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Gender Disparities in Climate-Smart Agriculture: Analyzing Awareness, Adoption Barriers, and Productivity Gaps among Base-of-Pyramid Farmers in Southeast Nigeria

[1]Obasi, R. O.1, [1,2]Onwusiribe, C. N., [1]Oteh, O. U., [1]Agwu, N. M. and [1]Okpokiri, C.
[1]Michael Okpara University of Agriculture, Umudike, Nigeria.
[2]School of Public Administration and Entrepreneurship, Ural Federal University named after the First President of Russia B. N. Yeltsin, Russia.
Corresponding author: obasi.raymond@mouau.edu.ng

ABSTRACT

This study examines gender-based differences in climate-smart agriculture (CSA) adoption among smallholder farmers in Southeast Nigeria, where women constitute over 60% of the agricultural workforce. The research investigates barriers to CSA adoption between male and female farmers using a mixed-methods approach, including household surveys (n=360), interviews, and focus groups across three states. The analysis employed Heckman's Double Hurdle Model, factor analysis, and Oaxaca decomposition to examine adoption patterns and gender productivity differentials. Results reveal that female farmers face a 43.6% productivity gap compared to male counterparts, with resource access disparities explaining 65.8% of this gap. Male farmers demonstrated higher awareness of CSA practices, particularly in technical innovations like soil conservation (male: 70%, female: 55%). Gender emerged as a significant determinant of adoption ($\beta = 0.342$, $p < 0.05$), while resource limitations were identified as the primary constraint, accounting for 26.75% of the variance. These findings suggest that targeted interventions combining improved resource access, technical training, and institutional reforms could significantly reduce gender disparities in agricultural productivity, enhancing the region's climate resilience and economic development.

KEYWORDS: Resource Endowments; Extension Services; Institutional Barriers; Oaxaca Decomposition; Productivity Differentials; Double Hurdle Model

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Introduction

Climate change threatens global food security, with smallholder farmers in Sub-Saharan Africa facing disproportionate impacts. In Southeast Nigeria's agricultural heartland, where over 70% of the population relies on smallholder farming (FAO, 2024), the intersection of climate vulnerability and gender inequality creates unique challenges for agricultural sustainability. Women, comprising nearly two-thirds of the agricultural workforce, face systemic barriers to adopting climate-smart agriculture (CSA) practices despite their crucial role in ensuring household food security and rural economic stability. However, the promise of CSA remains largely unrealized, particularly among women farmers who comprise nearly two-thirds of the agricultural workforce yet face systemic barriers to adoption (Mbanasor et al., 2024). Specifically, the agricultural sector's vulnerability to climate impacts, particularly in Sub-Saharan Africa, necessitates the adoption of innovative farming practices that enhance resilience while improving productivity (Ifeanyi-Obi et al., 2022). Unfortunately, the successful implementation of CSA practices is often hindered by gender disparities in access to resources, knowledge, and technical support.

Furthermore, the gender productivity gap in African agriculture tells a compelling story of systemic inequality. In Burkina Faso, female farmers produce 43.8% less than their male counterparts despite similar land quality (Valea & Noufé, 2024). Similarly, in Mali, women farmers show 20.18% lower productivity (Singbo et al., 2020). These disparities mirror patterns observed in Southeast Nigeria, where our preliminary research suggests female farmers face comparable challenges in accessing resources, knowledge, and support systems essential for CSA adoption.

Despite extensive research on CSA adoption, three critical knowledge gaps persist: (1) limited understanding of gender-specific adoption barriers in Southeast Nigeria's unique agricultural context, (2) insufficient analysis of the interaction between experiences and technical constraints in CSA implementation, and (3) inadequate examination of how gender shapes farmers' decision-making processes in climate adaptation strategies. These gaps have real consequences: In Southeast Nigeria's Ebonyi State, where women manage over 60% of smallholder farms, extension services primarily target male farmers, leaving female producers without crucial technical support. Furthermore, while studies have identified general adoption constraints (Boudalia et al., 2024; Mizik, 2021), we lack a nuanced understanding of how these barriers affect women farmers' decision-making, resource allocation, and ultimate productivity. Consequently, Tariku and Kebede (2024) highlight the need for a more nuanced analysis of demographic, economic, and institutional factors affecting CSA adoption across gender lines.

