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Climate-smart agriculture and technical efficiency of smallholder maize farmers in Wa East District of Ghana

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Abstract— Climate-smart agriculture (CSA) seeks to improve adaptation and mitigation to climate change and eventually, improve the productivity and sustainability of farming. However, CSA adoption particularly among smallholder farmers in developing countries remains low in spite of its potential benefits of improving productivity. Also, empirical evidence of the linkage between CSA adoption and technical efficiency (TE) of smallholder farmers remains scanty. This study therefore examined the drivers of adoption of CSA practices (CSAPs) and how adoption intensity affects TE of smallholder maize production in Wa East District of Ghana. Relying on survey data, generalized Poisson regression and stochastic frontier analysis, the study observed that uptake of multiple CSAPs increased TE of maize producers. The study therefore recommends the provision of CSA training and awareness creation to encourage uptake of multiple CSAPs to increase TE of smallholder maize producers.

***Keywords*— Climate-smart agriculture, technical efficiency, adoption intensity, smallholder farmers, Ghana**

INTRODUCTION

Smallholder farming plays a significant role in the livelihood of rural households in many developing countries. Agriculture serves as a major economic activity for the majority of rural dwellers in Ghana and is the main livelihood source (Kamara et al., 2019). Farming systems are experiencing changing patterns and dynamics as part of agrarian change arising from globalization and change in the climate (Yeboah et al., 2020). The adverse impact of climate change (CC) and variability on socio-economic activities and the environment has an increasing effect on crop production, thus affecting the welfare of smallholder farmers (Adu et al., 2018). Research indicates that the incidence of climate variation and its related deleterious effects is high on rural dwellers who depend on agriculture for their living (Cobbinah & Anane, 2016). Oxford Business Group (2019) reports that Africa's overall agriculture contributes approximately 15% to the global gross domestic product (GDP) but this is threatened by CC through lower fertility of the soil, erratic rainfall, high temperatures, floods, and droughts. Climate change poses a critical threat to humans and the environment (Derbile et al., 2022). The developmental challenges of Africa especially Ghana cannot be addressed until measures are put in place to change the indigenous farming systems which is threatened by CC. The promotion of adaptation, resilience, and mitigation mechanisms are key factors required to reduce and avert low agricultural productivity among smallholder farmers in most developing countries (Mabuku et al., 2019).

Climate-smart agriculture (CSA) has been touted as an appropriate response for reducing the negative impact of CC on smallholder agriculture in policy and development circles (Damba et al., 2021). The promotion of CSA is intended to integrate climate responsiveness to agriculture by increasing sustainable adaptation, productivity, and food security and also reducing the emission of harmful gases through agricultural activities (Ho & Shimada, 2019). The concept of CSA is new and evolving; however, some of its practices already existed for long (Chinseu et al., 2019). According to Martey et al. (2020), CSA practices have shown great potential to address the impact of extreme CC and improve the sustainability of maize cultivation in Ghana, especially in the semi-arid regions. The challenge is that smallholder farmers adopt CSA practices differently across a varied spectrum of practices, while some also abandon the practices due to lack of training and information about the benefits. Consequently, farmers have not derived the full benefits associated with CSA adoption such as improvement in maize production, reduction in poverty, and increase in food security among rural households (Khataza et al., 2018). Nonetheless, CSA has the prospect to contribute to meeting the Sustainable Development Goals (SDGs) which target to end hunger and reduce poverty (SDG 1 and 2).

Farmers over the years have relied on some traditional and emerging adaptation approaches to lessen the impact of CC on productivity and their livelihoods. Smallholder farmers in Ghana depend largely on rainfall agriculture, which consequently increases their susceptibility to the effects of climate change and variability (Derbile et al., 2022; Dinko, 2017). Thathsarani and Gunaratne (2018) posited that smallholder farmers with limited resources are prone to a higher risk of CC regardless of their location. Present evidence in literature indicates that the incidence of climate shocks such as droughts and floods affect farmlands across the country, hence affecting productivity (Adzawla & Alhassan, 2021). These CC shocks contribute to household poverty, reduce resilience and safety, and reduce food security in Ghana.

In order to reduce the influences of CC, farmers are encouraged to adopt coping strategies. Governmental and private organizations have over the years invested in various CC adaptation approaches to attain climate-smart sustainable food systems that reduce food insecurity in the midst of CC (Sam et al., 2021). Notwithstanding its benefits, little research attention has been paid to CSA adoption and its effect on farm performance, especially production efficiency. Thus, while the literature abounds with evidence of factors inducing uptake of CC adaptation strategies, little attention has been given to the impact of adaptation strategies on production efficiency of smallholder farmer households.

Technical efficiency (TE) of maize production has been investigated extensively in Ghana. Several researchers (Anang et al., 2022; Issahaku, & Abdulai, 2020; Kwawu et al., 2022; Tsiboe et al., 2022) have found high level of inefficient in the production of maize in Ghana. However, in the context of Ghana, there are not many studies that assess the effect of CSA adoption on TE of smallholder maize production. This means that there is little empirical evidence of the influence of CSA adoption on farmers' efficiency, which is necessary for effective policy formulation to alleviate the effects of CC and promote production efficiency. This study therefore fills a critical research gap by elucidating the effect of adopting multiple CSA practices on the efficiency of maize producers in the northern savanna ecological area of Ghana, specifically in the Wa-East Distrit of Ghana. The study is also important because the northern savanna ecological zone of Ghana is semi-arid and faces the brunt of CC more than other ecological zones on the country.

LITERATURE REVIEW

Climate-smart agriculture and technical efficiency of maize production

Climate-smart agriculture, which is defined as any improved agricultural practice, technology, or intervention undertaken to sustainably increase crop yield, build adaptive capacity, and remove or reduce greenhouse gas emissions from agricultural activities (Zougmoré et al., 2019), is one strategy for combating the effects of CC. Previous research has shown that employing CSA techniques can effectively reduce the risks associated with climate variation and agricultural systems (Issahaku & Abdulai, 2020). The goal of CSA is to revolutionize the agricultural industry and enhance food security in the face of a changing climate through a comprehensive planning of agricultural operations that is characterized by creating connections between efforts at adaptation and mitigation (Lipper et al., 2014).

The choice to adopt CSA techniques involves a behavioral reaction and is thus modeled within the random utility framework (Kassie et al., 2018), where a farmer selects components of CSA practices that increase utility. In line with Pannell et al. (2014), we view the decision of a household to adopt CSA practices in a particular year as a restricted optimization problem, where the choice to adopt CSA practices on a polychotomous basis depends on a variety of factors, including the information available, the relative costs and benefits of the CSA practices, and socioeconomic conditions of the farmer. A smallholder farmer may choose to adopt one or a multiple of the CSA practices. Examples of the CSA practices include conservation agriculture, climate information services, agroforestry practices, erosion control methods, among others (Partey et al., 2018; FAO, 2013).

