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Determinants of soil and water conservation practices adoption by smallholder farmers in the central highlands of Kenya

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ABSTRACT

The central highlands of Kenya play a vital role in supporting agricultural activities and sustaining the livelihoods of smallholder farmers. Despite its crucial role, the region faces substantial environmental challenges like soil erosion and land degradation, necessitating the adoption of sustainable land management practices. The aim of this study was to investigate the determinants of the adoption of Soil and Water Conservation Practices (SWCPs) among smallholder farmers in central Kenya. Primary data was collected from three administrative wards of Tharaka Nithi County (TNC) using 150 semi-structured household (HH) questionnaires, Key Informant Interviews (KII), and field observations. STATA and Microsoft Office Excel software were used to analyse the HH survey data, using descriptive statistics, inferential statistics, and the binary logistic regression model. Qualitative data from the KII was analysed through synthesized text summaries. The results show that 65.33 % of the respondents adopted SWCPs on their farms, while 34.67 % did not at the time of our study. The study findings further revealed that farm size ($\beta = 0.641$; $p < 0.05$), and Agro-ecological zone (AEZ) ($\beta = 1.341$; $p < 0.05$) positively influenced the adoption of SWCPs. On the other hand, distance from homestead to farm ($\beta = -0.003$; $p < 0.05$), and age ($\beta = -0.039$; $p \leq 0.05$) negatively influenced the adoption of SWCPs by the farmers. Challenges in SWCPs implementation included inadequate capital (76.53 %), high labor costs (62.24 %), lack of technical knowledge (34.69 %), lack of infrastructure (17.35 %), and insecure land tenure (1.02 %). These study findings hold the potential to guide the TNC government in formulating tailored strategies that can foster the adoption and sustainable implementation of SWCPs among smallholder farmers. If properly implemented, the strategies will bolster agricultural productivity, mitigate soil erosion, and enhance the region's overall environmental and economic well-being.

1. Introduction

Soil is a vital resource for maintaining ecosystem functions, carbon sequestration, and agricultural output (Lal, 2004; Baveye et al., 2016; Banerjee and van der Heijden, 2023). Soil, constituent elements, and water form prime assets in any productive agricultural land, therefore, they ought to be managed sustainably to achieve Sustainable Development Goals (SDGs) (Keesstra et al., 2018; FAO, 2021). Declining soil fertility is one of the greatest challenges facing agricultural production in most developing countries (Raimi et al., 2017; Dang, 2023). Various reasons are attributable to this trend, including land degradation, desertification, continued extractive farming practices, limited use of critical agricultural inputs, and minimal efforts to prevent or reverse soil erosion (Tittonell, 2014; Kopittke et al., 2022).

Soil and water erosion are significant sources of land degradation, making them a critical global concern. The Food and Agriculture Organization of the United Nations (FAO) reports that every year, about 12 million hectares of agricultural soils are lost worldwide through soil degradation (FAO, 2015). Globally, soil loss by water erosion is estimated at 28–36 Pg yr^{-1} (Borrelli et al., 2017; Quinton et al., 2010) while in Kenya, the mean soil erosion rates under the current land cover are estimated at ~5.5 t ha^{-1} yr^{-1} which is equivalent to ~320 Mt yr^{-1} of

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topsoil lost nationwide (Feeney et al., 2023). Whether caused by natural or human factors, soil erosion has short and long-term adverse effects on-site and off-site. Many studies have reported anthropogenic activities as the leading cause of degraded soils and water resources (Mugonola et al., 2013; Ashoori et al., 2016; Huang et al., 2020; Wang et al., 2022).

About 40 % of the earth's surface is covered by agricultural land under different managed ecosystems which face several challenges, including soil degradation (Lal, 2023). Poor agricultural practices among smallholder farmers lead to soil erosion and reduced agricultural productivity in Sub-Saharan Africa (SSA) (Mwanake et al., 2023). Sustainable use of land resources, soil erosion control, Soil and Water Conservation Practices (SWCPs), and appropriate cropping patterns has the potential to improve soil productivity, enhance carbon sequestration and prevent land degradation in SSA (Tiwari et al., 2008; Rotich et al., 2022; Tabe-Ojong et al., 2022). In principle, SWCPs help reduce environmental deterioration while preserving or boosting agricultural productivity (Nyamekye et al., 2018; Amfo et al., 2021; Ojo et al., 2021; Ngaiwi et al., 2023). Farmers in various countries have constituted diverse SWCPs to mitigate land degradation, including agroforestry, mulching, bench terraces, conservation tillage, and integrated nutrient management (Gachene et al., 2020; Diop et al., 2022; Hu et al., 2023). Other techniques include crop rotation, intercropping, fallowing, and water harvesting options such as tied ridges, pond construction, floodwalls, dams, dredging, and weeding of irrigation canals (Kpadonou et al., 2017; Moges and Taye, 2017; Fontes, 2020; Nyirahabimana et al., 2021).

Despite its benefits, the adoption level of SWCPs greatly varies in most developing nations (Teshome et al., 2016; Bagheri and Teymouri, 2022). Low adoption of SWCPs has been ascribed to large communication gaps among researchers, agricultural extension agents, and farmers among other factors (Njenga et al., 2021). Many studies have been conducted in different parts of the world to determine factors that influence the adoption of SWCPs among farmers (Ojo et al., 2021; Miheretu and Yimer, 2017; Degfe et al., 2023; Yifru and Miheretu, 2022). These factors can be grouped into five broad categories namely demographic (age, gender, marital status, household size), socio-economic (education, income, occupation, skills), farm characteristics (land tenure system, farm size, distance of farm from homestead, tropical livestock unit, perception of soil erosion), institutional factors, (access to capital and labor, training and awareness, access to agricultural extension services, access to farm inputs, social group membership, access to information) and bio-physical factors (slope of cultivated land, agro-ecological zonation) (Mugonola et al., 2013; Fontes, 2020; Bagheri and Teymouri, 2022; Asfew et al., 2023). Most of these factors such as agro-climatic conditions and natural resource endowments, affect the costs, returns, and risks of Soil and Water Conservation (SWC) investments and practices (Njenga et al., 2021).

Tharaka Nithi County (TNC) is a significant agricultural production area in the central highlands of Kenya, as it exhibits one of the highest crop diversity due to the favourable climate and soils (Mairura et al., 2022a; Wawire et al., 2023). Smallholder farmers in the Central Highlands of Kenya face numerous challenges related to sustainable agriculture, key among them being soil erosion and water scarcity. The TNC generally has a rugged terrain, making it highly susceptible to soil and land degradation (County Government of Tharaka Nithi, 2018; Wawire et al., 2021). Despite the region being identified as a suitable site for SWC due to the threats posed by land degradation and soil erosion (Nganga et al., 2019), SWCPs and their adoption by smallholder farmers remains uneven. While previous research has explored general soil fertility management patterns, there is a notable research gap in studies specifically dealing with SWCPs and the determinants of SWCPs adoption among smallholder farmers in the Central Highlands of Kenya. This research aims to bridge this gap by investigating the factors that either facilitate or hinder the adoption of SWCPs among smallholder farmers. Additionally, this study examines the limitations of SWCPs implementation. The study's specific objectives were: (a) To find out the factors that influence the adoption of SWCPs by smallholder farmers in central Kenya and (b) To identify challenges facing the adoption of SWCPs in the central highlands of Kenya. Understanding the factors that influence SWCPs adoption and related implementation challenges is crucial in providing a basis for informed policy decisions and designing effective interventions to promote sustainable farming practices in the Central Highlands of Kenya.

