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Advancing agriculture in Tanzania through climate-smart technologies

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Abstract

The hazards and impacts of climate change are exacerbating. They threaten crop productivity, farmers' resilience and the mitigation of greenhouse gas (GHG) emissions. Understanding climate-smart agriculture (CSA) and applying it is crucial. However, the adaptation measures of smallholder farmers remain contextual, particularly whether small-scale farmers adopting CSA boost crop productivity and income scarcity. This study examines the drivers of CSA adoption and its impacts on farm performance. We used nationally representative data from a sample of 1 862 farmers cultivating less than two hectares. Endogenous switching regression (ESR) was employed to address the selection and endogeneity issues of CSA adoption. Propensity score matching (PSM) was adopted for comparative purpose. The results of both models are consistent that CSA adoption augments productivity and income. Interestingly, if non-adopters had adopted, they would have gained remarkably. The results imply that plausible programmes, promotions, campaigns or policy support measures to scale up CSA adoption can make a significant contribution to food security and poverty reduction, build farmers' resilience, and mitigate the effects of GHG in the agricultural sector.

Key words: Tanzania, climate change impact, climate-smart agriculture, income, crop production, endogenous switching regression model, propensity score matching, farmers

1. Introduction

The hazards and impacts of climate change are globally overwhelming (Ray *et al*. 2019). The elements of weather, such as temperature, are continuously rising, and precipitation patterns are becoming unreliable. Severe events, such as prolonged droughts, extreme heatwaves, wildfires, floods, diseases and pests, melting glaciers, earthquakes, lake saturation, storms, hurricanes, water shortages, avalanches, human healthcare issues, and season and lifestyle changes, are occurring everywhere (Winthrop *et al*. 2018; Hussain *et al*. 2020). These events have persistently threatened anthropogenic activities and lives, ecosystems, biodiversity, animal habitats, land degradation, water bodies and forests (Hussain *et al*. 2020). There is the potential that they could increase and trigger significant damage in the future if no reliable measures are taken.

Livelihoods and the agricultural economy, especially in resource-poor countries, are at even higher risk (Huang *et al*. 2011). The well-being of small farmers and rural economies are affected, given that crop markets are interrupted by climate change, which harms the food supply (Hellin & Fisher, 2018). Consequently, poverty, hunger, food insecurity, low economic growth, environmental degradation and unemployment are predominant (FAO 2017a).

The increase in global population adds more pressure to crop production and food availability. For instance, the global population is projected to hit nine billion by 2050 (Rockström *et al*. 2016). In 2019, about 821 million people faced food insecurity globally, including 236 million people from Sub-Saharan Africa (SSA) (FAO, 2019). Furthermore, the effects of climate change on food security and income are more pronounced in low-income countries whose economies depend on agriculture. The data shows that, in 2022, about 2.8 billion people had no access to a healthy diet, and the severity of this is felt more in SSA. For instance, about 71.5% of the population in this region are from low-income countries, 52.6% from low middle-income countries, 21.5% from upper middle-income countries, and 6.3% are from high-income countries (FAO *et al*. 2024).

The impacts of climate change are projected to have the potential to cascade beyond food production systems (Mirzabaev *et al*. 2023). About 713 to 757 million people faced hunger in 2023, fuelled in the wake of the Covid-19 pandemic. This means that one out of 11 people in the world and one out of five people in Africa go to sleep without a meal. Hunger is still on the rise in Africa, while countries in Asia, Latin America and the Caribbean have remained relatively stagnant from 2021 to 2024. If no relevant initiatives are taken, about 582 million people will be chronically undernourished globally by 2030 (FAO *et al*. 2024).

Climate is crucial for crop productivity (Akter *et al*. 2022) and for agricultural income generation (Amadu *et al*. 2020a). Various measures have been put in place to mitigate the effect of climate change on crop production to improve farmers' adaptive ability, resilience and efficiency in the utilisation of scarce resources in agricultural activities (Islam & Nursey-Bray 2017).

The adoption of climate-smart agriculture (CSA) is the most popular and common adaptable approach to dealing with climatic shocks (FAO 2013). CSA reduces emissions of greenhouse gases (GHG), increases crop production, and increases farmers' resilience to extreme weather shocks in agriculture (Hellin & Fisher 2018; Mirzabaev *et al*. 2023). It is particularly crucial to adopt CSA to improve crop production to meet the demand-and-supply equilibrium and ensure food security (Hellin & Fisher 2018), which is likely to improve resilience in the face of adverse climatic conditions. Food production must increase between 60% to 110% to be able to feed the projected population increase (Pardey *et al*. 2014). This is possible because CSA does more than augmenting the productivity, mitigation and resilience of farmers (Amadu *et al*. 2020a). It is a holistic approach that brings together prominent stakeholders, including researchers, farmers, policymakers, societies and the public and private sectors (Lipper *et al*. 2014; Akter *et al*. 2022), to work together to face climate-induced shocks.

Furthermore, the adoption of CSA is in pursuit of sustainable development goal (SDG) 13 (combating the impacts of climate change) and the attainment of its targets (Newell *et al*. 2019). CSA adoption enhances agricultural transformation by improving farming performance, leading to a sustainable environment. CSA enhances crop productivity, mitigates the effect of greenhouse gas emissions, and increases agricultural resilience when facing the implications of climate change (Bhatnagar *et al*. 2024).

CSA, as a holistic approach, brings together all stakeholders to take every possible action aimed at increasing awareness of and developing strategies for adaptation by promoting environmentally friendly practices (Hussain *et al*. 2020). There is political will across the globe to adhere to agreements such as reducing GHG emissions. Governments devote funds to enhance adaptation to climate change and reinforce policies to promote the adoption of climate action such as CSA in agriculture (United Republic of Tanzania [URT] 2013).

The adoption of CSA enhances the attainment of the SDGs of ending poverty and hunger, promoting inclusive economic growth, and creating employment and decent jobs for all (United Nations Development Programme 2015) through agricultural transformation, which improves farmers' resilience (Amadu *et al*. 2020a). However, climate change is considered a complex problem (Hellin & Fisher 2018) and context/location-specific (Ngaiwi *et al*. 2023), requiring contextual investigation for critical understanding.

To date, several studies have been on CSA since its introduction as a concept by the FAO (2010) in Tanzania and the neighbouring countries that share some climatic characteristics. For instance, studies in Kenya investigated determinants of CSA usage and adoption constraints among smallholder farmers (Autio *et al*. 2021; Musa *et al*. 2022). In Uganda and Tanzania, Mwongera *et al*. (2017) evaluated context-specific issues for local community adoption of CSA technologies. Also in Tanzania, the literature includes studies about determinants, challenges, the impact of climate change on a crop-specific basis, and the impact of CSA on households' food security (Rowhani *et al*. 2011; Craparo *et al*. 2015; Kimaro *et al*. 2015; Kurgat *et al*. 2020; Mugabe 2020; Ogada *et al*. 2020, 2021; Bongole *et al*. 2022; Bongole 2023; Jones *et al*. 2023). While stakeholders believe that CSA augments productivity and income, there is scant empirical evidence in Tanzania in this regard for smallholder farmers. The link between climate change adoption measures with production and the income of smallholder farmers is not clear.

This study examines the determinants of CSA adoption and its effect on crop yields and income in Tanzania using nationally representative data from a sample of 1 862 smallholder farmers. The study applied the endogenous switching regression (ESR) and propensity score matching (PSM) models that address the weaknesses in impact assessment studies, such as potential endogeneity and sample selection bias (Ma *et al*. 2018).

Therefore, the paper contributes to the literature as follows: first, it contributes by advancing the literature on the determinants of CSA adoption and its effects on farm performance and income among small-scale farmers. Second, the paper contributes to the impacts of CSA adoption on crop production and income. Resource-poor communities can boost productivity and income through the effective adoption of CSA. Eventually, farmers' resilience is improved and the SDGs are attained in given climatic variations (Mwalupaso *et al*., 2020). Finally, the paper contributes to the formulation of policy support measures for CSA adoption. The analysis of crop specificity confirms the importance of feasible policy support measures. It is crucial to improve the adoption by and crop production of specific farmers, as crop requirements, climate change impacts and environmental factors vary among farmers (Khatri-Chhetri *et al*., 2016; Hellin & Fisher 2018).

The rest of this paper is structured as follows: Section 2 consists of the context of and background to CSA; Section 3 describes the methodology (data, variables and empirical approach); Section 4 presents the empirical results, the discussion and limitations, whereas Section 5 highlights the conclusion and policy implications.

2. The context and background

2.1 Empirical literature review

CSA has been well researched since the introduction of the idea (FAO 2010). The adoption of CSA practices in agriculture has been documented from different dimensions and capacities in the extant literature. The extant empirical literature outlines the determinants and benefits associated with CSA adoption, and several studies reveal a correlation between the adoption of CSA technologies and improved crop production, farmers' resilience, and climate-change mitigation. Furthermore, the CSA approach to climate change has attracted important research worldwide (Akter *et al*. 2022).

