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Climate-Smart Agriculture, Efficiency, and Commercialization: Pathways to Poverty Reduction among Smallholder Maize Farmers in Kenya

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Abstract

Despite employing over 75% of rural Kenyans, smallholder farming leaves nearly half of them in poverty and this is worsened by environmental, economic, and market challenges. To uncover mechanisms for reducing poverty, this study evaluates whether the adoption of climate-smart agriculture within a technically efficient production system, coupled with increased commercialization, could translate agricultural output into reduced multidimensional poverty. Using data from the KCSAP 2020–2021 survey, the study employs endogenous switching regression, propensity score matching, and sequential mediation analyses to explore direct and indirect pathways through which CSA influences multidimensional poverty. Results indicate that CSA adoption significantly reduces MPI, particularly among households with higher technical efficiency, while commercialization amplifies poverty reduction indirectly by facilitating market participation. Adoption intensity is shaped by household characteristics such as age, gender, education, access to credit, and group membership, with female-headed households and resource-constrained farmers facing lower adoption rates. Scenario and mediation analysis reveal that technical efficiency consistently drives MPI improvements, whereas CSA and commercialization provide supportive roles. Policy recommendations include targeted credit facilities for female-headed households, redesigning extension services to reduce labor and knowledge barriers, strengthening farmer networks, and linking productivity gains to market access.

Keywords: *Climate Change; Multidimensional Poverty Index; Resilience; Smallholder Farmers; Kenya*

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1. Introduction

Agriculture remains the backbone of Kenya's economy. It employs over 40% of the population and supports more than 70% of rural households (World Bank, 2022). However, the sector's heavy reliance on rainfed farming makes it highly susceptible to climate change. Increasingly, frequent extreme weather events have exacerbated food insecurity, water scarcity, and economic instability for farmers (IPCC, 2021). Between 2020 and 2022, a severe drought and locust infestation affected over 4.5 million people in Kenya. This led to livestock losses, reduced crop yields, and declining household incomes (NDMA, 2023). Additionally, erratic rainfall patterns have thrown planting and harvesting schedules off balance. Rising temperatures and shifting precipitation patterns have intensified the spread of pests and diseases, further threatening maize production (FAO, 2020).

To mitigate these climate-induced risks, Kenya has prioritized Climate-Smart Agriculture (CSA) under the National Climate Change Action Plan (Wamwea & Culas, 2024). CSA is thought to enhance agricultural resilience, increase productivity, and improve household MPI. Practices such as conservation agriculture, agroforestry, and integrated soil fertility management help restore soil health. They also improve water retention and minimize the risks posed by droughts and floods. Agroforestry promotes biodiversity and soil stabilization, while also providing alternative income sources and helping households buffer against climate-induced income losses. Improved seed varieties, efficient irrigation systems, and climate-informed farming techniques enhance crop yields even under erratic weather conditions. Adopters of CSA practices experience improved nutrition, higher earnings, and reduced vulnerability to poverty (Lipper et al., 2014; Mbow et al., 2020; Thornton et al., 2018).

Factors determining what CSA farmers adopt are diverse depending on the country, crops cultivated, access to resources and information, among others. Structural factors such as access to markets, extension services, agricultural credit, climate information, and supportive policy environments shape farmers' willingness to adopt CSA practices. These factors create the institutional and informational conditions that enable or constrain farmers' adoption opportunities. Resource-related factors including livestock ownership, asset endowments, farm size, soil fertility, household income, off-farm income, and labour availability determine households' capacity to invest and sustain adoption (Kassa & Abdi, 2022; Kifle et al., 2022; Ma & Rahut, 2024; Ndung'u et al., 2023; Sanogo et al., 2023).

Beyond structural and resource-related factors, socio-demographic characteristics play a critical role in shaping both the adoption and effectiveness of CSA practices. Gender dynamics influence access to land, credit, and extension services. They often constrain women's ability to adopt and benefit fully from CSA technologies. Studies show that female-headed households face higher transaction costs and lower access to productive resources. This limits their levels of commercialization and overall MPI gains (Ndung'u et al., 2023; Sanogo et al., 2023). Age affects CSA outcomes through the life cycle and risk preferences. Younger farmers are more open to innovation and technology adoption while older farmers rely more on experience and are less adaptable to climate-responsive practices. Education further enhances farmers' capacity to process climate information, adopt improved technologies, and engage effectively with markets (Kassa & Abdi, 2022).

The adoption benefits suggest that CSA holds promise for building resilience in rural areas. However, questions remain as to whether such gains translate into meaningful reductions in poverty. While CSA directly influences productivity, the impact on household multidimensional poverty is shaped by production efficiency, the extent of market participation, and the financial demands of CSA adoption. In settings where markets are thin or households already face budget pressures, the expected improvements may not materialize in sustained poverty reduction.

This dilemma highlights a gap in current literature where most of the existing literature has focused on the technical potential of CSA to boost yields and improve resilience. Fewer studies have examined the indirect pathways linking CSA to poverty outcomes. For instance, agroforestry can enhance soil fertility in the long term, yet it may reduce short-term food availability when it displaces food crops. Likewise, investment in improved seeds or irrigation often requires high upfront costs. For smallholder farmers with limited financial resources, these expenses can worsen financial stress before future gains are realized (Jung & Vendrametto, 2025; Zinnen et al., 2021). This study thus asks whether CSA adoption, when combined with technical efficiency and commercialization, can translate agricultural output into reducing multidimensional poverty among smallholder maize farmers in Kenya.

2. Literature Review

Understanding the relationship between CSA adoption and Multidimensional Poverty requires grounding in both theoretical insights and empirical evidence. The literature on poverty, technology adoption, and agricultural transformation provides important perspectives to explain why some households remain poor while others improve their multidimensional poverty through agricultural innovation. These perspectives illuminate how climate-smart agriculture can influence MPI outcomes through pathways such as productivity growth, technical efficiency, and commercialization.

One of the earliest explanations of poverty is the individual theory of poverty. It attributes poverty to personal characteristics such as lack of education, inadequate skills, low motivation, or poor decision-making. Proponents of this perspective argue that individuals remain poor because they fail to invest in human capital or fail to make decisions that improve their economic prospects (de Bruijn & Antonides, 2022; Turner & Lehning, 2007). From this standpoint, poverty reduction depends on individual effort and behavioral change.

However, this perspective has been criticized for oversimplifying the dynamics of poverty. Empirical research increasingly shows that poverty cannot be explained solely by individual characteristics. Structural conditions such as limited access to credit, weak institutions, market failures, and climate risks significantly shape multidimensional poverty levels. Mwabu (2023) notes that in many African contexts, poverty persists because households operate within low-productivity agricultural systems characterized by poor infrastructure, limited market integration, and weak institutional support. Under such conditions, even hardworking farmers may remain trapped in poverty because the economic environment restricts their ability to generate sustainable income.

In addition, the cultural theories of poverty emphasize the role of social norms, beliefs, and values in perpetuating poverty. The concept of a "culture of poverty," originally introduced by Lewis, suggests that poor communities develop survival-oriented norms that may unintentionally reproduce poverty across generations. These norms include limited long-term planning, distrust of institutions, and lower expectations regarding socioeconomic mobility (Addae-Korankye, 2019; Bradshaw, 2007). Children raised in such environments often internalize these behaviors, reducing their ability to take advantage of emerging opportunities. While this perspective highlights the importance of social context, critics argue that it risks blaming poor communities rather than addressing systemic inequalities that constrain opportunities.

Another strand of literature explains poverty through geographical disadvantages. It argues that spatial location significantly influences MPI outcomes by affecting access to markets, infrastructure, and essential services. Rural communities located in remote or environmentally fragile areas often face higher poverty levels due to poor road networks, limited market access, weak financial services, and exposure to climatic shocks (Bradshaw, 2007; Zhou & Liu, 2022). In agrarian economies such as Kenya, these spatial constraints interact with ecological conditions such as erratic rainfall, soil degradation, and drought, further limiting agricultural productivity. Empirical evidence demonstrates that households located far from markets and public services are more likely to remain poor than those with better geographic access (Okwi et al., 2007; Zhou & Liu, 2022).

Closely related to the geographical explanation is the structural theory of poverty, which emphasizes systemic barriers embedded in economic and institutional systems. According to this perspective, poverty persists because political, economic, and social structures restrict the opportunities available to certain groups. These constraints may arise from unequal resource distribution, limited access to education and healthcare, poorly functioning labor markets, or weak agricultural support systems. Studies examining rural poverty consistently show that structural barriers such as limited credit access, weak rural infrastructure, and market failures hinder the ability of smallholder farmers to improve their poverty outcomes (Daas, 2018; Miawonene et al., 2025).