2. Methodology

2.1. Study area

The study area is geographically located on the eastern slopes of Mount Kenya within longitudes 37° 12′E and 37° 54′ E and latitudes 0° 18′S and 0° 6′ S. It covers a land area of about 181.8 km^2 and has three administrative wards (Chogoria, Ganga and Mwimbi) of Maara sub-county, in TNC (Fig. 1). Chogoria ward lies within the Upper Midland (UM) Ago-Ecological Zones (AEZs) (UM1, UM2, UM3), Ganga in between the UM and Lower Midland (LM) AEZs (UM3, LM3, LM4) while Mwimbi covers the LM AEZs (LM3, LM4 and LM5) (Kenya National Bureau of Statistics, 2019; Mairura et al., 2022b). The UM AEZs receive high rainfall amounts ranging from 1280 to 1800 mm per year, while the LM AEZs are characterized by lower average annual rainfall amounts of between 800 and 1280 mm (Jaetzold et al., 2007). A bimodal rainfall pattern characterises the area, with the long rains occurring between March and June while the short rains occur between October and December, making two complete cropping seasons. Altitude ranges from 800m above the sea level (asl) in the lower Mwimbi ward to 1800m asl in the upper Chogoria ward, with an average temperature of 20 °C. Humic andosols are prevalent in the forestlands, while humic nitisols with moderate to high inherent soil fertility dominate the farmlands in Maara sub-county (Muchena and Gachene, 1988; Ngetich et al., 2014).

Roughly 80 % of the population in TNC is involved in agriculture for food and income where food crops occupy around 43,799 ha, while cash crops span 14,839 ha (County Government of Tharaka Nithi, 2018). TNC receives an estimated 8.7 billion Kenyan Shillings (KES) from crops and KES 1.6 billion from livestock and livestock products (MoALF, 2017). Common cash crops grown in the region are tea (*Camellia sinensis*) and coffee (*Coffea arabica*), while food crops mainly comprise maize (*Zea mays*), beans (*Phaseolus vulgaris*), sweet potatoes (*Ipomoea batatas*), and bananas (*Musa* spp.). Different varieties of fruits and vegetables are also grown by farmers for subsistence and commercial purposes (Mairura et al., 2021; Wawire et al., 2021). Livestock kept in the study area include both exotic and indigenous cattle, goats, sheep and poultry (Mugwe et al., 2009). Tree species grown in the farms comprise grevillea (*Grevillea robusta*), blue gum (*Eucalyptus* spp.), and cypress (*Cupressus lusitanica*) mainly for firewood and timber provision (Kenya Forest Service, 2010).

TNC faces several environmental challenges including deforestation, climate change, soil erosion, and land degradation (County Government of Tharaka Nithi, 2023). Farming on steep slopes, overgrazing, charcoal production, sand harvesting and quarrying are some of the drivers of land degradation in TNC (County Government of Tharaka Nithi, 2018). SWCPs have been used by some farming households in TNC as on-farm interventions to land degradation, although most SWCPs are geared towards soil erosion control and harvesting or conserving water to boost crop production and improve pastures (MoALF, 2017). About 23 % of the households in TNC have been trained on SWC (GoK, 2014).

2.2. Research design

A mixed research design was employed in this study, where qualitative and quantitative research methods were used concurrently. The quantitative research method was used to collect data on SWCPs and factors affecting their adoption, while the qualitative research method was used to collect and analyse qualitative data to strengthen and bridge the gap in the quantitative research method.

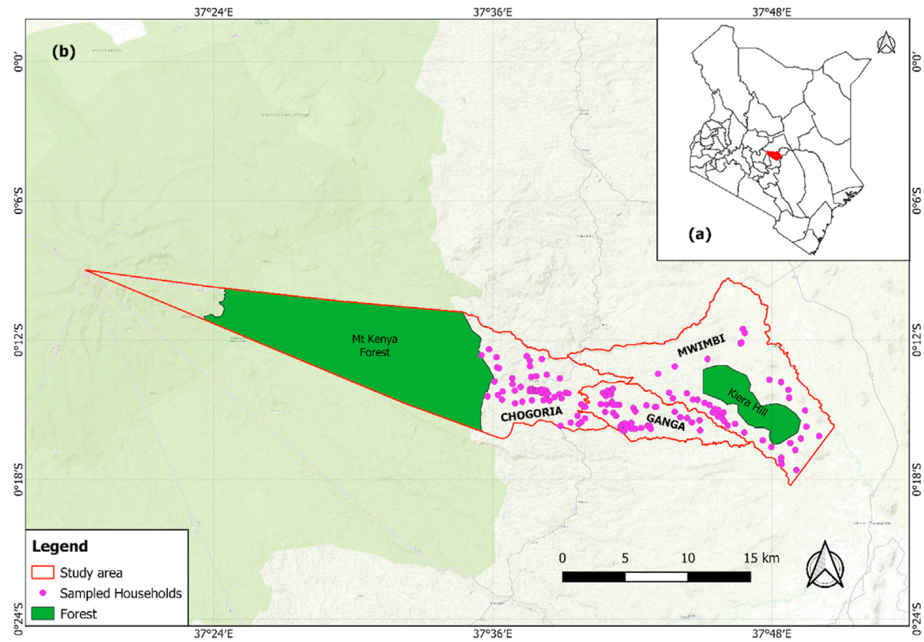

Fig. 1. Map of the study area; (a) Location of the study area in Kenya, (b) Sampled households within the three wards.

2.3. Sampling procedure, target population, and sample size

A multi-stage sampling approach was employed for this study where purposive and systematic sampling procedures were used in the selection of respondents. The first stage involved the selection of a sub-county to act as a representative of the TNC for this study. Maara sub-county was purposely selected due to its unique agro-ecological zonation, topographic variation, accessibility, and susceptibility to erosion based on literature review and discussions with TNC officers from the Department of Agriculture and Natural Resources. In the second stage, the target population was identified from three administrative wards in the upper, middle, and lower sections of the sub-county to represent the different AEZs and terrains. About 3798 active smallholder farming households (HHs) from the three wards in the study area formed the target population. This number of smallholder farmers was obtained from the local administrative officers' records, after which a sample size of 150 HHs was calculated using Equation (1) (Israel, 1992).

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

Where: n = sample size, N = Target population size, e = Level of precision (8 %)

Therefore, $n = \frac{3,798}{1+3,798(0.08^2)}$.

$n = 150.19 \approx 150$

Thirdly, proportionate sampling was used to distribute the number of respondents in each ward as guided by the respective number of farming HHs per ward, to enable equal representation (Table 1). Finally, systematic sampling was employed in data collection, where the sampling interval size (k) was arrived at by dividing the total number of farming HHs (N) in each ward by the sample size (n) of the respective ward.

Table 1
Sample size distribution and sampling intervals.