Among the studies that focus on the determinants of CSA adoption are Shemsanga *et al*. (2010), Dercon and Christiaensen (2011), Teklewold *et al*. (2013), Balew *et al*. (2014), Berger *et al*. (2017), Mwongera *et al*. (2017), Nyasimi *et al*. (2017), Wekesa *et al*. (2018), Kurgat *et al*. (2020), Teklewold *et al*. (2020), Habtewold (2021), Smith *et al*. (2021), Ogada *et al*. (2021), Belay *et al*. (2022), Bongole *et al*. (2022), Kifle *et al*. (2022), Musa *et al*. (2022) and Jena *et al*. (2023).

Some studies focus on the challenges or barriers that hinder the effective adoption of CSA (Nyasimi *et al*. 2017; Ogada *et al*. 2020), whereas others investigated the implications of CSA adoption and technological diffusion at farm level (Erekalo *et al*. 2024). Further studies have examined the effects of CSA adoption on the reduction of the carbon footprint for sustainable maize production (Feng *et al*. 2023).

Other studies have focused on the impact of CSA adoption on the production of specific crops. These have focused mostly on maize and the associated impact on income (Dercon & Christiaensen 2011; Teklewold *et al*. 2013; Balew *et al*. 2014; Murray *et al*. 2016; Berger *et al*. 2017; Amadu *et al*. 2020a; Habtewold 2021; Belay *et al*. 2022; Kifle *et al*. 2022; Coderoni & Pagliacci 2023; Jena *et al*. 2023).

Jena *et al*. (2023) and Rodríguez-Barillas *et al*. (2024) investigated the impact of the adoption of CSA on farmers' resilience, behaviour, policy acceptability and comprehensiveness, whereas Bongole *et al*. (2022) assessed how CSA adoption improves food security. These studies provide insights into how CSA adoption can variably be effective and relatively impact farm performance.

These studies further demonstrate limitations, such as being context specific, producing mixed results, and being crop specific, with a limited sample size. This means that researchers currently have produced relatively heterogeneous findings about the determinants of CSA adoption and its impacts on farm performance and income in Tanzania. If academics, policymakers and researchers want to understand the factors that drive CSA adoption and their relationship with crop farming and income, then investigating what influences the successful adoption of CSA and the impacts on crop yields and income is crucial.

This paper examines the determinants of CSA adoption, and its impacts on crop productivity and income using nationally representative cross-section data of 1 862 smallholder household farmers in Tanzania. The synthesis of the empirical literature shows that information on crop (maize, paddy and beans) productivity and the income impact of CSA in Tanzania remain scanty. This article aimed to fill this gap.

2.2 The agricultural sector, climate change, and CSA adoption in Tanzania

Agriculture is a key activity for livelihoods and the backbone of the Tanzanian economy (URT 2016; Bongole *et al*. 2022). Agriculture contributes 28% of GDP, 95% of all food, and about 80% of Tanzanians are involved in agriculture (Gwambene *et al*. 2023). A large part of this farming population comprises smallholder farmers who are resource-poor (Bongole *et al*. 2020; Ogada *et al*. 2021; Gwambene *et al*. 2023). About 65.5% of the workforce is in the sector (URT 2014), whereas 90% are small-scale farmers cultivating 0.2 to 2 hectares in rural areas (Rapsomanikis 2015).

About 60% of farmers are involved in crop production, 37% deal with mixed farming, and 1% engage in pastoralism. Crops cultivated annually as a percentage of land range from cereals (67%) to legumes (11%), oil seeds and nuts (11%), cash crops (7%), and fruits and vegetables (1%) (URT 2014). The staple food grains that are produced mainly include maize and paddy (Mrema *et al*. 2023), as well as beans, which are legumes that restore soil nutrients and are largely consumed (Mutungi *et al*. 2022). Farm productivity has remained relatively low for decades, at about 10%, partly due to exacerbating climate change impacts (Irish Aid 2011).

Agricultural practices in Tanzania depend on the natural levels of rain and temperature, with limited irrigation schemes (Kurgat *et al*. 2020; Ogada *et al*. 2021). Climate change has altered precipitation and temperature patterns, harming crop production. It is evident that there has been a decline in rainfall of 2.8 mm, which is 3.3%, over 10 years, and temperature has increased by 1.0°C since 1960 (Winthrop *et al*. 2018). It is further projected that mean annual temperature will increase by 1.0°C to 2.7°C in the 2060s, and by 1.5°C to 4.5°C in the 2090s (Winthrop *et al*. 2018).

Following the impact of climate change, smallholder farmers have experienced low crop productivity, strained water resources, and an increased incidence of pests and disease (Bongole *et al*. 2020; Jones *et al*. 2023). In the future, a change in temperature by 2°C is projected to lower yields by 13%, 8.8% and 7.6% for maize, sorghum and paddy, respectively by 2050 (Rowhani *et al*. 2011). Severe impacts will be felt in Africa and Asia, coupled with yield declines that are expected to reach 7% in potential food-growing zones in 2030 (Townsend 2015).

Farmers who are resource-poor suffer and are proportionately worse affected by climate change, given their low capacity for resilience (Amadu *et al*. 2020). It is expected that the situation will be worse for smallholder farmers who have no agricultural technological support (Jones *et al*. 2023). Without action, it is projected that climate change will add 2.6 million Tanzanians to the poverty pool by 2050, and 27% of the population and 29.4% of vulnerable societies have already experienced at least one climate change shock (World Bank Group 2024).

Tanzania is vulnerable to climate risks due to the country's reliance on rainfed agriculture and low crop productivity agriculture, urban-rural inequalities, unprecedented population increases (Jones *et al*. 2023), and limited infrastructure for energy, transport and digital connectivity (World Bank Group 2024). Acute food insecurity is predominant, hitting 54.6% (64% and 84% for urban and rural areas, respectively) (World Bank Group 2024).

To this end, the major challenge hinges on addressing the synergy and trade-offs between improving crop productivity, ensuring resilience to extreme climate change, and greenhouse gas mitigation. Planned CSA adoption enhances synergies and trade-offs between production, adaptation and mitigation (Ali & Erenstein 2017). A clear trade-off between these would address economic, environmental and social challenges for the effective, efficient and equitable functioning of food systems (Lipper & Zilberman 2018).

There are many initiatives to promote CSA as responses to climate change impacts and hazards (Akter *et al*. 2022; Jones *et al*. 2023). These range from policies and programmes to research that aim to improve adaptive strategies that support food security and income and strengthen resilience in the face of climate change variability. For instance, in Africa, CSA is included in the declarations of the African Union Malabo Declaration (Lipper *et al*. 2018; Daum *et al*. 2022), which sets out plans and targets to achieve productivity, ensure resilience and mitigate the effects of greenhouse gases in agricultural activities (URT 2017; Jones *et al*. 2023).

In Tanzania in particular, the initiatives range from national-level to specific agencies that enforce national adaptation plans, nationally determined contributions, and major national investment (Jones *et al*. 2023). In addition, CSA is promoted by government institutions, national agricultural research institutions, nongovernmental organisations (NGOs), academic institutions, research organisations and development partners in varying capacities (Lamanna *et al*. 2016).

The Tanzanian government has been actively promoting the adoption of CSA in its sectoral and multi-sectoral policies. Examples include the CSA program 2015-2025, the Agriculture Climate Resilience Plan (ACRP), the Tanzania Agricultural Research Institute (TARI), Sokoine University of Agriculture (SUA), Ruvuma Commercialization and Diversification of Agriculture (RUCODIA), and in the district councils, along with the Agricultural Sector Development Plan II (ASDPII). These contain several CSA targets and plans to be achieved by the agricultural sector by 2030 (The Alliance for a Green Revolution in Africa (AGRA) 2015; URT 2015; Rioux *et al*. 2017; Lipper & Zilberman 2018; Newell *et al*. 2019).

International organisations working with the government of Tanzania to bring CSA practices into reality include the African Green Revolution Alliance (AGRA), the One Acre Fund, SNV-Tanzania, the African Conservation Tillage Network (ACTN) and the Consultative Group on International Agricultural Research (CGIAR), which works along with the United Nations – Food and Agriculture Organization (UN-FAO) around the globe (Jones *et al*. 2023). The ACRP and ASDPII are the largest government initiatives, and coordinate on a nationwide basis to promote CSA adoption among farmers so as to ensure food security, reduce poverty, enable farmer resilience and promote stable disaster management (Jones *et al*. 2023). Farmers are encouraged and supported in various ways to adopt appropriate CSA practices in a particular location, given the resources and timing of threatening climatic conditions.

