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Exploring Socio-economic Determinants of Adoption Intensity of Soil Fertility Enhancement Technologies among Farmers in Drylands of Lower Eastern Kenya

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Catastrophic effects of climate change variation specifically intense rainfall have significantly contributed to decline in soil fertility. This problem has been exacerbated further by anthropogenic activities which are not limited to mono-cropping, over cultivation and overgrazing. There is therefore an urgent need to address this problem to enhance production of crops. Soil Fertility Enhancement Technologies (SFET) such as zero tillage, crop production, cereal-legume intercropping, organic and inorganic fertilizer, Zai pit, micronutrient supplementation, cover cropping, mulching and soil testing and mapping is among the current intervention that sought to address poor soils for better productivity particularly in the dryland areas. Despite their promotion, adoption of these technologies and the proportion of farmland treated with appropriate SFET remain low. A cross-sectional survey was utilized to gather data from 414 agricultural homes chosen via a multi-stage sampling method. The analysis included both descriptive and inferential statistics. The Heckman two-stage selection model was employed to analyze the association between the adoption and adoption intensity of SFET and socioeconomic factors. The model was used because it is able to accounts selection bias arising from other factors that might affect adoption other than the variables used by the study. The results indicated that off-farm income sources, involvement in SFET promotion initiatives, informal agricultural training, formal education level, farm size, access to agricultural information, and land use substantially impacted the choice to adopt SFET. Furthermore, farm size, land use, off-farm income sources, and livestock size significantly affected the intensity of SFET adoption. The study emphasizes the necessity for focused initiatives that improve access to agricultural information and expertise, especially about SFET. Integrating SFET into broader agricultural policies and strategies, such as subsidizing SFET inputs, will ensure the sustainability of agricultural production in dryland areas and improve the livelihoods of farmers.
Keywords: Intensification, drylands, agricultural productivity, adoption intensity, soil fertility.

INTRODUCTION

Rapid population growth worldwide which directly correlate with high demand for food has necessitated revitalization of crop production systems. More often, agricultural production is not able to merge the demand as a result of declining soil potential (Nepal *et al*., 2023). The reduction in soil fertility is a primary impediment to agricultural output in many developing nations (Mahmud *at el*., 2021). Decreasing levels of micro- and macro-nutrients, together with soil degradation, are the principal causes leading to a reduction in agricultural productivity in extensive regions of Sub-Saharan Africa (SSA) (Bakri *et al*., 2024). Agriculture is a significant contributor to the economies of many countries like Kenya (Rafael, 2023). Human activities such as overgrazing, deforestation, urbanization cause and expose soil to degradation, which ultimately lower agricultural productivity. This reduction leads to adverse social externalities like poverty, poor diets, and ultimately, higher mortality rates. Adequate and effective up-scaling the adoption of existing and emerging innovations that could promote food supply in response to the fast-expanding population is of great importance (Ferreira *et al*., 2022). A study by Nakashima *et al*. (2022) asserted that sustainable agriculture and food security in Sub-Saharan Africa may be attained by promoting and facilitating the intense and broad use of varied agricultural technologies,

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innovations, and management practices (TIMPs), particularly those that improve soil fertility. The proportion of individuals residing in extreme poverty in Sub-Saharan Africa rose, influenced by the region's swiftly expanding population, although agricultural output decreased from 57% in 1990 to 43% in 2021 (Wudil *et al*., 2022). A study by Rezaei *et al.* (2023) posited that under climate change conditions and insufficient soil fertility technology, projected crop output losses vary from 7% to 23%. Initiatives aimed at improving poor crop yields, especially in Sub-Saharan Africa, have encountered challenges due to the restricted utilization and acceptance of current soil fertility improvement methods by smallholder farmers (Ndegwa *et al*., 2023). Soil productivity enhancement, moisture retention improvement, and carbon sequestration augmentation can be accomplished by the use of SFET techniques, including crop rotation, mulching, Zai pits, and terracing; (Kiprotich *et al*., 2024; Mairura *et al*., 2022; Ndeke *et al*., 2021). These approaches enhance nutrient availability and absorption for crops, mitigate soil degradation, promote sustainable land use, and foster long-term soil health by integrating plant residues and organic amendments, augmenting soil organic matter, and increasing nutrient cycling. The advancement of methods designed to rehabilitate salinized land and improve soil fertility is crucial for agricultural growth (Feng *et al*., 2024). The efficacy of diverse soil fertility enhancement technologies is contingent upon geographical location, farmers' access to appropriate inputs (seeds and fertilizers), relevant information, and a conducive output market, all of which are crucial for the significant and sustained adoption of effective technologies (Lampach *et al*., 2021). Numerous research in Kenya have revealed socio-economic variables affecting the adoption of soil fertility enhancement technology among farmers (Javed *et al*., 2022; Mwaura *et al*., 2021). Factors such as employment, farming experience, perception of soil degradation, external help, and household size have been demonstrated to affect the acceptance and application of SFET by smallholder farmers in Central Kenya (Mairura *et al*., 2022; Musafiri *et al*., 2022). Additional factors, including gender, farm size, availability to extension services, and understanding of soil fertility management, affect both the decision to adopt and the degree of adoption of the technologies (Martey and Kuwornu, 2021; Mashi *et al*., 2022). Although previous studies have examined general soil fertility management practices that only focus on maintaining and using the existing techniques, scanty information have been documented regarding SFET that deals with introduction of better farming approaches to improve soil fertility. Similarly, little research has been done to determine the factors influencing SFET adoption among farming households in the arid regions of lower Eastern Kenya. This research seeks to address this gap by evaluating the socio-economic factors that either promote or impede the adoption and intensity of SFET among farmers in the region. Comprehending these characteristics, along with the associated implementation obstacles, is essential for guiding policy decisions and formulating effective interventions through funding and incentivize eco-friendly farming practices, which objectively advance sustainable agricultural production especially in the arid regions of Kenya.

