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Do Cooperative Governance and Social Capital Condition the Climate Resilience Returns to Precision Agriculture? Moderation Evidence from Smallholder Cooperative Members in Ogun State, Nigeria

Owolabi, O.I.[1] Abdulahi, T.O.[2*] and Ofulume, A.N.[3]
[1,2,3]Department of Cooperative Economics and Management, Faculty of Management Sciences, Nnamdi Azikiwe University, Awka, Nigeria
***Corresponding Author:** Abdulahi, T.O. (ao.taiwo@unizik.edu.ng; ORCID 0000-0003-0562-9134)

ABSTRACT: Precision agricultural technologies are promoted as tools for climate adaptation, yet little is known about whether the organisations through which smallholders access them shape the resilience they obtain. We test whether cooperative governance quality and social capital moderate the association between the adoption of precision agricultural techniques (PAT: precision irrigation, nutrient management, pest control and weather forecasting) and self-assessed climate change resilience (CCR). We used a cross-sectional survey of 357 members of 24 agricultural cooperatives from the four agricultural zones of Ogun State, Nigeria (92.97% response rate) and estimated a hierarchical moderated regression with mean-centred predictors. PAT adoption (B = .431, β = .463) and a combined governance and social-capital index (B = .218, β = .303) were each positively associated with resilience, and together with the interaction explained 41.0% of its variance. The PAT × governance/social-capital interaction was positive and statistically significant (B = .162, 95% CI [.033, .290], p = .014) but small, adding 1.0% of explained variance (Cohen's $f^2 \approx .02$). The estimated resilience slope of PAT rises from .431 at average institutional quality to .593 one scale point above it. The results are consistent with, but do not demonstrate, an institutional conversion mechanism, and the interaction is modest relative to the cluster-sampling and common-method concerns we discuss. For policy, public and donor support for precision agriculture in cooperatives should pair technology access with investment in the accountable management of shared assets and in member trust.

Keywords: precision agriculture; climate resilience; agricultural cooperatives; social capital; cooperative governance; moderation; Nigeria

1. INTRODUCTION

1.1 The global challenge: climate risk and the promise of precision agriculture

Agriculture is among the sectors most exposed to climate change, and the farms least able to absorb that exposure are small ones. Shifts in rainfall timing, longer dry spells, heat stress and floods destabilise yields from one season to the next, and the Intergovernmental Panel on Climate Change judges the risks to food production in the lower-latitude regions to be rising (IPCC, 2022). Building the resilience of farming systems, understood as their capacity to anticipate, absorb, adapt to and recover from climate shocks while maintaining production

and livelihoods, has therefore become a central objective of agricultural and climate policy (Folke et al., 2016; Tendall et al., 2015).

Precision agriculture is widely presented as one route to that objective. Sensor-guided irrigation, site-specific nutrient management, targeted pest monitoring and localised weather information aim to apply the right input in the right place at the right time and to warn farmers of hazards earlier (Gebbers and Adamchuk, 2010; Wolfert et al., 2017). In principle, these techniques tighten the feedback between what a crop needs and what a farmer does, so they are expected to stabilise output and limit losses under climatic stress (Zhang et al., 2002; McBratney et al., 2005).

1.2 The Regional Picture: Smallholders in West Africa and Nigeria

The promise is hardest to realise where it is most needed. In West Africa, farming remains largely rain-fed and small-scale, and it is exposed to delayed rainfall onset, dry spells and flooding (Sultan & Gaetani, 2016). Smallholders face a cluster of constraints that precision technologies, being capital-intensive, skill-intensive and information-intensive, tend to aggravate: limited capital for equipment, thin extension and advisory services, and unreliable access to timely information (Lowenberg-DeBoer & Erickson, 2019; Klerkx et al., 2019). Nigerian smallholders share these constraints. A technology that works under controlled conditions can therefore deliver little to a farmer who cannot afford it, maintain it or interpret what it reports. The central policy question for the region is accordingly not only which technologies to promote but through which organisations smallholders can obtain them and make them work.

1.3 The institutional channel: agricultural cooperatives and the Ogun State setting

Agricultural cooperatives are a natural answer to that question. By pooling funds, sharing equipment, organising training and circulating information, they can lower the entry barriers to technologies that are lumpy and knowledge-intensive (Ortmann & King, 2007). Evidence from several countries links cooperative membership to higher uptake of improved practices and to better farm outcomes (Bernard & Spielman, 2009; Fischer & Qaim, 2012; Ma & Abdulai, 2016; Wossen et al., 2017).

Ogun State, in south-western Nigeria, illustrates the scale of this channel. State records list 2,622 registered agricultural cooperative societies with an estimated 144,210 members (Ogun State Ministry of Community Development and Cooperatives, 2024), spread across four agricultural zones. For a very large number of farmers in the state, therefore, the cooperative rather than the individual farm is the practical unit through which a precision technology is accessed, shared and maintained.

