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Research Article

Effect of Climate-smart Agricultural Practices on Productivity and Income of Smallholder Maize Farmers: Micro-level Evidence from Botswana

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Abstract

Climate change presents considerable obstacles to agricultural productivity in Sub-Saharan Africa., resulting in low yields and reduced farmers' income. Climate-smart agricultural (CSA) practices offer a viable pathway to address these challenges through their triple benefits: enhanced productivity, increased income, and reduction of greenhouse gas emissions. This study examines the effect of adopting four interdependent CSA practices (crop rotation, use of improved seeds, application of inorganic fertilizers, and maize-legume diversification) and their combinations on productivity and income. Using recent cross-sectional data from 384 maize farmers in North East District, Botswana, the study utilizes a multinomial endogenous switching regression model to correct for selection bias and endogeneity caused by both observable and unobservable factors. The results show that adoption decisions are shaped by variables such as education, farm size, farming experience, livestock ownership, membership in groups, access to extension services, market access, and land tenure systems. Notably, adopting all four CSA practices results in a productivity increase of 3.56 units and a significant income gain of 3,691.17 Botswana Pula. These results suggest that farmers experience the greatest improvements in productivity and income when they adopt a comprehensive set of CSA practices. Building on the findings, the paper recommends that both government and non-governmental organizations promote the adoption of these practices by offering innovative extension services. These services would help farmers gain a better understanding of the advantages of alternative climate-smart agricultural practices.

Keywords

Climate-Smart Agriculture, Climate Change, Smallholder, Maize, Multinomial Endogenous Switching Regression Model, Botswana

1. Introduction

In sub-Saharan Africa (SSA), agriculture is the main livelihood for rural communities, playing a crucial role in food security, employment, and economic development. In Botswana, maize is a key staple crop, essential to local diets and an important income source for smallholder farmers. Despite its importance, the agricultural sector in Botswana faces a

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series of challenges, including unpredictable rainfall, prolonged droughts, declining soil fertility, and the growing impacts of climate change, [8, 10]. These challenges have placed smallholder maize farmers, who are already constrained by limited resources, at greater risk of food insecurity and poverty. Addressing these vulnerabilities requires targeted interventions that not only enhance productivity but also promote resilience and sustainability.

In recent years, climate-smart agriculture (CSA) has gained recognition as a transformative approach to addressing the dual challenges of food security and climate change. According to the Food and Agriculture Organization (FAO), CSA aims to achieve three interconnected objectives: sustainably increasing agricultural productivity and incomes, enhancing adaptation and resilience to climate change, and reducing greenhouse gas emissions where possible [9]. CSA practices include a variety of technologies and approaches, such as conservation agriculture, agroforestry, integrated soil fertility management, crop diversification, and water harvesting techniques. These practices are designed to optimize natural resource use while mitigating the adverse effects of climate variability and change.

Existing evidence suggests that CSA practices have the potential to significantly improve agricultural outcomes for smallholder farmers. Studies from various parts of SSA indicate that adopting CSA practices can lead to enhanced crop productivity, better resource use efficiency, and increased household incomes [2, 21]. However, although these studies offer important insights, they emphasize the necessity of context-specific research to explore the distinct factors affecting CSA adoption and its impact across various regions.

Botswana presents a compelling case for studying CSA practices due to its vulnerability to climate variability and the centrality of agriculture in rural livelihoods. Despite the increasing promotion of CSA practices through various programs, there is limited empirical evidence on their micro-level impacts on productivity and income among smallholder maize farmers. Most existing studies on CSA in SSA focus on broad regional assessments, often overlooking the localized socio-economic and agro-ecological factors that influence adoption and effectiveness [7, 14, 15]. This knowledge gap limits policymakers and development practitioners in designing targeted interventions that address the specific needs and constraints of farmers in Botswana. To bridge this gap, this study examines how local socio-economic and household characteristics influence the adoption and effectiveness of these practices. It also explores the micro-level effects of CSA practices on productivity and income among smallholder maize farmers in Botswana.

This paper presents micro-level evidence on the effects of CSA practices on the productivity and income of smallholder maize farmers in Botswana. By utilizing household-level data, this study aims to assess the socio-economic and agronomic impacts of CSA practices, highlighting their potential to transform smallholder farming systems in the country. The structure of the paper is as follows: Section two describes the materials and methods, Section three provides the descriptive and econometric results, and Section four offers the conclusions and policy recommendations.

2. Methodology

2.1. Analytical Framework

In a multiple adoption framework, farmers can select from 16 possible combinations of four CSA practices. Typically, farmers make independent choices regarding the adoption or non-adoption of these practices. Both observable and unobservable factors that relate to the desired outcomes can influence these decisions. One methodological challenge in this analysis is the potential for sample selection bias, as smallholder maize farmers might self-select into various CSA practices or possess inherent characteristics that are linked to their productivity and income. To address possible biases from unobserved factors, the study employs the multinomial endogenous switching regression (MESR) model. The MESR model corrects for both observable and unobservable biases caused by the non-random allocation of farmers to different CSA practices, thus yielding unbiased estimates of the impact of CSA practices on productivity and income. The MESR model consists of a two-step estimation procedure. The first step involves modeling the farmer's selection of individual or combined CSA practices using a multinomial logit model, accounting for unobserved heterogeneity. In the second step, the impact of these practices on maize productivity and income is analyzed using the average treatment effect.

