Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

Adoption, complementarity and productivity effects of modern maize inputs in Uganda

Christine Kanyenyeri

christinekanyenyeri2@gmail.com

Makerere University

John Ilukor

Makerere University

Alex Moruleng

Mountains of the Moon University

Jackline Bonabana

Makerere University

Research Article

Keywords: Input Choices, Adoption, Productivity effects, Multinomial Endogenous

Posted Date: November 17th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-11473933/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

Additional Declarations: Competing interest reported. John Ilukor is an employee of the World Bank. The remaining authors, Christine Kanyenyeri, Jackline Bonabana, and Alex Moruleng, declare no competing interests.

Adoption, complementarity and productivity effects of modern maize inputs in Uganda.

Christine Kanyenyeri[1] christinekanyenyeri2@gmail.com 0009-0007-3224-1625

John Ilukor[12] jilukor@worldbank.org 0000-0002-0476-4556

Alex Moruleng[3] alexmoruleng@gmail.com 0009-0004-6007-2062

Jackline Bonabana [1] jbexim@gmail.com

1. Department of Agribusiness and Natural Resource Economics, Makerere University, Kampala Uganda.
2. The World Bank, Development Data Group – Survey Unit, Uganda
3. Department of Agricultural and Resource Economics, Mountains of the Moon University, Fort Portal, Uganda.

Corresponding author: Christine Kanyenyeri christinekanyenyeri2@gmail.com 0009-0007-3224-1625

Word count: 7,319 words (excluding references, tables, figures and declarations).

Abstract

The adoption of modern agricultural inputs is a sustainable approach to productivity growth in developing countries, especially amid soil fertility decline and climate challenges. Governments have therefore prioritized access to improved seed and inorganic fertilizers to close productivity gaps. This study investigates factors influencing modern maize input adoption among smallholder farmers in Uganda and examines the effects of input choices on productivity, using data from the World Bank–funded Agriculture Cluster Development Project. A multinomial endogenous switching regression model was used to assess the drivers and impacts of input choices. Results show that adopters of only improved maize seed had access to credit and extension services, owned livestock, experienced drought, and cultivated smaller plots. Those adopting both improved seed and fertilizer were more educated, had higher incomes, cultivated larger areas, and accessed extension services. Non-adopters had the lowest education and income levels, smallest land sizes, limited access to credit, training, market information, and were mostly engaged in non-farm work. No significant factors were found for adopting only inorganic fertilizer. In terms of productivity, adoption of modern inputs significantly increased maize yields. Farmers using both improved seed and fertilizer achieved an Average Treatment Effect on the Treated (ATT) of 735 kg/ha (185.5% increase), those using only improved seed gained 698 kg/ha (138.5%), and those using only inorganic fertilizer gained 359 kg/ha (137.8%). The study highlights the importance of strengthening education, credit, and extension systems, and improving agro-input markets to enhance complementarity and reduce productivity gaps.

Keywords: Input Choices, Adoption, Productivity effects, Multinomial Endogenous

1.0 Introduction

Agricultural productivity in Sub-Saharan Africa (SSA) remains a critical concern due to its heavy reliance on rain-fed farming and vulnerability to climatic changes (1). Smallholder farmers in Sub-Saharan Africa continue to face challenges in managing soil fertility within their farming systems, with over 65% not using fertilizers. Additionally, approximately 75% of agricultural soils in the region have experienced severe nutrient depletion (2). As a result, agricultural productivity in SSA continues to lag behind other developing regions. For example, Sub Saharan Africa's agricultural productivity growth is 3.4% per year, which is half the rate of developing countries (3). This can be attributed largely to the minimal use of improved agricultural inputs such as seeds, fertilizers and agrochemicals (4-6). Moreover, most of the farmers use these inputs more as substitutes rather than complements (6, 7) and has been worsened by weak agro-input markets and single input subsidy packages per season (8, 9).

The initial solution under the Structural Adjustment Programs (SAPs), particularly in the agricultural sector during the 1980s and early 1990s, was to decentralize and privatize the input market (10). However, the objective shifted from improving market efficiency to primarily cutting government spending. This shift undermined the intended goals, and the approach ultimately failed. Cost-cutting efforts also failed, as the creation of numerous new districts increased administrative expenses, and inputs became more expensive and less accessible to farmers (11-14). When this approach failed, attention turned to

improving input delivery through subsidy programs. These subsidies aimed to enhance farmer knowledge by establishing demonstration gardens and raising awareness about the benefits of modern inputs, encouraging farmers to purchase them. However, many of these programs lacked inclusivity, failed to effectively disseminate information, and did not promote integrated use of multiple inputs. Over time, the focus drifted from farmer education to merely distributing inputs (15).

The distribution model faced several challenges, including poorly designed subsidies delivered through a uniform “one-size-fits-all” approach, absence of targeted support that led to the exclusion of non-users of fertilizer, elite capture and lack of a clear exit strategy. These shortcomings limited farmers’ input choices and ultimately hindered the expansion of input use (7, 16). Also, inputs were centrally procured which distorted agricultural markets by creating artificial demand thus reducing competition among input suppliers. Universal agricultural subsidies faced several challenges including escalating program costs driven by political pressure to broaden coverage or adjust for rising input prices, along with significant resistance to reducing or phasing out subsidies once implemented. Artificially low input prices encouraged inefficient input-intensive farming practices while better-off farmers gained more from the subsidies, marginalizing poorer smallholders. Additionally, these subsidies were subject to leakages and diversion particularly toward large-scale and well-connected commercial farmers, further undermining their intended impact (17, 18).

To address these issues, more targeted "smart" subsidies have been introduced focusing on specific farmer needs, promoting market participation and facilitating a sustainable

transition away from government support. These smart subsidy programs are primarily implemented to overcome the limitations of universal subsidies (19). To be considered "smart", subsidy programs have to meet three key design principles: they should target specific farmers such as resource constrained farming households who have not been using modern inputs by expanding the agro-input network, incorporate market-based solutions that encourage farmers to purchase inputs on commercial terms, guarantee choice of inputs and include an exit strategy that sets a time limit on the subsidy (20). Targeting in smart subsidies can be achieved through mechanisms like market-oriented voucher systems that allow farmers to choose their suppliers. This fosters competition among market actors, builds relationships between farmers and suppliers, and eliminates lengthy tender procedures involved in government-managed input supply processes. It also shields the private input sector by allowing commercial suppliers to freely participate in the trade of subsidized inputs (14, 21).

In 2018, Uganda launched the Agriculture Cluster Development Project (ACDP) to enhance on-farm production and productivity (22). This initiative aimed at increasing the production and marketable volumes of maize, rice, beans, cassava, and coffee across 57 districts organized into 12 agroecological clusters. An e-voucher system was employed as a means facilitating delivery of the subsidized inputs through matching grants primarily driven by the private sector or agro-input dealers. The total value of this package per season was US$180, redeemable for inputs such as improved seeds, fertilizers, pesticides, and farm equipment from registered agro-input dealers. In the first crop cycle, farmers contributed 33% of the total input cost, while the government covered 67%. In

the second cycle, both parties share the costs equally, each contributing 50%. By the third cycle, farmers contributed 67% while the government provided 33% (23).

After the third crop cycle, farmers were expected to graduate and independently cover the costs of farm inputs without subsidies. The program aimed to provide e-vouchers that would allow farmers to access improved inputs, facilitating experimentation with modern agricultural technologies. The ultimate goal was for farmers to recognize the benefits of these modern inputs, enabling them to make informed purchasing decisions once government support ended. This approach was also designed to gradually reduce reliance on government assistance, fostering long-term sustainability in input purchases once the subsidy ends (22, 24-26). This greatly improved input access, broadened farmers' options and raised input quality. By delivering inputs closer to farmers at the sub-county level, accessibility and adoption increased. The project sought to boost productivity by encouraging the complementary use of inputs rather than dependence on a single input. This was aligned with the country's key agricultural policy priorities, including increasing fertilizer application to at least 50 kg of nutrients per hectare annually and sustaining a 6% annual growth rate in the agricultural sector (23).

The e-voucher program initially aimed to encourage the mandatory joint adoption of two essential inputs: improved seed and fertilizer. However, the program relaxed this requirement, permitting farmers to select one inputs because some farmer may already have one input and due to affordability concerns. In this paper, we investigate maize farmers' use of modern inputs (improved seeds and fertilizers) and their impact on productivity. We investigate whether improved maize seed and inorganic fertilizer are used independently or in combination, assessing the types of farmers who adopt only

improved maize seed, both inputs or none. The study further examines whether complementarity between the two inputs leads to higher yields than using a single input, and, if only one input can be used, which one offers greater yield benefits. By addressing these questions, the study highlights the socio-economic and institutional factors shaping input choices and their effects on productivity, with the goal of guiding policymakers in targeting support and enhancing sustainable agricultural productivity.

2.0 Materials and methods

2.1 Data sources and description

Secondary data on maize production in Uganda was obtained from the monitoring and evaluation department of the Agriculture Cluster Development Project (ACDP) under the Ministry of Agriculture, Animal Industry and Fisheries (MAAIF). The project design covered twelve geographical clusters comprising 57 districts which were supported for improved inputs to intensify production and productivity of five priority commodities and that is; maize, rice, beans, cassava and coffee. This study specifically focuses on farmers cultivating maize (clusters 1, 2, 3, 4, 7, 8, 9 and 10) in the eight agroecological zones highlighted in Figure 1 below.