1.4 What is known, and What is not

Three strands of research bear on this setting. The adoption literature explains who adopts and when, drawing on diffusion theory (Rogers, 2003). The cooperative-economics literature shows that cooperatives are far from uniform: they differ in how accountable their leaders are, how openly resources are reported, how far members take part in decisions and how much members trust one another, and these differences are treated as decisive for performance (Cook, 1995; Ortmann & King, 2007). The social-capital and common-pool-resource literatures link such differences to collective action under environmental risk and to the management of

shared assets (Ostrom, 1990; Pretty, 2003; Adger, 2003).

What these strands do not supply is a test of whether institutional quality changes what adoption delivers. Adopting a technology is not the same as benefiting from it. A drip system helps members only if it is repaired and fairly shared; a weather alert protects them only if it reaches them in time and is believed; a coordinated pest response works only if neighbours act together. Whether adoption becomes resilience is therefore plausibly conditional on the quality of the cooperative that mediates it, yet the conditionality is typically assumed in programme design rather than examined.

Within Nigeria, a body of work has examined how cooperative membership, participation and organisational capability relate to member outcomes. Studies have looked at the effects of cooperative membership on women's economic empowerment (Abdulahi et al. (2015b)), on farmers' access to productive resources through cooperative societies (Abdulahi et al. (2015a)), on the performance of farmer multipurpose cooperatives in marketing members' produce (Anigbogu et al. (2016)), and on participation in FADAMA III user groups and its relation to farm income (Nwachukwu et al. (2016)). A parallel strand concerns capacity building, which has been related to the organisational performance of multipurpose cooperatives (Nwankwo et al. (2017); Gaddafi et al. (2024)) and discussed as a ground for change in cooperative organisations (Emejulu et al. (2019)).

More recent work from the same research programme has turned to collective entrepreneurship and members' financial inclusion, reporting a strong positive association between shared ownership of cooperative businesses and members' use of loan facilities among 864 members of one credit society (Abdulahi et al. (2024)), and to business innovation training for cooperative members (Abdulahi et al. (2023b)), knowledge management and innovativeness (Mgbemena et al. (2024)) and women's involvement in cooperative entrepreneurship (Lawal et al. (2023)). On farming risk and technology, related studies have addressed participation in an agricultural insurance scheme (Abdulahi et al. (2019)) and agricultural mechanisation and food security in a farmers' multipurpose cooperative in Awka North (Abdulahi et al. (2023a)). These studies treat the cooperative mainly as the setting, or the channel, through which member outcomes are produced. As far as we can tell, none tests whether the quality of the cooperative changes what a precision technology delivers in resilience terms, which is the question taken up here.

1.5 Research gap and problem statement

Most studies of precision agriculture or climate adaptation among cooperative farmers treat membership as a binary facilitator of access, or examine the determinants of adoption. They do not test whether institutional quality changes the strength of the adoption–resilience association, and we are not aware of an empirical test of this moderation for Nigerian cooperatives. The **research gap** is therefore the absence of evidence on whether cooperative governance and social capital condition the resilience returns to precision agriculture among smallholder cooperative members in sub-Saharan Africa.

The **problem** follows from the gap. Governments, donors and cooperative federations are promoting precision technologies through cooperatives on the assumption that adoption alone will raise resilience. If the returns depend on the quality of the cooperative, then programmes that scale technology without strengthening

governance and trust may deliver less than expected, and resources may be misdirected. Without moderation evidence, planners cannot tell whether to invest in technology, in institutions or in both.

1.6 Objectives and research questions

The general objective is to examine whether cooperative governance quality and social capital moderate the association between precision-agriculture adoption and climate change resilience among cooperative farmers in Ogun State, Nigeria. The specific objectives are to:

1. estimate the association between the adoption of precision agricultural techniques and farmers' climate change resilience;
2. estimate the association between cooperative governance and social capital and farmers' climate change resilience; and
3. determine whether cooperative governance and social capital strengthen the adoption–resilience association.

The corresponding research questions are:

i. **RQ1.** Is the adoption of precision agricultural techniques associated with higher climate change resilience among cooperative farmers?
ii. **RQ2.** Are stronger cooperative governance and social capital associated with higher resilience?
iii. **RQ3.** Does the adoption–resilience association become stronger as cooperative governance and social capital increase?

The hypotheses that answer these questions are developed in Section 2.

1.7 Contributions and structure

Using a survey of 357 members of 24 agricultural cooperatives across Ogun State, a major agricultural state in south-western Nigeria, we make three contributions. First, we bring cooperative institutions into the analysis of precision-agriculture outcomes as a conditioning factor rather than a background context. Second, we estimate the moderation with a standard hierarchical approach and report effect sizes, conditional slopes and sensitivity analyses that probe clustering and statistical power, not only significance levels. Third, we are explicit about what cross-sectional, self-reported evidence can and cannot establish, and we identify the design improvements needed for causal claims.

