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Research Article

Evaluating the impact of climate-smart agriculture practices on yield among smallholder maize and sorghum farmers in northern Ghana

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ABSTRACT

This study evaluates the impact of climate-smart agricultural practices (CSAP) on yield and income among smallholder farmers in Northern Ghana. Understanding the impact of CSAPs on maize and sorghum yield and income is crucial for enhancing agricultural productivity, boosting the region's economy, and ensuring food security. Data were collected through questionnaires from 1000 farmers. Multinomial endogenous treatment effects were used to examine the impact of CSAP adoption on the yield and income of maize and sorghum farmers. The study reveals that climate-smart agriculture practices like chemical fertiliser conservation agriculture, intercropping, and joint adoption significantly improve maize and sorghum yields and farmers' incomes. This is worrying given the effects of excessive reliance on chemical fertilisers on soil and environment. The government's active investment in research, capacity building, and infrastructure development to facilitate the widespread adoption of these practices in Northern Ghana is highly recommended.

INTRODUCTION

Agriculture is critical to global economic growth, contributing 4% to global GDP and supporting around 70% of impoverished individuals in rural areas (Raj *et al*., 2022). Yet, the sector is increasingly associated with climate change, using 40% of global land, 70% of fresh, and contributing 25% of human-induced greenhouse gas emissions. Climate change's effects on agriculture are exacerbated by population growth and rapid urbanization given the sector's reliance on natural resources (Geoge *et al*., 2020; Kurgat *et al*., 2020).

Sub-Saharan Africa, specifically Northern Ghana, faces significant climate change impacts, with projections indicating temperature increases of 1°C – 3°C by 2060 and up to 5.2°C by 2090 (Kyei-Mensah *et al*., 2019; Acheampong *et al*., 2022). Bawayelaazaa Nyuor *et al*., (2016) all reported that this has reduced crop yields and increased food insecurity, with about 1.2 million people in Ghana experiencing food insecurity due to these challenges. Northern Ghana is characterised by a dry deciduous to semi-arid climate and faces increasingly erratic rainfall patterns, frequent droughts, and floods, which severely undermine crop productivity and threaten the livelihoods of smallholder farmers (Nkegbe and Shankar, 2018; Alhassan *et al*., 2018).

These challenges necessitate innovative approaches to farming that can withstand climatic variability while maintaining agricultural productivity.

In response to these challenges, Climate-Smart Agriculture (CSA) offers a potential solution to these challenges, providing tailored practices like mulching, intercropping, and conservation agriculture to improve productivity and resilience (Botchway *et al.*, 2016). By adopting CSA, farmers can adapt to climate variability while mitigating greenhouse gas emissions. The Food and Agriculture Organization (FAO) identifies three key objectives for CSA: increasing productivity and income, enhancing resilience to climate shocks, and reducing emissions (FAO, 2016; IPCC, 2014; Khelifa *et al.*, 2021; Zougmoré *et al.*, 2021; Zubairu, 2021).

The study evaluates CSA's impact on smallholder maize and sorghum farmers in Northern Ghana, a region that experiences some of the highest levels of food insecurity and poverty. By examining CSA's role in sustainable agricultural development, the research aligns with the United Nations Sustainable Development Goals, specifically Goal 2 (Zero Hunger) and Goal 13 (Climate Action). The insights gained from this research are expected to guide efforts to improve food security and resilience across Northern Ghana and beyond

Finally, the study locations reflect the broader Northern Ghana demographic in terms of agricultural practices, socio-economic conditions, and climate challenges, allowing for broader regional applications of the findings. The outcomes are intended to benefit a diverse range of stakeholders, including farmers, policymakers, and international development agencies. The rest of this paper is structured as follows: Section 2 outlines the methodology, Section 3 discusses the results, Section 4 presents the conclusions, and Section 5 offers recommendations

MATERIALS AND METHODS

Study Area

Agriculture primarily characterized the Upper West, Upper East, and Northern Regions of Ghana, with farming as the predominant economic activity. The average minimum and maximum temperatures of the region are 14 ℃ at night and 40 ℃ during the day. The region experiences two seasons: the dry season (November to April) and the wet season (May to October), with an average annual rainfall of 750–1050 mm. The dry season started in November and concluded in March/April, characterized by the highest temperatures observed towards the end of this period (March-April), while December and January exhibited the lowest temperatures.

Harmattan winds normally occur from December and end in mid-February. The harmattan winds have a considerable effect on the temperature of the area, causing the temperature to vary between 14℃ at night and 40℃ during the day. Humidity is very low, aggravating the effect of daytime heat. Figure 3.1 shows the districts and communities of the study areas where data were collected from smallholder maize and sorghum farmers.