Ward	Land Area (km^2)	Farming HHs (N)	Sample size (n)	Percentage (%)	Sampling interval (k)
Chogoria	58.5	1596	63	42	11
Ganga	35.2	1139	45	30	8
Mwimbi	88.1	1063	42	28	7
Total	**181.8**	**3798**	**150**	**100**	

2.4. Ethical clearance, research license and consent

Ethical clearance to conduct this study was obtained from the ethics committee of the Doctoral School of Environmental Sciences of the Hungarian University of Agriculture and Life Sciences (MATE), Hungary. A research licence was also obtained from The National Commission for Science, Technology, and Innovation (NACOSTI) Kenya and shared with the local administration to facilitate the research. Additionally, verbal consent was obtained from HH heads before commencing the surveys.

2.5. Data sources and data collection tools

The fieldwork was conducted from June 25, 2023 to July 10, 2023. Semi-structured HH questionnaires, field observations, and Key Informants Interviews (KII) were used for primary data collection. A cross-sectional HH survey was used to collect data from the farmers using semi-structured questionnaires. The questions were developed in Open Data Kit (ODK), a digitized data collection interface after which they were pre-tested on 15 farmers in the neighboring Mitheru ward and adjusted accordingly. The questionnaires were then administered to the farmers by three trained research assistants from each of the wards of the study area under close supervision. The questions primarily focused on the types of SWCPs, socio-economic and demographic factors within which SWC were implemented and challenges faced by farmers in adopting SWCPs. In-depth interviews were also conducted with agricultural extension officers, community elders, and Community Based Organization (CBO) officers working with farmers on SWCPs in the study area to capture information that might have been overlooked in the HH questionnaires and simultaneously enrich information gathered through HH surveys. Field observations were also made at the farm level during the surveys.

2.6. Data analysis and presentation

Data gathered from the HH questionnaires was downloaded from the

ONA online platform and analysed using Microsoft Office Excel 2021, and STATA version 17 software. Farmers' demographic and socio-economic characteristics and challenges of SWCPs were analysed using descriptive and inferential statistics at a 95 % probability level. The analysis results were presented in the form of frequency counts, percentage tables, and graphs. Qualitative data were analysed by means of synthesized text summaries.

The binary logistic regression model was then used to explore the influence of demographic, farm, socio-economic, institutional, and bio-physical factors in the adoption of SWCPs using a dichotomous dependent variable (adopters and non-adopters). Adoption and non-adoption of SWCPs were captured at the farm level to provide a holistic view of the SWCPs on the entire farm and to understand the integrated impact of multiple practices across different plots within the farm. This study adopted the logit model given the binary nature of the adoption outcome and the flexibility of the logit model in handling various statistical considerations (Agresti, 2007; Jari and Fraser, 2009). Additionally, the outcome variables used (SWCPs adoption) were dichotomous in nature. It also provides a flexible and interpretable framework for analysing the complex relationships between various factors and the likelihood of SWCPs adoption (Agresti, 2007; Jari and Fraser, 2009).

Because the outcome variable is categorical in this case, we let $Y = (Y_1, \ldots, Y_k)$ be the vector of k that denotes outcome numbers of n trials of randomized k outcomes. The probability of each outcome's success is denoted by π_i. Therefore, for independent N observations, the multinomial probability that n_1 falls in the first category and π_k falls in k^{th} category, whereby $\sum_{i=1}^{n} y_j = n$. Thus, the probability function can be stated as:

$$f(y_1, \ldots, y_k, n, \pi_k) = P(Y_1 = y_1, \ldots, Y_k = y_k) = \left(\frac{n!}{y_1!, \ldots, y_k!}\right) \pi_k{}^{y_1} \ldots \pi_k{}^{y_k}$$

The binary logistic regression model utilizes maximum likelihood estimation to evaluate the probability of each categorical membership and is applicable when there is no natural order among categorical responses (Agresti, 2007). According to Tabachnick et al. (2013), the binary logistic regression model is useful in analysing a mix of explanatory variables such as continuous, dichotomous, and discrete, as it is in our case (Table 2).

Expressing the binary logistic regression model depicting the HH determinants of adopting SWCPs in stochastic form, the model is presented as follows:

$$Y_i = \ln\left(\frac{\mathrm{P}\,\pi_i}{1 - \mathrm{P}\,\pi_i}\right) = \beta_0 + \beta_1 X_1 + \beta_1 X_1 + \ldots \beta_k X_k + \beta_d D_d + \mu_i$$

Where Y_i is the binary outcome variable of interest (adoption of SWCPs), $\mathrm{P}\,\pi_i$ is the probability of adopting SWCPs and $1 - \mathrm{P}\,\pi_i$, is the probability of not adopting SWCPs, β_0 denotes the intercept, $\beta_1, \ldots, \beta_k$ denotes the coefficient estimates of the independent variables (HH factors), β_d is the coefficient estimate of the dummy variable for the ward arable fixed effect denoted by D, and the error term is denoted by μ_i. The subscript i denotes HHs $i = 1, \ldots, 150$. In this case, the adoption of SWCPs is the outcome variable taking value 1 if the HH adopted SWC and 0 if the HH is a non-adopter. Various HH factors such as age, gender, marital status, education level, family size, farm size, access to extension services, access to credit, labor type, and average monthly income were included as the explanatory variables of the SWCPs adoption (Table 2).

Table 2
Description of independent variables.

Variable name	Variable type	Variable Description	Expected Sign	Previous studies
Dependent variable				
Adoption	Binary	Farmers' adoption of SWCPs: adopters = 1; otherwise = 0		Asfew et al. (2023)
Independent variables				
Age	Discrete	Age of household head in years	+/−	Miheretu and Yimer (2017)
Household size	Discrete	No. of family members	+	Bekele et al. (2018)
Farm size	Continuous	Household farm size in acres	+/−	Moges and Taye (2017)
Distance	Continuous	Distance from home to farm in meters	−	Bekele et al. (2018)
Gender		Household head sex: female = 0; male = 1	+	Asfaw and Neka (2017)
Marital status	Dummy	Household head marital status: unmarried = 0; married = 1	−	Meresa et al. (2023)
Education	Dummy	Household head's education: no formal education = 0; formal education = 1	+/−	Belayneh (2023)
Income	Dummy	Household average monthly income (KES): <5000=0; >5000 = 1	+/−	Meresa et al. (2023)
Credit	Dummy	Household access to credit: yes = 1; no = 0	+	Asfaw and Neka (2017)
Labor type	Dummy	Household labor type: family = 0; hired = 1;	+	Teshome et al. (2016)
Extension services	Dummy	Household access to extension: yes = 1; no = 0	+	Degfe et al. (2023)

*KES = Kenya shillings.

3. Results and discussion

3.1. HH summary statistics

The study findings show that slightly more than a half (56 %) of the respondents were male while 44 % were female with HH heads having an average age of 52 years. The majority (78.5 %) of the respondents were married while the average HH size in the study area was 5 people. Most HHs reported a monthly income of between 6000 and 20,000 Kenyan shillings (KES). The average farm size in the study area was 1.71 acres, with an average distance from home of 79.43 m (m). Close to half of the farmers (47.0 %) had access to credit, and about 70 % had access to agricultural extension services. Most farmers (60.7 %) relied on family labor for their day-to-day farming activities. About 42.0 % of the respondents were residents of the UM AEZ of Chogoria (Table 3).