Technology is climate smart if it can enhance the attainment of either production, adaptation or mitigation. It can be traditional, innovative or imported (Khatri-Chhetri *et al*. 2016). A smallholder farmer is considered a CSA adopter if he/she implements CSA practices directly and indirectly following the initiatives promoting CSA adoption. A farmer must have used the technologies in farming for all land cultivated, whether with maize, paddy or beans.

The CSA technologies promoted include elements that are knowledge- and skills-smart (timing of crop planting, improved seeds, credit/loans and farmers' income, farm inputs and outputs, and education/training), weather-smart (technological advancement, crop agro-advisory, mobile phones, television (TV), radio and the internet), carbon-smart (integrated pest management and agroforestry), nutrient-smart (crop diversification, organic manure), energy-smart (minimum tillage and solar energy use), and water-smart (drip irrigation, channel (furrow) irrigation, bed planting, planting cover crops, rainwater harvesting and drainage management) (Khatri-Chhetri *et al*. 2016; Li *et al*. 2019; Bongole *et al*. 2022).

The adoption of CSA is voluntary and is generally low (some adopt and some do not adopt) (Lamanna *et al*. 2016; Mwongera *et al*. 2017; Bongole *et al*. 2022; Jones *et al*. 2023). Despite the various stakeholders' ardent efforts, they have not won enthusiastic and general support for CSA from farmers. The sectoral-led state and development partners' initiatives have not resulted in farmers' wide application of CSA technologies. The low response to stakeholders' promotion of CSA could arise from persistent factors that are unaddressed and their impact on farm performance.

3. Methodology

3.1 Data sources and variables

This study uses secondary data from the Tanzanian National Sample Census of Agriculture (NSCA) of 2020 (National Bureau of Statistics [NBS] 2020). The sampling procedures adopted a framework for household-level surveys of Tanzania that involved a number of stages. In the first stage, the rural and urban enumerated areas (EAs) were selected as primary sampling units (PSUs) by sorting the regions and districts before implementing probability proportionate to size (PPS). The second stage involved selecting agricultural farming households from the EAs for data collection.

The probability of a household being interviewed depended on the number of households in a particular EA, which were randomly selected. With respect to the sampling design, a total of 33 808 households were sampled in this national survey. Data was collected using structured questionnaires.

To avoid bias by the farmers in recalling the information/data, the survey was conducted immediately after the farming season. Reported financial information about income and off-farm income was also obtained by observing and recording the harvests in terms of kilograms and recording the harvest values reflecting the prevailing prices in the market.

The data was further screened to obtain a dataset that would best fit our research questions and be good for comparison between adopters and non-adopters of CSA. During data cleaning, we considered only smallholder farmers who were involved in full-time agriculture, smallholder farmers who mainly produced maize, paddy or beans as staple food and for sale, smallholder farmers who had experienced climate change shocks such as drought in the past, and farmers who cultivated less than two hectares.

We obtained a sample of 1 862 smallholder farmers who met the international standard that smallholder farmers are those who cultivate less than two hectares (Noltze *et al*. 2013; Rapsomanikis 2015; Tanzania National Council for Financial Inclusion [TNCFI] 2017; Acclassato *et al*. 2021). The study focuses on smallholder farmers because they occupy a large segment of the farming population and produce a large share of food (Rapsomankikis 2015; Roop *et al*. 2023).

The study adopted variables from the extant literature on CSA adoption. The outcome variables and the covariates are described, and the sources of each variable are provided in Table 1. The variables in this paper are consistent with past studies (Noltze *et al*. 2013; Lamanna *et al*. 2016; Amadu *et al*. 2020B; Akter *et al*. 2022; Bongole 2022). Smallholder farmers' CSA adoption status is a dummy variable, where 1 represents adopters and 0 non-adopters. The summary statistics and descriptions of the variables are contained in Table 1.

Several variables are statistically significantly, indicating the difference between the two regimes, as in the cases in other studies (Abdulai 2016; Amadu *et al*. 2020a; Akter *et al*. 2022). The results give an insight into the possibility of self-selection between the two groups, and the use of the ESR model is appropriate to address the possibility of selection bias.

Table 1: Summary of the statistics

Variables	Descriptions	Indicative references	Adopter	Non-adopter	Difference
Outcome variables					
All crop outputs	Total kg (maize, paddy, beans)	(Mukasa *et al*. 2017; Amadu *et al*. 2020b; Akter *et al*. 2022)	2 872.785	1 227.633	1 645.151*** (40.054)
Maize	Total kg (maize)	(Lamanna *et al*. 2016; Akter *et al*. 2022; Bouteska *et al*. 2024)	2 285.789	1 053.469	1 232.321*** (50.319)
Paddy	Total kg (paddy)	(Noltze *et al*. 2013; Lamanna *et al*. 2016; Akter *et al*. 2022)	2 710.396	1 229.222	1 481.174*** (89.996)
Beans	Total Kg (Beans)	(Lamanna *et al*. 2016; Siamabele 2021; Akter *et al*. 2022; Bouteska *et al*. 2024)	701.941	370.987	330.954*** (60.822)
Household income	Total household income in Tanzanian shillings (TZS)	(Noltze *et al*. 2013; Lamanna *et al*. 2016; Amadu *et al*. 2020a; Akter *et al*. 2022; Belay *et al*. 2022)	13.534	12.68	.855*** (.043)
Maize (income)	Household income in TZS (maize)	(Abdulai 2016; Akter *et al*. 2022)	12.923	12.108	.815***#(.044)
Paddy (income)	Household income in TZS (paddy)	(Noltze *et al*. 2013; Akter *et al*. 2022)	13.610	12.773	.837*** (.057)
Beans (income)	Household income in TZS (beans)	(Bouteska *et al*. 2024)	14.197	13.824	.374*** (.12)
Agricultural inputs					
Herbicide	If household uses herbicides: 1 = used; 0 = otherwise.	(Noltze *et al*. 2013; Lamanna *et al*. 2016)	0.169	.216	-.048*** (.018)
lnQnty_seedKg	Quantity of seeds used in kg	(Noltze *et al*. 2013; Lamanna *et al*. 2016)	2.551	2.358	.193*** (.038)
LnTotlQtyFertilizerMPB	Total quantity of chemical fertilisers in kg	(Noltze *et al*. 2013; Lamanna *et al*. 2016)	1.605	.698	.907*** (.088)
LnLandSize	Household's total land in hectares	(Noltze *et al*. 2013; Abdulai 2016; Akter *et al*. 2022)	0.822	.618	.205*** (.038)
Manure	If household used manure: 1 = used; 0 = otherwise	(Lamanna *et al*. 2016)	0.649	.564	.085*** (.022)
Socioeconomics					
gender	Sex of the farmer: 1 = male; 0 = female	(Nyasimi *et al*. 2017; Akter *et al*. 2022)	0.736	.588	.148*** (.022)
age	Age of the household head in years	(Abdulai 2016; Akter *et al*. 2022)	46.819	50.597	-3.777*** (.723)
LnNumber_male	Male adults in the household	-	0.623	.532	.09*** (.027)
LnNumber_female	Female adults in the household	-	0.708	.666	.042 (.027)

Variables	Descriptions	Indicative references	Adopter	Non-adopter	Difference
crop_failre	Crop failure in the past season: 1 = yes; 0 = no	(Amadu *et al*. 2020b; Akter *et al*. 2022)	0.305	.349	-.044** (.022)
lnHhSize	People in the household	(Akter *et al*. 2022; Bongole *et al*. 2022; Teklewold 2023)	3.682	3.631	.051 (.044)
Off_Fmincome	Involved in paid off-farm activity: 1 = yes; 0 = no	(Tambo & Wünscher 2018; Amadu *et al*. 2020a; Akter *et al*. 2022)	0.450	.349	.101*** (.022)
lntotal Lvstok	Total number of livestock as assets	(Erekalo *et al*. 2024)	0.149	.107	.043** (.02)
Access status					
LnDstnce_Markt	Distance to market (km)	(Abdulai 2016; Akter *et al*. 2022; Belay *et al*. 2022)	2.168	2.347	-.177*** (.052)
Institutional					
Crdit_accss	Farmer received credit: 1 = yes; 0 = no	(Abdulai 2016; Marenya *et al*. 2017; Rodríguez-Barillas *et al*. 2024)	0.057	.034	.024** (.009)
Biophysical status					
LnDstnce_Home	Distance from house to farm (km)	(Akter *et al*. 2022)	5.617	4.719	.898** (.355)
LnDstnce Road	Distance from farm to road (km)	(Kurgat *et al*. 2020)	1.126	1.174	-.048 (.042)
Ivs					
Years_Educ	Years of schooling	(Abdulai 2016; Akter *et al*. 2022)	6.064	3.885	2.179*** (.163)
GrandC ostsMPB	Total input costs	(Noltze *et al*. 2013; Abdulai 2016; Lamanna *et al*. 2016)	130 757.705	59 901.811	70 855.894*** (5 499.123)

Note: *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.
Source: National Sample Census of Agriculture (NSCA) (2020) of Tanzania (NBS 2020)

3.2 Theoretical review and the conceptual framework

The study was guided by the utility and production theories. Utility theory reveals individuals' preferences. It is assumed to explain small farmers' behaviour (Akter *et al*. 2022). It claims that choice is made based on maximum satisfactions attained (Fishburn 1970).