In the Nigerian context, evidence indicates that CSA adoption is influenced by multiple factors, including access to credit, extension services, and technical knowledge (Anugwa et al., 2021). Additionally, research reveals significant gender disparities in adopting climate-smart agricultural practices across various African regions. Typically, men are more likely to adopt high-return CSA practices such as modern chemical fertilizers and improved high-yielding varieties, while women tend to adopt low-risk, low-return practices like water harvesting and crop covering (Hailemariam et al., 2024). In Nigeria specifically, men are more empowered in four out of five domains of empowerment, influencing their likelihood to adopt practices like crop rotation, whereas women are more inclined towards green manure and agroforestry (Oyawole et al., 2020). Nevertheless, Fawole and Aderinoye-Abdulwahab (2021) and Mbanasor et al. (2024) note that existing research has not adequately addressed the gender dimensions of these influences, particularly in Southeast Nigeria's unique agricultural context.

Southeast Nigeria offers a compelling window into the complexities of gender and climate adaptation in agriculture. Here, where generations of farmers have traditionally relied on rainfall patterns their grandparents could predict, climate change has upended agricultural certainties. Igberi et al. (2022) indicate varying levels of CSA awareness and adoption among regional farmers, yet gender-specific analysis remains limited. Recent research by Mbanasor et al. (2024) reveals varying adoption rates of CSA practices across states, with Imo State leading in residue soil cover (57.7%) and crop rotation (51.1%). However, these aggregate statistics mask stark gender disparities in access to training, resources, and support services that determine farmers' ability to implement these practices. Therefore, this study aims to assess farmers' awareness of climate-smart agriculture, examine the usage of these practices along gender lines, and identify the constraints to adoption in Southeast Nigeria. The research addresses critical gaps in understanding gender-specific barriers to CSA adoption through a comprehensive methodological approach combining quantitative and qualitative methods. Ultimately, the findings contribute to the growing body of literature on gender-responsive climate-smart agriculture while providing practical insights for policy formulation and intervention design in the Nigerian context.

Finally, this study aims to shed light on the human dimensions of CSA adoption in Southeast Nigeria, examining how gender shapes farmers' awareness, choices, and capabilities in implementing climate-resilient practices. By understanding these dynamics, we seek to inform more effective, gender-responsive agricultural policies and programs. Our findings will help development practitioners, policymakers, and agricultural extension services better support both male and female farmers in building climate resilience while improving productivity and household food security.

Methodology

This research was conducted in Southeast Nigeria (6°-9°E, 4°-7°N), encompassing diverse agro-ecological zones and complex farming systems. The region's population of 21,619,400 (NPC, 2021) includes a substantial agricultural workforce, with women representing approximately 60% of smallholder farmers (Mbanasor et al., 2024). The study area selection aligns with Bryan et al.'s (2021) emphasis on examining regions where climate vulnerability intersects with gender-based agricultural constraints.

The research employed a sequential mixed-methods design to investigate gender dynamics in Climate-Smart Agriculture (CSA) adoption. A multistage sampling procedure was implemented following Jost et al.'s (2016) approach to gender-sensitive agricultural research. Three states—Enugu, Abia, and Ebonyi—were purposively selected based on their diverse agro-ecological characteristics and varying CSA implementation levels (Igberi et al., 2022). Four Local Government Areas within each state were randomly selected using stratified sampling to ensure representation across agricultural zones, consistent with Khoza et al.'s (2020) methodology.

The final sample included 360 households, evenly split between male-headed and female-headed households. While this gender-balanced approach does not reflect the actual gender distribution, it was chosen to ensure sufficient statistical power for gender-based comparisons, as Valea and Noufé (2024) recommended.

Data collection incorporated three complementary methods. Structured questionnaires were administered to household heads and developed using validated scales from Teklewold et al. (2019) and Singbo et al. (2020). Twenty-four gender-separated focus group discussions were conducted following Meshesha et al.'s (2022)

protocol, providing insights into how gender norms and power relations influence adoption decisions. Additionally, key informant interviews with agricultural extension officers, community leaders, and women's group representatives were conducted using Tariku and Kebede's (2024) approach.
The analytical framework employed a three-tiered approach combining descriptive statistics, Heckman's Double Hurdle Model, and factor analysis. The Heckman model analyzed adoption decisions and intensity while addressing potential selection bias (Kurgat et al., 2020). The model incorporated gender-specific variables identified through previous research (Lan et al., 2018). Factor analysis identified underlying patterns in adoption constraints, while the Oaxaca decomposition technique quantified gender-based productivity differentials, following methods established by Joe-Nkamuke et al. (2019) and refined by Mkuna and Wale (2023).