The dominance of male respondents in the study area is because in most SSA communities, men are the de facto HH heads in charge of decision making (Mugwe et al., 2009; Mwaura et al., 2021) although in some cases decisions can be made or greatly influenced by women even though they are not the HH heads (Nchanji et al., 2023). Women also have land use rights and execute most of the farm and household chores. Similar findings were noted in studies conducted in rural Kenya (Mugwe et al., 2009; Wawire et al., 2021), Tanzania (Mbaga-Semgalawe and Folmer, 2000) and Ethiopia (Belayneh, 2023). The youngest respondent was 26 years, while the oldest was 78 years with the average HH age being 52 years. Age is one of the factors affecting the ownership and ability to access production resources such as land, inputs, and capital, as well as their commitment to SWC investments (Byamukama et al., 2019). According to the Ministry of Agriculture, Livestock and Fisheries report (MoALF, 2017), 61 % of households headed by youths in TNC earn their income from farm wages. This underlines the importance of the agriculture sector for youth employment and livelihoods. Most respondents in our study area had attained either primary or secondary education. Educated farmers can read and write and are presumed to have a higher capacity to capture and synthesize technical information characteristic of

Table 3
Socio-economic characteristics of the sampled households.

Variables	Characteristic	(n = 150)	(%)	Min	Max	Mean ($\overline{X}$)	Std Dev (σ)
Gender	Male	84	56				
	Female	66	44				
Age (years)				26	78	51.58	10.38
Marital status	Single	7	4.7				
	Married	117	78.5				
	Widowed	18	12.1				
	Divorced	4	2.7				
	Separated	3	2				
Level of education	No formal education	6	4				
	Primary	70	46.7				
	Secondary	58	38.7				
	Tertiary	16	10.7				
Household size				1	9	4.54	1.35
Average monthly income (KES)	<5000	57	38				
	6000–20,000	66	44				
	21,000–35,000	22	14.7				
	36,000–50,000	4	2.7				
	>50,000	1	0.7				
Access to credit	Yes	71	47.33				
	No	79	52.67				
Access to extension	Yes	105	70				
	No	45	30				
Farm size (acres)				0.2	7	1.71	1.09
Distance of farm from homestead (m)				2	1000	79.43	152.84
UM AEZ	Yes	63	42				
	No	87	58				
Farm labor	Family	91	60.7				
	Hired	59	39.33				

*1 Kenyan shilling (KES) = 0.0072 USD at the time of data collection (June 2023).
*UM AEZ = Upper Midland Agro-ecological zone.

some SWC technologies (Marenya and Barrett, 2007). A study by Asfew et al. (2023) also revealed that educated farmers offer more cooperation to extension workers and are more willing to adopt new SWC technologies than less educated farmers.

3.2. Soil and water conservation practices

A total of 98 farmers (65.33 %) had adopted at least one SWCP on their farms while the remaining 52 (34.67 %) had not at the time of this study. Amongst the three wards, Chogoria, which lies in the UM AEZ had the most adopters of SWCPs (76.19 %) followed by Ganga (57.78 %) while Mwimbi (54.76 %) had the least adopters (Fig. 2).

Similar findings were reported by Mairura et al. (2022a), who also stratified their study area according to AEZs and established that the farmers' adoption rate of soil fertility management technologies was higher in the UM AEZs than in the LM AEZs. Nyangena (2008) also affirms that the location of a farm on the toposequence is a key determinant of SWC adoption by farmers.

A total of fifteen distinct SWCPs were documented in the study area (Fig. 3). Multiple responses from the HH heads showed that the top three most adopted SWCPs included terraces (54.67 %), minimum tillage (43.33 %) and crop rotation (35.33 %) while the three least practiced

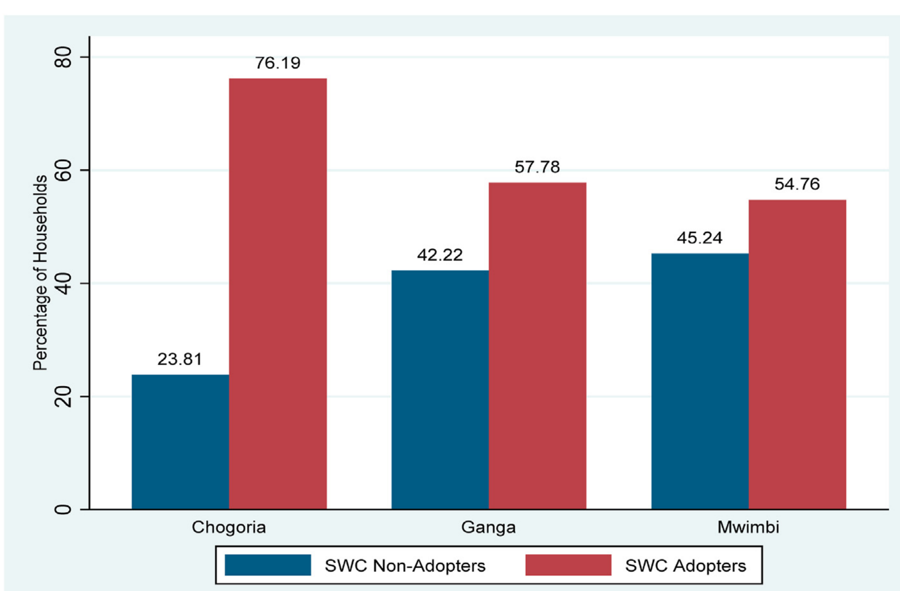

Fig. 2. Adoption of SWCPs per ward.

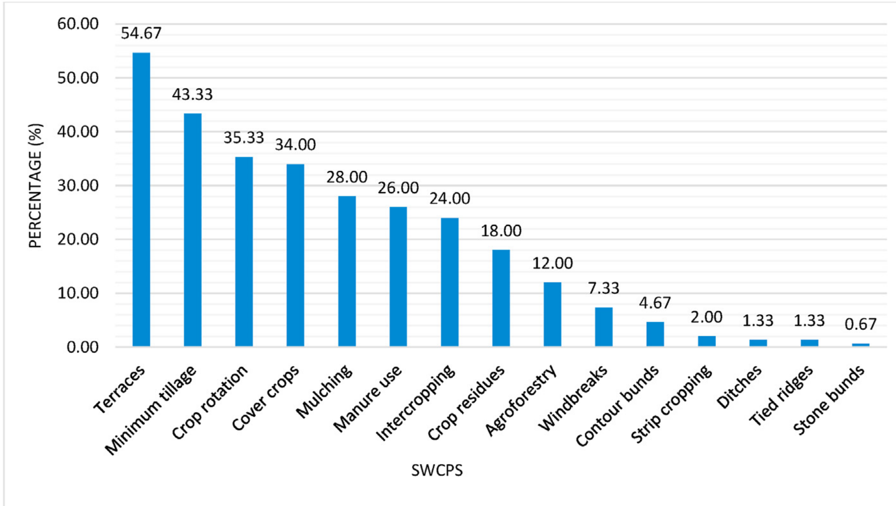

Fig. 3. Types of SWCPs adopted in the study area.

conservation measures were stone bunds (0.67 %), tied ridges (1.33 %) and ditches (1.33 %).

