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ORIGINAL ARTICLE

Farmers' adoption of multiple climate-smart agricultural technologies in Ghana: determinants and impacts on maize yields and net farm income

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Abstract

This study investigates the factors affecting maize farmers' decisions to adopt climate-smart agricultural (CSA) technologies and estimates the impacts of CSA technology adoption on maize yields and net farm income. Unlike most previous studies that analyze a single technology, we consider different combinations of three CSA technologies (zero tillage, row planting, and drought-resistant seed). A multinomial endogenous switching regression model addresses selection bias issues arising from observed and unobserved factors and analyses data collected from 3197 smallholder farmers in three Ghana regions (Brong-Ahafo, Northern, and Ashanti). The findings show that smallholder farmers' decisions to adopt multiple CSA technologies are influenced by farmer-based organization membership, education, resource constraints such as lack of land, access to markets, and production shocks such as perceived pest and disease stress and drought. We also find that adopting all three CSA technologies together has the largest impact on maize yields, while adopting row planting and zero tillage as a combination has the largest impact on net farm income. Governments should collaborate with farmer-based groups and extension officers to improve farmers' awareness and understanding of the benefits associated with CSA technologies and help them adopt multiple technologies that generate higher benefits.

Keywords Climate-smart agriculture · Maize yields · Net farm income · MESR model · Ghana

JEL Classification C21 · P36 · Q54

1 Introduction

Smallholder farmers in Africa are the largest private sector group, accounting for roughly 70% of the population in the continent (Alliance for a Green Revolution in Africa, AGRA 2017). These farmers cultivate fewer than 2 hectares of land, relying heavily on traditional farming practices. However, traditional farming practices are usually not sustainable. They are associated with poor soil fertility and lower productivity, leading to food insecurity and poverty (Kassie et al. 2015; Grabowski et al. 2016; Quarshie et al. 2023; Tabe-Ojong et al.

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2023; Wakweya 2023). In addition, African smallholder farmers are typically the most vulnerable to climate risks, resulting in weak farming system resilience.

Development partners and climate action stakeholders have made great efforts to promote farmers' adoption of climate-smart agricultural (CSA) technologies to mitigate the negative impacts of climate change on agriculture and improve farm performance. For example, there is a widespread promotion of drought-tolerant maize and stress-tolerant maize seeds among smallholder farmers to reduce their potential risk of meagre yields or total crop failure caused by erratic and low rainfall patterns in various maize-producing ecologies (Fisher et al. 2015; Setimela et al. 2017; Simtowe et al. 2019; Gebre et al. 2021). Other key CSA technologies, such as row planting and zero tillage, have also been promoted to help increase crop yields and income, as well as build climate resilience (Teklewold and Mekonnen 2017; Fentie and Beyene 2019; Martey et al. 2021). Sova et al. (2018) emphasized that the CSA technologies are especially suited to households that rely on rainfed agriculture, such as those in dryland areas of Africa and other parts of the world.

Like other SSA countries, smallholder farmers in Ghana are subject to climatic shocks. Therefore, the National Climate Change Policy has adopted CSA practices and technologies as a component of sustainable agricultural development policy (Atta-Aidoo et al. 2022). Despite the implementation of various initiatives aimed at promoting the adoption of CSA practices, the adoption rate among smallholder farmers in several regions of Ghana is still low (Martey et al. 2021; Atta-Aidoo et al. 2022; Tetteh Quarshie et al. 2023). As a result, evidence is required to comprehensively understand the drivers and barriers in CSA technology adoption to develop policies and programs that effectively address this issue.

Some studies in Africa have examined the impact of adopting CSA technologies on farm performance, focusing on the adoption of a single agricultural technology (Manda et al. 2016, 2018; Ng'ombe et al 2017; Teklewold and Mekonnen 2017; Martey et al. 2021). For example, Fentie and Beyene (2019) concluded that row planting positively impacts per-hectare crop income in Ethiopia. In practice, some farmers adopt a combination of technologies rather than one technology to address production challenges such as climate change and unexpected shocks. In this case, studies focusing on the effects of a single technology may overlook the importance of other complementary technologies that farmers may adopt to address such challenges.

This paper investigates the association between CSA technology adoption and farm performance, captured by maize yields and net farm income. We analyze data collected from 3197 smallholder farmers in Ghana's three regions (Brong-Ahafo, Northern, and Ashanti). These three regions are selected based on their status as the leading maize producers in Ghana. We focus on three CSA technologies in this study: row planting, zero tillage, and drought-tolerant maize seeds. We concentrated on these three technologies because they were the only ones disseminated to the maize farmers in our sample. Row planting is critical for improved soil fertility, temperature regulation, and moisture management. Drought-tolerant maize seeds are critical for stress (drought, heat, disease, and pest) management, whereas zero tillage is important for reducing soil erosion and increasing soil biological activity.

We attempt to make three contributions to the literature on climate-smart agriculture. First, we explore the factors affecting maize farmers' decisions to adopt different combinations of CSA technologies. To achieve this, we categorize the three CSA technologies (row planting, zero tillage, and drought-tolerant maize seeds) into eight groups by considering non-adoption, adopting only one type of technology, combining one technology with another, and adopting all three technologies. Second, we examine the impact of CSA adoption on maize yields and net farm income. As an exception, Martey et al. (2020) explored the impacts of adopting row planting and drought-tolerant maize varieties on the yields and intensity of maize commercialization. Still, they did not consider the adoption of zero tillage. Third, we employ the multinomial endogenous switching regression (MESR) model to address the selection bias issues arising from both observed factors (e.g., age, gender, farm size, and household size) and unobserved factors (e.g., farmers' innate ability and motivations). The MESR model acknowledges that farmers choose one of those eight technology options to maximize the expected benefit. The policy implications are significant. Identifying determinants that influence smallholder farmers' adoption of single or multiple CSA technologies could provide valuable insights into the effectiveness of various information channels, such as radio, extension services, and FBOs, in facilitating CSA technology adoption.

The remainder of the paper is structured as follows. The review of the literature is presented in Sect. 2. The econometric framework is introduced in Sect. 3, and the survey sites, data, and descriptive statistics are presented in Sect. 4. Section 5 presents and discusses the empirical results. The final section summarizes the findings, suggests policy implications, and discusses the limitations.

2 Literature review

Many studies have been conducted globally to investigate the factors influencing the adoption of CSA technologies in smallholder farming systems in Africa. There exist two strands of literature. The first strand of literature considers the single CSA technology, such as improved crop varieties and row planting (Teklewold et al. 2013; Keil et al. 2017; Amadu et al. 2020; Manda et al. 2020a; Martey et al. 2020; Ehiakpor et al. 2021; Guo et al. 2022; Mossie 2022). For example, Manda et al. (2018) found that socioeconomic, farm-level, and institutional factors influence farmers' decisions to adopt improved maize varieties in Zambia. Ayal et al. (2018) investigated the factors influencing row planting adoption in Ethiopia. They found that household heads' educational levels, family labor, farm size, membership in training and associations, and livestock ownership positively and significantly impact row planting adoption. According to Martey et al. (2020), the main factors influencing farmers' adoption of drought-tolerant maize varieties in Ghana are access to seeds and extension, gender, labor availability, and location. Kimathi et al. (2021) found that access to information, quality seeds, training, group membership, and variations in agroecological zones are the most important factors influencing farmers' decisions to adopt climate-resilient potato varieties.