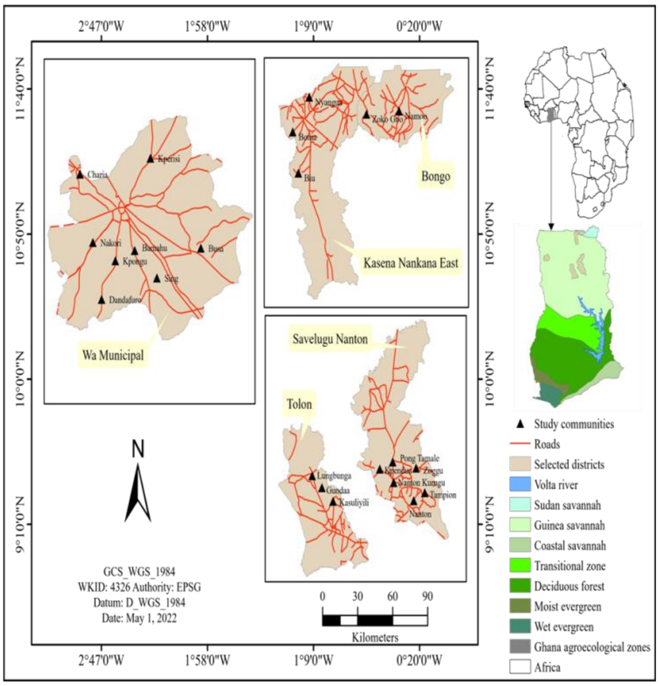

Figure 1. Map of the districts and communities where data were collected from farmers.

Sampling techniques and sample size

The study used a multistage sampling technique to select participants from the population of smallholder farmers in three regions: the Northern Region, the Upper East Region, and the Upper West Region. This approach involved several stages of selection to ensure a representative sample from these diverse areas.

Stage 1: Region Selection

The first stage involved selecting three regions where the study would be conducted. These regions were chosen based on their significant population of smallholder farmers and geographic representation. The regions selected were the Northern, Upper East, and Upper West regions.

Stage 2: District Selection

Within each selected region, the study identified specific districts where the study would occur. The districts were selected purposively based on their agricultural activity, access to climate-smart agricultural practices, and accessibility for the research team. For example:

In the Northern Region, the study chose the Savelugu and Tolon districts.

In the Upper East Region, the study chose the Bongo and Kasina-Nankana districts.

In the Upper West Region, the study chose the Wa West and Nadoli districts.

Stage 3: Community Selection

Within each selected district, the study further selected specific communities. This selection was also purposive, focusing on communities with a high density of smallholder farmers who had access to and used climate-smart agricultural practices. For example:

In the Savelugu district, the study selected the Nanton and Pong-Tamale communities.

In the Bongo district, the study selected the Namoo and Zoko Goo communities.

In the Wa West district, the study selected the Kpongu and Charia communities.

Stage 4: Participant Selection

Finally, the study selected individual smallholder farmers within each community. The selection was performed using a random sampling technique from a list of registered smallholder farmers maintained by the Ministry of Food and Agriculture (MoFA). The sample sizes for each community were proportionate to the population of smallholder farmers, ensuring balanced representation across regions and districts.

The total sample size for this study was 1,000, which was distributed across the three regions as follows:

Northern Region: 338 participants

Upper East Region: 330 participants

Upper West Region: 332 participants. The table summarises how multi-stage sampling was conducted.

Analytical framework and econometric model

In terms of impact analysis, existing studies use a count data model (Isgin *et al.*, 2008; Sharma *et al.*, 2011). In terms of agricultural innovative practice adoption, existing studies generally used propensity score matching (PSM) (Nakano *et al.*, 2018) to estimate the average treatment effect on the treated (ATT) and average treatment effect on the untreated (ATU). However, PSM can only correct the problem of sample selection bias caused by observable factors but fails to explain the impact of unobservable factors (Fischer and Qaim, 2012), potentially leading to bias in the estimates (Abdulai, 2016). Furthermore, multinomial endogenous switching regression (MESR) is applied to multivalued processing to explain observable and unobservable factors that affect the allocation and outcome of the treatment (Hörner & Wollni, 2022). However, it cannot estimate the average effect of the treatment from one treatment level to another. Based on these results, the multinomial endogenous treatment effects were used by Gao *et al.* (2019), Guo *et al.* (2020), and Zakaria *et al.* (2021) to evaluate the impact of agricultural innovative practices on the welfare of smallholder farmers. The multinomial endogenous treatment effects (METE) proposed by Deb and Trivedi (2006) was employed in this study to investigate the effect of maize and sorghum on smallholder farmers in Northern Ghana.

The study modelled farmers choice of practices (mulching, chemical fertiliser, conservation agriculture, intercropping, agroforestry, crop diversity, and crop choice) and their impact on the outcome variables using a multinomial endogenous treatment effect model as proposed by Deb and Trivedi (2006). The main advantage of this approach to impact evaluation is that it accounts for selectivity bias due to observed (through farm and household characteristics) and unobserved heterogeneity (via latent variables). This approach specifies a joint distribution of endogenous multivalued treatments and outcomes using observed and unobserved characteristics to link treatment and outcome equations.

