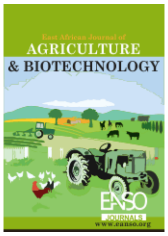

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Original Article

Socio-Economic Determinants of Climate-Smart Agricultural Practices Among Smallholder Farmers in Mwingi West Sub-County, Kitui County, Kenya

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Climate-Smart Agriculture (CSA), Adoption, Smallholder, Socio-economic, Mwingi West Sub-county.

ABSTRACT

Climate change presents a critical challenge to agricultural systems in Kenya's arid and semi-arid lands (ASALs), where smallholder farmers face recurrent droughts, erratic rainfall, and declining productivity. Climate-Smart Agriculture (CSA) offers a potential pathway to enhance resilience, productivity, and sustainability; however, adoption rates remain low in Mwingi West Sub-County, Kitui County. This study investigated the socio-economic determinants influencing the uptake of climate-smart agricultural practices (CSAPs) among 393 smallholder farmers, employing a cross-sectional survey design, multi-stage sampling, and both quantitative and qualitative methods. Data were analysed using chi-square tests and binary logistic regression. Results revealed that education level, household income (farm and off-farm), gender, and proximity to markets significantly and positively influenced CSA adoption, while larger farm size and younger age were negatively associated with uptake. Educated farmers were 4.36 times, and higher-income farmers 4.58 times, more likely to adopt CSAPs compared to their counterparts. Male farmers were 2.34 times more likely to adopt than female farmers, reflecting persistent resource access disparities. Findings underscore the need for targeted interventions that enhance farmer education, expand financial access, integrate gender-responsive extension services, and promote youth engagement in CSA. These measures are critical to strengthening climate resilience and advancing sustainable agricultural development in climate-stressed regions like Mwingi West.

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INTRODUCTION

Climate change poses a significant and escalating threat to global agricultural systems, particularly in Sub-Saharan Africa, where smallholder farmers depend heavily on rain-fed agriculture and possess limited adaptive capacity (IPCC, 2014). In Kenya, these impacts are especially pronounced in arid and semi-arid lands (ASALs) such as Mwingi West Sub-county. The region is increasingly affected by erratic rainfall, prolonged droughts, and extreme weather events, all of which negatively impact agricultural productivity and rural livelihoods (NDMA, 2017; Kogo et al., 2022; Mogeni, 2024). Projections suggest that, without effective adaptation measures, climate-related shocks could reduce crop yields by up to 50%, with potential revenue losses of up to 90% by 2100 (IPCC, 2023).

Agriculture remains central to Kenya's economy, contributing approximately 20% to the national GDP and supporting over 70% of rural households (Central Bank of Kenya, 2024). In Kitui County, agriculture contributes approximately 87% to rural household income and directly employs more than 35% of the local population, with an estimated 235,542 households engaged in farming activities (Ministry of Agriculture and Livestock Development, 2025). However, increasing climate variability has exposed the vulnerability of these communities and underscores the need for sustainable and climate-resilient agricultural solutions (Ngetich et al., 2022).

In response, Climate-Smart Agriculture (CSA) has emerged as a key strategy to address climate risks by enhancing agricultural productivity, improving resilience, and mitigating greenhouse gas emissions (Bekuma, 2024; Regmi & Paudel, 2024). Practices such as agroforestry, conservation agriculture, integrated soil fertility management, and water harvesting have demonstrated potential in improving food security and sustaining livelihoods in vulnerable regions (FAO, 2021; Ogada et al., 2020). In Mwingi West Sub-county, CSA interventions have been introduced through programs such as KCEP-CRAL, ASDSP, and SIVAP. Yet, adoption rates remain low, limiting the potential benefits of these initiatives (Waaswa et al., 2024).

Multiple studies have identified socio-economic and demographic factors, such as gender, education, age, household size, access to credit, land tenure, and extension services, as significant determinants of CSA uptake (Waaswa et al., 2021; Musafiri et al., 2022; Mogaka et al., 2021). For example, farmers with higher education levels and off-farm income are better positioned to understand and invest in climate-smart innovations, respectively (Mogaka et al., 2021; Njogu et al., 2024). Gender dynamics also significantly affect adoption, with male-headed households often enjoying greater access to

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resources and information, although women's contributions, particularly in livestock and household-level decision-making, are increasingly acknowledged as vital (Chepkochei et al., 2025; Lipper et al., 2014).