The paper is organised as a funnel from context to evidence. Section 2 develops the theory and hypotheses (H1 to H3), Section 3 describes the data and methods, Section 4 reports the results and their sensitivity, and Section 5 discusses interpretation, relation to previous research, implications and limitations. Section 6 concludes with answers to the research questions and implications for policy and practice.

2. THEORY AND HYPOTHESES

2.1 Precision adoption and climate resilience

We follow the resilience literature in treating climate change resilience as the capacity of a farming system to anticipate, absorb, adapt to and recover from climate shocks while maintaining production and livelihoods (Tendall et al., 2015; Folke et al., 2016). Rogers' (2003) diffusion-of-innovations theory explains why farmers adopt technologies they perceive as advantageous, compatible, observable and testable, and why adoption spreads through social systems along communication channels. It is, however, a theory of adoption rather than of what adoption yields. The link from adoption to resilience is supplied by a systems logic: precision techniques are feedback-control devices that sense a state (soil moisture,

nutrient status, pest pressure, weather), compare it with a target and adjust inputs accordingly (Wiener, 1948; Zhang et al., 2002; Meadows, 2008). Tighter feedback shortens the lag between a stress and the response, which is the mechanism through which each technique is expected to stabilise yields, protect productivity, limit losses or enable anticipatory action. Together, these arguments imply a positive average association.

H1. Adoption of precision agricultural techniques is positively associated with climate change resilience among cooperative members.

2.2 Cooperative governance and social capital

Cooperative governance refers to the rules and processes through which a cooperative is directed and held accountable, including leader accountability, transparency, member participation in decisions and the effective, fair management of collectively owned assets (Ortmann & King, 2007). These features echo design principles for successful commons governance, such as monitoring and accountable management of shared resources (Ostrom, 1990, 2009). Social capital refers to networks of trust, reciprocity and shared norms that reduce the costs of coordination and information exchange (Coleman, 1988; Putnam, 1993; Woolcock & Narayan, 2000). In rural settings, it facilitates collective responses to environmental stress (Pretty & Ward, 2001; Adger, 2003). Because both concern how members organise to use shared resources and respond jointly to risk, and because they are difficult to separate empirically in survey data, we treat them as a combined institutional-quality construct. Members of better-governed, higher-trust cooperatives should cope better with climate shocks independently of technology, for instance through mutual assistance and better access to inputs and advice.

H2. Cooperative governance and social capital are positively associated with climate change resilience.

2.3 Moderation: institutions as conversion conditions

Our focal argument is that institutional quality conditions how far adoption translates into resilience. Three channels are plausible. First, many precision technologies are capital-intensive assets that members use jointly, so their benefits depend on whether leaders manage, maintain and allocate them accountably and fairly (Ostrom, 1990; Jakku et al., 2019). Second, the value of information-based techniques such as forecasts and pest alerts depends on how reliably and quickly information flows through member networks and on whether members trust it (Nahapiet & Ghoshal, 1998; Adger, 2003). Third, climate shocks often require coordinated responses, such as synchronised planting or shared pumping, which are easier where trust and reciprocity are strong (Pretty, 2003). In organisational-learning terms, a cooperative with strong institutions has greater collective absorptive capacity, the ability to recognise, assimilate and apply new knowledge (Cohen & Levinthal, 1990). These channels imply that the slope of resilience on adoption is steeper where institutions are stronger.

Two rival expectations deserve mention. Strong institutions may substitute for technology, so technology adds less where institutions already deliver resilience, implying a negative interaction. Alternatively, weak governance may allow elites to capture shared assets, so that technology benefits are unevenly distributed (Platteau & Gaspart, 2003; Dasgupta & Beard, 2007), which reinforces the complementarity argument. Because the complementarity channels follow most directly from the technologies studied here, we predict a positive interaction.

H3. Cooperative governance and social capital positively moderate the association between adoption of precision agricultural techniques and climate change resilience: the association is stronger where governance and social capital are stronger.

2.4 Conceptual framework

This section draws the preceding arguments into one framework (Figure 1). It states what each construct is, what each path asserts and why, how each is measured, and what the framework does not claim.

