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Gendered Effects of Multiple Climate-Smart Agriculture on Nutrition and Poverty in Nigeria

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Abstract

There is significant potential to enhance food security and address nutrition and poverty in smallholder farming systems through the adoption of climate-smart agricultural (CSA) practices. However, adoption rates of CSA practices remain uneven across genders due to disparities in access to resources, decision-making power, and socio-economic barriers. Similarly, while CSA practices are widely recognized for their potential benefits, the combined effects of using multiple practices to improve food security, nutrition, and poverty reduction remain poorly studied and not fully understood. This study analyzes data from four waves of the Nigeria General Household Survey, using fixed effects multivariate logit models and a panel endogenous switching regression framework to examine the factors influencing CSA adoption and its outcomes. The results show notable gender differences: male farmers are more likely to adopt organic manure and practice mixed cropping, while women focus more on improved seeds and combining organic and inorganic manure. Integrated CSA strategies, especially combining organic manure with mixed cropping, lead to significant gains in food security and reductions in multidimensional poverty. Nonetheless, organic/inorganic manure combinations are underused, mainly due to resource constraints and perceived inefficiencies. Addressing gender-specific barriers and maximizing the benefits of CSA practices can provide valuable insights for policymakers and practitioners. The study recommends gender-sensitive policies, better financial inclusion, and customized extension services to promote sustainable farming practices that boost food security, resilience, and livelihoods in smallholder systems.

Keywords: Climate-Smart Agriculture (CSA), Gendered Adoption Patterns, Food Security, Synergistic Practices, Smallholder Farming Systems

JEL codes: Q16, Q12, Q18, D13, O13

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1. Introduction

The agricultural sector is increasingly confronted with the dual challenge of meeting the food demands of a rapidly expanding global population while mitigating the adverse impacts of climate change, resource degradation, and persistent socioeconomic inequalities. Ensuring food and nutritional security for farming households, alongside the reduction of multidimensional poverty, remains central to sustainable rural development (Cao et al., 2024). Addressing these interlinked challenges necessitates a paradigm shift from conventional farming systems toward more adaptive and integrative approaches. In this regard, Climate-Smart Agriculture (CSA) provides a comprehensive framework that simultaneously enhances productivity, builds resilience to climate-induced shocks, and reduces environmental footprints, thereby positioning itself as a pivotal pathway toward sustainable agricultural transformation (Dagunga et al., 2020).

In this paper, we used four waves of data from the General Household Survey for cassava producers in Nigeria to examine the cumulative and interactive effects of multiple Climate-Smart Agriculture (CSA) practices, specifically improved seeds, mixed cropping/intercropping, and the use of organic and inorganic manure on key development outcomes, focusing on their impact on nutritional security and multidimensional poverty. Our study examines how socioeconomic and gender-specific factors influence the adoption of CSA practices and investigates the synergies and trade-offs that arise when multiple practices are implemented together. To understand these dynamics, we employ a multivariate analytical framework (Hidalgo and Goodman, 2013) that captures the interdependencies among CSA practices, providing insight into their combined effects. Additionally, our framework incorporates a gender-sensitive perspective, recognizing that gender dynamics and socioeconomic contexts significantly influence adoption decisions. Despite their potential, the adoption of CSA practices remains uneven, constrained by socioeconomic barriers, limited resource access, and gender disparities (Hailemariam et al., 2024). For instance, women farmers, who often encounter systemic challenges such as restricted access to credit, land, and extension services, are less likely to adopt CSA practices despite being key stakeholders in agriculture (Atta-Aidoo and Antwi-Agyei, 2025). This uneven uptake highlights the need for inclusive strategies that address these barriers and promote equitable access to CSA innovations (Nguyen and Scrimgeour, 2022).

The adoption of multiple CSA practices is essential for tackling the dual challenges of food insecurity and poverty in farming systems worldwide (Raihan et al., 2024). By integrating sustainable practices such as improved seeds, mixed cropping/intercropping, and the use of organic and inorganic manure, CSA provides a pathway to boost agricultural productivity, resilience, and environmental sustainability (Haggai et al., 2023). These practices are especially effective in areas vulnerable to climate variability, as they improve soil health, optimize resource use, and increase crop diversity, which in turn enhances nutritional security and economic stability (Haggai et al., 2023). For example, mixed cropping systems enhance dietary diversity by producing a variety of food crops (Ume et al., 2023a), while the use of organic manure boosts soil fertility and reduces reliance on synthetic inputs, lowering environmental footprints (Ume et al., 2023b). Additionally, CSA practices support broader sustainability goals by decreasing greenhouse gas emissions and promoting ecosystem services such as carbon sequestration and biodiversity conservation (Mutengwa et al., 2023). Although CSA practices show great promise, their combined effects on nutritional security and multidimensional poverty are still not well understood, especially in contexts where multiple practices work together to create synergistic or conflicting outcomes. This knowledge gap highlights the need to examine not only the adoption of specific CSA practices but also how their combined and integrated use in cassava production influences core developmental outcomes.

This paper addresses this important knowledge gap by focusing on the numerous CSA practices in cassava farming, considering that their interactions may enhance or diminish their effectiveness (Teklu et al., 2023). Unlike other studies that examined CSA in isolation, this study recognizes that integrating several CSA practices—such as using improved seeds, mixed cropping or intercropping, and applying organic or inorganic manure—can create synergies or trade-offs that have significant potential to tackle food insecurity and poverty. It is crucial to close this gap in cassava farming in Nigeria because cassava is a vital food security and rural livelihood crop, serving as a staple for millions (Greene, 2018). The challenges faced by cassava farmers are unique and include soil degradation, climate change, and limited access to new technologies, making the adoption of effective CSA innovations essential. Additionally, the gender-sensitive approach of this study acknowledges existing disparities in access to resources, decision-making, and labor allocation, which greatly influence adoption decisions and outcomes (Opata et al., 2020). By bridging this gap, this research provides a clearer understanding of how adopting gender-sensitive CSA practices in cassava production can help improve food security, reduce multidimensional poverty, and promote gender equity in smallholder cassava farming systems in Nigeria. This will greatly aid in designing equitable policies aligned with the SDG goals of gender equality, poverty reduction, and food security.

To implement the panel endogenous switching regression (ESR) model, we went beyond standard econometric packages by integrating customized Python-based tools, combining linearmodels and statsmodels with tailored computational methods. Although linearmodels offer robust handling of panel data, including fixed effects, random effects, and instrumental variables, it does not inherently support endogenous switching regression. To address this, we created an innovative workflow that merges these packages with custom optimization routines and matrix operations using NumPy and SciPy. This method allowed us to estimate the selection and outcome equations simultaneously while capturing the temporal and individual-specific aspects inherent in panel data.

Besides its methodological contributions, the study bridges the gap between research and practice by tackling policy-relevant questions. What combinations of CSA practices produce the greatest improvements in nutritional security and poverty reduction? How can interventions be designed to consider gender-specific needs and constraints? Answering these questions helps inform the creation of targeted agricultural programs that are inclusive, effective, and scalable. The findings have wide-ranging implications for stakeholders, including policymakers, development agencies, and farmer organizations. By identifying scalable strategies for CSA adoption, the study supports global efforts to achieve Sustainable Development Goals (SDGs) related to zero hunger, gender equality, and poverty reduction. Additionally, its focus on evidence-based policy design highlights the importance of aligning agricultural innovations with broader social and economic goals.

2. Context and Conceptual Framework

2.1 Context

Cassava (Manihot esculenta), a staple crop cultivated widely in tropical and subtropical regions, is vital for global food security and rural livelihoods (FAO, 2013). Its versatility covers food, industrial uses, and biofuel production, making it a multipurpose crop essential to the economies of cassava-producing areas. Despite improvements in farming techniques and technology that have increased cassava yields (Ahmed et al., 2024), the inconsistent adoption of sustainable practices highlights systemic issues such as resource limitations, socio-economic inequalities, and climate variability (Atta-Aidoo and Antwi-Agyei, 2025). These challenges mainly affect smallholder systems, where access to resources is limited, and traditional practices prevail. Sustainable cassava farming, supported by Climate-Smart Agriculture (CSA) practices, has the potential to transform this landscape by filling critical gaps in food security, nutrition, and poverty reduction.

CSA adoption influences food security, nutrition, and poverty among cassava farmers through three interconnected pathways. First, practices like intercropping and organic manure application improve soil health, reduce dependency on inputs, and increase crop resilience, resulting in higher, more stable yields. These gains directly improve household food availability, and diversified cropping systems contribute to dietary diversity and better nutrition (Zheng et al., 2024). Second, CSA methods lower production costs and improve efficiency, boosting disposable income for smallholder farmers. This economic benefit allows households to access better healthcare, education, and more diverse food options, tackling both poverty and nutrition issues (Ma and Rahut, 2024). Third, CSA practices help prevent environmental damage caused by intensive cassava farming, such as soil erosion, loss of biodiversity, and greenhouse gas emissions. By incorporating organic inputs and reducing reliance on synthetic fertilizers, these methods support long-term agricultural sustainability, securing future food supplies and reducing vulnerability to climate shocks (Ume et al., 2022).

Global efforts to promote intercropping, organic inputs, and improved cassava varieties through agricultural extension services and policy measures are crucial for achieving these benefits. Nevertheless, adoption of CSA practices remains uneven, hindered by barriers such as limited resource access, knowledge gaps, and perceived short-term trade-offs. Understanding the underlying mechanisms driving CSA adoption is essential for designing interventions tailored to specific contexts and maximizing benefits. This study focuses on cassava farming to analyze how CSA adoption affects food security, nutrition, and poverty reduction, providing insights into systemic changes needed for resilient and equitable agricultural systems. By addressing these barriers and harnessing the pathways of impact, CSA adoption can transform cassava farming into a sustainable force for improving livelihoods and advancing socio-economic development.