The framework proposed by Deb and Trivedi (2006) has two components: the treatment equation and the outcome equation. These equations are connected by observed characteristics. Rosenbaum and Rubin (1983) and others (Cattaneo, 2010; Imbens & Wooldridge, 2009) have shown that individual farmers belong to different treatment groups but have similar socioeconomic characteristics (X) and can only be compared if the treatment assignment is random (Issahaku and Abdulai, 2020).

The adoption of CSA was categorised into non-adoption (0), adoption of chemical fertiliser (C. fertilise), only (1), adoption of conservation agriculture (CA) and intercropping (ITC) (2), adoption of chemical fertiliser and conservation agriculture (3), adoption of chemical fertiliser and intercropping (4) and joint adoption (5). Therefore, adoption occurs if the maize and sorghum farmers belong to any of these categories. Considering these categorisations, METE was applied to estimate the effects of each stage of adoption on maize and sorghum yields and income-setting non-adoption as a comparison group.

The multinomial treatment effect is a typical approach used in econometric models to address selectivity bias effects. It comprises two distinct segments that correspond to the generation processes of the treatment group indicators and outcome equations. In this context, the adoption of CSA practices by maize and sorghum farmers constitutes the treatment, whereas the observed outcome measures are the yields and income of these farmers. Specifically, a maize and sorghum farmer (i) decide whether to adopt these practices

CSA from a set of five treatments (t = 0, 1, 2, 3, 4, 5). Representing IU_{it}^{*} which denotes the indirect utility function with the t^{th} treatment, the indirect utility function can be stated as follows:

$$IU_{it}^{*} = K_i'\gamma_t + \delta_t\omega_{it} + \tau_{it}.$$

The indirect utility IU_{it}^{*} function comprises the latent factor ω_{it}unobservable characteristics generally common to individual maize and sorghum farmer treatment choices (i.e., C. fertiliser only, CA and ITC, C. fertiliser and CA, and joint adoption) and outcomes. It is assumed that ω_{it} is independent ofτ_{it}. Representing $t = 0$ as the based group (i.e., the decision of a maize and sorghum farmer not to adopt any of the CSAs), the indirect utility function would be set to zero for the based adoption. $IU_{it=0}^{*}$.

As. is unobservable, the binary variables b_t were represented for the observed treatment decision to adopt the CSA practice option available to maize and sorghum farmers. The b_t follow the mixed multinomial logit pattern structure $b_i = (b_{i1}, b_{12} \ldots \ldots . . d_{1t})$. Therefore, the probability function for a maize and sorghum farmer's decision to adopt CSA practices is expressed as a latent structure multinomial logit model

$$\Pr\left(\frac{b_i}{K_i\omega_i}\right) = \frac{\exp(K_i'\gamma_t + \delta_t\omega_{it})}{1 + \sum_{j=1}^{t}\exp(K_i'\gamma_k + \delta_k\omega_{ik})}$$

where *t,j = 0, 1, 2, 3, 4, 5, 6,*

The outcome equations (yield and income of maize and sorghum) can be expressed as follows:

$$E(y_i|b_t, K_i, \omega_i) = x_i'\beta + \sum_{t=1}^{T} \alpha_t b_{it} + \sum_{t=1}^{T} \pi_t \omega_{it}$$

The where is the set of all exogenous covariates within K_i and b_{it} is the treatment variable with the associated parameter vector β_i, $and\ \alpha_i$, are the treatment coefficients relative to the based group of no direct adoption of CSA efforts. The (y_i) is a function of each latent factor when the outcome variables are linked to unobservable effects that might have direct and/or indirect influence on the maize and sorghum farmers' decision to adopt CSAs. The loading factor coefficients (π_t) are estimated for each effect (impact) of the CSA option on maize and sorghum yields and income.

RESULTS AND DISCUSSION

The results from Table 2 showed the socio-demographic characteristics for the maize and sorghum farmer adopters and non-adopters of the CSA. The average age of adopters and non-adopters of CSA was 38 and 37 years, respectively, which is significant at the 5% level. This indicates that age plays a role in distinguishing CSA adopters from non-adopters. The number of adopters and non-adopters in male-headed households was 72% and 75%, respectively, but there was no significant difference between adopters and non-adopters. The results revealed that adopters and non-adopters among married household heads were 82% and 81%, respectively. The average household size was 11 for both adopters and non-adopters, but there were no significant differences between the two groups. Biosecurity was found to be similar between adopters and non-adopters, with no significant differences.