While theories of poverty explain poverty disparities, theories of technology adoption provide insights into why farmers adopt or reject innovations such as climate-smart agriculture. One influential framework is random utility theory (RUT), which posits that individuals choose an option among available alternatives that maximizes their expected utility. However, these choices are influenced by observable factors like costs, benefits, and yields, and unobservable elements such as social norms, risk preferences, and behavioral attitudes (Broecks, 2012). In agricultural contexts, farmers evaluate new technologies by comparing expected benefits against perceived risks and constraints. For example, a farmer may adopt drought-tolerant seeds if they are expected to improve yield stability under climate variability. Although adoption decisions are rarely deterministic, cultural expectations, household bargaining power, and access to information also influence choices (Ndeke, 2021). Research in Ghana shows that gender differences in adoption patterns are often linked to unequal access to productive resources rather than inherent differences in preferences (Doss & Morris, 2000).

Complementing this perspective is the theory of planned behavior (TPB), which explains technology adoption in terms of three behavioral determinants: attitudes, subjective norms, and perceived behavioral control (Ajzen, 2020). According to this theory, farmers are more likely to adopt agricultural innovations when they believe the practices will generate benefits such as higher yields or improved resilience to climate shocks. Social influences also play an important role. The endorsement of new technologies by extension officers, community leaders, or farmer groups can significantly influence adoption behavior. Equally important is perceived behavioral control, which reflects farmers' access to resources such as credit, labor, training, and agricultural inputs. When farmers feel capable of implementing new technologies, adoption becomes more likely. The theory of planned behavior is one of the most widely applied frameworks in technology adoption research, highlighting the importance of both psychological and institutional factors in shaping farmer decisions (Dhivya et al., 2024).

Beyond adoption decisions, recent literature emphasizes the importance of understanding the mechanisms through which agricultural innovations influence multidimensional poverty and mediation theory provides a useful framework for examining them. The theory posits that the effect of an independent variable on an outcome variable may operate through one or more intermediary variables. The total effect can be decomposed into direct and indirect pathways (El-Gharbawy et al., 2024). Applying this perspective to agriculture suggests that the impact of CSA adoption on poverty may not occur directly but instead through intermediate processes such as improved productivity, enhanced technical efficiency, or increased market participation. Empirical studies increasingly confirm the relevance of these pathways. For example, Wassihun et al. (2026) find that commercialization mediates nearly half of the total effect of CSA adoption on maize income among Ethiopian farmers. This highlights the importance of examining the mechanisms through which agricultural innovations translate into MPI improvements.

A growing body of empirical research examines the multidimensional poverty impacts of CSA adoption. Many studies report positive outcomes, including improved food security, higher household income, and reduced poverty. CSA-adopters experience substantial reductions in multidimensional poverty relative to non-adopters (Ali et al., 2022; Tesfaye et al., 2021). However, the evidence is not entirely consistent. Other studies find limited or insignificant effects on poverty outcomes, particularly in contexts characterized by weak markets, high adoption costs, or limited institutional support (Akpan & Zikos, 2023). These conflicting findings highlight the need for deeper investigation into the conditions under which CSA contributes to poverty reduction.

Methodologically, researchers have increasingly employed quasi-experimental approaches to estimate the impact of CSA adoption. Because farmers self-select into adoption, simple comparisons between adopters and non-adopters may produce biased estimates. As a result, techniques such as propensity score matching (PSM), endogenous switching regression (ESR), and instrumental variable (IV) approaches are widely used to correct for selection bias. PSM remains one of the most commonly applied methods, allowing researchers to match adopters with non-adopters who share similar observable characteristics (Aboye et al., 2025; Teklu et al., 2023). ESR models extend this approach by addressing both observable and unobservable heterogeneity in adoption decisions, making them particularly suitable for analysis of poverty (Ali et al., 2022; Mujeyi et al., 2021).

Despite the methodological rigor of these approaches, important limitations remain. PSM corrects for observable selection bias but cannot account for unobserved heterogeneity. ESR models address this limitation but depend heavily on the availability of strong exclusion restrictions. Similarly, instrumental variable approaches require valid instruments that are often difficult to identify. Difference-in-differences models provide another alternative but rely on strong assumptions such as parallel trends. Given these limitations, recent studies increasingly combine multiple estimation techniques to enhance robustness (Amare & Simane, 2017; Fentie & Beyene, 2019; Teklu et al., 2023).

In view of the foregoing, this study contributes to the literature by adopting a combination of ESR and PSM approaches to evaluate the effect of CSA on multidimensional poverty. It further integrates mediation analysis to uncover the channels through which CSA adoption translates into reductions in multidimensional poverty. In doing so, it provides deeper insights into the conditions under which climate-smart agriculture can effectively contribute to poverty reduction among smallholder farmers.

3. Conceptual Framework

The mediation analysis follows the causal mediation framework proposed by Kosuke Imai et al. (2010), which allows for the decomposition of the total effect of CSA adoption on multidimensional poverty into direct and indirect pathways operating through technical efficiency and commercialization. Identification of mediation effects relies on two sequential ignorability assumptions. First, conditional on observed household characteristics, CSA adoption is assumed to be independent of unobserved factors affecting technical efficiency and commercialization. Second, conditional on CSA adoption, technical efficiency, commercialization, and observed covariates, the mediators are assumed to be independent of unobserved factors affecting multidimensional poverty.

Although these assumptions cannot be tested directly, the analysis mitigates potential biases by controlling for a rich set of household demographic, institutional, and location-specific characteristics that jointly influence adoption decisions, productivity outcomes, and MPI. The hypothetical causal ordering, that CSA adoption influences technical efficiency, which subsequently affects commercialization and multidimensional poverty, is consistent with established theoretical and empirical evidence linking climate adaptation practices to productivity improvements and market participation among smallholder farmers. Bootstrapped confidence intervals are reported for indirect effects to ensure robust statistical inference, and Sobel test used to assess the statistical significance of mediation pathways. The conceptual framework is shown in Figure 1;

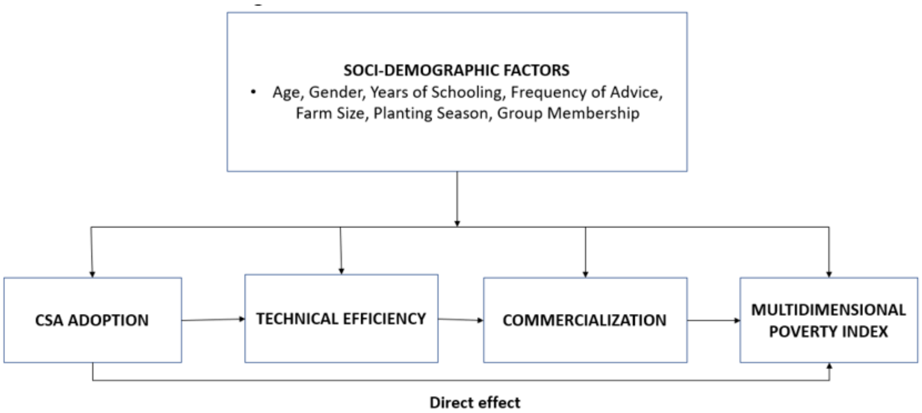

Figure 1. Conceptual Framework
Source: Author's drawing

The conceptual framework situates the study at the intersection of agricultural innovation, efficiency, market participation, and multidimensional poverty reduction. The framework posits that CSA adoption has two pathways of influence on household multidimensional poverty: a direct pathway, in which CSA adoption independently reduces multidimensional poverty, and an indirect, sequential pathway mediated by technical efficiency (TE) and commercialization intensity (HCI).

The direct pathway posits that CSA practices, such as conservation agriculture, agroforestry, and drought-tolerant crop varieties, can improve agricultural productivity, stabilize yields, and enhance resilience to climate variability. By reducing crop losses and increasing output, CSA can directly reduce multidimensional deprivation, particularly in dimensions such as food security, income, and health (Ali et al., 2022; Tesfaye et al., 2021).

The mediated pathways reflect more complex channels through which CSA influences MPI. First, CSA adoption is hypothesized to increase TE by optimizing input use, reducing inefficiencies, and promoting sustainable production practices. Technical efficiency gains allow households to achieve higher output with the same or fewer resources, enhancing income potential and food security. TE then contributes to commercialization intensity, reflecting households' capacity to engage more actively in markets. Higher HCI enables households to convert productivity gains into income, diversify income sources, and invest in health, education, and other MPI-enhancing assets. The framework captures a sequential mediation pathway: CSA - TE - HCI - MPI, reflecting the idea that MPI gains are often contingent upon both productive efficiency and market engagement (Wassihun et al., 2026).