We frame the adoption decision for different CSA practices within the context of a random utility model. Following [25], Within a multinomial model for adoption selection model, we assume that maize producers aim to maximize their utility, U_{ij}, by evaluating the yield per unit area and income generated from different CSA practices. Therefore, a maize producer i will select practice j over an alternative practice k if $U_{ij}, > U_{ik},$, where $k \neq j$. The expected yield per unit area, $U_{ij}, *$, that the producer derives from adopting practice j is a latent variable influenced by observed demographic, socio-economic, and farm-level factors (X_i) as well as unobserved characteristics $(\mathcal{E}_{ij})$. Let (U) represent an index that indicates the producer's selection of CSA practice, such that:

$$U_{ij} = X_i \beta_j + \mathrm{E}_{ij} \quad (1)$$

Where X_I represents the observed explanatory variables and $\mathcal{E}_{ij}$ denotes unobserved characteristics. Let (U) serve as an index indicating the producer's selection of a CSA practice, such that:

$$U = \begin{cases} 1 \; iff \;\; U_{i1} > max_{k\neq j}(U_{ik}) \;\; or \;\; n_{i1} < 0 \\ \quad\quad \vdots\vdots\vdots \text{ for all } k \neq j \\ 1 \; iff \;\; U_{ij} > max_{k\neq j}(U_{ik}) \;\; or \;\; n_{ij} < 0 \end{cases} \quad (2)$$

In the equation above, $n_{ij} = max_{k\neq j} \, (U_{ik} - U_{ij}) < 0$. Equation (2) indicates that the i^{th} maize producer will adopt CSA practice j to maximize their expected yield if practice j offers a higher expected yield per unit area and income than any other practice $k \neq j$, that is, if $n_{ij} = max_{k\neq j} \, (U_{ik} - U_{ij}) > 0$. Following [19], the likelihood that a maize producer i, with characteristics X_i, selects CSA practice j can be specified using a multinomial logit model as:

$$P_{ij} = \Pr(\eta_{ij} < 0 | X_i) = \frac{\exp X_i\beta_j}{\sum_{k=1}^{j} \exp(X_i\beta_k)}, \text{j} = 0, 1 \ldots \text{J} \quad (3)$$

Where j represents the alternatives, ranging from none to J and β is a vector of coefficients for each of the independent variables. Additionally, x, k denotes the number of categories into which the farmer's responses may fall.

2.2. Second Stage: Multinomial Endogenous Switching Regression Model

In the second stage of the MESR, the relationship between the outcome variables and a set of independent variables (Z) is estimated for each selected CSA practice. Within the model specification for the four CSA practices, maize farmers have 16 possible combination choices (j = 1, 2… 16). This study considers the non-adoption of CSA practices (j = 1) as the reference category, while the remaining alternatives (j = 2… 16) represent the adoption of at least one practice. The outcome equation for each possible regime j is expressed as follows:

$$\begin{cases} Regime \;\; 1\text{:} \;\; Y_{i1} = Z_{i1}\alpha_1 + u_{i1} \;\; if \;\; U = 1 \\ Regime \;\; J\text{:} \;\; Y_{ij} = Z_{ij}\alpha_j + u_{ij} \;\; if \;\; U = j \end{cases} \quad (4)$$

Let Y_{ij} represent the outcome variable for the ith farmer in regime j, where the error terms (u_{ij}) are assumed to have an expected value of E (u_{ij}X, Z) = 0 and a variance of Var (u_{ij} | X, Z) =σ^2. The outcome variable Y_{ij} is observed only when a specific CSA practice j is adopted. Additionally, the error term (u_{ij}) consists of both unobserved individual effects and a random disturbance component. Following [6], the multinomial endogenous switching model, as expressed in Equation (4), can be reformulated as Equation (5), commonly referred to as the selection bias-corrected outcome equation or the second stage of the multinomial endogenous switching regression.

$$\begin{cases} Regime \;\; 1\text{:} \;\; Y_{i1} = Z_{i1}\alpha_1 + \sigma_1\lambda_{i1} + e_{i1} \quad if \;\; U = 1 \\ Regime \;\; 1\text{:} \;\; Y_{ij} = Z_{ij}\alpha_1 + \sigma_j\lambda_{ij} + e_{ij} \quad if \;\; U = j \end{cases} \quad (5)$$

Where, e_{ij} represents the error term with an expected value of zero, while σ_j denotes the covariance between $\varepsilon_{ij}'s$ and u_{ij}'. Additionally, λ_{ij} refers to the inverse Mills ratio, which is derived from the estimated probabilities in Equation (3) as follows $\lambda_{ij} = \sum_{k\neq j}^{j} \rho_j [\frac{\acute{p}_{ik} \ln(\acute{p}_{ik})}{1-\acute{p}_{ik}} + \ln(\acute{p}_{ij})]$. Here, $\acute{p}$ is the correlation coefficient between $e_{ij}'s$ and $u_{ij}'s$. In a multinomial choice framework, J – 1 selection correction terms must be incorporated into the outcome equations, with each corresponding to a specific alternative CSA practice. To address heteroscedasticity arising from the generated explanatory variables in the estimation process, the standard errors in Equation (5) are bootstrapped.

2.3. Estimating Average Treatment Effects

The multinomial endogenous switching regression framework outlined above allows for the estimation of the average treatment effects on the treated (ATT). This is achieved by comparing the expected outcomes of CSA practice adopters and non-adopters under both actual and counterfactual scenarios, as represented in Equations (6) and (7), respectively.

