable (mean net profit ₦1,789,634/ha; benefit-cost ratio 7.82). Adoption was shallow: 41.2% of farmers were low adopters, 29.6% medium adopters and only 29.2% high adopters. Rice productivity did not differ significantly between adopters (4,183 kg/ha) and non-adopters (4,231 kg/ha; $p = 0.567$). After matching, however, high adopters earned ₦342,177/ha more net profit than comparable low/medium adopters ($t = 5.231$, $p < 0.001$). High adoption was more likely among farmers with more farming experience, larger farms, higher education, cooperative membership, extension access and credit access, with extension access having the strongest effect (odds ratio = 2.33). All seven barriers were rated moderately high (mean scores 3.35–3.53; agreement 53.6–58.0%), led by lack of government support, poor access to extension agents, and unavailability of stress-tolerant varieties and weather information. The results suggest that the economic benefit of CSA depends on the depth of adoption, and that policy should focus on moving farmers from low or medium to high adoption through extension, credit, cooperatives, and seed and climate-information systems.

Keywords— Climate-smart agriculture, rice, profitability.

I. INTRODUCTION

Rice is a strategic staple in Nigeria, and its production is exposed to rainfall variability, flooding and rising temperatures. Climate-smart agriculture (CSA) aims to sustainably increase productivity and incomes, build resilience and, where possible, reduce emissions (Lipper et al., 2014). Practices commonly grouped under CSA include integrated nutrient and pest management, flood- and salinity-tolerant varieties, conservation tillage, diversification, crop rotation and the use of climate and weather information. Evidence from Nigerian rice households links the adoption of improved rice technologies to higher incomes (Dontsop-Nguezet et al., 2011), but evidence on the economic returns to CSA specifically, and on how those returns vary with how intensively farmers adopt, is thin.

Two features of the existing evidence motivate this study. First, simple comparisons of adopters and non-adopters can be misleading, because farmers choose whether and how far to

adopt, and the characteristics that drive adoption may also drive outcomes. Second, adoption is usually treated as a binary status, which can hide the difference between farmers who use one or two practices occasionally and farmers who use many practices consistently. Kwara State is a suitable location since it is a significant rice-producing state in North-Central Nigeria with active value chain programs and CSA initiatives, despite the fact that adoption is inconsistent (Oba et al., 2022).

This paper therefore addresses three objectives: (i) to determine the profitability of rice farming in Kwara State; (ii) to evaluate the impact of CSA adoption on rice productivity and profitability, distinguishing the level of adoption and correcting for self-selection through propensity score matching; and (iii) to identify the barriers constraining adoption.

II. METHODOLOGY

2.1 Study area, sampling and data

The study was conducted in Kwara State, North-Central Nigeria (latitudes 8°30'N–10°30'N, longitudes 3°00'E–6°00'E), a Guinea savanna area suited to rice cultivation. A multi-stage sampling procedure was used. On the basis of production data and the existence of CSA initiatives, four Local Government Areas (Patigi, Edu, Asa, and Ifelodun) were purposefully selected. Three rice-producing villages were chosen at random from each LGA, and 250 smallholder rice farmers (who farm less than five hectares) were chosen at random from these villages. Trained enumerators conducted face-to-face interviews using a structured questionnaire in English, Yoruba, Nupe, and Hausa for four weeks as required, collecting primary data.

2.2 Analytical framework

Profitability. Gross revenue per hectare was productivity (kg/ha) multiplied by the selling price (₦/kg). Net profit was gross revenue less total production cost per hectare, and the benefit-cost ratio (BCR) was gross revenue divided by production cost.

Level of adoption. Farmers rated their use of eleven CSA practices on a five-point frequency scale (1 = never used to 5 = always used). The ratings were combined into a composite adoption index using PCA, and farmers were classified into low, medium and high adoption levels [state the cut-off rule used]. Farmers at the medium and high levels were treated as adopters, and those at the low level as non-adopters.