4. Data and Method

4.1. Data and Data Sources

The study used household-level data collected by the Tegemeo Institute of Agricultural Policy and Development. The data were collected in collaboration with the Ministry of Agriculture, Livestock, Fisheries, and Cooperatives under the Kenya Climate-Smart Agriculture Project (KCSAP) during the 2020–2021 survey. The maize production data encompassed 10,066 respondents distributed across nine randomly selected counties. These include Marsabit, Garissa, Nyandarua, Nyeri, West Pokot, Uasin Gishu, Baringo, Siaya, and Kisumu. The cross-sectional dataset contains four major dimensions: health, living standards, economic participation, and education. They capture relevant information used to measure the Multi-dimensional Poverty Index and household resilience. The dataset contains additional information relating to the adoption of CSA practices, maize production, and maize sales. The stratified random sampling was adopted to ensure a representative and balanced sample. The preliminary step was the selection of nine counties forming the major strata for geographical representation. In each stratum, households were further classified into two groups: those receiving an input subsidy and those who did not. Households were then randomly sampled from each sub-stratum for inclusion in the study. This multi-stage sampling approach guaranteed heterogeneity and a fairly representative sample, minimizing selection bias and increasing the validity and generalizability of the research findings.

4.2. Measuring Multidimensional Poverty

Household well-being is assessed using the Multidimensional Poverty Index (MPI), which captures deprivations across health, education, living standards, and income potential (Alkire & Foster, 2011). The study adopts the Alkire-Foster methodology, extending the conventional three-dimensional global MPI framework to include a fourth dimension, income potential. This adjustment reflects growing evidence from developing country contexts that country-specific indicators improve the relevance of poverty measurement. For example, Chile incorporated social security and housing into its MPI, while South Africa added economic activity (Bonareri, 2018).

The MPI framework used in this study was further refined using insights from focus group discussions with economists, who helped identify context-specific indicators relevant to Kenya. The suitability of the selected indicators was further assessed through analysis of deprivation headcounts from the 2015/16 Kenya Integrated Household Budget Survey (KIHBS). The resulting framework comprises four equally weighted dimensions: health, education, living standards, and income potential (Bonareri, 2018).

Equal weighting is adopted to ensure simplicity, transparency, and comparability across dimensions. This approach avoids overemphasizing any single dimension and facilitates clearer communication of results to policymakers while maintaining consistency across diverse contexts (Evans et al., 2024). The specific dimensions, indicators, and weights are presented below.

Table 1. The domesticated structure of the National MPI

Dimension	**Weights**	**Indicators**	**Weight**
Health	0.25	Nutrition	0.125
		Access to healthcare	0.125
Education	0.25	Years of schooling	0.125
		School attendance	0.125
Income Potential	0.25	Economic Engagement	0.125
		Transfers from outside HH	0.125
Living Standards	0.25	Cooking fuel	0.042
		Sanitation	0.042
		Electricity	0.042
		Sources of drinking water	0.042
		House's roofing material	0.042
		Asset ownership	0.042

Source: Authors' compilations

Table 2. Indicators of Deprivation in a Household.

Indicator	**A household is deprived when;**
Years of schooling	Any member has less than five years of schooling
School attendance	A child of school age does not go to school.
Health access	A household has no access to a health facility, or it takes more than 30 minutes to get to the health facility.
Nutrition	A household had skipped a meal
Cooking fuel	A household uses firewood, charcoal, or dung as cooking fuel.
Sanitation	A household does not have a toilet facility, or the ratio is too high (more than 1:8)
Electricity	They have no access to electricity
Asset ownership	A household owns one or less of the following: a bicycle, a mobile phone, a car, a television, a radio, a tractor, or a refrigerator
House Roofing Material	The roof is grass thatch, sisal, palm, or coconut leaves (makuti) thatch.
Sources of drinking water	A household has no access to clean water for drinking, or it takes more than 30 mins to get to the source of clean drinking water.
Economic engagement	No member of the household had economic activity
Transfers	A household has received no transfer from outside in the past 1 year

Source: Authors' compilations

A household is assigned a value of one if it experiences deprivation in a specific indicator. The deprivation score is calculated by multiplying this value by the corresponding weight of the indicator. In a framework with ten indicators, a household deprived of all ten would have a deprivation score of 1, while a household experiencing no deprivation across any indicator would have a score of 0. The deprivation score is summarized as follows;

$$D_s = \sum_{j=1}^{i=n} w_i d_i \tag{1}$$

In which

D_s is the deprivation score

w_i is the weight associated with the indicator i.

d_i is the deprivation of indicator i, taking on the value of 1 if the HH is deprived, and zero if otherwise.

After the deprivation score has been calculated, the weighted deprivation cut-off is determined. The deprivation cut-off for the global MPI is 0.33. However, for this study, four dimensions were used, giving a deprivation cut-off of 0.25 as implemented by Bonareri (2018). With a deprivation score of 0.25 or more, one is regarded as multidimensionally poor; if it is less than 0.25, they are classified as not being poor.

4.3. Estimating Technical Efficiency

To estimate technical efficiency, several alternative approaches were considered. The Deterministic Frontier Model (DFM) assumes that all deviations from the production frontier are solely due to inefficiency. However, in smallholder agricultural settings, output is influenced not only by managerial performance but also by exogenous factors such as weather variability, pest infestations, soil heterogeneity, and measurement errors. By excluding a stochastic error component, this model risks overstating inefficiency by attributing random shocks to poor performance (Ndirangu et al., 2018). Given the vulnerability of farm-level data to such disturbances, this assumption was deemed too restrictive, rendering the DFM inappropriate.

Data Envelopment Analysis (DEA) was also considered. Although DEA does not require a predefined functional form, it similarly attributes all deviations from the frontier to inefficiency. In contexts characterized by measurement error and environmental shocks, this can lead to biased efficiency estimates. Moreover, DEA is highly sensitive to outliers, which may distort the estimated frontier (Thomas et al., 2020). Since this study aims to distinguish inefficiency from statistical noise and allow for inference, a parametric approach was preferred.

Similarly, the one-step inefficiency effects model was not adopted due to its reliance on strong distributional assumptions, particularly that inefficiency follows a truncated normal distribution dependent on explanatory variables. Violations of these assumptions may lead to biased results, while inclusion of multiple variables risks multicollinearity and complicates interpretation (Belete, 2020). Therefore, standard Stochastic Frontier Analysis (SFA) was chosen for this study. SFA provides a balanced framework that allows separation of inefficiency from statistical noise while maintaining manageable distributional assumptions. It accommodates the stochastic nature of agricultural production, enables estimation of production elasticities, and produces consistent efficiency measures as in Thomas et al. (2020). The theoretical model is specified as:

$$Y_i = f(X_j; \beta)e^{(\nu_i - \mu_i)} \tag{2}$$

Where; Y_i is output, $X_(i,)$ is a vector of inputs, β is parameters to be estimated μ_i is the non-negative one-sided inefficiency term assumed to follow half-normal, truncated normal, exponential, or gamma distributions. ν_i is a symmetric random error term assumed to follow a normal distribution $N(0, \delta_V^2)$

Technical efficiency is then defined as;

$$TE_i = e^{(-\mu_i)} \tag{3}$$

For this study, the Cobb-Douglas production function, assuming constant elasticities and unitary substitution elasticity, was used. The analytical model is shown;

$$\ln y_i = \beta_0 + \beta_1 \ln X_1 + \beta_2 \ln X_2 + \beta_4 \ln X_4 + \beta_5 \ln X_5 + \nu - \mu_i \tag{4}$$

Where, X_1 is seed quantity (kg),

X_2 is labor used (Ksh),

X_3 is pesticides (Litres per acre),

X_4 is the quantity of fertilizer (Kg per Acre),

X_5 is the size of the farm (Acres).

Technical efficiency is then estimated as ;

$$TE_i = \frac{Y_i}{Y_{Max}} = e^{-\mu} \tag{5}$$

Where Y_i represents the maize output for household i and Y_{Max} is the maximum possible output.

4.4. Estimating Commercialization Index of Smallholder Maize Farming Households

The Household Commercialization Index (HCI) defined as the proportion of each household's total maize sold to the total value of maize produced, will be estimated in line with the model developed by von Braun (1995) and later adopted by Birhanu et al., (2021) as shown:

$$HCI_i = \frac{P_i S_i}{P_i Q_i} \tag{6}$$

Where;

HCI_i commercialization index of household i.