Recent studies have provided important information on how farmers view and act toward CSA. Nevertheless, these studies have mainly focused on self-reported data, which can be biased and contextually unreliable. Moreover, the socio-cultural and institutional frameworks, such as community expectations, informal groups, and local governance, remain largely unaddressed (Gudina et al., 2023; Gichuki et al., 2023). These gaps diminish the explanatory power of current studies and point towards the need to develop more holistic and context-sensitive frameworks of CSA adoption.

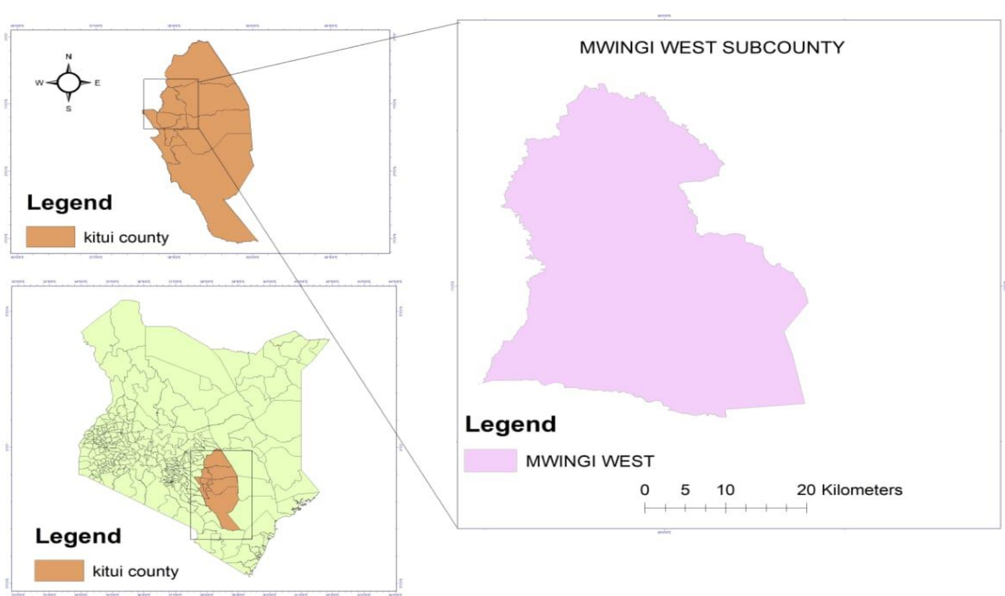
This study examined the socio-economic factors influencing smallholder farmers in Mwingi West Sub-county's adoption of Climate-Smart Agricultural Practices (CSAPs) in light of these difficulties. In order to produce context-specific insights that can guide focused policies and interventions, the study focused on demographic, economic, and institutional factors, including gender, age, education, income, and access to services. In climate-stressed regions, understanding patterns of CSA adoption is essential for enhancing the resilience of farming households and advancing sustainable agricultural development.

MATERIALS AND METHODS

Description of the Study Area

The study was carried out in the 1,090 km² Mwingi West Sub-county (Figure 1), Kitui County, Kenya, which is home to 115,816 people (KNBS, 2019). Agro-ecologically, the region is situated within the upper midland zones (UM3–4 and UM4) and the lower midland zone (LM4) (KCIDP, 2018). It has bimodal 300–600 mm of annual rainfall and 14–30 °C temperatures (Kenya Meteorological Department, 2022). Approximately 87% of rural households' income comes from agriculture, making it the most common source of income (Kenya County Climate Risk Profile: Kitui County, n.d.).

Figure 1: Map of the Study Area



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Research Design

This study adopted a cross-sectional survey design, enabling data to be gathered at one specific point in time. This design is appropriate for both descriptive and inferential analysis, facilitating the identification of relationships between variables (Sedgwick, 2014).