The land slope was found to be 73% and 65%, respectively, for adopters and non-adopters at the 1% significance level. This indicates that adopters tend to have steeper land slopes than non-adopters. It was also revealed that 16% and 26% of adopters and non-adopters, respectively, had the service of extension officers. This implies that non-adopters were more likely to have access to such support. The results revealed that access to climate information was 53% and 36% for adopters and non-adopters, respectively, indicating that adopters were more likely to have access to this type of information. Access to the agricultural market was found to be 30% and 27% for adopters and on-adopters, respectively, indicating that adopters had a slightly higher level of access to the market. The results found that land tenure was 45% and 61% for adopters and non-adopters, respectively, at a 1% significance level. This indicates that non-adopters were more likely to have secure land tenure than adopters.

Furthermore, the cost of hiring labour was 3.857 and 4.229 maize and sorghum for adopters and adopters, respectively, at the 10% significance level. This demonstrates that non-adopters typically face higher labour costs than adopters. Access to a phone was found to be between 43 % and 39 % for adopters and non-adopters, but there was no significant difference between adopters and non-adopters. This implies that both adopters and non-adopters in this context have relatively similar access to this technology.

The results showed that land size was 3.427 hectares and 4.077 hectares for adopters and non-adopters, respectively, at 1% significance. This supports the idea that non-adopters typically have larger land holdings than adopters. Educational level was found to be 8.031 and 8.554 at 1 % significance for adopters and non-adopters, respectively. The data support the notion that non-adopters tend to have slightly higher educational levels than adopters.

The maize output for adopters and non-adopters were 9.963 kg/ha and 9.9147 kg/ha, respectively, at a 1% significance level. This indicates that the adoption of the specified agricultural practice is associated with a statistically significant increase in maize output compared with the output of non-adopters.

It was revealed that maize income was GH₵1174.923 and GH₵1104.857 for adopters and non-adopters, respectively. This implies that adopters had a slightly higher income from maize production than non-adopters. The results revealed a slight difference in sorghum yield between CSA adopters (3.009kg/ha) and CSA non-adopters (3.030kg/ha). The results showed that sorghum had an income of GH₵218.939, while CSA non-adopters had an income of GH₵ 261.200. The total yield of adopters of CSAPs was 12.972 kg/ha compared with that of CSA non-adopters (12.177 kg/ha). Total Income: CSA adopters have slightly higher total income (GH₵ 1393.862) than CSA non-adopters (GH₵1366.057).

Table 2. Description of sampled smallholder maize and sorghum farmers

Variable	CSA adopters	CSA non-adopters	t-test/chi2	Pooled
Age	38.42	36.75	-2.2467**	37.836
Sex	0.717	0.746	0.9743	0.727
Marriage	0.818	0.811	-0.2735	0.816
Household size	11.170	11.19	-1.3889	11.52
Livelihood	0.951	0.949	-0.1520	0.950
Land slope	0.729	0.651	-2.5716***	0.702
Extension	0.163	0.263	3.800***	0.198
C. information	0.532	0.366	-5.0922***	0.474
A. market	0.295	0.269	-0.8944	0.286
Land tenure	0.452	0.606	4.6737***	0.506
Hired labour cost (log)	3.857	4.229	1.6756*	3.988
Phone	0.425	0.389	-1.1041	0.412
Land size	4.066	3.427	-3.3943***	3.859
Education	8.031	8.554	2.9518***	8.214
Maize output (kg/ha)	9.963	9.9147	-2.4966***	9.677
Maize income (GH₵	1174.923	1104.857	-0.8719	1150.40
Sorghum yield (kg/ha)	3.009	3.030	0.1631	3.017
Sorghum income (GH₵	218.939	261.200	0.9775	233.73
Total yield (kg/ha)	12.972	12.177	-2.1499***	12.694
Total income (GH₵)	1,393.862	1,266.057	-0.2812	1384.13

Source: Field data estimate using STATA, 2022.

Socioeconomic drivers for individual and joint adoption of CSA practices

Table 3 presents the results of the adoption of CSA practices on yield among maize and sorghum farmers. The Wald Chi2 value is 577.99, which is significant at the 1% level. The likelihood ratio test (chi2 = 2062.4719, prob > chi2 = 0.0000) was also significant. This model diagnosis justifies the use of a multinomial treatment effect model.

First, the age of the farmer was found to have a significant positive effect on the adoption of joint practices at the 10% level. This supports the finding of Fischer and Burton, (2014) that older farmers tend to have more experience and knowledge, making them more open to collaborative farming practices. Household size was found to have a positive and significant effect on the adoption of a combination of chemical fertiliser and CA at 1%. This implies that larger households may have more labour resources and the capacity to invest in and implement these agricultural practices effectively. Asfaw *et al.* (2016) and Kurgat *et al.* (2020) explained that the decision to adopt agricultural practices is associated with household size.

The study further revealed that livelihood had a significant positive effect on the adoption of a combination of CA and intercropping (ITC) at 10%. This is in line with Asfaw *et al.* (2016) and Kurgat *et al.* (2020), who indicated that households with more diverse or stable livelihoods may be more willing and able to invest in and adopt these sustainable farming practices to enhance their agricultural productivity.