S_i is quantity of maize output sold by household i, P_i is the per unit price of maize Q_i is the total quantity of maize output of household i A HCI_i score of zero denotes complete subsistence, while a score close to 1 denotes high commercialization.

4.5. Estimating CSA Intensity

CSA adoption was captured through farmer-reported use of practices such as irrigation, agroforestry, soil fertility management, manure management, and conservation agriculture. Adoption intensity was defined as the number of CSA practices adopted by a household, ranging from 0 (no adoption) to 5 (all practices adopted).

4.6. Impact Evaluation Strategy

To examine the impact of CSA on multidimensional poverty, the study employed the Endogenous Switching Regression (ESR) model, complemented by the Propensity Score Matching (PSM) technique to assess robustness. PSM, while useful for building matched samples based on observable characteristics, does not account for unobserved heterogeneity. These include variables that may influence both a household's uptake of CSA and MPI levels, but are not actively measured in the data. This leaves room for selection bias, in which unobserved variables skew the results, making it difficult to draw valid causal inferences. In contrast, ESR deals with unobserved selection bias by estimating separate outcomes for adopters and non-adopters while controlling for determinants of adoption. Our approach is strengthened by merging PSM and ESR through the comparison of each method's output. PSM provides a good first-stage match based on observed characteristics. On the other hand, ESR accounts for any remaining unobserved biases in these matched groups, as stipulated by Hu et al. (2021) and Sarma and Rahman (2020). Together, they allow comparison of the results, giving a more complete picture of the effect of CSA adoption on poverty.

The causal impact of an intervention under PSM or treatment is approximated through matching treated units (adopters of CSA strategies) and control units (non-adopters) based on similar characteristics. A propensity score in this case is the estimated likelihood of adopting the CSA strategy subject to a given set of covariates, as shown below;

$$PrPr(X_{ij}) = logit^{-1}(X_i\gamma_j) \tag{7}$$

Where D_{ij} is a binary variable indicating adoption of the j-th CSA strategy by household i

X_{ij} is a vector of covariates that influence adoption j-th CSA practice by household i

γ_j is a vector of coefficients to be estimated for j-th CSA practice.

The average treatment effect for the treated (ATT) is estimated as follows after the propensity scores have been estimated:

$$ATT = \frac{1}{N} \sum_{i \in Treated} (MPI_{i,j} - \widehat{MPI}_{i,j} \tag{8}$$

Where; N_j is the number of treated farmers in the j-th CSA strategy group.

$\widehat{MPI}_{i,j}$ is the Multidimensional Poverty Index of the i-th farmer in the j-th CSA strategy group.

$\widehat{MPI}_{i,j}$ is the estimated MPI of the matched control farmer.

To address unobserved selection bias, the study incorporates ESR method after matching. Given the potential endogeneity of CSA adoption, an instrumental variable is required. The literature identifies various potential instruments that can be used. These include distance to markets, distance to extension office, advice frequency, access to market information, land quality, land tenure, number of oxen, distance to input source, and availability of fertilizer subsidy (Battese & Coelli, 1995; Birhanu et al., 2021; Kumbhakar & Lovell, 2012; Mason & Jayne, 2012). The instruments selected must satisfy the two conditions cited by Wooldridge (2012), that they must exhibit a strong association with the endogenous independent variable (CSA adoption) while remaining uncorrelated with the regression error term. The instrument selected for this study was advice frequency by extension officers due to data availability and its ability to satisfy instrument validity conditions. The equations are presented as follows:

For adopters(T=1)

$$P_1 = M\beta_1 + \varepsilon \tag{9}$$

For non-adopters (T=0)

$$P_0 = M\beta + \varepsilon_0 \tag{10}$$

where $P_1$and P_0 are multidimensional poverty indices for adopters and non-adopters, respectively, M represents covariates influencing poverty, β_1 and β_0 are parameters to be estimated, ε_1 and ε_0 are error terms capturing unobserved factors affecting multidimensional poverty levels for adopters and non-adopters, respectively.

Since P_1 and P_0 cannot be observed simultaneously, the joint distribution of ε_1 and ε_0 cannot be directly identified. Assuming that $\rho_{0,1} = 1$,, a simultaneous equations model with ESR is estimated using the full information maximum likelihood method. The ESR then estimates two potential outcomes for each group, CSA adopters and non-adopters. This allows us to calculate what each household's poverty outcome would have been under the alternative adoption scenario (Khonje et al., 2015). For adopters (T=1), we estimate the observed multidimensional poverty outcome for households that adopted CSA, as well as their counterfactuals had they not adopted the CSA strategy as shown below;

$$\text{Actual} : E(T = 1) = X\beta_1 \tag{11}$$

$$\text{Counterfactuals} : E(T = 1) = X\beta_0 + \rho_{u,\epsilon_0\sigma_0\lambda(Z\gamma)} \tag{12}$$

The average treatment effect on the treated (ATT) measures the effect of CSA adoption for those households who adopted by comparing the observed outcome to their counterfactual outcome had they not adopted. It is calculated as shown below;

$$\text{ATT} = E(T - 1) - E(T = 1) \tag{13}$$

$$\text{ATT} = X\beta_1 - X\beta_0 - \rho_{u,\epsilon_0\sigma_0\lambda(Z\gamma)} \tag{14}$$

Similarly, for the non-adopters(T=0), the actual, counterfactual and average treatment effect on untreated are estimated as follows:

$$\text{Actual}(T = 0) = E(T = 0) = X\beta_0 \tag{15}$$

$$\text{Counterfactual} = E(T=0) = X\beta_1 + \rho_{u,\epsilon_1 \sigma_1 \lambda(-Z\gamma)} \tag{16}$$

$$\text{ATU} = E(T=0) - E(T=0) \tag{17}$$

$$\text{ATU} = X\beta_0 - X\beta_1 - \rho_u, \epsilon_1 \sigma_1 \lambda(-Z\gamma) \tag{18}$$

5. Results and Discussions

5.1. Diagnostic Test Results

Multicollinearity among explanatory variables was minimal (all VIF < 10), indicating that coefficient estimates are reliable as shown in Appendix 1. Heteroscedasticity was detected via the Breusch-Pagan test; hence, heteroscedasticity-robust standard errors were employed to ensure consistent inference.

5.2. Scenario-Based MPI Analysis

The scenario analysis categorizes the variables of interest, including household commercialization index (HCI), CSA intensity, and technical efficiency (TE), as binary indicators. A value of 0 denotes values below the sample mean, interpreted as not or moderate commercialization, efficiency, or CSA intervention intensity. Conversely, a value of 1 indicates levels above the mean, representing moderate to high engagement in commercialization, technical efficiency, or CSA intensity. Table 3 presents the number of households per scenario (N) and 95% confidence intervals for the mean MPI. These results are descriptive and reflect observed MPI levels across household categories without controlling for other household characteristics. Therefore, differences in MPI across scenarios cannot be interpreted as causal effects of HCI, TE, or CSA intensity.

The sample sizes per scenario vary from 416 to 2,511 households, ensuring reasonable precision for most cells. Technical efficiency consistently reduces MPI, while CSA intensity and commercialization show more complex effects. For example, households with high commercialization but low efficiency and low CSA intensity (HCI=1, TE=0, Intensity=0, N=538) have the highest mean MPI of 0.4671, whereas households with high TE, regardless of CSA intensity, exhibit lower MPI values (e.g., HCI=1, TE=1, Intensity=0, N=497, MPI=0.4370). An anomaly arises in the scenario with HCI=1, TE=1, Intensity=1, which shows a slightly higher MPI (0.4500) than HCI=1, TE=1, Intensity=0 (MPI=0.4370). Since these are descriptive averages, the difference may reflect household heterogeneity, short-term costs of CSA adoption, labor reallocation, or differences in household composition rather than a reversal of CSA's poverty-reducing effect. The overlap in confidence intervals further suggests that the observed difference could be due to sampling variation.

Table 3. Results of MPI Based on Different Scenarios

HCI	TE	CSA INTENSITY	N	MEAN MPI	[95% Conf. Interval]	
					Lower	Upper
0	0	0	2,511	0.4636	0.4586	0.4687
0	0	1	2,298	0.4486	0.4435	0.4537
0	1	0	443	0.4504	0.4393	0.4614
0	1	1	416	0.4373	0.4246	0.4500
1	0	0	538	0.4671	0.4557	0.4786
1	0	1	536	0.4435	0.4330	0.4539
1	1	0	497	0.4370	0.4272	0.4467
1	1	1	614	0.4500	0.4411	0.4588

Source: Authors' computation

5.3. Intensity of Climate Smart Agriculture Adoption in Kenya

More than half of households did not adopt any CSA practices (50.85%), while only 0.85% adopted 3 practices. The low adoption may be attributed to structural constraints such as limited access to land, water, and irrigation infrastructure, which restrict households' ability to implement multiple CSA strategies. Non-adoption can also be attributed to resource-related factors. These include inadequate capital for inputs, lack of credit, and limited access to improved seeds. In addition, informational barriers play a critical role. Many farmers have limited exposure to extension services, training programs, or peer networks that could provide knowledge on CSA techniques. Cultural practices and risk aversion may also influence adoption decisions, particularly where innovations require upfront investment or carry uncertain returns. Together, these structural, resource, and informational challenges help explain why adoption of multiple CSA strategies remains low despite programmatic support. The results are summarized as shown in Table 4 below.