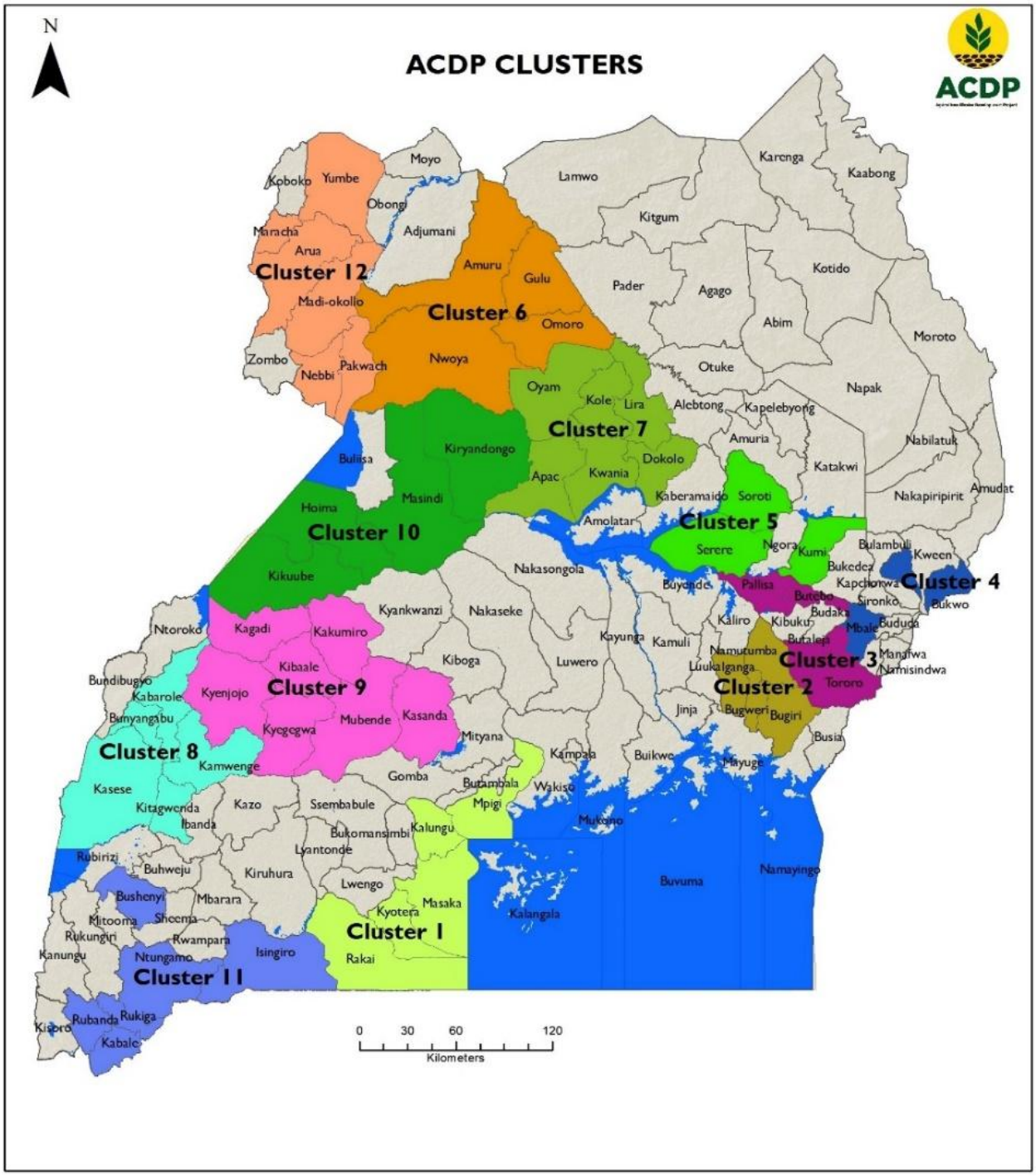


Fig. 1 A map of Uganda showing ACDP cluster districts. Source: MAAIF/ACDP

2.2 Sample size and Sampling design

This study relies on secondary data obtained from the end line survey implemented under the Agriculture Cluster Development Project (ACDP) e-voucher input program during the 2021/2022 agricultural season. The survey was conducted by the ACDP implementing team across all 57 participating districts. To ensure adequate representation of beneficiaries, cross-sectional data were collected from 4,692 households using a multistage sampling strategy. Districts, sub-counties, parishes, and villages were randomly selected, and within sampled locations, treatment and control farmers were randomly drawn from different villages.

For this study, only data relevant to maize production were extracted. Non-maize clusters were excluded, and within the remaining clusters, only farmers specifically supported for maize production were retained. Following a rigorous data cleaning process to remove outliers and observations with missing values for key variables such as crop yield, the final analytical sample comprised 2,243 smallholder maize farmers in Uganda.

The structured questionnaires administered by the ACDP survey team provided a comprehensive range of data modules, encompassing household demographics, socio-economic characteristics, group participation, input use, crop production, and access to services, as well as food security and technology adoption. This analysis specifically utilizes the household demographics, input use, and crop production modules, matching maize output and input data with individual farmer characteristics. Consequently, the explanatory variables include household demographics, farm-level factors, access to agricultural services, and exposure to external shocks. The dependent variable, input

choice, categorizes farmers into four distinct groups: (1) those who did not adopt any modern maize inputs, (2) those who adopted improved maize seed only, (3) those who adopted inorganic fertilizer only, and (4) those who adopted both improved maize seed and inorganic fertilizer as shown in table 1 below.

Table 1: Distribution of Farmers by Input Choice Combinations

Input Choice	Combinations	Improved maize Seed		Inorganic Fertilizer		Sample Observations	Percentage (%)
		Yes	No	Yes	No		
0	M_0F_0		✓		✓	348	15.51
1	M_1F_0	✓			✓	875	39.01
2	M_0F_1		✓	✓		43	1.92
3	M_1F_1	✓		✓		977	43.56
Total						2243	100.00

Note: *Adoption patterns for improved seed (M) and inorganic fertilizer (F), where 1 = adopted (Yes) and 0 = not adopted (No).*

Source: Authors' own analysis, 2025.

2.2 Analytical framework: Descriptive analysis and econometric model specification

We utilized the STATA software to conduct data analysis, incorporating both descriptive and inferential statistical techniques. The analysis was based on households, with each household represented by one plot in the dataset. T-tests were utilized to compute and compare means and proportions, facilitating the characterization of maize-producing households across varying input choice categories. Because the decision to adopt modern maize inputs is influenced by farmers' individual characteristics, those who adopt none, one or both inputs are likely to differ systematically. This creates selection bias which must be accounted for to obtain reliable estimates of the effect of input adoption.

Previous studies have applied a range of methods to address selection bias in analyzing binary technology adoption decisions. These methods include the Endogenous Switching Regression Model (ESRM) (27-31), the Inverse Probability Weighted Regression Adjustment (IPWRA) approach (32-36), treatment effects models (37), and the conditional mixed process model (38). However, many technology adoption contexts involve multiple adoption categories, necessitating more advanced methods such as the multivariate treatment effects model (39-41) and the Multinomial Endogenous Switching Regression Model (MESRM) (42-46), both of which are instrumental in addressing selection bias in such settings.

While the multivariate treatment effects model is non-parametric and helps address selection bias arising from observable factors, it does not account for how explanatory

variables influence the outcome variables and cannot handle bias stemming from unobserved heterogeneity. In contrast, the MESRM overcomes these limitations by addressing selection bias from both observed and unobserved factors, providing a robust structural modeling approach that ensures consistent estimates while also correcting for potential endogeneity and heteroscedasticity (47-49). Based on these advantages, this study utilizes the MESRM for consistent empirical analysis to examine the complex relationship between technology choices and their underlying factors. The MESRM follows a three-step estimation process: the first stage estimates a Multinomial Logit (MNL) model to assess farmers' input choice decisions. The independence of irrelevant alternatives (IIA) assumption is a key requirement for the validity of the multinomial logit (MNL) model. To assess whether this assumption holds in the context of farmers' input choices, a Hausman specification test was executed by estimating the full model and a restricted model with one alternative category excluded. The results (chi-square = 11.21, p-value = 0.8455) confirm that the use of the multinomial logit model is appropriate for modeling the input choices among maize farmers. This high p-value indicates that we fail to reject the null hypothesis that the difference in coefficients is not systematic (IIA assumption holds). Therefore, the IIA assumption holds in this model.

First Stage: A multinomial logit model

In the initial stage, farmers were hypothesized to optimize their maize yields, denoted as Y_i, by evaluating four input choices. The motivation for a farmer to choose a particular input 'j' is that it should yield a greater expected utility compared to an alternative (50). A farmer switches from non-modern inputs to modern maize inputs only if the expected yield from the latter is higher than from the former. If Y_{i0} is the yield derived from the use of

non-modern inputs, while Y_{ij} is the expected yield from the adoption of modern maize inputs, then the yield that a farmer i derived from adopting a given measure of modern inputs (j) can be expressed as:

$$Y_{ij} = X_i\beta_j + \varepsilon_{ij} \quad j = 1, 0; \quad i = 1, \ldots\ldots, n \qquad (1)$$

where X_i is a vector of explanatory variables, β_j is a parameter to be estimated, and ε_{ij} is an error term that captures unobserved factors potentially affecting the adoption decision process, assuming a mean of zero and constant variance. This means that X_i is not correlated with the error term ε_{ij}, hence complying with the principle of Independent Irrelevant Alternatives (IIA) hypothesis. The adoption variable is a dummy, with 1 indicating adoption and 0 otherwise. A farmer adopts any of the input categories $(j = 1)$, if $Y_{ij} > Y_{i0}$.