Impact on productivity and profitability. Mean productivity was compared between adopters and non-

adopters using an independent samples t-test. To address self-selection, a binary logit model (with a probit model as a robustness check) was estimated for the probability of high adoption ($D = 1$ for high adopters, $D = 0$ for low/medium adopters) on age, household size, farming experience, farm size, education, gender, cooperative membership, extension access and credit access. The predicted probabilities were used as propensity scores for one-to-one nearest-neighbour matching with a caliper [state caliper width and whether matching was with replacement]. Covariate balance was assessed using standardised bias before and after matching. The average treatment effect on the treated (ATT), $ATT = E[Y1 - Y0 | D = 1]$, was estimated for net profit (₦/ha) as the mean difference between matched high adopters and matched low/medium adopters, and tested with an independent samples t-test.

Barriers. Seven barriers were rated on a five-point Likert scale (1 = strongly disagree to 5 = strongly agree). Mean scores and the share of respondents scoring 4 or 5 (agreement) were computed for each barrier.

3. Results and discussion

3.1 Respondent characteristics

The sample was predominantly male (72.0%), with a mean age of 47.7 years (32.8% aged 56 or above), 21.7 years of farming experience and a mean farm size of 2.49 ha. Secondary education was the most common level (32.4%). Cooperative membership (57.2%) and extension access (59.6%) were moderate, while only 43.2% of farmers had access to credit.

3.2 Profitability of rice farming

Rice farming was highly profitable (Table 1). Mean production cost was ₦262,313/ha against mean gross revenue of about ₦2.05 million/ha, giving a mean net profit of ₦1,789,634/ha and a BCR of 7.82: each naira invested returned about ₦7.82. Mean productivity was 4,203 kg/ha and the mean selling price ₦487.74/kg.

TABLE 1: Profitability indicators (n = 250)

Indicator	Minimum	Mean	Maximum
Production cost (₦/ha)	183,052	262,313	349,744
Net profit (₦/ha)	654,022	1,789,634	3,446,293
Selling price (₦/kg)	359	487.74	650
Productivity (kg/ha)	2,358	4,203	5,965

Source: Field survey, 2026

The cost range is consistent with variation in land preparation, fertiliser use and reliance on hired versus family labour reported for north-central Nigeria (Ayoola et al., 2023). The favourable price environment, shaped by import-substitution policy (Okoruwa et al., 2023), is likely to have contributed to the high margins, so the results should be read as reflecting current market conditions. Net profit also varied widely (₦654,022–₦3,446,293/ha; SD = ₦498,099), in line with evidence that farm size, input quality, market access and managerial skill drive profit variability among rice farmers in the zone (Girei et al., 2022), and post-harvest losses may further erode realised returns (Abubakar et al., 2023). Credit constraints, which affected 56.8% of the farmers, are a

plausible further limit on input investment and returns (Magnan et al., 2022).

A raw comparison showed almost no profit difference between adopters and non-adopters (Table 2). Adopters earned ₦1,778,383/ha and non-adopters ₦1,805,690/ha, a gap of ₦27,307/ha (1.5%) in favour of non-adopters. This should not be read as evidence that CSA lowers profitability: the comparison pools farmers at different adoption levels and does not control for differences between farmers. Section 3.4 addresses both issues.

TABLE 2: Productivity and profitability of adopters and non-adopters

Category	Mean productivity (kg/ha)	Mean production cost (₦/ha)	Mean net profit (₦/ha)
Medium adopters (n = 177)	4,231	262,400	1,805,690
High adopters (n = 73)	4,183	262,227	1,778,383
Overall (n = 250)	4,203	262,313	1,789,634

Source: Field survey, 2026

3.3 Level of adoption

Because the impact analysis depends on how adoption is classified, Table 3 summarises the adoption levels. Practice-level use ranged from 57.6% (climate and weather information services) to 67.6% (integrated nutrient and pest management), but adoption at the farmer level was shallower: 147 farmers (58.8%) were adopters, yet only 73 (29.2%) were high adopters.

TABLE 3: Distribution of farmers by level of CSA adoption

Level of adoption	Farmers (n)	Percentage	Classification
Medium	177	70.8	Medium Adopters
High	73	29.2	High Adopters
Total	250	100	

Source: Field survey, 2026

3.4 Impact of CSA on rice productivity and profitability

3.4.1 Productivity. Adopters recorded a mean productivity of 4,183 kg/ha and non-adopters 4,231 kg/ha (Table 2). The 48 kg/ha difference was not statistically significant ($t = -0.574$, $p = 0.567$), so CSA adopters did not obtain higher productivity than medium adopters on average. Mean productivity in the sample was well above the national smallholder average of roughly 2,300–2,500 kg/ha, which suggests a high baseline with limited room for measurable gains. Other plausible explanations are the single-season, cross-sectional design, which cannot capture the gradual build-up of soil and water benefits; self-selection into adoption; and the pooling of medium adopters, whose use of CSA is partial, with high adopters.

