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DETERMINANTS OF AGRICULTURAL PRODUCTIVITY AND PERCEIVED CAUSES OF LOW PRODUCTIVITY AMONG RURAL FARMERS IN NIGERIA

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Abstract
This study assessed agricultural productivity performance and the perceived causes of low productivity among rural farmers in Nigeria. Primary data were collected through an electronic questionnaire from 120 crop, livestock, mixed and other agricultural producers recruited purposively through agricultural networks. Data were analysed using frequencies, percentages, mean scores, standard deviations, internal-consistency diagnostics and ordinary least-squares regression with HC3 heteroskedasticity-consistent standard errors. Majority (61.77) of the respondents were males, majority 81.7% operated farms below six (6) hectares, and mean farming experience was 13.6 years. Although recent output growth ($\bar{x}$ = 3.55) and technology-related improvement ($\bar{x}$ = 3.49) were acknowledged, only 38.3% reported obtaining higher output from comparable resources ($\bar{x}$ = 2.95), indicating a perceived gap between output expansion and efficiency improvement. Water scarcity ranked first among the causes of slowdown ($\bar{x}$ = 3.90), followed by government policy limitations ($\bar{x}$ = 3.61), climate and temperature pressure ($\bar{x}$ = 3.54), high input costs ($\bar{x}$ = 3.51) and low research and development investment ($\bar{x}$ = 3.49). In the exploratory regression (n = 115), enabling resource conditions were positively associated with productivity performance (B = 0.332, p = .046), farming experience was negatively associated with the outcome (B = -0.015, p = .036), and environmental constraints showed weak negative evidence (B = -0.263, p = .091); R^2 was 0.199. The study concludes that the reported slowdown reflects interacting resource, climatic and institutional constraints. It recommends climate-resilient water investment, timely access to affordable quality inputs, stronger research-extension linkages, and complementary finance and training for technology adoption.
Keywords: *Agricultural productivity, determinants, causes, low productivity, farmers*

1.0 Introduction

Agriculture remains central to Nigeria's rural economy, food system and employment structure. The sector contributed 20.97% of nominal Gross Domestic Product (GDP) in 2024, yet agricultural growth has remained insufficient to neutralise population pressure, food-price escalation and recurrent production shocks (National Bureau of Statistics [NBS], 2025). The November 2024 Cadre Harmonise analysis projected that 33.1 million Nigerians could face food insecurity during the 2025 lean season, underscoring the direct connection between farm performance, household welfare and national food security (Food and Agriculture Organization of the United Nations [FAO], 2024a). Improving agricultural productivity is therefore essential for affordable food, stronger rural incomes and reduced import dependence. Agricultural output growth and productivity growth are conceptually different. Output may increase because producers employ more land, labour, fertiliser, feed, machinery or water even when the efficiency with which those inputs are converted into output does not improve. Total factor productivity (TFP) represents the

portion of output growth not explained by aggregate input growth and reflects technical change, efficiency change, scale economies and improvements in input quality (Fuglie, 2018; United States Department of Agriculture, Economic Research Service [USDA-ERS], 2025). Lerner and Kimhi (2026) show the policy value of separating productivity change from input intensity and land expansion. The present survey follows that distinction but does not estimate national TFP because it lacks consistent farm-level quantities, prices and cost shares for index-number accounting.

Nigeria's productivity constraints are interdependent. Credit rationing and high input prices restrict timely use of improved seed, fertiliser and machinery services; fragmented holdings reduce the economic viability of mechanisation; weak infrastructure raises transaction and post-harvest costs; and limited irrigation exposes production to rainfall variability. Balana and Oyeyemi (2022) identify agricultural credit constraints as a binding restriction among Nigerian smallholders. Plot-level evidence further shows that farm size, climate variability, education, credit, farmer associations and access to climate information shape the adoption of productivity-enhancing and climate-smart practices (Adeagbo et al., 2023; Amankwah, 2023). These complementarities imply that distributing an isolated technology without finance, information, water control and market access may yield limited productivity gains. Environmental pressures intensify these structural limitations. FAO (2024b) reported extensive cropland submergence and market disruption from the 2024 floods, while global evidence indicates that anthropogenic climate change has substantially slowed agricultural productivity growth, with stronger effects in warmer regions (Ortiz-Bobea *et al*, 2021). Research, extension and digital advisory services can offset part of this risk by accelerating diffusion of stress-tolerant technologies and location-specific management information. Nigeria's agricultural investment priorities consequently emphasise improved seed and fertiliser systems, extension, digital advice, value-chain development and climate resilience (World Bank, 2026).