CSA techniques primarily focus on ensuring effective and responsible use of non-renewable resources in a way that allows for the maintenance of the economic sustainability of agricultural activities, TE as well as the development of a generally acceptable quality of living and environmental protection (Ho & Shimada, 2019). Farmers are one of the most important groups in the agricultural system when it comes to managing natural resources, and they have a crucial role to play in ecosystem protection (Tong et al., 2019). Indeed, risks to the ecosystem across the world are caused by human conduct that is not sustainable (Tong et al., 2019). Therefore, to achieve agricultural sustainability and TE, the promotion of CSA at the farmer level is required (Imran et al., 2019).

Climate variability has a negative impact on farm performance as well as the environment and society, endangering smallholder agricultural production and threatening rural livelihoods (Taylor, 2018). This calls for the promotion and adoption of CSA methods to increase food security, resilience to climate shocks, and adaptation to CC to ensure sustainable agricultural production, and improve the TE of maize production (Taylor, 2018). Maize is a major staple in most Ghanaian communities and the most important cereal crop, hence its choice for this study. A large portion of the CSA literature on developing nations (Imran et al., 2022; Mo et al., 2023; Mizik, 2021) indicate that crop output and agricultural revenue may be increased by farmers in the face of climatic stresses by adopting adaptation strategies like crop rotation, irrigation technologies, conservation agriculture, climate information services, agroforestry practices, and erosion control methods (Partey et al., 2018; FAO, 2013). For example, according to Thierfelder et al. (2015), conservation agriculture has beneficial impact on maize yield response across a variety of agro-ecosystems in southern Africa as opposed to conventional system of production. Also, row planting, a CSA component, has the ability to boost efficiency, agricultural output and incomes as well as increase resiliency to climatic shocks (Fantie & Beyene, 2019).

Similarly, the use of CSA has been identified to significantly boost yield, resource efficiency, net farm revenue, as well as decrease greenhouse gas emissions and the utilization of restricted resources (Mizik, 2021; Imran et al., 2019; Khatri-Chhetri et al., 2016). However, in Sub-

Saharan African nations like Ghana, there are few studies that have examined how different agricultural technology and management techniques affect farm revenue, productivity, and resource use effectiveness (Hussain et al., 2017; Imran et al., 2019; Akrofi-Atitianti et al., 2018).

Researchers have over the years paid attention to estimating the efficiency of peasant farmers to promote food security and decrease poverty in developing nations. Maize production is associated with high level of technical inefficiency, according to studies examining efficiency of small-scale farmers across Africa. From the findings of studies in Zambia (Ng'ombe, 2017) and Senegal (Okuyama et al., 2017), the mean TE of maize production ranges between 21% and 94%. Kibirige et al. (2014) estimated the average TE of maize production around 70%.

Crop-specific efficiency assessments make it possible to identify the characteristics specific to each crop that affect efficiency and this may help to formulate crop-specific policy strategies to increase household food security by increasing crop yield. It is important to comprehend the degree of TE of peasant maize cultivation and the factors impacting it given the rising economic significance of maize in Ghana.

MATERIALS AND METHODS

Study area

The research was carried out in Wa East District in the Upper West region of Ghana. The selection of the district was based on the area's location in the northern savanna ecological zone which is semi-arid and prone to climate shocks. Furthermore, the selection of the district was based on the fact that the area has received little research focus on climate-smart agriculture despite its agricultural potential and the potential impact of climate variability on production activities of farmers. Maize is an important crop grown by most farm households in the district. The study area experiences unimodal rainfall with CC and its effect being evident in the area based on previous records of droughts, floods, high temperatures, and erratic rainfall patterns which affect crop production, especially cereal cultivation. The major crops cultivated in the district range from roots and tubers, cereals, and grain legumes such as soybeans, groundnut, among others. Figure 1 shows the map of the area of study.

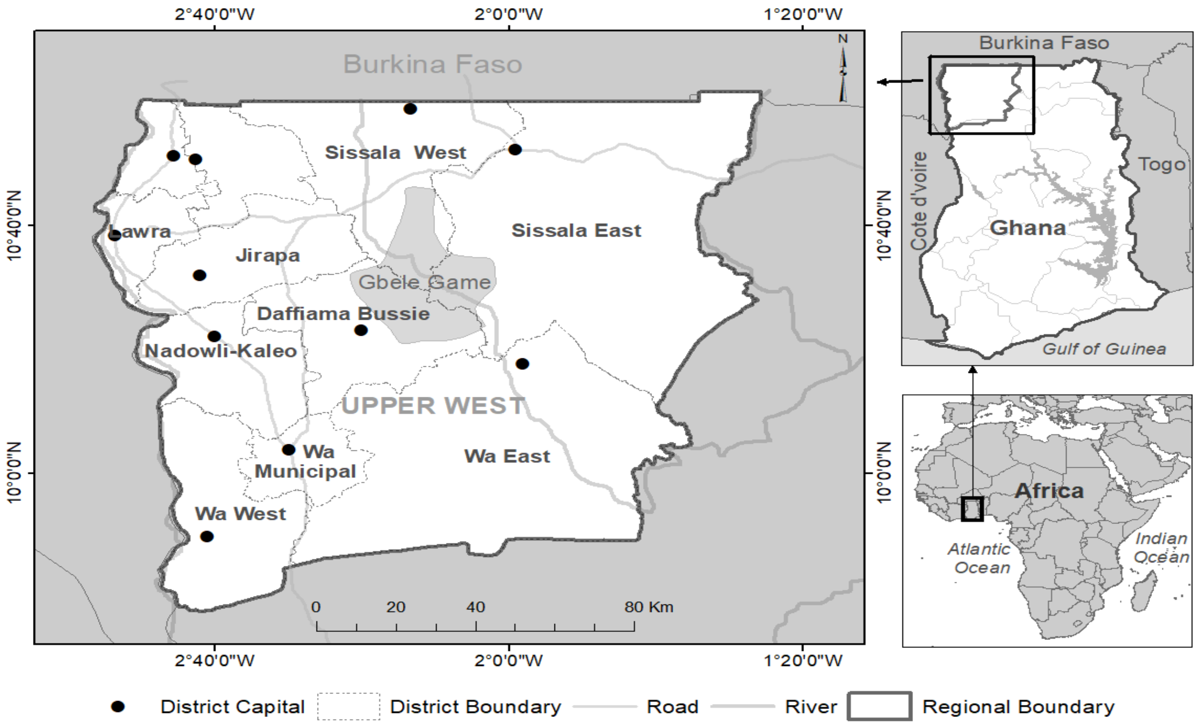

Figure 1. Map of Upper West region of Ghana

Sampling and data collection

Cross-sectional household data from 350 small-scale maize producers in 6 communities across the Wa East district in the Upper West region of Ghana was used for the study. Multi-stage sampling technique was used in the data collection. This involved the selection of the Wa East district purposively, followed by the sampling of 6 communities in the district. In the next stage, individual smallholder farmers were randomly sampled from the selected communities with the aid of a semi-structured questionnaire. The information solicited from the farmers included production and output data, farmers' socioeconomic characteristics, CSA adoption, access to agricultural extension and credit, among others.