Farmers who have chosen to adopt (observed outcome):

$$E \;\; (Y_{ij} | \;\; U = j; \;\; Z_{IJ}, \lambda_{IJ}) = \alpha_{IJ} Z_{ij} + \sigma_{ij}\lambda_{ij} \quad (6)$$

Farmers who have chosen not to adopt (counterfactual outcome):

$$E \;\; (Y_{1j} | \;\; U = j; \;\; Z_{IJ}, \lambda_{IJ}) = \alpha_{1J} Z_{ij} + \sigma_{1j}\lambda_{ij} \quad (7)$$

Equations (6) and (7) are employed to calculate the ATT, which is obtained by subtracting the counterfactual expected values from the actual values, or equivalently, by taking the difference between Equations (6) and (7)

$$ATT = E\big(\; Y_{ij} | \;\; U = j; \;\; Z_{IJ}, \lambda_{IJ}\big) - E(Y_{1j} | \;\; U = j; \;\; Z_{IJ}, \lambda_{IJ}) = \;\; (\alpha_J - \alpha_1) + (\sigma_j - \sigma_1)\lambda_{ij} \quad (8)$$

The first term (Z_{ij}) on the right-hand side of Equation (8) indicates the expected change in the mean outcome variable for adopters, assuming they share similar characteristics with non-adopters. The second term (λ_{ij}) represents the selection term on the right-hand side of Equation (8), which accounts for the potential effects of differences in unobserved variables.

3. Dataset and Variable Descriptions

3.1. Sources of Data and Sampling Methodology

This paper is based on data collected in July 2024 from three areas within the North east District sub district (NED) of Botswana, namely, Matsiloje, Matshelagabedi, and Tsamaya.

A multistage sampling approach was utilized to select respondents. Initially, the North-East District was chosen due to its high concentration of smallholder maize farmers, ensuring a greater likelihood of achieving the desired sample size. Secondly, the North-East Sub-District was purposively chosen from the two sub-districts in the region. In the third stage, three villages were randomly selected from the 23 villages within the sub-district. Lastly, a list of farmers in each selected village was compiled, and respondents were chosen using a systematic random sampling technique, ensuring proportional representation based on the population size of each village. A semi structured questionnaire was administered through interviews and gathered information on the farm, socioeconomic and institutional characteristics, household income, expenditures and maize farming returns from a sample of 384 respondents. Productivity is quantified as the total maize output (in kilograms) per one unit of cultivated (hectares) while income is the revenue that the smallholder maize farmer received from selling maize minus their production costs.

3.2. Variables Used and Summary Statistics

Table 1 presents the combined adoption choices of CSA practices, resulting in 16 possible combinations available to maize farmers. Among these, farmers implemented 9 out of the 16 potential packages. The findings reveal that 8.85% of farmers did not adopt any CSA practices ($M_0S_0C_0F_0$), while 22.14% adopted all four simultaneously ($M_1S_1C_1F_1$). A smaller portion, 14.32%, adopted only one practice, whereas the rest adopted combinations of two, three, or four practices. Specifically, 22.4% adopted two practices, and 32.03% adopted three practices. Overall, most farmers (54.17%) adopted three or more CSA practices. Understanding the factors that influence an individual's choice of specific packages from the available options is crucial for shaping policy direction.

The descriptive statistics on household, socio-economic and institutional attributes of the farmers are presented in Table 2. With regard to the adoption of CSA practices, an average of 71%, 68%, 56%, and 55% of maize farmers adopted maize-legume diversification, the use of improved seeds, crop rotation, and fertilizer application, respectively, in the last 12 months. The majority of respondents (60%) were female, with an average age of 48 years and a mean household size of four adults (Table 1). This suggests that maize farming in Botswana is primarily led by middle-aged women, with an average of 12 years of farming experience [11].

Most respondents had only a primary education, reflecting the generally low literacy levels among smallholder farmers. This highlights the need for additional capacity-building programs to enhance the skills and knowledge of maize farmers [22]. Regarding land tenure, 53% of farmers possessed land with title deeds, and the average area allocated to maize farming was 3.9 hectares. In terms of maize variety, 73% of the maize cultivated was hybrid, and the average distance to the output market was 23 km.

Table 1. Identification of combinations of CSA strategies to construct the packages.

Option	Quadruple binary	M_0	M_1	S_0	S_1	C_0	C_1	F_0	F_1	Frequency	Percentage
1	$M_0S_0C_0F_0$	√		√		√		√		34.0	8.85
2	$M_0S_0C_0F_1$	√		√		√			√	0.00	0.00
3	$M_0S_0C_1F_1$	√		√			√		√	0.00	0.00
4	$M_0S_1C_1F_1$	√			√		√		√	0.00	0.00
5	$M_1S_1C_1F_1$		√		√		√		√	85.0	22.4
6	$M_1S_1C_1F_0$		√		√		√	√		37.0	9.64
7	$M_1S_1C_0F_0$		√		√	√		√		37.0	9.64
8	$M_1S_0C_0F_0$		√	√		√		√		41.0	10.7
9	$M_0S_1C_0F_1$	√			√	√			√	0.00	0.00
10	$M_1S_0C_1F_0$		√	√			√	√		39.0	10.2
11	$M_1S_0C_0F_1$		√	√		√			√	10.0	2.60
12	$M_0S_1C_0F_0$	√			√	√		√		15.0	3.91
13	$M_0S_1C_1F_0$	√			√		√	√		0.00	0.00
14	$M_0S_0C_1F_0$	√		√			√	√		0.00	0.00
15	$M_1S_0C_1F_1$		√	√			√		√	31.0	8.07

Option	Quadruple binary	M_0	M_1	S_0	S_1	C_0	C_1	F_0	F_1	Frequency	Percentage
16	$M_1S_1C_0F_1$		√		√	√			√	55.0	14.2
Total										384	100

Note: The binary quadruplicate depicts the potential CSA packages. Each element in the quadruplicate corresponds to a binary variable representing a CSA combination: Maize-legume diversification (M), Use of improved seeds (S), Crop rotation (C), and Use of fertilizers (F). A subscript of 1 indicates adoption, while 0 indicates non-adoption.