The first stage involves estimating a multinomial logit model because respondents are categorized into mutually exclusive categories. This model is well-suited for analyzing categorical dependent variables with more than two outcomes. As noted by Mottaleb, Mohanty (51), a rational farmer decides which inputs to adopt. The selection model structure in equation one leads to a multinomial logit framework whereby the probability of selecting input choice 'j' is given by:

$$P_{ij} = \mathrm{P}\left(\varepsilon_{ij} < \frac{0}{X_i}\right)\frac{\exp(X_i\beta_j)}{\sum_{m=1}^{k}\exp(X_i\beta_m)} \qquad (2)$$

Second stage: a multinomial endogenous switching regression (MESRM).

This model imposes a strict exclusion restriction and heavily relies on the choice of instrumental variables (52). Choosing appropriate instrumental variables is essential for

obtaining robust estimates, but identifying such variables is often challenging. A variable qualifies as a valid instrumental variable if it influences the adoption decision without directly affecting the quantity produced per hectare (42, 53). For consistently estimating the MESRM model, at least one instrumental variable (IV) should be included in the selection equation but not in the outcome equation. A study by Di Falco and Veronesi (54) employed household characteristics as instrumental variables to evaluate the effects of adopting climate change adaptation strategies on downside risk and crop yields. In line with this approach, the key identification assumption in our study is that land tenure system influences maize yield only indirectly through its effect on the adoption of improved maize seed and inorganic fertilizer. We assess the validity of the instrument using a simple falsification test, following Liu, Min (30) and Ma, Vatsa (55), which confirms that the instrument significantly influences the adoption decision but does not have a direct statistically significant impact on maize yield. A simple falsification test showed that Tenure system had no statistically significant direct effect on yield (p=0.120), supporting its validity under the exclusion restriction. We therefore excluded this instrument from the maize yield outcome equation. Furthermore, we ensure accurate standard errors by applying the robust variance estimator (vce (robust)) and address the impact of extreme values by winsorizing the data at the 5th and 95th percentiles.

In the second stage, an Ordinary Least Squares (OLS) model is employed to examine the relationship between the outcome variable (maize yield) and a set of exogenous variables, represented by X, for each selected input category. A farmer encounters four distinct regimes, denoted as '*j*', with regime j=1 serving as the base category

(representing nonmodern inputs). For each possible regime (j), the yield outcome equation was specified as follows:

$$Regime\ 1: Y_{i1} = X_i\beta_1 + \varepsilon_{i1} \quad if\ 'j' = '1'$$

$$: \qquad :$$

$$Regime\ j: Y_{ik} = X_i\beta_k + \varepsilon_{ik} \quad if\ 'j' = 'k' \tag{3}$$

where Y_{ik} represents the yield of the *i*th (*i* = 1, 2, 3…n) farmer associated with regime j, j = *1, 2,3…*k. The vector X_i includes explanatory variables, β represents the parameter vector, and $\varepsilon_{i1}$and ε_{ik} are random disturbance terms with zero conditional expected value. Y_{ik} is observed if, and only if $'k'$ modern inputs are chosen, which occurs when $\pi^*_{ik} > max_{m \neq k}(\pi^*_{im})$.

Using a vector of observed covariates, denoted as Xi, Equation (3) helps address issues related to observed selection bias. However, if unobserved factors such as farmers' intrinsic motivation to adopt modern maize inputs simultaneously affect both the adoption decision and yield outcomes, the error terms in Equation (3) may become correlated. This results in unobserved selection bias. Ignoring this bias can lead to inaccurate and inconsistent estimates. To address this issue, selectivity correction terms are derived from the MESR framework following the estimation of Equation (2) and are then incorporated into Equation (3). This adjustment helps correct for the resulting bias. Accordingly, Equation (3) can be further specified as:

$$Regime\ 1: Y_{i1} = X_i\beta_1 + \sigma_1\lambda_1 + \emptyset_{i1}\ if\ 'j' = '1'$$

$$: \qquad :$$

$$(4)$$

$$Regime\ j: Y_{ik} = X_i\beta_k + \sigma_k\lambda_k + \emptyset_{ik}\ \ if\ 'j' = 'k'$$

Where σ_k represents the covariance between the error terms δ and ε; $\emptyset$'s are error terms with a zero expected value, λ_k is denotes the Inverse Mills Ratio (IMR) derived from the MESRM estimate of equation (2) and is represented as (56):

$$\lambda_k = \sum_{m \neq k}^{k} \rho_k \left[\frac{\hat{\rho}_{im} \ln(\hat{\rho}_{im})}{1 - \hat{\rho}_{im}}\right] + \ln(\hat{\rho}_{ik}) \qquad (5)$$

Where ρ_k represents the correlation coefficient among the three error terms, δ, ε and $\emptyset$. However, to account for potential heteroscedasticity arising from the generated regressor λ_k, we addressed this issue by conducting estimation with robust standard errors.

Estimation of Average Treatment Effects

In the third stage, the Average Treatment Effect on the Treated (ATT) and the Average Treatment Effect on the Untreated (ATU) for both the adopters and non-adopters of maize inputs were estimated. This was accomplished by systematically comparing yield outcomes between farmers who adopted a given modern input category (treatment group) and those who did not (control group), under both actual and counterfactual conditions. By comparing the yield outcomes under these contrasting conditions, we gain valuable insights into the effects of adopting improved maize seed and inorganic fertilizer (52, 57). The ATT is estimated for both the actual scenario (with adoption) and the counterfactual scenario (without adoption) using the following approach:

Adopters (actual expected value of yield for adopters of a particular maize input category)

$$E(Y_{i2}|j=2) = X_{2i}\beta_2 + \sigma_2\lambda_2 \qquad (6a)$$

Adopters had they decided not to adopt that particular alternative (counterfactual)

$$E(Y_{i1}|j=2) = X_{2i}\beta_1 + \sigma_1\lambda_2 \qquad (6b)$$

Non-adopters (actual expected value of yield for nonadopters of a particular maize input category)

$$E(Y_{ij}|j=k) = X_{ki}\beta_k + \sigma_k\lambda_k \qquad (7a)$$

Non-adopters had they decided to adopt that particular alternative (counterfactual)

$$E(Y_{1j}|j=k) = X_{ki}\beta_1 + \sigma_1\lambda_k \qquad (7b)$$

The Average Treatment Effect on the Treated (ATT) and the Average Treatment Effect on the Untreated (ATU) can be determined by subtracting equation (6b) from equation (6a) and equation (7b) from equation (7a), respectively (52).

$$ATT = E(Y_{i2}|j=2) - E(Y_{i1}|j=2)$$

$$ATU = E(Y_{i1}|j=2) - E(Y_{1j}|j=k)$$

2.3 Measurement of variables used in the model

This section provides an overview of the explanatory variables used in the analysis, focusing on household, socioeconomic, institutional and environmental factors that influence maize farmers' input choices and maize productivity. The dependent variable, Input Choice, indicates whether a farmer used no modern maize input, only improved maize seed, only inorganic fertilizer or a combination of both improved maize seed and inorganic fertilizer. The second dependent variable, Yield (Kg/ha), represents maize productivity. Table 2 summarizes the variables and data descriptions extracted for this analysis.

Table 2: Variables and statistical descriptions

Variable	Definition	Mean	S.D
Dependent Variables			
Input_Choice	0 = adopters of nonmodern maize inputs 1= only improved maize adopters 2 = only inorganic fertilizer adopters 3 = adopters of both improved maize seed and inorganic fertilizer)		
Yield (Kg/ha)	Yield in kilograms per Hectare (continuous)	2139	1854
Independent Variables			
SexHH_Head	Gender of household head (1 = Male; 0 = Female)	0 .78	0.41
HH_Size	Household size (continuous)	7.42	3.05
AgeHH_Head	Age of the household head (continuous)	50.42	13.09
Educ_Level	Education level of household head (1 = Secondary level and above; 0 = Primary and below	0.43	0.50
MartlstatusHH_Head	Marital status of the farmer (1 = married; 0 = unmarried)	0.84	0.37

Occupation	Occupation of the farmer (1 = farm employment; 0 = non-farm employment)	0.82	0.38
Log_HH_income	Logarithm of household income	4635075	615715 9
AgricTrainings	1 if the farmer received training in agronomy, 0 otherwise (dummy)	0.44	0.50
AccesstoCredit	1 if the farmer accessed credit, 0 otherwise (dummy)	0.50	0.50
nearestmarket	Distance to the nearest market (continuous)	4.01	5.81
Market_Info	Farmer accessed market information (dummy)	0.62	0.49
Own_Lvstock	Farmer owns livestock (dummy)	0.90	0.30
Ext_Access	Farmer received extension services (dummy)	0.60	0.49
Drought	Farmer experienced drought (dummy)	0.81	0.39
Land_Ha	Land area used for growing the crop (continuous)	0.77	1.88
HHhead_FO_Member	Farmer is a member of a farmer organization (dummy)	0.71	0.45
Soil_Quality	Perceived soil quality by the farmer (1= Good)	0.97	0.17
TenureSystem	Land tenure system (1 = individual land, 0 = public land)	0.95	0.22

S.D represents standard deviation.