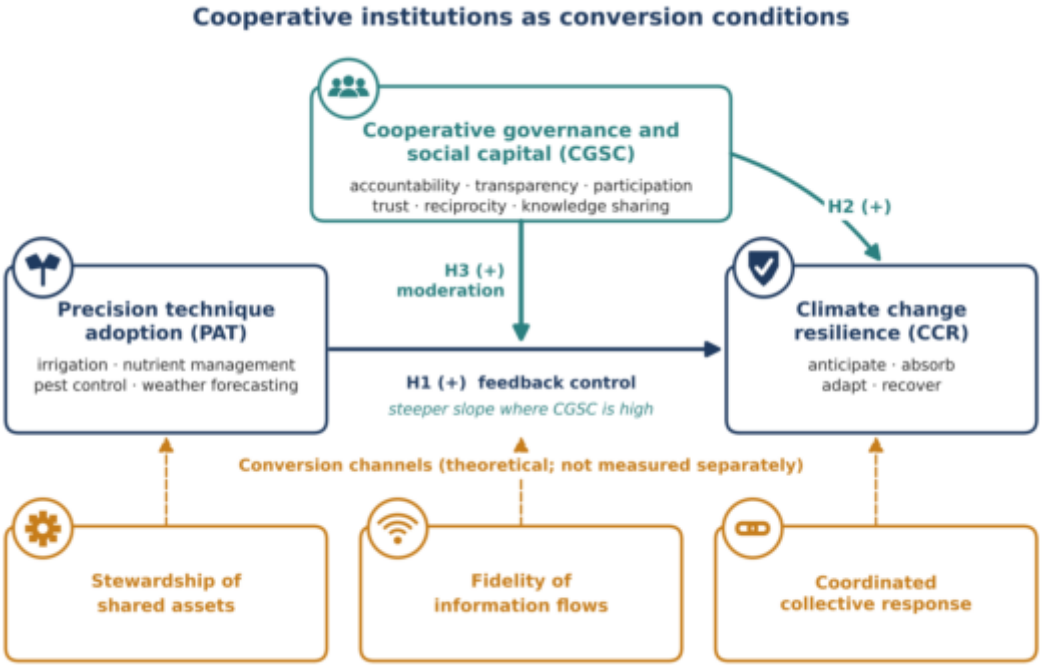


Figure 1. Conceptual framework: cooperative governance and social capital as conversion conditions for the resilience returns to precision agriculture

Note. PAT = precision agricultural technique adoption; CGSC = cooperative governance and social capital; CCR = climate change resilience. Solid arrows are the hypothesised paths (H1 to H3). Dashed arrows show the three conversion channels, which are the theoretical reasons for H3 and are not measured separately in the data.

Constructs. The framework has three constructs. *Precision technique adoption (PAT)* is the extent to which the member uses precision irrigation, nutrient management, pest control and weather forecasting; it is measured as the mean of four ten-item scales. *Climate change resilience (CCR)* is the member's capacity to anticipate, absorb, adapt to and recover from climate shocks, measured as the mean of the resilience items. *Cooperative governance and social capital (CGSC)* is the institutional setting in which the member operates.

It combines governance (leader accountability, transparency, member participation in technology decisions, fair allocation and upkeep of shared equipment) with social capital (trust, interaction,

reciprocity and collective action, knowledge sharing), measured as a ten-item index. The two components are combined because the three conversion channels draw on both. A rule that is not trusted is not followed, and trust that is not backed by a rule does not survive a dispute over shared equipment (Ostrom, 1990; Coleman, 1988).

Path H1 (PAT → CCR): the direct effect. Precision techniques shorten the loop between a signal (soil moisture, nutrient status, pest count, forecast) and a response. In control terms, this tightens feedback (Wiener, 1948), so that a shock is detected earlier and corrected sooner. We therefore expect a positive association. This is the baseline against which the institutional effects are judged, and it keeps the framework consistent with the diffusion literature, in which adoption is the proximate driver of benefit (Rogers, 2003).

Path H2 (CGSC → CCR): the direct institutional effect. Cooperatives support resilience without any technology. Members share labour, inputs, advice and informal insurance, and they face shocks together. These are the standard mechanisms through which social capital improves welfare outcomes (Coleman, 1988; Nahapiet & Ghoshal, 1998). Including this path separates the general benefit of a well-run cooperative from the specific role it plays in technology use. Without it, an interaction could reflect an omitted main effect.

Path H3 (PAT × CGSC → CCR): moderation. This is the central path and the contribution of the paper. A precision technique delivers only part of its potential if the equipment is poorly maintained, the information it generates is distorted or ignored, or members respond separately instead of together. Strong governance and social capital address each failure through three channels:

1. *Stewardship of shared assets.* Accountable leaders and fair rules for allocating and maintaining equipment keep it working and keep access equitable (Ostrom, 1990).
2. *Fidelity of information flows.* Trust and transparency make it more likely that forecasts, alerts and agronomic advice are passed on accurately and acted upon, which is a form of collective absorptive capacity (Cohen & Levinthal, 1990).
3. *Coordinated collective response.* Where members act together, for example in planting dates, irrigation scheduling or pest control, the benefit of a signal is no longer limited to those who acted alone.

Each channel raises the resilience yield of a unit of adoption. The expected effect is therefore a steeper PAT–CCR slope where CGSC is higher, which is a positive interaction. Formally, the conditional effect of PAT is $\beta_1 + \beta_3 \cdot CGSC$, and H3 predicts $\beta_3 > 0$.

Rival expectation. A negative interaction is also plausible. Where governance and social capital are strong, the cooperative may already supply much of the resilience that technology would otherwise provide, so the two would substitute (Section 2.3). The framework treats the sign of β_3 as an empirical question, with the complementarity direction preferred on the grounds above. A positive and a negative estimate are both informative, and the result for H3 in Section 4 is interpreted with this in mind.

