Climate-Smart Agricultural Technologies and Farm Household Welfare Nexus in Sub-Saharan Africa.

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Abstract

Global climate change has threatened sustainable agricultural growth over the years. The Climate-Smart Agricultural Technologies (CSAT) offers pathways for mitigating the negative effect of climate change on crop farmers. This study uses cross-country (Mali and Niger) cross-sectional data to examine the welfare impact of multiple adoptions of CSAT on smallholder farmers' households. To control for potential endogeneity that leads to bias estimates, we employed the multivalued multinomial endogenous treatment effect (METE) model for the analysis. The results revealed that sociodemographic (education, location, assets), plot (farm size, soil topography and fertility), institutional (farmer-based organization, access to credit and extension service) and crop disease shock significantly influence different combinations of CSAT adoption. The impact estimates show that adopting joint combinations of CSAT leads to higher crop sales revenue and income among the farmers. Therefore, these findings suggest that government and non-governmental organizations should disseminate and promote the multiple adoptions of CSAT packages in the West Africa Sahel region. Moreover, some sociodemographic and institutional factors such as education, credit access, farmer-based organizations and extension service system could be strengthened for easy and rapid adoption of CSAT by smallholder farmers, which subsequently improve their economic welfare.

Keywords: Adoption, Climate-smart agricultural technologies (CSAT), Smallholder farmers, West Africa Sahel region.

1. Introduction

It’s evident that the current trend and future projections of changing climate pose a significant threat to people's livelihood globally. According to Intergovernmental Panel on Climate Change (IPCC) (2018), the potential risk imposed by climate change includes ecosystem degradation and weather disaster (such as flood, drought, tsunami, and hurricane, among others), which directly or indirectly affects human development. Developing countries in Africa and elsewhere are more prone to this negative impact due to the current devastating infrastructure and technology to prepare/respond to extreme weather events.

According to recent climate predictions, in the high-emission scenario, temperatures over Sub-Saharan Africa (SSA) will rise more quickly than the global average and most likely surpass 2°C by 2050 (Niang et al., 2014; Tesfaye et al., 2018). Although the expected change in rainfall across SSA in the middle and end of the twenty-first century is uncertain, it is relatively likely that extreme climatic events such as severe storms, flooding, and droughts will occur more frequently and with greater severity (AGRA, 2014). Furthermore, it is anticipated that by 2050, many areas of SSA, such as the Sahel, will experience a 20% decline in the growing period length (GPL), a measure of how well moisture is available and how conducive the temperature is for plants (AGRA, 2014; Tesfaye et al., 2018). An implication of this changing climate is decreased food production and poverty rate in this region.

Recently, experts, stakeholders and organizations promoting different strategies to achieve sustainable development goals (SDGs), which include SDGs one and two relating to no poverty and zero hunger, agreed that agricultural production remains one of the best main options to achieve these two goals (Zegeye et al., 2022). Agriculture contributes significantly to enhancing the welfare of inhabitants of developing countries via food security and employment creation. In SSA, the majority of the population depends on agriculture for their living, and the sector accounts for a significant portion of the gross domestic product (GDP) of many countries in the region.

However, the technological advancement in the SSA agricultural sector is relatively low, making it vulnerable to climate change. Smallholder farmers who are highly dependent on rain-fed agriculture cultivate over 90% of the food produced in the SSA (Bello et al., 2021). Therefore, extreme weather events affect crop yields, further exacerbating food insecurity, nutritional disorders and social instability. The welfare of farmers in rural SSA will thus be compromised by the instability and decline in farm production over the course of seasons (Mwungu et al., 2019).

The fluctuations and variability of agricultural production have threatened both the present and future economic conditions of farmers in Africa, including the West Africa Sahel region (WASR). Farmers in the WASR encounter numerous challenges, such as unpredictable rainfall, recurring droughts, desertification, pest and disease infestation, poor soil quality, as well as meagre market access and infrastructures (Kpadonou et al., 2017). However, climate change remains one of the notable impediments faced by farmers. The average temperature in the WASR is projected to rise by 3^0 to 6^0 C and reduced/extreme rainfall during the rainy season by 2100 (USAID, 2017). In the WASR, the major food crops such as cowpea, maize, millet, rice, sorghum, and groundnut are produced below potential yield. For example, in Mali and Niger, the national average yield between 2010 and 2020 for crops such as cowpea is below 700kg/ha, maize (<3000kg/ha), millet (<1000kg/ha), sorghum (<1500kg/ha), and groundnut (<1500kg/ha). These estimates are below average yields in other African countries such as Nigeria, Ghana, South Africa and Kenya. According to Ouédraogo et al. (2018), the future effect of climate change in the WASR is projected to decrease cereal crop yields by about 5 to 25%. This calls attention to an urgent need for strategies and solutions to mitigate the adverse effect of climate change on poor rural smallholder farmers in this region.

In recent years, experts have been promoting the use of technologies and practices known as climate-smart agricultural technologies (CSAT) to cushion the adverse effect of extreme weather events on farm production (CCAFS, 2022). Di Falco and Veronesi (2013) posited that the implementation of appropriate CSAT could reduce the impacts imposed by climate change and, in the long run, improves agricultural production. CSAT includes a wide range of agronomic practices and technologies such as sustainable land management (SLM) practices (such as soil and water conservation (SWC), minimum tillage, improved grazing, intercropping e.t.c.), agrochemicals (fertilizers and pesticides), improved genetics of crops and animals, among others. The decision to adopt CSAT is mainly determined by the agroecological conditions and farmers' culture (Ruzzante et al., 2021; Zegeye et al., 2022). The adoption of CSAT is essential in the WASR due to the vulnerability of farm production to climate change events. Although there are various CSAT that farmers can use to reduce climate risks, promoting and augmenting farmers' access to these CSAT remains a significant challenge in many parts of SSA, including the Sahel (Mali and Niger inclusive), which has led to the predominantly low adoption rate of CSAT (Olayide et al., 2020; Ouédraogo et al., 2018).

Since the conception of CSAT as a novel strategy for allocating agricultural investment in the context of climate change, CSAT has motivated various empirical investigations (Amadu, Miller, et al., 2020; Awotide et al., 2022; Bello et al., 2021; Khonje et al., 2018; Kimathi et al., 2021; Kpadonou et al., 2017; Lu et al., 2021; Ojo & Baiyegunhi, 2020; Zakari et al., 2022; Zegeye et al., 2022). However, most of these studies analyze CSAT in a binary framework (i.e., adopters of any

CSAT or not), while few focused on joint adoption ((Khonje et al., 2018; Kpadonou et al., 2017; Lu et al., 2021; Zegeye et al., 2022). The studies on joint CSAT adoption are single-crop specific (mainly maize or rice) and conducted in diverse agroecological areas of SSA. However, empirical evidence on the synergy between the adoption of different CSAT categories among multiple crops has received less attention. We extend the literature by addressing the research question: Does multiple adoptions of CSAT improve smallholder farmers' welfare? We accomplish this by estimating the welfare (sales revenue and crop income) impact of three unique CSAT categories[1], which are improved seed varieties (ISVs), agrochemicals (AGC), and sustainable land management technologies (SLM) in a multinomial econometric framework. We examined if CSAT improves the welfare of adopters and subsequent pathways i.e., different CSAT combinations (either in singles or multiple)

Furthermore, this study fills the literature gap by focusing on multiple adoptions of CSAT among smallholder farmers cultivating major staple crops (millet, sorghum, cowpea, groundnut, and maize) in the Sahel. To the best of our knowledge, this is the first study to evaluate the impacts of multiple adoption of CSAT on the welfare of multiple crop farmers in the Sahel. In addition, the inclusion of crop income[2] (revenue from crop minus production cost excluding farm labour) in our outcome variable makes our study unique because CSAT adoption is known to be financially dependent, which increases farmers' production costs; however, previous studies have drifted away from focusing on this important outcome variable. The results from our study will provide relevant information and policy guidelines towards the promotion of CSAT (via appropriate

[1] The different practices and technologies under these three categories are shown in Table A1.
[2] Existing Studies have focused on farm income which includes both incomes generated from crop output, residues and other farm activities. We focused on crop income to reveal the direct effect of CSAT adoption on income generated from crop output.

combinations) in improving rural farm households' welfare in drylands environments like the WASR and similar regions around the world.

2. Research Methodology

2.1. Theoretical framework

The adoption of technology such as CSAT revolves around three major concepts, which are the diffusion of innovation, induced innovation and utility (Binswanger et al., 1978; Fishburn, 1968; Rogers et al., 2014). According to the theory of diffusion of innovations, an innovation's comparative advantage, observability and trialability will influence the rate of acceptance (Rogers et al., 2014). It's important to note that technologies don't necessarily need to be brand-new to fit the definition and dynamics of innovation; rather, even outdated technology may be repackaged and introduced (Rogers et al., 2014). A typical example is CSAT, which are known to be indigenously innovated (in the case of SLM) or scientifically innovated (such as ISVs, chemicals among others), these technologies are promoted and disseminated according to the suitable agroecological farming environments. We hypothesized that farmers' access to information via socio-institutional factors such as farmer-based organizations (FBOs) and extension services will increase CSAT adoption.

The notion of induced innovation emphasizes that farmers' availability or limitations of resources, such as assets, capital and labour, will influence the acceptance of inventions (Janvry & Sadoulet, 2006). Receiving CSAT support externally, from governmental and non-governmental agencies (NGOs) via inputs donations, construction (physical structures) or subsidizing of CSAT prices (such as ISVs, AGC) in poor rural areas could scale up adoption. Therefore, the financial dependency of most CSAT underpins the role of resource endowment in enhancing CSAT adoption. Based on this fact, we expect that access to productive farm resources and external support (such as credit and subsidy) would scale up CSAT adoption, most especially multiple adoptions.