Method of data analysis: The Generalized Poisson (GP) regression model

The Generalized Poisson (GP) regression model was used to assess the determinants of adoption intensity of CSAPs based on the nature of the response variable and test of dispersion of the count variable. The GP model is generally used for estimating count data and has the advantage of dealing with under-dispersed data, unlike the standard Poisson model which is suitable only when the data displays equi-dispersion (that is, when the mean of the count dependent variable is equal to the variance) (Consul & Famoye, 1992). The dependent variable for the GP model in this study is the number of CSA practices adopted by a respondent.

Considering the GP model, the probability mass function assumes the form

$$f(y_i\theta_i\delta) = \frac{\theta_i(\theta_i+\delta y_i)^{y_i-1}}{y_i!} \quad y_i = 0,1,2,\dots \quad (1)$$

where $\theta_i > 0$, and $max(-1, -\theta_i/4) < \delta < 1$.

This implies that the mean and variance of the random GP variable Y_i are given as

$$\mu_i = E(y_i) = \frac{\theta_i}{1-\delta}, Var(y_i) = \frac{\theta}{(1-\delta)^3} = \frac{1}{(1-\delta)^2}E(y_i) = \emptyset E(y_i) \quad (2)$$

The term $\emptyset = \frac{1}{(1-\delta)^2}$ plays the role of the dispersion factor. Its value determines the type of dispersion. When $\delta = 0$, the data exhibits equi-dispersion, but over-dispersion and under-dispersion prevails when $\delta > 0$ and $\delta < 0$ respectively.

The empirical structure of the GP model takes the following form

$$log\frac{\theta_i}{1-\delta} = \sum_{r=1}^{p} x_{ir}\gamma_r \quad (3)$$

where x_{ir} represent the covariates influencing adoption intensity, p denotes the number of covariates, and γ_r denotes parameters to be estimated.

Stochastic Frontier Analysis

Stochastic frontier analysis (SFA) was used to evaluate the TE of maize production. Three measures of efficiency which have made efficiency analysis popular in the literature include economic, allocative, and TE (Farrell, 1957). This study focuses on TE which implies the attainment of the highest output with the least amount of input. Efficiency can be estimated either with the nonparametric (data enveloping analysis or DEA) or the parametric (SFA) approach. The SFA approach suits the objective of this study, hence its application to fit the data. This is because it has the ability to account for the stochastic nature of agricultural production and also easily accommodates the inclusion of contextual variables such as CSA practices in either the production function or inefficiency model, or both.

The stochastic frontier model is represented as

$$Q_i = \beta_0 + \beta X_i + e_i \quad (4)$$

where Q_i represents the output variable, X_i represents the input quantities, β is the unknown parameters to be estimated, and e_i is the random disturbance term which consists of the inefficiency in production (u_i) as well as statistical noise (v_i). Thus, e_i is represented as follows:

$$e_i = v_i - u_i \quad (5)$$

Equation (4) can be expressed as

$$Q_i = f(X_i\beta)\exp(v_i - u_i) \quad (6)$$

where $f(.)$ can assume any production functional form. For the purpose of this study, the Cobb-Douglas functional form was employed and this was based on an empirical test using the likelihood ratio test. The Cobb-Douglas specification, though more restrictive compared to the translog model, does not suffer from multicollinearity issues, and has been widely used in other studies (see Anang et al., 2016; Abdallah & Abdul-Rahman, 2017; Boateng et al., 2022).

Technical efficiency, which measures the proportion of observed output to the maximum frontier output, can be estimated as

$$TE = \frac{Q_i}{Q_i^*} = \frac{f(X_i\beta)\exp(v_i - u_i)}{f(X_i\beta)\exp(v_i)} \quad (7)$$

Therefore, technical efficiency is given as

$$TE = \exp(-u_i) \quad (8)$$

The input variables used in the production function include farm size, quantity of labour, seed, fertilizer, as well as cost of ploughing and value of farm capital. The variables in the inefficient model include the intensity of CSA adoption, respondent's age, sex, years of education, cattle ownership, farming experience, farmer group membership, access to farm credit, and land ownership.

The CSA adoption variable is potentially endogenous in the inefficiency model. Thus, using the intensity of adoption directly in the inefficiency model could lead to the problem of endogeneity. Consequently, to address the endogeneity issues associated with CSA adoption, the predicted values of adoption intensity were used in the estimation of the inefficiency model. This is in line with other studies such as Mgomezulu et al. (2022) and Anang et al. (2020) who used the predicted values of sustainable agricultural practices (SAP) adoption and improved variety adoption, respectively, to assess the determinants of TE. While Mgomezulu et al. (2022) used a two-stage censored Tobit model to assess the effect of SAP on technical and profit efficiency, Anang et al. (2020) used truncated regression to assess the effect of modern variety adoption on TE. Both studies, however, did not estimate TE and its determinants in a single step as suggested by Battese & Coelli (1995). This study therefore addresses the endogeneity issue and estimates TE and the determining factors in a single step using maximum likelihood estimation.

Definition of variables for the study

The socioeconomic and demographic variables alongside their expected signs are presented in Table 1. Age of the respondents is expected to have an indeterminate influence on adoption intensity of CSA practices, while male farmers are anticipated to have higher adoption. Years of formal education, cattle ownership, participation in off-farm work, access to agricultural extension, farmer group membership, farming experience and access to credit are all expected to have a positive influence on CSA adoption intensity and TE (Anang et al., 2022; Dokyi et al., 2021). However, distance to local market is expected to negatively influence intensity of adoption, while all the input variables are anticipated to positively influence maize output.

Table 1. Definition and expected signs of variables included in the study

Variable	Definition	Expected sign
Socio-demographic variables		
Intensity of CSA	Number of CSA practices adopted (count)	
Age	Age of farmers in years	±
Sex	Dummy: 1 = male and 0 = female)	+
Education years	Years of formal education	+
Cattle ownership	1 if yes, 0 otherwise	+
Off-farm activities	1 if yes, 0 otherwise	+
Farmer group membership	1 if yes, 0 otherwise	+
Extension access	1 if yes, 0 otherwise	+
Distance to local market	Distance to the local market in kilometers	-
Farm credit	1 if yes, 0 otherwise	+
Land ownership	Dummy: 1 = purchase; 2 = rented; 3= inherited	±
Farming experience	Numbers of years of maize farming	+
Knowledge about CSA	How long farmer has known about CSA	+
Inputs and output variables		
Maize output	Quantity of maize yield in kilograms	
Farm size	Maize land area in acres	±
Labour	Quantity of labour in man-days	±
Fertilizer	Quantity of fertilizer in kilograms	±
Ploughing	Total cost of ploughing in Ghana cedis	±
Capital	Value of farm capital	±

RESULTS

Socio-demographic characteristics of the sampled farmers

The socio-demographic characteristics of the farmers are presented in Table 2. As shown in the table, majority of the respondents (79%) are male with a mean age of 41 years which is within the active age group for agricultural production. Smallholder farmers in the sample possessed averagely 5 years of formal education and had approximately 11 household members. Rural farm household in most developing nations usually have large household size since most farm households depend on household labour for farm operations.