Despite substantial macro-level evidence, less is known about how producers jointly perceive recent output performance, resource constraints, environmental pressures, technology access, research-extension support and the causes of productivity slowdown. A producer-level analysis is useful for identifying intervention priorities, but the evidence must be interpreted as descriptive and associational because non-probability recruitment and cross-sectional perceptions cannot establish national prevalence or causality. This study addresses that evidence gap by integrating item-level rankings with an exploratory multivariable model.

2.0 Objectives of the Study

The broad objective was to assess agricultural productivity performance and determine perceived factors associated with productivity slowdown among agricultural producers in Nigeria. The specific objectives were to:

i. describe the socioeconomic characteristics of the agricultural producers;
ii. measure producers' perceived recent output growth, resource-use efficiency and technology-related productivity improvement using five-point Likert-type items;
iii. rank the perceived resource, environmental, technological and institutional causes of agricultural productivity slowdown and preferred policy responses; and
iv. estimate the associations between the enterprise-neutral productivity-performance perception score and technology adoption, environmental constraints, enabling resources, resource constraints, research-extension support and farming experience.

3.0 Methodology

The study covered Nigeria, a Federation of 36 States including the Federal Capital Territory, with production environments ranging from humid coastal and forest zones to derived, Guinea and Sudan savannahs and the Sahel. The diversity of rainfall, temperature, soil, water access, market connectivity and security conditions produces substantial farm-level heterogeneity. A quantitative

cross-sectional survey design was used. Recruitment invitations were circulated through agricultural networks across Nigeria; however, State-specific prevalence estimates were not produced because some location entries were incomplete and individual State subsamples were small. The final analytical dataset contained 120 agricultural producers: 61 crop producers (50.8%), 20 livestock producers (16.7%), 37 mixed farmers (30.8%), and 2 respondents in other or unspecified activities (1.7%). Participants were purposively selected and reached through network-assisted electronic recruitment, and the questionnaire was administered through Google Forms. Purposive sampling was necessary because the study required respondents actively engaged in agricultural production and no complete, accessible nationwide sampling frame of eligible producers was available. Agricultural networks provided a practical route for screening and reaching qualified producers across several States. The approach is suitable for describing this sample and exploring associations, but it does not permit design-based generalisation to all Nigerian farmers (Bethlehem, 2010; Dillman et al., 2014).

The structured questionnaire covered demographic and farm characteristics; recent agricultural production performance; resource and input conditions; water, land and environmental constraints; technology and innovation adoption; agricultural research and extension support; perceived causes of slow productivity growth; and food-security and policy priorities. All attitudinal items used a five-point Likert-type scale coded 1 = strongly disagree, 2 = disagree, 3 = undecided, 4 = agree and 5 = strongly agree. Negatively worded items were interpreted in their stated direction. Mean scores of 3.00 or higher were accepted as indicating agreement or an important constraint or priority, while means below 3.00 indicated disagreement or low importance. For distributional clarity, “high response” combined agree and strongly agree and is reported as frequency and percentage.