3.4.2 Determinants of high adoption. The logit model was significant ($\chi^2 = 31.842$, $p < 0.001$; Nagelkerke $R^2 = 0.168$) and classified 71.2% of farmers correctly (Table 4). Farming experience, farm size, education, cooperative membership, extension access and credit access significantly raised the probability of high adoption, while age, household size and gender did not. The largest impact came from extension access, with farmers who had access having 2.33 times the

likelihood of high adoption. The probit model gave the same set of significant variables, supporting the robustness of the specification. These results indicate that high adoption is shaped by access to information, networks and finance as well as by individual characteristics.

TABLE 4: Logit estimates of high CSA adoption

Variable	B	S.E.	Wald	Sig.	Exp(B)
Age	0.018	0.010	3.240	0.072	1.018
Household size	-0.041	0.046	0.793	0.373	0.960
Farming experience	0.031	0.012	6.668	0.010	1.031
Farm size (ha)	0.286	0.094	9.246	0.002	1.331
Education	0.417	0.170	6.017	0.014	1.517
Gender	0.251	0.207	1.471	0.225	1.285
Cooperative membership	0.682	0.263	6.721	0.010	1.978
Extension access	0.847	0.267	10.057	0.002	2.333
Credit access	0.526	0.250	4.430	0.035	1.692
Constant	-3.184	0.811	15.418	<0.001	0.041

Model: $\chi^2 = 31.842$, $p < 0.001$; Nagelkerke $R^2 = 0.168$; correct classification = 71.2%. Source: Field survey, 2026

3.4.3 Propensity score matching. The 73 high adopters were matched one-to-one with 73 medium adopters drawn from the remaining 177 farmers. Matching substantially reduced observable differences: the standardised bias for farm size fell from 29.1% to 7.0% and for extension access from 25.7% to 7.1%. Among matched farmers, high adopters earned ₦2,084,615/ha and low/medium adopters ₦1,742,438/ha, an ATT of ₦342,177/ha, or about 19.6% above the comparison group (Table 5). The difference was statistically significant ($t = 5.231$, $df = 144$, $p < 0.001$).

TABLE 5: Impact of high CSA adoption on net profit after matching

Group	N	Mean net profit (₦/ha)	Std. deviation	Std. error
High adopters (matched)	73	2,084,615	386,743	45,254
Low/medium adopters (matched)	73	1,742,438	401,527	46,983
ATT		342,177		

Levene's $F = 0.421$ ($p = 0.518$); $t = 5.231$; $df = 144$; $p < 0.001$. Source: Field survey, 2026

This result contrasts with the negligible raw profit difference in Table 2 and the absence of a productivity difference in Section 3.4.1. The contrast suggests that the economic benefit of CSA depends on the depth of adoption: the raw comparison pools medium adopters, whose partial use may not yet pay off, with high adopters, and ignores differences in farmer characteristics, whereas the matched comparison isolates high adopters and compares them with similar farmers who adopt less. Positive economic effects of CSA adoption among Nigerian smallholders have been reported elsewhere (Saadu et al., 2024 [add full reference]); the present study adds evidence for rice farmers and shows that the effect is concentrated at high adoption levels. The mechanism is plausibly more efficient resource use and fewer climate-related losses where practices are used together and consistently, and the importance of extension, cooperatives and credit in Table 4 suggests that institutional support helps farmers reach that level. Because the productivity comparison was not repeated on the matched sample, the study cannot say

whether the profit gain operates through higher output, lower costs or both.

3.5 Barriers to CSA adoption

All seven barriers were rated moderately high, with mean scores of 3.35–3.53 and agreement rates of 53.6–58.0% (Table 6). The narrow clustering of scores indicates that no single constraint dominates; adoption appears to be limited by several institutional, financial, informational and structural barriers acting together.