The study indicated that topography had a significant positive effect on the adoption of chemical fertiliser, but only at the 1% level. This indicates that certain topographical features, such as soil types or landscape characteristics, may make it more favourable or conducive for farmers to use chemical fertilisers to improve crop yields in those specific areas. Furthermore, the availability of climate information had a positive and significant effect on the adoption of a combination of C. fertiliser and CA, C. fertiliser and ITC, and joint adoption at 1% and 5%, respectively. This implies that access to climate information empowers farmers to make informed decisions about agricultural practices, helping them adapt to changing weather patterns and improve their farming practices accordingly. Accessible information significantly enhances the likelihood that smallholder farmers will embrace new and innovative practices (Keshavarz and Karami, 2014).

The results of the study revealed that market availability had a significant positive effect on the adoption of C. fertiliser and ITC at the 1% level. This indicates that easy access to markets and opportunities to sell crops incentivize farmers to invest in these practices, as they can expect better returns and profitability through increased agricultural productivity and diversified crop options. In addition, land size had a significant positive effect on adoption in all practices such as C. fertiliser and CA, C. fertiliser and ITC, and joint adoption at the 1% level. This may mean that larger landholdings provide farmers with the resources and capacity to implement these practices more extensively.

Location (Northern) had a significant positive effect on adoption of C fertiliser only, and C fertiliser and CA at 1% and 5% levels, respectively, compared with the Upper East Region. This seems to indicate that factors such as soil conditions, climate, or access to resources in the Northern Region may be more favourable for the adoption of these agricultural practices than in the Upper East Region. Furthermore, the Upper West had a significant positive effect on adoption of C. fertilizer only at a 1% level more than the Upper East Region. This indicates that compared with the Upper East Region, conditions, resources, or agricultural support in the Upper West Region may be more beneficial for the adoption of chemical fertiliser, making it a more appealing option for farmers there.

Table 3. Socioeconomic drivers for individual and joint adoption of CSA

Variables	C. Fertiliser only	CA+ITC	C. fertiliser + CA	CF+ ITC	Joint adoption
Age	0.0206	0.0139	-0.0133	-0.0189	0.0216*
	(0.0136)	(0.0175)	(0.0137)	(0.0190)	(0.0118)
Sex	-0.555**	0.511	-0.202	-0.499	-0.243
	(0.257)	(0.437)	(0.282)	(0.367)	(0.249)
Marital status	-0.128	0.419	-0.288	0.0738	0.426
	(0.330)	(0.439)	(0.350)	(0.456)	(0.309)
Household size	-0.0659***	-0.0108	0.0740***	-0.0711*	0.0206
	(0.0242)	(0.0384)	(0.0216)	(0.0383)	(0.0207)
Livelihood	0.359	1.771*	-1.076**	-1.630**	0.610
	(0.586)	(0.915)	(0.540)	(0.658)	(0.600)
Farm size	-0.507***	-0.00404	-0.202*	-0.186	-0.212**
	(0.106)	(0.134)	(0.104)	(0.153)	(0.0880)
Topography	0.864***	0.0736	-0.0106	-0.531	-0.126
	(0.286)	(0.364)	(0.301)	(0.361)	(0.248)
Availability of AEAs	-0.961***	-0.145	-0.435	0.0926	-0.394
	(0.321)	(0.477)	(0.357)	(0.407)	(0.292)
Available information	0.209	0.325	0.833***	0.893**	1.259***
	(0.247)	(0.381)	(0.278)	(0.396)	(0.255)
Market availability	-1.778***	-0.731	-0.353	1.184***	0.353
	(0.355)	(0.459)	(0.326)	(0.368)	(0.258)
Own land	-0.321	-0.344	-0.709***	-1.256***	-0.687***
	(0.253)	(0.363)	(0.269)	(0.367)	(0.239)
Labour cost	-0.0461	-0.165***	0.0227	-0.0529	-0.0163
	(0.0355)	(0.0584)	(0.0405)	(0.0507)	(0.0360)
IT phone	0.388	0.0451	-0.856***	0.281	-0.311

Variables	C. Fertiliser only	CA+ITC	C. fertiliser + CA	CF+ ITC	Joint adoption
	(0.269)	(0.367)	(0.304)	(0.383)	(0.275)
Land size	0.458***	-0.595***	0.467***	0.561***	0.333***
	(0.107)	(0.156)	(0.107)	(0.146)	(0.0881)
Years of education	-0.0928*	0.0177	-0.132***	-0.173***	0.0762
	(0.0479)	(0.0627)	(0.0487)	(0.0549)	(0.0473)
Northern	1.896***	-3.066***	0.702**	-1.147**	-0.0423
	(0.423)	(0.789)	(0.339)	(0.502)	(0.302)
Upperr West	1.495***	-3.268***	-1.444***	-0.473	-1.457***
	(0.411)	(0.614)	(0.393)	(0.437)	(0.316)
Constant	-1.100	-2.082	0.626	1.944	-3.230***
	(1.057)	(1.446)	(1.027)	(1.385)	(1.050)
Model diagnosis					
Wald chi2 (96) =	577.99				
Prob > chi2 =	0.0000				
Log-likelihood =	-2062.4719				
Observations	1,000				