The second strand of literature has investigated the factors that influence smallholder farmers' decisions to adopt multiple agricultural innovations/technologies (Makate et al. 2019; Ehiakpor et al. 2021; Bese et al. 2021; Antwi-Agyei and Amanor 2023; Jones et al. 2023). For example, Makate et al. (2019) found that access to extension, fertilizer, credit, marital status, experience, and residential status are the main factors affecting farmers' adoption of multiple CSA innovations (conservation agriculture, improved legume, and drought-tolerant maize) in Malawi and Zimbabwe. Amadu et al. (2020) found that program participation has a positive and statistically significant effect on the adoption of CSA practices (residue addition, non-woody plant cultivation, assisted regeneration, woody plant cultivation, physical infrastructure, and mixed measures) in general, with the strongest effects on resource-intensive CSA categories in southern Malawi. Ehiakpor et al. (2021) found that off-farm income, perceived low soil fertility, pest and disease incidence, experience, field demonstration and group membership, land ownership, distance to market, and credit access all influence the adoption of multiple sustainable practices (e.g., adoption of improved maize seeds, maize-legume rotation, animal manure, legume intercropping, and crop residue retention). By estimating data from southern Ghana, Jones et al. (2023) reported a positive relationship between mobile phone agriculture extension delivery and the adoption of CSA practices.

In addition to the factors influencing CSA technology adoption, the existing studies have also assessed the effects of CSA technology adoption. Most of those studies have focused on the impact of adopting a single CSA technology on various outcome variables such as farm income, agrochemical use, labor demand, crop yields, and poverty (Manda et al. 2016; Ng'ombe et al. 2017; Teklewold and Mekonnen 2017; Martey et al. 2020). Only a few studies have assessed the effects of adopting multiple CSA technologies (Gebremariam and Wünscher 2016; Manda et al. 2016; Khonje et al. 2018; Makate et al. 2019). For example, Makate et al. (2019) found that adopting CSA technologies (conservation agriculture, improved legumes, and drought-tolerant maize) increases farm productivity and income in southern Africa than using them separately. Khonje et al. (2018) demonstrated that in Zambia, the simultaneous adoption of innovative technologies (improved maize varieties and conservation agriculture practices) has a greater impact on farm output, income, and poverty than individual innovation package adoption.

Although the studies above have provided rich insights into the factors influencing CSA technology adoption and its impacts, significant research gaps remain. Specifically, most previous research on the adoption of multiple CSA technologies has focused on Eastern and Southern African countries (Teklewold et al. 2013; Makate et al. 2019; Bese et al. 2021), with little focus on West African countries such as Ghana (Ehiakpor et al. 2021; Lu et al. 2021; Faye et al. 2021; Setsoafia et al. 2022). The maize production environment in West Africa differs from that in Southern and Eastern Africa due to different varieties and production practices. In their meta-analysis, Xie and Huang (2021) emphasized that technology adoption is heterogeneous, so policymakers and other stakeholders must consider geographical differences and farming systems, the technology needs of different farmers, and costs when designing policies to encourage the adoption of agricultural technologies. Given that no predefined combinations of CSA technologies work in every environment, it has been claimed that adopting CSA technologies is context-specific (Amadu et al. 2020; Xie and Huang 2021). As a result, empirical studies demonstrating the impact of CSA technologies in various environmental settings are critical for designing policies and technologies. This study adds to the literature by examining how adopting CSA technologies, specifically row planting, zero tillage, and drought-tolerant maize seeds, affects maize yields and net farm income in Ghana.

3 Econometric framework

3.1 Selection bias issue and model selection

Agriculture is risky, especially in much of the developing world, where farmers rely heavily on rainfall, plant in degraded soils, face pest and disease outbreaks, and frequently lack access to high-quality inputs or markets (Sova et al. 2018). These external shocks may prompt smallholder farmers to adopt CSA technologies to mitigate crop production shocks. Farmers' decisions to adopt one of the CSA technologies can be influenced by socioeconomic factors that can be observed (e.g., age, gender, size of the farm, and years of education) as well as factors that cannot be observed (e.g., motivations and managerial skills) (Kassie et al. 2013; Teklewold et al. 2013; Manda et al. 2016; Ehiakpor et al. 2021). Due to self-selection issues, farmers who adopt CSA technologies may systematically differ from those who do not adopt the technologies regarding observed and unobserved characteristics. It should be emphasized that any selection bias issues that arise should be addressed to estimate the impacts of CSA technology adoption on farm performance consistently.

When technology adoption is a binary decision (i.e., adoption or non-adoption), approaches such as the propensity score matching (PSM) model (Ma et al., 2022) or endogenous switching regression (ESR) model (Liu et al. 2021; Zheng et al. 2021) can be used to estimate its impact. However, when technology adoption involves multiple choices, PSM and ESR models become inefficient in addressing selection bias issues. In this case, previous studies have suggested using the multinomial endogenous switching regression (MESR) model (Kassie et al. 2015; Lu et al. 2021; Oparinde 2021; Ahmed 2022; Asante et al. 2023) and multivalued treatment effects (MVTE) model (Cattaneo 2010; Lu et al. 2021; Ma and Zheng 2021; Czyżewski et al. 2022; Asante et al. 2023). The MESR model enables one to account for both observed and unobserved factors when addressing the selection bias issues, while the MVTE model only mitigates the observed selection bias issues. Because the MVTE model has limitations in addressing unobserved selection bias, we use the MESR model in this study to estimate the treatment effects of CSA technology adoption on farm performance.

3.2 Multinomial endogenous switching regression

The MESR model consists of three steps. The first stage is to investigate the factors influencing farmers' decisions to adopt the three CSA technologies: drought-resistant seeds (D), row planting (R), and zero tillage (Z). These three CSA technologies can present eight options for an individual farmer. If a farmer chooses not to adopt the three CSA technologies, it can be recorded as (1) non-adoption ($D_0R_0Z_0$). That is, farmers did not adopt any of those three CSA technologies. Adopters have seven options which are (2) drought-resistant seeds only ($D_1R_0Z_0$); (3) row planting only ($D_0R_1Z_0$); (4) zero tillage only ($D_0R_0Z_1$); (5) drought-resistant seeds and row planting ($D_1R_1Z_0$); (6) drought-resistant seeds and zero tillage ($D_1R_0Z_1$); (7) row planting and zero tillage ($D_0R_1Z_1$); and (8) combination of drought-resistant seed, row planting and zero tillage ($D_1R_1Z_1$). These eight combinations are all mutually exclusive. An individual farmer, therefore, chooses one of those eight possible options in farm production to maximize their expected benefits.