Model Specification

The Heckman's Double Hurdle Model for the adoption of Climate-Smart Agricultural Practices can be specified as follows:
First Hurdle: Adoption Decision (Probit Model)
The first hurdle determines whether a farmer decides to adopt CSA practices or not. It is modeled using a probit specification:
First Hurdle: Adoption Decision (Probit Model):

$$Y_i^* = X_{i'}\beta + \varepsilon_i \quad (1)$$

Where;

- y_i^* is the latent variable
- y_i is the observed binary outcome
- x_i' is a vector of explanatory variables
- β is a vector of parameters
- ε_i is the error term, ε_i ~ N(0,1)

Second Hurdle: Extent of Adoption (Truncated Regression)
The second hurdle models the extent of adoption, conditional on the decision to adopt:

$$Z_i^* = W_{i'}\gamma + \nu_i \quad (2)$$

Where;

- z_i^* is the latent variable for the extent of adoption
- z_i is the observed level of adoption
- w_i' is a vector of explanatory variables
- γ is a vector of parameters
- ν_i is the error term, $\nu_i \sim N(0,\sigma^2)$

Log-likelihood Function
The log-likelihood function for the double-hurdle model is:

$$L = \sum(Y_i = 0)(\log[1 - \Phi(X_{i'}\,\beta)]) + \sum(Y_i = 1)(\{\log[\Phi(X_{i'}\,\beta)] + \log[f\left(\frac{Z_i}{Y_{i=1}}\right)]\}) \quad (3)$$

Where;

- $\Phi(\cdot)$ is the standard normal cumulative distribution function
- $f(\cdot)$ is the density function of the truncated normal distribution

Explanatory Variables

The vectors Xi and Wi include the following variables:

1. Gender (1=Male, 0=Female)
2. Age of the farmer
3. Education level (years of schooling)
4. Farm size (hectares)
5. Access to credit (1=Yes, 0=No)
6. Number of extension contacts
7. Climate change awareness score
8. Household size
9. Off-farm income
10. Land quality index
11. Market access index

Note that the sets of variables in Xi and Wi may differ, allowing for different factors to influence the adoption decision and the extent of adoption.
This model specification allows for the separate estimation of factors affecting the decision to adopt CSA practices and the intensity of adoption while accounting for potential selection bias. The results from this model can provide insights into the gender differentials in both the likelihood of CSA adoption and the extent of adoption among adopters.
Factor Analysis Model

$$X = \Lambda F + \varepsilon \tag{4}$$

Where;

- X is a p × 1 vector of observed variables
- Λ (Lambda) is a p × m matrix of factor loadings
- F is an m × 1 vector of common factors
- ε (epsilon) is a p × 1 vector of unique factors

Expanded Form:

$$X_i = \lambda_{i1}F_1 + \lambda_{i2}F_2 + \cdots + \lambda_{im}F_m + \varepsilon_i \tag{5}$$

For i = 1, 2, ..., p

Assumptions

E(F) = 0 Cov(F) = I (Identity matrix) E(ε) = 0 Cov(ε) = Ψ (Psi, diagonal matrix) Cov(F, ε) = 0

Covariance Structure

$$\Sigma = \Lambda\Lambda' + \Psi \tag{6}$$

Where;

- Σ (Sigma) is the p × p covariance matrix of observed variables
- Λ' is the transpose of Λ
- Ψ (Psi) is the p × p diagonal matrix of unique factor variances

Communality

$$h_{i^2} = \sum(\mathrm{j} = 1)^{\mathrm{m}}[(\lambda_{\mathrm{ij}^2})] \tag{7}$$

Where;

- h_i^2 is the communality of the i-th variable

- λ_{ij} is the factor loading of the i-th variable on the j-th factor

Proportion of Variance Explained

$$PVE_j = \frac{\left(\sum(\mathrm{i}=1)^P\left[\left(\lambda_{ij^2}\right)\right]\right)}{P} \tag{8}$$

Where;

- PVE_j is the proportion of variance explained by the j-th factor
- p is the number of observed variables

The qualitative data from focus group discussions and key informant interviews were analyzed using thematic content analysis, following Hailemariam et al.'s (2024) framework. We employed NVivo software to identify recurring themes and patterns, particularly focusing on gender-specific narratives around CSA adoption constraints and opportunities. This analysis provided crucial context for interpreting the quantitative findings and understanding the sociocultural dimensions of adoption decisions.

To ensure research quality, we employed several validation strategies. First, instrument validity was established through expert review and pilot testing. Second, we used triangulation to cross-validate findings across different data sources. Third, reliability was enhanced through proper enumerator training and standardized data collection procedures. Following Adeyeye and Fischer's (2024) recommendations, we also conducted member checking with key informants to verify our interpretation of qualitative findings.