2.4 Diagnostic tests

To assess potential multicollinearity and examine relationships among the independent variables, a pairwise correlation analysis was conducted. While some correlations were statistically significant, most variables exhibited moderate to weak associations, with values close to zero, suggesting that multicollinearity is not a major concern. Additionally,

a Variance Inflation Factor (VIF) test was performed for a more formal assessment of multicollinearity. The results indicated that all VIF values were well below the commonly accepted threshold of 5, with the highest value at 1.98 and an average VIF of 1.22, confirming that multicollinearity is not an issue in these models.

Measurement error is not a concern in this study, as data collection was carefully managed to ensure accuracy. However, potential sources of endogeneity include simultaneity between yield and variables such as income, as well as selection bias due to the study's focus on maize input choices, specifically improved seed and inorganic fertilizer. To test for endogeneity in variables like income, we applied the Durbin-Wu-Hausman (DWH) test using a two-step procedure. First, an auxiliary regression was estimated, regressing income on all exogenous explanatory variables to obtain residuals capturing any unexplained variation. These residuals were then included in the main outcome regression, where the yield variable served as the dependent variable. The significance of the residuals was evaluated using the DWH test, with the null hypothesis stating that income is exogenous. The test produced an F-statistic of 0.0000, which is statistically significant at the 5% level, resulting in the rejection of the null hypothesis and confirming the presence of endogeneity in the income variable. This finding supports the assumption of endogeneity in the input adoption decision and justifies the use of an instrumental variable approach. To address this issue, the study employed a multinomial endogenous switching regression model (MESRM), which accounts for both endogeneity and selection bias while ensuring robust estimation of the impact of input choices on yield outcomes. Additionally, the Inverse Probability Weighted Regression Adjustment (IPWRA), also known as the doubly robust method, was applied to estimate treatment

effects while adjusting for selection bias. The IPWRA results aligned with the MESRM findings, revealing the same direction and percentage changes in yield, thereby confirming the consistency of the estimates.

3.0 Results

3.1 Descriptive characteristics of adopters and non-adopters of different input choices

Table 3 presents socio-demographic and agronomic characteristics of adopters and non-adopters of different input choices. For each category, the table shows the mean value of each variable for households that adopted the input (YES) versus those that did not (NO), the difference between these means (Diff), and the associated p-value, which indicates the statistical significance of the difference. This dataset sheds light on potential factors that shape farmers' decisions regarding their preferred choices for modern maize inputs.

Farmers who did not adopt modern maize inputs had a smaller household size and were less educated compared to those who adopted modern maize inputs. Non-adopters were not engaged in farming as their main occupation and fewer were married. They also had the smallest average land sizes, limited access to agronomic training and extension services. Additionally, only 45% of the non-adopters had access to market information and 42% had access to credit.

Those that adopted improved maize seed only had larger household sizes, were married and primarily engaged in farming activities compared to non-adopters. Also, more of these farmers were educated, cultivated larger land sizes and had greater access to agronomic training and extension services. They also had better access to market

information and credit. Farmers who adopted inorganic fertilizer only cultivated larger land sizes, and had more access to agronomic training and extension services.

Farmers who adopted both improved maize seed and inorganic fertilizers had larger household sizes, were slightly younger and more educated. A greater proportion of them were married and belonged to male-headed households. They also cultivated larger land sizes (0.98 hectares) compared to non-adopters. Furthermore, they had better access to agronomic training, extension services, market information and credit.

Table 3: Descriptive statistics of variables, by input choices and pooled sample.

	(n=348)				(n=875)				(n=43)				(n=977)			
Variable	**No modern maize input**				**Improved maize seed only**				**Inorganic fertilizer only**				**Improved maize and fertilizer**			
	YES	**NO**	**Diff**	**P-Value**	**YES**	**NO**	**Diff**	**P-Value**	**YES**	**NO**	**Diff**	**P-Value**	**YES**	**NO**	**Diff**	**P-Value**
Household size	6.97	7.50	0.53	0.00***	7.55	6.97	-0.57	0.00***	7.02	6.97	-0.05	0.91	7.47	6.97	-0.50	0.01***
Age of household head	51.29	50.26	-1.03	0.18	51.17	51.29	0.12	0.89	51.63	51.29	-0.34	0.88	49.39	51.29	1.90	0.02**
Sex of household head (1=Male)	0.75	0.79	0.04	0.07	0.77	0.75	-0.03	0.32	0.79	0.75	-0.04	0.53	0.81	0.75	-0.06	0.02**
Education of household head (1=Sec & above)	0.29	0.46	0.17	0.00***	0.40	0.29	-0.11	0.00***	0.35	0.29	-0.06	0.45	0.52	0.29	-0.23	0.00***
Marital Status of household head (1=Married)	0.77	0.85	0.08	0.00***	0.83	0.77	-0.06	0.02**	0.79	0.77	-0.02	0.73	0.88	0.77	-0.11	0.00***
Primary occupation (1=Farm employment)	0.79	0.83	0.04	0.05**	0.84	0.79	-0.05	0.03**	0.86	0.79	-0.07	0.26	0.82	0.79	-0.04	0.13
Distance to the market (km)	4.06	4.00	-0.06	0.87	4.09	4.06	-0.03	0.94	4.30	4.06	-0.24	0.69	3.91	4.06	0.15	0.63
Land cultivated (Ha)	0.48	0.82	0.34	0.00***	0.64	0.48	-0.16	0.00***	0.73	0.48	-0.25	0.01**	0.98	0.48	-0.50	0.00***
Access to training in agronomy (1=Yes)	0.25	0.48	0.22	0.00***	0.43	0.25	-0.17	0.00***	0.42	0.25	-0.17	0.02**	0.52	0.25	-0.27	0.00***
Access to extension services (1=Yes)	0.32	0.66	0.33	0.00***	0.55	0.32	-0.22	0.00***	0.53	0.32	-0.21	0.01***	0.76	0.32	-0.44	0.00***
Access to market information (1=Yes)	0.45	0.65	0.19	0.00***	0.62	0.45	-0.16	0.00***	0.58	0.45	-0.13	0.11	0.68	0.45	-0.23	0.00***
Access to credit (in the last 12 months)	0.42	0.52	0.10	0.00***	0.53	0.42	-0.11	0.00***	0.47	0.42	-0.05	0.54	0.50	0.42	-0.09	0.00***

*Note: *** and ** indicate significance levels at 1% and 5% levels respectively.*

3.2 Determinants of adoption of modern maize inputs

We categorized farmers based on their input choices; those that did not adopt any modern maize input, adopters of improved maize seed only, adopters of inorganic fertilizer only and adopters of both improved maize seed and inorganic fertilizer. Table 4 reports the results of the multinomial logit regression used to investigate the factors influencing these choices among farmers.

Our findings show that education has a significant negative effect on the adoption of non-modern inputs and a positive effect on the adoption of improved maize seed and fertilizer simultaneously. The occupation of the household head significantly influences input adoption decisions, especially among those engaged in farm-related activities. Such farmers tend to eschew non-modern inputs by 4.13 percent. The results also show that access to agronomic training reduces the likelihood of adopting non-modern maize inputs by 3.4 percent. Access to credit increases the likelihood of adopting improved maize seed only by 4.0 percent and decreases the likelihood of adopting non-modern maize inputs by 3.2 percent. Farmers who had access to market information were less likely to adopt non-modern maize inputs. Extension services significantly decreased the likelihood of adopting non-modern maize inputs by 8.8 percent and improved maize seed alone by 11.4 percent, while increasing the probability of adopting both improved maize seed and inorganic fertilizer by 20.6 percent.

Livestock ownership, on the other hand, significantly increased the likelihood of adopting only improved maize seed by 7.9 percent likely due to the availability of organic manure that supplements seed use. As household income increases, the likelihood of adopting both improved maize seed and inorganic fertilizer increases by 4.3 percent and reduces

the likelihood of adopting non-modern maize inputs. Additionally, exposure to drought conditions motivates farmers to adopt modern inputs, especially improved maize seeds. Specifically, drought increases the likelihood of adopting only improved maize seed by 14.0 percent, while decreasing the probability of adopting both improved maize seed and fertilizer by 12.4 percent. An increase in cultivated land size increases the likelihood of adopting both improved maize seed and inorganic fertilizer by 9.5 percent, while it reduces the likelihood of adopting non-modern maize inputs by 4.7 percent and improved maize seed only by 5.1 percent.

The results also indicated that households with heads who were members of farmer organizations were less likely to adopt non-modern maize inputs. However, membership in a farmer organization had no significant effect on the adoption of both improved maize seed and inorganic fertilizer. Farmers with individually owned land were significantly less likely to adopt both improved maize seed and inorganic fertilizer, with the probability decreasing by 9.9 percent.