We assume that the random terms are identical and independently distributed based on the Gumbel distribution, with the likelihood that an ith farmer with H_i attributes would select jth CSA technology from those eight possible options. This is captured by a multinomial logit (MNL) model within the MESR model framework (Ma et al. 2022; Teklewold et al. 2013; Zhou et al. 2020), which is specified as follows:

$$L_{ij} = \Pr\left(\vartheta_{ij} < 0 | H_i\right) = \frac{\exp(H_i\alpha_j)}{\sum_{s=1}^{j}\exp(H_i\alpha_j)} \quad j = 1, 2, \ldots, 8 \tag{1}$$

where L_{ij} refers to the likelihood that ith farmer selects to adopt jth CSA technology; H_i is a vector of observed explanatory factors captured by household, farm level, institutional and location variables; α_j is a vector of parameters to be estimated.

In the second step of the MESR model, an ordinary least squares (OLS) approach was employed to examine the relationship between a set of explanatory variables (represented as X_i) and outcome variables (i.e., maize yields and net farm income). The non-adoption ($D_0R_0Z_0$) of the CSA technology is represented by $j = 1$, while other combinations are represented by $j = 2, 3, 4, \dots, 8$. Thus, we express each regime of equations as follows:

$$\begin{cases} Regime\ 1: W_{i1} = X_i\beta_1 + \mu_{i1}\ if\ I = 1 \\ . \\ . \\ . \\ Regime\ J: W_{iJ} = X_i\beta_J + \mu_{iJ}\ if\ I = J \end{cases} \tag{2}$$

where W_{iJ} refers to the outcome variable for the ith farmer when adopting CSA technology J; X_i indicates a vector of explanatory variables; β_1 and β_J are parameters to be estimated; μ_{i1} and μ_{iJ} refer to disturbance terms.

In Eq. (2), X_i could help address the observed selection bias issues. However, when the same unobserved factors (e.g., farmers' innate abilities and aspirations) influence farmers' decisions to adopt CSA technologies and outcome variables simultaneously, the disturbance terms in Eqs. (1) and (2) will be correlated. If the correlation coefficients of the disturbance terms do not equal zero, selection bias issues occur (Setsoafia et al. 2022). Failure to account for such an issue may result in biased and inconsistent estimates. Therefore, the MESR model includes the selectivity-correction terms computed after estimating Eq. (1) and automatically fit into Eq. (2) to eliminate the unobserved selection bias. By including the selectivity-correction terms, Eq. (2) can be rewritten as follows:

$$\begin{cases} Regime\ 1: W_{i1} = X_i\beta_1 + \lambda_1\sigma_1 + \varepsilon_{i1}\ if\ I = 1 \\ . \\ . \\ . \\ Regime\ J: W_{iJ} = X_i\beta_J + \lambda_J\sigma_J + \varepsilon_{iJ}\ if\ I = J \end{cases} \tag{3}$$

where λ_1 and λ_J refer to selectivity-correction terms; σ_1 and σ_J are covariances between disturbance errors in Eqs. (1) and (2). The rest of the parameters are already defined from the above equations. Further, the multinomial selection framework allows for $J - 1$ selectivity-correction terms where one represents each option of CSA technology combination.

According to Di Falco et al. (2011) and Asante et al. (2023), estimations of the MESR model must include at least one instrumental variable (IV) for model identification. The employed IV is included in the H_i of the MNL model in Eq. (1), but not in the X_i of the outcome Eq. (2). In this paper, we use four information variables (i.e., membership of a farmer-based group, information from radio, colleague farmer, and extension contacts) as IVs for the identification purpose of the model. The selected IVs are not expected to influence maize yields and net farm income directly. The validity of these IVs was evaluated using the falsification test (Di Falco et al. 2011; Ma and Zheng 2021; Asante et al. 2023) and Pearson correlation analysis (Asante et al. 2023; Ma and Zheng 2021; Ma et al. 2022). Tables 5 and 6 in the Appendix present the validation results for the instruments.

In the third stage, the average treatment effect on the treated (ATT) is computed by comparing the expected outcome variables of CSA technology adopters and non-adopters. In practice, estimating the impacts on experimental data is easier, whereas it is quite challenging to establish the impacts using cross-sectional data. The MESR model helps calculate the counterfactual outcome (i.e., the outcome of CSA technology adopters if they had not adopted the CSA technology), making the calculation of ATT possible. Following previous studies (see Ahmed 2022; Asante et al. 2023; Kassie et al. 2015; Oparinde 2021), the ATT estimates for the actual and counterfactual scenarios are derived using the following equations.

CSA technology adopters with adoption (actual adoption observed):

$$\begin{cases} E\left(W_{i2}|I=2\right)=X_i\beta_2+\lambda_2\sigma_2 \\ . \\ . \\ . \\ E\left(W_{iJ}|I=J\right)=X_i\beta_J+\lambda_J\sigma_J \end{cases} \tag{4}$$

The CSA technology adopters had they decided not to adopt (counterfactual):

$$\begin{cases} E\left(W_{i1}|I=2\right)=X_i\beta_1+\lambda_1\sigma_1 \\ . \\ . \\ . \\ E\left(W_{iJ}|I=J\right)=X_i\beta_1+\lambda_J\sigma_1 \end{cases} \tag{5}$$

Finally, subtracting Eq. (5) from Eq. (4) gives the ATT. It is specified as

$$\mathrm{ATT}=E\left[\left(W_{i2}|I=2\right)-E\left(W_{i1}|I=2\right)\right]=X_i\left(\beta_2-\beta_1\right)+\lambda_2(\sigma_2-\sigma_1) \tag{6}$$

4 Survey sites, data, and descriptive statistics

4.1 Survey sites

The data used in the present study were collected from Ghana's Brong-Ahafo, Northern, and Ashanti regions (Fig. 1) from August to September 2022. These three regions are considered in our analysis because they account for most maize production in Ghana (Kankam-Boadu et al. 2018; Food and Agriculture Organization 2019). The Brong-Ahafo region is in the southern half of the country between longitude 0° 15′ E-3° W and 8° 45′ N-7° 30′ S. The region is bordered on the north by the Northern region, the south by the Ashanti and Western regions, the east by the Volta region, and the west by the Eastern region. Its population is 2,282,128, and 69.1% is engaged in agriculture (Ghana Statistical Services 2021). The region has fertile soils, favorable climatic conditions, and a diverse vegetation cover. It is also considered an agricultural-based economic activity in Ghana, contributing about 30% of its food supply (GSS 2021).