This methodological approach provides a robust framework for examining gender disparities in CSA adoption, combining statistical rigor with rich qualitative insights. The multiple analytical methods allow for a comprehensive examination of observable and unobservable factors influencing adoption patterns.
Endogenous Variables (CSA Practices):

- Drought-tolerant crops (yes=1, no=0)
- Intercropping (yes=1, no=0)
- Soil conservation (yes=1, no=0)
- Water harvesting (yes=1, no=0)
- Agroforestry (yes=1, no=0)

The survey identified these practices and aligned with findings from Igberi et al. (2022) and Mbanasor et al. (2024) in Southeast Nigeria.
Exogenous Variables:

1. Gender (GE): Male=1, Female=0 Rationale: Valea and Noufé (2024) found significant gender-based productivity differences.
2. Age (AG): Years Rationale: Mthethwa et al. (2022) identified age as influencing CSA adoption decisions.
3. Education (ED): Years of schooling Rationale: Sisay et al. (2023) found that education positively correlates with CSA adoption.
4. Farm size (FS): Hectares Rationale: Aryal et al. (2018) identified farm size as a key determinant of adoption.
5. Access to credit (AC): Yes=1, No=0 Rationale: Tariku and Kebede (2024) highlight credit access as crucial for CSA adoption.
6. Extension contact (EC): Number of visits Rationale: Gemtou et al. (2024) emphasize extension services' role in adoption.
7. Climate change awareness (CA): Score (1-5) Rationale: Meshesha et al. (2022) link climate awareness to adoption decisions.

8. Household size (HS): Number of members Rationale: Khoza et al. (2022) found that household characteristics influence adoption.
9. Off-farm income (OF): Naira value Rationale: Lan et al. (2018) identified income as affecting adoption patterns.
10. Market access (MA): Index score Rationale: Mizik (2021) emphasizes market access importance for CSA adoption.

Results

The analysis of farmer awareness of climate-smart agricultural practices (CSA) in Southeast Nigeria reveals significant gender disparities across all assessed practices, as presented in Table 1. The findings demonstrate a consistent trend where male farmers exhibit higher awareness levels across all practices, though the magnitude of these disparities varies notably by practice type.

Intercropping emerges as the most widely recognized CSA practice, with high awareness levels among male (90%) and female (85%) farmers. This prevalence can be attributed to its traditional roots in Nigerian agriculture (Igberi et al., 2022). Intriguingly, while awareness levels show gender disparity, actual adoption rates present a different picture. Adzawla et al. (2019) found that female farmers slightly surpass males in intercropping adoption (70% versus 69%), suggesting that awareness does not always directly correlate with implementation.

More technical practices reveal wider gender gaps, particularly in soil conservation, where a 15 percentage point difference exists between male (70%) and female (55%) farmers. The economic significance of soil conservation practices is substantial, as highlighted by Chakraborty et al. (2023), who found that soil erosion control facilities account for approximately 26% of mean land values in Nigerian agricultural lands.

Despite its economic viability, water harvesting demonstrates the lowest awareness levels across genders (male: 50%, female: 40%). Nnaji & Aigbavboa (2020) demonstrate that rainwater harvesting presents a cost-effective alternative to traditional water supply methods, with potential unit costs ranging from 0.07–0.54 ₦/liter, depending on the implementation scale.

These findings align with previous research by Jellason et al. (2020), emphasizing the crucial need for gender-responsive CSA approaches. The persistent gender gaps in awareness, particularly in technical practices, suggest structural barriers to access to agricultural knowledge and extension services. As Fawole and Aderinoye-Abdulwahab (2021) argue, targeted interventions and gender-sensitive training programs are essential to bridge these awareness gaps and promote equitable agricultural development.

Table 1: Descriptive Statistics: Farmer Awareness of Climate-Smart Agricultural Practices

Climate-Smart Practice	Gender	Aware (n)	Aware (%)	Unaware (n)	Unaware (%)	Mean Awareness Score*
Drought-tolerant crops	Male	135	75.0%	45	25.0%	3.8
	Female	108	60.0%	72	40.0%	3.2
Intercropping	Male	162	90.0%	18	10.0%	4.5
	Female	153	85.0%	27	15.0%	4.2
Soil conservation	Male	126	70.0%	54	30.0%	3.6
	Female	99	55.0%	81	45.0%	2.9
Water harvesting	Male	90	50.0%	90	50.0%	2.7
	Female	72	40.0%	108	60.0%	2.3
Agroforestry	Male	108	60.0%	72	40.0%	3.1
	Female	81	45.0%	99	55.0%	2.6

*Mean Awareness Score is on a scale of 1-5, where 1 = Not at all aware, and 5 = Very aware

As shown in Table 2, Heckman's Double Hurdle Model reveals several significant determinants influencing farmers' adoption of climate-smart agricultural (CSA) practices in Southeast Nigeria. The empirical results demonstrate a complex interplay of socio-demographic and institutional factors in shaping adaptation decisions.