Table 4: Determinants of adoption of modern maize inputs

Independent Variables	No modern maize input	Improved maize seed only	Inorganic fertilizer only	Both modern inputs
Household Size	-0.0044	0.0053	-0.0010	0.0001
	(0.0025)	(0.0035)	(0.0012)	(0.0034)
Age of Household head (Years)	-0.0001	0.0015	0.0001	-0.0014
	(0.0005)	(0.0008)	(0.0002)	(0.0007)
Sex of Household head (1=Male)	0.0408	-0.0024	0.0090	-0.0474
	(0.0252)	(0.0331)	(0.0127)	(0.0314)
Education level (1=Secondary)	-0.0519***	-0.0328	-0.0054	0.0900***
	(0.0158)	(0.0214)	(0.0061)	(0.0200)
Marital Status (1=Married)	-0.0390	-0.0139	-0.0111	0.0641
	(0.0268)	(0.0376)	(0.0127)	(0.0363)
Occupation (1=Farm Employment)	-0.0413**	0.0122	0.0053	0.0239
	(0.0185)	(0.0283)	(0.0087)	(0.0272)
Training in agronomy	-0.0339**	0.0210	0.0027	0.0103
	(0.0173)	(0.0229)	(0.0077)	(0.0215)
Access to Credit	-0.0318**	0.0401***	-0.0013	-0.0070
	(0.0144)	(0.0203)	(0.0058)	(0.0194)
Access to Market Information	-0.0386***	0.0274	-0.0029	0.0142
	(0.0145)	(0.0217)	(0.0064)	(0.0209)
Access to Extension services	-0.0880***	-0.1135***	-0.0047	0.2062***
	(0.0157)	(0.0231)	(0.0076)	(0.0212)
Distance to the nearest market (Km)	0.0007	-0.0001	0.0003	-0.0009
	(0.0010)	(0.0017)	(0.0003)	(0.0016)
Livestock ownership	-0.0250	0.0790**	-0.0018	-0.0522
	(0.0213)	(0.0362)	(0.0090)	(0.0349)
Log Household Income	-0.0382***	-0.0046	-0.0001	0.0429***
	(0.0055)	(0.0090)	(0.0027)	(0.0092)
Drought Experience	-0.0093	0.1396***	-0.0063	-0.1240***
	(0.0173)	(0.0268)	(0.0067)	(0.0240)
Log land cultivated (Hectares)	-0.0474***	-0.0510***	0.0037	0.0946***
	(0.0106)	(0.0140)	(0.0048)	(0.0138)
Farmer organization membership	-0.0430***	0.0419	-0.0075	0.0087
	(0.0153)	(0.0234)	(0.0066)	(0.0225)
Soil quality	-0.0001	0.0403	0.0045	-0.0447
	(0 .0350)	(0.0628)	(0.0200)	(0.0622)
Tenure System	0.0261	0.0698	0.0033	-0.0992***

	(0.0331)	(0.0464)	(0.0134)	(0.0402)
Constant	-	-5.3791***	-6.4480**	-6.0720***
	-	(0.9146)	(2.8976)	(0 .9867)
Number of Observations	2241			
Wald chi2(51)	426.11			
Log pseudolikelihood	-2179.1879			
Prob > chi2	0.0000			
Pseudo R2	0.1114			

*Robust standard errors are in parentheses; ** and *** show the significance level at 5%, and 1%*

3.3 Effect of input choices on maize yield

The input choice of the farmer could directly influence the potential maize yields they obtained, ceteris paribus. The effect of various input choices on maize yield is analyzed using a Multinomial Endogenous Switching Regression Model (MESRM), with the resulting estimates reported in Table 5. The results revealed that farmers who did not adopt any modern maize inputs had the lowest yield levels. Notably, all adoption choices showed positive effects for both average treatment on the treated (ATT) and average treatment on the untreated (ATU).

The model estimates showed that farmers who adopted only improved maize seed achieved a yield of 1,722 kg/ha, those who adopted only inorganic fertilizer obtained 1,717 kg/ha while those who combined both inputs attained the highest yield of 2,061 kg/ha. The ATT for farmers who adopted both improved maize seed and inorganic fertilizer is 735 kg/ha, indicating a significant yield gain compared to those who did not adopt any modern maize input. Similarly, farmers who adopted only improved maize seed obtained an ATT of 698 kg/ha compared to non-modern maize input adopters, while those who adopted only inorganic fertilizer achieved an ATT of 359 kg/ha. The ATU estimates also show that non-adopters of both inputs could have gained up to 253 kg/ha had they adopted both inputs, and; 143 kg/ha and 122 kg/ha had they adopted only improved maize seed and inorganic fertilizer only, respectively.

Table 5: Average expected yield in kg/ha from modern input use (2nd stage of MESRM).

Input Category		Adopters (A)	Non-adopters (B)	ATT/ATU (C) = (A) – (B)
Improved maize seed only (M_1F_0)	Adopters	1722	1024	ATT = 698***
	Non-adopters	865	722	ATU = 143
Inorganic fertilizer only (M_0F_1)	Adopters	1717	1358	ATT = 359***
	Non-adopters	844	722	ATU = 122
Both improved maize seed and fertilizer (M_1F_1)	Adopters	2061	1326	ATT = 735***
	Non-adopters	975	722	ATU = 253

Note: *ATT and ATU refer to the average treatment effects for the treated and untreated groups, respectively. *** shows the level of significance at 1%.*

4.0 Discussion

Our study aimed to examine the factors influencing input choices among maize farmers and their effects on yield. Our findings showed that education plays as a key role in reducing reliance on non-modern maize inputs and promotes adoption of both improved maize seed and inorganic fertilizer. This is possibly because educated farmers are more likely to access, comprehend and apply information regarding these modern agricultural technologies with ease compared to their uneducated counterparts. Their ability to analyze costs and benefits, interpret extension advice, and manage risks more effectively may enhance their willingness and capacity to adopt a combination of inputs to improve productivity. This is consistent with findings by Selejio and Lasway (58) in Tanzania who reported that more educated household heads are significantly less likely to choose traditional inputs and were more likely to adopt both improved maize seeds and inorganic fertilizer. The results are consistent with more studies that highlight the influence of education in reducing reliance on traditional inputs through enhancing the farmers' understanding of complementarity benefits from adopting both inputs (59-62).

The results also reveal that the occupation of the household head plays a significant role in input adoption decisions, particularly for those employed in farm-related activities. Farmers in this category are less likely to adopt nonmodern maize inputs. This aligns with Sánchez-Toledano, Kallas (63) who reported that farmers prioritize improved seed adoption to enhance productivity, likely due to their deep involvement in farming and greater awareness of its potential benefits. Access to technical knowledge and support services plays a pivotal role in shaping farmers' decisions to adopt modern maize inputs

(64, 65). Farmers who receive agronomic training are less likely to adopt non-modern maize inputs due to their ability to understand the benefits and management practices of improved maize seed and inorganic fertilizers. Such support builds their confidence, mitigates perceived risks and equips them with the knowledge needed to make more comprehensive and informed decisions regarding the adoption of these inputs (66).

Access to credit significantly decreases the likelihood of using nonmodern maize inputs while increasing the probability of adopting improved maize seeds only as financial resources enable farmers to invest in better-quality seeds. Credit facilities play a crucial role in encouraging farmers to adopt improved maize seeds, as household income is often prioritized for essential needs such as health and education. However, we find that our results show no significant relationship between credit access and the adoption of only inorganic fertilizer or both inputs. This implies that whereas farmers are accessing credit, it is possibly not sufficient enough to enable them purchase inorganic fertilizer. Our finding is consistent with Kehinde (67) who found out in Osun State, that credit access has a significant positive effect on the adoption intensity of improved maize varieties. This is indeed the case with Simtowe and Zeller (68) who categorized households into credit constrained and unconstrained households. Their results show that credit access had no impact among unconstrained households and only increased adoption of hybrid maize in credit constrained households.

Our results on access to market information align with Kalinda, Tembo (61), who reported that farmers with market information are less likely to rely on non-modern maize inputs but rather adopt improved maize seeds. This could possibly be attributed to the fact that

much of the market information available is about improved seeds and not so really on inorganic fertilizer. The limited information on fertilizer availability, cost and proper use may constrain the farmers' ability to adopt both inputs (69, 70). Access to extension services significantly decrease the likelihood of adopting nonmodern maize inputs while increasing the probability of adopting either improved maize seed alone or a combination of improved maize seed and inorganic fertilizer. Our results are consistent with Uaiene (71) who highlights the importance of knowledge from extension services in driving adoption of modern agricultural technologies. While the results from our study are consistent with Akudugu, Guo (72), Walisinghe, Ratnasiri (73) and Gao, Zhao (74) who found that extension services are effective in encouraging joint adoption of modern agricultural technologies through provision of technical advice and support to farmers, they are contrary to Sennuga, Fadiji (75) who found that agricultural extension agents were not considered significant sources of agricultural information by the respondents. Extension support serves as an instrument for exposing farmers to practical guidance on the appropriate input usage and synergistic benefits of combining improved maize seed and inorganic fertilizer, thereby enhancing their confidence and capacity to adopt these inputs (76, 77).

We find a significant positive relationship between ownership of livestock and the adoption of only improved maize seed, likely due to the availability of organic fertilizers such as manure which complements the use of improved seeds. This finding aligns with Ahmed, Geleta (78), who reported that livestock-owning farmers tend to depend more on organic manure as a substitute for inorganic fertilizers. This finding is also consistent with Waithaka, Thornton (79) and Ogada, Mwabu (60) who found that smallholder farmers in

the process of intensifying, rely on regular use of manure from livestock for production of food crops. On the contrary, our findings differ from those of Okoboi and Barungi (70), who observed that livestock owners are more likely to use fertilizers than non-livestock owners, as they own a valuable asset that may generate extra household income to invest in modern agricultural inputs. Regarding household income, the results of this study are in agreement with Ketema and Kebede (80) who found evidence of higher household income as a more powerful force for adoption of modern inputs. Wealthier households are better equipped to invest in modern agricultural technologies, as demonstrated by the positive effect on combined adoption by the study results. This result partially aligns with Kalinda, Tembo (61) who emphasized the importance of financial capacity in enabling smallholder farmers to shift away from non-modern inputs and adopt modern alternatives like improved maize seed.