The Northern region, located in northern Ghana, covers a total area of 70,384 km^2. The region lies approximately within N 9° 32′ 38.1372″, W 0° 54′ 20.3832 and is bordered on the west by the Savannah region, on the east by the international border with Togo, on the

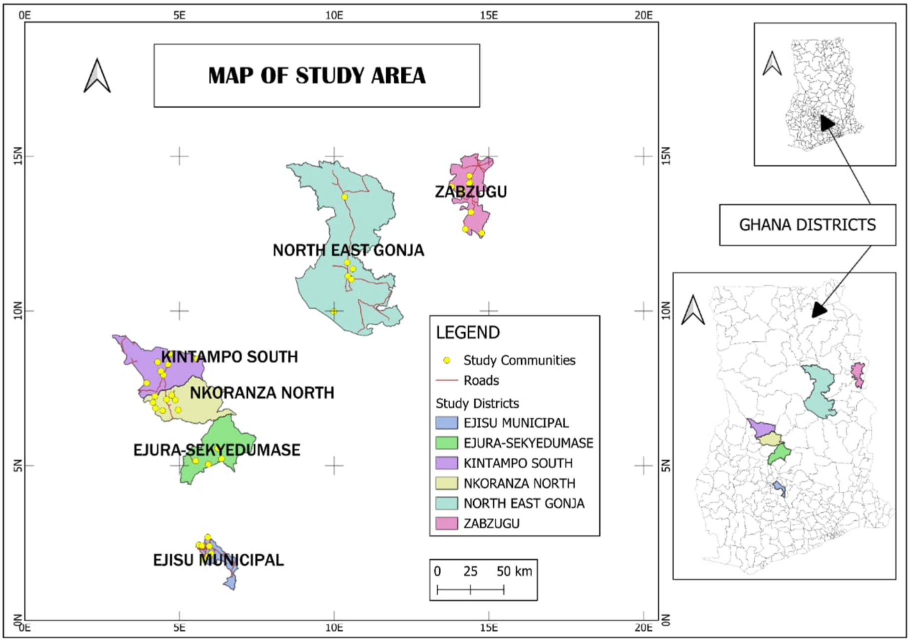

Fig. 1 Map of the study area

south by the Oti region, and in the north by the North East region. The Northern region has a population of approximately 1,948,913 people (GSS 2021), with agriculture being the primary source of income for approximately 75% of the population, primarily cultivating sorghum, cowpea, millet, and maize. The region lies within the Guinea Savannah agroecological zone, characterized by aridity, densely clustered grassland, and drought-resistant trees. Temperatures in the region range from 14 °C at night to 40 °C during the day.

The Ashanti region, located in the center of Ghana, has a total land area of 24,389 km^2 and is located between longitudes 0.15° E and 2.25° W and latitudes 5.50° N and 7.46° S. The region shares its southern, northern, western, and eastern borders with the Central, Bono East, Western, and Eastern regions. With a population of 5,924,498 in 2020, the Ashanti region was Ghana's most populous (GSS 2021). Agriculture is the primary source of income for the majority of the population in the region. The region has a bimodal rainfall pattern, with annual precipitation ranging from 1300 to 1500 mm (GSS 2021), and relatively rich soils supporting major crops such as maize, rice, roots and tubers, and sorghum.

4.2 Data

A total of 3197 maize farmers were sampled from six districts (Nkoranza North, Kintampo South, Ejura-Sekyeredumasi, Zabzugu, Ejisu municipal and Northeast Gonja), two districts for each of the three regions (Brong-Ahafo, Northern and Ashanti). A multistage sampling technique was used to select a district purposively, in which three communities were purposively sampled in each district, and 180 farmers were also randomly selected to obtain a total of 540 from each district. Each region had a sample size of 1080 maize farmers. The final analysis included a sample of 3197 farmers (see Fig. 2 for the methodological flow

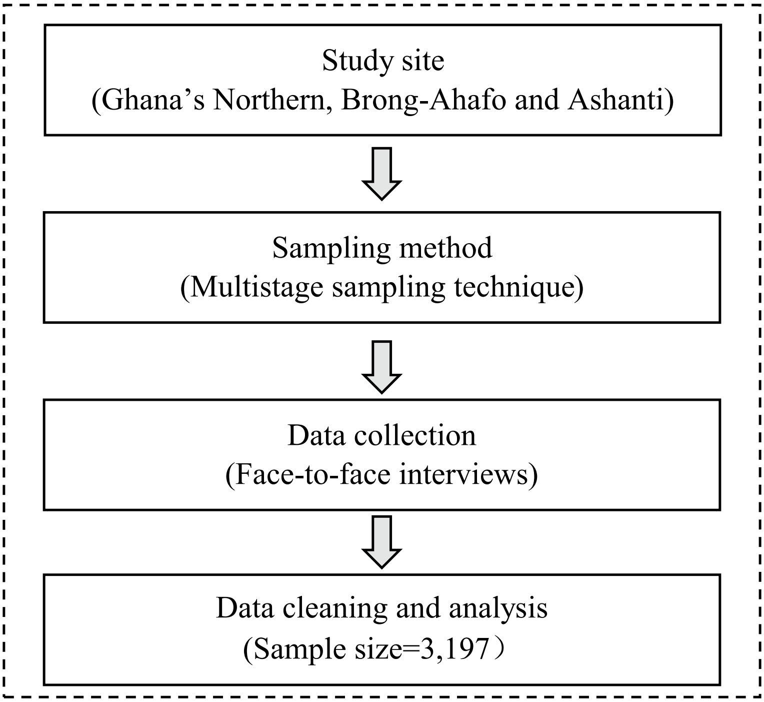

Fig. 2 Survey methodological flow diagram

chart). The data have various socioeconomic characteristics, agricultural land holdings, maize outputs and sales, livestock production, farmers' access to CSA technology information, institutional factors, and income.

Following previous studies that estimate the impact of adopting CSA technologies and other agricultural innovations (e.g., Bopp et al. 2019; Kassie et al. 2013; Ma and Wang 2020; Ma and Zheng 2021; Manda et al. 2016; Setsoafia et al. 2022; Teklewold et al. 2013) we consider two outcome variables: maize yields and net farm income. The maize yields are measured by the maize output per unit of land during the 2021/2022 production season, i.e., kg/acre. The net farm income refers to the difference between the gross revenue of maize production and the maize production costs of all variable inputs (such as labor, seed, agrochemicals, and fertilizers), which is measured at GHS/acre.

4.3 Descriptive statistics

Table 1 shows the definitions and summary attributes of farmers. The average maize yields are 2490 kg/acre, and the net farm income is 3716 GHS/acre. Of the sampled farmers, 86.6% are males, and their mean age is 47.49 years. Most of the farmers (86.5%) were married, with a mean family size of 6.7. A typical farmer has 8.91 years of formal education and 21.32 years of farming experience. Fifty-five percent of farmers were members of farmer-based organizations. Approximately 58.7% of farmers received CSA technology information from extension agents, while 83.9% and 41.3% received it from colleague farmers and radio, respectively.