Regarding, the context of utility in this study, farmers consider a wide range of CSAT and choose a certain package (single or multiple) that will help in enhancing crop productivity with a corresponding reduction in the effects of climate change. Thus, if a risk-averse farmer chooses a package, the advantages of adopting CSAT, minus the cost of adoption, outweigh the gains obtained without adoption. We, therefore, envisage that farmers adopting multiple CSAT would experience higher welfare than those adopting in singles.

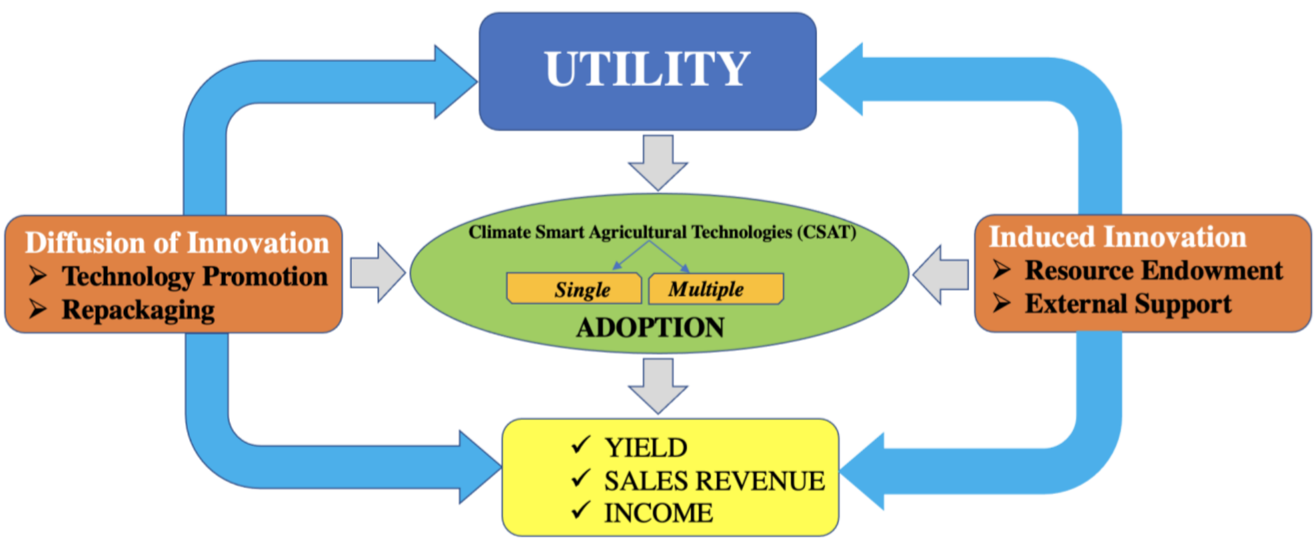

Figure 1: CSAT adoption nexus and welfare outcomes
Source: Authors (2023)

2.2. Conceptual and empirical strategy

In this study, we evaluate the welfare effect of CSAT adoption, accounting for the impact via multiple CSAT combinations[3]. The most appropriate approach to analyze this objective is the multinomial model due to its ability to handle more than two treatment variables simultaneously. Therefore, we employed the random utility multinomial framework to model the decision of a smallholder farmer in selecting a package out of six different CSAT combinations (including non-adoption). Smallholder farmers' decision is based on their anticipated costs and benefits as well as the preferences of CSAT. However, this decision might be endogenous, as farmers might self-select or choose to adopt a CSAT package based on observable (such as information access, literacy rate, resource endowment) or unobservable (such as innate ability or skills) characteristics. Failure to take account of these concerns could result in inconsistent and biased estimates of joint adoption of CSAT on the welfare variables i.e., crop sales revenue and income. We systematically address the issue of potential endogeneity that might occur due to self-selection of technology adoption in our study by employing a multinomial endogenous treatment effect (METE) model developed by Deb and Trivedi (2006) with the inclusion of an instrumental variable.

The METE involves a two-stage estimation process. The first stage captures the multinomial probability of CSAT adoption combinations while the second stage captures the treatment effect of CSAT on the outcome variables (crop sales revenue and income). Following Deb and Trivedi (2006), a farmer f tends to select one of the six CSAT packages k. Assuming EU_{fk}^{*} indicate the indirect utility that the farmer would achieve by choosing the kth package/treatment, $k = 0,1,2,\dots\dots K$ and

$$EU_{fk}^{*} = z_f'\beta_k + \delta_k \upsilon_{fk} + \xi_{fk} \tag{1}$$

[3] Combinations and packages are used interchangeably in this study

where subscripts f and k represent smallholder farmers and the six treatment statuses, respectively. k can take a value of 0 = non-adopters of CSAT, 1= adopters of AGC only ($\mathrm{I_0A_1S_0}$), 2= adopters of SLM only ($\mathrm{I_0A_0S_1}$), 3= adopters of AGC and SLM only ($\mathrm{I_0A_1S_1}$), 4= adopters of ISVs only[4] or with a combination of either SLM or AGC ($\mathrm{I_1A_0S_0|I_1A_1S_0|I_1A_0S_1}$), and 5= adopters of AGC, SLM and ISVs jointly ($\mathrm{I_1A_1S_1}$). $\mathbb{Z}_f$ represents a set of exogenous variables with associated parameter β_f, and ξ_{fk} is an independently and identically distributed error term. The latent factor υ_{fk} denotes unobserved characteristics that influence both CSAT adoption choice and welfare of the farmer f, with the assumption of being independent of ξ_{fk}. Assuming k=0, (the non-adopters) for which EU_{f0}^{*} = 0. Though we don't observe, EU_{fk}^{*} directly but a set of binary variables, $\mathbb{C}_f = (\mathbb{C}_{f1}, \mathbb{C}_{f2}, \dots \dots \dots, \mathbb{C}_{fk})$ which represents the observed choice of CSAT packages adopted by the farmer. Furthermore, let $\upsilon_f = (\upsilon_{f1,}\upsilon_{f2,\dots,}\upsilon_{fk})$. Thus, the probability of CSAT adoption (treatment) can be given as:

$$\Pr\left(\mathbb{C}_{fk} \middle| \chi_f, \mathbb{Z}_f, \upsilon_{fk}\right) = g\big(\chi_f'\varpi_1 + \alpha_1\mathbb{Z}_f + \delta_1\upsilon_{f1},\ \chi_f'\varpi_2 + \alpha_2\mathbb{Z}_f + \delta_2\upsilon_{f2},\ \chi_f'\varpi_3 + \alpha_3\mathbb{Z}_i + \delta_3\upsilon_{f3},\ \chi_f'\varpi_4 + \alpha_4\mathbb{Z}_f + \delta_4\upsilon_{f4},\ \chi_f'\varpi_5 + \alpha_5\mathbb{Z}_f + \delta_5\upsilon_{f5}\big) \quad (2)$$

where g denotes an appropriate multinomial probability distribution. $\Pr\left(\mathbb{C}_{fk} \middle| \chi_f, \mathbb{Z}_f, \upsilon_{fk}\right)$is the probability that farmers adopt one of the CSAT packages ($\mathbb{C}_{fk}$), given the exogenous variables (χ_f), instrument[5] ($\mathbb{Z}_f$) and unobserved characteristics (υ_{fk}), while ϖ_f, α_f and δ_f are parameter estimates.

Finally, the impact of the outcome variables are estimated using the equation described below.

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[4] The sample size for farmers who adopt ISVs only is too small to run the METE model, therefore, we included farmers who adopt ISVs in combination with AGC or SLM to increase the number of observations in this category.
[5] We used a binary dummy variable for crop disease shocks in the last three years as an instrument, because this variable can influence the adoption of CSAT in the survey year but not farmers' production which transforms into the outcome variables.

$$\mathrm{E}\left(\mathbb{W}_f \middle| \chi_f, \mathbb{C}_{fk}, \upsilon_{fk}\right) = \chi_f' \beta + \eta_1 \mathbb{C}_1 + \eta_2 \mathbb{C}_2 + \eta_3 \mathbb{C}_3 + \eta_4 \mathbb{C}_4 + \eta_5 \mathbb{C}_5 + \lambda_1 \upsilon_{f1} + \lambda_2 \upsilon_{f2} + \lambda_3 \upsilon_{f3} + \lambda_4 \upsilon_{f4} + \lambda_5 \upsilon_{f5} + \xi_f \tag{3}$$

where $\mathbb{W}_i$ denotes welfare outcome variables (crop sales revenue and crop income), χ_f is a vector of exogenous variables with associated parameter β. η_f refers to the treatment (adopting either of CSAT packages) effects relative to the control (non-adopters). υ_{fk} control for potential unobserved factors that influence the selection of farmers who adopt CSAT and outcome variables. λ_k represents parameter estimating whether there is a positive or negative correlation between CSAT adoption status and outcome variables via the unobserved characteristics (Deb and Trivedi, 2006).