Category 1 is the control group (base category). Source: Field survey, 2021.

a. Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Impact of climate-smart agricultural practices on yield

Table 4 presents the results of the impact of adoption of CSA practices on maize and sorghum yield (productivity). F (chemical fertiliser only), CA (conservation agriculture), ITC (intercropping), C fertiliser and CA, and joint adoption denote the treatment indicators that assessed the impact. This study investigates the impact of these CSA practices on adoption with the base category "no adoption" in all cases. The CSA practices all have statistically significant and positive effects on both maize and sorghum yields, indicating that adoption of CSA practices generally tends to have a favourable and considerable impact on maize and sorghum yields. Thus, the adoption of a multinomial treatment effect model is justified because there is evidence of a selectivity bias effect, as shown by the statistical significance of the lambdas. Using OLS for the estimation would have produced a biased and inconsistent estimate.

Interesting conclusions were drawn from the multinomial treatment effects of implementing several CSA practices on maize, sorghum, and pooled yields. Among these practices chemical fertiliser application (CF) alone significantly increased maize and sorghum yields, with an effect of approximately 0.246 kg/ha and 0.094 kg/ha, respectively. When considering combined yields, the "CF only" treatment factor showed a positive impact, with an effect size of approximately 0.145 kg/ha, indicating a higher level of statistical significance. The finding supports that of Leslie *et al.* (2018), who revealed that the adoption of organic fertiliser was significant and positive for the yield of maize and legumes in Malawi.

Conservation agriculture and intercropping (CA+ITC) significantly and markedly impacted all three areas. This contributed to an increase of approximately 0.375 kg/ha for maize, 0.0243 kg/ha for sorghum, and 0.363 kg/ha for pooled yields. This finding supports the findings of Rosenstock *et al.* (2019), who reported that CA improves maize production among smallholder farmers from 34 % to 56% in Tanzania. Furthermore, in Mozambique, for instance, a study among smallholder maize crop farmers revealed that farmers adopted intercropping because they found the practice to increase crop yield, improve income, and therefore increase food security (Osman *et al.*, 2011).

Similar to this, CF+ CA" practices had a very beneficial overall impact. This resulted in an increase in yield of approximately 0.298 kg/ha for maize, approximately 0.196 kg/ha for sorghum, and approximately 0.0345 kg/ha for pooled yield. "CF only" practice also had a favourable impact on all three categories, increasing yields by approximately 0.0947 kg/ha in sorghum and 0.0246 kg/ha in maize. Finally, the "Joint adoption" treatment factor significantly impacts maize yield, with an effect size of approximately 0.166 kg/ha. Sorghum yield shows a minimal change, with an effect size of 0.00291 kg/ha; however, when considering the combined yields of maize and sorghum, it has a positive effect of approximately 0.0422 kg/ha.

In terms of socioeconomic factors, an increase in farmer age by 1 year is associated with a slight but significant increase in both maize and sorghum yields. For every additional year of a farmer, maize yield increases by approximately 0.00250 kg/ha, and sorghum yield increases by approximately 0.00262 kg/ha. As older farmers become more attuned to the specific needs of their crops, they are better equipped to optimize their farming practices resulting in increased yields for both maize and sorghum. This is consistent with the findings of Ngigi (2009) and Abegunde *et al*. (2019).

The study findings further revealed that male farmers tend to have lower yields than female farmers. Specifically, being male is associated with a decrease in maize yield by approximately 0.101 kg/ha., a decrease in sorghum yield by approximately 0.0464 kg/ha, and a significant decrease in the overall pooled yield by approximately 0.103 kg/ha. This result is consistent with that of Oyetunde-Usman *et al.* (2021), who also revealed that male-headed households tend to engage more intensively in sustainable agricultural practices. This trend has been partly attributed to the limited access that female-headed households must essential agricultural inputs

Farm size significantly impacted maize and sorghum yields in northern Ghana. Increasing farm size by 1 % is associated with a notable increase in yields. Specifically, for every 1 % increase in farm size, maize yield increases by approximately 0.0556 kg/ha, sorghum yield increases by approximately 0.0162 kg/ha, and the overall pooled yield increases by approximately 0.0606 kg/ha. These findings agree with those of Aryal *et al.* (2018) and Zougmoré *et al.* (2021), supporting evidence that farm size and agricultural yields are interconnected. They reinforce the notion that larger farms can harness economies of scale, leading to optimised resource allocation and the adoption of improved farming practices ultimately resulting in higher crop yields.