Table 2. *Definition of variables and summary statistics.*

Variables	Variable description	Mean	Std. Dev
Dependent			
Crop rotation system	Dummy = 1 if HH adopted crop rotation system, 0 Otherwise	0.56	0.25
Use of improved seeds	Dummy = 1 if farmer was using improved seeds, 0 otherwise	0.68	0.24
Efficient use of fertilisers	Dummy = 1 if HH adopted efficient fertilizer use, 0 otherwise	0.55	0.25
Maize-legume diversification system	Dummy = 1 if HH has adopted maize-legume diversification system, 0 otherwise	0.71	0.23
Independent			
Age	Age of the farmer in years	47.46	0.39
Gender	Dummy=1 if male and 0, otherwise	0.39	0.25
Education	Number of years of schooling by farmer	10.39	0.20
Household size	Number of adult household members	3.99	0.56
Group membership	Dummy =1 if HH belong to a farmer group, 0 Otherwise	0.26	0.22
Training	Dummy =1 if HH have received training on CSA, 0 otherwise	0.36	0.02
Experience	Years of experience in maize farming.	11.84	0.33
Maize type	Dummy = 1 if HH used hybrid, 0 otherwise	0.73	0.02
Land size	Maize area planted in hectare (s)	4.28	0.05
Land tenure system	Dummy = 1 if HH owned land with title deed, 0 otherwise	0.53	0.25
Distance to output market	Distance to the output market in KM	22.87	0.56
Access to climate info.	Dummy= 1 if HH had access to climate info, 0 otherwise	0.73	0.23
Access to contracts	Dummy= 1 if HH had written contracts, 0 otherwise	0.29	0.02
Off farm income	Dummy = 1 if the farmer has access to off-farm income, and 0, Otherwise	0.83	0.01
Credit access	Dummy =1 if HH have received credit, 0 otherwise	0.05	0.01
Pest and disease shocks	Dummy =1 if plot experienced pests and diseases, 0 otherwise	0.73	0.02
Soil fertility perception	Dummy =1 if plot is perceived fertile, 0 otherwise	0.86	0.03

4. Results and Discussion

4.1. Determinants of Choice of Specific CSA Packages

This section discusses the factors that determine the choice of CSA packages, followed by an analysis of the impact of package use on the productivity and income of smallholder maize farmers in the final stage. This analysis was conducted using the MESR model, a two-stage regression approach. The first stage employs the multinomial logit model (MNL) to identify the factors influencing CSA package choices, which is crucial for guiding interventions aimed at enhancing CSA adoption. In the second stage, the effect of CSA package usage on household productivity and income was assessed. The marginal effects from the MNL model, which show the expected change in the probability of a specific choice occurring due to a unit change in an independent variable, are presented in Table 3. The base category was the non-use of all practices ($M_0S_0C_0F_0$), in comparison to the other nine packages utilized by farmers (see Table 2 for details on the packages). The results present nine sets of parameter estimates, each corresponding to a distinct, mutually exclusive combination of strategies. The Wald test, which tests the null hypothesis that all regression coefficients are equal to zero, was rejected. This indicates that the estimated coefficients vary significantly across the different alternative packages.

Age demonstrated a significant negative impact on the adoption of combinations such as maize-legume diversification, use of improved seeds, crop rotation, and the application of fertilizers ($M_1S_1C_1F_1$) at 10% significance level. An additional year in the age of a maize farmer decreased the probability of adopting the package $M_1S_1C_1F_1$ by 0.96%. This implies that as age increases maize farmers are less likely to use a package of $M_1S_1C_1F_1$. A possible explanation is that as maize farmers age, they accumulate more experience with the adoption of different CSA practices. As farmers grow older, they gain exposure to both the successes and challenges associated with implementing various CSA practices hence they become more risk-averse due to past experiences, making them hesitant to adopt certain combinations of CSA practices. Moreover, older maize farmers are often less educated, which may lead them to prefer relying on the knowledge and skills they have accumulated over time, making them less inclined to adopt new CSA practices. The result aligns with the conclusions drawn by [18] who found that older farmers were more risk averse in their study on determinants of soil fertility management practices in Kenya.

With regard to gender, male farmers are more likely to use packages $M_1S_1C_0F_0$, $M_1S_0C_1F_0$, $M_1S_1C_0F_1$, $M_1S_0C_1F_1$ and $M_1S_1C_1F_1$. This could be attributed to the prevailing cultural norm where men retain sole authority over farm decision-making, including both short-term and long-term adjustments. Women typically encounter barriers related to resource access and time availability. [5] highlighted that gender continues to be a major obstacle for women in adopting CSA practices, primarily due to traditional gender roles. The report also emphasized that women have less access than men to critical resources such as land, inputs, credit, education, and extension services, all of which are essential for supporting the shift to CSA practices.