Conceptual Framework

Our study is based on the principles of Prospect Theory (Kahneman and Tversky, 1979), which diverges from traditional utility-based models by considering how individuals perceive and evaluate risks and uncertainties relative to a reference point. This theory is especially relevant to Climate-Smart Agriculture (CSA) adoption, where farmers face uncertainties related to new methods, resource limitations, and potential trade-offs with existing practices. Farmers tend to be loss averse, preferring to avoid losses rather than gain equivalent benefits, which affects their risk preferences and decisions to adopt new practices.

To build on this, we incorporate the principles of Mental Accounting (Thaler, 1999), which describe how farmers categorize and assess resources, risks, and outcomes. This segmentation helps us model how they allocate limited resources—such as labor, capital, and time—toward adopting CSA practices, like using improved seeds, intercropping, or organic manure. Additionally, our framework includes a gender-sensitive behavioral perspective, recognizing that decision-making processes vary by gender due to systemic inequalities such as reduced access to credit, land, and extension services (Atta-Aidoo and Antwi-Agyei, 2025; Hailemariam et al., 2024).

We define the farmer's utility U for adopting CSA practices based on a value function $v(x)$, as per prospect theory:

$$U(x) = \begin{cases} (x-\eta)^p & \text{if } x \geq \eta, \\ -\lambda(\eta - x)^q & \text{if } x < \eta, \end{cases} \tag{1}$$

where:

- x represents the realized welfare outcome for the household (e.g., food security, dietary diversity, or poverty reduction).
- η)denotes the household-specific reference point, representing the farmer's current or expected welfare level before adopting CSA practices. In this study, the reference point reflects the baseline household welfare condition, rather than a national or aggregate benchmark.,
- $p \text{ and } q \text{ are curvature parameters } (0 < p, q \leq 1) \text{ capturing diminishing sensitivity to gains and losses.}$

$\lambda \text{ represents the loss} - \text{aversion parameter, measuring the relative weight farmers assign to losses compared with gains}$
If λ = 0 and x > η, the utility function simplifies to $U(x) = (x-\eta)^p$, meaning that the farmer evaluates only gains relative to the reference point and assigns no weight to losses. In this case, farmers would behave as gain-seeking agents without loss aversion, implying a higher likelihood of adopting new agricultural technologies. However, empirical evidence suggests that farmers typically exhibit positive loss aversion (λ > 1), meaning that potential welfare losses associated with adopting unfamiliar practices often discourage adoption. This behavioral mechanism helps explain why risk perceptions influence CSA adoption decisions.

Farmers weigh the expected outcomes of adopting a set of CSA practices $\{c_1, c_2, \ldots, c_n\}$ relative to potential losses from resource investments.

The farmer's budget constraint is modeled as:

$$\sum_{i=1}^{n} r_i \, c_i \leq R, \tag{2}$$

where:

- r_i is the cost of implementing CSA practice i,
- $c_i \in \{0,1\}$ indicates adoption (1) or non-adoption (0),
- R is the total available resources (e.g., financial, labor).

Farmers allocate resources to maximize expected utility:

$$\max \mathbb{E}[U(x)] = \sum_{i=1}^{n} \pi_i \cdot v(c_i), \tag{3}$$

subject to the budget constraint, where π_i is the perceived probability of success for practice i.

The interaction effects of CSA practices are modeled using a Cobb-Douglas production function:

$$Y = A \prod_{i=1}^{n} c_i^{\alpha_i}, \tag{4}$$

where:

- Y is the outcome (e.g., nutritional security or poverty reduction),
- A is the efficiency parameter,
- α_i measures the contribution of practice i to the outcome.

Interaction effects between practices c_i and c_j are captured by adding cross terms:

$$Y = A \prod_{i=1}^{n} c_i^{\alpha_i} + \sum_{i \neq j} \beta_{ij} \, c_i c_j, \tag{5}$$

where β_{ij} represents the synergy (positive) or trade-off (negative) between practices i and j.

We extend the model by incorporating gender g as a moderator in the utility function:

$$U_g(x) = \begin{cases} \left(x - \eta_g\right)^p & \text{if } x \geq \eta_g, \\ -\lambda_g\left(\eta_g - x\right)^q & \text{if } x < \eta_g, \end{cases} \tag{6}$$

where η_g and λ_g vary by gender, reflecting gender-specific reference points and risk preferences. For example, women may prioritize immediate household needs (η_g is lower) and exhibit higher loss aversion ($\lambda_g > \lambda_m$) due to systemic inequities.

The combined framework integrates these dimensions into a multivariate endogenous switching regression model:

$$Y_{it} = \begin{cases} \mathbf{X}_{it}\boldsymbol{\beta}_1 + \epsilon_{1,it} & \text{if } D_{it} = 1, \\ \mathbf{X}_{it}\boldsymbol{\beta}_0 + \epsilon_{0,it} & \text{if } D_{it} = 0, \end{cases} \tag{7}$$

where:

- Y_{it} is the outcome (e.g., nutritional security, poverty status) for farmer i at time t,
- D_{it} is the binary decision to adopt CSA practices,
- $\mathbf{X}_{it}$ is a vector of explanatory variables, including gender, resource access, and CSA practices,
- $\boldsymbol{\beta}_1, \boldsymbol{\beta}_0$ are coefficients for adopters and non-adopters,
- $\epsilon_{1,it}, \epsilon_{0,it}$ are error terms capturing unobserved factors.

Following standard household production models (e.g., Singh et al. (1986)), we define a utility maximization problem constrained by resources and technology. The optimal choices of CSA technologies are determined by the first-order conditions (FOC) and second-order conditions (SOC), which are detailed in Annex A. These conditions capture the trade-offs and synergies households face when allocating resources among CSA options under specified constraints.

To estimate the cumulative and interactive impacts of CSA practices while addressing selection bias, we use a multivariate endogenous switching regression model. This approach estimates separate outcome equations for adopters and non-adopters, reflecting differences in their decision-making processes and outcomes. The adoption decision itself is modeled as a selection equation, where the likelihood of adoption depends on observable factors and unobservable preferences. This structure helps disentangle the effects of adoption from the factors influencing the decision, providing a robust framework for analyzing the drivers and impacts of CSA adoption. By integrating insights from Prospect Theory, Mental Accounting, and gender-specific behavioral dynamics, this framework offers an approach to understanding CSA adoption and its outcomes. It emphasizes the importance of addressing behavioral, resource-related, and gender-specific constraints to increase CSA adoption. Additionally, the framework's focus on interactions among practices highlights the need for integrated strategies that maximize synergies and reduce trade-offs. This conceptual framework provides a solid basis for analyzing how CSA practices impact nutritional security and multidimensional poverty, offering valuable insights for policymakers, development agencies, and farmer organizations.

3. Methodology

3.1 Data

The data for this study were collected from four waves of the Nigerian General Household Survey (GHS) Panel, conducted in 2011/2012, 2013/2014, 2015/2016, and 2018/2019. The GHS is a nationally representative survey designed to provide comprehensive insights into household living conditions, agricultural practices, and welfare. Each wave initially sampled approximately 5,000 households, using a stratified two-stage sampling method to ensure representativeness at both national and zonal levels. In the first stage, enumeration areas (EAs) were selected based on probability proportional to size, followed by the random selection of households within each EA in the second stage. For this study, households involved in cassava farming were isolated, resulting in a final sample of 1,925 observations. Attrition across the survey waves was analyzed to ensure the consistency and reliability of the panel data. We specifically examined the reported attrition rates and the strategies used to address their effects. According to World Bank documentation, the overall attrition rate since 2010 in the GHS Panel for Nigeria has been 13.5 percent, with notable differences between urban areas (17.8 percent) and rural areas (11.4 percent). The highest attrition was observed in rural enumeration areas in the Southwest (28.8 percent), while the lowest occurred in North Central rural areas (5.3 percent). To address these attrition issues and maintain the representativeness of our sample, we employed the recalibrated sampling weights provided by the World Bank. These weights adjust for nonresponses and dropout effects, improving the robustness of our findings.

3.2 Description of Variables

Outcome Variables

Food Insecurity Experience Scale (FIES): The FIES measures the severity of food insecurity experienced by households over a 12-month period . The GHS data includes responses to a set of questions that assess various aspects of food insecurity, ranging from anxiety about food access to actual shortages that affect eating patterns and food consumption. The scale ranges from 0 to 8, with higher scores indicating more severe food insecurity. We used the inverse of the FIES to measure food security, operationalizing it as $1 - \frac{\text{FIES score}}{8}$, to facilitate a more intuitive interpretation where higher values indicate better food security. This approach aligns with studies that inversely relate food insecurity measures to reflect positive attributes of food access and stability.

Household Dietary Diversity Score (HDDS): The HDDS evaluates the variety of food groups consumed by households within a defined period . This score, reflecting the consumption of 12 distinct food groups including grains, meats, and vegetables, serves as a proxy for nutritional quality. A higher HDDS indicates a more diverse diet, which is often associated with better micronutrient sufficiency and overall health outcomes (Kennedy et al., 2010). In the GHS-Panel, dietary diversity is collected at the household level; consistent, wave-comparable individual-level diet modules are not available across all four waves. Consequently, HDDS in this study is standardized at the household level. We flag this as a limitation for gender-disaggregated nutrition analysis and interpret results accordingly.

Multidimensional Poverty Index (MDPI): Following the Alkire and Foster (2011) methodology, the Multidimensional Poverty Index (MPI) was employed to assess deprivations across three dimensions and constructed using ten indicators grouped under three core dimensions: *health*, *education*, and *living standards* (Alkire and Santos, 2013; Alkire et al., 2014). The selection was tailored to the rural Nigerian context, drawing from previous MPI studies and available data. The index computation followed Alkire-Foster (2011)'s method, which begins with the selection of relevant indicators that effectively represent each dimension of poverty. Each indicator was assigned a weight, reflecting its relative importance based on expert assessments and a review of relevant literature.