The productivity-performance score (AP) was the respondent-level mean of three five-point items: recent output growth, higher output from comparable resources, and technology-related improvement. It is therefore an enterprise-neutral perception index applicable across crop, livestock and mixed farms, not a physical aggregation of tonnes, litres, livestock units or monetary output. TECH was the mean of technology-access, use and productivity-improvement items; ENV was the mean severity score for temperature, rainfall, pests, diseases and water-related pressures; RES was the mean score for enabling access to productive assets, finance, quality inputs and water; RCON was the mean severity of land, labour, capital and input constraints; RDE was the mean score for research investment, extension contact, training and information support; and EXP was years of farming experience. Higher index values denoted more of the named construct. Several indices were formative because their items captured distinct causal components rather than interchangeable manifestations of one latent trait; Cronbach's alpha was therefore treated only as a diagnostic, while item-level results remained primary (Hayes & Coutts, 2020).

Frequencies and percentages were used to summarise categorical variables. Means, standard deviations, ranks, and the number and percentage selecting the upper two Likert categories summarised ordered items. Mean scores were ranked from highest to lowest; tied means shared the same substantive interpretation. The decision threshold was $\bar{x} \geq 3.00$ for agreement or importance. An ordinary least-squares (OLS) model estimated productivity performance as a function of technology adoption, environmental constraints, enabling resources, resource constraints, research-extension support, and farming experience. OLS selected the coefficient vector that minimised the sum of squared residuals, $\hat{\beta} = (X'X)^{-1}X'Y$. HC3 heteroskedasticity-consistent standard errors were used because conventional standard errors can be unreliable under heteroskedasticity, and HC3 provides additional finite-sample protection (White, 1980). We omitted five records with incomplete model variables, leaving n = 115 for regression.

$$AP_i = \beta_0 + \beta_1 TECH_i + \beta_2 ENV_i + \beta_3 RES_i + \beta_4 RCON_i + \beta_5 RDE_i + \beta_6 EXP_i + \varepsilon_i$$

where AP is the enterprise-neutral productivity-performance perception score; TECH is the technology-adoption index; ENV is environmental-constraint severity; RES is enabling-resource

support; RCON is resource-constraint severity; RDE is research and extension support; EXP is farming experience in years; β_0 is the intercept; β_1-β_6 are partial regression coefficients; and ε_i is the disturbance term. Coefficients, HC3 robust standard errors, 95% confidence intervals, and exact p-values were reported. The six-predictor specification reduced overfitting risk, and all coefficients were interpreted as associations rather than causal effects.

4.0 Results and Discussion

4.1 Socioeconomic Characteristics

Table 1: socioeconomic characteristics of agricultural producers (n = 120)

Characteristic	Category	Frequency	Percentage
Age (years)	Below 30	20	16.7
	30-39	25	20.8
	40-49	21	17.5
	50-59	37	30.8
	60 and above	16	13.3
	Not specified	1	0.8
Sex	Male	74	61.7
	Female	46	38.3
Education	Non formal education	7	5.8
	Primary	19	15.8
	Secondary	31	25.8
	Tertiary	63	52.5
Farming experience	0-5 years	22	18.3
	6-10 years	32	26.7
	11-20 years	37	30.8
	Above 20 years	24	20.0
	Not specified	5	4.2
Farming activity	Crop production	61	50.8
	Livestock	20	16.7
	Mixed farming	37	30.8
	Other/unspecified	2	1.7
Farm size	Less than 1 ha	44	36.7
	1-5 ha	54	45.0
	6-10 ha	12	10.0
	Above 10 ha	9	7.5

Table 1 indicates that 61.7% of respondents were male and 38.3% were female. More than half had tertiary education (52.5%), while crop production was the dominant enterprise (50.8%), followed by mixed farming (30.8%). The sample was strongly smallholder-oriented: 36.7% operated below one hectare and 45.0% operated 1-5 hectares, meaning that 81.7% farmed below six hectares. This profile is directly relevant to the reported constraints because small farms often face indivisibilities in machinery and irrigation investment and depend more heavily on accessible finance, shared services, and functioning input markets. Nigerian studies similarly identify smallholder resource and credit constraints as barriers to timely investment and productivity-enhancing adoption (Balana & Oyeyemi, 2022; Chiaka et al., 2022).