Years of schooling of the maize farmers is positively correlated with adoption of $M_1S_1C_0F_1$ and $M_1S_1C_1F_1$. This imply that, as the years of schooling increases, so does the probability of using a package of $M_1S_1C_0F_1$ and $M_1S_1C_1F_1$ increases. An additional year of education resulted in an increase in the probability of using packages $M_1S_1C_0F_1$ and $M_1S_1C_1F_1$ by 0.35% and 1.44%, at 5 and 1% significance level, respectively. With more years of schooling, farmers are more likely to gain additional knowledge and skills, which enhances their access to CSA practices aimed at boosting maize income and productivity. Furthermore, they tend to be more aware of the availability of CSA practices. Therefore, schooling years increases the maize farmer's knowledge and market opportunities which could enhance the adoption of maize legume diversification, use of improved seeds, crop rotation and use of fertilisers. The result is consistent with the findings of [20], who found that more educated farmers were more likely to adopt combinations of improved agricultural technologies in Kenya.

Table 3. Marginal effect for the determinants CSA packages by multinomial logit model (dy/dx).

Variables	$M_1S_0C_0F_0$ dy/dx	$M_0S_1C_0F_0$ dy/dx	$M_1S_1C_0F_0$ dy/dx	$M_1S_0C_1F_0$ dy/dx	$M_1S_0C_0F_1$ dy/dx	$M_1S_1C_1F_0$ dy/dx	$M_1S_1C_0F_1$ dy/dx	$M_1S_0C_1F_1$ dy/dx	$M_1S_1C_1F_1$ dy/dx
Sample size (n)	41	15	37	39	10	37	55	31	85
Age (years)	0.0053	0.0014	-0.0001	-0.0006	0.0007	-0.0064	-0.0011	-0.0010	-0.0096**
Gender (male=1)	0.0632	0.0066	0.0697***	0.0235**	0.0027	0.0165	0.0409*	0.0133**	0.0836***
Years of schooling	0.0010	0.0005	0.0004	0.0001	0.0015	0.0043	0.0035**	0.0057	0.0144***
Household size	0.0103**	0.0162**	0.0176	0.0146**	0.0146**	0.0186	-0.0294	0.0046	-0.0069
Experience (years)	-0.0006	-0.0008	0.0040*	-0.0032	0.0056**	0.0063**	-0.0005	0.0015	0.0060**

Variables	$M_1S_0C_0F_0$ dy/dx	$M_0S_1C_0F_0$ dy/dx	$M_1S_1C_0F_0$ dy/dx	$M_1S_0C_1F_0$ dy/dx	$M_1S_0C_0F_1$ dy/dx	$M_1S_1C_1F_0$ dy/dx	$M_1S_1C_0F_1$ dy/dx	$M_1S_0C_1F_1$ dy/dx	$M_1S_1C_1F_1$ dy/dx
Land tenure	0.0720	-0.0510	0.0696***	0.0472**	0.0465***	0.0376**	0.0886***	0.0301***	0.2829***
Land size	-0.0660	-0.0133	0.0053*	0.0243**	-0.0165	0.0350***	0.0384	0.0215**	0. 0680***
Maize type	0.0394*	0.0563***	0.0927*	0. 0789	-0.0245	0.0414*	0.0945***	0.0045**	0.0278***
Access to contract	0.0331	-0.0026	0.0032	0.0144	-0.0171	-0.0200	0.0086	-0.0201	0.0068
Access to credit	0.3995	0.2575	0.2019	0.1977	-0.2278	0.0343	0.1569	0.1086	0.0902
Training on CSA	-0.0473	-0.0368	0.0679**	-0.0613	-0.0239	0.1039**	0.0422	0.0583	-0.0116
Group membership	0.0474	-0.0689	0.0730	0.0131	0.0102	0.0564**	0.0065	0.0933***	0.0505**
Off farm income	-0.0859	0.3498	-0.0983	-0.0489	0.0090	0.0122	-0.0158	0.0101	-0.0740
Distance to market	-0.0038	-0.0012**	-0.0032***	-0.0023**	-0.0003**	-0.0039***	-0.0025	-0. 0007***	-0.0012*
Access to climate-information	0.0254	0.0092	0.0006	0.0370	0.0531**	0.0350	0.0887***	0.0122	0.0679***
Pest and disease	-0.0010	-0.0434	-0.0205	-0.0257	-0.0000	-0.0125	0.0630	-0.0025	-0.0486
Soil fertility	-0.0262	0.0114	-0.0089	0.0190	-0.0181	-0.0443	0.0523	-0.0380	0.0216
Number of observations	384								

Notes: The reference group is $M_0S_0C_0F_0$ (no adoption of CSA practices). ***, **, * indicate significant level at 1%, 5% and 10% level respectively.

Household size was found to have a positive and statistically significant influence on the choice of $M_0S_0C_0F_0$, $M_0S_1C_0F_0$, $M_1S_0C_1F_0$, $M_1S_0C_0F_1$ and $M_1S_1C_1F_0$. The positive sign suggests that a larger household size would lead to an increase in the adoption of different combinations of CSA practices. Instead of not adopting any package, a larger household size raised the likelihood of adopting these five packages by 1.03, 1.62, 1.46 and 1.46%, at 5% significance level, respectively. The plausible reason could be that the greater the household members, the greater family labor availability which is costless, hence they have more labor available to implement and maintain these practices. Larger households may also have greater resilience to risk, enabling them to implement more advanced practices. Similar findings by [4] also revealed that larger households in Ethiopia had a higher probability of implementing various sustainable agricultural practices.