Within the *health* dimension, deprivation was measured using two indicators: access to a health facility within 5 km and the absence of recent illness among adults or children within the past two weeks (where households reporting no illness are considered non-deprived). The *education* dimension included years of schooling, defined as at least one adult in the household having completed six or more years of education, and school attendance, measured by whether all school-aged children in the household are currently enrolled in school. The *living standards* dimension was captured using six indicators: housing quality (based on wall and roof materials), access to electricity, the main source of drinking water (e.g., piped, protected well, river), type of sanitation facility (e.g., flush, pit latrine, none), primary cooking fuel (clean versus biomass/firewood), and household asset ownership, including items such as livestock, mobile phones, bicycles, or motorcycles.

Each indicator was weighted equally within its dimension, and households were classified as multidimensionally poor if their weighted deprivation score exceeded 30%. This adaptation ensures that the MPI reflects relevant deprivations in the context of smallholder cassava farmers in rural Nigeria.

For each household, a deprivation score was computed: d_{ij} equals 1 if household i is identified as deprived in dimension j, and 0 otherwise. These individual scores were aggregated using the assigned weights w_j for each dimension, and the total number of dimensions n considered:

$$\mathrm{MDPI}_i = \frac{1}{n}\sum_{j=1}^{n} w_j \, d_{ij}$$

To make the MDPI more interpretable, especially for policy implications, the index values were converted into percentages. This conversion illustrates the proportion of total possible deprivation that each household faces. The calculation is given by:

$$\mathrm{MDPI}\ \%_i = \mathrm{MDPI}_i \times 100$$

Expressing the MDPI as a percentage allows for an intuitive understanding of the extent of deprivation and facilitates a clearer comparison across different households and regions. The MDPI is constructed at the household level as the GHS-Panel does not provide a harmonized set of individual deprivation indicators across waves. We therefore refrain from individual-level poverty statements and explicitly note this as a boundary condition of the data.

Climate-Smart Agriculture (CSA)

Climate-smart agriculture (CSA) comprises a broad range of practices designed to enhance agricultural productivity, strengthen resilience to climate change, and reduce environmental impacts (Food and Agriculture Organization, 2013; 2021). This study focuses on four practices, organic manure, inorganic fertilizer, improved seeds, and mixed cropping, based on their relevance to cassava-based farming systems and their consistent availability in the survey data. These practices are widely promoted in Nigeria as key strategies to improve soil fertility, increase productivity, and enhance resilience among smallholder farmers (Opata et al., 2021; Nasar et al., 2019; Ume et al., 2023b). In addition, they are among the most frequently reported practices in the dataset across survey waves, enabling reliable analysis of adoption behavior. Other CSA practices, such as agroforestry or water harvesting, were either not promoted during the survey period or reported by only a small number of respondents. Adoption rates by gender are shown in Figure 1. Restricting the analysis to these practices also ensures tractable estimation of joint adoption decisions within the multinomial endogenous switching regression framework, since including more practices would substantially increase the number of possible adoption regimes and lead to sparse observations across combinations.

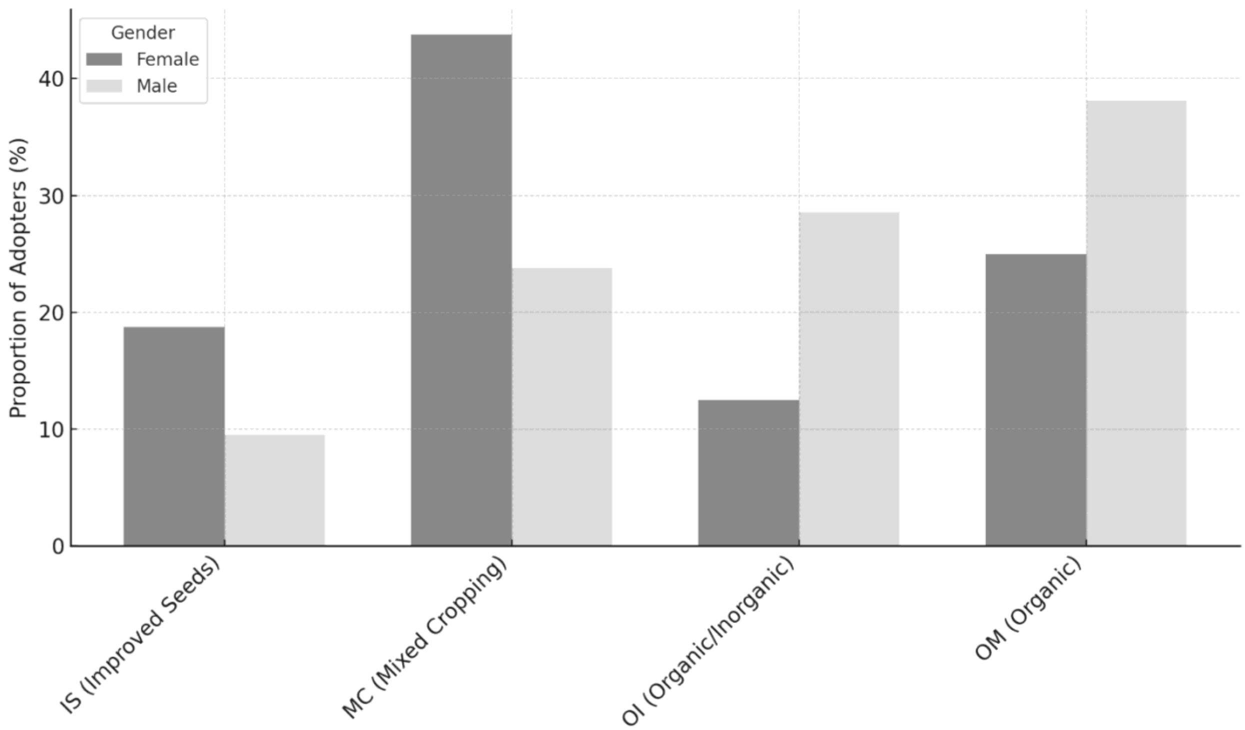

Figure 1: Proportion of Respondents Adopting CSA Practices (% of Total Sample)

Figure 1 reveals significant gender disparities in the adoption of climate-smart agriculture (CSA) practices. Improved cassava stems show moderate overall adoption, with a slightly higher rate among female farmers, possibly reflecting women's relatively greater willingness to experiment with low-cost, labor-efficient technologies and their engagement in household-level risk management (Awoke et al., 2025; Gupta et al., 2026). Mixed cropping/intercropping is the most popular method, especially among female farmers, who adopt this practice more frequently than males. This preference may stem from its benefits in enhancing crop resilience and soil health, critical considerations in regions facing climate variability and soil degradation, while requiring minimal capital investment. Conversely, male farmers show higher adoption of inorganic and combined organic–inorganic fertilizers, which are more input- and resource-intensive, likely reflecting men's greater control over land, credit, and access to extension services (Gupta et al., 2026). The balanced use of organic manure between genders suggests its broad acceptability as a simple, low-risk soil fertility improvement strategy. These patterns underscore the need for gender-responsive strategies to promote CSA practices, ensuring interventions consider differences in resource access, labor constraints, and technology preferences to achieve equitable benefits and empowerment across all farming communities.

In this study, the climate-smart agriculture (CSA) practices analyzed include organic manure application, improved seed varieties, mixed cropping/intercropping, and the combined use of organic and inorganic fertilizers. These practices are widely recognized in the CSA literature because they enhance soil fertility, improve water retention, increase crop diversification, and strengthen farmers' resilience to climate variability. Importantly, the classification of these practices as CSA does not depend on the inclusion of climate variables in the adoption regression. Rather, their designation as climate-smart is based on their agronomic and resilience-enhancing properties documented in the literature (FAO, 2013; Arslan et al., 2015; Wossen et al., 2019). The adoption model therefore focuses on socioeconomic, institutional, and farm-level factors influencing farmers' decisions to adopt these practices.

In addition to the CSA adoption variables and outcome measures, the analysis includes several household-level and contextual control variables to account for factors that may influence both technology adoption and welfare outcomes. These include demographic characteristics such as age, education, marital status, and household size, as well as economic indicators including income level, credit access, land ownership, and livestock holdings. The model also incorporates variables capturing access to information and institutional services, such as extension visits, mobile phone ownership, internet access, and access to digital financial services (e-wallets). These variables are commonly used in the agricultural technology adoption literature as proxies for information access and institutional support.

To capture gender dynamics within households, we include gender-sensitive indicators such as the presence of adult female members, women's access to credit and extension services, and joint decision-making in farm activities. These variables allow us to examine how intra-household power relations and gender roles shape CSA adoption decisions. Finally, agroecological and risk-related variables, including previous flooding experience and land loss, are included to account for environmental factors that may influence farmers' incentives to adopt climate-smart agricultural practices.n. Descriptive statistics for these variables are presented in Table 1.