4.2 Production Performance

Table 2 shows the distribution of agricultural production performance and perceived slowdown among the agricultural producers.

Table 2: Agricultural production performance and perceived slowdown

Rank	Item	Mean	SD	High response n (%)
1	Farm output increased recently	3.55	1.13	70 (58.3)
2	Technology improved farm productivity	3.49	1.17	70 (58.3)
3	Production growth has slowed	3.33	1.30	69 (57.5)
4	Production increases were mainly input-driven	3.16	1.31	53 (44.2)
5	Higher output was obtained from comparable resources	2.95	1.20	46 (38.3)

Recent output growth received the highest performance score ($\bar{x}$ = 3.55), and 58.3% agreed that technology had improved productivity ($\bar{x}$ = 3.49). Nevertheless, respondents also perceived that production growth had slowed ($\bar{x}$ = 3.33), while only 38.3% agreed that they obtained higher output from comparable resources ($\bar{x}$ = 2.95). The pattern is a producer-perceived productivity paradox: output may increase, yet efficiency gains remain weak when growth depends on additional land, labour or purchased inputs. This accords with the distinction between input-driven output growth and TFP growth (Fuglie, 2018; Fuglie & Rada, 2013; Lerner & Kimhi, 2026). Because the study did not measure input quantities and prices, the result should be interpreted as perceived resource-use efficiency rather than a measured TFP trend.

4.3 Resource, Environmental, Technology and Institutional Conditions

Table 3 shows the results of resource, input, and environmental conditions of the agricultural producers.

Table 3: Selected resource, environmental, technology and institutional indicators

Domain	Item	Mean	SD	High response n (%)
Resource/environment	Rising temperature reduces productivity	3.66	1.16	82 (68.3)
Resource/environment	Pests and diseases are increasing	3.65	1.19	82 (68.3)
Resource/environment	High input costs reduce efficiency	3.64	1.14	80 (66.7)

Domain	Item	Mean	SD	High response n (%)
Resource/environment	Rainfall changes affect production	3.62	1.15	85 (70.8)
Resource/environment	Water availability constrains productivity	3.59	1.29	82 (68.3)
Technology/institution	Modern irrigation raises productivity	3.75	1.12	82 (68.3)
Technology/institution	Government R&D investment raises productivity	3.74	1.10	86 (71.7)
Technology/institution	Technology access is limited	3.72	1.18	86 (71.7)
Technology/institution	Declining R&D support reduces innovation	3.68	1.06	81 (67.5)
Technology/institution	Digital information improves decisions	3.61	1.15	75 (62.5)
Technology/institution	Extension transfers technology effectively	3.38	1.28	70 (58.3)
Technology/institution	Farmers receive adequate training	3.32	1.25	65 (54.2)

The strongest resource and environmental pressures were rising temperature ($\bar{x}$ = 3.66), pests and diseases ($\bar{x}$ = 3.65), high input costs ($\bar{x}$ = 3.64) and rainfall change ($\bar{x}$ = 3.62). Water availability also constrained productivity ($\bar{x}$ = 3.59). These results are consistent with Nigerian plot-level evidence that climate variability affects both practice adoption and productivity (Amankwah, 2023) and with the scale of recent flood-related cropland and market disruption (FAO, 2024b). The combination of recognised fertiliser benefits in the full item set ($\bar{x}$ = 3.61) and high input-cost pressure indicates a complementarity problem: producers may know that an input raises yields but be unable to apply it at the economically appropriate rate or time.

Modern irrigation ($\bar{x}$ = 3.75) and government R&D investment ($\bar{x}$ = 3.74) received the highest technology and institutional ratings, but limited technology access also scored strongly ($\bar{x}$ = 3.72). Only 54.2% reported adequate training. The gap between expected technological returns and realised access characterises a constrained innovation system. Effective adoption generally requires a bundle of finance, water, knowledge, maintenance and market access; equipment or improved seed alone may not move farms towards the production frontier (Fuglie et al., 2020). Stronger research-extension linkages and locally actionable advisory services are therefore necessary (Davis et al., 2020; World Bank, 2026).