The model results in Table 2 indicate that gender significantly influences adoption probability ($\beta = 0.342$, $p < 0.05$), with male farmers showing higher adoption rates. This gender disparity, consistent with Huyer et al. (2024), reflects structural inequalities in resource access and adaptation capacities. However, Antwi & Antwi-Agyei (2023) present a contrasting perspective, noting that less educated female farmers may show higher adoption rates due to their dependence on farming income.

Age exhibits a negative correlation with CSA adoption ($\beta = -0.015$, $p < 0.05$) in Table 2, suggesting younger farmers' greater receptiveness to innovative practices. This finding aligns with Mbanasor et al. (2024), who attribute this trend to older farmers' risk aversion. However, Alhassan et al. (2024) argue that age's influence on adaptation decisions is more complex and potentially ambiguous.

The Table 2 coefficients for education and farm size ($\beta = 0.089$ and $\beta = 0.173$ respectively, $p < 0.001$) emerge as robust positive influences, supporting Sisay et al.'s (2023) findings. These factors are complemented by access to credit ($\beta = 0.286$, $p < 0.05$) and extension contact ($\beta = 0.056$, $p < 0.002$), which Kurgat et al. (2020) identify as crucial institutional support mechanisms. This relationship is further corroborated by Alhassan et al. (2024), who emphasize how credit access enables investment in climate-smart practices.

Table 2 shows that climate change awareness demonstrates substantial influence ($\beta = 0.412$, $p < 0.003$), indicating that farmers' understanding of climate risks significantly affects their adoption decisions. This finding, supported by Meshesha et al. (2022), suggests that enhancing climate change awareness could be a crucial pathway for promoting CSA adoption among farmers.

Table 2: First Hurdle - Adoption Decision (Probit Model)

Variable	Coefficient	Std. Error	z-value	p-value
Gender (1=Male, 0=Female)	0.342	0.156	2.192	0.028
Age	-0.015	0.007	-2.143	0.032
Education (years)	0.089	0.025	3.560	<0.001
Farm size (ha)	0.173	0.048	3.604	<0.001
Access to credit (1=Yes)	0.286	0.142	2.014	0.044
Extension contact (number)	0.056	0.018	3.111	0.002
Climate change awareness	0.412	0.138	2.986	0.003
Constant	-2.156	0.458	-4.707	<0.001

Number of observations: 360 Log-likelihood: -186.34 Pseudo R-squared: 0.218

The empirical findings in Table 3 reveal several significant determinants of Climate-Smart Agriculture (CSA) adoption intensity among farmers. The second-hurdle results demonstrate that gender plays a significant role ($\beta = 0.187$, $p < 0.05$), with male farmers showing a higher likelihood and extent of CSA adoption. This gender disparity aligns with Huyer et al.'s (2024) observation that gender significantly influences climate adaptation capacities, though interestingly, Antwi & Antwi-Agyei (2023) found that less educated female farmers tend to adopt CSA interventions more frequently than their more educated counterparts.

Education emerges as a critical factor ($\beta = 0.052$, $p < 0.001$) in determining the comprehensiveness of CSA implementation, supporting Gemtou et al.'s (2024) emphasis on education's role in facilitating a deeper understanding of climate-smart practices. The analysis also reveals that farm size exhibits the strongest positive influence ($\beta = 0.128$, $p < 0.001$), while access to credit shows substantial impact ($\beta = 0.215$, $p < 0.008$). These findings are corroborated by Alhassan et al. (2024), who emphasized that larger farm sizes and credit access significantly enhance farmers' ability to invest in climate-smart practices.

The significant positive effects of extension contact ($\beta = 0.038$, $p < 0.001$) and climate change awareness ($\beta = 0.246$, $p < 0.002$) underscore the crucial role of institutional support and knowledge dissemination. This aligns with recent research by Alhassan et al. (2024), who highlighted the importance of agricultural extension services in facilitating rural farmers' adaptation decisions. The findings also support Erekalo and Yadda's (2023) observation regarding the critical nature of extension services and climate information access in promoting sustained CSA adoption. These results collectively suggest that comprehensive CSA adoption requires a multi-faceted approach addressing educational, financial, and institutional support mechanisms.

Table 3: Second Hurdle - Extent of Adoption (Truncated Regression)

Variable	Coefficient	Std. Error	t-value	p-value
Gender (1=Male, 0=Female)	0.187	0.089	2.101	0.036
Age	-0.008	0.004	-2.000	0.046
Education (years)	0.052	0.014	3.714	<0.001
Farm size (ha)	0.128	0.027	4.741	<0.001
Access to credit (1=Yes)	0.215	0.081	2.654	0.008
Extension contact (number)	0.038	0.010	3.800	<0.001
Climate change awareness	0.246	0.079	3.114	0.002
Constant	0.754	0.262	2.878	0.004

Number of observations: 218 (adopters only) Log-likelihood: -142.68 Sigma: 0.386 (Std. Error: 0.019)

The factor analysis presented in Table 4 reveals four distinct dimensions of constraints that impede the adoption of climate-smart agricultural practices in Southeast Nigeria, collectively explaining 90% of the total variance. Resource limitations emerge as the predominant barrier, accounting for 26.75% of the variance, with lack of capital demonstrating the highest factor loading (0.85). This finding resonates with Mishra et al. (2024), who identified economic constraints as critical impediments to CSA adoption.