Drought plays a role in driving farmers toward modern inputs, specifically improved maize seeds. This is probably because improved maize varieties have attributes like shorter maturity period, high yields and drought tolerant. This result is consistent with findings from Fisher, Abate (81), Wossen, Abdoulaye (82) and Martey, Etwire (83) who found a significant increase in the probability of adopting improved maize seeds as farmers turn to more resilient seed varieties during drought conditions. However, drought reduces the likelihood of adopting both improved maize seeds and inorganic fertilizer. This finding correlates with what Holden and Quiggin (84) found in Malawi, that risk-averse households prefer options that minimize uncertainty such as Drought Tolerant (DT) maize, and are less likely to adopt new, less familiar technologies. In our study, drought experience had a negative effect on the adoption of both inputs likely due to a natural

response behavior towards shocks by farmers. Farmers recognize the critical role of water in the uptake of nutrients and strive to use these expensive inputs as efficiently as possible (85, 86). This can also be attributed to the financial constraints faced by smallholder farmers as shocks experienced may limit their capacity to adopt inputs jointly. Land is an important factor of production and a key indicator of wealth. Our findings are in agreement with Hu, Li (87), who reported that farmers with larger landholdings are more likely to adopt modern inputs, invest time and resources in acquiring agricultural knowledge, and focus more on productive technologies. As expected, farmers with larger landholdings are more inclined to adopt both improved maize seeds and inorganic fertilizers due to benefits from economies of scale that make input use more feasible. Farmers with larger landholdings have greater production incentives, which encourages them to invest in the adoption of both improved inputs rather than opting for partial adoption or relying on nonmodern inputs (61).

Our results show that membership in a farmer organization significantly reduces the reliance on nonmodern maize inputs. This is possibly due to the fact that these organizations serve as a platform for farmers to access trainings and information and collective bargaining power during purchases which can enhance their capacity to adopt modern inputs (88-90). Strengthening and promoting farmer organizations could be an effective strategy to increase modern input adoption among smallholder farmers. Regarding land tenure, our findings showed that while individual ownership of land is important, it is not sufficient on its own to influence full adoption of modern maize inputs. This may be attributed to factors such as limited access to credit despite land ownership, low perceived returns on investment or risk aversion among smallholders which may

prevent them from fully utilizing their land's potential (64, 91). Some studies show that much of the individual land may be leased or gifted customary land, under informal ownership arrangements, which can hinder farmers from fully implementing various agricultural practices on their farms under insecure tenure (92, 93).

We did not find any significant variables explaining the adoption of inorganic fertilizer alone, which may be due to the limited number of observations in this category, a constraint in our sample as well as the fact that this adopting only inorganic fertilizer is relatively uncommon among farmers given the cost of fertilizer. This may be explained by our summary statistics which showed that 97 percent of households in our sample considered their soils to be of good quality. While Amankwah and Gwatidzo (46) found that education of the household head, wage employment and soil quality significantly influence inorganic fertilizer adoption, they noted that households are less likely to apply inorganic fertilizer to plots they perceive as having good soil quality, which aligns with our own findings.

Farmers who adopted only improved maize seed achieved an average yield of 1,722 kg/ha while those who adopted only inorganic fertilizer obtained 1,717 kg/ha. Those who adopted both inputs achieved the highest yield of 2,061 kg/ha. Compared to the base group which comprised of farmers who did not adopt any modern maize input and obtained 722 kg/ha, our results represent a yield increase of 138.5% for only improved maize seed, 137.8% for inorganic fertilizer only, and 185.5% for the adoption of both inputs. The highest yield increase was observed among farmers that adopted both inputs across all categories. This may be attributed to the synergistic benefits that arise from combining improved maize seed with inorganic fertilizer, as modern maize varieties are

specifically bred to perform optimally when used together with inorganic fertilizer as a complete package (94). Our findings align with findings from previous studies by Ahmed (95) and Nyangena and Juma (96). Farmers who adopted either improved maize seed alone or inorganic fertilizer alone also experienced notable yield increases. However, those who used improved maize seed only obtained a greater yield gain compared to those who used only inorganic fertilizer. While numerous studies have highlighted the importance of plant genetics in improving yield, evidence from Sinclair and Rufty (86) underscores the need to complement genetic improvements with inputs like fertilizer to effectively enhance crop productivity.

Our results are in agreement with Takam-Fongang, Kamdem (28), Abro, Debela (97) and Abdoulaye, Wossen (98) who reported that adoption of modern maize inputs enhances yield. The pattern from our findings suggests that farmers who complementarily used the inputs achieved higher yields than those who relied on either improved maize seed only, inorganic fertilizer only or non-modern inputs. However, farmers who adopted either improved maize seed or inorganic fertilizer experienced better yield compared to those who did not adopt any modern maize inputs.

4.1 Conclusion and recommendation

Our findings suggest that farmers who adopted only improved maize seed had access to credit, extension services and owned livestock. These farmers cultivated smaller land sizes compared to those who adopted both inputs and had experienced drought conditions that significantly promoted the adoption of improved maize seed alone. Our results revealed that farmers who adopted both improved maize seed and inorganic fertilizer were more educated, had higher household income, cultivated larger land sizes

and had greater access to extension services compared to those that did not. Conversely, farmers who did not adopt any modern maize inputs generally had lower education levels and household incomes, cultivated smaller land sizes and were mainly involved in non-farm activities. Additionally, few household heads in this group were members of farmer organizations, and they faced limited access to agronomic training, extension services, credit and market information.

The ATT estimates showed that the adoption of modern maize inputs leads to a significant increase in yield. The greatest gain was observed among farmers who used both improved maize seed and inorganic fertilizer, with an ATT of 735 kg/ha, corresponding to a 185.5% increase compared to non-adopters. In comparison, farmers who adopted only improved maize seed obtained an ATT of 698 kg/ha (a 138.5% increase), while those who adopted only inorganic fertilizer achieved a gain of 359 kg/ha, equivalent to a 137.8% increase. Among the single-input adopters, improved maize seed results in greater yield gains than inorganic fertilizer, highlighting the stronger impact of genetic improvement over environmental enhancement. Our findings underscore the importance of using at least one modern input over none, and emphasize that improved seed and fertilizer are not substitutes but complementary. Therefore, farmers should be encouraged to combine improved maize seed and inorganic fertilizer. However, if constrained to choose only one, improved maize seed offers the better yield advantage. The results also revealed a modest yield difference between farmers who adopted only improved maize seed and those who adopted both improved seed and inorganic fertilizer, potentially indicating misapplication of inputs. This points to the need for further investigation into farmers' input application practices and how these affect yield outcomes. Targeted interventions that

improve access to education, credit and extension services are essential for encouraging broader adoption of modern inputs among smallholder maize farmers in Uganda. Improving these services can support a transition from isolated input use to complementary adoption that combines improved maize seed with inorganic fertilizers hence narrowing the productivity gap.

Ethics Statement

This study is a secondary analysis of data collected by the Agriculture Cluster Development Project (ACDP) monitoring and evaluation team of the Ministry of Agriculture, Animal Industry and Fisheries (MAAIF), Uganda, during the 2021/2022 end-line survey. The authors obtained the data with the permission of the ACDP monitoring and evaluation department and had no direct contact with survey participants. The research proposal was reviewed and approved by the School of Agriculture, Makerere University, which also waived the need for separate ethical approval because the study used existing secondary data and the authors did not collect data from human participants. The study was conducted in accordance with the principles of the Declaration of Helsinki and applicable national research guidelines in Uganda. Participants gave informed consent at the start of the original survey, through a consent statement at the beginning of the digital questionnaire. No additional consent was required for this secondary analysis.

Consent for publication

Not applicable. This manuscript does not contain any individual person's identifiable data, images or videos.

Data availability statement

The data supporting the findings of this study are available in [Makerere University Institutional Repository – MakIR] at [https://makir.mak.ac.ug/handle/10570/16737] from the corresponding author [CK] upon reasonable request.

Declaration of interest statement

John Ilukor is an employee of the World Bank. The remaining authors, Christine Kanyenyeri, Jackline Bonabana, and Alex Moruleng, declare no competing interests.

Funding statement

This research received no specific grant from any funding agency, commercial, or not-for-profit sectors. The analysis was conducted using secondary data provided by the Ministry of Agriculture, Animal Industry and Fisheries (MAAIF) and the World Bank.

Author Contributions

C.K. contributed to Conceptualization, Data curation, Formal analysis, Methodology, Validation, Visualization, Writing – original draft, and Writing – review & editing. J.I. contributed to Conceptualization, Data curation, Formal analysis, Methodology, Supervision, and Writing – review & editing. A.M. contributed to Formal analysis, Methodology, Validation, and Writing – review & editing. J.B. contributed to Supervision and Writing – review & editing. All authors reviewed and approved the final manuscript.

Acknowledgements

The authors gratefully acknowledge the support of the Ministry of Agriculture, Animal Industry and Fisheries (MAAIF) and the World Bank for providing access to the dataset

used in this study. Appreciation is also extended to all individuals and institutions whose guidance and assistance contributed to the successful completion of this research.

Use of generative AI

No generative AI tools were used in the preparation of this manuscript.

Clinical trial registration

Not applicable. This study is not a clinical trial.

References

1. Kotir JH. Climate change and variability in Sub-Saharan Africa: a review of current and future trends and impacts on agriculture and food security. Environment, Development and Sustainability. 2011;13:587-605.