Internal-consistency estimates ranged from 0.241 to 0.749. Environmental constraints (0.702) and policy support (0.749) reached 0.70, whereas performance (0.393) and slowdown (0.241) were low because their components were formative; item-level rankings therefore remained primary.

4.4 Perceived Causes of Productivity Slowdown and Policy Priorities

Composite domains measuring perceived productivity and productivity slowdown in agriculture among farmers are presented in Table 4

Table 4: Ranked perceived causes of agricultural low productivity (n=120)

	Causes	Mean	SD	High response n (%)
1	Water scarcity	3.90	1.13	90 (75.0)
2	Government policy limitations	3.61	1.25	81 (67.5)
3	Climate change and temperature increase	3.54	1.14	74 (61.7)
4	High input costs	3.51	1.30	78 (65.0)
5	Low R&D investment	3.49	1.27	75 (62.5)
6	Market and price uncertainty	3.48	1.29	75 (62.5)
7	Labour shortages	3.46	1.28	72 (60.0)
8	Poor extension access	3.43	1.26	73 (60.8)
9	Declining soil quality	3.43	1.28	71 (59.2)
10	Limited technology access	3.38	1.31	71 (59.2)

Note: Items were rated on a five-point Likert-type scale (1 = strongly disagree to 5 = strongly agree). $\bar{x} \geq 3.00$ indicated agreement or importance. High response combines agree and strongly agree and is reported as n (%); valid n = 120. R&D = research and development.

Water scarcity was the foremost perceived cause of slowdown ($\bar{x}$ = 3.90; 75.0% high response), followed by government policy limitations, including inconsistent implementation and weak programme delivery ($\bar{x}$ = 3.61), climate and temperature pressure ($\bar{x}$ =3.54), high input costs ($\bar{x}$ =3.51) and low R&D investment ($\bar{x}$ =3.49). The ordering indicates that productivity weakness is not attributed to a single technological failure but to interacting environmental, institutional and market constraints. Water investment should consequently combine irrigation, drainage, watershed management, maintenance and early-warning systems rather than focus solely on abstraction. Policy consistency and predictable delivery of input, finance and advisory programmes are also important because uncertainty lowers expected returns to long-term farm investment (FAO, 2023; IPCC, 2022; OECD & FAO, 2024).

Climate adaptation was the highest-ranked policy priority ($\bar{x}$ = 3.70), followed by strengthening domestic production to reduce import dependence ($\bar{x}$ =3.68), government investment in innovation (3.62), support for technology adoption ($\bar{x}$ =3.60), and concern that productivity decline threatens food security ($\bar{x}$ =3.58). Between 65.0% and 67.5% selected the two highest response categories for these statements. The priorities are consistent with Nigeria's recent food-security and flood shocks (FAO, 2024a, 2024b), but implementation must be location-specific: water-control investment requires agroecological suitability, extension content must be actionable, and technology finance must reflect small farm sizes and high risk exposure.

4.5 Multivariable Determinants of Productivity Performance

Table 5 presents the results of an OLS model of agricultural productivity performance.

Table 5: OLS model of agricultural productivity performance with HC3 robust standard errors

Predictor	B	Robust SE	T	p	95% CI low	95% CI high
Constant	1.926	0.719	2.679	0.009	0.501	3.352
Technology adoption	0.143	0.151	0.946	0.346	-0.157	0.443
Environmental constraints	-0.263	0.154	-1.703	0.091	-0.569	0.043
Enabling resource conditions	0.332	0.165	2.016 **	0.046	0.006	0.659
Resource constraints	0.098	0.104	0.942	0.348	-0.108	0.305
Research-extension support index	0.156	0.159	0.983	0.328	-0.159	0.472
Farming experience	-0.015	0.007	-2.129 **	0.036	-0.030	-0.001

Note: n = 115; R^2 = 0.199; adjusted R^2 = 0.155. The dependent variable is the enterprise-neutral mean score of perceived recent output growth, higher output from comparable resources, and technology-related productivity improvement; it is not a physical aggregation of crop and livestock outputs. CI = confidence interval; R&D = research and development.