Target Population and Sample Size Determination

The target population consisted of 22,705 smallholder farmers in Mwingi West Sub-county, Kitui County (Ministry of Agriculture and Livestock Development, 2024). Furthermore, extension officers and farmer group leaders were incorporated to offer comprehensive perspectives on the social-economic determinants affecting the adoption of climate-smart agricultural practices.

Yamane's formula of 1967 was used to determine the sample size:

$$n = \frac{N}{1+N(e)^2}$$

$$n = \frac{22,705}{1+ 22,705\ (0.05)^2}$$

n=393

Sampling Techniques

A multi-stage sampling method was used in the study. In the first stage, Mwingi West Sub-county was purposively chosen due to its increased vulnerability to climate-related hazards and comparatively low adoption of climate-smart agriculture (CSA) (Campbell et al., 2020). The sub-county was divided into its four administrative wards in order to guarantee both ecological and geographic representation (Iliyasu & Etikan, 2021). Simple random sampling was used to choose smallholder farmers within each stratum (Noor et al., 2022).

Data Collection Methods

Data were collected primarily through questionnaires, which included both closed- and open-ended questions. Questionnaires were selected for their effectiveness in obtaining information from a large sample within a single point in time. Additional qualitative data were obtained through 7 key informant interviews with agricultural extension officers, guided by an interview checklist, and 8 focus group discussions with farmers. The focus groups facilitated interactive dialogue to explore shared experiences, opinions, and challenges in farming. All qualitative data were transcribed, categorised, examined for patterns and relationships, and interpreted.

Methods of Data Analysis

Using the Statistical Package for Social Sciences (SPSS) version 26, binary regression analysis and chi-square tests were used to assess the institutional and socio-economic factors influencing smallholder farmers' adoption of climate-smart agriculture (CSA) practices.

Binary Logistic Regression Model

Binary logistic regression analysis was conducted to determine the influence of various farmer characteristics on the likelihood of adopting climate-smart agriculture (CSA) practices. The logistic regression model.

$$\text{Logit}(P)=\text{In}\left(\frac{P}{1-P}\right) = \beta 0 + \beta 1X1 + \beta 2X2 + \beta 3X3 + \beta 4X4 + \beta 5X5 \ldots BnXn$$

Where:

P: Probability of adopting CSA practices.

1−P: Probability of not adopting CSA practices.

β0: Intercept of the model.

β1, β2, β3, β4, β5: Coefficients for the independent variables.

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X1, X2, X3, X4, X5: Independent variables (education level, age, gender, income level, farm size).

Adoption of CSA practices, coded as:

1 = Adoption of CSA practices ,0 = Non-adoption of CSA practices

Independent Variables (X1, X2, X3, X4, X5…Xn**)**

RESULTS

Demographic Information

The demographic profile of respondents, summarised in Table 1, offers an in-depth perspective on the study population engaged in climate-smart agriculture (CSA) adoption. Gender distribution revealed a predominance of female participants (59.3%) compared to males (40.7%), underscoring the significant role women play in smallholder farming within the study area. This pattern likely reflects their active engagement in agricultural production and household food security management.

In terms of age, the largest proportion of household heads (28.8%) were aged 50–59 years, followed by those aged 60–69 years (22.4%) and individuals over 69 years (19.8%). Respondents in the 40–49-year bracket constituted 20.9%, while only 8.1% were younger than 40 years. This age distribution suggests that farming is predominantly managed by older individuals, indicating a potential generational gap that could influence the uptake of contemporary CSA innovations.

Educational attainment data show that 44.0% of respondents had completed primary school, 26.0% had tertiary-level qualifications, and 21.9% had attained secondary education, while 8.1% lacked formal schooling. This relatively high literacy rate among farmers could facilitate the comprehension and adoption of CSA practices.

Household size analysis indicates that most households (51.4%) comprised 4–7 members, followed by 26.0% with 8–11 members, and 22.6% with fewer than 4 members. No household exceeded 11 members. Larger household sizes may enhance labour availability, which can be beneficial for implementing CSA practices.