Knowledge and information constraints constitute the second most significant dimension, explaining 23.92% of the variance, with lack of technical knowledge showing the highest loading (0.88). This aligns with Tariku and Kebede's (2024) research highlighting the crucial role of institutional factors in CSA adoption patterns. The third dimension comprises institutional barriers (21.17% variance), emphasizing structural challenges such as land tenure insecurity (0.84) and weak market linkages (0.77). These findings correspond with Mizik's (2021) emphasis on land use security and market access as vital factors affecting smallholder farmers' CSA adoption.

Risk and uncertainty emerge as the fourth dimension (18.16% variance), with climate variability showing the highest loading (0.86). This corresponds with Kassa and Abdi's (2022) observations regarding farmers' climate change perceptions influencing adoption decisions. The robust factor analysis results, indicated by the high KMO value (0.812), underscore the reliability of these findings. Alhassan and Haruna (2024) further support these results, emphasizing how financial constraints hinder farmers' adoption capabilities. Similarly, Wakweya (2023) highlights how resource limitations exacerbate climate change challenges, threatening food security and agricultural productivity.

These findings suggest the need for comprehensive policy interventions that simultaneously address multiple constraint dimensions. Such interventions should combine financial support mechanisms with enhanced extension services, institutional reforms, and strengthened risk management strategies to promote CSA adoption in Southeast Nigeria effectively.

Table 4: Factor Analysis Results

Constraint	Factor 1: Resource Limitations	Factor 2: Knowledge and Information	Factor 3: Institutional Barriers	Factor 4: Risk and Uncertainty
Lack of capital	**0.85**	0.12	0.18	0.09
Limited access to credit	**0.79**	0.15	0.22	0.11
High input costs	**0.76**	0.08	0.14	0.25
Lack of technical knowledge	0.14	**0.88**	0.09	0.17
Insufficient information	0.18	**0.82**	0.15	0.13
Limited extension services	0.21	**0.75**	0.26	0.08
Land tenure insecurity	0.16	0.12	**0.84**	0.11
Weak market linkages	0.23	0.18	**0.77**	0.16
Inadequate policy support	0.20	0.25	**0.73**	0.14
Climate variability and uncertainty	0.13	0.16	0.12	**0.86**
Fear of yield reduction	0.17	0.14	0.15	**0.79**
Labor intensiveness	0.22	0.11	0.19	**0.72**

Eigenvalues: 3.21; 2.87; 2.54; 2.18. Variance explained (%) 26.75; 23.92; 21.17; 18.16. Cumulative variance explained (%) 26.75; 50.67; 71.84; 90.00. Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy: 0.812 Bartlett's test of sphericity: $\chi^2 = 2187.43$, df = 66, $p < 0.001$

The analysis of Table 5 reveals a hierarchical structure of constraints impeding Climate-Smart Agriculture (CSA) adoption in Southeast Nigeria, with financial obstacles emerging as the most significant barriers. The data indicates that lack of capital and limited credit access are the predominant constraints, scoring means of 4.32 and 4.18, respectively, affecting over 80% of farmers. This aligns with Lan et al.'s (2018) findings regarding the influence of profitability gaps and income inequality on CSA adoption patterns.

Knowledge-related constraints emerge as the second most critical category, with technical knowledge deficits (mean=3.97) and insufficient information (mean=3.68) impacting 79.4% and 73.6% of farmers, respectively. This observation supports Gemtou et al.'s (2024) emphasis on extension services' crucial role in facilitating CSA adoption. Notably, climate variability and uncertainty (mean=3.85) and high input costs (mean=3.79) rank as the fourth and fifth most significant constraints, echoing Rachel et al.'s (2020) findings in Northern Nigeria regarding the impact of input costs on CSA adoption.

Recent research reinforces these findings, with Ogisi & Begho (2023) and Abdullahi et al. (2021) highlighting how limited credit access significantly hinders farmers' ability to adopt climate-smart practices. Furthermore, Huyer et al. (2024) and Mbanasor et al. (2024) emphasize how knowledge-related constraints and climate uncertainty compound these challenges, particularly for smallholder farmers struggling to predict weather patterns and implement adaptive strategies.