The fifteen SWCPs in the study area can be grouped into three broad categories namely; agronomic practices (cover crops, mulching, crop rotation, minimum tillage, crop rotation, crop residues); vegetative practices (agroforestry, windbreaks, strip cropping, intercropping); and structural/mechanical measures (terraces, ditches, tied ridges, stone bunds) (Karuku, 2018; Gachene et al., 2020). From the results (Fig. 3), it is evident that agronomic and vegetative SWCPs were dominant over structural SWCPs in the study area. This observation can be linked to the low adoption costs of the vegetative and agronomic practices compared to structural measures which require high initial capital and labor input. In SSA, agronomic and vegetative SWCPs have been applied widely due to their low cost of adoption (Gachene et al., 2020). The unique high adoption of terraces (a structural measure) in our study area can be attributed to it being an indigenous technology among Eastern African (EA) communities and its effectiveness in reducing surface runoff (70–92 %), especially in steep slopes (Gachene et al., 2020). Terracing and reduced tillage can reverse elevated rates of topsoil decline from agricultural practices across Kenya (Feeney et al., 2023). An informal discussion with community elders revealed that the implementation of terraces in the study area dates back to the 1960's after the initial introduction by the colonial government. Destaw and Fenta. (2021) further assert that in highland and midland areas characterized by medium to steep slopes, farmers are more likely to adopt terracing as a SWCP and climate change adaptation strategy. Structural and vegetative SWCPs have proven effective in tackling water runoff and erosion when properly implemented (Diop et al., 2022).

Among those farmers who practiced SWC, the majority (76.53 %) implemented a combination of two or more SWCPs while the remaining 23.47 % implemented only one type of conservation practice (see examples in Fig. 4). An interview with agricultural extension officers revealed that a combination of more than one SWCP is advisable as they complement each other. This results in more effective outcomes of

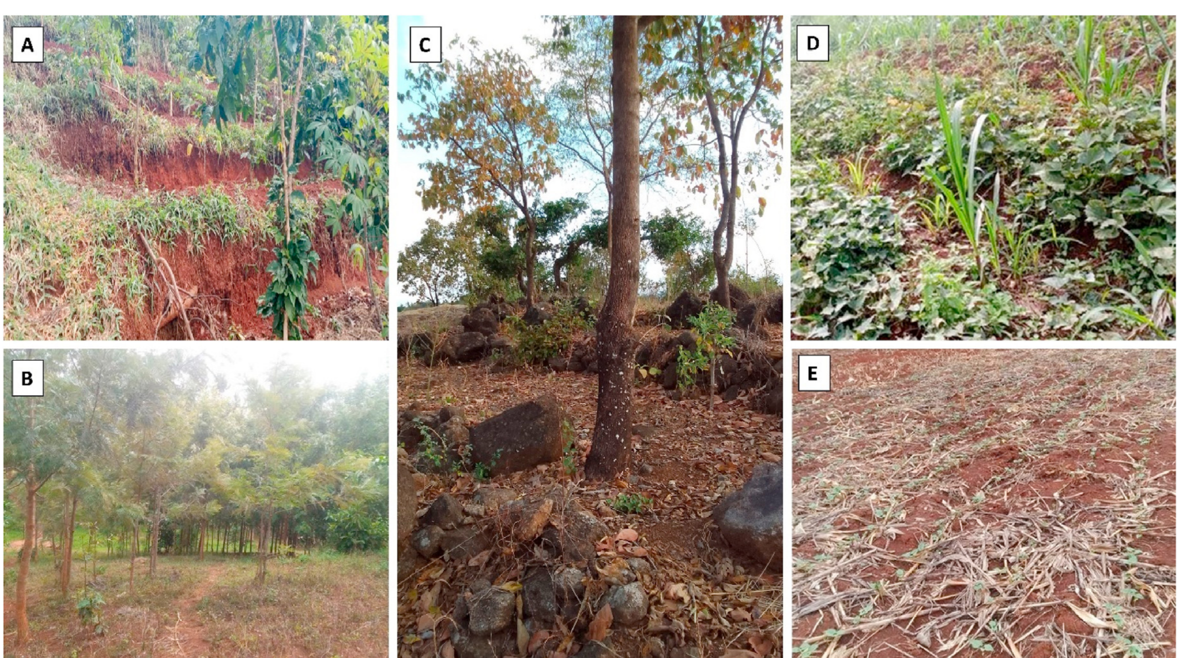

Fig. 4. Photos of select SWCPs: A - Terraces, B - Windbreaks, C - Stone bunds, D -Intercropping + Cover crops, E − Mulching.

reducing erosion, conserving water for plant use, and improving soil fertility, especially when practices like manure application, agroforestry and crop residues are in the mix. These findings contrast those of Mwanake et al. (2023), in the transboundary region of Kenya and Uganda, who found out that most farmers applied a single SWCP as most farms in the region were highly fragmented.

3.3. Factors influencing the adoption of SWCPs

The factors influencing the adoption of SWCPs in the Maara sub-county were determined by analysing the adoption of SWCPs (dichotomous dependent variable) against the various explanatory variables. All the hypothesized exogenous variables were checked for the probable presence of multicollinearity before running the binary logistic regression model, since there could be cases of recall bias in the HH responses. Correlation analysis was conducted to check for multicollinearity problems among the independent variables with a requisite threshold correlation coefficient of less than 0.8, implying the absence of multicollinearity issues. Accordingly, as depicted in the correlation coefficient heat map (Fig. 5), all explanatory variables had a correlation coefficient of less than 0.8, implying an absence of multicollinearity in the model.

Although all independent variables displayed no evidence of multicollinearity due to weak correlation, we conducted a variance inflation factor (VIF) to validate whether multicollinearity was absent or present (Table 4). This paper relied on the VIF test to detect the presence of multicollinearity. The rule of thumb for the VIF test is that VIF values greater than 5 and tolerance values less than 0.1 indicate the presence of a multicollinearity problem, while the converse is true (Miles, 2014; Studenmund, 2014). The results (Table 4) shows that the VIF and tolerance values for all selected variables are less than 5 and greater than 0.1, respectively. These collaboratively signify that including the explanatory variables together doesn't result in strong multicollinearity in the subsequent regression models.

The findings of the predicted binary logistic regression model coefficient estimates, marginal effect, standard error, and the associated significance values are shown in Table 5. The likelihood ratio test value (−84.34) indicates that the binary logit model and the selected explanatory variables fit the data correctly, signifying that log odds, probability of adopting SWCPs and the included independent variables collectively contribute to significant explanation of HH determinants. Although individually, some explanatory variables were insignificant, the pseudo-R^2 value (0.134), with a significantly ($P = 0.010 < 0.05$) higher LR Chi-square value (26.17) finding pointed out that the estimated model has sufficient explanatory power, hence the appropriateness of the model information.

Table 4
Multicollinearity test results.