2. Masso C, Nziguheba G, Mutegi J, Galy-Lacaux C, Wendt J, Butterbach-Bahl K, et al. Soil fertility management in sub-Saharan Africa. Sustainable agriculture reviews. 2017:205-31.

3. Nin-Pratt A. Inputs, productivity, and agricultural growth in Africa South of the Sahara. 2015.

4. Nin-Pratt A. Inputs, productivity, and agricultural growth in Africa South of the Sahara. International Food Policy Research Institute (IFPRI) Discussion Paper. 2015;1432.

5. Fuglie K, Rada N. Resources, policies, and agricultural productivity in sub-Saharan Africa. USDA-ERS Economic Research Report. 2013(145).

6. Christiensen L, Demery L. Agriculture in Africa: Telling Myths from Facts. Policy Research Working Paper. 2018;7979.

7. Luc C, Lionel D. Agriculture in Africa: telling myths from facts. What we do Africa myths and facts agriculture in Africa: telling facts from myths World Bank, World Bank Available online at https://openknowledge worldbank org/handle/10986/28543 License: CC BY. 2018;3.

8. Walls H, Matita M. Lessons from Malawi's Farm Input Subsidy Programme. Nature Food. 2023;4(9):734-5.

9. Carter M, Laajaj R, Yang D. Subsidies and the African Green Revolution: direct effects and social network spillovers of randomized input subsidies in Mozambique. American Economic Journal: Applied Economics. 2021;13(2):206-29.

10. Crawford EW, Jayne TS, Kelly VA. Alternative approaches for promoting fertilizer use in africa, with emphasis on the role of subsidies. 2005.

11. Ilukor J, Birner R, Rwamigisa PB, Nantima N. The provision of veterinary services: who are the influential actors and what are the governance challenges? A case study of Uganda. Experimental Agriculture. 2015;51(3):408-34.

12. Belshaw D, Lawrence P, Hubbard M. Agricultural tradables and economic recovery in Uganda: The limitations of structural adjustment in practice. World Development. 1999;27(4):673-90.

13. Mwakalobo A, Kashuliza A, editors. Impact of Structural Adjustment Policies on smallholder farming systems in Tanzania. The example of Mbeya region. Agricultural Productivity and Siista inability in Developing countries: Strategies, Achievements and Constraints Agricultural Economics Society of Tanzania (AGREST) Scientific Conference Proceedings; 1998.

14. Kato T, Greeley M. Agricultural input subsidies in sub-Saharan Africa. IDS Bulletin. 2016;47(2):33-48.

15. Chinsinga B, Poulton C. Beyond technocratic debates: the significance and transience of political incentives in the Malawi farm input subsidy programme (FISP). Development Policy Review. 2014;32(s2):s123-s50.

16. Agyemang SA, Ratinger T, Bavorová M. The impact of agricultural input subsidy on productivity: The case of Ghana. The European Journal of Development Research. 2022:1-26.

17. Wanzala-Mlobela M, Fuentes P, Mkumbwa S. Practices and policy options for the improved design and implementation of fertilizer subsidy programs in sub-Saharan Africa. NEPAD Agency Policy Study, A joint publication by the NEPAD Planning and Coordinating Agency (NPCA), the United Nations Food and Agriculture Organization, and the International Fertiliser and Development Centre (IFDC). 2013;35(155.254):0.

18. Ricker-Gilbert J, Jayne T, Shively G. Addressing the “wicked problem” of input subsidy programs in Africa. Applied Economic Perspectives and Policy. 2013;35(2):322-40.

19. Baltzer K, Hansen H. Evaluation Study Agricultural input subsidies in Sub-Saharan Africa. Institute of Food and Resource Economics, University of Copenhagen Rolighedsvej. 2011;25:1958.

20. Shively GE, Ricker-Gilbert J. Measuring the impacts of agricultural input subsidies in Sub-Saharan Africa: Evidence from Malawi's farm input subsidy program. Purdue Policy Research Institute (PPRI) Policy Briefs. 2013;1(1):4.

21. Baltzer K. Agricultural input subsidies in sub-Saharan Africa: Ministry of Foreign Affairs of Denmark, Danida; 2011.

22. Rafael BM. The importance of agricultural development projects: A focus on sustenance and employment creation in Kenya, Malawi, Namibia, Rwanda, and Uganda. Journal of Agricultural Chemistry and Environment. 2023;12(2):152-70.

23. CPAS. Technical Evaluation of the e-Voucher Input Subsidy Program in Uganda. College of Business and Management Sciences (CoBAMS), Makerere University; 2023 December 2023.

24. WorldBank. Global financial development report 2014: Financial inclusion: World Bank Publications; 2013.

25. WorldBank. World development report 2008: Agriculture for development: The World Bank; 2007.

26. MAAIF. AGRICULTURE CLUSTER DEVELOPMENT PROJECT. 2021.

27. Tesfay MG. Does fertilizer adoption enhance smallholders' commercialization? An endogenous switching regression model from northern Ethiopia. Agriculture & Food Security. 2020;9:1-18.

28. Takam-Fongang GM, Kamdem CB, Kane GQ. Adoption and impact of improved maize varieties on maize yields: Evidence from central Cameroon. Review of Development Economics. 2019;23(1):172-88.

29. Missiame A, Nyikal RA, Irungu P. What is the impact of rural bank credit access on the technical efficiency of smallholder cassava farmers in Ghana? An endogenous switching regression analysis. Heliyon. 2021;7(5).

30. Liu M, Min S, Ma W, Liu T. The adoption and impact of E-commerce in rural China: Application of an endogenous switching regression model. Journal of Rural Studies. 2021;83:106-16.

31. Li J, Ma W, Renwick A, Zheng H. The impact of access to irrigation on rural incomes and diversification: Evidence from China. China Agricultural Economic Review. 2020;12(4):705-25.

32. Zheng H, Ma W. Smartphone-based information acquisition and wheat farm performance: insights from a doubly robust IPWRA estimator. Electronic Commerce Research. 2023;23(2):633-58.

33. Zegeye MB, Fikrie AH, Asefa AB. Impact of agricultural technology adoption on wheat productivity: Evidence from North Shewa Zone, Amhara Region, Ethiopia. Cogent Economics & Finance. 2022;10(1):2101223.

34. Lu W, Addai KN, Ng'ombe JN. Impact of improved rice varieties on household food security in Northern Ghana: A doubly robust analysis. Journal of International Development. 2021;33(2):342-59.

35. Kapoor S, Pal BD. Impact of adoption of climate smart agriculture practices on farmer's income in semi-arid regions of Karnataka. Agricultural Systems. 2024;221:104135.

36. Danso-Abbeam G, Dagunga G, Ehiakpor DS. Rural non-farm income diversification: implications on smallholder farmers' welfare and agricultural technology adoption in Ghana. Heliyon. 2020;6(11).

37. Zhu Z, Ma W, Leng C. ICT adoption and tourism consumption among rural residents in China. Tourism Economics. 2022;28(6):1669-75.

38. Zhu Z, Ma W, Leng C, Nie P. The relationship between happiness and consumption expenditure: Evidence from rural China. Applied Research in Quality of Life. 2021;16:1587-611.

39. Zhou X, Ma W. Agricultural mechanization and land productivity in China. International Journal of Sustainable Development & World Ecology. 2022;29(6):530-42.

40. Ma W, Zhu Z, Zhou X. Agricultural mechanization and cropland abandonment in rural China. Applied Economics Letters. 2022;29(6):526-33.

41. Essilfie FL. Varietal seed technology and household income of maize farmers: an application of the doubly robust model. Technology in Society. 2018;55:85-91.

42. Teklewold H, Kassie M, Shiferaw B, Köhlin G. Cropping system diversification, conservation tillage and modern seed adoption in Ethiopia: Impacts on household income, agrochemical use and demand for labor. Ecological Economics. 2013;93:85-93.

43. Setsoafia ED, Ma W, Renwick A. Effects of sustainable agricultural practices on farm income and food security in northern Ghana. Agricultural and Food Economics. 2022;10(1):1-15.

44. Pan D, Zhang N, Kong F. Does it matter who gives information? The impact of information sources on farmers' pesticide use in China. Journal of Asian Economics. 2021;76:101345.

45. Kassie M, Teklewold H, Marenya P, Jaleta M, Erenstein O. Production risks and food security under alternative technology choices in Malawi: Application of a multinomial endogenous switching regression. Journal of Agricultural Economics. 2015;66(3):640-59.

46. Amankwah A, Gwatidzo T. Food security and poverty reduction effects of agricultural technologies adoption− a multinomial endogenous switching regression application in rural Zimbabwe. Food Policy. 2024;125:102629.

47. Ravi Kumar KN, Shafiwu AB, Prabhavathi Y. Does the participation in modern marketing channels for dry chillies affect economic welfare? Evidence from India. Cogent Food & Agriculture. 2024;10(1):2338652.

48. Oduniyi OS, Chagwiza C, Wade T. Welfare impacts of conservation agriculture adoption on smallholder maize farmers in South Africa. Renewable Agriculture and Food Systems. 2022;37(6):672-82.

49. Lu W, Addai KN, Ng'ombe JN. Does the use of multiple agricultural technologies affect household welfare? Evidence from Northern Ghana. Agrekon. 2021;60(4):370-87.

50. Feder G, Umali DL. The adoption of agricultural innovations: a review. Technological forecasting and social change. 1993;43(3-4):215-39.