What the framework does not claim. It is a cross-sectional association model and makes no causal claim. The channels are theoretical and not measured separately, so the data cannot distinguish them. CGSC is a property of the cooperative but is measured from members' perceptions, so it is partly an

individual-level rating. Members are clustered in 24 cooperatives, which weakens the evidence on any path that depends on between-cooperative variation, and above all H3 (Section 4.4).

Box 1. Hypotheses, theoretical basis and expected sign

Hypothesis	Relationship	Main theoretical basis	Expected sign
H1	PAT → CCR	Feedback control; diffusion of innovations	Positive
H2	CGSC → CCR	Social capital; collective action	Positive
H3	PAT × CGSC → CCR	Institutional conversion; collective absorptive capacity	Positive (steeper PAT slope at higher CGSC)

Note: PAT = precision agricultural technique adoption; CGSC = cooperative governance and social capital; CCR = climate change resilience. The rival substitution expectation (negative interaction) is discussed in Section 2.3.

3. DATA AND METHODS

3.1 Study setting and sampling

Ogun State lies in south-western Nigeria and is one of the country's leading agricultural states, with cassava, maize, cocoa, rice, oil palm and vegetables among its main crops. State records list 2,622 registered agricultural cooperative societies with an estimated 144,210 members (Ogun State Ministry of Community Development and Cooperatives, 2024). The Ogun State Agricultural Development Programme divides the state into four agricultural zones: Abeokuta, Ijebu, Ilaro and Ikenne.

We used a four-stage procedure. All four zones were included. Two local government areas were selected at random in each zone (eight in total), and three registered agricultural cooperatives were selected at random in each of those areas (24 cooperatives). Respondents were then drawn at random from the membership registers of the selected cooperatives, with the sample allocated to zones in proportion to zonal membership (Abeokuta 114; Ijebu 100; Ilaro 91; Ikenne 79). The target sample was derived with Cochran's (1977) formula for a proportion (95% confidence, 5% margin of error, $p = .5$), which gives $n_0 = 384.16$; the finite-population correction yields 383, and 384 was adopted so that zonal allocations sum exactly. Of 384 questionnaires administered in August 2026, 357 were properly completed (92.97%) and form the analytic sample. The sampling frame was the membership register; the share of crop producers among registered members was not known, and respondents were restricted to members engaged in crop production. Table 1 describes the sample.

Table 1. Characteristics of respondents (n = 357)

Characteristic	Category	n	%
Gender	Male	215	60.2
	Female	142	39.8
Age (years)	18–25	52	14.6

Characteristic	Category	n	%
	26–35	115	32.2
	36–45	118	33.1
	46 and above	72	20.2
Education	No formal education	49	13.7
	Primary	73	20.4
	Secondary	130	36.4
	Tertiary	105	29.4
Farm size (ha)	Less than 1	74	20.7
	1–2	145	40.6
	2.1–5	103	28.9
	More than 5	35	9.8
Farming experience	Less than 5 years	66	18.5
	5–10 years	162	45.4
	More than 10 years	129	36.1
Cooperative membership	Less than 2 years	57	16.0
	2–5 years	157	44.0
	More than 5 years	143	40.1

Source: Field survey, August 2026. Marital status is not tabulated here (66.4% of respondents were married).

3.2 Instrument and measures

The first author developed a structured questionnaire. Content validity was assessed by the supervisor and two other academics in the department, and the instrument was piloted on 30 cooperative members outside the sample. All attitudinal items used a five-point agreement scale (1 = strongly disagree to 5 = strongly agree).

Precision agricultural technique adoption (PAT) is the mean of four ten-item dimension scales covering precision irrigation, precision nutrient management, precision pest control and precision weather forecasting (pilot Cronbach's α = .821, .836, .852 and .843, respectively; α = .865 across all 80 items of the eight dimension and outcome scales). *Climate change resilience (CCR)* is the mean of the resilience items. *Cooperative governance and social capital (CGSC)* is a ten-item index: four items on governance (leader accountability, transparency, member participation in technology decisions, and fair allocation and maintenance of shared equipment), four on social capital (trust, frequency of interaction, reciprocity and collective action, and knowledge sharing) and two overall items.

3.3 Estimation

We estimated a two-step hierarchical regression (Aiken & West, 1991; Hayes, 2018). We mean-centred PAT and CGSC before forming the product term. Step 1 regresses CCR on the two centred main effects; Step 2 adds their interaction:

CCR_i = \beta_0 + \beta_1 PAT_i + \beta_2 CGSC_i + \beta_3 (PAT_i \times CGSC_i) + \varepsilon_i

Moderation is inferred from the sign and significance of β_3 and from the R^2 change test. Because significance in a sample of 357 can accompany small effects, we also report ΔR^2 and Cohen's (1988) $f^2 = \Delta R^2 / (1 - R^2$ of the full model), for which .02, .15 and .35 are conventional benchmarks for small, medium and large effects. Diagnostics comprised the Durbin–Watson statistic and variance inflation factors. Analyses used SPSS 29 (IBM Corp., 2023), with a 5% significance level. The design features that most affect inference (clustering in 24 cooperatives, common-source self-reports and the absence of covariates) are treated as limitations in Section 5; sensitivity analyses addressing them are reported in Section 4.4, and the robustness checks are still to be run on the unit-record data in Section 4.5.