Farmers' satisfaction refers to the gains obtained from crop productivity and income. Small farmers' CSA technology adoption is binary. A small farmer may decide to adopt or not to adopt. The decision is based on the satisfaction maximisation emanating from the impact of CSA technologies on crop productivity and income gains. The benefits for adopters is Y_{1i}, in comparison with non-adopters, which is Y_{0i}. Small farmer i^{th} can opt to adopt CSA technologies if $Y_{1i} > Y_{0i}$ and the net gain is $U_{1i} > 0$. Despite farmers' preferences and CSA adoption being clear to farmers and researchers through observation, but the net benefits accrued by farmers are unobservable.

Thus,

$$U^*_{1i} = Y_{1i} - Y_{0I} > 0 \quad (1)$$

Production theory describes crop productivity per hectare given agricultural inputs, and other factors (CSA technologies) at a particular level of technology (Førsund *et al*. 1980; Missiame *et al*. 2021). It demonstrates the technical combination of agricultural inputs and crop productivity, as well as the optimal crop productivity at a fixed level of inputs (Farrell 1957; Fried *et al*. 1993) so that variables affecting the productivity are realised (Meeusen & Van den Broeck 1977). It advances the Cobb-Douglas production function in its first-order condition, which can be expressed as:

$$Y_{1i} = AL^{\alpha 1i} K^{\alpha 2i} Q^{\alpha 3i}, \tag{2}$$

where Y_{1i} is crop productivity per hectare, A is a constant term, L is labour employed (adult male and female farmers), K is capital (here of fertilisers, seeds, land), Q summarises biophysical factors (distance to farm) and other factors used in production (here of socio-economics and institutional), while $\alpha 1i$, $\alpha 2i$ and $\alpha 3i$ are estimated vector elasticities.

CSA adoption improves productivity, farmer' resilience, farm and crop management, and the delegation of farm tasks, and farmers engage in paid off-farm activities (Amadu *et al*. 2020a; Rasheed *et al*. 2020; Akter *et al*. 2022). Therefore, the impact of CSA technologies on crop productivity follows that net benefit in Equation (1) is determined by observable variables (biophysical, institutional and socioeconomical) and the unobservable factors, such as motivations or preferences affecting farmer's decision, ε_i, such that

$$U^*_I = \beta X_i + \gamma G_i + \varepsilon_i, \tag{3}$$

where U^*_I is crop productivity of the i^{th} smallholder household farmer, X_i is a vector of farm and socio-economic profiles (here of gender, age, education, household size, etc.), G_i is the CSA technology-adoption status of each i^{th} farm household, β and γ are coefficients to be estimated, and ε_i is the error term with zero mean and constant variance, δ^2.

Furthermore, smallholder farmers' satisfaction is a function of observable factors (farm inputs, socio-economic, biophysical and institutional) and unobservable (preference, inborn techniques, motivation, social network, management skills, experience or risks) (Abdulai 2016; Amadu *et al*. 2020b; Akter *et al*. 2022).

With respect to the influence and stress of climate change, farmers' agricultural production decisions are claimed to be dependent. We assume that farmers are risk neutral. The insight into whether adopting CSA improves crop productivity and income after selling crops is the foundation of their decisions. CSA adoption enables greater plant uptake of nutrients and organic matter, prevents soil erosion, and ensures the use of improved seed (Jones *et al*. 2023), which augments crop productivity and income after the sale of the increased crop harvest (Noltze *et al*. 2013; Akter *et al*. 2022).

We contribute to the existing literature by investigating the determinants of CSA adoption and the impact of CSA on crop productivity and income. We constructed the following hypotheses (see **H1** and **H2**) and the conceptual framework in Figure 1. They were composed on the basis of extant theoretical and empirical literature.

H1: Socio-economic, farm input, biophysical and institutional factors affect CSA adoption, crop productivity and income.

H2: CSA adopters achieve higher crop productivity and income than non-adopters.

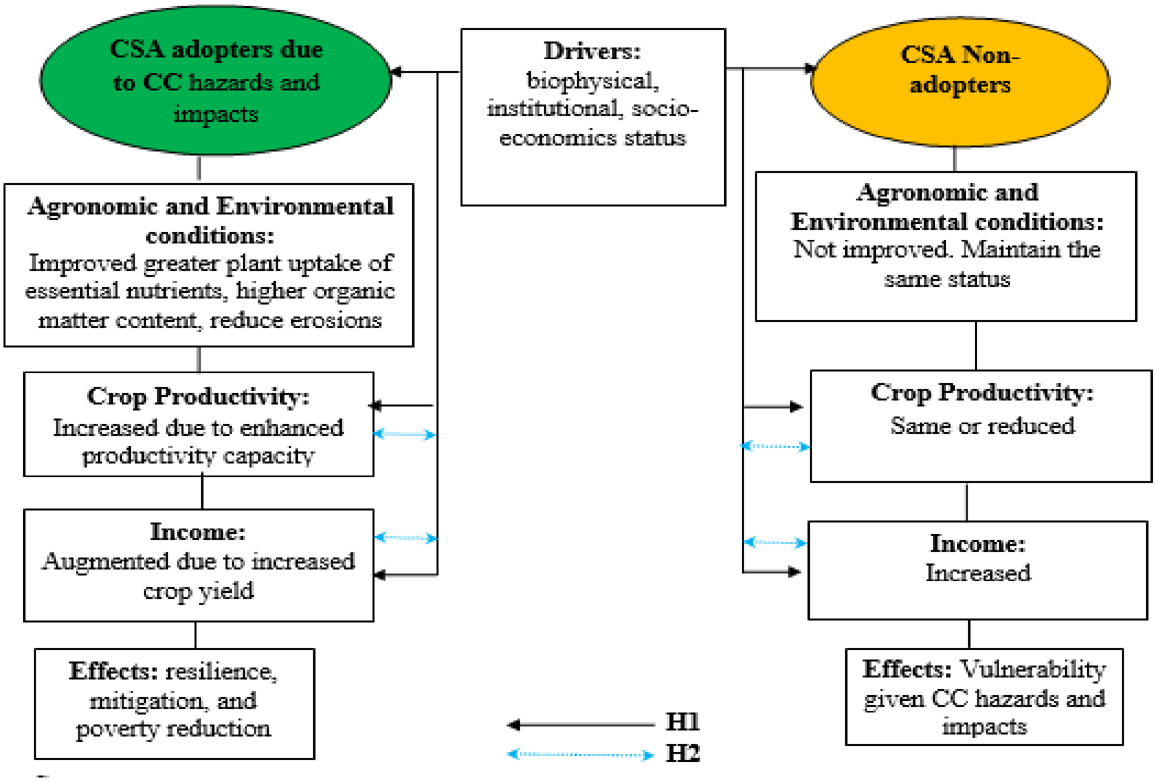

Figure 1: The conceptual framework
Source: Author

3.3 Econometric model

3.3.1 Decision to adopt CSA technologies

Endogenous switching regression (ESR) has the power to account for endogenous factors due to selection bias in impact assessment (Shahzad & Abdulai 2020). This article estimates crop productivity (maize, paddy and beans) and income in Tanzania while accounting for the endogeneity of CSA and selection bias. ESR is an instrumental variable (IV) approach that clears endogeneity and selection bias, with no restriction as of the typical IV techniques (Coulibaly *et al*. 2017). The ESR model is a Heckman selection correction approach that treats the problem of selection bias as an omitted variable (Heckman 2013).

The ESR model involves two dependent variables (adopters and non-adopters). In line with random utility maximisation theory, the study assumes that Tanzanian farmers are risk neutral, and they can choose to be either adopters or non-adopters, given the anticipated crop productivity and income.

Thus, farmers' decision-making to adopt CSA technologies depends on their perception of whether it will maximise gains or not. Net crop productivity and income are an unobservable (latent) variable, $\Lambda i*$, containing the differences between crop productivity and income for CSA adopters ($\gamma 1i$) and non-adopters ($\gamma 0i$) respectively. A rational i^{th} household will adopt CSA technologies if, and only if, the anticipated net benefits are high in Equation (1). It follows that:

$$\Lambda i *= \gamma 1i - \gamma 0i > 0, \qquad (4)$$

where $\Lambda i*$ is the function of observed variables such as farmer demographics, socio-economic status, and institutional and biophysical variables. The study models the decision to adopt CSA technologies as part of unobservable knowledge, thus adopting the procedures of Amadu *et al*. (2020a) in Malawi and Akter *et al*. (2022) in Bangladesh, such that:

$$\Lambda i *= \alpha\gamma i + \mu i, \tag{5}$$

where α is a vector of parameters to be estimated; γi is a vector of independent variables; and μi is an error term (vector of unobserved factors affecting the adoption decision).