Furthermore, the result indicates that about 36% of the farmers owned cattle while 30% were engaged in other economic activities. This implies that about 70% of the respondents depend mainly on farming for their livelihood. Farm households that owned cattle are expected to be wealthier compared to farm households without cattle, and this could enhance adoption of CSA practices. This is because cattle ownership is typically used as a proxy for wealth in studies involving smallholder farmers (Anang et al., 2022).

Table 2. Socio-demographic characteristic of smallholder maize producers

Variable	Mean	S. D.	Min.	Max.
Age	40.65	10.98	20	67
Sex	0.789	0.409	0	1
Education years	5.117	6.425	0	26
Household size	10.76	5.954	2	28
Cattle ownership	0.366	0.482	0	1
Off-farm activities	0.300	0.459	0	1
Farmers group member	0.303	0.460	0	1
Extension access	0.669	0.471	0	1
Distance to market	4.489	2.726	0.24	12
Farm credit	0.374	0.485	0	1
CSA training	0.520	0.500	0	1
Knowledge about CSA	3.114	3.351	1	20
Inputs and output variables				
Maize output	1846	1439	100	8500
Farm size	4.401	2.726	1	17
Labour	31.65	13.38	7	69
Fertilizer	210.3	141.8	0	875
Ploughing	364.5	224.1	75	1530
Capital	172.6	134.9	12	910

S. D. means standard deviation

Furthermore, the distance to the local market is 4.5 km. It is expected that the longer the distance to the local market, the higher the transaction costs and the less likely a farmer may adopt new technology. The respondents had about 3 years knowledge of CSA while about 52% have ever participated in CSA training. Also, about 30% of the respondents were members of a farmer group which could serve as medium for access to credit, extension services and general information on farming. The result shows that 67% and 37% had access to extension service and credit respectively.

Averagely, farmers produced 1846 kg of maize (with a minimum of 100 kg and a maximum of 8500 kg) using an average farm size of 4.4 acres. According to Nyanteng and Seini (2000), farmers with farm size of 3 ha or less account for approximately 90% of the nation's food output. Smallholder farmers usually cultivate on a small scale due to resource constraints. The result further indicates that on the average, a household used about 32 man-days of labour in production. The mean quantity of fertilizer applied was 210 kg while the value of farm capital used in production was 174 Ghana cedis. Meanwhile, a household on average spent 364 Ghana cedis as the cost of ploughing their farm land.

CSA practices adopted by farmers

Table 3 shows the various CSA practices adopted by the smallholder maize farmers. Majority of the farmers comprising 63.7% applied inorganic fertilizer and a little over half of them (51.1%) applied organic fertilizer to alleviate the impact of CC. The study further revealed that many of the farmers adopted improved crop varieties (56%) and mixed cropping (53.7%) to alleviate the effects of CC. About 41% of the farmers adopted planting in rows to cope with CC impact. Row planting enhances plant population density, reduces weed growth, and increases output level. Row planting also contributes to soil moisture conservation. Again, the study indicates that some farmers adopted irrigation (33.7%), mixed farming (38.6%), crop rotation with legumes (36%), changing planting time/date (36%), and mulching (23.4%) in adapting to the impact CC. The results further show that less than 20% of respondents adopted cover crops and tree planting as CC coping strategies.

Table 3. CSAPs adopted by farmers

Variable	Freq.	Percent
Irrigation	118	33.7
Used of improved crop varieties	196	56.0
Compost/organic fertilizer	179	51.1
Crop rotation with legumes	126	36.0
Application of inorganic fertilizer	223	63.7
Used of mulching	82	23.4
Used of cover crops	45	12.8
Planting in rows	142	40.6
Changing planting time/date	126	36.0
Mixed farming	135	38.6
Mixed cropping	188	53.7
Tree planting	51	14.6

The intensity of adoption of climate-smart agriculture practices

The generalized Poisson regression model was used to estimate the factors affecting CSAPs adoption intensity and the results are presented Table 4. The likelihood ratio test with a chi-square value of 126.98 was statistically significant indicating the suitability of the generalized Poisson model for the analysis. The Wald chi square was statistically significant implying that exogenous variables included in the model jointly explained smallholder farmers' intensity of adoption of the CSA practices.

The results indicate that age is highly significant at 1% and positively influences the intensity of adoption of CSAPs. This implies that older farmers have a higher likelihood to adopt multiple CSA practices. Furthermore, male farmers were more likely to adopt multiple CSA practices compared to females. Also, years of education had a significant and positive influence on the extent of adoption. In other words, the more years a farmer spends in school, the more likely that the farmer will adopt multiple CSA technologies. Again, cattle ownership was significant at 5% and negatively influenced adoption intensity. This indicates that farmers who own cattle are less likely to adopt multiple CSA practices. Furthermore, the distance to the local market positively influenced the number of CSA practices that farmers adopted, which contradicts the study's a prior expectation that proposes that an increase in distance to the local market will decrease the adoption of CSA practices. In line with a priori expectations, training on CSA practices positively influenced the extent of adoption of CSA practices at a significant level of 1%. Additionally, how long a farmer had known about CSA practices positively correlated with the intensity of adoption.

Table 4. GP regression estimates of factors affecting adoption intensity of CSA technologies

Variables	Coefficient	S. E.
Age	0.010***	0.003
Sex	0.143*	0.080
Education years	0.024***	0.005
Household size	0.006	0.005
Cattle ownership	-0.157**	0.069
Off-farm activities	0.069	0.062
Farmers group membership	-0.011	0.064
Extension access	-0.016	0.071
Distance to the local market	0.029***	0.011
Farm credit	0.062	0.061
Farm size	-0.015	0.011
CSA training	0.443***	0.068
Knowledge about CSA	0.035***	0.009
Constant	0.359**	0.167
Model diagnostics		
LR chi^2 (13)	126.98***	
Log-likelihood	-801.96	
Pseudo R^2	0.0734	

****, **, and * represented 1%, 5% and 10% significant level respectively*

Maximum likelihood estimates of the stochastic production frontier

The results of the maximum likelihood estimation of the stochastic production frontier are presented in Table 5.