Table 1: Extended Descriptive Statistics Including Gender Interaction Terms

Variable	Description	Mean	SD
Gender	Gender (0 = Female, 1 = Male)	0.497	0.500
Adult Female Present	Adult female child in household	0.83	0.38
Adult Male Present	adult male child in household	0.87	0.34
Joint Decision-Making	Joint decision on farm activities (1 = Yes)	0.47	0.50
Women's Access to Credit	Female member has access to credit	0.21	0.41
Women's Access to Extension	Female member has access to extension	0.19	0.39
Time Use	Labor Contribution by Gender	0.576	0.494
Resource Contl	Women's Control Over Resources	0.319	0.466
Gender Balance	Female Share of Adults in Household	0.740	0.347
FemaleAdult × JointDecision	Interaction	0.116	0.320
Age	Age of respondent in years	39.42	12.30
Marital Status	Marital status (1 = Married, 0 = Otherwise)	0.658	0.474
Mobile Phone	Mobile phone ownership (1 = Yes, 0 = No)	0.762	0.426
Internet Access	Internet access (1 = Yes, 0 = No)	0.496	0.410
Income Level	Monthly household income in USD	41.28	62.25
Education	Years of formal education	8.34	4.10
Household Size	Number of people in the household	4.25	2.31
Credit Access	Access to credit (1 = Yes, 0 = No)	0.32	0.467
Extension Visits	Number of extension service visits	2.51	1.45
Land Size	Farm size in hectares	1.65	0.97
Food Insecurity	Inverse of FIES score	4.72	2.50
HDD	Household Dietary Diversity Score	6.4	1.90
Poverty Index	Multidimensional Poverty Index (%)	32.1	18.5
Flood Experience	Experience of flooding (1 = Yes, 0 = No)	0.154	0.361
Remittances	Remittances from abroad (1 = Yes, 0 = No)	0.26	0.438
Economic Sector	Economic sector (1 = Rural, 0 = Urban)	0.78	0.02
Purchased or Free Seeds	Seed source (1 = Purchased, 0 = Free)	0.14	0.01
Amount Purchased	% of fertilizer bought with own money	0.33	28.3
Primary Occupation	Farming as primary occupation (1 = Yes)	0.84	0.11
Type of Land Ownership	Legal status of land (1 = Titled, 0 = Leased)	0.55	0.13
Quantity Used	Amount of Organic fertilizer used (kg)	127	59

Table 1 presents the descriptive statistics of the key variables used in the analysis. The sample consists of 1,925 observations of cassava-producing households drawn from four waves of the

Nigerian General Household Survey Panel. The table reports the mean and standard deviation for the outcome variables, CSA adoption variables, and household characteristics. On average, the inverse Food Insecurity Experience Scale is 4.72, while the Household Dietary Diversity Score averages 6.4 food groups. The mean multidimensional poverty index is 32.1 percent, indicating substantial welfare deprivation among cassava farming households. The descriptive statistics also show that mixed cropping and organic manure are among the most commonly adopted CSA practices in the sample.

3.3 Econometric Strategy

Building on the conceptual framework in Section 2.2 and the optimization problem detailed in Annex D, we model CSA adoption as the result of a constrained utility maximization process. Households select from available CSA practices to optimize their welfare based on resource endowments, information, and access to technology. These decisions are affected by observed and unobserved factors, including gender dynamics, risk preferences, and agro-ecological conditions. Since multiple, non-mutually exclusive CSA practices are possible, we use a multivariate logit model to capture potential correlations among adoption decisions. Additionally, to assess how CSA adoption influences welfare outcomes such as nutrition and multidimensional poverty, we employ an Endogenous Switching Regression (ESR) to address selection bias and endogeneity issues. Our model incorporates both household and non-household factors, recognizing the multilevel determinants of CSA adoption. Besides standard controls like age, education, income, and household size, we include variables related to intra-household gender dynamics (e.g., joint decision-making, adult male/female presence, gender balance), access to services (extension, credit, e-wallets), and agroecological risks (flooding history, land loss). These variables affect the likelihood of CSA adoption through improved access to information and resources but do not directly determine household nutrition or poverty outcomes once adoption decisions and other socioeconomic controls are accounted for. Although the use of secondary data limited our ability to include certain village-level or agroecological indicators, we mitigate this by including wave fixed effects and plot-level controls to account for time-specific shocks and location characteristics. This approach enhances the causal interpretation of our estimates while respecting the data limitations typical of large-scale panel surveys.

Multivariate Logit Model Specification: To understand the factors influencing the adoption of Climate-Smart Agriculture (CSA) practices—improved cassava stems, mixed cropping/intercropping, organic manure, and the combined use of organic and inorganic manure—we employed a *multivariate logit model* separately for male and female farmers. This approach enabled us to capture interdependencies among the four CSA practices and account for gender-specific adoption dynamics. Given that farmers may adopt multiple CSA practices simultaneously, we employ a multivariate logit model, which estimates correlated binary outcomes jointly and allows for interdependence between adoption decisions. Unlike the multinomial logit model, the multivariate logit does not impose the Independence of Irrelevant Alternatives (IIA) assumption, making it more appropriate for analyzing complementary or substitutable technologies (Train, 2009; Belderbos, 2004).

The use of panel data provided a unique opportunity to control for individual-specific heterogeneity and temporal variations.

The panel multivariate logit model for each gender g in wave t is specified as follows:

$$P(y_{ijt} = 1) = \frac{\exp(\alpha_j + X_{it}\beta_j + Z_{it}\gamma_j)}{1 + \exp(\alpha_j + X_{it}\beta_j + Z_{it}\gamma_j)},$$

where:

y_{ijt} is the binary adoption outcome for CSA practice j (1 = adopted, 0 = not adopted), X_{it} includes socio-economic and demographic characteristics (e.g., age, education, income, household size, land ownership), Z_{it} represents external factors influencing adoption, such as extension visits, credit access, and exposure to flooding, α_j is the constant term for practice j, β_j and γ_j are coefficients for X_{it} and Z_{it}, respectively.

This model is advantageous for capturing the joint adoption probabilities of interrelated practices. Pairwise correlations between adoption decisions were tested using a correlation matrix, which confirmed the need for a multivariate approach . The correlation between adoption choices was modeled as:

$$\rho_{jk} = \text{Corr}(\epsilon_j, \epsilon_k), \quad \forall\, j \neq k,$$

where ρ_{jk} represents the correlation between the error terms of CSA practice j and k.

Identification of the endogenous switching regression model relies on the inclusion of variables that influence the adoption decision but do not directly affect outcome variables such as food security, dietary diversity, or multidimensional poverty. Following previous studies on agricultural technology adoption (Di Falco et al., 2011; Lokshin and Sajaia, 2004), we use three exclusion restrictions: extension visits, access to digital financial services (e-wallet), and exposure to previous flooding events.

Extension services primarily provide information about agricultural technologies and management practices, thereby influencing farmers' awareness and adoption decisions. However, conditional on household characteristics and production inputs, extension visits are not expected to directly affect household dietary diversity or multidimensional poverty outcomes. Similarly, access to digital financial tools facilitates the acquisition of agricultural inputs and encourages adoption of climate-smart practices but does not directly influence nutritional outcomes once farm production and income controls are included. Exposure to flooding events captures farmers' perceived climate risk and therefore affects their incentive to adopt risk-mitigating CSA practices; however, past flooding shocks are unlikely to directly determine current food security or dietary diversity once farm productivity and household characteristics are controlled for. These variables therefore satisfy the relevance and exclusion conditions required for valid identification of the selection equation, allowing the ESR framework to distinguish the effect of CSA adoption from underlying selection processes.

Endogenous Switching Regression Framework

To address the potential endogeneity in CSA adoption and its impacts on key outcomes such as food security, dietary diversity, and multidimensional poverty, we employed a *two-stage Endogenous Switching Regression (ESR) framework*. This methodology is particularly suited for analyzing scenarios where treatment assignment (CSA adoption) is non-random and potentially influenced by observed and unobserved factors (Heckman, 1979; Lokshin and Sajaia, 2004).

The first stage of the ESR framework estimates the likelihood of households adopting specific CSA practice combinations. This stage uses a multinomial logit model:

$$P(C_k|X_i, Z_i) = \frac{\exp(X_i\beta_k + Z_i\gamma_k)}{\sum_{j=1}^{K} \exp\left(X_i\beta_j + Z_i\gamma_j\right)},$$

where: C_k is the categorical variable representing the adoption choice of CSA combination k, X_i includes household-level socio-economic characteristics (e.g., income, education, gender), Z_i includes instruments (e.g., extension visits, access to financial services, exposure to climate shocks), and β_k and γ_k are the coefficients for covariates and instruments, respectively. Because the first-stage selection uses a multinomial logit, we assessed the Independence of Irrelevant Alternatives (IIA) using the Hausman–McFadden and Small–Hsiao tests. The diagnostics do not indicate material IIA violations, supporting the MNL specification. For robustness, results are consistent when re-estimating a multinomial probit model (see Appendix E, Tables E1–E2), and MNP robustness showing substantively similar marginal effects.

The instruments Z_i were carefully chosen to satisfy relevance (strongly correlated with CSA adoption) and exogeneity (uncorrelated with unobserved determinants of outcomes). The model provides the predicted probabilities for CSA adoption, which are later used to compute the inverse Mills ratio (IMR) for each observation.

The IMR, derived from the multinomial logit probabilities, adjusts for selection bias caused by unobserved heterogeneity. For each CSA adoption category k, the IMR is calculated as:

$$\lambda_k = \frac{\phi(X_i\beta_k + Z_i\gamma_k)}{\Phi(X_i\beta_k + Z_i\gamma_k)},$$

where:

- $\phi(\cdot)$ is the probability density function of the standard normal distribution, and
- $\Phi(\cdot)$ is its cumulative distribution function.

The IMR captures the expected value of the error term conditional on the selection into CSA adoption. Including λ_k in the second-stage regression controls for unobservable factors influencing both CSA adoption and outcomes. The second stage estimates the impact of CSA adoption on outcomes by incorporating the IMR into the outcome equations.

For food security (inverse Food Insecurity Experience Scale) and HDD (Household Dietary Diversity), both count variables, we used a *Poisson regression model*:

$$E(Y_i|C_k, X_i) = \exp(X_i\beta + \delta_k C_k + \lambda_k),$$

where: Y_i is the outcome (food security or HDD score), C_k represents the CSA adoption category, δ_k measures the treatment effect, and λ_k accounts for selection bias.

For MDPI, expressed as a percentage, we employed a *fractional logit model*:

$$\text{logit}\big(E(MDPI_i|C_k, X_i)\big) = X_i\beta + \delta_k C_k + \lambda_k.$$

This method ensures the predictions remain within the unit interval [0,1], addressing the bounded nature of MDPI (Papke and Wooldridge, 1996)..