We only observe the CSA adoption status, Λi , as

$$\Lambda i = \begin{cases} 1 \quad if\ \Lambda i *> 0, \\ 0 = if\ \Lambda i * \\ < 0, \end{cases} \tag{6}$$

where Λi is a binary variable, 1 indicates CSA adoption by i^{th} farmer, and 0 if otherwise.

3.3.2 Small farmer impact evaluation and selectivity bias

Whether a farmer decides to adopt or not, the net benefits for crop productivity and income can be expressed as in Equation (7a) and Equation (7b) respectively, conditional on Λi:

CSA adopters' regime:

$$\gamma 1i = \pi 1 \times 1i + \omega 1i, if\ \Lambda i = 1 \tag{7a}$$

Non-adopters' regime:

$$\gamma 0i = \pi 0 \times 0i + \omega 0i, if\ \Lambda i = 0, \tag{7b}$$

where $\gamma 1i$ and $\gamma 0i$ are crop productivity or income corresponding to adopters and non-adopters of CSA for the i^{th} smallholder farmer, respectively; $\pi 1$ and $\pi 0$ are vectors of the parameters to be estimated; $\times 1i$ and $\times 0i$ are vectors of variables influencing crop productivity and income for the i^{th} smallholder farmer; and $\omega 0i$ and $\omega 1i$ are error terms.

Vectors in $\times i$ may overlap with vectors of determinants of γi (Amadu *et al*. 2020b; Akter *et al*. 2022).

Proper identification was achieved by making sure that at least some variables are excluded in γi. Years of schooling and total agricultural input costs were the instrumental variables (IVs), and a test was conducted to confirm their validity as IVs. The IVs were statistically significantly correlated with the adoption of CSA technologies (0.029 and 0.0295 ($p < 1\%$)), but not with smallholder farmer income (-0.0034 ($p = 0.999$)) and productivity (-0.0070 ($p = 0.991$)).

The random disturbance term, μi, in Equation (5) and the $\omega 1i$ in Equation (7a) and $\omega 0i$ in Equation (7b) are assumed to be normally distributed with zero mean and a covariance matrix that is non-singular (Fuglie & Bosch 1995), such that:

$$Cov(\mu_i, \omega_{0_i}, \omega_{1_i}) = \begin{pmatrix} \sigma_i^2 & \sigma_{i0} & \sigma_{i1} \\ \sigma_{i0} & \sigma_0^2 & \sigma_{10} \\ \sigma_{1i} & \sigma_{10} & \sigma_1^2 \end{pmatrix}, \tag{8}$$

where:

$\sigma_{10} = cov\ (\omega_1 . \omega_0), \sigma_{1i} = cov\ (\omega_1 . \mu_i)$ and $\sigma_{0i} = cov\ (\omega_0 . \mu_i)$ are covariances, respectively; $\sigma_i^2 = var\ (\mu_i)$, $\sigma_0^2 = var\ (\omega_0)$ and $\sigma_1^2 = var\ (\omega_1)$ are variances. Furthermore, σ_1^2, σ_0^2 and σ_μ^2 are variances that equal to one (Greene 2003) of the random terms, μ_i, ω_{0_i} and ω_{1_i}, respectively.

The adoption of CSA technologies is non-random. The unobservable variables (preference, inborn techniques, motivation, social network, management skills, experience or risks) are only realised by smallholder farmers, not by the researcher. The researcher observes the status reported by the farmers during the survey.

In this context, there is potential selection bias emanating from the endogeneity of CSA adoption based on the non-random observed and unobserved features for self-selection into groups of adopters and non-adopters (Amadu *et al*. 2020b). If this scenarios holds it means that the group of adopters and non-adopters are systematically different (Issahaku & Abdulai 2019). Accordingly, the unobserved features in the outcome equations (7a) and (7b) are related to the random term in the selection Equation (5), and then the impact of CSA adoption on productivity and income are expected to be biased in its failure to address selection bias.

The endogeneity and selection bias are addressed in the literature by applying the IV techniques or a generalised Heckman selection correction technique (Akter *et al*. 2022). We applied the same technique in the context of the omitted variable problem to account for selectivity bias and unobserved heterogeneity (Amadu *et al*. 2020a; Akter *et al*. 2022).

In particular, the inverse Mills ratios or selection terms from the selection equation for the adopters and non-adopters are realised (Heckman 2001). The outcome variables, $\gamma 0i$ and $\gamma 1i$, are assumed not to be observed simultaneously, and then $\sigma 10$ is assumed to be equal to 0. Given the sample selection effects, the values of the error terms in equations (7a) and (7b) are non-zero due to a conditional on the selection criteria (Maddala 1986). Estimation using ordinary least squares (OLS) would result in a biased estimate of the outcome variables of $\gamma 0i$ and $\gamma 1i$ (Lee 1982). Thus, the error term in equations (7q) and (7b) – $[\omega 1i|\Lambda i = 1]$ and $[\omega 0i|\Lambda i = 0]$ – are condensed as:

$$\mathrm{E}\left[\omega_{1_i}\middle|\Lambda_\mathrm{i} = 1\right] = \sigma_{1\mu}\frac{\emptyset[\alpha\gamma_\mathrm{i}]}{\phi[\alpha\gamma_\mathrm{i}]} = \sigma_{1\mu}\tau_{1\mathrm{i}}, \text{ and} \tag{9a}$$

$$\mathrm{E}\left[\omega_{0_i}\middle|\Lambda_\mathrm{i} = 0\right] = -\sigma_{0\mu}\frac{\emptyset[\alpha\gamma_\mathrm{i}]}{1-\phi[\alpha\gamma_\mathrm{i}]} = \sigma_{0\mu}\tau_{0\mathrm{i}}, \tag{9b}$$

where:

$\tau_{1\mathrm{i}} = \frac{\emptyset[\alpha\gamma_\mathrm{i}]}{\phi[\alpha\gamma_\mathrm{i}]}$ and $\tau_{0\mathrm{i}} = \frac{\emptyset[\alpha\gamma_\mathrm{i}]}{1-\phi[\alpha\gamma_\mathrm{i}]}$ are the standard normal probability density function (pdf),

$\emptyset(.)$ and $\phi(.)$ are the standard normal cumulative distribution function (cdf), and

τ_{1i} and τ_{0i} constitute the inverse Mills ratios evaluated at $\alpha\gamma_i$.

To determine the impact of CSA adoption on crop productivity and income, the study estimated the expected values for the actual (real data) and counterfactual scenarios. The average treatment effect on the treated (ATT) and untreated (ATU) was estimated for CSA adopters and non-adopters (for actual and their counterfactual scenarios), as follows:

For CSA technology adopters (actual data/observed):

$$E\left(\gamma_{1i\mathrm{Adopter}}\middle|\Lambda_i = 1\right) = \alpha_{1A} \times_{1i} + \sigma_{1\mu}\tau_{1i} \tag{10}$$

For CSA adopters had they not adopted (counterfactual), or "what if they did not adopt":

$$E\left(\gamma_{1i\mathrm{Non-adopters}}\middle|\Lambda_i = 1\right) = \alpha_{1N} \times_{1i} + \sigma_{10}\tau_{1i} \tag{11}$$

For non-adopters of CSA technologies (real data/observed):

$$E\left(\gamma_{1i\mathrm{Non-adopters}}\middle|\Lambda_i = 0\right) = \alpha_{1N} \times_{1i} + \sigma_{10}\tau_{10i} \tag{12}$$

For non-adopters had they adopted CSA (counterfactual), or "what if they adopted":

$$E\left(\gamma_{1i\mathrm{Adopters}}\middle|\Lambda_i = 0\right) = \alpha_{1A} \times_{1i} + \sigma_{1\mu}\tau_{1i} \tag{13}$$

Equations (10) to (13) have τ_{1i} constant, meaning that the outcome variables estimation, ATT (change in productivity and income following CSA adoption) and ATU (change in productivity and income due to CSA non-adoption account for unobserved factors. The estimation of outcome variables depends only on observable factors. All the unobservable influences, $(\sigma_{1\mu} - \sigma_{0\mu})$ and $(\sigma_{1\mu} - \sigma_{0\mu})$, are cancelled out, as applied in the work of Abdulai and Huffman (2014), Amadu *et al*. (2020a) and Akter *et al*. 2022). This is obtained by Equation (11) minus Equation (12) and Equation (14) minus Equation (13). Equation (13) provides the change in crop productivity and income due to CSA adoption and non-adoption respectively.