Table 1 Descriptions and summary statistics by combinations of CSA technologies

Variables	Measurement	Full sample		$D_0R_0Z_0$	$D_1R_0Z_0$	$D_0R_1Z_0$	$D_0R_0Z_1$	$D_1R_1Z_0$	$D_1R_0Z_1$	$D_0R_1Z_1$	$D_1R_1Z_1$
		Mean	Std. Dev	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean
Outcome variables											
Maize yields	1000 kg/acre	2.490	1.415	2.225	2.478	2.365	2.317	2.899	2.506	2.511	2.712
Net farm income	1000 GHS/acre	3.716	2.042	2.880	3.292	3.179	3.006	3.988	4.055	5.197	4.063
Control variables											
Household characteristics											
Age	Years	47.49	10.65	45.90	45.44	45.45	48.54	47.34	48.49	48.37	48.25
Age squared	Age square in years	2369.4	1050.7	2208.1	2145.2	2172.6	2484.9	2367.5	2466.8	2469.8	2445.1
Sex	1 = male; 0 = otherwise	0.866	0.340	0.876	0.851	0.859	0.851	0.874	0.871	0.891	0.854
Household head	1 = household head (HH); 0 = otherwise	0.922	0.267	0.919	0.930	0.949	0.905	0.911	0.923	0.935	0.917
Education	Years	8.91	3.75	9.16	9.75	9.51	8.32	10.16	8.42	9.04	8.78
Marital status	1 = married; 0 = otherwise	0.865	0.339	0.831	0.844	0.848	0.873	0.851	0.902	0.861	0.865
Experience	Farming experience in years	21.32	12.53	20.54	20.77	20.55	20.91	19.99	22.11	20.63	22.10
Household size	Number of members living in a household	6.67	3.51	6.03	6.44	6.74	6.72	7.45	7.14	6.29	6.59
Resource constraints and market availability variables											
Farm size	Total cultivated land area in acre	4.87	3.24	5.03	4.53	5.30	4.43	5.19	4.57	5.44	5.14
Market information	1 = household has access to market information such as price of maize; 0 = otherwise	0.377	0.484	0.119	0.325	0.398	0.180	0.600	0.440	0.458	0.540
Market distance	Distance to the nearest market in km	2.90	2.57	2.65	3.59	3.56	2.27	4.19	2.66	2.81	2.94
Land ownership	1 = land owner; 0 = otherwise	0.654	0.475	0.485	0.644	0.589	0.575	0.711	0.725	0.653	0.747
Production shocks											
Drought stress	1 = a farmer perceived drought stress; 0 = otherwise	0.379	0.485	0.176	0.224	0.101	0.319	0.274	0.613	0.203	0.501
Pest and disease	1 = a farmer perceived pest and disease stress; 0 = otherwise	0.562	0.496	0.671	0.689	0.662	0.525	0.548	0.453	0.623	0.524
Information sources											

Table 1 (continued)

Variables	Measurement	Full sample		$D_0R_0Z_0$	$D_1R_0Z_0$	$D_0R_1Z_0$	$D_0R_0Z_1$	$D_1R_1Z_0$	$D_1R_0Z_1$	$D_0R_1Z_1$	$D_1R_1Z_1$
		Mean	Std. Dev	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean
Extension information	1 = HH got CSA information from an extension officer; 0 = otherwise	0.587	0.492	0.534	0.562	0.662	0.553	0.548	0.609	0.597	0.611
FBO membership	1 = HH got CSA information from FBO; 0 = otherwise	0.550	0.497	0.399	0.489	0.477	0.541	0.607	0.612	0.645	0.600
Radio information	1 = HH got CSA information from the radio; 0 = otherwise	0.413	0.492	0.426	0.291	0.280	0.613	0.281	0.285	0.244	0.591
Colleague farmer information	1 = a farmer got CSA information from a colleague farmer; 0 = otherwise	0.839	0.367	0.700	0.753	0.803	0.813	0.725	0.896	0.943	0.925
Locations variables											
Brong Ahafo	1 = household is located in the Northern region; 0 = otherwise	0.473	0.499	0.358	0.398	0.494	0.496	0.533	0.511	0.484	0.521
Northern	1 = household is located in the Northern region; 0 = otherwise	0.301	0.459	0.248	0.337	0.331	0.360	0.444	0.289	0.277	0.284
Ashanti	1 = household is located in the Ashanti region; 0 = otherwise	0.340	0.473	0.230	0.164	0.308	0.313	0.185	0.435	0.428	0.414
Sample size		3197									

GHS refers to Ghanaian cedis, with $1 = GHS6.508

Table 1 also shows that males make up the majority of CSA adopters who use at least two types of CSA technologies. Farmers who adopted at least two types of CSA technologies were more educated, implying that they may be better able to understand the benefits of CSA technologies than farmers who adopted a single technology or were non-adopters. Relatively large family sizes used at least two types of CSA technologies. The majority (54%) of farmers who adopted all three CSA technologies had market information, and 74.7% owned their farmland. Furthermore, farmers who experienced shocks, such as pest and disease stress (52.4%) and drought stress (50.1%), are more likely to adopt a combination of all CSA technologies.

Table 2 shows the distributions of various categories of CSA technologies maize farmers adopt. Out of the eight possible CSA groups, around 15.98% of farmers did not adopt any type of CSA technology ($D_0R_0Z_0$). Among the adopters, the largest proportion of farmers (26.62%) adopted drought-resistant seeds and zero-tillage ($D_1R_0Z_1$). This is followed by the proportion of farmers (20.21%) who adopted all three CSA technologies ($D_1R_1Z_1$). Only 4.22% of farmers combined drought-resistant seeds and row planting ($D_1R_1Z_0$) as CSA technologies.

5 Empirical results and discussions

5.1 Determinants of choosing different combinations of CSA technologies

Table 3 presents the results of the MNL model estimates, revealing the factors influencing farmers' decisions to select and adopt CSA technologies. We used non-adopters ($D_0R_0Z_0$) as the reference group in MNL estimations. Because the interpretation of the coefficients is not straightforward and it gives only the direction of the variables, the marginal effects of the MNL model are presented in Table 3 to provide a better understanding of factors influencing maize farmers' decisions to adopt CSA technologies (Nguyen-Van et al. 2017). Our results show that the marginal effects differ greatly among the different CSA technology combinations.