To leverage the panel structure of the data, we extended the ESR framework to account for temporal and individual-specific unobserved heterogeneity (Di Falco et al., 2011; Greene, 2018):

$$Y_{it} = X_{it}\beta + \delta_k C_{k,it} + \lambda_k IMR_{k,it} + \bar{X}_i\theta + \eta_t + \varepsilon_{it}$$

with:

$\bar{X}_i$represents the household-level mean of time-varying explanatory variables and implements the correlated random effects (Mundlak) correction**,** which allows the unobserved household effect to be correlated with the explanatory variables. $\eta_t$represents wave-specific fixed effects capturing time shocks common to all households, and $\varepsilon_{it}$is the idiosyncratic error term.

The ESR framework enables the estimation of counterfactual outcomes. This involves predicting:

- Outcomes for adopters had they not adopted CSA practices: $E(Y_i|C_k = 0, X_i)$.
- Outcomes for non-adopters had they adopted CSA practices: $E(Y_i|C_k = 1, X_i)$.

These counterfactuals provide insights into the net benefits of CSA adoption. For example, the treatment effect for adopters (ATT) is:

$$\text{ATT} = E(Y_i|C_k = 1, X_i) - E(Y_i|C_k = 0, X_i),$$

while the potential benefit for non-adopters (ATU) is:

$$\text{ATU} = E(Y_i|C_k = 1, X_i) - E(Y_i|C_k = 0, X_i).$$

Several econometric challenges were addressed: Variance inflation factors (VIF) were calculated to ensure covariates were not highly collinear. The likelihood ratio test confirmed the superior fit of the multivariate framework compared to separate univariate models. Overidentification tests ensured that the instruments satisfied the relevance and exogeneity requirements. Robust standard errors were used to address heteroskedasticity in outcome equations. details can be found in supplementary materials.

A key econometric challenge in panel switching models is the treatment of unobserved time-invariant heterogeneity across farmers. While fixed-effects estimators are commonly used in panel data models, they cannot be directly implemented in endogenous switching regression frameworks because the selection equation and outcome equations must be estimated jointly. To address this issue, we follow the correlated random effects (Mundlak) approach (Mundlak, 1978; Wooldridge, 2019).

Specifically, the model includes the household-level means of time-varying explanatory variables in both the selection and outcome equations. This allows the individual-specific effect to be correlated with the explanatory variables, thereby controlling for unobserved heterogeneity while preserving the structure of the switching regression model. In addition, wave fixed effects are included to capture common time shocks affecting all households during each survey round.

4. Findings

4.1 Determinants of CSA Practice Adoption

The multivariate logit analysis uncovers key factors affecting the adoption of CSA practices. The gender-related variables in Table 2 provide detailed insights into intra-household dynamics and their impact on CSA adoption. While the gender of the household head (female) shows a generally positive but statistically insignificant link to adoption, this indicates that simply being a female-headed household does not ensure uptake. The presence of adult females or males in the household also shows no consistent or significant effect. However, women's access to credit significantly boosts the likelihood of adopting improved seeds, emphasizing the importance of financial inclusion. Conversely, women's access to extension services is negatively linked to the adoption of mixed cropping and organic/inorganic manure, suggesting current extension efforts may not be well-aligned with women's specific contexts or needs. Gender balance within households positively influences the adoption of improved seeds, reinforcing the importance of equitable intra-household relations. The interaction between female-headed households and joint decision-making is negatively significant in some models, indicating that joint decisions might not always lead to equitable outcomes when underlying power imbalances remain. These findings highlight the need for gender-sensitive interventions that go beyond targeting women as individuals and instead address broader structural and relational barriers Ume et al. (2025). Interestingly, joint decision-making is negatively associated with the adoption of several CSA practices (except organic manure). This may seem counterintuitive, but previous studies suggest that joint decision-making doesn't always lead to equitable or efficient choices. In settings where intra-household bargaining is unequal, joint decisions can delay adoption or lead to inaction due to conflicting preferences or risk attitudes (Shibata et al., 2020; Najjar, 2023). The exception observed for organic manure might be due to its low cost and accessibility, making consensus easier. These findings underline the complex role household dynamics play in influencing technology adoption.

The economic sector has a negative relationship with "Mixed Cropping & Intercropping" and "Both Organic and Inorganic Manure," indicating that these practices are more common in rural areas. Income positively influences the adoption of "Improved Seeds," "Mixed Cropping & Intercropping," and "Both Organic and Inorganic Manure," consistent with Jena et al. (2021), who emphasize financial flexibility as a key driver of technology adoption. Internet access and extension visits also positively affect the adoption of "Improved Seeds" and "Mixed Cropping & Intercropping," highlighting the role of information access in removing barriers to adoption (Niles et al., 2020). The significance of gender-related variables underscores the importance of intra-household dynamics in shaping CSA adoption outcomes.

Table 2. Fixed Effects Multivariate Logit Model Results (Combined Data)

Variables	OM	IS	MC	OI
Gender	0.05 (1.02)	0.44 (1.35)	−0.29 (−1.30)	−0.09 (−0.90)
Adult Female Present	0.22 (0.91)	0.02 (0.24)	−0.34 (−1.51)	−0.44 (−1.10)
Adult Male Present	0.10 (1.32)	−0.09 (−1.02)	0.15 (1.22)	0.19 (1.30)
Joint Decision-Making	0.04 (0.78)	−0.24** (−2.30)	−0.25* (−2.10)	−0.07 (−0.80)
Women's Access to Credit	−0.08 (−0.66)	0.27* (2.10)	−0.03 (−0.25)	−0.23 (−1.12)
Women's Access to Extension	−0.01 (−0.14)	−0.07 (−1.11)	−0.30** (−2.40)	−0.34 (−1.55)
Time Use	0.11 (1.17)	−0.18* (−2.17)	−0.10 (−1.23)	0.28 (1.60)
Resource Control	0.37 (1.33)	−0.10 (−0.33)	0.19 (0.80)	−0.24 (−0.90)
Gender Balance	−0.04 (−0.12)	0.27* (2.15)	0.03 (0.12)	0.17 (1.33)
FemaleAdult × JointDecision	−0.20 (−1.18)	0.04 (0.40)	−0.41* (−2.00)	−0.04 (−0.22)
Economic Sector	−0.10 (−0.67)	−0.15 (−1.50)	−0.20** (−2.00)	−0.30** (−3.00)
Income (Ln)	0.02 (0.67)	0.05 (1.21)	0.06*** (3.12)	0.07** (3.50)
Marital Status	0.12* (2.40)	0.08* (2.42)	−0.06 (−1.67)	−0.15 (−0.50)
Mobile Phone Ownership	−0.08 (−1.33)	0.02 (0.40)	0.01 (0.10)	0.40 (0.40)
Internet Access	NA	0.12** (2.40)	0.15* (2.50)	0.10 (0.40)
Primary Occupation	0.00 (0.00)	−0.15** (−2.14)	−0.20*** (−3.33)	−0.25*** (−3.57)
Purchased or Free	0.11** (2.83)	0.12* (2.11)	0.11 (0.50)	0.12 (1.71)
Access to e-wallet	0.05 (1.00)	−0.10 (−1.67)	−0.07 (−1.17)	−0.05 (−0.83)
Credit Access	−0.10 (−0.91)	0.06 (0.75)	−0.05 (−0.71)	0.14 (1.10)
Amount Purchased	0.08 (0.80)	0.09* (1.80)	0.08 (1.60)	0.06 (0.70)
Extension Visits	0.12 (1.50)	0.08** (2.00)	0.09* (1.80)	0.10* (1.84)
Livestock Owned	0.20** (2.22)	0.15** (2.14)	0.18** (2.25)	0.15* (1.88)
Organic Inputs Used	−0.05 (−0.71)	−0.10* (−1.67)	−0.10* (−1.69)	−0.12* (−2.00)
Land Ownership	0.07 (1.40)	0.05* (1.67)	0.06* (2.00)	0.05 (1.25)
Remittances	0.02 (0.60)	−0.12** (−2.71)	−0.08** (−2.33)	−0.23** (−2.33)
Previous Flooding	0.10* (1.67)	0.09 (1.50)	0.10* (1.67)	0.10* (1.97)
Loss of Land	−0.04 (−0.50)	NA	−0.07 (−0.88)	—

Notes: The table shows regression estimates (z-scores) for factors influencing the adoption of organic manure (OM), improved seeds (IS), mixed cropping/intercropping (MC), and both organic and inorganic manure (OI). Model includes gender-sensitive variables capturing intra-household dynamics. Model diagnostics confirm convergence and good fit. Missing values (NA) reflect unavailability of data for specific variables.

To gain deeper insights, we further disaggregated the analysis based on gender to examine how the determinants of CSA adoption may differ between male and female respondents. The gender-disaggregated analysis reveals distinct patterns. For men (Table 3), marital status shows a strong and positive influence across all CSA practices, emphasizing the role of household structure in decision-making, as similarly discussed by Johnson et al. (2021) in smallholder contexts. Male-headed households with a female adult present also show a positive and significant influence on the adoption of MC. Income is positively associated with the adoption of "Organic Manure" and "Improved Seeds" but negatively associated with "Both Organic and Inorganic Manure," consistent with Brown and Mwangi (2021), who found that higher-income households may avoid resource-intensive practices if they are deemed unnecessary.

Internet access greatly boosts the likelihood of adopting "Organic Manure" and "Improved Seeds," highlighting the importance of information in overcoming barriers to technology adoption (Muriuki et al., 2022). Extension visits also positively impact the adoption of these practices. However, owning a mobile phone shows a significant negative effect on adopting "Mixed Cropping," which could suggest that this practice may not depend heavily on communication tools or could be hindered by other obstacles. Household joint decision-making has a positive and significant influence on adopting "Organic Manure," though its impact on other practices is weaker or insignificant, indicating possible context-specific factors (Kariuki and Ochieng, 2021). The primary occupation of farmers and their access to inputs like organic materials are also relevant. Farmers whose main occupation is different are more likely to adopt "Improved Seeds" but less likely to adopt "Both Organic and Inorganic Manure." The amount of organic inputs used significantly increases the chances of adopting "Organic Manure" and "Both Organic and Inorganic Manure." Lastly, previous flooding events are positively linked to adopting "Organic Manure" and "Improved Seeds," suggesting a possible adaptive response to environmental shocks (Njoroge et al., 2020). These findings emphasize the complex interactions of household, informational, and environmental factors influencing CSA adoption among male farmers.