Thus, the "average treatment effect on the treated" (ATT) and untreated (ATU) are computed as:

$$ATT = E\left(\gamma_{1i\mathrm{Adopter}}\middle|\Lambda_i = 1\right) - E\left(\gamma_{1i\mathrm{Non-adopters}}\middle|\Lambda_i = 1\right) = x_{i\mathrm{Adopter}}(\alpha_A - \alpha_N) + \tau_{ai}\left(\sigma_{1\mu} - \sigma_{10}\right) \tag{14}$$

$$ATU = E\left(\gamma_{1i\mathrm{Adopter}}\middle|\Lambda_i = 0\right) - E\left(\gamma_{1i\mathrm{Non-adopters}}\middle|\Lambda_i = 0\right) = x_{i\mathrm{Non-adopter}}(\alpha_A - \alpha_N) + \tau_{ni}\left(\sigma_{1\mu} - \sigma_{10}\right) \tag{15}$$

3.3.3 Controlling for bias affecting CSA technologies adoption

The estimates of the effect of the adoption of CSA technologies on outcomes may bear bias emanating from three important sources: a) endogeneity of CSA technologies following the self-selection, b) bias emanating from the existence of the endogenous covariates that confound the effect, such as off-farm income, and c) implementation bias from policy/promotion/emphasis. If the biases are ignored, the impact of the adoption of CSA technologies on outcomes may be biased.

The bias stemming from self-selection is addressed by applying the ESR model. The bias emanating from endogenous covariates, which are likely to influence the effect of the adoption of the CSA technologies on outcomes, is that the covariates are jointly determining the CSA adoption (Shahzad & Abdulai 2020) dealt with in this paper.

In our case, the covariate confounding the impact of CSA on outcomes is off-farm income. The existence of scarce resources to enable smallholder farmers to adopt CSA and paid off-farm activities influences CSA adoption and eventually affects the outcomes, as found in previous studies (Amadu *et al*. 2020a; Akter *et al*. 2022).

In our case, off-farm income similarly influenced the adoption of CSA. We applied the two-stage control function (CF) strategy to deal with endogenous covariates, as detailed in Amadu *et al*. (2020b), Akter *et al*. (2022), Issahaku and Abdulai (2019), and in Wooldridge (2015). In our context, the first stage used dummy off-farm income, with 1 if the farmer had engaged in paid activities other than agriculture, and 0 otherwise. This was regressed in conjunction with other independent variables in the outcomes. The second stage involved the choice equation of the ESR model, where residual variables from the first stage were included as independent variables. The residuals were statistically insignificant, and the endogenous covariates were realised (Wooldridge 2015).

The study came up with a crucial way to fully satisfy the exclusion restriction, and this is depicted by the statistical insignificance and significance of the instrumental variables (IVs) in the outcomes (first stage) of the control function and the second stage (choice), respectively (see Table A in the Appendix for details).

The bias due to policy/promotion/emphasis was addressed during the sampling when the NSCA survey was conducted. We were aware that the policy/promotion/emphasis on the use of CSA technologies in agriculture is for all farmers in their respective areas. The grouping of the participating and non-participating farmers, based on randomly collected data from the National Census Survey of Agriculture (NCSA) (NBS 2020), is different from that found elsewhere – in Malawi by Amadu *et al*. (2020b) and in Bangladesh by Akter *et al*. (2022).

The approach used in this study reflects that used by Abdulai (2016) in Zambia, thus we obtained the adopters and non-adopters from the entire population of farmers in Tanzania, making sure that the sample selection really represented the true population. In this context, the adopters and non-adopters live in the same localities in all sampled areas, and had the same characteristics to realise the impact of CSA.

There are no naturally existing control and treated groups as a unique intervention programme requirement, as in the works of Amadu *et al*. (2020a) and Akter *et al*. (2022), which have adopter and non-adopter villages participating in a programme. Hence, this implies that the policy/promotion/emphasis of the adoption of CSA technologies by all farmers and the random sampling of all farmers means that the adopters and non-adopters share similar observable characteristics, which possibly reduces the endogeneity and selection that are likely to originate from various programmes that emphasise the application of CSA technologies by farmers. The sampling strategy therefore enables us to estimate the model by assigning 1 to adopters, and 0 otherwise.

4. Empirical results and discussion

4.1 Factors influencing CSA adoption

The results of the endogenous switching regression (ESR) are summarised in Table 2. The estimation from the first stage depicts that the determinants of the adoption of climate smart agriculture (CSA) range from the availability and usage of agricultural input, socio-economic factors and access factors. Chemical fertilisers, land size, number of women, distance to the market and years of education are important factors. Distance to the market negatively influences CSA adoption. Access to the market enables farmers to access other farm inputs and knowledge about farming (Mwalupaso *et al*. 2020; Akter *et al*. 2022). The farmers living far from the market are less likely to adopt CSA technologies.

Land size plays a big role in influencing the use of CSA technologies. Farmers feel that, without the adoption of CSA technologies, land alone cannot improve productivity in the face of climate change variations. Land size increases the propensity to adapt CSA practices and is consistent with a study in Bangladesh that found that land is positively related to CSA adoption (Akter *et al*. 2022).

In the African context, especially in rural areas, women are a considerable source of farming labour. The number of adult women in a household is largely associated with CSA adoption. Farmers who frequently are involved in agriculture for their livelihoods and income are more likely to adopt CSA technologies. These results are similar to the findings of Teklewold *et al*. (2020) that women involved in agriculture are likely to adopt CSA and frequently do so.

The instrument (years of schooling) in CSA for the criterion function is positive and statistically significant. The education of a household head influences CSA adoption due to knowledge and awareness of the effects or threats of climate change on soil fertility, and the propensity to adapt depends on awareness of the severity of the climatic shocks, resources availability and other coping strategies.

Issues relating to education suggest that CSA adoption is confined by a lack of awareness of the broad goals of CSA, which include creating awareness about the importance of counteracting climate change threats (FAO 2017b). Education or training programmes increase awareness and adoption of CSA. Education is revealed to be crucial for acquiring new knowledge, skills and technologies for the improvement of crop productivity. The same observations were made in Zambia by Abdulai (2016).

Furthermore, the off-farm income residual is negatively and statistically insignificant, implying that estimates of the endogenous variables are bias-free. We employed the ESR model, the second stage of which specifies the production function, where part of the diagnostic test confirms that the model fits the data. Furthermore, heterogeneity is confirmed in Table 2 below, and shows that, if not dealt with, it would alter the results to be incorrect. This validation confirms the use of ESR as a better method of identification compared to other methods.

Table 2: Estimation results of the endogenous switching regression (ESR) model

Determinants of CSA adoption		Second-stage estimation of the ESR	
Variables	**Coefficient estimates (standard errors)**	**Adopters' coefficient estimates (standard errors)**	**Non-adopters' coefficient estimates (standard errors)**
Constant	-1.550* (0.820)	3369.758*** (344.500)	1 310.487*** (177.341)
Agricultural inputs			
Herbicide	-0.175 (0.106)	-124.989 (83.876)	-127.454** (61.197)
lnQnty_seedKg	0.018 (0.053)	-33.395 (44.338)	14.651 (32.428)
LnTotlQtyFertilizerMPB	0.100*** (0.032)	34.755 (21.627)	29.209* (17.251)
GrandCostsMPB	0.000 (0.000)	0.001*** (0.000)	0.001** (0.000)
LnLandSize	0.115** (0.057)	-175.569*** (38.407)	-121.423*** (33.720)
Manure	0.112 (0.092)	-45.066 (72.596)	28.049 (52.131)
Socioeconomics			
gender	0.095 (0.110)	158.749* (83.761)	20.315 (56.559)
age	0.005 (0.007)	-1.271 (2.295)	-3.313** (1.611)
LnNumber_male	0.039 (0.058)	-58.113 (56.994)	-38.923 (45.158)
LnNumber_female	0.035* (0.055)	1.088 (54.228)	-72.331* (43.273)
crop_failre	-0.040 (0.067)	15.264 (68.565)	17.168 (50.804)
lnHhSize	0.040 (0.034)	-76.912** (32.232)	-11.008 (24.784)
Off_Fmincome	1.406 (1.477)	-84.159 (66.337)	33.677 (51.718)
Access status			
LnDstnce_Markt	-0.082*** (0.029)	-45.316 (31.222)	45.324** (21.594)
Institutional			
Crdit_accss	0.222 (0.153)	172.811 (135.499)	-28.491 (133.729)
Biophysical status			
LnDstnce_Home	0.002 (0.006)	1.540 (3.766)	14.662*** (3.594)
Ivs			
Years_Educ	0.055** (0.026)		
Off_fmincomeResdl	-1.337 (1.478)		
Statistical diagnostics			
LR test of independent equations: $chi^2(1)$	0.22		
Prob > chi^2	0.6407		
Log likelihood	-16 210.56		
sigma_1		931.226*** (22.023)	
sigma_2			720.842*** (17.385)
rho_1		-0.034 (0.250)	
rho_2			0.074 (0.151)
N	1 857	1 857	

Note: *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.
Source: NBS 2020

Regimes one and two appear in the third and fourth columns of Table 2, respectively. The cost of input is positive and statistically significant, influencing crop productivity. The relatively low cost improves productivity by improving the uptakes of important agricultural inputs for both adopters and non-adopters of CSA technologies. Input uptake or usage greatly influences involvement in agricultural activities and productivity. The relatively low cost of agricultural inputs allows farmers to use more inputs and improve productivity (Noltze *et al*. 2013).