The considerable variation in farmers' experiences, indicated by standard deviations ranging from 0.89 to 1.35, supports Abegunde et al.'s (2019) advocacy for context-specific interventions. These findings underscore the need for integrated support mechanisms that address financial and knowledge barriers while accounting for regional constraint-priority variations.

Table 5: Descriptive Statistics and Ranking of Constraints

Rank	Constraint	Mean score*	Std. Deviation	% of Farmers Reporting**
1	Lack of capital	4.32	0.89	86.4%
2	Limited access to credit	4.18	0.95	83.6%
3	Lack of technical knowledge	3.97	1.02	79.4%
4	Climate variability and uncertainty	3.85	1.08	77.0%
5	High input costs	3.79	1.05	75.8%
6	Insufficient information	3.68	1.12	73.6%
7	Limited extension services	3.56	1.18	71.2%
8	Weak market linkages	3.43	1.21	68.6%
9	Inadequate policy support	3.35	1.24	67.0%
10	Fear of yield reduction	3.21	1.28	64.2%
11	Labor intensiveness	3.09	1.31	61.8%
12	Land tenure insecurity	2.94	1.35	58.8%

* Mean score on a scale of 1-5, where 1 = Not a constraint at all, and 5 = Very severe constraint

** Percentage of farmers reporting the constraint as moderate to very severe (score≥ 3)

The Oaxaca decomposition results reveal significant gender-based productivity differentials in climate-smart agriculture adoption. The analysis shows a substantial productivity gap of 0.436 log points (approximately 43.6%) between male and female farmers, with male farmers achieving higher productivity (7.892) compared to female farmers (7.456). This finding aligns with Valea and Noufé's (2024) observation of a 43.8 percentage point gender gap in agricultural productivity in similar contexts.

The decomposition indicates that 65.8% of this gap is explained by observable differences in resource endowments and characteristics, while 34.2% remains unexplained, potentially attributable to structural barriers and discrimination. This pattern echoes Singbo et al.'s (2020) findings, where female-specific structural disadvantages influenced 56% of the productivity gap.

The magnitude of the explained portion (0.287) suggests that tangible factors such as access to resources, inputs, and services play a crucial role in creating gender disparities. This corresponds with Slavchevska's (2015) findings that observable factors like plot area and labor significantly influence gender productivity differentials.

The implications are particularly significant for policy formulation. As Joe-Nkamuke et al. (2019) suggest, addressing access to productive inputs could significantly reduce the gender gap. The substantial unexplained portion (0.149) indicates the need for deeper structural reforms beyond resource allocation. According to Mkuna and Wale (2023), such reforms should focus on institutional factors like land tenure security and market access to reduce gender-induced productivity gaps effectively. The findings underscore the necessity of targeted interventions that address both resource disparities and structural barriers to achieve gender equity in agricultural productivity.

Table 6: Overall Decomposition of Gender Productivity Gap

Component	Coefficient	Std. Error	Percentage
Male productivity (log)	7.892	0.068	-
Female productivity (log)	7.456	0.072	-
Difference	0.436	0.099	100%
Explained	0.287	0.078	65.8%
Unexplained	0.149	0.094	34.2%

Note: The dependent variable is the log of agricultural productivity (measured as the value of output per hectare).

The detailed decomposition reveals nuanced patterns in the gender productivity gap in climate-smart agriculture adoption. CSA adoption emerges as the largest contributor to the explained gap (20.4%), followed by farm size (11.9%) and education (9.9%). This aligns with Adzawla et al.'s (2020) findings that resource endowment differences significantly influence gendered productivity gaps.

Access to credit (8.7%) and extension services (7.1%) also contribute substantially to the explained portion, supporting Obisesan and Awolala's (2021) conclusion that structural disadvantages in financial services access drive gender differentials. The negative coefficient for age (-1.1%) suggests younger farmers may have some advantage in productivity, though its effect is minimal. CSA adoption remains the largest contributor (8.0%) in the unexplained portion, indicating persistent structural barriers beyond resource access. Education's unexplained component (5.0%) suggests differential returns to education between genders, echoing Singbo et al.'s (2020) findings about female-specific structural disadvantages in Mali. The relatively small unexplained components for factors like household size (1.4%) and off-farm income (2.1%) suggest these variables' effects are largely captured through observable characteristics. However, market access shows a larger unexplained component (3.0%), indicating possible gender-based discrimination in market participation, consistent with Mkuna and Wale's (2023) observations.

These findings suggest that while resource redistribution is crucial, addressing structural barriers in CSA adoption, education returns, and market access is equally important for closing the gender productivity gap in Southeast Nigeria's agricultural sector.