4. RESULTS

4.1 Descriptive overview

Respondents generally agreed with the statements on the use of precision techniques and on cooperative institutions: mean agreement across the item blocks ranged from 3.47 to 3.55 on the five-point scale, above the midpoint. The twenty governance and social-capital statements averaged 3.49 (item-level SD = 0.91). Mean CCR was 3.52 (SD ≈ 0.44, derived from the total sum of squares). These are self-reported perceptions of use and effect and should not be read as evidence of widespread intensive adoption; respondents are cooperative members, whose cooperatives pool access to technology and training.

4.2 Main effects and interaction

Table 2 reports the hierarchical regression. In Step 1, PAT and CGSC jointly explained 40.0% of the variance in CCR (R^2 = .400, adjusted R^2 = .396, $F(2, 354) = 117.769$, $p < .001$). Both were positive and significant: a one-point higher PAT score was associated with a .416-point higher CCR score (β = .446), and a one-point higher CGSC score with a .214-point higher CCR score (β = .297), supporting H1 and H2.

Entering the interaction in Step 2 raised R^2 to .410 (adjusted R^2 = .405; $F(3, 353) = 81.698$, $p < .001$). The change was significant (ΔR^2 = .010, $F(1, 353) = 6.138$, $p = .014$), and the interaction coefficient was positive (B = .162, SE = .065, β = .103, $t = 2.478$, $p = .014$, 95% CI [.033, .290]), which supports H3. The main effects were stable across steps. Multicollinearity was not a concern (largest VIF = 1.241), and the Durbin–Watson statistic was 2.069.

Table 2. Hierarchical moderated regression predicting climate change resilience (n = 357)

Predictor	Step 1: B (SE)	Step 1: β	Step 1: 95% CI	Step 2: B (SE)	Step 2: β	Step 2: 95% CI
Constant	3.522*** (.018)		[3.487, 3.558]	3.503*** (.019)		[3.465, 3.541]
PAT (centred)	.416*** (.042)	.446	[.333, .499]	.431*** (.042)	.463	[.347, .514]
CGSC (centred)	.214*** (.033)	.297	[.150, .279]	.218*** (.033)	.303	[.154, .282]

Predictor	Step 1: B (SE)	Step 1: β	Step 1: 95% CI	Step 2: B (SE)	Step 2: β	Step 2: 95% CI
PAT × CGSC				.162* (.065)	.103	[.033, .290]
R^2 (adjusted)	.400 (.396)			.410 (.405)		
ΔR^2				.010*		
F	117.769 (2, 354)***			81.698 (3, 353)***		

Note: PAT = precision agricultural technique adoption; CGSC = cooperative governance and social capital. Dependent variable: climate change resilience (mean of items, 1–5). * p < .05; *** p < .001. Source: authors' calculations from survey data.

4.3 Interpreting the interaction

Because PAT and CGSC are centred, the conditional slope of CCR on PAT equals .431 + .162 × CGSC (in points relative to the sample mean). Table 3 shows how the slope changes with institutional quality.

Table 3. Conditional association of PAT with CCR at different levels of CGSC

CGSC relative to sample mean (scale points)	Conditional slope of PAT	Difference from slope at the mean
−1.0	.269	−38%
−0.5	.350	−19%
0	.431	0
+0.5	.512	+19%
+1.0	.593	+38%

The PAT slope is therefore about 38% steeper one scale point above the mean institutional score and about 38% flatter one point below it. In terms of explained variance, however, the moderation is very small: $f^2 = .010 / (1 - .410) = .017$, just under Cohen's (1988) benchmark of .02, and the interaction accounts for 1.0 percentage point of the variance in CCR against 40.0 points for the main effects. 4.4 Sensitivity analyses from the published statistics

The unit-record data are needed for the full robustness suite in Section 4.5. However, three questions can be answered now from the reported coefficients: how sensitive each test is to clustering of respondents in cooperatives, whether the study could detect an interaction of the observed size, and how large the interaction is relative to plausible alternatives.

Clustering. Respondents are nested in 24 cooperatives (about 15 per cooperative), so the standard errors in Table 2 assume more information than the design provides. The design effect is $DEFF = 1 + (m - 1)\rho$, where $m \approx 14.9$ is the mean cluster size, and ρ is the intra-cooperative correlation of the model residual. Dividing each reported t statistic by $\sqrt{DEFF}$ approximates the cluster-adjusted statistic. A ρ of about .04 gives $DEFF \approx 1.5$, .07 gives 2.0, and .14 gives 3.0.