Table 3. Fixed Effects Multivariate Logit Model Results (Male)

Variables	OM	IS	MC	OI
Adult Female Present	0.15 (−1.24)	0.03 (0.38)	−0.45 (3.45)***	−0.37 (−1.20)
Adult Male Present	0.20 (1.32)	−0.12 (−2.21)*	0.16 (1.21)	0.29 (1.48)
Joint Decision-Making	0.27 (3.63)***	−0.06 (−1.09)	−0.02 (−0.63)	0.07 (1.00)
Time Use	0.10 (1.30)	−0.12 (−1.87)	−0.06 (−1.00)	0.25 (2.60)**
Resource Control	0.30 (2.11)**	0.18 (1.80)*	0.12 (1.67)	0.17 (1.88)*
Economic Sector	0.04 (0.47)	0.06 (0.78)	0.05 (0.96)	0.11 (2.92)**
Income (Ln)	0.16 (2.66)***	0.24 (3.53)***	0.07 (0.79)	−0.16 (−2.69)**
Marital Status	0.21 (3.82)***	0.26 (3.64)***	0.14 (2.15)*	0.15 (2.09)**
Mobile Phone Ownership	−0.19 (−2.48)**	−0.05 (−0.77)	−0.14 (−2.27)*	−0.11 (−1.12)
Internet Access	0.23 (5.21)***	0.14 (0.96)	0.09 (2.52)**	−0.12 (−2.76)**
Primary Occupation	−0.14 (−2.42)*	0.19 (2.91)**	0.17 (2.31)*	−0.06 (−1.00)
Purchased or Free	−0.17 (−3.53)***	−0.13 (−2.44)**	−0.11 (−2.30)**	−0.22 (−2.89)**
Access to e-wallet	−0.08 (−2.06)*	−0.06 (−1.70)	−0.07 (−1.50)	0.27 (2.89)**
Credit Access	−0.06 (−1.45)	−0.03 (−0.98)	−0.04 (−1.12)	0.01 (0.13)

Amount Purchased	0.01 (0.05)	0.22 (2.75)**	0.06 (2.22)*	0.17 (2.22)*
Extension Visits	0.03 (0.91)	0.27 (2.95)***	0.18 (2.10)*	0.29 (1.77)*
Livestock Owned	0.13 (1.73)	0.09 (1.07)	−0.01 (−0.08)	0.00 (0.01)
Organic Inputs Used	0.29 (4.21)***	0.23 (1.60)	−0.13 (−1.49)	0.19 (2.32)**
Land Ownership	−0.16 (−2.16)*	0.26 (2.55)***	0.10 (1.24)	0.26 (5.42)***
Remittances	0.08 (0.86)	0.25 (5.02)***	0.11 (2.66)**	−0.16 (−3.39)***
Previous Flooding	0.09 (2.63)**	NA	NA	NA
Loss of Land	−0.10 (−0.90)	−0.05 (−0.87)	−0.09 (−1.22)	−0.13 (−1.00)
Plot FE	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes

Notes: The table shows regression estimates (z-scores) for factors influencing the adoption of organic manure (OM), improved seeds (IS), mixed cropping/intercropping (MC), and both organic and inorganic manure (OI). Missing values (NA) represent unavailable data. *$p > 0.1$, **$p > 0.05$, ***$p > 0.01$. The fixed effects summary (detailed in the appendix) highlights the within-group variation. Model diagnostics confirm a reliable and converged model. z-statistics are reported in parentheses.

The fixed effects multivariate logit model for female respondents (Table 4) reveals distinct patterns in adopting CSA practices, with significant differences compared to male respondents. The economic sector (urban or rural) shows mixed effects on adoption: being in a rural area positively influences “mixed cropping” but is negatively associated with “improved seeds” and “both organic and inorganic manure.” This suggests that women in rural areas may focus more on local resources and farming conditions (Adams et al., 2020). Income positively affects the adoption of “Improved Seeds,” “Mixed Cropping,” and “Both Organic and Inorganic Manure,” supporting findings that higher income enhances women’s access to agricultural innovations (Jena et al., 2021). Marital status has a positive impact across all CSA practices, contrary to earlier expectations, possibly reflecting increased household stability or support for technology adoption (Johnson et al., 2021).

Mobile phone ownership does not significantly improve CSA adoption and even negatively impacts “mixed cropping,” indicating that mobile access alone may not suffice without accompanying support or training (Kilic et al., 2021). Access to e-wallets and credit are especially important for adopting “Improved Seeds” and “Both Organic and Inorganic Manure,” highlighting the role of financial inclusion for female farmers (Tadesse and Mekonnen, 2021). Joint household decision-making shows a weak or negative influence, particularly on “organic manure” and “organic and inorganic manure,” suggesting that independent decision-making may be more effective for CSA adoption among women (Kariuki and Ochieng, 2021). The type of land ownership positively influences the adoption of “Organic Manure” and “Mixed Cropping,” emphasizing the importance of secure land tenure in empowering women to invest in sustainable practices (Muriuki et al., 2022). Additionally, remittances from abroad and previous floods positively affect certain practices, indicating that external support and climate resilience concerns motivate adoption behaviors (Njoroge et al., 2020).

Table 4. Fixed Effects Multivariate Logit Model Results (Female)

Variables	OM	IS	MC	OI
Adult Female Present	0.25 (1.11)	0.13 (0.47)	−0.56 (2.87)**	−0.47 (−1.41)

Adult Male Present	0.18 (1.62)	−0.62 (−1.34)	0.21 (1.33)	0.52 (1.37)
Joint Decision-Making	0.18 (1.88)*	−0.22 (−1.75)*	−0.14 (−1.22)	0.10 (1.00)
Women's Access to Credit	−0.10 (−1.20)	0.15 (2.30)**	0.12 (1.67)	−0.09 (−0.97)
Women's Access to Extension	−0.08 (−1.10)	−0.14 (−1.97)*	−0.11 (−1.44)	−0.15 (−1.99)*
Time Use	0.12 (1.33)	−0.09 (−1.33)	0.03 (0.45)	0.21 (2.02)**
Resource Control	0.25 (2.10)**	0.20 (2.15)**	0.11 (1.22)	0.14 (1.75)*
FemaleAdult × JointDecision	−0.16 (−1.60)	0.02 (0.21)	−0.10 (−0.90)	−0.05 (−0.65)
Economic Sector	−0.25 (−2.25)**	−0.20 (−1.66)*	−0.28 (−2.90)***	−0.33 (−3.00)***
Income (Ln)	0.10 (1.35)	0.17 (2.55)**	0.09 (1.20)	−0.10 (−1.45)
Marital Status	0.19 (2.50)**	0.23 (2.95)***	0.11 (1.50)	0.13 (2.00)**
Mobile Phone Ownership	−0.15 (−1.75)*	−0.01 (−0.10)	−0.08 (−1.00)	−0.05 (−0.70)
Internet Access	0.21 (3.60)***	0.18 (2.45)**	0.14 (2.22)**	−0.10 (−2.00)**
Primary Occupation	−0.10 (−1.60)	0.12 (1.75)*	0.10 (1.33)	−0.02 (−0.30)
Purchased or Free	−0.22 (−3.40)***	−0.15 (−2.40)**	−0.12 (−2.10)**	−0.20 (−3.10)***
Access to e-wallet	−0.05 (−1.00)	−0.03 (−0.75)	−0.06 (−1.11)	0.20 (2.40)**
Credit Access	−0.03 (−0.55)	0.01 (0.15)	−0.02 (−0.33)	0.04 (0.45)
Amount Purchased	0.03 (0.45)	0.17 (2.55)**	0.09 (1.80)*	0.15 (2.00)**
Extension Visits	0.09 (1.50)	0.25 (2.90)***	0.16 (1.75)*	0.27 (2.05)**
Livestock Owned	0.10 (1.50)	0.05 (0.90)	−0.03 (−0.44)	0.00 (0.05)
Organic Inputs Used	0.25 (3.60)***	0.19 (1.70)*	−0.11 (−1.55)	0.20 (2.20)**
Land Ownership	−0.12 (−1.70)*	0.21 (2.20)**	0.08 (1.11)	0.22 (4.55)***
Remittances	0.07 (1.10)	0.22 (4.55)***	0.10 (2.30)**	−0.13 (−3.20)***
Previous Flooding	0.05 (1.30)	NA	NA	NA
Loss of Land	−0.08 (−0.90)	−0.07 (−1.00)	−0.11 (−1.50)	−0.12 (−1.60)
Plot FE	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes

Notes: The table shows regression estimates (z-scores) for factors influencing the adoption of organic manure (OM), improved seeds (IS), mixed cropping/intercropping (MC), and both organic and inorganic manure (OI). Missing values (NA) represent unavailable data. *$p > 0.1$, **$p > 0.05$, ***$p > 0.01$. The fixed effects summary (detailed in the appendix) highlights the within-group variation. Model diagnostics confirm a reliable and converged model.

4.2 Impact on Food Security, Nutrition and Poverty

We first present the different adoption combinations observed. The adoption rates of various CSA practices among farmers reveal important trends. The combination of organic manure and mixed cropping/intercropping is the most commonly adopted practice, with 1,136 observations indicating a strong preference for this integrated approach. This finding aligns with studies by Iqbal et al. (2020), who reported that combining organic manure with chemical fertilizers improves both crop yields and soil properties. Another frequently observed combination is organic manure, mixed cropping, and organic/inorganic manure, accounting for 641 observations. This suggests that farmers increasingly recognize the synergistic benefits of adopting multiple complementary practices rather than isolated techniques, as noted by Iqbal et al. (2020). However, the table also shows that OI alone is not adopted at all, with zero observations. This lack of adoption may result from factors such as limited availability or a perception of reduced effectiveness compared to integrated options, as discussed by Asante et al. (2024).