The results reveal that the farmer's age has a positive and significant marginal effect (see columns 5, 6, 7, and 8 of Table 3). The findings imply that older farmers are more likely to integrate drought-resistant seeds and row planting ($D_1R_1Z_0$), drought-resistant seeds and zero

Table 2 Distributions of CSA technologies adopted in maize production

Choice (*j*)	CSA technologies	Drought-resistant seeds (D)		Row planting (R)		Zero tillage (Z)		Frequency	Percentage (%)
		D_1	D_0	R_1	R_0	Z_1	Z_0		
1	$D_0R_0Z_0$		✓		✓		✓	511	15.98
2	$D_1R_0Z_0$	✓			✓		✓	329	10.29
3	$D_0R_1Z_0$		✓	✓			✓	178	5.57
4	$D_0R_0Z_1$		✓		✓	✓		316	9.88
5	$D_1R_1Z_0$	✓		✓			✓	135	4.22
6	$D_1R_0Z_1$	✓			✓	✓		851	26.62
7	$D_0R_1Z_1$		✓	✓		✓		231	7.23
8	$D_1R_1Z_1$	✓		✓		✓		646	20.21
Total								3197	100

Subscript 1 = adoption and 0 = non-adoption

Table 3 Determinants of adopting various combinations of CSA technologies: MNL model estimates

Variable	$D_1R_0Z_0$ Marginal effects	$D_0R_1Z_0$ Marginal effects	$D_0R_0Z_1$ Marginal effects	$D_1R_1Z_0$ Marginal effects	$D_1R_0Z_1$ Marginal effects	$D_0R_1Z_1$ Marginal effects	$D_1R_1Z_1$ Marginal effects
Age	0.211 (0.573)	0.610 (0.676)	−0.018 (0.653)	0.160** (0.068)	0.977* (0.515)	0.244*** (0.064)	0.107** (0.052)
Age squared	−0.021 (0.028)	−0.002 (0.004)	0.040 (0.032)	−0.003 (0.004)	−0.005 (0.012)	−0.010 (0.030)	−0.012*** (0.003)
Sex	−0.197 (0.319)	−0.567 (0.363)	−0.477 (0.330)	0.570 (0.497)	−0.189 (0.282)	0.503 (0.430)	−0.131 (0.292)
Household head	0.337 (0.426)	0.854 (0.585)	0.477 (0.452)	0.081 (0.572)	−0.066 (0.332)	0.366 (0.587)	−0.346 (0.336)
Education	−0.074 (0.219)	−0.117 (0.245)	−0.307 (0.203)	0.081 (0.307)	−0.256 (0.176)	0.336 (0.263)	0.232*** (0.088)
Marital status	−0.043 (0.263)	0.235 (0.319)	0.305 (0.301)	−0.015 (0.362)	0.265 (0.246)	0.689** (0.349)	0.186 (0.251)
Experience	−0.222 (0.194)	−0.570** (0.222)	0.546** (0.231)	−0.626*** (0.237)	0.075 (0.175)	−0.304 (0.226)	0.212 (0.187)
Household size	0.034 (0.181)	0.383* (0.217)	−0.116 (0.193)	0.183 (0.251)	0.016 (0.159)	0.659*** (0.191)	0.387** (0.155)
Farm size	0.026 (0.158)	0.238 (0.182)	−0.340* (0.174)	0.001 (0.207)	−0.210 (0.139)	−0.154 (0.172)	0.470*** (0.138)
Market information	0.108*** (0.023)	0.148*** (0.026)	0.100*** (0.025)	0.210*** (0.029)	0.211*** (0.020)	0.217*** (0.025)	0.244*** (0.021)
Market distance	0.150 (0.133)	0.234 (0.165)	−0.484*** (0.124)	0.236 (0.192)	−0.551*** (0.106)	−0.440*** (0.141)	−0.534*** (0.109)
Land ownership	0.239 (0.184)	0.064 (0.224)	0.160 (0.197)	0.378 (0.275)	0.594*** (0.167)	0.260 (0.227)	0.462*** (0.174)
Drought stress	0.110*** (0.023)	−0.825** (0.398)	0.373 (0.251)	0.131 (0.328)	0.189*** (0.020)	0.384 (0.281)	0.153*** (0.020)
Pest and disease stress	0.302 (0.214)	−0.029 (0.246)	−0.577*** (0.213)	−0.086 (0.281)	0.716*** (0.176)	−0.175 (0.243)	0.564*** (0.183)
Extension information	0.152*** (0.021)	0.240 (0.276)	−0.090 (0.266)	0.131*** (0.029)	−0.051 (0.213)	0.131 (0.272)	0.061 (0.219)
FBO membership	−0.259 (0.189)	−0.271 (0.224)	0.341* (0.199)	0.229 (0.260)	0.484*** (0.163)	0.638*** (0.222)	0.285* (0.170)
Radio information	0.777*** (0.187)	−0.919*** (0.229)	0.679*** (0.199)	0.833*** (0.259)	0.554*** (0.164)	−0.119*** (0.023)	0.135*** (0.017)
Colleague farmer information	0.484** (0.203)	0.108*** (0.027)	0.282 (0.246)	0.073 (0.270)	0.679*** (0.210)	0.163*** (0.033)	0.175*** (0.024)
Brong Ahafo	0.788** (0.359)	0.095 (0.329)	0.142 (0.312)	15.070 (482.667)	−0.063 (0.253)	−0.173 (0.328)	−0.146 (0.265)
Ashanti	0.135*** (0.037)	−0.180 (0.370)	−0.237 (0.341)	15.494 (482.667)	−0.186 (0.275)	−0.459 (0.374)	−0.330 (0.289)
Wald χ^2	295.83***						
LR χ^2 (147)	227.59***						
Sample size	3197						

Standard errors are in parenthesis; $D_0R_0Z_0$ is the reference base group (non-adoption); the reference region is Northern. ***$p<0.01$, **$p<0.05$, *$p<0.1$

tillage ($D_1R_0Z_1$), row planting and zero tillage ($D_0R_1Z_1$), and combinations of all the CSA technologies ($D_1R_1Z_1$). For example, the positive and significant marginal effect in column 5 of Table 3 suggests that older farmers are 16% more likely to integrate drought-resistant seeds and row planting ($D_1R_1Z_0$) than younger ones. The findings on age resonate with the results of previous studies (Vatsa et al. 2023; Zhou et al. 2023), opining that older farmers have more knowledge and experience, motivating them to adopt productivity-enhancing technologies. Also, the age square variable, which captures the long-term effect of age on CSA technology adoption, has a significant and negative coefficient. This implies that as farmers grow older beyond a certain age, their likelihood of adopting CSAs decreases. Older farmers are 1.2% less likely to adopt CSAs. This finding suggests that diminishing physical strength over time may contribute to the reduced adoption of CSA technologies among older farmers. This is consistent with the findings of Mossie (2022) and Tanti et al. (2022), who found an inverse relationship between the age square of farmers and the adoption of CSA technology.

Education positively and significantly affects all the combinations in the last column. The finding suggests that one 1-year increase in education would increase the probability of adopting drought-resistant seed, row planting, and zero tillage ($D_1R_1Z_1$) by 23.2%. Better education improves farmers' awareness and understanding of the benefits associated with CSA technologies, increasing their adoption motivation. This finding resonates with the findings of Gebremariam and Wünscher (2016) and Li et al. (2024).

Married farmers are 68.9% more likely to incorporate row planting and zero tillage ($D_0R_1Z_1$) as CSA technologies. Married households have more members due to increased household size; hence, there is a desire to produce more food using CSA technologies. Makate et al. (2019) reported similar findings. They indicated that married farmers are more likely to adopt CSA technologies, specifically to improve legume seeds, because marriage is an institution in Southern Africa. The results also show that an additional year spent on farming by a typical farmer would reduce the likelihood of adopting row planting alone ($D_0R_1Z_0$) by 57% and reduce the likelihood of incorporating drought-resistant seeds and zero tillage ($D_1R_1Z_0$) by 62.6%. Most experienced farmers are more conservative in their adoption of modern productivity-enhancing technologies. However, the experience variable positively affects adopting CSA technology, specifically zero tillage alone ($D_0R_0Z_1$). Experience is linked to training and information obtained on CSA technologies, as well as less drudgery and no/low cost of zero tillage, which could encourage farmers to adopt zero tillage technology easily.