Table 1: CSAT adoption combinations for smallholder farmers in the study area

Choice (c)	**CSAT adoption combinations**	**ISV**		**AGC**		**SLM**		**Full-sample**	**Mali**	**Niger**
		$\mathbf{I_0}$	$\mathbf{I_1}$	$\mathbf{A_0}$	$\mathbf{A_1}$	$\mathbf{S_0}$	$\mathbf{S_1}$	**Frequency**	**Frequency**	**Frequency**
0	$\mathrm{I_0A_0S_0}$	✓		✓		✓		490 (14.54)	384 (19.16)	106 (7.75)
1	$\mathrm{I_0A_1S_0}$		✓	✓		✓		533 (15.81)	476 (23.75)	57 (4.17)
2	$\mathrm{I_0A_0S_1}$	✓			✓	✓		578 (17.15)	182 (9.08)	396 (28.97)
3	$\mathrm{I_0A_1S_1}$	✓		✓			✓	845 (25.07)	438 (21.86)	407 (29.77)
4	$\mathrm{I_1A_0S_0 \vert I_1A_1S_0 \vert I_1A_0S_1}$		✓	✓	|✓	✓	|✓	424 (12.58)	256 (12.77)	68 (12.29)
5	$\mathrm{I_1A_1S_1}$		✓		✓		✓	501 (14.86)	268 (13.37)	233 (17.04)
Total								3,371 (100)	2,004 (100)	1,367 (100)

Note: ISV-Improved seed varieties, AGC-Agrochemicals, SLM- Sustainable land management. Percentage in parenthesis

2.3. Study area and data source

This study focused on two vital countries (Mali and Niger) in the Sahel that are currently among the most adversely affected by climate change in Africa. Mali and Niger are neighbouring landlocked countries that experience similar climatic conditions. The three main climatic zones in these countries are the Saharan desert, Sahel and Sudan climate. Agriculture (crop production and livestock rearing) is the most prevalent occupation and source of income in both countries. Most of the inhabitants are rural dwellers who are engaged in farming and herding.

We utilized cross-sectional baseline survey data collected in 2019 by the International Institute of Tropical Agriculture (IITA), social science and agribusiness department, Bamako, Mali. A multistage random sampling was used to select regions, communes and farm households for both Mali and Niger. The first stage involves the purposive selection of four major crop production regions in Mali and Niger. These regions were selected based on the agroecological condition, cropping intensity, accessibility and security. The main crops produced by the farmers include cowpea, groundnut, millet, maize, rice, sorghum, soybean, and vegetables.

Subsequent stages involved a random selection of 32 communes and 320 villages in each country. About seven smallholder farm households per village were selected for the survey using a well-structured and standardized survey tool. A pre-test was done using two close villages, to ascertain the reliability of the survey instrument by trained enumerators and supervisors who are also fluent in the local language of the farmers. The pre-test experience was used to address the requirement for extra questions and fix all the reported issues. The data set contains a total of over 4000 farm households. We selected 3371 smallholder farm households (2004 in Mali and 1367 in Niger) that cultivated the five staple crops (millet, sorghum, cowpea, groundnut, and maize) for our study.

3. Results and discussion

3.1 Summary statistics

Table 2 defines and summarizes the important variables of the pooled, Mali and Niger sampled farm households. The average sales revenue for the pooled sample, Mali and Niger is 227.54, 246.87 and 199.20 (‘000 FCFA[6]), respectively. Moreso, it can be observed that the income generated from the respective crop production for the pooled sample, Mali and Niger, is 141.06, 120.08 and 171.82 (‘000 FCFA), respectively. The majority (over 90%) of the farmers are male and have low years (about 2) of formal education, equivalent to or lower than primary school education. This shows that there is a high illiteracy rate among the smallholder farmers in the study area, which might influence CSAT adoption. The average farm size for the pooled, Mali and Niger are 6.47 ha, 7.28 ha, and 5.29 ha, respectively. The average labour employed during the production season is 67.73, 82.29 and 46.38 for the pooled, Mali and Niger sampled farmers. The high rate of labour used in production signifies the low mechanization rate and high dependency on manual labour in the study area.

Institutional factors play a crucial role in providing support (information and financial) for smallholder farmers. In contrast to other studies, we define farmers access to credit as farmers who (can) obtain credit from a formal organization such as banks, microfinance, local cooperatives or farm organizations. We excluded credits from family and friends and other sources. We used this variable to provide an overview of the current state of farmers’ access to a reputable and guaranteed credit facility in the Sahel. It can be observed that access to formal credit is generally low at 11% for the pooled, 17% and 1% for Mali and Niger farm households respectively. About 59% of the pooled sample had contact with extension agents but farmers in Mali had more contact (73%) than those in Niger (38%).

Table 3 reports the summary statistics across the six CSAT combinations of the pooled sample[7]. The crop sales revenue and income of CSAT adopters are higher than that of non-adopters. Also,

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[6] As at the time of the survey 1$ equals 545 FCFA

[7] The CSAT combinations descriptive statistics by country can be found in the appendix.

farm households who adopted multiple CSAT ($I_1A_1S_1$) have higher sales revenue than those who adopted a single package. However, farmers, who adopted CSAT package ($I_0A_0S_1$) has the highest crop income. A plausible explanation is that the production cost increases based on the type and number of packages adopted, as CSAT is known to be generally capital-intensive. Moreover, the production cost of some SLM package components (such as intercropping and cover cropping) is lower than that of the other packages (such as $I_1A_1S_0$, $I_0A_1S_1$, and $I_1A_1S_1$). The farming experience of non-adopters is higher than that of both single and multiple CSAT adopters.

In terms of resource endowment (such as total household assets, productive assets, total livestock unit (TLU) and farm size), adopters of the three CSAT packages are better off than non-adopters. Furthermore, multiple CSAT adopters ($I_1A_1S_1$) have higher access to socio-institutional factors such as Farmers-based organizations (FBO) (66% vs 57%), formal credit (15% vs 3%), extension agent (75% vs 42%) than non-adopters. Experiencing shock from crop disease is more prevalent among farm households who adopted all the CSAT combinations than their single adopters and non-adopters' counterparts. It's important to note that the Table 3 results showing the simple descriptive statistics among CSAT adopters and no-adopters does not justify the real impact of CSAT adoption as there may be other potential confounders not considered. We provide a substantial impact analysis in sub-section 3.4.

The proportion of the crops produced among the smallholder farmers in the study area (total sample) is shown in Figure 2. The majority of the farmers planted millet (68%), followed by sorghum (33%), maize (30%), and groundnut (18%), while cowpea is the least (3%) cultivated. Millet is a climate-resilient crop that withstands harsh climatic conditions (low rainfall or high temperature) than other cereal crops. Thus, many farmers in the WASR cultivate millet, serving as one of the important staple crops consumed in the region. This study, therefore, takes a step further to estimate the welfare impact of CSAT adoption combinations among farmers cultivating this essential crop (i.e., millet).

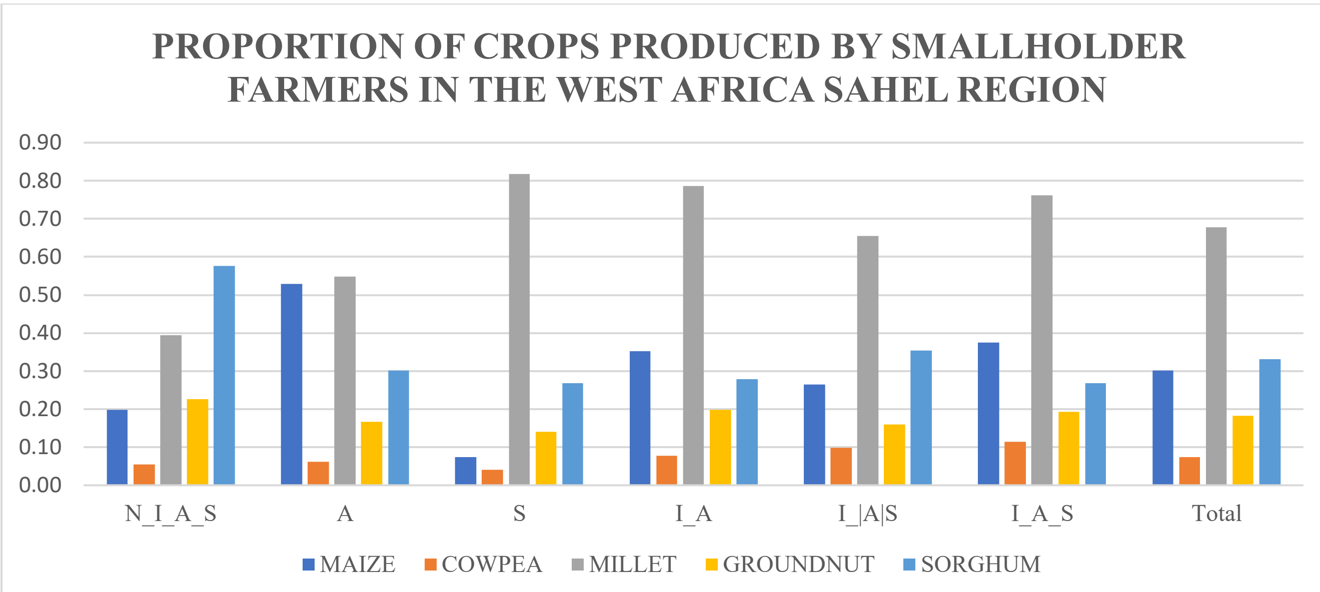

Figure 2: Proportion of crops produced by sampled smallholder farmers in the WASR (Mali and Niger)
Source: Authors 2023

Table 2: Definition and descriptive statistics of the smallholder farmers in the study area

Variable	Description	Full sample (3371)	Mali (2004)	Niger (1367)
Outcome (Welfare)				
Crop sales revenue	The market value/sales of crop output (‘000 FCFA)	227.54	246.87	199.20
Crop income	Values of output/yield minus production cost (‘000 FCFA)	141.06	120.08	171.82
Sociodemographic Characteristics				
hhHead gender	1 if farmer is male, 0 other wise	0.93	0.99	0.83
hhHead age	Age of the household head in years	53.45	56.34	49.22
hhSize	Number of household members	8.91	7.49	10.99
Edu_year	Formal education years of farmer	2.25	2.34	2.11
farmExp yrs	Years of farming experience	33.40	38.24	26.32
dstnceFrmRsd	Distance from residence to farm in minutes	39.63	34.19	47.61
dstnceNrst_ mkt	Distance to nearest market in minutes	13.67	16.95	8.86
Totval hhst	Total value of household asset (‘000 FCFA)	1738.78	2485.60	643.97
Tot prod asset	Total value of farm productive asset (‘000 FCFA)	738.08	1071.77	248.88