The farmers experience in maize farming is positive and statistically significant in the choice of $M_1S_1C_0F_0$, $M_1S_0C_0F_1$, $M_1S_1C_0F_1$ and $M_1S_1C_1F_1$. This implies that an increase in farming experience by 1 year increases the probability of using packages $M_1S_1C_0F_0$, $M_1S_0C_0F_1$, $M_1S_1C_0F_1$ and $M_1S_1C_1F_1$ by 0.40, 0.56, 0.63 and 0.60%, at 10 and 5% significance level, respectively. This is likely attributed to the fact that the longer the duration in maize farming, the more it is likely to influence farmer's adoption of different combinations of CSA practices so as to diversify their risks, reduce expenses and maximize profits. The findings of this study are consistent with [12], who concluded that experience helps farmers better understand the long-term benefits of sustainable practices.

Land tenure positively and significantly affects adoption of $M_1S_1C_0F_0$, $M_1S_0C_1F_0$, $M_1S_0C_0F_1$, $M_1S_1C_1F_0$, $M_1S_1C_0F_1$, $M_1S_0C_1F_1$ and $M_1S_1C_1F_1$ combinations. Land ownership, as compared to renting or other access arrangements, is anticipated to enhance long-term investment incentives in maize farming. This is likely because secure tenure provides farmers with greater confidence to make long-term investments in soil health, crop rotation, and other sustainable practices, knowing they will reap future benefits [13], also found out that secure land rights incentivized farmers to adopt practices that improved productivity and reduced soil erosion.

With regard to land size, maize farmers are likely to adopt combinations of $M_1S_1C_0F_0$, $M_1S_0C_1F_0$, $M_1S_1C_1F_0$, $M_1S_0C_1F_1$ and $M_1S_1C_1F_1$. This indicates that a 1-hectare increase in land size raised the likelihood of adopting packages $M_1S_1C_0F_0$, $M_1S_0C_1F_0$, $M_1S_1C_1F_0$, $M_1S_0C_1F_1$ and $M_1S_1C_1F_1$ by 0.53, 2.43, 3.50, 2.15 and 6.80%, respectively. Results implies that as the land size increases, probability of using different combinations of CSA practices increases. One potential rationale for this could be that larger landholdings may provide more flexibility for farmers to implement a variety of practices and dedicate sections of their land to testing or investing in new techniques without jeopardizing their entire yield. The impact of land area size complements the findings of [3], who discovered that farmers with larger landholdings are more inclined to alter their farming practices and thus possess greater capacity to invest in additional climate adaptation strategies.

Growing hybrid maize positively and significantly affects adoption of $M_1S_0C_0F_0$, $M_0S_1C_0F_0$, $M_1S_1C_0F_0$, $M_1S_1C_1F_0$, $M_1S_1C_0F_1$, M$_1$S0C$_1$F$_1$ and $M_1S_1C_1F_1$ combinations. This suggests that utilizing exotic maize varieties notably raises the probability of adopting various CSA combinations. This could be due to several factors, including better yields, disease resistance, and overall productivity associated with improved maize varieties, which may incentivize farmers to adopt sustainable practices that complement these varieties. According to [23] use of improved seed varieties enhances farmer's willingness to adopt CSA practices, as they seek to maximize the benefits from improved crops.

Training on CSA practices is statistically and positively significant at 5% levels in the choice of two combinations ($M_1S_1C_0F_0$ and $M_1S_1C_1F_0$). This implies that training on CSA practices significantly increases the likelihood of adopting packages $M_1S_1C_0F_0$ and $M_1S_1C_1F_0$ by 6.79% and 10.39% at 5% significance level, respectively. Training provides farmers with critical knowledge and skills, empowering them to implement these practices effectively. Training can also guide farmers on how to select appropriate CSA combinations and manage them for optimal results, this, in turn, boosts the uptake of CSA practices. [24], indicated that targeted training could effectively address barriers to adoption, enhancing the likelihood of implementing sustainable practices.

With regard to group membership, maize farmers who belong to farmers group are likely to adopt combinations of $M_1S_1C_1F_0$, M1S$_0$C$_1$F$_1$ and $M_1S_1C_1F_1$. Being part of a farmer group enhanced the likelihood of adopting these three packages by 5.64%, 9.33%, and 5.05%, respectively, compared to not using any package. Group membership can foster collaboration, support, and knowledge exchange among farmers, resulting in increased uptake of CSA practices. Thus, through access to group membership, maize farmers explore various combinations of CSA practices aiming to enhance profitability while reducing production costs. The results are similar to [16], who found that group membership significantly enhanced the likelihood of adopting new practices due to increased access to information, resources, and peer support.

The proximity to the nearest output market exhibited a significant negative relationship at 5% and 1% levels, with $M_0S_1C_0F_0$, $M_1S_1C_0F_0$, $M_1S_0C_1F_0$, $M_1S_0C_0F_1$, $M_1S_1C_1F_0$, $M_1S_1C_0F_1$ and $M_1S_1C_1F_1$ combinations. A 1-kilometer increase in the distance to the output market lowered the likelihood of package utilization of $M_0S_1C_0F_0$, $M_1S_1C_0F_0$, $M_1S_0C_1F_0$, $M_1S_0C_0F_1$, $M_1S_1C_1F_0$, $M_1S_1C_0F_1$ and $M_1S_1C_1F_1$ by 0.12, 0.32, 0.23, 0.03, 0.39, 0.07 and 0.12%, respectively. This is logical because, increased distance raises barriers to adoption, as farmers face higher transportation and transaction costs and challenges in accessing necessary resources. These findings align with those reported by [1] who revealed that distance to output market negatively influences the adoption of sustainable agricultural practices in Central America.