The positive and significant effect of household size on all CSA technologies adoption ($D_1R_1Z_1$) suggests that a one-member increase in family size would increase the probability of adopting the three CSA technologies ($D_1R_1Z_1$) together by 38.7%. Bigger families generally signal greater resource endowment, such as labor, assisting farmers in crop cultivation and adopting CSA technologies, than smaller families. Previous studies have also found that household units positively influence the adoption of sustainable agricultural practices in Ghana (Setsoafia et al. 2022). An additional acre increase in farm size would increase the likelihood of adopting all three CSA technologies ($D_1R_1Z_1$) by 47%. Farmland is commonly described as a source of wealth, which motivates farm families, particularly those with large farms, to adopt CSA technologies. Anang and Amikuzuno (2015) discovered similar results in northern Ghana. In addition, land ownership has a positive and significant effect on the adoption of drought-resistant seeds and zero tillage ($D_1R_0Z_1$), as well as all three CSA technologies ($D_1R_1Z_1$), which increases the adoption probability by 59.4% and 46.2%, respectively.

The distance from the farmer's homestead to the nearest market positively influences the adoption of all three CSA technologies ($D_1R_1Z_1$). This finding indicates that the greater the distance farmers travel to the nearest agricultural market, the less probability of adopting CSA technologies. This is consistent with the findings of Anang and Amikuzuno (2015), who asserted that longer market distances are associated with higher transportation and transaction costs, thus reducing the likelihood of adopting CSA practices. The variable representing the perceived pest and disease stress positively and significantly influences the adoption of all CSA technologies. Specifically, farmers who encountered an infestation of pests and diseases are more likely to adopt a blend of drought-resistant seeds and zero tillage ($D_1R_0Z_1$) and all three ($D_1R_1Z_1$). This is consistent with Teklewold et al. (2013), who found that increased pest and disease stress increases the adoption of improved seeds in Ethiopia. In Ghana, Danso-Abbeam and Baiyegunhi (2018) indicated that high-incidence pests and diseases encourage adopting pesticide management practices. However, this may not be the case everywhere, as our findings indicate that pest and disease stress negatively affect the adoption of zero tillage ($D_0R_0Z_1$), giving rise to the diverse influences of CSA technologies among Ghanaian smallholder farmers.

Farmers who receive CSA technology information via extension have a higher likelihood of adopting CSA technologies such as drought-resistant seeds ($D_1R_0Z_0$) alone and drought-resistant seeds and row planting ($D_1R_1Z_0$), which increases their adoption probability by 15.2% and 13.1%, respectively. Better extension services for farmers, such as training and education on climate-sustainable agricultural practices, tend to boost crop productivity, which may drive most farmers' adoption of CSA technologies. Membership in farmer-based organizations has a positive and significant effect on the adoption of multiple CSA technologies, specifically incorporating drought-resistant seeds and zero tillage ($D_1R_0Z_1$), combining row planting and zero tillage ($D_0R_1Z_1$) and all three CSA technologies ($D_1R_1Z_1$). The findings confirm the extensive discussions about the advantages of farmer-based groups (see Manda et al. 2020a, b; Yu et al. 2021; Zhang et al. 2020). For example, being a FBO member increases the desire to adopt improved seeds in Zambia (Manda et al. 2020a, b) and soil and water conservation practices in Ghana (Amadu et al. 2020). Also, farmers who obtain information from a colleague are more likely to adopt multiple CSA technologies. Specifically, the likelihood of adopting a combination of drought-resistant seeds and zero tillage ($D_1R_0Z_1$), row planting and zero tillage ($D_0R_1Z_1$), and all three CSA technologies ($D_1R_1Z_1$) would increase by 67.9%, 16.3%, and 17.5%, respectively, if they received CSA technology information from colleagues.

The location dummies in columns 2, 4, and 5 are statistically significant. Our findings suggest that farmers in Ashanti and Brong-Ahafo are more likely to adopt only drought-resistant seeds ($D_1R_0Z_0$) than farmers in the Northern region (reference group). The findings highlight the importance of including location control variables in model estimations by demonstrating how other socioeconomic conditions, resource endowments, climatic conditions, and institutional arrangements may influence smallholder farmers' decisions to adopt CSA technologies.

5.2 Treatment effects of CSA technology adoption

Table 4 shows the treatment effects of CSA technology adoption on maize yields and net farm income. The results estimated from the second stage of the MESR model are not presented in the study for simplicity but are available upon request. The results show that relative to non-adoption ($D_0R_0Z_0$), adopting either row planting only ($D_0R_1Z_0$) or zero tillage only ($D_0R_0Z_1$) significantly reduces maize yields by 80 kg/acre and 94 kg/acre, respectively. One possible explanation for this phenomenon is that smallholder maize farmers in Ghana fail to adopt row planting and zero tillage appropriately, resulting in yield losses. Furthermore, the common practice of slash-and-burn agriculture among Ghana's rural farmers can have a negative impact on soil performance, resulting in lower yields.

Table 4 ATT estimates of MESR model

Treated group	Control group	Maize yields (1000 kg/acre)	Net farm income (1000 GHS/acre)
$D_1R_0Z_0$	$D_0R_0Z_0$	0.041 (0.028)	0.054 (0.070)
$D_0R_1Z_0$	$D_0R_0Z_0$	−0.080*** (0.049)	0.643*** (0.115)
$D_0R_0Z_1$	$D_0R_0Z_0$	−0.094** (0.039)	0.143** (0.071)
$D_1R_1Z_0$	$D_0R_0Z_0$	0.208*** (0.066)	0.677*** (0.134)
$D_1R_0Z_1$	$D_0R_0Z_0$	0.153*** (0.031)	0.583*** (0.073)
$D_0R_1Z_1$	$D_0R_0Z_0$	0.098*** (0.036)	2.078*** (0.161)
$D_1R_1Z_1$	$D_0R_0Z_0$	0.548*** (0.023)	0.815*** (0.079)

Robust standard errors are in parenthesis. ***$p < 0.01$ and *$p < 0.1$

In comparison, adopting any two combinations of CSA technologies significantly increases maize yields. For example, relative to non-adoption ($D_0R_0Z_0$), adopting drought-resistant seeds and row planting ($D_1R_1Z_0$) together significantly increases maize yields by 208 kg/acre, and adopting drought-resistant seeds and zero tillage ($D_1R_0Z_1$) significantly increases maize yields by 153 kg/acre. The yield effect is the largest when adopting all three technologies together. Specifically, relative to non-adoption ($D_0R_0Z_0$), the adoption of all three technologies ($D_1R_1Z_1$) significantly increases maize yields by 548 kg/acre.