TTLU	Number of Total livestock unit owned	11.89	15.56	6.51
INC Off farm	income generated from non-farm activities (‘000 FCFA)	64.63	66.48	61.93
Plot Characteristics				
Farm size	Total farm size area in hectares (Ha)	6.47	7.28	5.29
Nb_plot	Number of plots cultivated	1.99	1.81	2.24
Nb_crp	Number of crops cultivated	1.57	1.72	1.34
good soilfert	1 if soil fertility condition is good, 0 therwise	0.40	0.37	0.44
poor soilfertt	1 if soil fertility condition is poor, 0 therwise	0.15	0.11	0.21
med soilfert	1 if soil fertility condition is fair, 0 therwise	0.60	0.52	0.73
flat slope	1 if the land topography is flat/normal, 0 therwise	0.62	0.57	0.70
Med slope	1 if the land topography is fair, 0 therwise	0.44	0.38	0.54
steep slope	1 if the land topography is steepy, 0 therwise	0.08	0.04	0.12
TLB	Total number of labour employed in man days	67.73	82.29	46.38
Institutional factors				
FBO	1 if the farmer is a member of farmer-based organization, 0 otherwise	0.59	0.82	0.27
Fm_Crd	1 if the farmer has access to formal credit, 0 otherwise	0.11	0.17	0.01
conctExtAgnt	1 if the farmer has access to extension, 0 otherwise	0.59	0.73	0.38
Climate_Specific_factors				
Shock_crop_disease	1 if the farmer has experienced crop disease infestation in the last three years, 0 otherwise	0.34	0.19	0.56

Table 3: Summary statistics of the smallholder farmers in the study area based on CSAT adoption – Pooled sample

Variable	$I_0A_0S_0$	$I_0A_1S_0$	$I_0A_0S_1$	$I_0A_1S_1$	$I_1A_0S_0 \vert A_1S_0 \vert A_0S_1$	$I_1A_1S_1$
Outcome						
Crop sales revenue	70.20	250.96	187.44	269.42	267.39	298.42
Crop income	46.60	116.00	160.66	153.19	186.92	178.25
Sociodemographic Characteristics						
hhHead gnder	0.90	0.97	0.88	0.94	0.93	0.93
hhHead age	56.05	55.44	52.94	50.82	54.71	52.78
hhSize	8.01	8.54	9.72	9.36	8.53	8.81
edu yr	1.56	2.27	1.82	2.87	1.81	2.73
farmExp yrs	38.88	37.01	30.15	30.61	35.01	31.32
dstnceFrmRes	53.45	29.57	36.48	40.17	39.46	39.68
dstnceNrst_mkt	15.29	14.95	10.53	13.67	13.29	14.67

Totval hhast	1517.52	2573.82	1336.43	1553.29	1940.91	16728.11
Tot prod ast	523.64	903.02	382.86	872.95	835.71	872.03
TTLU	12.43	13.07	8.56	11.50	12.37	14.21
INC Off farm	52.57	61.44	43.56	67.96	76.08	88.84
Plot Characteristics						
Nb plot	1.59	1.78	1.90	2.32	1.84	2.25
Nb crp	1.45	1.61	1.34	1.69	1.54	1.71
good soilf~t	0.37	0.30	0.38	0.44	0.40	0.48
poor soilf~t	0.14	0.15	0.17	0.17	0.13	0.11
med soilfert	0.55	0.59	0.64	0.63	0.58	0.61
flat slope	0.55	0.57	0.64	0.62	0.66	0.70
med slope	0.47	0.39	0.46	0.48	0.40	0.42
steep slope	0.04	0.05	0.10	0.10	0.05	0.08
Farm Size	5.43	6.17	5.21	7.62	7.38	6.56
TLB	52.37	73.77	49.04	75.64	63.17	88.40
Institutional Factors						
FBO	0.57	0.74	0.41	0.60	0.61	0.66
Fm_Crd	0.03	0.16	0.02	0.14	0.12	0.15
conctExtAgnt	0.42	0.66	0.47	0.61	0.62	0.75
Climate_Specific_factors						
Shock_crop_disease	0.28	0.16	0.44	0.34	0.39	0.45

3.3 Determinants of CSAT adoption combinations among smallholder farmers

The results from Table 4 show the probability of CSAT adoption among five packages with non-adopters ($\mathrm{I_0A_0S_0}$) being the base category. We conducted a diagnostic test to ascertain if the multinomial logit model (MLM) is fit for our analysis. The results from the Wald's test rejected $[\chi^2\ (105) = 1256.03;\ p = 0.000]$ the hypothesis that all regression coefficients are equal to zero in combinations. This result suggests that MLM is suitable for estimating the data and explanatory variables used in the analysis.

The smallholder farm household size has a negative and significant influence on CSAT packages $\mathrm{I_1A_1S_0}$, $\mathrm{I_1A_0S_0|A_1S_0|A_0S_1}$ and $\mathrm{I_1A_1S_1}$, suggesting that farmers with larger household size are less likely to adopt these packages. A reason behind this result is that farmers with larger household size will spend more on consumption and other household needs than smaller households which might affect their investment in farm technologies such as CSAT. This result supports the finding of Khan et al. (2020) but deviates from that of Zegeye et al. (2022) who found household size to increases the likelihood of agricultural technology adoption in rural Ethiopia. Similarly, the age of the household head is significant and negatively influences the adoption of $\mathrm{I_1A_1S_0}$, indicating that older farmers are less likely to adopt improved varieties and agrochemical than young and energetic farmers. A plausible explanation is that young farmers are more risk-averse and willing to try innovation than older farmers who are accustomed to traditional farming system. This findings corroborates with Assefa et al. (2021) and Zegeye et al. (2022). Similar to the age effect, farm experience significantly reduces the likelihood of smallholder farmers adopting $\mathrm{I_0A_0S_1}$, $\mathrm{I_1A_1S_0}$ and $\mathrm{I_1A_1S_1}$. This is in tandem with Lu et al. (2021).

Education is a vital human capital that pre-exposes individuals to crucial information, such as the current trend of climate change and agricultural technology, as in the case of CSAT. As expected, years of formal education positively and significantly influences $\mathrm{I_1A_1S_0}$ and $\mathrm{I_1A_1S_1}$ adoption. This shows that an additional year of farmers' schooling increases the adoption of all three CSAT packages and ISVs, and AGC only. This result is consistent with Zegeye et al. (2022). Distance to farm has a negative and significant influence on all CSAT combinations, suggesting that the farther the distance from farmers' residences to their farm plots, the lesser they are to adopt CSAT packages. This might be due to erratic road networks and mode of transportation in rural areas of the Sahel, making it difficult for farmers to move technologies such as AGC and increase the cost of farm labour needed in utilizing CSAT packages. This finding contradicts that of Lu et al. (2021) for multiple agricultural technology adoption among rice farmers in Ghana.

Household (for all combinations) and productive (for $I_1A_1S_0$ and $I_1A_1S_1$) assets significantly and positively increase farmers' likelihood of CSAT adoption. This is not surprising because CSAT is capital-intensive therefore, farmers who are resource endowed tend to try innovations that will enhance their productivity. This result supports the findings of Khonje et al. (2018), who documented that the value of farmers' productive assets improved the adoption of CSAT in eastern Zambia. TLU has a positive and significant effect on the adoption of CSAT combinations $I_1A_0S_0|A_1S_0|A_0S_1$ and $I_1A_1S_1$, indicating that the more TLU possessed by farm households, the higher the likelihood of CSAT adoption. Livestock rearing serves as an additional source of income generation for farmers, and it could enhance adoption of more capital dependent CSAT such as $I_1A_0S_0|A_1S_0|A_0S_1$ and $I_1A_1S_1$. Our result is in tandem with that of Amadu, McNamara, et al. (2020) and Zegeye et al. (2022).

Surprisingly, off-farm income reduces the likelihood of adopting CSAT packages $I_0A_1S_0, I_0A_0S_1$ and $I_1A_1S_0$. A reason behind this could be that farmers who engage in off-farm activities might be exposed to other income-generating enterprises and prefer investing in these sources over agricultural production via technology adoption. This finding is contrary to Danso-Abbeam and Baiyegunhi (2018) and Alwang et al. (2019).

Regarding farm household plot characteristics, farm size, farm labour, good and medium soil fertility and flat land slope has a positive and significant influence on the adoption of CSAT adoption packages. Specifically, farm households with larger farm sizes are more likely to adopt ISVs and AGC jointly. Farmers are known to accept new technology by trial on a portion of their farmland before adopting fully. Therefore, farmers with extensive farmland can dedicate more plots to try and adopt new technology, as in the case of ISVs and AGC, than those with less farmland. This result is in line with Lu et al. (2021) findings. A positive correlation between total labour employed and CSAT adoption combinations $I_0A_1S_1$, $I_1A_1S_0$ and $I_1A_1S_1$, upholds the high labour requirement of CSAT, especially in developing countries such as the WASR where mechanized farming is limited. This finding is parallel to the study of Amadu, Miller, et al. (2020) for CSAT adoption in Southern Malawi. The results further revealed that farmers whose soil fertility is perceived to be excellent and moderate are more likely to adopt CSAT combinations $I_1A_1S_0$ and $I_1A_1S_1$ than those with poor soil fertility. In agreement with the work of Khonje et al. (2018) and Zegeye et al. (2022), farmers who have moderate and good fertile soil tend to be more willing to invest in farm technologies that will further improve their crop productivity. Gentle or flat farm plot has a positive correlation across all CSAT combinations, revealing that planting on a flat land surface increases farmers' propensity to adopt CSAT packages. A plausible reason is that the cost of investing in different CSAT packages on a flat soil surface is cheaper and less risky than derelict land. Contrary to this result, Amadu, Miller, et al. (2020) found no statistically significant difference between farm plot topography and CSAT adoption among maize farmers in southern Malawi.