Variables	SWCP Adoption	
	VIF	1/VIF
Age (years)	1.16	0.862
Household size	1.19	0.837
Farm size (acres)	1.36	0.737
Distance of farm from home (m)	1.40	0.713
Gender	1.20	0.832
Marital status	1.21	0.830
Level of education	1.37	0.729
Average monthly income (KES)	1.68	0.594
Access to credit	1.32	0.755
Labor type	1.51	0.660
Access to extension	1.72	0.583
Dummy variable for UM AEZ	1.61	0.620

*KES = Kenyan shilling; UM AEZ = Upper Midland Agro-ecological zone.

The HH head's age, farm size, distance from home to farm, and a dummy variable for HHs located in UM AEZ were the significant predictors of HH SWCPs adoption at 5 % significance level. Accordingly, HH age had a negative significant influence on HH SWCPs adoption ($\beta = -0.039$; $P = 0.050 \leq 0.05$). The marginal effect indicates that an increase in HH head's age by 1 year leads to a decline in the probability of adopting SWCPs by 0.7 %, holding all other variables constant. This can be alluded to the fact that as farmers age, they become weary and can no longer provide the intensive labor required for implementing labor intensive SWCPs. On the contrary, young farmers are more energetic and willing to invest in SWCPs whose benefits may not be realised immediately but in the long run. This finding is in line with that by Nyangena (2008); Asfaw and Neka. (2017); Degfe et al. (2023), who reported that HH head's age has a significant negative influence on the adoption of SWCPs. Conversely, Yifru and Miheretu (2022); Meresa et al. (2023) observed an insignificant influence of HH head's age on the adoption of SWCPs. Therefore, it is worth noting that as farmers get old, they gain more experience and could also want to adopt more productive practices with lesser labor.

The findings also indicated a significant negative effect of distance between homesteads and farms on the adoption of SWCPs; where an increase in distance by 1 unit would result in a decline in HH adoption of SWC ($\beta = -0.003$; $P = 0.036 < 0.05$). The marginal effect (Table 5)

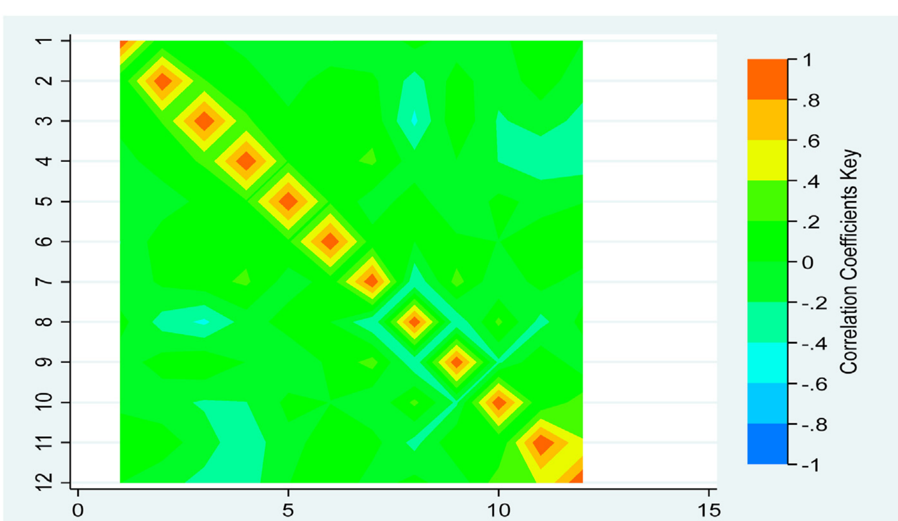

Fig. 5. Correlation matrix heat map for model multicollinearity test.

Table 5
Summary of binary logistic regression model output for factors influencing the adoption of SWCPs.

Variables	Coeff	Marginal Effects	Std. Err	Z	P-value >|Z|
Household head age	−0.039**	−0.007**	0.020	−1.96	0.050
Household size	0.091	0.017	0.150	0.60	0.545
Household farm size	0.641**	0.122**	0.259	2.47	0.013
Distance from home to farm	−0.003**	−0.001**	0.002	−2.09	0.036
Household head gender	−0.025	−0.005	0.400	−0.06	0.950
Household head marital status	−0.104	−0.020	0.449	−0.23	0.817
Household level of education	0.330	0.063	0.301	1.10	0.273
Household average monthly income	0.242	0.046	0.258	0.94	0.348
Household access to credit	0.599	0.114	0.472	1.27	0.205
Household labor type	−0.160	−0.031	0.403	−0.40	0.691
Household access to extension	0.192	0.037	0.550	0.35	0.727
Dummy for UM AEZ	1.341**	0.256**	0.519	2.58	0.010
Constant	−0.418		2.001	−0.21	0.835
LR $Chi^2(12)$	26.17				
Prob > Chi^2	0.010				
Pseudo R^2	0.134				
Log Likelihood	−84.34				
No. of Observations	150				

Note: ***p < 0.01; **p < 0.05; *p < 0.1.

shows that an increase in distance from home to farm by 1m reduces the probability of adopting SWCPs by 0.1 % at a 5 % significance level. This finding can be alluded to the fact that most smallholder farmers would want to invest more in nearby farms as distant farms disrupt or interfere with their daily home chores and other farm management practices. These findings align with the findings observed by previous studies (Moges and Taye, 2017; Wordofa et al., 2020; Degfe et al., 2023), which deduced that the longer the distance between homestead and farms, the lower the likelihood of adopting SWCPs.

The farm size showed a strong significant positive influence on the adoption of SWCPs ($\beta = 0.641$; $P = 0.013 < 0.05$). Farmers with larger tracks of cultivatable land are more likely to adopt new SWCPs, more so the physical practices. This is because farmers' perceived long-term farm benefits can be achieved by implementing physical SWC structures, which in most cases consume significant portions of the land. Therefore, farmers with small farm sizes are unwilling to adopt such SWCPs because the structures can further reduce the land size thereby lowering agricultural output. On the contrary, farmers holding large sizes of land do not give much attention to the land lost to SWC structures. As indicated by the marginal effect, an increase in the size of the land by one acre implies that the HH's adoption of SWCPs increases by 12.2 % at a 5 % significance level. In line with this observation, Kifle et al. (2016) and Belayneh. (2023) deduced that farmers with large sizes of land have a greater likelihood of adopting SWCPs compared to the farmers with small land sizes. Similar studies in rural Ethiopia and the Eastern and Southern Regions of Cameroon revealed that HHs with large farm sizes are prone to accepting new technologies because they can devote a section of their land to testing emerging innovations, while farmers with smaller farm sizes are less willing to do so (Gebremariam and Tesfaye, 2018; Ngaiwi et al., 2023).

The dummy variable accounting for the UM AEZ ward (Chogoria) showed a strong significant positive influence on the adoption of SWCPs ($\beta = 1.341$; $P = 0.019 < 0.05$). This implies that HHs residing in highland regions have a higher likelihood (25.6 %) of adopting SWCPs compared to HHs in the middle and lowest regions. This is due to the high and frequent precipitations received and the steep nature of the terrain in the highlands. Steeper slopes have a higher vulnerability to erosion and landslides (Nyangena, 2008). Consequently, farmers who operate on farmlands with steep slopes are more likely to adopt SWCPs due to the severity of soil erosion and property damage caused by landslides. Similarly, Amsalu et al. (2007); Teshome et al. (2016); and Sileshi et al. (2019) observed that HHs owning farms in highland regions are more likely to adopt SWCPs compared to the HHs operating on farms located in the middle or lowland regions as they have higher perception rate of probable soil erosion.