Table 4. Tabulation of CSA Intensity

# of adopted strategies	Freq.	Percent	Cum.
0	4115	50.86	50.86
1	3106	38.39	89.25
2	801	9.90	99.15
3	69	0.85	100.00
Total	8091	100.00	

Source: Authors' computation

5.4. Effect of Adopting CSAs on Multidimensional Poverty among Maize Farmers in Kenya

5.4.1. Instrument Relevance Test

To test the relevance of frequency of advice by extension officers for instrument relevance, a two-step instrumental variable regression was estimated, and the instrument F-statistic was obtained. The instrument F-statistic was 13.4121 with a corresponding p-value of 0.0003, confirming the relevance of using frequency of advice as an instrument for CSA intensity. To test for endogeneity of the instrument, the Durbin–Wu–Hausman test was conducted to test the null hypothesis that the CSA intensity is exogenous. The results show a robust chi-square score of 58.751 and a corresponding p-value of 0.000, indicating that CSA intensity is endogenous. Therefore, the use of an instrumental variable approach was justified.

5.4.2. Endogenous Switching Regression (ESR)

To evaluate the effect of climate-smart agriculture adoption on household multidimensional poverty among the adopters and non-adopters, ESR regression was estimated, and the results are presented in Table 5.

Table 5. Endogenous Switching Regression Results

Variable	MPI0	MPI1	Selection
HH Age	-0.0008***	-0.0006	0.0076***
	(0.0001)	(0.0004)	(0.0017)
HH Gender	-0.0030	-0.0124	-0.0796
	(0.0038)	(0.0123)	(0.0564)
HH Education	-0.0040***	-0.0008	0.0230***
	(0.0004)	(0.0011)	(0.0046)
Farm Size	0.0011	-0.0069	0.0040
	(0.0019)	(0.0049)	(0.0250)
Planting Season	-0.0032	-0.0059	0.0311
	(0.0046)	(0.0144)	(0.0696)
Credit Access	0.0054	-0.0218	0.2048**
	(0.0085)	(0.0190)	(0.0987)
Group Membership	-0.0063***	-0.0110***	0.0496***
	(0.0008)	(0.0021)	(0.0099)
Garissa	0.0390	-0.0391	-0.1846
	(0.0283)	(0.1161)	(0.4857)
Marsabit	0.0325***	0.0125	-0.2623**
	(0.0064)	(0.0254)	(0.1092)
Nyandarua	-0.0108*	0.0667**	-0.6044***
	(0.0062)	(0.0258)	(0.1018)
Nyeri	-0.0182***	-0.0332**	-0.0186
	(0.0051)	(0.0153)	(0.0749)
West Pokot	0.0759***	0.0149	-0.0149
	(0.0053)	(0.0168)	(0.0784)
Baringo	0.0239***	-0.0499***	0.4897***
	(0.0058)	(0.0139)	(0.0586)
Siaya	0.0174***	-0.0205	-0.2653***
	(0.0056)	(0.0205)	(0.0896)
Kisumu	0.03946	0.0413*	-0.3712***
	(0.0225)	(0.0229)	(0.0935)
Advice Frequency (Instrument)	—	—	0.0062***
	—	—	(0.0011)
Constant	0.5497***	0.6453***	-1.9855***
	(0.0106)	(0.0629)	(0.1506)

Source: Authors' computation

Among non-adopters, the age of the household head significantly reduces multidimensional poverty (β = -0.0008, p $<$ 0.01). This suggests that experience accumulated over time improves households' ability to manage mp even without CSA adoption. Similarly, education significantly reduces multidimensional poverty (β = -0.0040, p $<$ 0.01), reinforcing the role of human capital in improving multidimensional poverty. Group membership also significantly reduces poverty among non-adopters (β = -0.0063, p $<$ 0.01), indicating that social networks provide poverty-reducing benefits even in the absence of CSA adoption.

Regional differences are pronounced. Households in Marsabit, West Pokot, Baringo, and Siaya experience significantly higher multidimensional poverty relative to the reference county, while those in Nyandarua and Nyeri experience lower poverty levels. These variations reflect differences in infrastructure access, exposure to climate vulnerability, and market integration across counties, which condition both baseline multidimensional poverty levels and the effectiveness of climate adaptation strategies.

Among CSA adopters, group membership remains a strong determinant of reduced multidimensional poverty (β = -0.0110, p $<$ 0.01). This suggests strong complementarities between social capital and CSA adoption in improving household MPI. This enhances the effectiveness of CSA technologies by facilitating access to climate information, improved inputs, and collective marketing opportunities that improve multidimensional outcomes from adoption.

County-level effects remain significant for adopters as well. Multidimensional poverty is significantly higher among adopters in Nyandarua and Kisumu, but lower among adopters in Nyeri and Baringo. These results suggest that the poverty-reducing benefits of CSA adoption vary across locations depending on agro-ecological suitability, market integration, and complementary institutional support.

The variance and covariance estimate in Table 6 show that lns0 (-2.021, p $<$ 0.01) and lns1 (-2.088, p $<$ 0.01) depict heteroskedasticity in the outcome equations across regimes. After exponentiation, the estimated standard deviations are σ_0= 0.132 and σ_1 = 0.124, indicating relatively similar dispersion in multidimensional poverty outcomes between CSA adopters and non-adopters.

The correlation coefficients ρ_0 = -0.879 and ρ_1 = -0.449 capture the relationship between the unobserved determinants of CSA adoption and Multidimensional Poverty in the two regimes. Both coefficients are negative and statistically significant, indicating the presence of selection bias arising from unobserved heterogeneity confirming that households self-select into CSA adoption based on factors that also influence their Multidimensional Poverty Index. This suggests that unobserved characteristics that increase the likelihood of not adopting CSA are associated with higher multidimensional poverty levels, and the unobserved characteristics that increase the likelihood of adopting CSA are associated with lower multidimensional poverty outcomes. This confirms the presence of endogenous selection into CSA adoption, validating the suitability of the ESR framework for estimating unbiased treatment effects in the analysis.

Table 6. Variance–Covariance and Selection Correction Parameters from the Endogenous Switching Regression (ESR) Model

	Coef.	Std.Err.	z	P>z	[95%Conf.	Interval]
/lns0	-2.021	0.012	-175.57	0	-2.044	-1.999
/lns1	-2.088	0.071	-29.45	0	-2.227	-1.949
/r0	-1.372	0.08	-17.21	0	-1.528	-1.216
/r1	-0.483	0.191	-2.53	0.011	-0.858	-0.109
σ_0	0.132	0.002			0.13	0.136
σ_1	0.124	0.009			0.108	0.142
ρ_0	-0.879	0.018			-0.91	-0.838
ρ_1	-0.449	0.153			-0.695	-0.108

Source: Authors' computation

To empirically test the effect of CSA on the multidimensional poverty index among smallholder maize-farming households in Kenya, ATT and ATU estimates were obtained, as shown in Table 7. For CSA adopters, the results suggest that the multidimensional poverty index decreased by 0.018 compared to what it would have been had they not adopted CSA. This reflects a substantial reduction in deprivation across multiple dimensions, suggesting that CSA adoption effectively improves farmers' overall well-being as measured by MPI.

Similarly, for non-adopters, adopting CSA is expected to reduce MPI by 0.026, slightly more than the effect for adopters. This larger potential impact is likely because non-adopters have a higher baseline MPI, so the benefits of CSA adoption are greater for households that are initially poorer. This highlights the untapped potential of CSA interventions to alleviate poverty for households that have not yet adopted such practices (Islam and Farjana, 2024).

Table 7. ATT and ATU for Adopters and Non-Adopters

Group	MPI (Observed)	MPI (Counterfactual)	Difference	Std Error	T-stat
Adopters (ATT)	0.438	0.456	-0.018	0.003	-2.31
Non-adopters (ATU)	0.458	0.432	0.026	0.004	3.44

Source: Authors' computation

5.4.3. A Propensity Score Matching Approach

The logit model was estimated to determine the factors influencing the likelihood of adopting climate-smart agriculture (CSA) practices and to generate propensity scores used in the matching procedure. The results are presented in Table 8.