TABLE 6: Barriers to CSA adoption (n = 250; frequency, with percentage in brackets)

Barrier	SD	D	N	A	SA	Mean	Agree (%)
Lack of government support	28 (11.2)	28 (11.2)	51 (20.4)	69 (27.6)	74 (29.6)	3.53	57.2
Poor access to extension agents	20 (8.0)	33 (13.2)	52 (20.8)	88 (35.2)	57 (22.8)	3.52	58.0
Unavailability of stress-tolerant varieties / poor access to weather information	22 (8.8)	38 (15.2)	45 (18.0)	80 (32.0)	65 (26.0)	3.51	58.0
CSA practices are labour-intensive	25 (10.0)	28 (11.2)	59 (23.6)	76 (30.4)	62 (24.8)	3.49	55.2
Lack of knowledge/training	29 (11.6)	34 (13.6)	49 (19.6)	75 (30.0)	63 (25.2)	3.44	55.2
Lack of access to finance/credit	27 (10.8)	32 (12.8)	53 (21.2)	81 (32.4)	57 (22.8)	3.44	55.2
High cost of CSA inputs	28 (11.2)	42 (16.8)	46 (18.4)	83 (33.2)	51 (20.4)	3.35	53.6

SD = strongly disagree; D = disagree; N = neutral; A = agree; SA = strongly agree. Source: Field survey, 2026

Lack of government support was the most strongly rated barrier (mean 3.53; 57.2% agreement). This is consistent with reports of a gap between CSA policy and implementation at state and local levels in Kwara and Oyo States (Adeleke et al., 2022). Poor access to extension agents (mean 3.52; 58.0%) is notable because 59.6% of respondents reported nominal access to extension, which suggests that the frequency and quality of contact, rather than access alone, are the problem. This is plausible given reported extension agent-to-farmer ratios in north-central Nigeria of about 1:2,500 (Ayoade et al., 2023). The joint barrier of unavailable stress-tolerant varieties and poor weather information (mean 3.51; 58.0%) points to last-mile delivery failures in seed supply (Alibu et al., 2023) and in the trust and usability of climate information (Zougmore et al., 2021).

Labour intensity (mean 3.49; 55.2%) is relevant given the ageing profile of the sample, and gender differences in labour burdens may add to it (Twyman et al., 2022). Knowledge and training deficits and credit constraints scored identically (mean 3.44; 55.2%), indicating that farmers face a combined constraint of knowing how to implement practices and being able to finance them. High input costs scored lowest (mean 3.35; 53.6%) but were still acknowledged by over half of respondents, in line with input price inflation in Nigerian agriculture (Nwachukwu et al., 2022). Taken together with the determinants in Table 4, the barriers map closely onto the

factors that raise the odds of high adoption (extension, credit, cooperatives), which reinforces the case for packaged rather than single-point interventions.

III. CONCLUSIONS AND POLICY IMPLICATIONS

Rice farming in Kwara State is highly profitable under current conditions (mean net profit ₦1,789,634/ha; BCR 7.82), but CSA adoption is broad and shallow: 58.8% of farmers are adopters, yet only 29.2% adopt at a high level. Rice productivity did not differ significantly between adopters and non-adopters, and the raw profit difference was negligible. After propensity score matching, however, high adopters earned ₦342,177/ha more net profit than comparable low/medium adopters, which suggests that the economic benefit of CSA depends on the depth of adoption rather than on adoption status alone. Adoption is held back by interlinked institutional, financial, informational and structural barriers.

The findings support four policy directions. First, extension and promotion efforts should aim to move farmers from low and medium to high adoption, not only to increase the number of adopters. Second, extension reform, for example through farmer field schools and better agent coverage, together with strengthened cooperatives and wider access to credit, should be the priority entry points, since each significantly raised the odds of high adoption. Third, seed and climate-information systems need attention so that stress-tolerant varieties and usable, localised weather information reach farmers. Fourth, because the barriers are mutually reinforcing, interventions should be coordinated across policy implementation, extension, seed, finance and mechanisation rather than delivered singly.

4.1 Limitations

The cross-sectional design captures one season and cannot track benefits that accumulate over time. Data are self-reported. PSM controls only for observed characteristics, and no sensitivity analysis for hidden bias is reported. The PSM analysis was applied to net profit; productivity was compared only between adopters and non-adopters and was not re-estimated on the matched sample. The study covers four LGAs in one state, and the adoption-level classification depends on the cut-offs used. Future work could use panel data, apply matching to productivity and costs separately, and report sensitivity bounds.

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