Table 4. Reported t statistics adjusted for clustering at assumed design effects

Coefficient	Reported t (p)	DEFF = 1.5	DEFF = 2.0	DEFF = 3.0
PAT (main effect)	9.83 (< .001)	8.03 (< .001)	6.95 (< .001)	5.68 (< .001)
CGSC (main effect)	6.55 (< .001)	5.35 (< .001)	4.63 (< .001)	3.78 (< .001)
PAT × CGSC	2.48 (.014)	2.02 (.044)	1.75 (.081)	1.43 (.153)

Note: p values use the t distribution with 353 degrees of freedom. With 23 degrees of freedom, as cluster-robust inference would use for 24 clusters, the interaction p-values are .021, .055, .093 and .166. Source: authors' calculations from the statistics in Table 2.

The two main effects survive any plausible clustering. The interaction does not: it is significant at the 5% level only if the intra-cooperative correlation is below about .04, and with 24 clusters it is borderline even at the reported precision. H3 is therefore best regarded as provisional until the cluster-robust re-estimation in Section 4.5 is reported.

Power and effect size. With n = 357 and one tested term, the smallest effect detectable with 80% power at the 5% level is $f^2 \approx .022$, which corresponds to $\Delta R^2 \approx .013$ at the observed full-model R^2 of .410. The observed ΔR^2 of .010 ($f^2 = .017$) is below that threshold, and the power to detect an effect of this size was about .69. A significant result from an under-powered test tends to overstate the true effect, so the interaction coefficient should be read as an upper-end estimate (McClelland & Judd, 1993).

Implication of the Analyses. The adoption–resilience and institution–resilience associations are robust to clustering; the conditioning of the adoption slope by institutions is suggestive but fragile. The paper therefore frames the interaction as consistent with, and not as confirmation of, the conversion argument.

4.5 Robustness analyses to run on the unit-record data

(a) Standard errors clustered by cooperative; with only 24 clusters, a wild cluster bootstrap (Cameron et al., 2008; Cameron & Miller, 2015). (b) Re-estimation with controls for age, gender, education, farm size, farming experience and years of membership. (c) Heteroscedasticity-consistent (HC3) standard errors. (d) Separate governance and social-capital sub-indices, to show which carries the interaction. (e) Leave-one-zone-out estimates. Decision rule: H3 is reported as supported only if the interaction remains positive and significant at the 5% level under (a) and (b).

5. DISCUSSION

5.1 Main findings

Three results emerge. First, adoption of precision techniques and the quality of cooperative institutions are each strongly and independently associated with farmers' assessed resilience, consistent with the feedback-control logic of precision agriculture and with the social-capital literature. Second, the adoption–resilience association is steeper where governance and social capital are stronger, as the conversion argument predicts. Third, this moderation is small: the interaction adds one percentage point to explained variance.

The small size should not be dismissed. Interactions are hard to detect in non-experimental data because measurement error in the product term attenuates them, and moderation effects observed in field studies are typically small (McClelland & Judd, 1993). A slope that differs by about 38% per

scale point is substantively noticeable even where the added variance is small. Equally, it should not be over-read: with 357 respondents nested in 24 cooperatives, one percentage point is a narrow margin, and the significance level ($p = .014$) is the uncorrected one. Section 4.4 shows how fragile it is: the interaction falls to $p = .044$ at a design effect of 1.5 and to $p = .081$ at 2.0, and the study had about 69% power to detect an effect of this size.

5.2 Interpretation and Rival Explanations

The pattern is consistent with complementarity between technology and institutions, but cross-sectional data cannot separate it from several alternatives. This include:

- **Selection.** Better-governed cooperatives may attract or retain more capable farmers who both adopt more and fare better.
- **Reverse causality.** Farmers who are already resilient may be more willing to adopt technology and to trust their peers.
- **Common-method variance.** PAT, CGSC and CCR were reported by the same respondents in the same instrument, which can inflate associations and distort interactions in ways that are hard to sign (Podsakoff et al., 2003, 2012).
- **Halo effects.** Respondents who regard their cooperative favourably may rate all of its activities favourably.
- **Heterogeneous institutions.** Governance and social capital may work in opposite directions in some cooperatives, for example where tight networks enable elite capture or exclusion (Portes, 1998; Platteau & Gaspart, 2003). A combined index averages over such cases.

We therefore describe the finding as an association that is consistent with institutional conversion, not as evidence that improving governance would raise the resilience returns to technology.

5.3 Limitations

i. *Design and controls.* The data are cross-sectional and self-reported, and the models are unadjusted for farmer and farm characteristics that plausibly confound the relationships.
ii. *Clustering.* The reported standard errors assume independent observations, although respondents are nested in 24 cooperatives; true standard errors are probably larger (Cameron & Miller, 2015).
iii. *Measurement.* CGSC combines two constructs; CCR is perception-based; PAT captures perceived use rather than intensity or area under technology; and reliability evidence for the composites rests partly on a 30-member pilot.
iv. *Frame and scope.* The sampling used membership registers in which the share of crop producers was unknown, covers one state, and includes only cooperative members, so it cannot show whether cooperatives outperform non-members.