The results that estimate the treatment effects of CSA technology adoption on net farm income are presented in the last column of Table 4. The results provide some interesting insights. When a single CSA technology is adopted, row planting has the largest impact on net farm income ($D_0R_1Z_0$). Relative to non-adoption ($D_0R_0Z_0$), adopting row planting ($D_0R_1Z_0$) significantly increases net farm income by 643 GHS/acre. When farmers combine two of the three CSA technologies, row planting and zero tillage (D0R1Z1) adoption have the largest impact of any CSA technology adoption option, increasing net farm income by 2078 GHS/acre. Relative to non-adoption ($D_0R_0Z_0$), adoption of all three CSA technologies ($D_1R_1Z_1$) significantly increases net farm income by 815 GHS/acre, and the impact is the second largest among all CSA technology options. Our findings corroborate with the recent findings (Amadu et al. 2020; Oduniyi and Chagwiza 2021; Setsoafia et al. 2022), highlighting that the adoption of multiple agricultural innovations has greater impacts on farm performance than the adoption of a single innovation.

5.3 Additional estimations

To ensure the robustness of our findings, we conducted an additional analysis using ordinary least squares (OLS) to estimate the impact of CSA technology adoption on maize yields and net farm income. The results are presented in Table 7 in the Appendix. The estimates reveal that the intensity of CSA adoption is associated with a 2.1% increase in maize yields and an 11.9% increase in net farm income. These findings provide valuable insights into the relationship between the intensity of CSA technology adoption and smallholder maize farmers' maize yields and net farm income. Nevertheless, we emphasize here the OLS regression cannot account for the endogeneity related to the CSA technology adoption variable, and it tends to generate biased estimates regarding the impacts of CSA adoption intensity. Therefore, the results obtained from the MESR model should be considered more reliable and comprehensive in understanding the association between CSA technology adoption, maize yields, and the net farm income of smallholder maize farmers.

6 Conclusions, implications, and limitations

The research and development community and governments are increasingly promoting the adoption of CSA technology to enhance food security and alleviate poverty among smallholder farmers in developing nations. We used random sampling to gather data from a sample of 3197 farmers to evaluate the concurrent adoption and effects of CSA technology in Ghana. The MESR model and OLS regressions were used to assess the impact of CSA adoption on maize yields and net farm income. While the OLS model estimates provide insight into the impact of CSA adoption on maize yields and net farm income, the model does not adequately address the endogeneity problem associated with the CSA technology adoption variable. Therefore, the MESR was utilized to account for potential selection bias arising from both observed and unobserved factors, and hence, the results from this model are used for our analysis.

According to the treatment effects estimates, integrating any CSA technology or adopting all three CSA technologies will greatly enhance maize yields and net farm income. Furthermore, our results showed that the adoption of all three CSA technologies has the largest impact on maize yields, while row planting and zero tillage have the greatest impact on net farm income. Most importantly, our findings suggest that smallholder farmers in Ghana and other developing areas in Sub-Saharan Africa should combine CSA technologies rather than use them separately to reap the greatest benefits from the essential synergistic effects of CSA technologies.

The MESR model has identified several factors influencing smallholder farmers' decisions to adopt multiple CSA technologies. These factors include farmer-based organization (FBO) membership, education, access to land, market access, and production shocks such as perceived pest and disease stress and drought. The findings suggest that enhanced institutional and policy measures are necessary to remove barriers that prevent smallholder farmers from adopting multiple CSA technologies. For instance, the implications of FBO membership, education, and extension services highlight the importance of governments working with farmer-based groups to improve extension services and educate farmers about the benefits of CSA technologies through radio programs and extension services. Through these channels, the likelihood of smallholder farmers adopting multiple CSA technologies will likely increase, which will provide greater benefits.

The study has three limitations that need to be addressed in future research. Firstly, the analysis was unable to capture the adoption and impacts of CSA technology adoption over time because only cross-sectional data was available. When panel data is available, future studies should explore the dynamic relationship between CSA technology adoption, farm performance, and household welfare. Secondly, this study only considered three CSA technologies (row planting, zero tillage, and drought-resistant seeds) because farmers in Ghana are heavily encouraged to use these three technologies to combat the effects of climate change and variability. However, CSA technology adoption is context-specific to the local environment, and some farmers may adopt more than three CSA technologies. Therefore, more studies focusing on other CSA technologies and other countries could be carried out to improve our understanding of this field. Lastly, further studies should examine the intensity of CSAs on household welfare to understand better the impact of CSA technology adoption on household welfare.

Appendix

Table 5 Falsification test results of instruments selection

Information sources	Probit	OLS	OLS
	CSA technology adoption	Maize yields by non-adopters	Net farm income by non-adopters
Extension information	0.080 (0.055)	−82.487 (130.397)	53.653 (51.552)
FBO membership	0.389*** (0.054)	−20.914 (32.778)	400.716 (256.145)
Radio information	−0.165*** (0.057)	36.519 (39.195)	43.449 (46.852)
Colleague farmer information	0.626*** (0.069)	−79.519 (139.195)	439.581 (291.088)
Constant	0.321*** (0.070)	23.616*** (8.899)	2382.081*** (268.131)
Wald test on information sources	$\chi^2 = 139.98$*** Pseudo $R^2 = 0.490$	F-stat = 0.87; $p = 0.4799$; $R^2 = 0.690$	F-stat = 1.44; $p = 0.2192$; $R^2 = 0.113$
Sample size	3197	511	511

Standard error are in parenthesis. *** < 1%

Table 6 Testing validity of instrumental variables using Pearson correlation analysis

Instrumental variables	Correlation	*p* value	Outcome variables
Extension information	0.0480***	0.0067	
FBO membership	0.1500***	0.000	CSA technology adoption
Radio information	– 0.1400***	0.0223	
Colleague farmer information	0.2242***	0.000	
Extension information	– 0.0052	0.7674	
FBO membership	0.0141	0.4258	Maize yields
Radio information	0.0263	0.1367	
Colleague farmer information	0.0086	0.6288	
Extension information	– 0.1395***	0.0000	
FBO membership	0.0293	0.3210	Net farm income
Radio information	0.0387	0.2881	
Colleague farmer information	0.0396	0.3272	

*** < 0.01

Table 7 Impacts of CSA adoption intensity on maize yields and net farm income: OLS estimations

	Maize yields Coefficient	Net farm income Coefficient
CSA adoption intensity	0.021 (0.010)**	0.119 (0.046)***
Control variables	Yes	Yes
Location variables	Yes	Yes
Constant	1.945 (0.446)***	1.990 (0.721)***
R-squared	0.609	0.614
Prob > *F*	0.000	0.000
F-test	14.491	20.36
Sample size	3197	3197

Maize yields and net farm income are measured in log-transformed forms. ***$p < 0.01$ and **$p < 0.05$

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Data availability The data that support the findings of this study are available from Bright Asante upon request.

Declarations

Conflict of interest The authors declare no competing interests.

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