51. Mottaleb KA, Mohanty S, Nelson A. Factors influencing hybrid rice adoption: a Bangladesh case. Australian Journal of Agricultural and Resource Economics. 2015;59(2):258-74.

52. Kassie M, Teklewolde H, Erenstein O. Adoption Pathways project discussion paper 2 February 2015. Technology. 2015.

53. Danso-Abbeam G, Baiyegunhi LJ. Welfare impact of pesticides management practices among smallholder cocoa farmers in Ghana. Technology in Society. 2018;54:10-9.

54. Di Falco S, Veronesi M. Managing environmental risk in presence of climate change: the role of adaptation in the Nile Basin of Ethiopia. Environmental and Resource Economics. 2014;57:553-77.

55. Ma W, Vatsa P, Zhou X, Zheng H. Happiness and farm productivity: insights from maize farmers in China. International Journal of Social Economics. 2022;49(1):97-106.

56. Bourguignon F, Fournier M, Gurgand M. Selection bias corrections based on the multinomial logit model: Monte Carlo comparisons. Journal of Economic surveys. 2007;21(1):174-205.

57. Di Falco S, Veronesi M. How can African agriculture adapt to climate change? A counterfactual analysis from Ethiopia. Land Economics. 2013;89(4):743-66.

58. Selejio O, Lasway JA. Economic analysis of the adoption of inorganic fertilisers and improved maize seeds in Tanzania. 2019.

59. Wainaina P, Tongruksawattana S, Qaim M. Tradeoffs and complementarities in the adoption of improved seeds, fertilizer, and natural resource management technologies in Kenya. Agricultural Economics. 2016;47(3):351-62.

60. Ogada MJ, Mwabu G, Muchai D. Farm technology adoption in Kenya: a simultaneous estimation of inorganic fertilizer and improved maize variety adoption decisions. Agricultural and food economics. 2014;2:1-18.

61. Kalinda T, Tembo G, Kuntashula E, Lusaka Z. Adoption of improved maize seed varieties in Southern Zambia. Asian Journal of Agricultural Sciences. 2014;6(1):33-9.

62. Bedeke S, Vanhove W, Gezahegn M, Natarajan K, Van Damme P. Adoption of climate change adaptation strategies by maize-dependent smallholders in Ethiopia. NJAS-Wageningen Journal of Life Sciences. 2019;88:96-104.

63. Sánchez-Toledano BI, Kallas Z, Palmeros Rojas O, Gil JM. Determinant factors of the adoption of improved maize seeds in Southern Mexico: A survival analysis approach. Sustainability. 2018;10(10):3543.

64. Tura M, Aredo D, Tsegaye T, La Rovere R, Kassie G, Mwangi W, et al. Adoption and continued use of improved maize seeds: Case study of Central Ethiopia. 2010.

65. Makate C, Makate M. Interceding role of institutional extension services on the livelihood impacts of drought tolerant maize technology adoption in Zimbabwe. Technology in Society. 2019;56:126-33.

66. Mgendi G, Mao S, Qiao F. Does agricultural training and demonstration matter in technology adoption? The empirical evidence from small rice farmers in Tanzania. Technology in Society. 2022;70:102024.

67. Kehinde A-D. Does credit access improve adoption intensity of improved maize seed varieties? 2021.

68. Simtowe F, Zeller M. The Impact of Access to Credit on the Adoption of hybrid maize in Malawi: An Empirical test of an Agricultural Household Model under credit market failure. 2006.

69. Shiferaw B, Kebede T, Kassie M, Fisher M. Market imperfections, access to information and technology adoption in Uganda: Challenges of overcoming multiple constraints. Agricultural economics. 2015;46(4):475-88.

70. Okoboi G, Barungi M. Constraints to fertilizer use in Uganda: Insights from Uganda census of agriculture 2008/9. Journal of Sustainable Development. 2012;5(10):99.

71. Uaiene RN. Determinants of agricultural technology adoption in Mozambique. 2011.

72. Akudugu MA, Guo E, Dadzie SK. Adoption of modern agricultural production technologies by farm households in Ghana: What factors influence their decisions. Journal of biology, agriculture and healthcare. 2012;2(3).

73. Walisinghe BR, Ratnasiri S, Rohde N, Guest R. Does agricultural extension promote technology adoption in Sri Lanka. International Journal of Social Economics. 2017;44(12):2173-86.

74. Gao Y, Zhao D, Yu L, Yang H. Influence of a new agricultural technology extension mode on farmers' technology adoption behavior in China. Journal of Rural Studies. 2020;76:173-83.

75. Sennuga SO, Fadiji TO, Thaddeus H. Factors influencing adoption of improved agricultural technologies (IATs) among smallholder farmers in Kaduna State, Nigeria. International Journal of Agricultural Education and Extension. 2020;6(2):382-91.

76. Maffioli A, Ubfal D, Vazquez-Bare G, Cerdan-Infantes P. Improving technology adoption in agriculture through extension services: evidence from Uruguay. Journal of Development Effectiveness. 2013;5(1):64-81.

77. Emmanuel D, Owusu-Sekyere E, Owusu V, Jordaan H. Impact of agricultural extension service on adoption of chemical fertilizer: Implications for rice productivity and development in Ghana. NJAS-Wageningen Journal of Life Sciences. 2016;79:41-9.

78. Ahmed MH, Geleta KM, Tazeze A, Mesfin HM, Tilahun EA. Cropping systems diversification, improved seed, manure and inorganic fertilizer adoption by maize producers of eastern Ethiopia. Journal of Economic Structures. 2017;6:1-16.

79. Waithaka MM, Thornton PK, Shepherd KD, Ndiwa NN. Factors affecting the use of fertilizers and manure by smallholders: the case of Vihiga, western Kenya. Nutrient Cycling in Agroecosystems. 2007;78:211-24.

80. Ketema M, Kebede D. Adoption intensity of inorganic fertilizers in maize production: empirical evidence from smallholder farmers in eastern Ethiopia. Journal of Agricultural Science. 2017;9(5):124-32.

81. Fisher M, Abate T, Lunduka RW, Asnake W, Alemayehu Y, Madulu RB. Drought tolerant maize for farmer adaptation to drought in sub-Saharan Africa: Determinants of adoption in eastern and southern Africa. Climatic Change. 2015;133:283-99.

82. Wossen T, Abdoulaye T, Alene A, Feleke S, Menkir A, Manyong V. Measuring the impacts of adaptation strategies to drought stress: The case of drought tolerant maize varieties. Journal of Environmental Management. 2017;203:106-13.

83. Martey E, Etwire PM, Kuwornu JK. Economic impacts of smallholder farmers' adoption of drought-tolerant maize varieties. Land use policy. 2020;94:104524.

84. Holden ST, Quiggin J. Climate risk and state-contingent technology adoption: shocks, drought tolerance and preferences. European Review of Agricultural Economics. 2017;44(2):285-308.

85. Bora K. Rainfall shocks and fertilizer use: a district level study of India. Environment and Development Economics. 2022;27(6):556-77.

86. Sinclair TR, Rufty TW. Nitrogen and water resources commonly limit crop yield increases, not necessarily plant genetics. Global Food Security. 2012;1(2):94-8.

87. Hu Y, Li B, Zhang Z, Wang J. Farm size and agricultural technology progress: Evidence from China. Journal of Rural Studies. 2022;93:417-29.

88. Danso-Abbeam G, Bosiako JA, Ehiakpor DS, Mabe FN. Adoption of improved maize variety among farm households in the northern region of Ghana. Cogent Economics & Finance. 2017;5(1):1416896.

89. Awotide BA, Karimov AA, Diagne A. Agricultural technology adoption, commercialization and smallholder rice farmers' welfare in rural Nigeria. Agricultural and Food Economics. 2016;4:1-24.

90. Shiferaw B, Muricho G. Farmer organizations and collective action institutions for improving market access and technology adoption in sub-Saharan Africa: review of experiences and implications for policy. Towards priority actions for market development for African farmers. 2011.

91. Sserunkuuma D. The adoption and impact of improved maize and land management technologies in Uganda. eJADE: electronic Journal of Agricultural and Development Economics. 2005;2(1):67-84.

92. Kolapo A, Didunyemi AJ, Aniyi OJ, Obembe OE. Adoption of multiple sustainable land management practices and its effects on productivity of smallholder maize farmers in Nigeria. Resources, Environment and Sustainability. 2022;10:100084.

93. Adimassu Z, Langan S, Johnston R. Understanding determinants of farmers' investments in sustainable land management practices in Ethiopia: Review and synthesis. Environment, development and sustainability. 2016;18(4):1005-23.

94. Sheahan M, Barrett CB. Ten striking facts about agricultural input use in Sub-Saharan Africa. Food policy. 2017;67:12-25.

95. Ahmed MH. Impact of improved seed and inorganic fertilizer on maize yield and welfare: Evidence from Eastern Ethiopia. Journal of Agriculture and Food Research. 2022;7:100266.

96. Nyangena W, Juma M. Impact of improved farm technologies on yields: the case of improved maize varieties and inorganic fertilizer in Kenya. 2014.

97. Abro ZA, Debela BL, Kassie M. The joint impact of improved maize seeds on productivity and efficiency: implications for policy. 2019.

98. Abdoulaye T, Wossen T, Awotide B. Impacts of improved maize varieties in Nigeria: ex-post assessment of productivity and welfare outcomes. Food security. 2018;10:369-79.