A plethora of studies (Awotide et al., 2022; Bello et al., 2021; Danso-Abbeam & Baiyegunhi, 2018; Khan et al., 2020; Lu et al., 2021) has documented that policy, and institutional factors/variables are essential in elucidating the pathways of farm technology adoption. This assertion has been affirmed, as our results show that being a member of FBO, having access to credit and extension service increases farmers' probability of adopting all the CSAT packages. Furthermore, our findings revealed that crop disease shock has a positive and statistically significant influence on the adoption of CSAT combinations $I_0A_1S_0$ and $I_1A_1S_0$, but positively affects package $I_1A_1S_1$ adoption.

The negative relationship between farm households who experienced shock arising from crop disease and the adoption of CSAT combinations $I_0A_1S_0$ and $I_1A_1S_0$, might be ascribed to the incidence of the widespread disease outbreak of army fall worm which occurs in West Africa (including the study area) between the last three year (2016-2019) before the survey. Farmers who used agrochemicals and ISVs were also affected by the disease because most of these farmers don't use the recommended rate of these technologies, as observed in the survey interviews. Therefore, a risk-averse farmer having gone through this experience might reduce the urge to adopt these CSAT packages. However, the positive relationship between $I_1A_1S_1$ adoption and crop disease signify that farmers are more likely to adopt multiple CSAT combinations to mitigate the future attack of crop disease and subsequently boost crop productivity. This result contradicts the findings of Lu et al. (2021). The location variable Mali is significant but negatively affects all CSAT combinations, indicating that farm households in Mali country are less likely to adopt these packages than their counterparts in Niger. Although Mali and Niger share similar climatic conditions, Niger experienced more harsh and variable weather conditions than Mali. Therefore, farmers in Niger might have a higher propensity to adopt the CSAT packages than those in Mali to cushion the adverse effect of climate change on farm production.

Table 4: Multinomial logit model estimates of CSAT combinations adoption – Pooled Sample

Variables	$I_0A_1S_0$	$I_0A_0S_1$	$I_1A_1S_0$	$I_1A_0S_0 \vert A_1S_0 \vert A_0S_1$	$I_1A_1S_1$
lnHHSz	0.091	-0.13	-0.30**	-0.25*	-0.52***
	(0.13)	(0.13)	(0.13)	(0.15)	(0.15)
lnHHage	-0.13	0.36	-0.71***	-0.067	-0.20
	(0.29)	(0.28)	(0.27)	(0.33)	(0.30)
lnEdu_yrs	0.096	0.043	0.25***	0.017	0.23***
	(0.079)	(0.074)	(0.074)	(0.085)	(0.079)
lnfm_exp	-0.18	-0.30**	-0.26**	0.033	-0.29**

	(0.13)	(0.13)	(0.13)	(0.15)	(0.14)
lndst_Mkt	-0.064	-0.073	-0.016	-0.081	-0.029
	(0.060)	(0.054)	(0.055)	(0.059)	(0.060)
lndst_rsd	-0.32***	-0.34***	-0.44***	-0.25***	-0.39***
	(0.069)	(0.065)	(0.068)	(0.071)	(0.073)
lnHH_ast	0.18***	0.13***	0.15***	0.11***	0.14***
	(0.049)	(0.033)	(0.031)	(0.036)	(0.033)
lnPrd_ast	0.083	0.042	0.27***	0.033	0.12**
	(0.059)	(0.047)	(0.051)	(0.048)	(0.052)
lnTTLU	-0.040	0.034	-0.095	0.16**	0.19**
	(0.079)	(0.079)	(0.075)	(0.080)	(0.086)
lnFm_Sz	0.086	0.22	0.33**	0.21	-0.033
	(0.16)	(0.16)	(0.15)	(0.15)	(0.16)
lnTLB	0.32***	0.14	0.58***	0.14	0.84***
	(0.11)	(0.12)	(0.11)	(0.12)	(0.12)
lnoff_inc	-0.028**	-0.032**	-0.028**	-0.0094	0.0024
	(0.013)	(0.012)	(0.012)	(0.013)	(0.013)
good_soilfert	-0.17	0.12	0.45***	0.14	0.44**
	(0.19)	(0.16)	(0.16)	(0.18)	(0.17)
med_soilfert	0.32*	0.17	0.41**	0.13	0.28
	(0.18)	(0.16)	(0.16)	(0.18)	(0.18)
flat_slope	0.36*	0.32*	0.33*	0.52**	0.52**
	(0.19)	(0.19)	(0.18)	(0.22)	(0.20)
med_slope	0.10	-0.036	0.19	-0.033	0.068
	(0.19)	(0.17)	(0.17)	(0.20)	(0.18)
FBO	0.29*	0.40**	0.64***	0.53***	0.87***
	(0.17)	(0.18)	(0.17)	(0.17)	(0.18)
conctExtAgnt	1.58***	0.0093	1.71***	1.52***	1.71***
	(0.31)	(0.45)	(0.32)	(0.33)	(0.33)
Fm_Crd	0.78***	1.16***	1.23***	1.18***	1.89***
	(0.16)	(0.16)	(0.15)	(0.17)	(0.18)
MALI	-0.70**	-3.44***	-3.80***	-2.42***	-3.91***
	(0.33)	(0.27)	(0.29)	(0.30)	(0.30)
Shock_crop_disease	-0.60***	-0.10	-0.26*	0.16	0.27*
	(0.18)	(0.16)	(0.16)	(0.18)	(0.17)

Note: Robust standard errors are in parenthesis. *** p<0.01, ** p<0.05, * p<0. $I_0A_0S_0$ signifies the reference category of CSAT non-adoption.

3.4 Welfare effects of multiple CSAT adoption – METE

The causal effects of CSAT adoption combinations on farm household welfare (crop sales revenue and income) obtained from the multinomial endogenous treatment effect (METE) model are presented in Tables 5 and 6. The results for farmers who cultivated all five crops (millet, sorghum, cowpea, groundnut, and maize) are in Table 5. We further estimated the welfare effect of the most cultivated crop i.e., millet, in the study area, as shown in Table 6. Specifically, the total sample results indicate a positive and statistically significant impact of all the CSAT combinations on crop sales revenue and income, suggesting that farmers who adopted the CSAT packages are better off than non-adopters. For sales revenues, adopters of the three CSAT packages ($I_1A_1S_1$) realized the highest gains (181095.9 FCFA), while adopters of ISVs in isolation or in combination with AGC or SLM ($I_1A_0S_0|A_1S_0|A_0S_1$) had the highest crop income. This result revealed that adopting CSAT packages in multiples has a greater welfare impact than adopting them in singles. This result is in tandem with previous studies on the welfare impact of joint agricultural technology adoption in Zambia (Khonje et al., 2018) and Ghana (Lu et al., 2021).

With regards to smallholder farm households in Mali, adopters of all the CSAT packages would have realized fewer crop sales revenue and income had they not adopted. Precisely, the adoption of $I_1A_0S_1$ leads to the highest crop sales revenue (317666.6 FCFA) and income (131591.6 FCFA), followed by $I_1A_1S_1$ (289957.0 FCFA and 124913.5 FCFA). These results also affirm that adopting CSAT packages jointly provides a higher welfare impact than adopting them in isolation.

Surprisingly, the adoption of $I_1A_0S_1$ has a significant but negative impact on crop sales revenue and income among smallholder farmers in Niger. A plausible explanation behind this unexpected result is that while farmers adopt these CSAT packages, some don't apply them appropriately. As our data emanated from a baseline survey, thus these farmers utilized these CSAT packages discretionally without receiving appropriate field training. During the interview schedules, it was discovered that some farmers misuse ISVs (applying below or above recommended rate) and SLM (e.g., inappropriate space intervals for intercropping and SWC techniques). However, the adoption of $I_1A_0S_0|A_1S_0|A_0S_1$ and $I_1A_1S_1$ increases the welfare of smallholder farm households.

The causal impact of multiple welfare adoption on millet crop farmers is similar to that of the combined (five) crop farmers, as shown in Table 6. Adopting all CSAT packages increases the crop sales revenue and income for the pooled smallholder farm households and those in Mali. The results further revealed that there is no statistical and significant effect of adopting CSAT combinations ($I_0A_1S_0$, $I_0A_0S_1$, and $I_1A_0S_1$) on crop sales revenue and income of the farmers. Similar to the combined crop result, farm households who adopted $I_1A_0S_0|A_1S_0|A_0S_1$ and $I_1A_1S_1$ realized higher gains in crop sales revenue (93069.6 and 52256.7 FCFA) and income (127784.4 and 44747.6 FCFA) than non-adopters. This result concludes that joint adoption of CSAT packages transforms into better welfare than single adoption.