Enabling resource conditions had a positive association with productivity performance (B = 0.332, 95% CI [0.006, 0.659], p = .046). Farming experience had a small negative coefficient (B = -0.015, 95% CI [-0.030, -0.001], p = .036), while environmental constraints showed weak negative evidence at the 10% exploratory level (B = -0.263, p = .091). Technology adoption, resource constraints, and research-extension support were not statistically significant after simultaneous adjustment. The model explained 19.9% of sample variation, leaving prices, insecurity, soil conditions, output mix, actual input quantities, and other omitted factors as likely influences.

The positive resource coefficient supports the descriptive evidence that productive assets, finance, quality inputs, and water access operate as complements. This is consistent with Nigerian evidence that credit constraints limit smallholder investment and input use (Balana & Oyeyemi, 2022) and that access to credit, climate information and farmer organisations shape adoption of productivity-enhancing practices (Adeagbo et al., 2023; Amankwah, 2023). The negative experience coefficient should not be interpreted as evidence that experience is harmful. It may reflect cohort effects, older production systems, lower adoption intensity among long-established farmers, or unmeasured differences in enterprise and asset quality. Likewise, the imprecise technology coefficient does not negate the item-level importance of technology: international evidence shows that technology raises agricultural productivity most reliably when supported by finance, knowledge, infrastructure and institutions (Fuglie et al., 2020). Because the outcome and predictors were self-reported in a cross-sectional non-probability sample, the estimates are exploratory and non-causal.

5.0 Conclusion and recommendations

5.1 Conclusion

The study identifies a perceived productivity paradox among surveyed Nigerian agricultural producers. Respondents reported recent output gains and recognised technology's contribution, yet fewer than two-fifths agreed that they obtained higher output from comparable resources. Water scarcity, policy limitations, climate pressure, high input costs, and low R&D investment were the leading perceived causes of slowdown. The multivariable analysis reinforces the importance of

enabling resource conditions while showing that environmental pressure and producer heterogeneity require cautious, context-specific interpretation. Agricultural productivity weakness is therefore best understood as a systemic interaction among resource, environmental, technological, and institutional constraints rather than as a single-input problem.

Three limitations define the boundary of inference. First, purposive and network-assisted online recruitment does not support national prevalence estimates. Second, the cross-sectional design cannot establish temporal productivity change or causality. Third, the measures are perception-based rather than physical TFP indices. Future research should use a probability-based multistage design where a sampling frame can be constructed, collect plot-level output and input quantities and prices over multiple seasons, integrate georeferenced weather and soil indicators, and estimate stochastic-frontier, Malmquist or Tornqvist productivity measures.

5.2 Recommendations

i. Federal and State institutions should prioritise climate-resilient water systems, including irrigation rehabilitation, water harvesting, drainage, watershed protection and reliable maintenance arrangements, because water scarcity was the highest-ranked perceived cause of slowdown.

ii. Agricultural finance and input programmes should improve the timely affordability and quality assurance of seed, fertiliser, feed and mechanisation services, reflecting the high ranking of input costs and the positive association between enabling resources and productivity performance.

Research institutes, extension agencies and producer organisations should strengthen two-way research-extension-farmer linkages, expand locally relevant digital advice and provide practical training for climate-smart and resource-efficient production.

iii. Technology programmes should finance complementary bundles - equipment or improved varieties together with credit, training, maintenance, water access and market linkages - rather than isolated asset distribution.

iv. Government should stabilise agricultural policy implementation, strengthen market-information systems, support sustainable soil and land management, and publish transparent monitoring indicators for productivity, resilience and programme delivery.

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