In addition, the availability of family labour significantly influences maize and sorghum yields. An increase in family labour by 1 unit is associated with a significant increase in maize yield by approximately 0.0305 kg/ha and a significant decrease in sorghum yield by approximately 0.0264 kg/ha. However, the impact on the overall pooled yield was smaller, with an increase of approximately 0.0111 kg/ha. These results corroborate the findings of Issahaku and Abdulai (2020), who illustrated a positive and substantial relationship between larger household sizes and the adoption of CSA. They argued that the presence of a larger household can have a significant and positive impact on the adoption of CSA practices especially when considering the labour requirements in certain CSA activities such as mulching. However, it is important to acknowledge that a larger household size also implies a greater number of mouths to feed. Finally, the cost of hired labour plays a significant role in crop yields. An increase in the cost of hired labour by 1 unit is associated with a significant increase in maize yield by approximately 0.0113 kg/ha. and a significant increase in the overall pooled yield by approximately 0.00840 kg/ha. This study result affirmed the findings of previous studies (Parashar *et al*., 2000; Ferdinand *et al*., 2021), which highlighted the significance of labour allocation in influencing production efficiency within smallholder farmer households.

Table 4 indicates that the “Lambda for CF only” showed positive and significant effects. This implies that unobserved factors that increase farmers’ likelihood of adopting CF also increase farmers’ yields of both maize and sorghum, and the correlation between these unobservable factors is statistically significant with magnitudes of 0.277 and 0.132, respectively.

The lambda for CF + CA also shows a positive and significant effect of (0.299) and (2.209), implying that unobservable factors that increase farmers’ likelihood of adopting CF combined with CA also increase yields of both maize and sorghum. Furthermore, the correlation between these unobservable factors and the adoption of CF + CA was statistically significant, with magnitudes of 0.299 and 0.209. This means that there are common, unobservable elements that influence both the choice to adopt CF + CA and higher crop yields.

The lambda for CF + ITC further indicated a positive and significant effect of (0.311). This implies that unobservable factors that increase farmers’ likelihood of adopting CF combined with ITC also increase yields of only maize. The correlation between these unobservable factors and the adoption of CF + ITC is statistically significant, with a magnitude of 0.311. This indicates that common, unobservable elements influence both the choice to adopt CF + ITC and higher crop yields for maize.

The “Lambda for joint adoption” was found to have a positive and significant effect. This implies that the unobserved factors that increase the farmer’s likelihood of adopting joint CSA practices also increase the yield of both maize and sorghum, and the correlation between them is unobservable are significant with magnitudes of 0.109 and 0.0527, respectively.

Increasing Agricultural Productivity

The results in Table 4.5 clearly indicate the adoption of multiple agricultural practices including chemical fertiliser (C. fertiliser) alone, conservation agriculture (CA), and intercropping, C. fertiliser, CA, and C. Fertiliser and intercropping have a significant positive effect on maize and sorghum yields. This result aligns with the first goal of CSA, which is to enhance agricultural productivity. The adoption of these practices leads to higher yields of maize and sorghum, contributing to increased food and income security for farmers. This boost in productivity is essential for meeting the growing demand for food in a changing climate. This is in line with (Lipper *et al*., 2018), who emphasize that certain sustainable agricultural practices, including precision farming, agroforestry, and conservation agriculture, can significantly contribute to increased productivity by optimising resource use and improving crop yields.

Enhancing Resilience to Climate Change

The significant effects of joint adoption, where farmers simultaneously embrace C. Fertiliser, CA, and intercropping, signify a remarkable synergy in terms of yield enhancement. This synergistic effect aligns with the second goal of CSA, which is to enhance resilience to climate change. By adopting a combination of practices, farmers are better equipped to withstand the adverse effects of climate variability and change. Collectively, these factors enhance soil health, water retention, and nutrient management, making farming systems more robust and adaptable to varying climatic conditions. The IPCC (2017) highlights in its special report on climate change and land practices such as conservation agriculture, crop diversification, and improved water management, which enhance the resilience of agriculture systems to climate change impacts.

Reducing Greenhouse Gas Emissions

While the analysis primarily focuses on yield improvements, the adoption of certain practices such as CA and intercropping can also have ancillary benefits related to reducing GHG emissions. This relates to the third goal of CSA, which is to reduce GHG emissions from agriculture. Conservation agriculture practices, for instance, can help reduce the need for synthetic fertilisers, which are associated with emissions. Intercropping can also optimise resource use efficiency, potentially leading to lower emissions per unit of production. The work (Smith, 2020) underscores the potential of sustainable land management practices, including agroforestry, crop choice, and intercropping, to reduce greenhouse gas emissions from agricultural activities, contributing to climate change mitigation efforts.