Table 5. Maximum likelihood estimates of the stochastic production frontier

Variables	Coefficient	S. E.
Farm size	1.155***	0.409
Labour quantity	0.192	0.242
Seed quantity	0.066	0.163
Fertilizer quantity	0.032	0.035
Ploughing cost	-0.517*	0.271
Capital	0.040	0.026
Constant	0.262***	0.054
Return to scale	1.231	
Wald chi^2	789.35***	

**** and * represent 1% and 10% significance level respectively. Number of observations = 350.*

The significant value of the Wald chi-square (789.35) indicates that the input variables jointly explain the output variations of the maize producers. The result depicts an increasing return to scale (1.231) from the summation of all coefficients of the Cobb-Douglas function. This implies that a 1% increase in all the variable inputs is expected to increase output by 1.23%. The results further show that a 1% increase in farm size increases maize output by 1.16% holding all factors constant. Also, an increase in ploughing cost by 1% resulted in a decrease in output by 0.517% holding other variables constant.

Distribution of technical efficiency scores

The distribution of the TE scores is provided Table 6. The farmers had an average TE of 74% suggesting that with the same level of input and the existing technology, they could potentially increase output by 26%. Farmer are therefore making a significant loss in their production which may be attributed to managerial and environmental factors. Close to 67% of the respondents had TE levels exceeding 70%, suggesting that majority of the farmers are producing at a relatively high TE level. Farmers whose TE did not exceed 50% were only about 8%.

Table 6. Distribution of technical efficiency scores

Efficiency range	Frequency	Percent
Up to 0.30	2	0.57
0.31 – 0.40	5	1.43
0.41 – 0.50	20	5.71
0.51 – 0.60	19	5.43
0.61 – 0.70	71	20.29
0.71 – 0.80	101	28.86
0.81 – 0.90	122	34.86
0.91 – 1.00	10	2.86
Total	350	100
Mean	0.74	
Maximum	0.92	
Minimum	0.23	

Estimation of factors influencing technical inefficiency

Table 7 depicts the variables influencing the technical inefficiency of smallholder maize farmers. A positive coefficient denotes an increase in technical inefficiency while a negative coefficient depicts an increase in TE.

Adoption intensity had a negative and significant influence on technical inefficiency. This implies that smallholder farmers who adopt more CSA practices are more technically efficient compared to farmers who adopt less or none of the CSA practices. Again, years of education decreased TE, which is contrary to the study's a priori expectation. Furthermore, maize farming experience positively influenced TE inferring that producers who have farmed maize for more years are more efficient than those with fewer years of experience. Contrary to expectations, access to extension decreased the TE of maize producers. The study also revealed that farmers who purchased their land were less efficient than those who inherited their farm lands.

Table 7. Maximum likelihood estimation of factors influencing technical inefficiency

Variables	Coefficient	Std. Err.
Adoption intensity of CSA	-0.215**	0.097
Age	0.024	0.016
Gender	-0.329	0.309
Education years	0.041*	0.023
Cattle ownership	-0.399	0.318
Maize experience	-0.046**	0.019
FBO membership	-0.387	0.311
Extension access	0.567**	0.284
Farm credit	-0.352	0.258
Land ownership		
Rented land	-0.440	0.454
Inherited land	-0.558**	0.275
Constant	-0.875	0.675

*** and * represent 5% and 10% significance level respectively.*

DISCUSSIONS

Adoption of CSA practices by farmers

Generally, farmers adopted multiple CSA practices to alleviate the impact of CC. For instance, majority (63.7%) of the farmers in the study applied inorganic fertilizer while a little over half of them (51.1%) applied organic fertilizer to lessen the influence of CC. The application of fertilizer (organic or inorganic) helps to improve the nutrient content of the soil and helps to promote an increase in maize productivity and hence an increase in economic returns. These results affirm the studies by Arif et al. (2021) who established a positive relationship between the application of inorganic and organic fertilizer and maize productivity and farm profitability.

The study further revealed that many of the farmers adopted improved crop varieties (56%) and mixed cropping (53.7%) among other practices to lessen the shocks of CC. This finding supports the studies by Ifie et al. (2022) who indicated that there is a positive effect of improved varieties of maize on yields of smallholder farmers. Hence, farmers adopting improved varieties may seek to maximize their output level whilst farmers adopting mixed cropping technology may be seeking to decrease the risk of a total crop loss due to CC.

Determinants of adoption intensity of climate-smart agriculture practices

The results show that age positively influences the rate of adoption of CSAPs. This implies that older farmers are more likely to adopt multiple CSA practices since they are more experienced in farming. The results contradict the findings of Danso-Abbeam et al. (2017) who indicated in their studies that younger farmers were comparatively more likely to embrace modern technologies. Their explanation was that younger farmers are more adventurous, innovative and dynamic with regards to technology adoption in comparison with older farmers. These older farmers may find it difficult to switch to new methods of farming and may prefer to stick to their conventional farming methods in order to avoid taking higher risks. Our findings suggest that older farmers with much knowledge of climate variability in agriculture are more likely to adopt multiple strategies to mitigate the impact of CC.

The results also show that male farmers are more likely to adopt more CSA practices than females. A possible explanation is that female farmers are more resource-constrained compared to male farmers which limits their adoption rate since the adoption of new technology involves a cost. The result aligns with the findings of Addai et al. (2022) who observed that men were more likely to adopt irrigation because of their greater access to productive resources.

A farmer's years of formal education also had a positive relationship with adoption intensity of CSAPs. In other words, the more years a farmer spends in school the more likely the farmer is to adopt multiple CSA technologies. This is not only consistent with the study's *a prior* expectation that education increases the level of adoption of CSA, but it also goes to affirm the findings of Danso-Abbeam et al. (2017) and Issahaku & Abdulai (2020). Danso-Abbeam et al. (2017) posited that information about technologies is easily accessed by educated farmers and hence increases their adoption if the utility is appealing. Also, Bruce (2015) indicated that education is a key determinant of the adoption of improved rice variety.

Cattle ownership had a significantly negative influence on the intensity of adoption of CSA practices suggesting that farmers who own cattle are less likely to adopt multiple CSA practices. Owners of cattle are considered to be relatively wealthier and thus expected to have the wherewithal to adopt modern technology. However, the result is contrary to our expectation.

Distance to the local market positively correlated with CSAPs adoption intensity. This result, however, contradicts *a prior* expectation of the study that proposes that an increase in distance to the local market will decrease the adoption of CSA practices since the cost of inputs will increase with an increase in distance to the local input shops. The result contradicts the finding of the study by Donkoh & Awuni (2011), which posits that distance to the local market or input shops reduces the adoption of inputs as it has the potential of making inputs expensive due to the extra cost that may be associated with transportation.

Training of farmers on the CSA practices positively influenced the intensity of adoption. This confirms *a prior* expectation of the study that training exposes farmers to the knowledge and skill set required for adoption of CSA technology. Hence, training empowers farmers to apply the knowledge and skill to improve their coping strategy to CC. This further affirms the findings of studies by Azumah et al. (2017) and Donkoh & Awuni (2011) which revealed that training is an added input which results in an increase in the adoption of technologies by farmers.