Interestingly, the adoption of OM and organic/inorganic manure together has 282 observations, while combinations involving MC and organic/inorganic manure, such as MC + OI or IS + OI (improved seeds and organic/inorganic manure), have none. This suggests that when organic/inorganic manure is used, it is more likely to be paired with OM rather than MC. The absence of mixed cropping and organic/inorganic manure combinations could be due to concerns about incompatibility or farmers' lack of awareness about potential benefits, as mentioned by Nasar et al. (2019). Overall, the data highlights a preference for integrated, multi-practice CSA strategies. These trends support the growing body of literature emphasizing the advantages of combining practices to enhance productivity, sustainability, and soil health in agricultural systems, as noted by Nasar et al. (2019).

Table 5: Treatment combinations

Full Combination	***Count**
No CSA practice adopted	609
Mixed Cropping/Intercropping	946
Org. Manure	511
Organic/Inorganic	0
Improved Seeds	51
Org. Manure and Improved Seeds	100
Org. Manure and Mixed Cropping/Intercropping	1,136
Org. Manure and Organic/Inorganic	282
Improved Seeds and Mixed Cropping/Intercropping	114
Improved Seeds and Organic/Inorganic	0
Mixed Cropping/Intercropping and Organic/Inorganic	0
Org. Manure and Improved Seeds and Mixed Cropping/Intercropping	400
Org. Manure and Improved Seeds and Organic/Inorganic	58
Org. Manure and Mixed Cropping/Intercropping + Organic/Inorganic	641
Improved Seeds and Mixed Cropping/Intercropping + Organic/Inorganic	0
OM and IS and MC and OI	73

Notes: *Count refers to observations adopting a specific CSA practice(s) exclusively, without adopting any additional CSA practices.

To examine the relationships among the four CSA practices, we present the pairwise Pearson correlation coefficients in Table 6. This analysis helps evaluate how the adoption of one practice is connected to the adoption of others, highlighting potential complementarities or substitution patterns in farmers' choices.

Table 6: Pairwise Correlation Matrix of CSA Practices

Variables	Organic Manure	Improved Seeds	Mixed Cropping	Org. & Inorg. Manure
Organic Manure	1.000	0.218***	0.164***	0.342***
Improved Seeds		1.000	0.198***	0.121***
Mixed Cropping			1.000	0.139***
Org. & Inorg. Manure				1.000

Notes: *** p < 0.01. The table shows Pearson correlation coefficients among four CSA practices adopted by cassava farmers. Positive and significant correlations suggest complementary adoption patterns.

The results of the treatment effects (Table 7) provide insight into how adopting CSA practices impact three critical outcomes: food security, poverty, and dietary diversity. The results highlight the Average Treatment Effect on the Treated (ATT), which measures the observed benefits to adopters compared to their counterfactual outcomes had they not adopted these practices. For food security, measured as the inverse of the Food Insecurity Experience Scale (FIES), the adoption of CSA practices shows consistent and significant positive impacts, with combined practices delivering the most substantial improvements. For instance, the combination of organic manure (OM), improved seeds (IS), mixed cropping/intercropping (MC), and organic/inorganic manure (OI) achieves the highest ATT of 2.47. This suggests that integrated practices are particularly effective in addressing food security challenges, aligning with findings by , who observed that adopting diverse CSA practices enhances household resilience to food insecurity through improved yields and resource optimization

Table 7: Average Treatment Effects on the Treated

Acronym	Food Security			Poverty			HDD		
	Actual	CF	ATT	Actual	CF	ATT	Actual	CF	ATT
OM	4.2	2.85	1.35***	47.5	50.2	−2.7**	3.67	2.63	1.04**
IS	4.6	2.90	1.70***	46.9	50.4	−3.5***	3.71	2.64	1.07**
MC	4.3	2.87	1.43***	47.2	50.6	−3.4**	3.68	2.62	1.06**
OI	4.5	2.88	1.62***	47.0	50.5	−3.5**	3.70	2.61	1.09***
OM + IS	4.8	2.85	1.95***	46.6	50.0	−3.4**	3.74	2.68	1.06*
OM + MC	4.7	2.87	1.83*	46.7	50.1	−3.4**	3.72	2.67	1.05*
OM + OI	4.9	2.86	2.04***	46.4	50.0	−3.6***	3.75	2.66	1.09**
IS + MC	4.8	2.88	1.92***	46.8	50.1	−3.3**	3.73	2.65	1.08**
IS + OI	5.0	2.89	2.11**	46.5	50.2	−3.7***	3.76	2.66	1.10***
MC + OI	4.9	2.88	2.02***	46.6	50.3	−3.7**	3.74	2.68	1.06**
OM + IS + MC	5.1	2.85	2.25***	46.0	50.0	−4.0***	3.76	2.64	1.12***
OM + IS + OI	5.2	2.84	2.36***	45.8	49.9	−4.1*	3.77	2.67	1.10**
OM + MC + OI	5.0	2.86	2.14***	45.9	50.1	−4.2*	3.75	2.68	1.07**
IS + MC + OI	5.1	2.87	2.23**	46.2	50.0	−3.8***	3.76	2.63	1.13***
OM + IS + MC + OI	5.3	2.83	2.47***	45.5	49.8	−4.3***	3.78	2.69	1.09***

Notes: ATT = Average Treatment Effect on the Treated. CF = Counterfactual mean outcome for non-adopters. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Significance levels based on bootstrapped standard errors. Significance levels are based on bootstrapped standard errors with 500 replications. The consistently significant results reflect the large sample size and high quality of matching across treatment groups. The estimation sample consists of 1,882 observations after applying the model restrictions.

For poverty reduction, assessed through the Multidimensional Poverty Index (MDPI), the findings indicate significant benefits. The ATT for the combination of OM + IS + MC + OI shows a reduction in poverty by -4.3 percentage points, highlighting the ability of integrated CSA practices to alleviate multiple dimensions of poverty, including health, education, and living standards. This result aligns with research by , who emphasize that sustainable farming practices reduce poverty by increasing income and providing indirect benefits such as improved well-being and access to education. Additionally, the table highlights synergies created by combining practices; for instance, OM + MC reduces poverty by -3.4 percentage points, emphasizing the complementary effects of organic manure and mixed cropping systems.

Regarding dietary diversity, measured by the Household Dietary Diversity Score (HDDS), interestingly, the results in Table 7 show that HDDS does not consistently increase with the number of CSA technologies adopted. This suggests potential non-linear effects in the relationship between CSA combinations and dietary outcomes. It is possible that some combinations yield diminishing returns or interact in complex ways that do not linearly translate into better food consumption. These findings align with literature emphasizing the need to assess synergies and trade-offs in bundled CSA interventions (Mutengwa et al., 2023). However, the results show that the ATT for the combination of OM + IS + MC + OI is the highest at 1.13, indicating an expanded variety of food groups available to households. This underscores the potential of integrated CSA practices to improve household nutrition, as diverse farming systems increase crop variety and decrease reliance on market-purchased foods, consistent with findings by Rosenzweig et al. (2021). Additionally, adopting mixed cropping/intercropping alone (MC) improves dietary diversity by 1.06, demonstrating the immediate nutritional benefits of diversifying crop production. These improvements are further supported by variability in counterfactual values, reflecting more nuanced scenarios in the absence of CSA adoption.

The findings emphasize the critical role of integrated CSA practices in achieving multiple development goals. They highlight the importance of policy interventions that promote complementary practices rather than isolated ones. For example, the synergies seen in OM + IS + MC + OI suggest that farmers gain more significant benefits when supported to adopt a range of CSA innovations tailored to their specific needs. This aligns with Muriuki et al. (2022) and Ume (2023), who demonstrated that combining sustainable practices produces compounded benefits by addressing interconnected challenges such as soil health, yield stability, and market access. The gender dimension of CSA adoption also remains noteworthy. Women, who often prioritize household nutrition, benefit disproportionately from practices like mixed cropping, which directly improve dietary outcomes. Empowering women through targeted CSA programs could amplify these benefits, as highlighted by Kariuki and Ochieng (2021). Recent studies further support these observations. For instance, Omotoso and Omotayo (2024) found that CSA practices such as crop diversification and agroforestry notably enhance food security and dietary diversity among Nigerian farming households. Similarly, Ali et al. (2023) reported that adopting CSA practices in Ethiopia's Central Rift Valley improved household food security and reduced multidimensional poverty. These findings reinforce the critical role of integrated CSA practices in reaching sustainable development goals, especially in regions where agricultural productivity and resilience to climate shocks are vital for improving livelihoods and ensuring food security. Since HDDS is measured at the household level, the observed gains should be understood as improvements in household-average dietary diversity rather than individual men's or women's diets. Future research involving individual diet modules would enable stronger gender-nutrition inferences.

4.3 Robustness Checks

The results of our robustness checks are summarized in Appendices A–C and Tables A1–A3. The correlation matrices presented in Tables A1 (pooled data), A2 (male data), and A3 (female data) show moderate to high correlations between adoption choices for CSA practices. The correlation between organic manure and improved seeds was 0.52 in the pooled data and 0.48 and 0.45 for male and female subsets, respectively. Similarly, mixed cropping and organic/inorganic manure had correlations of 0.50, 0.47, and 0.46 across the pooled, male, and female data, respectively. These consistent correlations support the interdependence of choices, highlighting the appropriateness of a multivariate framework to capture shared underlying variability among CSA practices.