With respect to farming experience, 36.1% of respondents reported more than 20 years in farming, while 25.7% had 30–39 years of experience. Interestingly, only 9.1% reported 20–29 years, a pattern that may point to either an inconsistency in reporting or demographic shifts in the farming community.

Regarding technology use, 52.2% of respondents possessed a smartphone, whereas 47.8% did not. This near-balanced distribution reflects increasing digital connectivity in rural farming communities, offering opportunities for disseminating CSA-related information, improving market access, providing weather forecasts, and delivering remote training.

Table 1: Demographic Information

Demographic data	Responses	F (%)
Gender	Male	160 (40.7)
	Female	233 (59.3)
Age of the house head	<40	32(8.1)
	40-49	82(20.9)
	50-59	113 (28.8)
	60-69	88(22.4)
	>69	78 (19.8)

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Demographic data	Responses	F (%)
Academic level	None	32(8.1)
	Primary	173(44.0)
	Secondary	86(21.9)
	Tertiary	102(26.0)
Family size	<4	89(22.6)
	4-7	202(51.4)
	8-11	102(26.0)
	>11	0(0.0)
Farming experience in years	>20	53(36.1)
	20-29	142(9.1)
	30-39	101(25.7)
Own smart phone	Yes	205(52.2)
	No	188(47.8)

Socio-economic Factors and Adoption of CSA among Smallholder Farmers

The results in Table 2 illustrate the influence of socio-economic factors and the adoption of climate-smart agriculture (CSA) among smallholder farmers. The analysis revealed statistically significant relationships between CSA adoption and land size, income levels (both farm and off-farm), as well as the distance of farms to the market.

In terms of land size, the majority of respondents (44.8%) owned between 4 to 7 acres, followed by 29.3% who owned less than 4 acres. Those owning between 7 and 10 acres made up 19.6%, while only 6.4% had land exceeding 10 acres. The chi-square value ($\chi^2 = 0.643$) with a p-value of 0.000 indicates a significant association between land size and CSA adoption. These results suggest that farmers with medium land holdings are more inclined to adopt CSA practices, likely because they have sufficient space to implement new farming methods without the complexity or cost burden faced by larger-scale farmers.

With regard to income from farming, 36.9% of farmers earned between KES 1,000 and 5,000 per month, while 35.9% earned less than KES 1,000. A further 20% reported earning between KES 5,001 and 10,000, and only 6.6% earned more than KES 10,000. The relationship between farm income and CSA adoption was statistically significant ($\chi^2 = 0.571$, $p = 0.022$), suggesting that farmers with slightly higher earnings from agriculture are better positioned to adopt CSA, possibly due to improved capacity to invest in necessary inputs or technologies.

Similarly, income from non-farm sources emerged as a significant factor ($\chi^2 = 0.921$, $p = 0.000$). A large portion of farmers (44.5%) earned less than KES 1,000 from off-farm activities, while 22.9% earned between KES 1,000 and 5,000. Others earned between KES 5,001 and 10,000 (19.9%), and over KES 10,000 (12.7%). These findings imply that additional income from other sources supplements household finances, enabling farmers to afford CSA investments. Thus, off-farm income appears to enhance the likelihood of CSA adoption.

Lastly, the distance from farms to market centres also significantly influenced CSA adoption ($\chi^2 = 0.564$, $p = 0.001$). More than half of the respondents (51.4%) lived 10–19 kilometres from the market, followed by 26% who were located 20 kilometres or more away. Only 13.5% lived less than 5 kilometres from a market, while 9.2% were within a 5–9 kilometre range. These figures suggest that farmers located closer to market centres have better access to inputs, information, and sales opportunities, making them more likely to adopt CSA practice.