Table 5: Welfare impact of multiple CSAT adoption among smallholder farmers–Multinomial Endogenous Treatment Effect (METE) Pooled (five crops)

Sample	CSAT Packages	Sales revenue	Crop income
Full-sample	$I_0A_1S_0$	112261.5***	56299.89***
		(23768.15)	(15354)
	$I_0A_0S_1$	173021.3***	34657.87***
		(15503.32)	(13351)
	$I_1A_0S_1$	130274.4***	88880.32***
		(17978.13)	(19619)
	$I_1A_0S_0\|A_1S_0\|A_0S_1$	145001.7***	116930.1***
		(16224.89)	(20606.2)
	$I_1A_1S_1$	181095.9***	114986.6***
N = 3, 371		(27897.6)	(14535.9)
Mali	$I_0A_1S_0$	136982.7***	65621.9***

		(16663.0)	(22043.4)
	$I_0A_0S_1$	151718.1***	96912.9***
		(17608.5)	(21818.2)
	$I_1A_0S_1$	317666.6***	131591.6***
		(23913.9)	(22536.9)
	$I_1A_0S_0 \| A_1S_0 \| A_0S_1$	199557.9***	117049.7***
		(24660.1)	(44794.4)
	$I_1A_1S_1$	289957.0***	124913.5***
N = 2, 004		(25128.7)	(20357.8)
Niger	$I_0A_1S_0$	-23507.8	-10112.7
		(23157.5)	(18124.7)
	$I_0A_0S_1$	17066.2	-15550.3
		(16544.5)	(15287.0)
	$I_1A_0S_1$	-43009.7***	-28152.5*
		(15954.0)	(14370.2)
	$I_1A_0S_0 \| A_1S_0 \| A_0S_1$	93069.6***	127784.4***
		(17447.3)	(17947.9)
	$I_1A_1S_1$	52256.7***	44747.6**
N = 1, 367		(17620.1)	(17562.7)

Note: Robust standard errors are in parenthesis. *** p<0.01, ** p<0.05, * p<0

Sample	Combination	Sales revenue	Crop income
Full-sample	$I_0A_1S_0$	116169.0***	76332.1***
		(17351.7)	(14746.0)
	$I_0A_0S_1$	95384.1***	64261.8***
		(23116.3)	(15926.3)
	$I_1A_0S_1$	106866.1***	67137.8***
		(15226.0)	(13087.4)
	$I_1A_0S_0 \| A_1S_0 \| A_0S_1$	128001.6***	106562.6***
		(16426.3)	(18991.1)
	$I_1A_1S_1$	167547.3***	131483.3***
N = 2, 282		(21945.0)	(26924.8)
Mali	$I_0A_1S_0$	158730.8***	84832.5***

		(18876.5)	(22369.9)
	$I_0A_0S_1$	107465.3***	203386.5***
		(23474.8)	(29296.5)
	$I_1A_0S_1$	204465.1***	146641.6***
		(19444.9)	(20295.8)
	$I_1A_0S_0 \vert A_1S_0 \vert A_0S_1$	291391.8***	188673.3***
		(34287.6)	(34442.5)
	$I_1A_1S_1$	203018.3***	175890.1***
N = 987		(25101.2)	(23788.7)
Niger	$I_0A_1S_0$	17530.3	894.8
		(23012.9)	(19848.3)
	$I_0A_0S_1$	-12481.9	-16552.5
		(15698.7)	(13796.0)
	$I_1A_0S_1$	1841.3	-6619.4
		(24975.4)	(18941.1)
	$I_1A_0S_0 \vert A_1S_0 \vert A_0S_1$	136868.7***	139920.2***
		(28380.0)	(22409.5)
	$I_1A_1S_1$	68511.9**	53133.4***
N = 1, 295		(27229.3)	(17482.1)

Table 6: Welfare impact of multiple CSAT adoption among Millet farmers – Multinomial Endogenous Treatment Effect (METE)

Note: Robust standard errors are in parenthesis. *** p<0.01, ** p<0.05, * p<0

4.0 Conclusion and Policy implication

This study evaluated the potential welfare impact of adopting different CSAT combinations (in singles and multiple) among smallholder crop farmers in the WASR using a multinomial endogenous treatment effect model. The results from the first stage (MNL model) revealed that several socio-demographic, farm plot, institutional and production shock variables significantly influenced the probability of adopting various CSAT packages. The findings from this study can be utilized as policy guidelines for farm-level programs targeted towards scaling up CSAT adoption and subsequently improving the welfare of smallholder farm households in the WASR. Specifically, the positive and statistically significant effect of institutional variables such as farmer-based organization (FBO), access to formal credit and extension services on all the CSAT combinations (both single and multiple) emphasizes the need to strengthen these vital socio-institutions. For instance, FBOs could be supported by non-governmental organizations (NGOs) to create comprehensive sensitization programs about the benefits of farmers becoming a member. In addition, the NGOs could assist in forming FBOs in villages or communities where FBOs are not in existence.

Furthermore, the result indicated that access to formal credit is very low among farmers in the study area, and it has a positive influence on all CSAT packages. This finding spurs the urgent need for more formal credit organizations in the study area. Where formal credits are available low-interest rates and flexible loan terms/repayments could bourgeon farmers' accessibility which would, in turn, enhance CSAT adoption. Similarly, extension access stimulates farmers' probability of adopting all CSAT combinations. Likewise, an additional year of farmers' education years increases the likelihood of CSAT adoption. These findings suggest that extension service can be bolstered through a modern form of adult education such as farm demonstrations, and technology enlightenment among others.

Finally, the second stage estimation of the METE revealed that the adoption of all CSAT combinations increases the crop sales revenue and income among the sampled smallholder farmers (except in Niger) in almost all cases. However, the positive significance of adopting all three CSAT packages (AGC, ISVs, SLM) in all cases, including Niger, implies that multiple CSAT adoption improves the welfare of smallholder farmers in the study area. Therefore, this study recommends that agricultural stakeholders and policymakers should encourage and promote a multiple adoption of CSAT packages among smallholder farmers in the Sahelian region of west Africa and other similar dry environments in developing nations.

This study is limited to a cross-sectional baseline survey of a cropping calendar year. Future research could focus on a similar but more rigorous analysis based on several rounds of surveys or panel data to show how the welfare of smallholder farmers transforms over several periods based on CSAT adoption.

APPENDIX

Table A1: CSAT Combinations used in the study

Improved Seed Varieties (ISVs)	Agrochemicals (AGC)	Sustainable Land Management Technologies (SLMT)
Early maturing,	Inorganic Fertilizer	Soil and water Conservation
High yielding	Herbicide	Mulch_compost
Drought and disease resistant	Pesticide	Cover Cropping
		Minimum Tillage
		Improving grazing and pasture
		Integrated pest mangement
		Intercropping

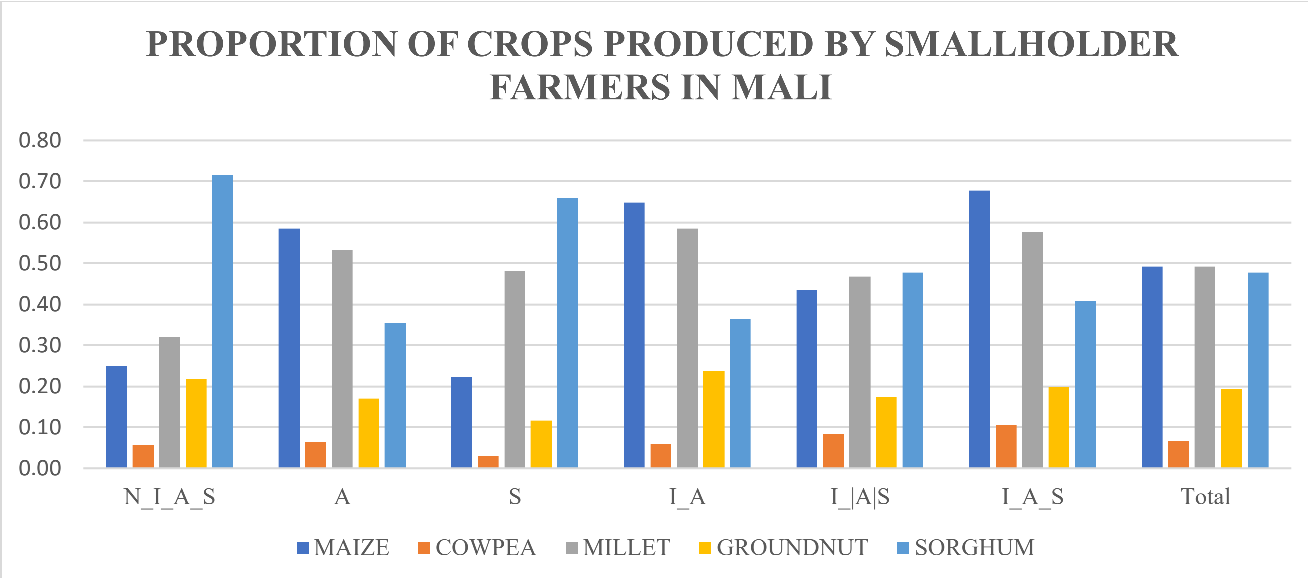

Figure A1: Proportion of crops produced by sampled smallholder farmers in Mali
Source: Authors 2023