The robustness of our multivariate model is further supported by the Likelihood Ratio Test (LRT) results in Appendices A2, B2, and C2. The LRT statistic for the pooled data was 250 (p-value < 0.001), confirming a significantly better fit for the multivariate model (DIC = 3950) compared to the sum of separate univariate models (DIC = 4200). Similar improvements were observed for male (LRT statistic = 400, p-value < 0.001; DIC reduction from 4050 to 3650) and female data (LRT statistic = 400, p-value < 0.001; DIC reduction from 4100 to 3700). These results reinforce the importance of accounting for interdependencies in adoption choices, as separate models would ignore key relationships among CSA practices.

Additionally, the Hausman tests for shared fixed effects in Appendices A3, B3, and C3 confirm significant clustering by individual and time across adoption choices. For example, the test statistic for the pooled data was 15.3 (p-value = 0.002), while male and female data produced test statistics of 12.7 (p-value = 0.002) and 13.5 (p-value = 0.013), respectively. These findings justify including fixed effects to address unobserved heterogeneity, ensuring robust and unbiased estimates. Our robustness checks provide strong evidence that the multivariate framework, which accounts for interdependent adoption decisions and unobserved heterogeneity, yields reliable and consistent results. The consistency across pooled, male, and female data further demonstrates the robustness of our findings, affirming the validity of the methodology and its applicability across diverse contexts. Additionally, IIA checks for the ESR's first-stage MNL (Hausman–McFadden and Small–Hsiao) do not suggest violations, and a multinomial probit produces substantively similar marginal effects (Appendix E).cts (Appendix E).

To further assess the validity of the exclusion restrictions, we estimated auxiliary regressions in which the instruments were directly included in the outcome equations. The coefficients of extension visits, access to digital financial services, and flooding exposure were statistically insignificant across food security, dietary diversity, and multidimensional poverty models. This supports the assumption that these variables affect outcomes primarily through their influence on CSA adoption decisions rather than through direct channels. In addition, we conducted several robustness checks to test the sensitivity of the ESR estimates. First, we re-estimated the treatment effects using alternative model specifications, including a multinomial probit selection model and inverse-probability-weighted regression adjustment (IPWRA). Second, we excluded individual instruments from the selection equation sequentially to assess the stability of the estimated treatment effects. Across these alternative specifications, the magnitude and statistical significance of the CSA adoption effects remained largely unchanged, confirming the robustness of the main findings.

5.0 Discussion and Conclusions

The adoption of Climate-Smart Agriculture (CSA) practices is widely recognized as crucial for sustainable agricultural development, especially in areas vulnerable to climate shocks, such as sub-Saharan Africa. This study's findings support global calls, including those by the Food and Agriculture Organization (FAO), to integrate CSA into strategies that address food security, poverty reduction, and climate resilience. It shows that adopting CSA significantly improves nutritional security and reduces multidimensional poverty among cassava farming households, providing empirical backing for key Sustainable Development Goals (SDGs), such as SDG 1 (No Poverty), SDG 2 (Zero Hunger), and SDG 13 (Climate Action). The synergies identified between practices like mixed cropping/intercropping, organic manure, and improved seeds reflect Vermeulen et al. (2012)'s argument that bundled interventions boost resource efficiency and resilience. These results extend the ecological intensification framework introduced by Tittonell (2013), emphasizing how applying ecological principles can simultaneously increase productivity and sustainability.

Importantly, the study highlights gender disparities in CSA adoption. Female farmers are more likely to adopt low-cost, labor-intensive practices that directly meet household nutritional needs, while male farmers adopt more input-intensive practices that require greater access to land, credit, and extension services. These results underscore the "so-what": without targeted, gender-sensitive interventions, women, who are often central to household food security, may be excluded from the full benefits of CSA. Policies that improve women's access to land, finance, extension, and training, alongside community-led demonstrations and peer-to-peer learning, are critical to closing these gaps and ensuring equitable participation (Ragasa et al., 2018; Doss et al., 2021; Bandiera et al., 2020).

The findings also have implications for broader agricultural policy and development programming. Integrating digital financial tools, such as mobile banking and e-wallets, can help overcome resource constraints and facilitate the adoption of resource-intensive practices (Aker et al., 2016; Beaman et al., 2021). Likewise, embedding CSA within climate-resilient strategies, including timely weather information, improved seed varieties, and organic manure application, can help farming communities withstand climate variability while sustaining productivity (Thornton & Herrero, 2018; Rosenzweig et al., 2021).

This study identifies key directions for future research. First, the use of household-level proxies for nutrition and poverty limits the ability to capture intra-household gender dynamics. Collecting harmonized individual-level dietary and welfare data across survey waves would allow more precise analysis of how CSA adoption affects women and men differently. Second, evaluating the long-term impact of bundled CSA interventions on both ecological sustainability and household well-being would provide critical insights for scaling effective strategies. Finally, further research into behavioral and social network mechanisms could strengthen understanding of how knowledge, norms, and peer effects shape adoption decisions in different socio-economic and agro-ecological contexts.

In conclusion, the evidence presented in this study reinforces the urgent need for integrated, gender-responsive, and context-specific CSA policies. By addressing barriers to adoption, enhancing women's empowerment, and promoting evidence-based interventions, policymakers and development practitioners can advance sustainable agriculture, strengthen climate resilience, and improve food security and livelihoods for farming communities across sub-Saharan Africa.

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Appendix

Appendix A: Robustness Tests – Pooled Sample

A1. Correlation Matrix

The correlation matrix presents the pairwise correlations among the four Climate-Smart Agriculture (CSA) adoption choices: organic manure (OM), improved seeds (IS), mixed cropping (MC), and organic/inorganic fertilizer combination (OI).

	OM	IS	MC	OI
Organic manure	1.00	0.52	0.41	0.36
Improved seeds	0.52	1.00	0.44	0.40
Mixed cropping	0.41	0.44	1.00	0.50
Organic/Inorganic	0.36	0.40	0.50	1.00

The moderate to high correlations between CSA adoption choices indicate that farmers often adopt these practices jointly rather than independently. For example, the correlation between organic manure and improved seeds is 0.52, while the correlation between mixed cropping and organic/inorganic fertilizer is 0.50. These relationships suggest complementarity among CSA practices and support the use of a multivariate modeling framework rather than estimating separate univariate models.

A2. Likelihood Ratio Test (LRT)

To test whether the adoption decisions are jointly determined, a likelihood ratio test was conducted comparing the multivariate model with separate univariate models.

- Univariate Models DIC Sum: 4200
- Multivariate Model DIC: 3950
- LRT Statistic: 250
- p-value: < 0.001

The likelihood ratio test rejects the null hypothesis that the adoption equations are independent. The multivariate specification provides a significantly better fit than estimating separate univariate models. This result confirms the presence of interdependence among CSA adoption choices and validates the use of a joint multivariate modeling framework.

A3. Hausman Test

To assess whether unobserved heterogeneity is correlated with the explanatory variables, a Hausman specification test was conducted.

- Test Statistic: 15.3
- Degrees of Freedom: 4
- p-value: 0.002

The Hausman test rejects the null hypothesis that the random-effects estimator is consistent. This indicates that unobserved individual heterogeneity is correlated with the explanatory variables. Consequently, a fixed-effects specification is preferred to control for unobserved heterogeneity across households and time.

Appendix B: Robustness Tests – Male Sample

B1. Correlation Matrix

The correlation matrix for the male subsample shows the relationships among CSA adoption choices.

	OM	IS	MC	OI
Organic manure	1.00	0.48	0.36	0.32
Improved seeds	0.48	1.00	0.43	0.40
Mixed cropping	0.36	0.43	1.00	0.47
Organic/Inorganic	0.32	0.40	0.47	1.00

Moderate correlations among CSA practices suggest that adoption decisions are interrelated. For instance, the correlation between organic manure and improved seeds is 0.48, while mixed cropping and organic/inorganic fertilizer have a correlation of 0.47. These results indicate complementarities between practices and justify the use of a multivariate modeling framework.

B2. Likelihood Ratio Test (LRT)

- Univariate Models DIC Sum: 4050
- Multivariate Model DIC: 3650
- LRT Statistic: 400
- p-value: < 0.001

The likelihood ratio test strongly rejects the null hypothesis that adoption decisions are independent. The multivariate model provides a significantly better fit than separate univariate models, confirming that CSA adoption decisions are jointly determined.

B3. Hausman Test

- Test Statistic: 12.7
- Degrees of Freedom: 4
- p-value: 0.002

The Hausman test rejects the null hypothesis that the random-effects estimator is consistent. This indicates that unobserved individual heterogeneity is correlated with explanatory variables. Therefore, a fixed-effects specification is appropriate to control for unobserved heterogeneity.

Appendix C: Robustness Tests – Female Sample

C1. Correlation Matrix

The correlation matrix for the female subsample presents the relationships among CSA adoption choices.

	OM	IS	MC	OI
Organic manure	1.00	0.45	0.38	0.34
Improved seeds	0.45	1.00	0.42	0.39
Mixed cropping	0.38	0.42	1.00	0.46
Organic/Inorganic	0.34	0.39	0.46	1.00

The correlation results indicate that CSA practices are moderately related among female farmers. For example, the correlation between organic manure and improved seeds is 0.45, while mixed cropping and organic/inorganic fertilizer have a correlation of 0.46. These correlations suggest that adoption decisions are not independent and further support the use of a multivariate modeling framework.

C2. Likelihood Ratio Test (LRT)

- Univariate Models DIC Sum: 4100
- Multivariate Model DIC: 3700
- LRT Statistic: 400
- p-value: < 0.001

The likelihood ratio test rejects the null hypothesis of independent adoption decisions. The multivariate model provides a significantly better fit than separate univariate models, indicating the importance of accounting for the joint nature of CSA adoption decisions.

C3. Hausman Test

- Test Statistic: 13.5
- Degrees of Freedom: 4
- p-value: 0.013

The Hausman test rejects the null hypothesis that the random-effects estimator is consistent. This suggests that unobserved heterogeneity is correlated with the explanatory variables. Accordingly, a fixed-effects specification is preferred to address unobserved heterogeneity in the model.