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Table 2: Socio-economic Factors and Their Adoption among Smallholder Farmers

		F (%)	Chi-square (χ^2)	p-value
Land size owned in acres	<4	115(29.3)	0.643	0.000
	4-7	176(44.8)		
	7-10	77(19.6)		
	>10	25(6.4)		
Income from the farm	<1000	141(35.9)	0.571	0.022
	1000-5000	145(36.9)		
	5001-10000	81(20.0)		
	>10000	26(6.6)		
Income from other sources	<1000	175(44.5)	0.921	0.000
	1000-5000	90(22.9)		
	5001-10000	78(19.9)		
	>10000	50(12.7)		
Distance of the farm to the market	<5	53(13.5)	0.564	0.001
	5-9	36(9.2)		
	10-19	202(51.4)		
	20 and above	102(26.0)		

Logistic Regression Analysis for Demographic Factors and Adoption of CSA among Smallholder Farmers

Further, a binary logistic regression analysis was conducted to determine the influence of various farmer characteristics on the likelihood of adopting climate-smart agricultural (CSA) practices. The results in Table 3 indicate that education level significantly predicts CSA adoption. The odds of adoption among educated farmers were 4.36 times higher than among uneducated farmers (B = 1.473, $p < 0.001$). Similarly, farmers with higher income levels were significantly more likely to adopt CSA, with odds nearly 4.6 times greater than those with lower income (B = 1.523, $p < 0.001$).

Gender also played a significant role, with male farmers being 2.34 times more likely to adopt CSA than female farmers (B = 0.852, $p = 0.024$), likely due to differences in access to resources and decision-making power.

Conversely, large farm size had a negative influence on adoption. Farmers with larger farms were 75% less likely to adopt CSA practices compared to those with smaller farms (B = -1.403, $p < 0.001$), suggesting that implementation over large areas may be more resource-intensive or harder to manage.

In addition, younger farmers were significantly less likely to adopt CSA than older farmers. The odds ratio of 0.18 (B = -1.739, $p < 0.001$) implies that older farmers are more likely to implement CSA, possibly due to more experience, access to land, or engagement with agricultural programs

Table 3: Logistic Regression Output on the Adoption of CSA Practices

Predictor	B (Coefficient)	S.E.	Wald	(p-value)	Exp(B) (Odds Ratio)
Education	1.473	0.411	12.84	0.000	4.36
Gender (Male)	0.852	0.378	5.08	0.024	2.34
Income (High)	1.523	0.428	12.63	0.000	4.58
Farm Size (Large)	-1.403	0.381	13.57	0.000	0.25
Age (Young)	-1.739	0.412	17.83	0.000	0.18
Constant	0.456	0.198	5.3	0.021	1.58

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DISCUSSION

Socio-economic Factors and Climate-Smart Agriculture (CSA) Practices among Smallholder Farmers.

The analysis revealed statistically significant relationships between CSA adoption and farm size, income levels (both farm and off-farm), as well as the distance of farms to the market.

The study revealed that there was a significant association between farm size and CSA adoption. These results agree with Ahmed (2004), who argued that farm size plays a critical role in the adoption of climate-smart agricultural practices, particularly among smallholder farmers. He further argued that farm size is a key determinant influencing the uptake of new agricultural technologies, though the findings have often been mixed. While some studies suggest a positive correlation between larger farm sizes and the adoption of advanced agricultural practices, others highlight complexities in the relationship. Ndung'u et al. (2023) assert that farmers with larger landholdings are more likely to adopt new technologies, as they have the capacity to dedicate portions of their land for experimentation without jeopardising overall production.

The study established that gender was an influential factor in the adoption of CSA, with male farmers adopting CSA practices more readily than female farmers. This result agrees with Musafiri et al. (2022), who argued that gender dynamics significantly shape the adoption of climate-smart agricultural (CSA) practices, with the influence varying across contexts and studies. The results were in line with the argument by Musafiri et al. (2022) that male-headed households often exhibit higher adoption rates of agricultural technologies, attributed to their relatively greater access to resources, information, and training opportunities compared to female-headed households. According to Njuguna (2020) observed a positive and significant relationship was observed between male household heads and the likelihood of adopting water harvesting and management techniques. Similarly, Muriithi (2021) found that male farmers adopt crop rotation and agroforestry practices at higher rates than females. However, Asfaw et al. (2012) disagreed with the findings of this study by arguing that male-headed households were less likely to adopt wheat technology packages compared to female-headed households. Despite men often having greater decision-making authority, women's roles, sometimes indirect, remain critical.