Access to climate information positively and significantly affects adoption of $M_1S_0C_0F_1$, $M_1S_1C_0F_1$ and $M_1S_1C_1F_1$ combinations. Instead of not adopting any package, having access to climate information increased the probability of using these three packages by 5.31%, 8.87% and 6.79%, respectively. This implies that farmers who have access to climate information are more likely to adopt specific CSA practices combinations. A plausible explanation is that it empowers farmers with the knowledge to make informed decisions about when to plant, what crops to choose, and how to manage resources effectively in the face of climate variability. The results are consistent with findings by [26], who concluded that improved access to climate data and forecasts enabled farmers to optimize their agricultural strategies, leading to enhanced adoption of sustainable practices.

4.2. Average Treatment Effects of Adopting CSA Packages

After identifying the factors influencing the selection of CSA packages in the first stage, the second stage focused on estimating treatment effects to assess the impact of package utilization on productivity and income. An ordinary least squares regression was conducted to estimate maize productivity and household income for each CSA practice combination, incorporating selection bias correction terms from the first stage. At this stage, the treatment effects, which form the core of the analysis, were reported. The estimates for maize productivity and income were derived using the MESR model, capturing both ATT and ATU effects. Table 4 presents the average effects of CSA adoption on productivity and income under both actual and counterfactual scenarios. In this table, X_1 represents adopters, while X_2 denotes non-adopters. Similarly, β_1 corresponds to the characteristics of adopters (adoption state), whereas β_2 reflects the characteristics of non-adopters (non-adoption state). The heterogeneity effect measures the difference in productivity and income resulting from the adoption of a given package. This impact is determined by the difference between the treated group (ATT) with adoption characteristics and the untreated group (ATU) with non-adoption characteristics, expressed as $(\beta_1 X_1) - (\beta_2 X_2)$.

The results indicate that maize productivity increases most significantly when farmers adopt all four CSA practices ($M_1S_1C_1F_1$), resulting in a rise of 3.56 units. The adoption of $M_1S_0C_0F_1$, $M_1S_1C_1F_0$, $M_1S_1C_0F_1$ and $M_1S_1C_1F_1$ shows a statistically significant ATU value at the 1% level. The result indicates that CSA non-adopters would increase their productivity if they adopted combinations of CSA by about 4.9, 2.43, 3.02 and 2.76 units, respectively. In contrast, the CSA combinations of $M_1S_0C_0F_0$ and $M_1S_0C_1F_0$ has a significant negative effect on maize productivity for non-adopters, with a decrease of 1.61 and 1.83 units, respectively. This negative effect may be attributed to the fact that maize-legume diversification and crop rotation typically offer long-term benefits, such as enhanced soil structure and nutrient availability. However, these benefits might not result in immediate yield improvements, especially in small-scale farming contexts. Non-adopters may, therefore, find it more beneficial to stick with their current practices rather than adopting these specific CSA combinations. This aligns with findings in the literature that emphasize the benefits of combined CSA strategies on productivity gains [4].

Regarding maize income, both ATT and ATU effects show positive outcomes for farmers using combinations of $M_1S_1C_0F_1$ and $M_1S_1C_1F_1$. These combinations not only increased the income of adopters but also have the potential to improve the income of non-adopters if they adopted these practices. Specifically, the income gains for adopters using $M_1S_1C_0F_1$ and $M_1S_1C_1F_1$ are BWP 1009.45 and BWP 3961.17, respectively. For non-adopters, adopting these combinations could lead to income improvements of BWP 1547.97 and BWP 2293.85, respectively. The significant income reductions observed among non-adopters in the CSA combinations, specifically BWP 1,658.31 for $M_1S_0C_0F_0$, BWP 2,140.59 for $M_0S_0C_0F_0$, BWP 918.96 for $M_1S_1C_0F_0$, and BWP 2,957.98 for $M_1S_0C_1F_0$ suggest that partial adoption of CSA practices may be less effective than full adoption. Research indicates that while individual CSA practices can enhance income compared to non-adoption, the most substantial income gains are achieved when farmers implement a comprehensive suite of CSA practices. The results show that income increases most significantly when farmers adopt all four CSA practices ($M_1S_1C_1F_1$), leading to an increase of BWP 3691.17. These results are consistent with [17], who reported that adopting a combination of CSA practices significantly enhances both maize yields and income compared to adopting individual CSA practices. This suggests that encouraging smallholder farmers to adopt a holistic set of CSA practices could lead to greater economic and productivity benefits.

Table 4. The average impact of CSA practice selection on maize productivity and income: Estimation from MESR Model.