Table 8. Logistic Regression Model

CSA Adoption	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
HH Age	.017	.003	5.39	.000	.011	.023	***
HH Gender	-.192	.110	-1.75	.080	-.407	.023	*
Yrs of Schooling	.048	.009	5.65	.000	.031	.065	***
Farm Size	.008	.047	0.16	.871	-.085	.100	
Planting Season	.060	.135	0.44	.657	-.204	.324	
Credit Access	.318	.180	1.77	.077	-.035	.671	*
Group Membership	.098	.018	5.49	.000	.063	.133	***
Garissa	-.410	1.036	-0.40	.692	-2.441	1.621	
Marsabit	-.486	.226	-2.15	.032	-.929	-.042	**
Nyandarua	-1.150	.210	-5.47	.000	-1.562	-.738	***
Nyeri	.125	.139	0.90	.367	-.147	.398	
West Pokot	-.011	.152	-0.07	.942	-.309	.287	
Baringo	.886	.106	8.33	.000	.678	1.095	***
Siaya	-.540	.184	-2.94	.003	-.900	-.180	***
Kisumu	-.714	.195	-3.66	.000	-1.097	-.332	***
Constant	-3.664	.289	-12.69	.000	-4.23	-3.098	***
Diagnostics							
Mean dependent var	0.108		SD dependent var		0.310		
Pseudo r-squared	0.064		Number of obs		7374		
Chi-square	324.129		Prob > chi2		0.000		
Akaike crit. (AIC)	4741.968		Bayesian crit. (BIC)		4852.459		

*** p<.01, ** p<.05, * p<.1
Source: Authors' computation

The results indicate that household head age and education significantly increase the likelihood of adopting CSA practices, suggesting that farming experience and human capital play important roles in shaping adoption decisions. Access to credit and membership in farmer groups also positively influence adoption, highlighting the importance of financial access and social networks in facilitating the uptake of climate-resilient agricultural technologies. Gender of the household head shows a negative effect on the adoption of CSA practices. Male-headed households were less likely to adopt CSA strategies.

County-level effects further reveal spatial variation in CSA adoption, reflecting differences in agro-ecological conditions, access to extension services, and infrastructure across regions. Compared to the reference county of Uasin Gishu, households in Marsabit, Nyandarua, Siaya, and Kisumu counties were less likely to adopt CSA, while households in Baringo County were more likely to adopt CSA practices. Balance diagnostics were conducted to assess the effectiveness of propensity score matching in reducing observable differences between CSA adopters and non-adopters. Prior to matching, substantial differences existed between the treated and control groups. For instance, the years of schooling exhibited a standardized bias of 30.2%, and membership in social groups showed a bias of 21.4%. Counties such as Baringo also displayed high imbalances with a bias of 45.8%, indicating significant differences in the regional distribution of treated versus control households. These imbalances suggest that the control group may not provide a reliable counterfactual for estimating the effect of CSA adoption. After applying PSM, the balance between treated and control groups improved considerably. Most covariates experienced a marked reduction in the mean standardized bias, reflecting better comparability between the groups. For example, HH age's bias decreased from 11.8% to 5.4%, and years of schooling's bias dropped from 30.2% to 11.4%. Variance ratios for most continuous covariates approached unity (e.g., HH Age $V(T)/V(C) = 0.99$), indicating improved homogeneity of variance between groups. However, some covariates retained residual imbalance even after matching. For example, membership in social groups and Baringo showed standardized biases of 16.4% and 43.5%, respectively, and remained statistically significant.

Table 9. Balance Diagnostic Results

		Mean		%reduc		t-test		V(T) /
Variable	Matched/Unmatched	Treated	Control	%bias	bias	t	p>t	V(C)
HH Age	U	53.274	51.694	11.8	3.14	0.002	0.96	
	M	53.274	52.553	5.4	54.4	1.09	0.278	0.99
HH Gender	U	1.152	1.216	-16.4	-4.19	0	0.76*	
	M	1.152	1.164	-3.1	81.2	-0.66	0.512	0.94
Yrs of schooling	U	10.429	8.939	30.2	8	0	0.93	
	M	10.429	9.869	11.4	62.4	2.32	0.02	1.01
Farm Size	U	0.952	0.886	7.8	2.16	0.031	1.19*	
	M	0.952	0.909	5	35.2	1	0.318	1.14
Planting Season	U	1.131	1.147	-4.6	-1.2	0.23	0.91	
	M	1.131	1.147	-4.5	1.1	-0.91	0.365	0.91
Credit Access	U	0.056	0.031	12.1	3.68	0	.	
	M	0.056	0.043	6.5	46.6	1.23	0.22	.
Group Membership	U	3.486	2.995	21.4	6.01	0	1.31*	
	M	3.486	3.109	16.4	23.1	3.22	0.001	1.23*
Garissa	U	0.001	0.003	-3.2	-0.76	0.445	.	
	M	0.001	0.002	-1.8	44.9	-0.39	0.697	.
Marsabit	U	0.031	0.067	-16.8	-3.99	0	.	
	M	0.031	0.05	-8.9	47	-1.95	0.051	.
Nyandarua	U	0.04	0.086	-19.4	-4.6	0	.	
	M	0.04	0.093	-22.1	14.2	-4.34	0	.
Nyeri	U	0.171	0.135	10.1	2.81	0.005	.	
	M	0.171	0.144	7.6	24.2	1.51	0.131	.
West Pokot	U	0.09	0.111	-6.8	-1.77	0.076	.	
	M	0.09	0.094	-1.3	80.6	-0.28	0.782	.
Baringo	U	0.292	0.113	45.8	14.44	0	.	
	M	0.292	0.122	43.5	5.2	8.63	0	.
Siaya	U	0.055	0.088	-13	-3.23	0.001	.	
	M	0.055	0.088	-12.9	0.8	-2.6	0.009	.
Kisumu	U	0.046	0.089	-17.4	-4.21	0	.	
	M	0.046	0.09	-17.7	-1.6	-3.55	0	.

Source: Authors' computation

Similarly, Table 10 presents the summary statistics for covariate balance before and after propensity score matching. Prior to matching, the pseudo R^2 was 0.064, and the likelihood-ratio chi-square was 323.11 ($p < 0.001$), indicating substantial systematic differences between treated and control households. The mean standardized bias was 15.8%, median bias was 13%, and Rubin's B (67.6) and R (1.28) further confirmed a notable imbalance in the unmatched sample.

After matching, covariate balance improved considerably. The pseudo R^2 decreased to 0.056, the likelihood-ratio chi-square fell to 123.61 ($p < 0.001$), and mean standardized biases declined to 11.2%, while median standardized biases declined to 7.6%. In addition, Rubin's B, R statistics, and the percentage of variance explained dropped to 57.1, 1.3, and 17%, respectively. This indicates that the matched sample achieved substantially better comparability. Overall, these results confirm that the PSM procedure effectively reduced covariate imbalance, providing a more reliable basis for estimating the causal effect of CSA adoption on multidimensional poverty.

Table 10. Matching summary Statistic

Sample	Ps	R2	LR	chi2	p>chi2	MeanBias	MedBias	B
Unmatched	0.064	323.11	0	15.8	13	67.6*	1.28	50
Matched	0.056	123.61	0	11.2	7.6	57.1*	1.3	17

Source: Authors' computation

5.4.4. Treatment-Effect Estimation Results

As shown in Table 11 the results suggest that the adopters of CSA strategies experience a reduction in their Multidimensional Poverty Index by 0.006 units. These findings conform with the ESR result estimated, indicating that the CSA adoption significantly reduces multidimensional poverty among the smallholder maize farming households in Kenya. Similar results were reported by Ali et al. (2022), who reported that households adopting CSA practices exhibited a substantially lower multidimensional deprivation score compared to non-adopters.

Table 11. Treatment-Effect Estimation Results

PSM	MPI (Observed)	MPI (Counterfactual)	Difference	Std Error	T-stat	On support	Off support
Adopters (ATT)	0.438	0.444	-0.006	0.005	-1.3	7570	4

Source: Authors' computation

5.5. Post Estimation Diagnostics

5.5.1. Check for Common Support

A summary of the distribution between the treated and control groups in Table 12 shows that the estimated propensity scores ranged from 0.052 to 0.85 for treated households and 0.037 to 0.738 for control households, indicating substantial overlap and satisfying the common support condition. In addition, results in Table X show that 7570 observations fell within the common support, while 4 were off support. This suggests that the ATT estimate is reliable for the entire treated sample.