5.4 Contributions

Theoretically, the paper moves the analysis of precision agriculture from the determinants of adoption towards the institutional conditions under which adoption yields benefits. Empirically, it offers what we believe is a first test of this moderation for Nigerian agricultural cooperatives, reporting effect sizes and conditional slopes. Methodologically, it shows how to present a modest interaction transparently and states the design changes (panel data, objective outcome measures, multilevel models) that would allow stronger claims.

5.5 Relation to previous research

The positive adoption–resilience association agrees with the logic of precision agriculture as feedback control (Zhang et al., 2002; McBratney et al., 2005) and with reviews that stress its stabilising potential while warning that benefits depend on context (Lowenberg-DeBoer & Erickson, 2019; Klerkx et al., 2019). The positive institution–resilience association agrees with the long-standing finding that the quality of collective organisation shapes performance and collective action under environmental risk (Cook, 1995; Ostrom, 1990; Pretty, 2003; Adger, 2003). This study contributes through the third result. Earlier work on cooperatives mostly asks whether membership or institutional quality raises adoption and farm outcomes (Bernard & Spielman, 2009; Fischer & Qaim, 2012; Ma & Abdulai, 2016; Wossen et al., 2017); our moderation test asks whether institutions change what adoption delivers. The small and fragile interaction suggests that, for these farmers, institutions work mainly as a direct correlate of resilience and only weakly as a multiplier of technology, a more cautious picture than programme rhetoric implies.

The study also extends the Nigerian cooperative literature in two respects. Earlier work related cooperative-level inputs such as membership, capacity building and participation to member performance (Abdulahi et al., 2015b; Nwankwo et al., 2017; Gaddafi et al., 2024; Nwachukwu et al., 2016); this paper treats governance and social capital as a condition on the returns to a specific technology. Moreover, it moves from financial and marketing outcomes (Abdulahi et al., 2024; Anigbogu et al., 2016) to climate resilience. The positive but fragile interaction suggests that the capacity-building and access channels examined earlier (Emejulu et al., 2019; Abdulahi et al., 2015a) call for cooperative-level data and designs that separate between-cooperative from within-cooperative variation. Mechanisation and insurance participation (Abdulahi et al., 2023a; Abdulahi et al., 2019) are plausible companions to precision adoption in cooperative settings, and future work should include them as controls. Training and innovation-oriented studies (Abdulahi et al., 2023b; Mgbemena et al., 2024; Lawal et al., 2023) relate to the skills and knowledge that the information-fidelity channel of Section 2.4 depends on.

5.6 Theoretical and practical implications

For theory, the findings support treating diffusion theory and the institutional literature as complements: diffusion explains adoption, and institutions help to explain whether adoption is converted into outcomes (Rogers, 2003; Nahapiet & Ghoshal, 1998; Cohen & Levinthal, 1990). The modest interaction also cautions against assuming that complementarity is large; its size is an empirical matter that may differ by technique, by component of institutional quality and by shock regime, which the companion manuscripts examine.

For practice, the results are best read as a case for pairing, not for substitution. Cooperative leaders can treat transparent management of shared equipment and reliable member communication as part of the technology package. Extension agencies and donors can add institutional diagnostics to technology programmes and monitor realised resilience rather than adoption counts alone. Because the moderation evidence is provisional, such pairing should be piloted and evaluated before it is scaled.

6. CONCLUSIONS AND POLICY IMPLICATIONS

Among 357 cooperative members in Ogun State, both the adoption of precision

agricultural techniques and the quality of cooperative governance and social capital were positively associated with climate change resilience, and the adoption–resilience association was stronger where institutions were stronger. The moderation is statistically significant but small, and the cross-sectional, self-reported design supports association rather than causation.

Answers to the research questions are as follows. In answer to RQ1, adoption was positively and strongly associated with resilience (B = .431 in the full model). In answer to RQ2, cooperative governance and social capital were positively associated with resilience (B = .218). In answer to RQ3, the adoption–resilience association was steeper where governance and social capital were stronger (B = .162, p = .014). However, the interaction was small (ΔR^2 = .010) and sensitive to clustering, so the answer is a provisional yes.

Three implications follow for cooperative leaders, extension agencies and development partners.

1. **Bundle technology with institutional support.** Programmes that supply precision equipment or alerts to cooperatives should budget for the management of shared assets, including maintenance rules, transparent record-keeping and fair scheduling of access.
2. **Invest in the information channels that members trust.** Regular member meetings, demonstration plots and peer-learning sessions are the routes through which forecasts, pest alerts and technique know-how are likely to reach members reliably.
3. **Target by institutional quality.** Where resources are limited, pairing technology support with governance strengthening in weaker cooperatives may matter as much as extending technology to stronger ones, a hypothesis that deserves a controlled test.

Future work should use panel or experimental designs (for example, randomising technology access or governance training across cooperatives), objective yield and loss measures, multilevel models that treat cooperatives as clusters, and separate measures of governance and social capital.

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