		Maize productivity			Maize income		
Climate-Smart Agriculture Practices (CSA) Combinations		**Adopters (β_1)**	**Non- adopters (β_2)**	**Impact (ATT/ATU)**	**Adopters (β_1)**	**Non-adopters (β_2)**	**Impact (ATT/ATU)**
$M_1S_0C_0F_0$	Adopters (X_1)	11.3	12.77	-1.47***	4629.51	6160.60	-1531.09***
	Non-adopters (X_2)	11.26	12.87	-1.61***	4559.27	6207.58	-1658.31***
	Heterogeneity effect	0.04	-0.1	0.14	70.24	-46.58	117.22
$M_0S_1C_0F_0$	Adopter	9.72	12.61	-3.08	5378.00	6498.74	-1120.74***
	Non-adopter	0.28	12.80	-12.52	3925.37	6065.96	-2140.59***
	Heterogeneity effect	9.44	-0.19	9.63	1452.63	432.78	1019.85
$M_1S_1C_0F_0$	Adopters	12.24	12.85	-0.61	5464.85	5961.31	-496.46*
	Non-adopters	12.38	12.73	-0.35	5181.04	6100.00	-918.96***
	Heterogeneity effect	-0.14	0.12	-0.26	283.81	-138.69	422.50
$M_1S_0C_1F_0$	Adopters	11.40	12.40	-1.00	5414.10	6359.90	-695.64***
	Non-adopters	11.00	12.83	-1.83***	5814.52	6109.74	-2957.98***
	Heterogeneity effect	0.40	-0.43	0.83	-400.42	250.16	-650.58
$M_1S_0C_0F_1$	Adopters	12.25	13.40	-1.15	5394.00	6108.95	-714.95
	Non-adopters	17.64	12.69	4.95***	6283.07	6056.34	226.73
	Heterogeneity effect	-5.39	0.71	-6.10	-889.07	52.61	-941.68
$M_1S_1C_1F_0$	Adopters	13.76	12.34	1.42***	6340.51	6425.56	-85.05
	Non-adopters	15.00	12.57	2.43***	5232.23	6006.95	-774.72***
	Heterogeneity effect	-1.24	-0.23	-1.01	1108.28	418.61	689.67
$M_1S_1C_0F_1$	Adopters	14.86	12.65	2.21***	6528.18	5518.74	1009.44***

Climate-Smart Agriculture Practices (CSA) Combinations		Maize productivity Adopters (β_1)	Non- adopters (β_2)	Impact (ATT/ATU)	Maize income Adopters (β_1)	Non-adopters (β_2)	Impact (ATT/ATU)
	Non-adopters	15.34	12.32	3.02***	7505.29	5957.33	1547.96***
	Heterogeneity effect	-3.6	-2.2	-1.4	-977.11	-438.59	-538.52
$M_1S_0C_1F_1$	Adopters	12.96	12.85	0.11	6064.52	6019.33	45.19
	Non-adopters	12.89	12.65	0.24	6385.15	6036.86	348.29***
	Heterogeneity effect	0.07	0.2	-0.13	-320.63	-17.53	-303.10
$M_1S_1C_1F_1$	Adopters	15.55	11.99	3.56***	9267.79	5576.62	3691.17***
	Non-adopters	15.10	12.34	2.76***	7665.82	5372.03	2293.79***
	Heterogeneity effect	-0.45	0.35	-0.8	-1601.87	-204.59	-1397.28

Note: M=Maize-legume diversification, S=Use of improved seeds, C=Crop rotation, F= Use of fertilisers. ***, **, * indicate significant level at 1%, 5% and 10% level respectively. The exchange rate is BWP1= US$0.076

5. Conclusions and Policy Implications

Climate change presents substantial challenges in sub-Saharan Africa (SSA), limiting rural farm households' ability to enhance productivity and income. This study employs survey data to analyze the factors influencing the adoption of four interdependent CSA practices (maize-legume diversification, use of improved seeds, crop rotation, and fertilizer application) and their combined impacts on maize productivity and income in Botswana. To correct for selection bias and endogeneity resulting from both observable and unobservable factors, the study applies a MESR model.

The findings from the MNL model reveal that the probability of adopting CSA practices is shaped by a combination of socioeconomic, household and institutional factors. Key determinants include age, gender, education level, farming experience, land size, livestock ownership, group membership, and distance to output markets, land tenure systems, and access to climate information. These results underscore the need for policies and programs by governments and development partners to improve the uptake of various interconnected CSA practices. For example, the strong positive relationship between access to training and CSA adoption highlights the importance of providing targeted training that equips farmers with knowledge on the benefits of CSA practices.

Among the CSA combinations analyzed, the most comprehensive package; incorporating maize-legume diversification, improved seeds, crop rotation, and fertilizer use ($M_1S_1C_1F_1$) demonstrates the greatest impact on maize productivity and income. This package help improves soil fertility and structure, enhance crop resilience, and reduce soil degradation, ultimately contributing to greater production stability under diverse field and soil conditions. To maximize benefits, farmers are encouraged to adopt integrated CSA approaches that combine multiple practices. Additionally, the study reveals that the adoption of CSA practices leads to a notable increase in both maize productivity and farmer income. Considering the beneficial impacts of adopting CSA practices on productivity and income, efforts should focus on raising farmers' awareness of alternative CSA practices and supporting their adoption. It is crucial for researchers, extension officers, and policy designers to identify the optimal combinations of CSA practices that ensure maximum benefits in terms of productivity and income. Through this approach, CSA can be successfully expanded to strengthen the resilience and sustainability of smallholder farming systems in Botswana.

Abbreviations

AERC	African Economic Research Consortium
ATT	Average Treatment Effects on the Treated
ATU	Average Treatment Effect on Untreated
BWP	Botswana Pula
CSA	Climate-smart Agriculture
MNL	Multinomial Logit Model
MESR	Multinomial Endogenous Switching Regression
NED	North East District
SSA	Sub- Saharan Africa

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Author Contributions

Moitlamo Ookeditse Mpinda: Conceptualization, Data curation, Formal Analysis, Methodology, Software, Visualization, Writing – original draft

Hillary Kiplangat Bett: Conceptualization, Investigation, Supervision, Validation, Visualization, Writing – review & editing

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Data Availability Statement

The data for this study can be obtained from the Department of Agricultural Economics and Agribusiness Management at Egerton University, Kenya, as well as from the authors. Access to the data is granted upon special request, with approval from both the department and the authors.

Conflicts of Interest

The authors declare no conflicts of interest.

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