3.3.1. Estimating determinants of major SWCPS (terraces, crop rotation and minimum tillage)

Having estimated the binary logit model examining the household determinants on aggregated SWCPs, we disaggregated the analysis to specific majorly adopted SWCPs (terraces, minimum tillage, and crop rotation) in the next step. Table 6 presents the binary logistic results for minimum tillage, crop rotation and terraces. The binary logistic results showed that household head age ($\beta = -0.058$; $p < 0.05$), gender ($\beta = -1.471$; $p < 0.1$), hired labor ($\beta = -2.110$; $p < 0.01$) and the dummy for households residing in highland ($\beta = -3.775$; $p < 0.01$) were significant negative predictors of minimum tillage (Table 6). The study findings imply that as the household head's age increases, the odds of adopting minimum tillage decreases. Older household heads tend to be more cautious and risk-averse compared to their younger counterparts and thus, are less likely to adopt practices like minimum tillage. Similar findings were observed among smallholder farmers in the Kyrgyzstan (Tadjiev et al., 2023).

Male-headed households negatively affected minimum tillage adoption because women conduct majority of farm activities in Kenya and are likely adopt minimum tillage due to the less labor demands (Mugwe et al., 2009; Wawire et al., 2021). Similarly, most smallholder farmers implementing minimum tillage use family labor due to less labor demands and resource scarcity hence the negative predictor associated with hired labor. On the other hand, household access to credit ($\beta = 2.513$; $p < 0.01$) and farm size ($\beta = 0.655$; $p < 0.1$) have a significant positive influence on the adoption of minimum tillage. Access to credit provides the necessary funding which enables farmers to deploy SWC measures

Table 6
Binary logistic model showing household determinants of minimum tillage, crop rotation and terraces.

Variables	Minimum tillage	Crop rotation	Terraces
	Coefficient	Coefficient	Coefficient
Age	−0.058** (0.029)	−0.030 (0.022)	0.034 (0.025)
Household size	−0.198 (0.722)	0.900 (0.780)	0.155 (0.841)
Farm size	0.655* (0.342)	0.400 (0.319)	0.032 (0.199)
Distance of farm from home	0.005 (0.004)	0.004 (0.003)	−0.001 (0.001)
Gender	−1.471* (0.820)	−0.834 (0.743)	0.235 (0.545)
Marital status	−0.455 (0.729)	−0.400 (0.615)	0.002 (0.571)
Education level	1.254 (0.847)	−0.347 (0.528)	−0.526 (0.537)
Average monthly income	−1.686 (1.293)	−0.762 (0.824)	−0.113 (0.694)
Credit access	2.513*** (0.844)	1.800*** (0.564)	−0.497 (0.508)
Labor type	−2.110*** (0.809)	−0.931* (0.507)	−0.506** (0.646)
Extension access	−0.605 (0.699)	−0.431 (0.754)	0.834 (0.710)
Dummy for UM AEZ	−3.775*** (1.130)	−2.709*** (0.722)	0.486 (0.730)
Constant	5.345** (2.670)	1.902 (1.733)	−0.296 (1.896)
Wald Chi^2 (12)	37.21	46.21	14.55
Prob > Chi^2	0.0002	0.0000	0.0260
Pseudo R^2	0.6197	0.4654	0.1032
Log Likelihood	−37.767	−53.171	−56.722
No. of Observations	150	150	150

Note: ***p < 0.01; **p < 0.05; *p < 0.1. Robust standard errors are enclosed in parenthesis.

(Darkwah et al., 2019; Asfew et al., 2023). Udimal et al. (2017) further assert that access to credit is a positive driver of agricultural technology adoption. Similarly, household access to credit increased the adoption of crop rotation ($\beta = 1.800; p < 0.01$). Credit access creates an opportunity for farmers to address liquidity problems as it provides for the acquisition of different crop varieties for rotational purposes (Wawire et al., 2021). However, residing in the highland reduced the adoption of crop rotation ($\beta = -2.709; p < 0.01$). This can be linked to the suitability of certain crops for the highland zones and their effectiveness in controlling soil erosion. Moreover, hired labor ($\beta = -0.506; p < 0.05$) reduced the adoption of terraces due to the intensive labor requirements which are costly. Similar findings were reported by Chichongue et al. (2020) and Ojo et al. (2021) among the smallholder farmers in Mozambique and Southwest Nigeria respectively.

3.3.2. *Extended analysis and robustness checks: dealing with probable endogeneity*

We extended the analysis to ascertain the sensitivity of the results to different model specifications. Accordingly, we argue that the adoption of specific SWCPs by smallholder farmers is not independent or mutually exclusive from other alternative measures implemented on the same farm (Amare et al., 2014). Nevertheless, several econometric models that have been used in analysing the adoption of various SWCPs have failed to capture nexuses or interdependence between them and probable correlation between the error term or unobserved disturbances. For example, binary logit or ordered Probit models are only capable of estimating the adoption of one exclusive SWCP, with strictly only two dichotomous outcomes (Wooldridge, 2010). Addressing this shortcoming, multinomial models have been argued to be useful when dichotomous response models are mutually exclusive or unordered, and smallholder farmers can only select one of them from among the set of independent options (Young et al., 2009). Accordingly, in this paper we adopted Multivariate Probit (MVP) regression model as an alternative robust model in identifying significant household factors influencing adoption of terraces, minimum tillage, and crop rotation SWCPs (Amare et al., 2014). The main advantage of this model is that it allows a probable correlation between error terms and the correlation between the adoption of every SWCP (Belderbos et al., 2004; Young et al., 2009). Table 7 presents the findings of the overall summated SWCPs, and specific SWCPs (minimum tillage, crop rotation and terraces).

Before interpreting the results presented in Tables 7 and it is essential to look at the statistical validity of the model and interdependence of the selected dependent (SWCPs) variables. The models fitted reasonably well with Wald Chi-Squared values having $p < 0.05$. Therefore, this verified that adoption decisions among the three major SWCPs were independent, confirming that the coefficient estimates obtained are efficient. The MVP model revealed distinct results for joint and specific SWCPs estimations. Accordingly, the adoption of summated SWCPs increased with HH farm size and residing in the highland at 1 and 5 %, respectively. However, it appeared to decrease with distance from home to farm, and household head age at 5 %. Breaking the analysis to specific SWCPs, the MVP results showed that minimum tillage practice increased with farm size and household access to credit at 10 and 5 %, correspondingly. Nevertheless, it decreased with HH's head age and HHs residing in UM AEZ. Adoption of crop rotation increased with access to credit while it decreased in households residing in the highland. Moreover, while most HH's factors did not significantly influence adoption of terraces, HHs residing in UM AEZ increased its adoption. Qualitatively, the MVP results confirm the findings presented in Tables 5 and 6 Thus, the findings are consistent and reliable across different model specifications.

Table 7
Results of the Multivariate Probit Model for adoption of SWCPs (Minimum tillage, Crop rotation and Terraces).