Furthermore, land and household size are negatively and statistically significant. Land is related to productivity, implying that it is not the only factor increasing productivity. Land is a significant input, but must be combined with other inputs. Inputs such as chemical fertilisers improve the quality of soil and fertility, leading to increased productivity. Large family size contributes negatively to crop productivity.

Herbicides, quantity of seeds and manure negatively influence the productivity of adopters, implying that CSA technologies are crucial for the improvement of productivity. In terms of agricultural inputs, productivity cannot be improved in isolation from CSA. An insight from the findings is that CSA technologies improve crop productivity, that herbicides are not appropriate for all soil conditions, and that large families decrease productivity, as also found in the work of Akter *et al*. (2022).

Total chemical fertilisers were positively related to productivity for non-adopters, implying that for farmers who did not adopt CSA technologies, chemical fertilisers were important to them. Fertilisers improved soil quality and fertility, which eventually improve crop productivity. Lamanna *et al*. (2016) also found that chemical fertilisers are crucial for soil nutrients, which improve crop productivity.

Gender is an important determinant of crop productivity. Being a man increases the probability of being productive, as agriculture requires physical fitness and resources to adopt CSA. The same findings were obtained by Teklewold *et al*. (2020) in Tanzania. Age was negative and statistically significant in its contributing to the productivity of non-adopters. This may imply that non-adopters become less active in adopting new farming technologies, and also less active physically, which leads to a decline in crop productivity. In this regard, elders are less productive compared to other age groups (Akter *et al*. 2022). Also, female adults are negatively and statistically related to crop productivity for non-adopters, implying that being involved in agriculture without CSA adoption reduces productivity. CSA technologies, if accompanied by other production inputs, such as physical fitness, may augment crop productivity.

Distance between the market and home is positively and statistically significant in the influence of crop productivity for non-adopters. The market is a place for the acquisition of knowledge, advice, inputs and other social benefits that improve crop productivity. These findings are similar to those of Akter *et al*. (2022), who found that market and physical characteristics greatly influence crop productivity.

4.2 Influence of CSA on crop productivity

On count, the productivity effect indicates that smallholder farmers benefit from CSA adoption. In Table 3, the third and fourth columns represent the factual and counterfactual for both regime functions, respectively. The first row has aggregate crop productivity in factual mean from regime one function, which is 2 873.614 kg, but their counterfactual mean is 2 835.665 kg. The difference, which is the ATT, shows an increase of 1.34% in productivity.

Referring to the second row, the factual for non-adopters is 1 226.304 kg, but if had they adopted their productivity would be 1 393.722 kg, giving an ATU of 13.65%. The findings reveal that the ATT is positively consistent with the findings of Amadu *et al*. (2020b) in Malawi and Akter *et al*. (2022) in Bangladesh. Furthermore, crop productivity indicates that adopters on average gain relatively more than non-adopters. However, adopters gain more in beans, at 86.6%, for the factual compared to their counterfactual.

Table 3: Productivity effects

Grain type	Effect	CSA technologies		Diff (SE)	% change
		Mean (adopters)	Mean (non-adopters)		
Aggregated productivity (kg)	ATT	2 873.614	2 835.665	37.949*** (11.143)	1.34
	ATU	1 393.722	1 226.304	167.418*** (10.407)	13.65
Maize (kg)	ATT	2 286.052	2 158.344	127.708*** (16.861)	5.92
	ATU	1 252.439	1 053.703	198.736*** (11.737)	18.86
Paddy (kg)	ATT	2 710.396	2 525.928	184.468*** (24.929)	7.30
	ATU	1 639.13	1 233.064	406.066*** (26.181)	32.93
Beans (kg)	ATT	702.129	374.272	327.857*** (37.281)	86.60
	ATU	381.028	370.98	10.048*** (13.895)	2.71

Notes: *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively; SE = standard error.
Source: NBS 2020

With regard to applying endogenous switching regression to income, the regression results for the first and second stages are presented in Table 4. From the first stage, it can be seen that the cost of input, gender, distance between the market and home, education, and the off-income residual are negatively and statistically significantly related to CSA adoption. Distance between the market and home in Table 2 is consistent with the results in Table 4, and has already been discussed.

Table 4: Endogenous switching regression (ESR) results for income

First-stage estimation of ESR		Second-stage estimation of ESR	
Variables	**Coef. estimates (standard errors)**	**Adopters' coef. estimates (standard errors)**	**Non-adopters' coef. estimates (standard errors)**
Constant	-4.313 (0.458)	12.904*** (0.178)	12.945*** (0.243)
Agricultural inputs			
GrandCostsMPB	-1.67e-06*** (5.01e-07)	3.08e-06*** (2.24e-07)	3.95e-06*** (4.78e-07)
LnTotlQtyFertilizerMPB	0.198*** (0.023)	-0.018 (0.014)	0.023 (0.025)
LnLandSize	0.258*** (0.044)	0.196*** (0.029)	0.180*** (0.049)
Socioeconomics			
gender	-0.146* (0.081)	0.170*** (0.058)	0.236*** (0.085)
age	0.029*** (0.004)	-0.005*** (0.002)	-0.007*** (0.002)
LnNumber_male	0.017 (0.056)	0.075* (0.044)	-0.017 (0.069)
LnNumber_female	0.042 (0.054)	0.043 (0.042)	0.187*** (0.066)
lnHhSize	0.083*** (0.032)	-0.035 (0.025)	0.028 (0.038)
Off_Fmincome	6.979*** (0.773)	-0.046 (0.050)	0.059 (0.078)
lntotal_Lvstok	0.057 (0.071)	0.037 (0.052)	0.143 (0.094)

First-stage estimation of ESR		**Second-stage estimation of ESR**	
Variables	**Coef. estimates (standard errors)**	**Adopters' coef. estimates (standard errors)**	**Non-adopters' coef. estimates (standard errors)**
Access status			
LnDstnce_Markt	-0.061** (0.028)	-0.016 (0.023)	-0.002 (0.034)
LnDstnce_Road	0.098** (0.038)	-0.041 (0.030)	-0.078** (0.041)
Institutional			
Crdit_accss	0.256* (0.150)	-0.022 (0.106)	0.078 (0.200)
Biophysical status			
LnDstnce_Home	-0.015*** (0.005)	-0.001 (0.003)	0.013** (0.005)
Ivs			
Years_Educ	-0.060*** (0.016)		
Off_fmincomeResdl	-6.921*** (0.774)		
Statistical diagnostics			
LR test of indep. eqns.: $chi^2(1)$	43.51		
Prob > chi^2	0.0000		
Log likelihood	-3 380.5912		
sigma_1		0.777*** (0.033)	
sigma_2			1.214*** (0.050)
rho_1		0.683*** (0.065)	
rho_2			0.751*** (0.047)
N	1 860	1 860	1 860

Note: *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.
Source: NBS 2020

4.3 Income impact of CSA

The results from the second stage of ESR are reported in Table 4. The determinants of smallholder farmers' income of regimes one and two are summarised in the third and fourth columns, respectively. Factors such as land size and gender (being a man) are crucial, as they increase income. More land may increase income. Also, being a man is related to high income due to the advantages of physical fitness and resources they possess. Farmers with more land can cultivate and rent the land to other farmers, which increases their income. These findings are consistent with the findings of Akter *et al*. (2022) in Bangladesh.

For the adopters of CSA technologies, land size, costs of input, age and number of adult men are crucial determinants of income, while for non-adopters, factors such as distance between the market and home and number of adult women influence their income.

The differences in the determinants justify the use of ESR. Interestingly, age reduces the productivity and income of the household, implying that a unit increase in age reduces the income of the household because of usual farming habits being used from experience. The higher the age, the less the ability to produce or generate income; the elderly are less energetic, and low in the acquisition of new farming knowledge or technologies, and this makes them unproductive compared to the young. The findings are in line with those of Noltze *et al*. (2013) in Timor Leste.