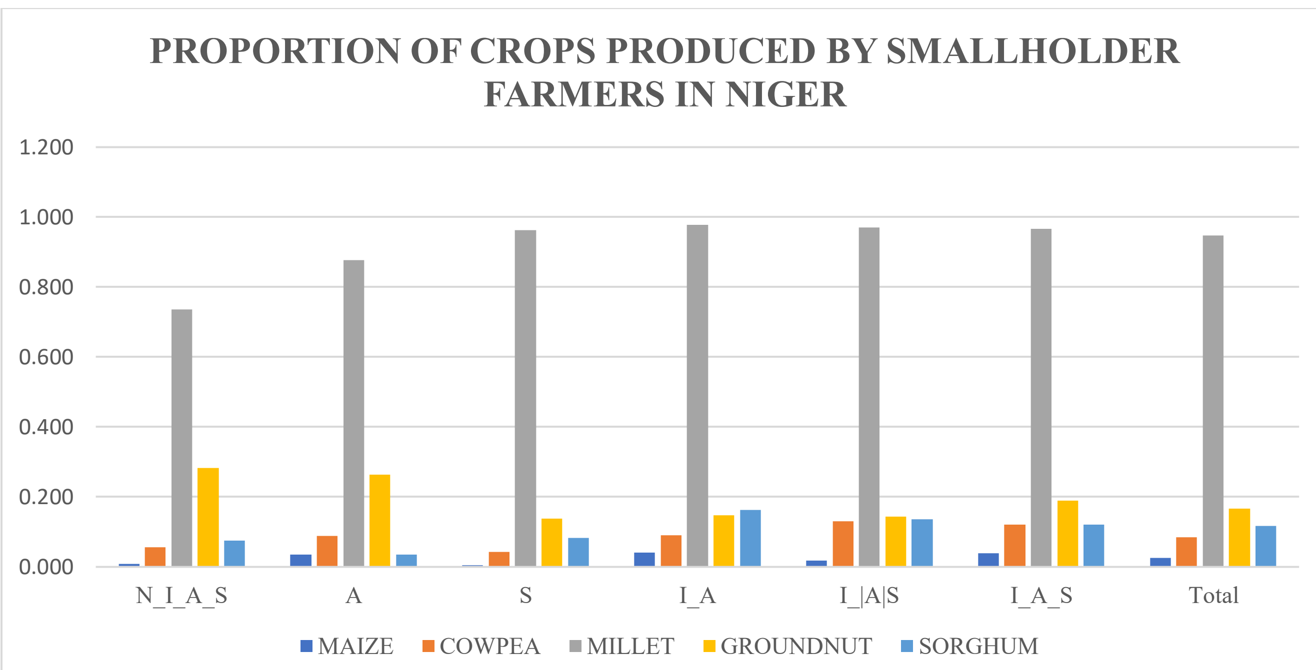

Figure A2: Proportion of crops produced by sampled smallholder farmers in Niger
Source: Authors 2023

Table A2: Multinomial logit model estimates of CSAT combinations adoption – MALI

Variables	$I_0A_1S_0$	$I_0A_0S_1$	$I_1A_1S_0$	$I_1A_0S_0\|A_1S_0\|A_0S_1$	$I_1A_1S_1$

lnHHSz	0.10	-0.27	-0.31**	-0.38**	-0.60***
	(0.15)	(0.17)	(0.16)	(0.17)	(0.18)
lnHHage	0.15	1.05***	-0.61*	0.15	-0.091
	(0.32)	(0.40)	(0.34)	(0.39)	(0.37)
lnEdu_yrs	0.059	-0.11	0.24***	0.078	0.31***
	(0.088)	(0.100)	(0.092)	(0.10)	(0.098)
lnfm_exp	-0.26*	-0.41**	-0.21	-0.11	-0.35**
	(0.16)	(0.18)	(0.18)	(0.19)	(0.18)
lndst_Mkt	-0.10	-0.099	-0.019	-0.11	-0.053
	(0.069)	(0.071)	(0.071)	(0.071)	(0.080)
lndst_rsd	-0.39***	-0.44***	-0.51***	-0.33***	-0.37***
	(0.079)	(0.090)	(0.085)	(0.086)	(0.091)
lnHH_ast	0.15**	0.045	0.050	0.0053	-0.054
	(0.062)	(0.078)	(0.055)	(0.062)	(0.058)
lnPrd_ast	0.15**	0.25***	0.45***	0.19***	0.43***
	(0.077)	(0.083)	(0.082)	(0.072)	(0.093)
lnTTLU	-0.10	-0.090	-0.20**	0.053	0.098
	(0.087)	(0.11)	(0.091)	(0.092)	(0.11)
lnFm_Sz	0.17	0.29	0.53***	0.27	0.18
	(0.17)	(0.22)	(0.18)	(0.18)	(0.19)
lnTLB	0.23*	0.026	0.30**	0.099	0.83***
	(0.13)	(0.17)	(0.14)	(0.15)	(0.15)
lnoff_inc	-0.024*	-0.019	-0.035**	-0.0096	-0.0026
	(0.014)	(0.017)	(0.015)	(0.016)	(0.017)
good_soilfert	-0.26	0.41*	0.45**	-0.019	0.26
	(0.22)	(0.24)	(0.23)	(0.24)	(0.26)
med_soilfert	0.10	-0.100	0.19	-0.24	-0.030
	(0.20)	(0.23)	(0.20)	(0.22)	(0.25)
flat_slope	0.54**	0.53*	0.39	0.84***	0.62**
	(0.23)	(0.31)	(0.26)	(0.26)	(0.28)
med_slope	0.24	-0.091	0.24	0.31	0.14
	(0.22)	(0.30)	(0.24)	(0.25)	(0.26)
FBO	0.52***	0.39*	0.73***	1.09***	1.42***
	(0.18)	(0.22)	(0.21)	(0.24)	(0.30)
Formal_Credit	1.64***	-0.26	1.79***	1.54***	1.59***
	(0.33)	(0.52)	(0.33)	(0.35)	(0.35)
conctExtAgnt	0.76***	1.10***	1.38***	1.10***	2.18***
	(0.17)	(0.21)	(0.19)	(0.22)	(0.27)
SHOCK_CROP_DISEASE	-0.79***	-0.39	-0.72***	-0.067	-0.36*
	(0.20)	(0.24)	(0.20)	(0.22)	(0.21)

Note: Robust standard errors are in parenthesis. *** p<0.01, ** p<0.05, * p<0. $I_0A_0S_0$ signifies the reference category of CSAT non-adoption.

Table A3: Multinomial logit model estimates of CSAT combinations adoption – NIGER

Variables	$I_0A_1S_0$	$I_0A_0S_1$	$I_1A_1S_0$	$I_1A_0S_0\|A_1S_0\|A_0S_1$	$I_1A_1S_1$

lnHHSz	-0.47	0.20	-0.28	0.20	-0.20
	(0.44)	(0.29)	(0.29)	(0.31)	(0.32)
lnHHage	-0.68	0.093	-0.43	-0.27	-0.19
	(0.93)	(0.49)	(0.52)	(0.60)	(0.59)
lnEdu_yrs	0.41**	0.23	0.38**	0.0065	0.30*
	(0.21)	(0.16)	(0.16)	(0.18)	(0.16)
lnfm_exp	0.22	-0.27	-0.49**	0.19	-0.23
	(0.40)	(0.23)	(0.24)	(0.26)	(0.25)
lndst_Mkt	0.14	-0.028	0.041	-0.031	0.015
	(0.13)	(0.098)	(0.099)	(0.12)	(0.11)
lndst_rsd	-0.050	0.010	-0.053	0.15	-0.042
	(0.19)	(0.11)	(0.13)	(0.14)	(0.13)
lnHH_ast	0.13*	0.14***	0.21***	0.15***	0.24***
	(0.075)	(0.033)	(0.037)	(0.043)	(0.050)
lnPrd_ast	0.11	-0.13*	0.091	-0.13*	-0.073
	(0.10)	(0.071)	(0.075)	(0.079)	(0.076)
lnTTLU	0.21	0.35***	0.27*	0.47***	0.46***
	(0.19)	(0.14)	(0.14)	(0.15)	(0.15)
lnFm_Sz	-0.20	-0.18	-0.22	-0.16	-0.59**
	(0.29)	(0.23)	(0.23)	(0.22)	(0.25)
lnTLB	0.53*	0.19	0.93***	0.054	0.82***
	(0.30)	(0.20)	(0.21)	(0.22)	(0.22)
lnoff_inc	-0.071**	-0.035	-0.020	-0.0095	0.0096
	(0.034)	(0.024)	(0.025)	(0.027)	(0.025)
good_soilfert	0.14	0.16	0.66**	0.37	0.74***
	(0.40)	(0.27)	(0.28)	(0.29)	(0.29)
med_soilfert	0.74*	0.90***	1.14***	0.93***	1.09***
	(0.41)	(0.27)	(0.29)	(0.31)	(0.32)
flat_slope	-0.33	0.15	0.34	0.35	0.53
	(0.43)	(0.32)	(0.32)	(0.40)	(0.37)
med_slope	-0.29	0.015	0.20	-0.28	0.11
	(0.43)	(0.29)	(0.29)	(0.35)	(0.31)
FBO	-0.66	0.048	0.35	-0.34	0.36
	(0.48)	(0.29)	(0.30)	(0.35)	(0.30)
Formal_Credit	-0.83	12.3***	12.0***	12.2***	13.0***
	(0.52)	(0.59)	(0.62)	(1.06)	(0.52)
conctExtAgnt	1.06**	1.09***	0.93***	1.18***	1.68***
	(0.42)	(0.36)	(0.35)	(0.37)	(0.37)
SHOCK_CROP_DISEASE	-0.33	0.60**	0.48*	0.72**	1.24***
	(0.37)	(0.25)	(0.26)	(0.28)	(0.29)

Note: Robust standard errors are in parenthesis. *** p<0.01, ** p<0.05, * p<0. $I_0A_0S_0$ signifies the reference category of CSAT non-adoption.