Variables	SWCP	**Minimum tillage**	**Crop rotation**	**Terraces**
	Coefficient	Coefficient	Coefficient	Coefficient
Age	−0.021**	−0.026*	−0.016	0.017
	(0.011)	(0.015)	(0.013)	(0.013)
Household size	0.302	−0.143	0.590	0.104
	(0.366)	(0.380)	(0.428)	(0.452)
Farm size	0.387***	0.266*	0.182	0.024
	(0.135)	(0.158)	(0.152)	(0.113)
Distance of farm from home	−0.002**	0.004	0.002	−0.001
	(0.001)	(0.003)	(0.002)	(0.001)
Gender	−0.001	−0.590	−0.371	0.088
	(0.241)	(0.359)	(0.352)	(0.290)
Marital status	−0.025	−0.105	−0.232	−0.014
	(0.275)	(0.358)	(0.323)	(0.311)
Education level	0.361	0.412	−0.214	−0.349
	(0.258)	(0.416)	(0.303)	(0.287)
Average monthly income	−0.216	−0.426	−0.312	−0.055
	(0.291)	(0.601)	(0.400)	(0.359)
Credit access	0.319	1.172***	0.999***	−0.282
	(0.293)	(0.390)	(0.305)	(0.293)
Labor type	−0.010	−0.956**	−0.465	−0.309
	(0.276)	(0.380)	(0.292)	(0.334)
Extension access	−0.125	−0.300	−0.299	0.506
	(0.356)	(0.355)	(0.393)	(0.378)
Dummy for UM AEZ	0.769**	−1.845***	−1.501***	0.238*
	(0.324)	(0.445)	(0.346)	(0.354)
Constant	0.241	2.246	0.849	0.000
	(0.864)	(1.1260)	1.001	(1.016)
Wald Chi^2(12)	27.93	59.50	61.21	15.25
Prob > Chi^2	0.0057	0.000	0.000	0.0225
Log Likelihood	−84.038	−40.572	−53.729	−56.746
No. of Observations	150	150	150	150

Note: ***p < 0.01; **p < 0.05; *p < 0.1. Robust standard errors are enclosed in parenthesis.

3.4. *Challenges facing SWCPs adoption*

The farmers who carried SWCPs indicated they faced numerous challenges in the adoption and maintenance of the said practices and structures. The challenges encompassed inadequate capital (76.53 %), high labor costs (62.24 %), lack of technical knowledge (34.69 %), lack of infrastructure (17.35 %) and insecure land tenure (1.02 %) (Fig. 6).

The implementation and maintenance of SWCPs, especially structural measures, requires high startup capital and labor inputs. This can be challenging for smallholder farmers who in most cases have limited resources. This can result in low adoption, improper implementation, or poor maintenance, thereby failing to meet the desired goals. This finding resonates with that by Bojago et al. (2022) who identified lack of capital and material support as key challenges facing the implementation of SWCPs in Offa Woreda, Wolaita Zone, Ethiopia. Intensive labor in the construction and maintenance of SWC technologies was similarly cited as a major constraint by farmers in Lege-Lafto watershed, Dessie zuria district, South Wollo, Ethiopia (Yifru and Miheretu, 2022). Technical knowledge and infrastructure are also necessary for the establishment of most SWCPs, particularly the mechanical structures. In the Wenago district of southern Ethiopia, lack of technical knowledge and skills was reported as a limitation in the adoption of improved and introduced SWCPs by more than a half of the interviewed farmers (Meresa et al., 2023). Insecure land tenure was another challenge in adopting SWCPs in the Maara sub-county since some farmers had leased the land for a short period. A report by the Kenyan Ministry of Agriculture (Republic of Kenya, 2020) indicates that farmers may be unwilling to invest in long-term structural SWCPs such as terracing if they are not sure of reaping the benefits from such work in the long run.

4. Conclusions

This study sought to find out the adoption, and challenges of SWCPs in the central highlands of Kenya. The binary logistic regression model

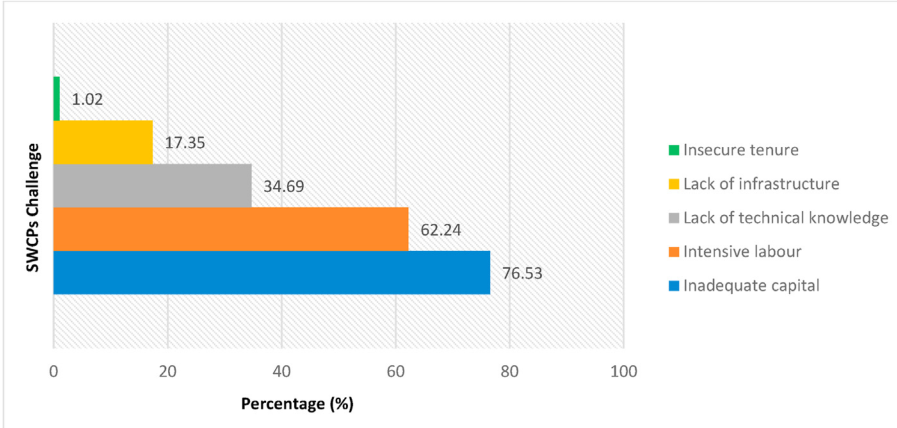

Fig. 6. Challenges facing SWCPs adoption in Maara sub-county.

was used to explore the factors influencing the adoption of SWCPs. Multivariate Probit Model was also used to identify significant household factors influencing the adoption of the three most popular practices (minimum tillage, crop rotation and terraces). It was established that fifteen different vegetative, agronomic, and structural SWCPs were implemented by smallholder farmers individually or in combination in the study area. Farmers' adoption of these practices was influenced (positively or negatively) by demographic, socio-economic, bio-physical, farm, and institutional characteristics. SWCPs adopters also encountered financial, labor, and infrastructural-related challenges in implementing the said practices.

Findings from this study are pertinent for shaping policies that address environmental, agricultural, and socio-economic challenges in TNC and other regions with similar settings. It also aligns with Kenya's vision 2030, big four agenda and the Malabo Declaration on Accelerated Agricultural Growth and Transformation for Shared Prosperity and Improved Livelihoods. This can be achieved by providing incentives to farmers practicing SWC, especially the youth to stimulate adoption by non-practicing young farmers. Improved access to credit among smallholder farmers can also help provide the much-required capital to initiate and maintain SWCPs. Promoting the adoption of more productive practices with smaller land sizes, labor, and capital requirements could also help solve some of the adoption challenges faced by the smallholder farmers in TNC. By improving adoption and addressing the existing SWCPs challenges, the livelihoods of farmers in the Maara sub-county can be enhanced, contributing to food security and rural development. Finally, we recommend detailed field assessments in the future of select farms practicing the various SWC techniques in the region, to measure the impact and effectiveness of the different SWCPs currently in place.

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Author contributions

Conceptualization: B.R. Writing-original draft: B.R., I.M., H.K., M.A.M. Methodology: B.R., I.M., H.K., C.M.O. Formal analysis: B.R., I.M. Visualization: B.R., I.M. Writing-Review and editing: B.R., I.M., H.K., M.A.M., C.M.O., P.N.J., A.C., E.M. Supervision: A.C., E.M.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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