Furthermore, how long a farmer has been exposed to CSA practices positively influenced the farmer's adoption of these practices. The result is expected because the longer a farmer knows about a technology and its associated benefits, the higher the likelihood of adoption. This implies that farmers' familiarity with technologies positively influences their adoption rate.

Technical efficiency of maize farmers

From the results of the stochastic frontier analysis, two out of the 5 conventional input variables significantly influence the output of maize. A 1% increase in farm size increases maize output by 1.16% holding all factors constant. This result is consistent with other findings such as Adzawla & Alhassan (2021). The study also revealed that an increase in ploughing cost by 1% resulted in a decrease in output by 0.517% holding all other factors constant. The result contradicts the findings of Silva et al. (2019), who observed a positive influence of ploughing on the output of cereal-based crop farmers. The mean TE was estimated at 74%, which points to the existence of inefficiency in production among the farmers. With the same input level, farmers could potentially increase their output level by 26%.

Effect of CSA adoption intensity on technical efficiency

Climate-smart agricultural practices are intended to alleviate the impact of CC, thereby enhancing the productivity and incomes of farmers. The findings of this study support this assertion as the adoption intensity of CSA practices positively influenced TE level of maize farmers in the study area. This indicates that producers who adopt more CSA practices are more technically efficient compared to farmers who adopt less or none of the CSA practices. These results confirm the *a priori* expectation that the intensity of adoption of CSA has a negative influence on technical inefficiency, indicating that producers are more technically efficient if they adopt more CSA practices. The results confirmed that of Adzawla & Alhassan (2021), who identified a positive effect of adaptation strategies on maize TE. Similarly, the findings agree with that of Anang et al. (2020) who observed a positive effect of adoption of improved maize variety on TE of smallholder farmers.

Other determinants of technical efficiency

Other factors influencing TE of maize farmers in the study area include years of schooling, which contrary to expectation, decreased TE. This could be attributed to educated farmers engaging in other economic activities which may reduce their time allocation to farming thereby reducing their efficiency. Farmers with formal education have a higher likelihood to obtain off-farm employment, hence may be part-time farmers, whereas those without formal education are often full-time farmers as reported by Abdulai et al. (2018). Educated farmers who engage in other work/income activities spend less time on their farms making them more technically inefficient in their maize production. The results however contrary to expectation other researchers in Ghana have reported the outcome, despite it being unexpected. In northern Ghana, Donkoh et al. (2013), found that educated farmers were less technically proficient. Anang et al. (2022) also observed that farmers with education recorded lower TE scores. Similar findings were made by Asante et al. (2014), who found educated farmers in Ghana to be less technically proficient than uneducated ones.

Maize farming experience had a positive effect on TE indicating that producers who have farmed maize for a longer time are more efficient than those farmers with fewer years of maize farming experience. Experienced farmers have acquired adequate skill and knowledge which enable them to maximize output relative to less experienced farmers. This agrees with Addai & Owusu (2014) who found that maize farming experience increased TE of smallholder maize producers in Ghana.

On the contrary access to extension decreases TE of maize production in the study area. Extension access was expected to improve TE since it serves as an avenue for agricultural information dissemination to the farmers on how to maximize their output and new technologies. While the result is unexpected, it could suggest that the information extension officers share with farmers may not match with their information needs.

Farmers who inherited their land were more efficient than farmers who purchased their farm lands. In most Ghanaian farming communities, few farmers purchase their farmlands whereas majority of the land for farming is inherited. Farmers who inherit farm lands may have access to more fertile lands and the freedom to improve the land over a long-term compared to the few farmers who purchase their land for farming.

CONCLUSIONS

The study assessed the effect of CSA adoption intensity on TE of maize production among small-scale producers in Wa-East District of Ghana. The generalized Poisson regression model and stochastic frontier analysis were used in the analysis to draw conclusions.

The study concluded that age, sex, years of education, distance to the local market, CSA training, and years of exposure to CSA practices positively influenced the adoption intensity of CSAPs. Specifically, CSA training enhanced the adoption of CSA practices, underscoring the need to enhance farmers' expertise on climate change adaptation. Again, the results discovered that CSA adoption intensity improved TE of maize farming. This means that in the face of CC, promoting adoption of CSA practices is critical to improve the TE of smallholder farmers.

The study recommends that farmers should be trained on CSA practices to increase their level of knowledge and adoption of the practices since higher adoption of CSAPs correlates positively with TE. Training will expose farmers to the benefits of CSA practices and the technical know-how to apply these practices effectively. The study also calls for the provision of education at the rural level to enhance adoption of CSA practices. CSA adoption increased with formal education, indicating that provision of formal education is critical to accelerate uptake of CSA practices. This should be augmented with the provision of informal/non-formal education especially to adult learners to enhance their numeracy and decision-making. Additionally, it was observed that farmers who inherited their lands were more efficient, suggesting that land tenure security improves efficiency of production. The study therefore proposes land ownership reforms that guarantees land tenure security to allow long-term investment in land management to improve efficiency of production of smallholder farmers.

REFERENCES

Abdallah, A. H., & Abdul-Rahman, A. (2017). Technical efficiency of maize farmers in Ghana: a stochastic frontier approach. International Journal of Innovation and Scientific Research, 29(2), 110-118.

Addai, K. N., Ng'ombe, J. N., Temoso, O. and Poverty, F. (2022). Vulnerability, and food consumption inequality among smallholder households in Ghana: a gender- based perspective. Social Indicators Research, 163(2), 1-29. doi: 10.1007/s11205-022-02913-w.

Anang, B. T., Bäckman, S., & Sipiläinen, T. (2016). Agricultural microcredit and technical efficiency: The case of smallholder rice farmers in Northern Ghana. Journal of Agriculture and Rural Development in the Tropics and Subtropics, 117(2), 189–202.

Boateng, V. F., Donkoh, S. A., & Adzawla, W. (2022). Organic and conventional vegetable production in northern Ghana: farmers' decision making and technical efficiency. Organic Agriculture, 12(1), 47-61.

Chiona, S., Kalinda, T., & Tembo, G. (2014). Stochastic frontier analysis of the technical efficiency of smallholder maize farmers in Central Province, Zambia. Journal of Agricultural Science, 6(10), 108.

Damba, O. T., Kizito, F., Bonilla-Findji, O., Yeboah, S., Oppong-Mensah, B., Clottey, V., Duah, S., Gaitu, C., Mantey, F., Dalaa, M. A. and Obeng, F. (2021). Climate Smart Agriculture (CSA)-Climate Smart Information Services (CIS) Prioritization in Ghana: Smart Assessments and Outcomes. Accelerating Impacts of CGIAR Climate Research for Africa (AICCRA) Technical Report.