Table 7: Detailed Decomposition of Gender Productivity Gap

Factor	Explained		Unexplained	
	Coefficient	% of Gap	Coefficient	% of Gap
CSA adoption	0.089	20.4%	0.035	8.0%
Farm size	0.052	11.9%	0.018	4.1%
Education	0.043	9.9%	0.022	5.0%
Access to credit	0.038	8.7%	0.015	3.4%
Extension services	0.031	7.1%	0.012	2.8%
Age	-0.005	-1.1%	0.008	1.8%
Household size	0.018	4.1%	0.006	1.4%
Off-farm income	0.021	4.8%	0.009	2.1%
Land quality	-0.002	-0.5%	0.011	2.5%
Market access	0.002	0.5%	0.013	3.0%
Total	0.287	65.8%	0.149	34.2%

Note: Percentages may not sum exactly due to rounding.

Discussion of Findings

This comprehensive study provides important insights into gender disparities in climate-smart agriculture (CSA) adoption in Southeast Nigeria while revealing methodological strengths and limitations. The research convincingly demonstrates significant gender gaps in CSA awareness and adoption, with male farmers consistently showing higher awareness levels across practices. For instance, male farmers exhibited 75% awareness of drought-tolerant crops compared to 60% of female farmers, aligning with Valea and Noufé's (2024) findings of persistent gender gaps in agricultural productivity.

The Heckman's Double Hurdle Model results effectively establish that gender significantly influences CSA adoption ($\beta = 0.342$, $p < 0.05$), with male farmers showing higher adoption probabilities. This finding is strengthened by its consistency with Aryal et al.'s (2018) research on household characteristics' influence on CSA adoption. The model also reveals that education and farm size are highly significant factors ($p < 0.001$), supporting Sisay et al.'s (2023) conclusions about education's positive correlation with CSA adoption. Potential endogeneity concerns arise regarding the relationship between CSA adoption and productivity. Farmers' decisions to adopt CSA practices may be influenced by unobserved characteristics affecting productivity, potentially biasing our estimates. While the Heckman model partially addresses selection bias, future research should employ instrumental variables or experimental designs for stronger causal inference.

A key strength of the methodology lies in its mixed-methods approach, combining quantitative analysis with qualitative insights through focus group discussions. However, the study's reliance on self-reported data may introduce response bias, potentially affecting the reliability of awareness measurements. Additionally, while the sample size of 360 households provides reasonable statistical power, the equal selection of male and female respondents may not reflect actual gender distribution in farming populations.

The factor analysis effectively identifies four major constraint dimensions, with resource limitations accounting for 26.75% of the variance. This finding resonates with Mizik's (2021) emphasis on economic constraints as critical barriers. However, the study could have benefited from a more detailed analysis of how these constraints affect female farmers.

The Oaxaca decomposition reveals a substantial productivity gap of 0.436 log points between male and female farmers, with 65.8% explained by observable differences in resource endowments. This finding provides crucial evidence for policy interventions, supporting Joe-Nkamuke et al.'s (2019) conclusion that addressing access to productive inputs could significantly reduce gender gaps.

The study's theoretical grounding in Innovation Diffusion Theory provides a robust framework for understanding adoption patterns, though it could have more explicitly connected theoretical predictions with empirical findings. The research makes a valuable contribution to understanding gender-specific barriers to CSA adoption while highlighting the need for targeted interventions addressing both resource disparities and structural barriers. These findings have important implications for policy formulation, suggesting the need for integrated approaches that combine resource access with institutional reforms to achieve gender equity in agricultural productivity.

Conclusion

This study provides critical insights into the gender dynamics of climate-smart agriculture (CSA) adoption in Southeast Nigeria, addressing a significant gap in understanding how gender influences agricultural innovation and adaptation to climate change. The research reveals substantial gender disparities in CSA awareness and adoption, with male farmers consistently demonstrating higher awareness levels and adoption rates across various practices. Notably, the study found a significant productivity gap of 0.436 log points between male and female farmers, with 65.8% explained by observable differences in resource endowments. These findings have important implications for agricultural policy and development interventions. The identification of specific constraints, particularly resource limitations accounting for 26.75% of adoption barriers, provides clear direction for targeted interventions. Understanding that gender disparities are largely driven by structural barriers and resource access challenges rather than inherent differences suggests that well-designed policy interventions could effectively reduce these gaps.

Future research should focus on developing and evaluating gender-responsive interventions that address resource disparities and structural barriers. Additionally, longitudinal studies examining how CSA adoption patterns change over time and their long-term impacts on productivity and resilience would be valuable. There is also a need for research investigating the intersection of gender with other social factors in CSA adoption and studies evaluating the effectiveness of different intervention strategies in reducing gender gaps in agricultural productivity.

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