Considering the ATT and ATU of the income effect of CSA presented in Table 5, the results reveal that the impact of CSA technologies is varied. For income from aggregate crops, the factual increased income by about 8.31%, whereas the counterfactual (had they adopted CSA) would have increased their income by 13.55%. Interestingly, for individual crops, CSA adopters on average gain relatively more income than their counterfactuals; adopters of CSA for beans receive about 14.31% more income, followed by a gain in income from maize of 8.74%.

The results suggest that, for non-adopters, ATU shows that they would have gained more income if they had adopted. For instance, if non-adopters had adopted maize, they would have increased their income by 13.81%. The findings are consistent with other findings, such as those of Amadu *et al*. (2020a) in Malawi, of Belay *et al*. (2022) in Ethiopia, and of Noltze *et al*. (2013) in Timor Leste

Table 5: Income effects

Grain type	Effect	CSA technologies		Diff (SE)	% Change
		Mean (adopters)	Mean (non-adopters)		
Total income	ATT	13.542	12.503	1.039*** (.017)	8.31
	ATU	14.384	12.667	1.717*** (.022)	13.55
Maize income	ATT	12.949	11.908	1.041*** (.0248)	8.74
	ATU	13.763	12.093	1.670*** (.029)	13.81
Paddy income	ATT	13.609	13.438	.171*** (.04)	1.27
	ATU	12.999	12.775	.224*** (.044)	1.75
Beans income	ATT	14.226	12.445	1.781*** (.098)	14.31
	ATU	15.086	13.782	1.304*** (.087)	9.46

Notes: *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively; SE = standard error.
Source: NBS 2020

To validate the PSM results, we undertook a robustness check by comparing the results of matching before matching, which is crucial (see Figure 2) for both the income and productivity models. It is important to make sure that the observable statuses are comparable and that bias is reduced (Caliendo & Kopeinig 2008).

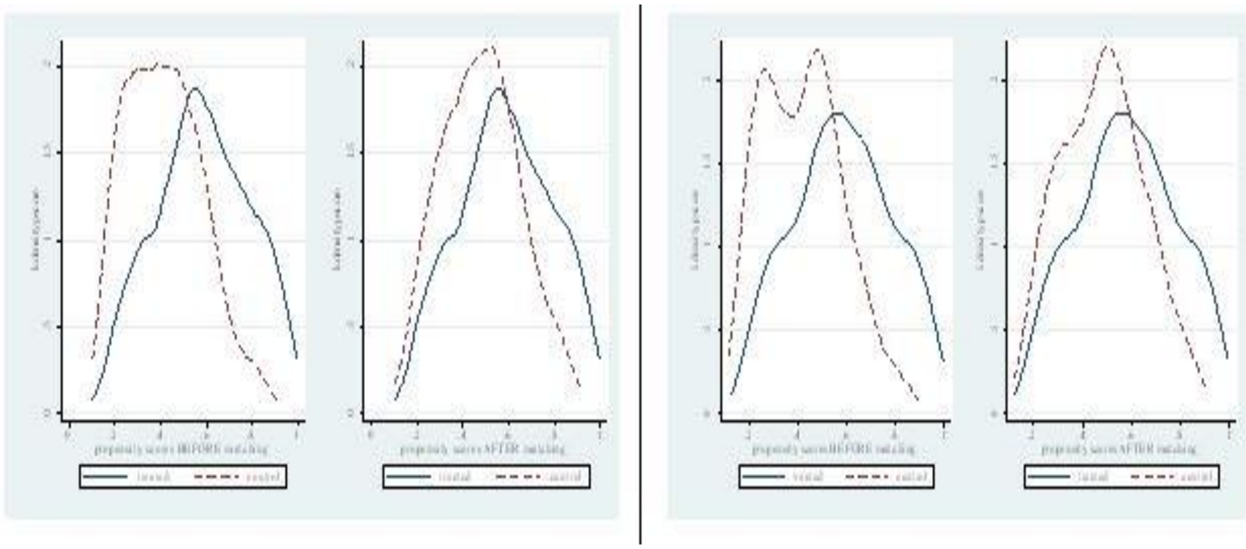

Figure 2: Before and after matching both productivity and income
Source: NBS 2020

As part of the robustness check we find consistent results for both productivity and income models using PSM in Table 6.

Table 6. PSM results for Productivity and Income effects

Effect	Variable sample	Treated	Controls	Difference	SE	T-stat.
Productivity	Grain productivity unmatched	2 873.616	1 226.309	1 647.307***	40.108	41.07
	ATT	2 873.616	1 333.52	1 540.096***	78.615	19.59
Income	Household income unmatched	13.535	12.679	.856***	.043	19.81
	ATT	13.535	13.066	.469***	.109	4.32

Notes: *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively
Source: NBS 2020

4.4 Limitations of the study

We applied a robust identification strategy and have presented the crucial results. However, the study faces some limitations. The major limitation may emanate from the type of data used. We employed cross-section data, which fails to capture the time-variant effects, such as weather data.

5. Conclusion and policy implications

This study has examined the determinants of CSA adoption and its impacts on farm performance and income. We controlled for any potential biases that might have affected the estimates, such as endogenous variables and selection.

The results of the determinants reveal that land size, education, chemical fertilisers, adult women, credit access, off-farm income and distance between the market and the farm are crucial for explaining CSA adoption, crop productivity and income. To have a sustainable scale-up of the integration of CSA technologies into agriculture, the findings highlight that stakeholders should promote CSA through campaigns, workshops, education provision through extension officers, credit provision, and friendly procedures for the acquisition of farming land.

The results furthermore indicate that the conscious adoption of CSA technologies affects crop production and income. Non-adopters, if they had adopted, would have significantly increased their productivity and income.

The government, in collaboration with other development partners and stakeholders in agricultural transformation, could reinforce the adoption of CSA technologies based on the evidence in this study and other studies, which show that CSA adoption improves farm performance and income.

Generally, the results on the determinants and effects of CSA adoption have both policy and academic implications. First, the findings help in answering the question of how we can scale up the use of CSA to be able to achieve production, adaptation and mitigation. Second, the effects of CSA adoption on crop productivity and income help to answer questions on how we can boost productivity and income for food security and poverty reduction, eventually increasing farmers' resilience in the face of adverse climatic conditions. Lastly, the study adds knowledge to the extant literature about the determinants and impact of CSA adoption on farm performance and income.

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Appendix

Table A: First stage regression controlling for endogeneity in CSA adoption

Variables	CSA adoption selection/choice equation				Endogenous variable: Off-farm income			
	Model 1: For productivity		Model 2: For income		Logit regression associated with Model 1		Logit regression associated with Model 2	
	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
Constant	1 094.439	686.533	16.471***	.327	-.658*	.362	-.569*	.328
Agricultural inputs								
LnLandSize	-75.233	47.415	-.013	.03	.138**	.065	.154**	.063
LnTotlQtyFertilizerMPB	102.21***	26.26	-.14***	.016	.144***	.031	.138***	.031
GrandCostsMPB	.001	.001	6.40e-06***	3.43e-07	4.10e-06***	6.32e-07	4.04e-06***	5.78e-07
Herbicide	-254.573***	88.608			-.159	.132		
lnQnty_seedKg	31.165	43.963			-.022	.069		
Manure	27.4	76.491			.351***	.106		
Socioeconomics								
gender	108.394	92.075	.488***	.057	.454***	.116	.459***	.115
age	3.573	5.939	-.036***	.003	-.009**	.003	-.009**	.003
lnHhSize	-16.125	28.462	-.059***	.022	.048	.052	.055	.052
crop_failre	-8.165	56.332			-.049	.108		
LnNumber_male	-33.928	48.172	.016	.038	.056	.094	.031	.093
LnNumber_female	-10.456	45.958	.084**	.037	.035	.089	.023	.089
Off_Fmincome	1 406.843	1 234.943	-6.942***	.557				
Access status								
LnDstnce_Markt	-43.864*	24.058	-.01	.019	-.141***	.046	-.133***	.047
LnDstnce_Road			-.17***	.026			-.029	.059
Institutional/Wealth								
Crdit_accss	231.537*	125.011	-.021	.099	.283	.247	.268	.247
lntotal_Lvstok			.043	.048			.099	.118
Biophysical status								
LnDstnce_Home	5.003	4.596	.025***	.003	.01	.007	.011	.007
IVs								
Years_Educ	18.902	21.142	.128***	.011				
Off_fmincomeResdlPctn	-1 396.632	1 236.173	6.956***	.558	.191*	.105	.211**	.105
Statistical diagnostics								
Pseudo r-squared					0.106		0.101	
Chi-square					272.883		259.437	

Prob > chi2					0.000		0.000	
N	1 857		1 860		1 857		1 860	

Notes: *, ** and *** represent significance at the 10%, 5% and 1% levels, respectively; Coef. = coefficient; SE = standard error
Source: NBS 2020