Donkoh, S. A., & Awuni, J. A. (2011). Adoption of farm management practices in lowland rice production in Northern Ghana.

Danso-Abbeam, G., Bosiako, J. A., Ehiakpor, D. S., & Mabe, F. N. (2017). Adoption of improved maize variety among farm households in the northern region of Ghana. Cogent Economics & Finance, 5(1), 1416896.

Ho, T. T., & Shimada, K. (2019). The effects of climate-smart agriculture and climate change adaptation on the technical efficiency of rice farming—an empirical study in the Mekong Delta of Vietnam. Agriculture, 9(5), 99.

Ifie, B. E., Kwapong, N. A., Anato-Dumelo, M., Konadu, B. A., Tongoona, P. B., & Danquah, E. Y. (2022). Assessment of farmers readiness to adopt maize hybrid varieties for high productivity in Ghana. Acta Agriculturae Scandinavica, Section B—Soil & Plant Science, 72(1), 506-515.

Issahaku, G., & Abdulai, A. (2020). Adoption of climate-smart practices and its impact on farm performance and risk exposure among smallholder farmers in Ghana. Australian Journal of Agricultural and Resource Economics, 64(2), 396-420.

Issahaku Z. A., Maharjan KL (2014) Crop substitution behavior among food crop farmers in Ghana: an efficient adaptation to climate change or costly stagnation in traditional agricultural production system? Agricultural and Food Economics 2(16): 1–14

Nyanteng, V. K., & Seini, A. W. (2000). Agricultural policy and the impact on growth and productivity 1970-95. Economic Reforms in Ghana, The Miracle and The Mirage.

Oxford Business Group. (2019). Agriculture in Africa 2019 [Special Report]. Accessed November 7 2019. https://oxfordbusinessgroup. com/sites/default/files/blog/specialreports/949525/africa_2019_special_report.pdf.

Abdulai, S., Nkegbe, P. K., & Donkoh, S. A. (2018). Assessing the technical efficiency of maize production in northern Ghana: The data envelopment analysis approach. Cogent Food & Agriculture, 4(1), 1512390.

Addai, K. N., & Owusu, V. (2014). Technical efficiency of maize farmers across various agro ecological zones of Ghana. Journal of Agriculture and Environmental Sciences, 3(1), 149-172.

Adu, D. T., Kuwornu, J. K., Anim-Somuah, H., & Sasaki, N. (2018). Application of livelihood vulnerability index in assessing smallholder maize farming households' vulnerability to climate change in Brong-Ahafo region of Ghana. Kasetsart Journal of Social Sciences, 39(1), 22-32.

Adzawla, W., & Alhassan, H. (2021). Effects of climate adaptation on technical efficiency of maize production in Northern Ghana. Agricultural and Food Economics, 9(1), 1-18.

Akrofi-Atitianti, F., Ifejika Speranza, C., Bockel, L., & Asare, R. (2018). Assessing climate smart agriculture and its determinants of practice in Ghana: A case of the cocoa production system. Land, 7(1), 30.

Anang, B. T., Alhassan, H. & Danso-Abbeam, G. (2020) Estimating technology adoption and technical efficiency in smallholder maize production: A double bootstrap DEA approach, Cogent Food & Agriculture, 6:1, 1833421.

Anang, B. T., Dokyi, E. O., Asante, B. O., & Donkoh, S. A. (2022). Technical efficiency of resource-poor maize farmers in northern Ghana. Open Agriculture, 7(1), 69-78.

Arif, M., Ali, S., Ilyas, M., Riaz, M., Akhtar, K., Ali, K., ... & Wang, H. (2021). Enhancing phosphorus availability, soil organic carbon, maize productivity and farm profitability through biochar and organic–inorganic fertilizers in an irrigated maize agroecosystem under semi-arid climate. Soil Use and Management, 37(1), 104-119.

Asante, B. O., Villano, R. A., & Battese, G. E. (2014). The effect of the adoption of yam minisett technology on the technical efficiency of yam farmers in the forest-savanna transition zone of Ghana. African Journal of Agricultural and Resource Economics, 9(311-2016-5576), 75-90.

Azumah, S. B., Donkoh, S. A., & Ansah, I. G. K. (2017). Contract farming and the adoption of climate change coping and adaptation strategies in the northern region of Ghana. Environment, Development and Sustainability, 19(6), 2275-2295.

Battese, G. E. & Coelli, T. J. (1995). A model for technical inefficiency effects in a stochastic frontier production function for panel data, Empirical Economics, 20, 325-332.

Chinseu, E., Dougill, A., & Stringer, L. (2019). Why do smallholder farmers dis-adopt conservation agriculture? Insights from Malawi. Land Degradation & Development, 30(5), 533-543.

Cobbinah, P. B., & Anane, G. K. (2016). Climate change adaptation in rural Ghana: Indigenous perceptions and strategies. Climate and Development, 8(2), 169–178. https://doi.org/10.1080/17565529.2015.1034228.

Consul, P. C., & Famoye, F. (1992). Generalized Poisson regression model. Communications in Statistics - Theory and Methods, 21(1), 89–109. doi:10.1080/03610929208830766.

Coulibaly, T. P., Du, J., Diakité, D., Abban, O. J., & Kouakou, E. (2021). A proposed conceptual framework on the adoption of sustainable agricultural practices: The role of network contact frequency and institutional trust. Sustainability, 13(4), 2206.

Derbile, E. K., Chirawurah, D., & Naab, F. X. (2022). Vulnerability of smallholder agriculture to environmental change in North-Western Ghana and implications for development planning. Climate and Development, 14(1), 39-51.

Dinko, H. (2017) 'Climate change and changing food security risk in Ghana', African Journal of Agriculture and Food Security, 5(3), 186–192.

Dokyi, E., Anang, B. T. and Owusu, V. (2021). Impacts of Improved Seed Maize Technology Adoption on Productivity and Technical Efficiency in Northern Ghana. Open Economics, 4(1), 118-132.

Donkoh, S. A., & Awuni, J. A. (2011). Adoption of farm management practices in lowland rice production in Northern Ghana.

Donkoh, S. A., Ayambila, S., & Abdulai, S. (2013). Technical efficiency of rice production at the Tono irrigation scheme in northern Ghana.

Farrell, M. J. (1957) 'The measurement of productive efficiency', Journal of the Royal Statistical Society, 120(3), pp. 253–290.

Ho, T. T., & Shimada, K. (2019). The effects of climate smart agriculture and climate change adaptation on the technical efficiency of rice farming—an empirical study in the Mekong Delta of Vietnam. Agriculture, 9(5), 99.

Imran, M. A., Ali, A., Ashfaq, M., Hassan, S., Culas, R., & Ma, C. (2019). Impact of climate smart agriculture (CSA) through sustainable irrigation management on Resource use efficiency: A sustainable production alternative for cotton. Land Use Policy, 88, 104113.