The findings (Table 4) provide empirical support for the alignment between the adoption of specific agricultural practices and the goals of climate-smart agriculture. These practices not only enhance productivity but also contribute to building resilience in farming systems and, in some cases, mitigate GHG emissions. Joint adoption, as highlighted by this analysis, holds particular promise in achieving multiple CSA objectives simultaneously, offering a holistic approach to address the challenges posed by a changing climate in agricultural systems. The findings of this study are firmly aligned with a substantial body of research from a diverse array of sources, affirming the profound impact of climate-smart agriculture (CSA) practices on crop yields. These include (FAO, 2010; Arslan *et al.*, 2016; Zougmoré *el al.*, 2016; Mutenje *et al.*, 2016; Issahaku and Abdulai, 2020; Zakaria *et al.*, 2021) all converge on a common narrative. Their collective research reinforces the notion that CSA practices whether examined individually or holistically, consistently yield higher crop outputs. These studies provide a robust foundation of evidence, illuminating the path toward a more sustainable, resilient, and prosperous future for agricultural communities.

These findings provide a sufficient indication that the adoption of CSA practices is beneficial to some smallholder maize and sorghum farmers in the study area, as many of them can recount their successes upon adopting CSA practices. These findings reveal that the adoption of climate-smart agricultural practices has generally improved the yield of maize and sorghum of the sampled smallholder farmers in the 2022 farming season preceding the survey in Northern Ghana.

Table 4. Effect of Climate-Smart Agriculture practices on Yield of maize and sorghum

Variable	Maize yield	Sorghum yield	Pooled yield
Treatment factors			
CF only	0.246*	0.0947*	0.145**
	(0.139)	(0.0493)	(0.0808)
CA+ITC	0.375***	0.0243**	0.363***
	(0.106)	(0.0608)	(0.0801)
CF+ CA	0.298**	0.196***	0.0345
	(0.129)	(0.0454)	(0.0785)
CF+ITC	0.278***	0.111*	0.228**
	(0.107)	(0.0653)	(0.0892)
Joint adoption	0.166***	0.00291	0.0422***
Socio-economic factors	(0.121)	(0.0550)	(0.109)
Age	0.00250	0.00262**	0.00347**
	(0.00183)	(0.00102)	(0.00159)
Sex	-0.101**	-0.0464*	-0.103***
	(0.0454)	(0.0251)	(0.0392)
Farm size	0.0556***	0.0162**	0.0606***
	(0.0134)	(0.00736)	(0.0115)
Education	-0.0120	-0.00451	-0.0131
	(0.0136)	(0.00792)	(0.0121)
Family labour	0.0305**	-0.0264***	0.0111
	(0.0151)	(0.00859)	(0.0131)
Hire labour	0.0113***	-0.00499**	0.00840***
	(0.00357)	(0.00206)	(0.00314)
Constant	1.940***	1.297***	2.173***
	(0.108)	(0.0605)	(0.0901)
Selectivity diagnosis			
Lnsigma	1.194***	-1.400***	-0.974***
	(0.195)	(0.0988)	(0.136)
Lambda for CF only	0.277*	0.132***	0.140
	(0.150)	(0.0489)	(0.0889)
Lambda for CA + ITC	0.0538	0.0165	0.124*
	(0.0891)	(0.0668)	(0.0742)
Lambda for CF + CA	0.299**	0.209***	0.109
	(0.149)	(0.0420)	(0.0803)
Lambda CF + ITC	0.311***	0.0106	0.313***
	(0.0762)	(0.0564)	(0.0676)
Lambda for Joint Adoption	0.109**	0.0527**	0.00848**
	(0.124)	(0.0535)	(0.123)
Observations	1,000	1,000	1,000

Source: Field data estimates using STATA, 2022.
Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

CONCLUSION

With careful evaluation of the summary of findings from the study, the following conclusions were reached: first, the study concludes that climate-smart agriculture practices including the use of chemical fertiliser, conservation agriculture, intercropping, and joint adoption, significantly improve maize and sorghum yields. Older farmers tend to achieve higher yields, whereas male farmers experience lower yields. Factors such as farm size, family labour availability and labour costs also influence maize and sorghum yields.

RECOMMENDATION

To ensure sustainable and environmentally conscious agricultural practices in Northern Ghana, the government should spearhead the promotion of conservation agriculture through the formulation and implementation of policies specifically designed to support the adoption of Climate-Smart Agricultural Practices (CSAP). A pivotal aspect of this initiative involves substantial investment in training and deploying additional extension officers who can deliver essential services and comprehensive training to smallholder farmers.

Conservation agriculture, unlike chemical fertilisation, offers a holistic and resilient approach by promoting soil health, reducing erosion, and enhancing water retention. By prioritizing CSAP, the government not only addresses environmental concerns but also empowers smallholder farmers with knowledge and skills to navigate the challenges of climate change, fostering a sustainable and prosperous agricultural future in the region.

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