The study established that age had a large influence on the majority of respondents. The study agrees with Manono et al. (2025), who argued that the age of household heads plays a critical role in the adoption of agricultural technologies, although its impact varies across different studies. The older farmers are more likely to adopt new technologies due to their accumulated experience and knowledge, which enables them to evaluate and apply technological innovations effectively. These farmers often possess a deeper understanding of farming practices, making them well-equipped to assess the potential benefits of new technologies. However, other studies, such as those by Mumo (2021) and Mauceri et al. (2005), indicated that as farmers age, they become more risk-averse and less inclined to invest in long-term innovations, potentially hindering their adoption of new technologies. Conversely, younger farmers are generally more open to innovation, are less risk-averse, and often have better access to information, enabling them to adopt new technologies more readily (Totin et al., 2018).

The study established that education plays a critical role in the adoption of CSA. The logistic regression results indicate that education level significantly predicts CSA adoption. The odds of adoption among educated farmers were 4.36 times higher than among uneducated farmers (B = 1.473, $p < 0.001$). Similarly, farmers with higher income levels were significantly more likely to adopt CSA, with

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odds nearly 4.6 times greater than those with lower income (B = 1.523, $p < 0.001$).

These results agree with Mogaka et al. (2021), who asserted that education plays a pivotal role in shaping farmers' capacity to adopt climate-smart agricultural (CSA) practices and that there is a significant positive relationship between education levels and the uptake of agricultural innovations. The results were supported by Nyang'au et al. (2021), who noted that higher education equips farmers to process information effectively and identify suitable technologies to address production constraints.

The study also revealed that household income had a significant influence on CSA adoption. Implying that, financial capacity enhances the ability to adopt innovative agricultural practices. These results were in line with Njogu et al. (2024), who argued that income levels, particularly off-farm income, play a crucial role in enabling the adoption of climate-smart agricultural practices. Off-farm income helps rural households address financial barriers, facilitating the purchase of essential inputs such as improved seeds and fertilisers. Similarly, Wanjira (2021) noted that off-farm income frequently serves as an additional financial resource, helping farmers cover expenses related to climate-smart agriculture, such as acquiring inputs or paying for labour.

CONCLUSIONS

Socio-economic Factors and Climate-Smart Agriculture (CSA) Practices among Smallholder Farmers.

The demographic profile reveals a farming population largely composed of older, literate women with moderate to large family sizes and significant farming experience. While digital penetration is still growing, the presence of smartphones among more than half of the respondents provides a potential avenue for promoting CSA practices. The study concluded that education, income, and gender positively influence CSA adoption, while large farm size and youthfulness are associated with a lower likelihood of adoption. These findings underscore the importance of targeted support for young and large-scale farmers and suggest expanding education and financial resources to increase CSA uptake.

RECOMMENDATIONS

To enhance the adoption of climate-smart agriculture (CSA) practices among smallholder farmers, policymakers, development agencies, and extension services should prioritise targeted interventions that address the key socio-economic determinants identified in this study. Specifically, programs should:

- Strengthen farmer education and training by developing accessible, locally relevant curricula that improve farmers' capacity to evaluate and apply CSA technologies, with particular attention to women who already play a dominant role in agricultural production.
- Expand financial support mechanisms, including affordable credit facilities, input subsidies, and promotion of off-farm income opportunities—to overcome financial barriers that limit CSA adoption, especially for resource-constrained households.
- Promote gender-responsive extension services that ensure equitable access to information, resources, and decision-making opportunities for female farmers, while addressing the cultural and structural barriers influencing adoption patterns.
- Leverage digital technology by using mobile platforms and smartphone applications to disseminate CSA-related information, weather forecasts, and market opportunities, capitalising on the growing rate of smartphone ownership.
- Design youth-inclusive programs that incentivise younger farmers to adopt CSA practices through innovation hubs, mentorship,

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and technology demonstrations, thereby closing the generational gap in adoption.

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