Table 12. Propensity Score Distribution

Variable	Obs	Mean	Std. Dev.	Min	Max
Treated	807	0.127	0.086	0.052	0.85
Not-treated	6763	0.105	0.04	0.037	0.738

Source: Authors' computation

5.5.2. Sensitivity Analysis

To ascertain the robustness of the obtained PSM results, sensitivity analysis using different matching algorithms, including nearest neighbour, kernel, and radius matching, was conducted, as shown in Table 13. The results show that the estimated ATT remains consistently negative across all matching methods, indicating that CSA adoption is associated with a reduction in MPI. The magnitude of the effect ranges from -0.0041 to -0.0068, the standard errors remain similar across methods and none of the estimates are statistically significant at the 5% significance level. This suggests that the ATT estimates are based on comparable treated and control households and the results are robust to alternative matching specifications.

Table 13. Sensitivity Analysis with Different Algorithms

Matching Method	ATT (Treated)	Std. Error	t-stat	On Support	Off Support
Nearest neighbour (1)	-.0068	.005	-1.30	7,570	4
Nearest neighbour (3)	-.0041	.006	-0.71	7,570	4
Kernel	-.0059	.005	-1.30	7,570	4
Radius (0.05)	-.0061	.005	-1.30	7,570	4

Source: Authors' computation

5.5.3. Rosenbaum Bounds Sensitivity Analysis

Rosenbaum bounds sensitivity analysis was conducted to assess the robustness of the estimated treatment effect to potential hidden bias arising from unobserved confounders. The results are summarized in Table 14

Table 14. Rosenbound Test Results

Γ (Gamma)	Upper-bound p-value (sig+)	Lower-bound p-value (sig–)
1	0.00112	0.00112
1.1	0.00001	0.02960
1.2	0.00000	0.20520
1.3	0.00000	0.56130
1.4	0.00000	0.85530
1.5	0.00000	0.97150
2	0.00000	1.00000
3	0.00000	1.00000

Source: Authors' computation

The results indicate that the estimated treatment effect remains statistically significant across all examined values of Γ up to 3. This suggests that even if an unobserved factor increased the odds of CSA adoption by as much as threefold between otherwise similar households, the estimated treatment effect would remain statistically significant. These findings indicate strong robustness of the estimated treatment effect to potential unobserved heterogeneity.

5.6. Sequential Regression Results for the CSA–Technical Efficiency Commercialization Poverty Nexus

The mediation analysis to assess whether Commercialization and Technical Efficiency act as channels through which CSA intensity influences Poverty outcomes was conducted as summarized in Table 15.

Table 15. Sequential Analysis Results

Variables	Technical Efficiency (TE)	Commercialization Index (HCI)	Multidimensional Poverty (MPI)
CSA Intensity	0.008	0.021***	-0.002
	(0.017)	(0.006)	(0.002)
TE		0.027***	-0.006***
		(0.004)	(0.001)
HCI			-0.005
			(0.004)
HH Age	-0.001	-0.001***	-0.001***
	(0.001)	(0.000)	(0.000)
HH Gender	0.007	-0.024**	-0.009***
	(0.030)	(0.010)	(0.004)
Yrs of Schooling	0.004	0.006***	-0.005***
	(0.003)	(0.001)	(0.000)
Advice frequency	-0.001	0.000	0.000
	(0.001)	(0.000)	(0.000)
Farm Size	-0.141***	0.097***	0.003
	(0.015)	(0.005)	(0.002)
Season	-0.066**	-0.035***	-0.012***
	(0.034)	(0.011)	(0.004)
Credit Access	-0.071	0.027	0.004
	(0.065)	(0.022)	(0.008)
Group Membership	0.013**	0.006***	0.008***
	(0.006)	(0.002)	(0.001)
Constant	0.598***	0.216***	0.608***
	(0.078)	(0.026)	(0.009)
Observations	7,374	7,374	7,374
R^2	0.015	0.083	0.077
F-statistic	12.117***	66.782***	55.474***

Source: Authors' computation

The results indicate that the intensity of climate-smart agriculture adoption has a positive but statistically insignificant effect on technical efficiency ($\beta = 0.008$, $p > 0.10$). Although the sign suggests that increased adoption of CSA practices may improve the efficiency with which farmers utilize production inputs, the absence of statistical significance implies that the efficiency gains associated with CSA adoption are not sufficiently strong within the sampled population. This could be because many CSA practices, particularly those related to soil management and conservation agriculture, often generate productivity benefits gradually rather than immediately. Consequently, efficiency improvements may take time to materialize as farmers accumulate experience and adapt management practices. This could also be due to the heterogeneity of CSA practices. Some practices may be primarily oriented toward climate resilience rather than immediate efficiency gains. Similar findings have been reported in empirical studies, noting that while CSA practices improve long-term sustainability and resilience, their short-term efficiency impacts may be limited due to adjustment costs, knowledge constraints, and labor requirements (Petros et al., 2025; Tunio et al., 2024). This suggests that the benefits of CSA adoption may be realized through indirect pathways rather than direct improvements in production efficiency.

The second stage of the sequential model shows that technical efficiency has a positive and highly significant effect on commercialization intensity ($\beta = 0.027$, $p < 0.01$). This finding implies that farmers who utilize inputs more efficiently are more likely to participate actively in agricultural markets. Increased efficiency often translates into higher output levels and reduced production costs, thereby generating greater marketable surplus and incentivizing farmers to sell their produce. Additionally, CSA adoption intensity directly and positively influences commercialization ($\beta = 0.021$, $p < 0.01$). This suggests that CSA practices directly improve market participation through mechanisms such as improved productivity, stability, and enhanced resilience to climatic shocks. When farmers experience fewer production risks, they are more likely to engage in markets and commercialize their output.

The final stage of the sequential model examines the effect of commercialization and technical efficiency on multidimensional poverty. The results reveal that technical efficiency significantly reduces multidimensional poverty ($\beta = -0.006$, $p < 0.01$). This finding indicates that households that manage agricultural inputs more efficiently tend to experience lower levels of deprivation across multiple poverty dimensions. Efficiency improvements likely increase agricultural productivity and income, enabling households to meet essential needs such as education, health, and nutrition.

Commercialization intensity, on the other hand, exhibits a negative but statistically insignificant relationship with multidimensional poverty ($\beta = -0.005$, $p > 0.10$). While the negative sign suggests that greater market participation may reduce poverty, the lack of statistical significance indicates that commercialization alone may not guarantee improvements in multidimensional poverty outcomes. This finding highlights the complexity of the commercialization–poverty relationship and suggests that market participation does not automatically translate into improved living standards. Commercialization primarily influences income-based outcomes, whereas multidimensional poverty encompasses dimensions such as education, health, and living standards. As a result, even when commercialization increases household income, the gains may not translate into improvements across all poverty indicators captured by the multidimensional poverty index. In some cases, income generated from crop sales may be reinvested into agricultural production or used to meet short-term consumption needs rather than improving long-term multidimensional poverty outcomes such as education or housing conditions.

In addition, smallholder farmers often engage in markets under imperfect conditions characterized by price volatility, high transaction costs, and limited bargaining power. Under such circumstances, the benefits of commercialization may be partially eroded by unfavorable market structures, reducing the potential multidimensional poverty gains associated with increased market participation. Consequently, commercialization may increase production and sales volumes without necessarily improving household well-being in a statistically measurable way (Ngalande, 2022).

The results provide partial support for the hypothesized CSA–technical efficiency commercialization poverty nexus. While CSA adoption intensity does not significantly improve technical efficiency directly, it significantly increases commercialization, and technical efficiency itself significantly enhances commercialization while also reducing multidimensional poverty. These findings suggest that the impacts of climate-smart agriculture operate primarily through productivity and market participation pathways rather than through direct effects on multidimensional poverty. The results imply that improvements in production efficiency play a crucial role in enabling farmers to engage more effectively with agricultural markets, which may subsequently influence household MPI. This highlights the importance of strengthening institutional and market systems to ensure that productivity gains resulting from climate-smart agriculture translate into tangible MPI improvements for smallholder farmers.

The Sobel test for the serial mediation pathway (CSA intensity - technical efficiency -

commercialization - MPI) shows an insignificant indirect effect of -0.0000011 (Z = -0.44, p = 0.66). This suggests that there is no evidence that CSA intensity influences MPI through this serial pathway.

Among the control variables, household size, membership in farmer groups, household head age, gender, education level, and planting season emerged as significant predictors across the sequential models. Collectively, these variables highlight the interplay between demographic, social, and contextual factors in shaping technical efficiency, commercialization, and multidimensional poverty outcomes.