Imran, M. A., Ali, A., Culas, R. J., Ashfaq, M., Baig, I. A., Nasir, S., & Hashmi, A. H. (2022). Sustainability and efficiency analysis wrt adoption of climate-smart agriculture (CSA) in Pakistan: a group-wise comparison of adopters and conventional farmers. Environmental Science and Pollution Research, 1-15.

Issahaku, G., & Abdulai, A. (2020). Adoption of climate-smart practices and its impact on farm performance and risk exposure among smallholder farmers in Ghana. Australian Journal of Agricultural and Resource Economics, 64(2), 396-420.

Kassie, M., Marenya, P., Tessema, Y., Jaleta, M., Zeng, D., Erenstein, O., Rahut, D., (2018). Measuring farm and market level economic impacts of improved maize production technologies in Ethiopia: evidence from panel data. J. Agric. Econ. 69 (1), 76–95.

Khataza, R. R., Doole, G. J., Kragt, M. E., & Hailu, A. (2018). Information acquisition, learning and the adoption of conservation agriculture in Malawi: A discrete-time duration analysis. Technological Forecasting and Social Change, 132, 299-307.

Kibirige, D., Raufu, M., & Masuku, M. (2014). Efficiency Analysis of the Sub-Saharan African Small-scale Agriculture: A Review of Literature on Technical Efficiency of Maize Production. Journal of Agriculture and Veterinary Science, 7(12), 124-131.

Kwawu, J. D., Sarpong, D. B., & Agyire-Tettey, F. (2022). Technology adoption intensity and technical efficiency of maize farmers in the Techiman municipality of Ghana. African Journal of Science, Technology, Innovation and Development, 14(2), 532-545.

Lipper, L., Thornton, P., Campbell, B. M., Baedeker, T., Braimoh, A., Bwalya, M., ... & Torquebiau, E. F. (2014). Climate-smart agriculture for food security. Nature Climate Change, 4(12), 1068-1072.

Mabuku, M. P., Senzanje, A., Mudhara, M., Jewitt, G. P. W., & Mulwafu, W. O. (2019). Strategies for coping and adapting to flooding and their determinants: A comparative study of cases from Namibia and Zambia. Physics and Chemistry of the Earth, Parts A/B/C, 111(1), 20–34. https://doi.org/10.1016/j.pce.2018.12.009.

Martey, E., Etwire, P. M., & Abdoulaye, T. (2020). Welfare impacts of climate-smart agriculture in Ghana: Does row planting and drought-tolerant maize varieties matter? Land use policy, 95, 104622.

Mgomezulu, W. R., Machira, K., Edriss, A. K., Pangapanga-Phiri, I., & Chitete, M. M. (2022). Responding to inefficiencies on smallholder maize farms: Can sustained adoption of sustainable agricultural practices make a difference? African Journal of Agricultural and Resource Economics, 17(4), 313–329.

Mizik, T. (2021). Climate-smart agriculture on small-scale farms: A systematic literature review. Agronomy, 11(6), 1096.

Mo, T., Lee, H., Oh, S., Lee, H., & Kim, B. H. (2023). Economic Efficiency of Climate Smart Agriculture Technology: Case of Agrophotovoltaics. Land, 12(1), 90.

Ng'ombe, J. N. (2017). Technical efficiency of smallholder maize production in Zambia: a stochastic meta-frontier approach. Agrekon, 56(4), 347-365.

Okuyama, Y., Maruyam, A., Takagaki, M., & Kikuchi, M. (2017). Technical efficiency and production potential of selected cereal crops in Senegal. Journal of Agriculture and Rural Development in the Tropics and Subtropics, 118(2), 187-197.

Oxford Business Group. (2019). Agriculture in Africa 2019 [Special Report]. Accessed November 7 2019. https://oxfordbusinessgroup.com/sites/default/files/blog/specialreports/949525/africa_2019_special_report.pdf.

Pannell, D. J., Llewellyn, R. S., & Corbeels, M. (2014). The farm-level economics of conservation agriculture for resource-poor farmers. Agriculture, ecosystems & environment, 187, 52-64.

Partey, S. T., Zougmoré, R. B., Ouédraogo, M., & Campbell, B. M. (2018). Developing climate-smart agriculture to face climate variability in West Africa: Challenges and lessons learnt. Journal of cleaner Production, 187, 285-295.

Sam, K. O., Botchway, V. A., Karbo, N., Essegbey, G. O., Nutsukpo, D. K., Segnon, A. C., & Zougmoré, R. B. (2021). Achievements and lessons learnt in promoting Climate-Smart Agriculture implementation in Ghana through Science-Policy dialogue platforms.

Silva, J. V., Baudron, F., Reidsma, P., & Giller, K. E. (2019). Is labour a major determinant of yield gaps in sub-Saharan Africa? A study of cereal-based production systems in Southern Ethiopia. Agricultural Systems, 174, 39-51.

Taylor, M. (2018). Climate-smart agriculture: what is it good for? The Journal of Peasant Studies, 45(1), 89-107.

Thathsarani, U. S. & Gunaratne, L. H. P. (2018) 'Constructing and index to measure the adaptive capacity to climate change in Sri climate change in Sri Lanka', Procedia Engineering. Elsevier B.V., 212, pp. 278–285. doi: https://doi.org/10.1016/j.proeng.2018.01.036.

Thierfelder, C., Matemba-Mutasa, R., Rusinamhodzi, L. (2015). Yield response of maize (Zea maysL.) to conservation agriculture cropping system in southern Africa. Soil Tillage Research, 146, 230–242.

Tong, Q., Swallow, B., Zhang, L., & Zhang, J. (2019). The roles of risk aversion and climate-smart agriculture in climate risk management: Evidence from rice production in the Jianghan Plain, China. Climate Risk Management, 26, 100199.

Tsiboe, F., Asravor, J., Owusu, V., & Mensah-Bonsu, A. (2022). Production technology, efficiency, and productivity of cereal farms: Prospects for enhancing farm performance in Ghana. Agricultural and Resource Economics Review, 1-31.

Yeboah, P. A., Dordaa, F., & Derbile, E. K. (2020). Livelihood Systems of Smallholder Cashew Farmers in the Guinea Savannah Woodland and Semi-Deciduous Forest Zones of Ghana. African Journal of

Agricultural Economics and Rural Development, 8(10), 1-15.

Zougmoré, R. B., Partey, S. T., Totin, E., Ouédraogo, M., Thornton, P., Karbo, N., ... & Campbell, B. M. (2019). Science-policy interfaces for sustainable climate-smart agriculture uptake: lessons learnt from national science-policy dialogue platforms in West Africa. International Journal of Agricultural Sustainability, 17(5), 367-382. https:// doi. org/ 10. 1080/ 14735 903. 2019. 16709 34.