Table A4: Multinomial logit model estimates of CSAT combinations adoption among Millet crop farmers– Pooled Sample

Variables	$I_0A_1S_0$	$I_0A_0S_1$	$I_1A_1S_0$	$I_1A_0S_0 \vert A_1S_0 \vert A_0S_1$	$I_1A_1S_1$
lnHHSz	0.21	0.066	-0.25	-0.072	-0.34*
	(0.20)	(0.19)	(0.18)	(0.21)	(0.20)
lnHHage	-0.35	0.11	-0.67*	-0.30	-0.31
	(0.39)	(0.36)	(0.35)	(0.45)	(0.38)
lnEdu_yrs	0.13	0.13	0.34***	0.062	0.33***
	(0.12)	(0.11)	(0.10)	(0.12)	(0.11)
lnfm_exp	0.12	-0.093	-0.089	0.39*	-0.062
	(0.19)	(0.16)	(0.17)	(0.20)	(0.18)
lndst_Mkt	0.12	0.0091	0.043	-0.0052	0.026
	(0.080)	(0.071)	(0.068)	(0.079)	(0.075)
lndst_rsd	-0.16	-0.21**	-0.27***	-0.060	-0.22**
	(0.11)	(0.088)	(0.092)	(0.10)	(0.097)
lnHH_ast	0.24***	0.10***	0.15***	0.093**	0.16***
	(0.069)	(0.038)	(0.039)	(0.045)	(0.039)
lnPrd_ast	0.19**	0.11*	0.34***	0.11	0.18***
	(0.080)	(0.063)	(0.066)	(0.071)	(0.066)
lnTTLU	0.16	0.15	0.068	0.25**	0.33***
	(0.12)	(0.11)	(0.11)	(0.12)	(0.12)
lnFm_Sz	-0.12	0.084	0.11	0.17	-0.25
	(0.21)	(0.21)	(0.20)	(0.21)	(0.21)
lnTLB	0.13	0.042	0.50***	-0.096	0.67***
	(0.15)	(0.14)	(0.14)	(0.15)	(0.14)
lnoff_inc	-0.0077	-0.017	-0.010	0.00064	0.023
	(0.018)	(0.017)	(0.017)	(0.019)	(0.017)
good_soilfert	-0.13	-0.23	0.30	0.15	0.23
	(0.25)	(0.21)	(0.21)	(0.23)	(0.22)
med_soilfert	0.25	0.29	0.44**	0.31	0.28
	(0.24)	(0.20)	(0.20)	(0.23)	(0.22)
flat_slope	0.051	-0.028	0.15	0.20	0.23
	(0.26)	(0.25)	(0.23)	(0.29)	(0.26)
med_slope	-0.18	-0.090	0.15	-0.25	-0.019
	(0.25)	(0.22)	(0.21)	(0.25)	(0.23)
FBO	0.23	0.15	0.35	0.25	0.57**
	(0.26)	(0.25)	(0.24)	(0.25)	(0.24)
conctExtAgnt	1.00**	-0.53	1.00**	1.30***	1.30***
	(0.46)	(0.66)	(0.44)	(0.49)	(0.47)
Fm_Crd	0.58**	0.93***	0.96***	1.11***	1.55***
	(0.23)	(0.22)	(0.21)	(0.24)	(0.23)
MALI	-0.93**	-3.31***	-3.49***	-2.36***	-3.50***
	(0.44)	(0.39)	(0.39)	(0.41)	(0.40)
Shock_crop_disease	-0.76***	0.0058	-0.11	0.33	0.50**
	(0.27)	(0.22)	(0.22)	(0.24)	(0.23)

Note: Robust standard errors are in parenthesis. *** p<0.01, ** p<0.05, * p<0. $I_0A_0S_0$ signifies the reference category of CSAT non-adoption.

Table A5: Multinomial logit model estimates of CSAT combinations adoption among Millet crop farmers – MALI

Variables	$I_0A_1S_0$	$I_0A_0S_1$	$I_1A_1S_0$	$I_1A_0S_0 \vert A_1S_0 \vert A_0S_1$	$I_1A_1S_1$

lnHHSz	0.37	0.039	-0.17	-0.25	-0.38
	(0.23)	(0.27)	(0.25)	(0.29)	(0.25)
lnHHage	-0.20	0.22	-0.81*	-0.52	-0.58
	(0.47)	(0.61)	(0.46)	(0.67)	(0.50)
lnEdu_yrs	0.052	0.012	0.32**	0.10	0.44***
	(0.15)	(0.16)	(0.14)	(0.17)	(0.14)
lnfm_exp	0.16	0.13	0.23	0.54*	0.016
	(0.22)	(0.24)	(0.23)	(0.31)	(0.22)
lndst_Mkt	0.055	0.032	-0.011	-0.091	-0.029
	(0.100)	(0.11)	(0.092)	(0.11)	(0.11)
lndst_rsd	-0.31**	-0.38***	-0.42***	-0.22	-0.27*
	(0.13)	(0.14)	(0.13)	(0.14)	(0.14)
lnHH_ast	0.25***	-0.0051	0.055	-0.078	-0.093
	(0.092)	(0.11)	(0.087)	(0.099)	(0.095)
lnPrd_ast	0.24*	0.29*	0.53***	0.34**	0.56***
	(0.14)	(0.15)	(0.14)	(0.17)	(0.15)
lnTTLU	-0.054	-0.22	-0.22	-0.11	0.074
	(0.16)	(0.18)	(0.16)	(0.16)	(0.18)
lnFm_Sz	0.32	0.77**	0.76***	0.84**	0.51
	(0.27)	(0.39)	(0.28)	(0.34)	(0.31)
lnTLB	0.017	0.10	0.24	-0.080	0.69***
	(0.18)	(0.25)	(0.19)	(0.21)	(0.20)
lnoff_inc	0.028	0.028	0.015	0.025	0.051**
	(0.021)	(0.027)	(0.021)	(0.026)	(0.024)
good_soilfert	0.18	0.071	0.73**	0.65	0.28
	(0.35)	(0.43)	(0.34)	(0.40)	(0.38)
med_soilfert	0.12	0.32	0.27	0.19	-0.034
	(0.30)	(0.35)	(0.28)	(0.35)	(0.33)
flat_slope	0.25	0.23	0.29	0.54	0.32
	(0.33)	(0.45)	(0.35)	(0.38)	(0.37)
med_slope	0.082	-0.031	0.30	0.100	0.17
	(0.30)	(0.44)	(0.32)	(0.37)	(0.34)
FBO	0.59*	0.0035	0.21	1.23***	0.82**
	(0.34)	(0.38)	(0.33)	(0.41)	(0.38)
Formal_Credit	1.09**	-1.07	1.13**	1.28**	1.21**
	(0.47)	(0.84)	(0.47)	(0.52)	(0.51)
conctExtAgnt	0.50*	0.72**	1.11***	1.45***	1.60***
	(0.27)	(0.31)	(0.28)	(0.44)	(0.37)
SHOCK_CROP_DISEASE	-1.09***	-0.56	-0.54	0.26	-0.13
	(0.37)	(0.43)	(0.34)	(0.39)	(0.35)

Note: Robust standard errors are in parenthesis. *** p<0.01, ** p<0.05, * p<0. $I_0A_0S_0$ signifies the reference category of CSAT non-adoption.

Table A6: Multinomial logit model estimates of CSAT combinations adoption among Millet crop farmers – NIGER

Variables	$I_0A_1S_0$	$I_0A_0S_1$	$I_1A_1S_0$	$I_1A_0S_0 \mid A_1S_0 \mid A_0S_1$	$I_1A_1S_1$
lnHHSz	-0.59	0.23	-0.31	0.24	-0.19
	(0.48)	(0.34)	(0.34)	(0.36)	(0.37)
lnHHage	-1.30	0.24	-0.27	0.044	-0.037
	(0.92)	(0.51)	(0.55)	(0.63)	(0.61)
lnEdu_yrs	0.43*	0.24	0.43**	0.087	0.35*
	(0.24)	(0.19)	(0.18)	(0.20)	(0.19)
lnfm_exp	0.69	-0.24	-0.40	0.22	-0.15
	(0.48)	(0.25)	(0.26)	(0.28)	(0.28)
lndst_Mkt	0.28**	0.059	0.14	0.088	0.093
	(0.14)	(0.11)	(0.11)	(0.12)	(0.11)
lndst_rsd	0.022	0.083	0.015	0.24	0.053
	(0.22)	(0.13)	(0.14)	(0.15)	(0.14)
lnHH_ast	0.16*	0.11***	0.18***	0.11**	0.21***
	(0.084)	(0.036)	(0.041)	(0.046)	(0.047)
lnPrd_ast	0.27**	0.048	0.26***	0.037	0.11
	(0.11)	(0.073)	(0.078)	(0.082)	(0.077)
lnTTLU	0.36*	0.50***	0.43***	0.61***	0.61***
	(0.21)	(0.14)	(0.15)	(0.16)	(0.16)
lnFm_Sz	-0.41	-0.47**	-0.50**	-0.41*	-0.91***
	(0.30)	(0.23)	(0.23)	(0.23)	(0.25)
lnTLB	0.45	-0.029	0.69***	-0.21	0.57***
	(0.30)	(0.21)	(0.22)	(0.23)	(0.22)
lnoff_inc	-0.085**	-0.046*	-0.031	-0.016	-0.0020
	(0.037)	(0.026)	(0.027)	(0.029)	(0.027)
good_soilfert	-0.37	-0.27	0.22	-0.065	0.31
	(0.43)	(0.29)	(0.30)	(0.31)	(0.30)
med_soilfert	0.32	0.57*	0.81**	0.54	0.74**
	(0.45)	(0.30)	(0.32)	(0.34)	(0.34)
flat_slope	-0.28	0.18	0.40	0.38	0.56
	(0.46)	(0.36)	(0.36)	(0.43)	(0.41)
med_slope	-0.45	0.026	0.21	-0.28	0.084
	(0.47)	(0.31)	(0.31)	(0.37)	(0.33)
FBO	-0.66	0.16	0.48	-0.14	0.53
	(0.55)	(0.36)	(0.36)	(0.40)	(0.36)
Formal_Credit	-0.89	12.2***	12.1***	12.4***	13.2***
	(0.63)	(0.72)	(0.66)	(1.00)	(0.67)
conctExtAgnt	1.06**	1.13***	0.97**	1.15***	1.70***
	(0.46)	(0.40)	(0.39)	(0.41)	(0.41)
SHOCK_CROP_DISEASE	-0.61	0.29	0.15	0.33	0.87***
	(0.40)	(0.28)	(0.30)	(0.31)	(0.32)

Note: Robust standard errors are in parenthesis. *** p<0.01, ** p<0.05, * p<0. $I_0A_0S_0$ signifies the reference category of CSAT non-adoption.

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