Farm size exhibits a strong negative relationship with technical efficiency (β = -0.141, $p < 0.01$) but a positive effect on commercialization (β = 0.097, $p < 0.01$). This suggests that while larger farms may face challenges in managing resources efficiently, they simultaneously have greater capacity to engage in market-oriented production. Membership in farmer groups consistently improves outcomes, reflecting the importance of social capital in enhancing both productivity and market participation. Household head characteristics such as age, gender, and education further influence outcomes: younger, male-headed, and more educated households tend to achieve higher commercialization and lower multidimensional poverty, indicating that human capital and decision-making capacity are key for translating agricultural innovations into MPI gains. Seasonality remains a significant factor, affecting both technical efficiency and poverty, which highlights the vulnerability of agricultural outcomes to temporal climatic and market shocks. These controls indicate that CSA adoption and its MPI effects are embedded in a complex socio-economic and agro-ecological context. Policies aiming to improve productivity, commercialization, and poverty reduction should therefore address technology adoption, farm scale management, social networks, human capital, and seasonal vulnerabilities to achieve sustainable impacts.

To validate the results, bootstrap confidence intervals for the indirect effect were estimated. The results in Table 16 indicate that the indirect effect of technical efficiency on multidimensional poverty (MPI) through commercialization is negative and statistically significant (β = -0.018, $p < 0.05$). This suggests that commercialization serves as an important transmission mechanism through which technical efficiency influences MPI. Improvement in households' technical efficiency enhances market participation and commercialization, which in turn contributes to reductions in multidimensional poverty. This finding supports the argument that productivity gains alone may not directly translate into MPI improvements unless they are complemented by market integration.

Table 16. Bootstrap Confidence Interval for Indirect Effect of Technical Efficiency

	Observed Coef.	Std. Err.	Bootstrap z	P>z	Normal-based [95%Conf.	Interval]
_bs_1	-0.018	0.007	-2.57	0.01	-0.032	-0.005

Source: Authors' computation

5.6.1. Sensitivity Analysis

Sensitivity analysis was conducted to examine whether the mediation effect of technical efficiency (TE) on multidimensional poverty (MPI) through commercialization (HCI) is robust to alternative binary poverty thresholds (k = 0.20, 0.25, 0.33, and 0.40). Across all cutoffs, the TE-HCI coefficient remains positive (0.027), implying that technically efficient households have improved market participation as shown in Table 17. On the other hand, the HCI-MPI direct effects remain negative (-0.0094). The indirect effect, on the other hand, ranges from -0.015 to -0.02 with $p < 0.05$. These results confirm that higher technical efficiency reduces the likelihood of multidimensional poverty through increased commercialization, and the mediation mechanism is robust across different poverty cut-offs.

Table 17. Sensitivity Analysis with Different MPI Cut-offs

Cut-off	TE → HCI (Mediator)	HCI → MPI (Direct Effect)	TE → HCI → MPI (Indirect Effect)	Significance
0.20	0.027	-0.0094	-0.015	$p < 0.05$
0.25	0.027	-0.0094	-0.018	$p < 0.05$
0.33	0.027	-0.0094	-0.020	$p < 0.05$
0.40	0.027	-0.0094	-0.017	$p < 0.05$

Source: Authors' computation

5.7. Interaction Effects of CSA Intensity, Technical Efficiency, and Commercialization on Multidimensional Poverty

To formally test whether the effect of CSA intensity on multidimensional poverty is conditional on household technical efficiency (TE) or commercialization intensity (HCI), the study estimated interaction terms between CSA intensity, TE, and HCI while controlling for other variables such as farm size, seasonality, credit access, and group membership. The results are presented in Table 18.

Table 18. Results of the Moderation Analysis

MPI	Coef.	Std. Err.	t-value	p-value	[95% Conf	Interval]	Sig
TE × HCI	-0.006	0.002	-4.05	0.000	-0.0090	-0.003	***
CSA × TE	-0.013	0.009	1.44	0.149	-0.0310	0.005	
CSA × HCI	-0.002	0.014	0.15	0.882	-0.0300	0.026	
HH Age	-0.001	0.000	-10.71	0.000	-0.0010	-0.001	***
HH Gender	-0.009	0.004	-2.60	0.009	-0.0170	-0.002	***
Yrs of schooling	-0.005	0.000	-16.42	0.000	-0.0060	-0.004	***
Advice Frequency	0.000	0.000	1.49	0.136	0.0000	0.000	
Farm Size	0.003	0.002	1.50	0.133	-0.0010	0.006	
Planting Season	-0.012	0.004	-2.92	0.003	-0.0200	-0.004	***
Credit Access	0.003	0.008	0.38	0.704	-0.0120	0.018	
Group Membership	-0.008	0.001	-12.23	0.000	-0.0090	-0.007	***
Constant	0.608	0.009	64.55	0.000	0.5900	0.627	***

Source: Authors' computation

The results indicate that the interaction between technical efficiency and commercialization is negative and significant (β= -0.006, $p < 0.01$). This suggests that households that are both technically efficient and commercially active experience lower levels of multidimensional poverty. This finding highlights a synergy between production efficiency and market participation. Technical efficiency alone may have a limited impact on poverty reduction if households lack access to markets to sell surplus produce. Similarly, commercialization alone may be ineffective if households cannot produce efficiently. When both conditions are met, households are better positioned to diversify their income sources, improve nutrition, and invest in education and health, thereby achieving more substantial reductions in multidimensional poverty.

In contrast, the interactions between CSA intensity and TE and between CSA intensity and HCI are negative but not statistically significant. This suggests that while there is a potentially beneficial moderating effect of CSA intensity, the current sample does not provide strong evidence that CSA intensity directly amplifies the poverty-reducing effects of either efficiency or commercialization. The absence of statistical significance may be partly due to heterogeneity in CSA practices, as different practices vary in their immediate impact on productivity and market outcomes. Some practices enhance climate resilience rather than short-term efficiency or commercialization, diluting the observable moderation effect. Additionally, some CSA practices, such as irrigation, integrated manure management, and agroforestry, involve high upfront costs, while other practices, such as integrated soil management and conservation agriculture, require learning requirements that temporarily strain household resources.

Household and farm-level controls remain broadly consistent with prior analyses: Households with younger, female-headed, and less-educated heads experience higher multidimensional poverty, whereas group membership and planting during the main season reduces poverty.

6. Conclusions and Policy Suggestions

The study demonstrates that the adoption of climate-smart agriculture practices significantly contributes to the reduction of multidimensional poverty among smallholder maize farmers in Kenya by enhancing technical efficiency and market participation. While CSA adoption alone does not uniformly guarantee poverty reduction, it amplifies the MPI benefits when combined with efficient input use and active commercialization. Scenario-based analysis reveals that households with high technical efficiency consistently experience lower multidimensional poverty, whereas the effects of CSA intensity and commercialization are more context-dependent. The sequential mediation results indicate that technical efficiency drives MPI improvements, partly through its influence on commercialization. Socioeconomic factors such as household head age, education, gender, credit access, and group membership also significantly shape CSA adoption and poverty outcomes. Overall, CSA adoption presents a critical pathway for improving household MPI, but its effectiveness is contingent upon addressing structural, informational, and resource-related constraints. These findings result in the following policy implications;

i. Gender-targeted credit facilities: Develop financial products specifically for female-headed households to facilitate investment in capital-intensive CSA practices, such as irrigation and mechanized soil management, thereby bridging the resource gap and promoting equitable adoption.

ii. Redesign extension services: Tailor advisory services to address perceptions of labor intensity and low-priority practices, highlighting both short-term and long-term benefits of CSA adoption. Promote labor-saving techniques and provide hands-on training suited to female and male farmers.

iii. Strengthen farmer networks and cooperatives: Encourage inclusive participation in farmer groups, cooperatives, and peer-learning platforms to improve knowledge sharing, resource pooling, and collective market access, which enhances adoption and MPI outcomes.

iv. Integrate technical efficiency with market support: Complement CSA promotion with interventions that enhance input use efficiency and market participation, ensuring productivity gains translate into measurable reductions in multidimensional poverty, with attention to farm size, seasonal constraints, and household composition.

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6.1. Conflicts of Interest

The authors report there are no competing interests to declare.

6.2. Data Availability Statement

The data used in this study were obtained from the Tegemeo Institute of Agricultural Policy and Development. The dataset is not publicly available due to data access restrictions and ownership policies of the Institute. Access to the data can be granted upon reasonable request and with formal approval from the Tegemeo Institute of Agricultural Policy and Development.

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