MATERIALS AND METHODS

***Study area*:** This research was carried out in lower Eastern Kenya, especially in Makueni County. As an ASAL, the County endures severe climatic change and variability, leading to frequent droughts. The County comprises the Sub Counties of Makueni, Mbooni, Kibwezi East, Kibwezi West, Kaiti, and Kilome. The County, including an area of 8,176.7 km², is situated between 1º 35' and 3º 00' South latitude and 37º 10' and 38º 30' East longitude, as reported by (KNBS ,2019). Rainfall ranging from 300 mm to 400 mm on the lower slopes makes agriculture, the County's primary economic sector very difficult to rely on sustainably. The study focused on agro-ecological zones of LM 5 and LM 6 where common crops grown are beans, maize, green grams, cowpeas, mangoes, and vegetables (RoK, 2017). The County was selected because most SFET have been promoted in the region yet adoption intensities of such strategies is still low (Mwaura *et al*., 2021) .

***Research design, sample size and sampling technique*:** A Cross-sectional survey approach was utilized to gather data from farming households in the arid areas of Makueni County, particularly in Lower Midland 5 and 6. The sample size was calculated using Cochran formula and 414 farming households were used in this study method (Cochran, 1977). Makueni County was chosen in the initial phase due to its semi-arid conditions, which represent the wider lower Eastern Kenya region, significantly impacted by climate change and variability, and predominantly dependent on traditional agriculture for income and food. In the second step, two of the three sub-counties were randomly chosen, followed by the random selection of two wards from each of these sub-counties. In the third step, two sites were randomly picked from the four designated wards, and in the fourth stage, one sub-location was randomly chosen from each location. The Probability Proportionate to Size (PPS) technique was employed, whereby the number of farming households sampled from each sub-location was calculated by dividing the total number of farmers in the selected sub-locations by the total number of farmers across all selected sub-locations and multiplying by the overall sample size. Ultimately, individual farming households were chosen using simple random selection for the provision of questionnaires.

***Data collection instruments*:** The study used a semi-structured questionnaire to gather information from respondents. The questionnaire focused on the adoption of fourteen SFETs, as well as farmer and farm characteristics,

Table 1. Variable definition expected sign.

Variable	Definition	Expected sign
Gender	Gender of the household head (1=Male; 2=Female)	+/-
Education	Level attained by the household head (1=None; 2=primary; 3= Secondary;4=College;5 University)	+
Challenge on information access	Difficulties experienced in accessing agricultural information (1=Yes; 0 otherwise)	-
Main occupation	Type of job done by household head (1= Farming; 2=Self-Employed;3=Civil servant;4= Retired)	+/-
Reason for off-farm	Purpose of engaging in off farm activities (1=Supplement farming; 2=Manage financial risk; 3=Insufficient income;4 = Support expenses; 5=Expand investment)	+/-
Land use	Operations in the household farm (1= Food crop; 2=Cash crop; 3=Grazing; 4=Woodlots; 5=Bushes)	+/-
Off-farm income	Engagement of household head in off-farm activities (1=Yes; 0 otherwise)	+/-
Participation in SFET programs	Involvement of household head in programs promoting SFET technologies (1=Yes; 0 otherwise)	+
Informal training	Whether the household head has received informal agricultural training (1=Yes; 0 otherwise)	+
Age	Age of the household head	-
Household size	Number of family members of an household	+/-
Farming experience	Years spent in farming	+
Farm size	Total land size owned or used by a household in Acres	+/-
Livestock size	Number of livestock owned by a household	-
Land under cultivation	Size of land cultivated by a household in Acres	+
Family labor	Percentage of family labor dependence	+
Hired labor	Percentage of hired labor depended by a household	-

and socio-economic factors that influence the intensity of technology adoption (Table 1). The SFET of interest included compost manure, farmyard manure, inorganic fertilizer, micro-nutrient supplementation, crop rotation, use of cover crops, mulching, irrigation, zero tillage, soil testing and mapping, legume intercropping, crop residue, zai pit, and terracing.

***Model specification*:** Heckman two-stage selection model was employed to quantify adoption intensity of SFET. This model was appropriate because it addressed selection bias, which occurs when not all farmers opt to adopt SFET leading to potential bias in the observed adoption intensity data. In the first stage, probit model was run to identify factors influencing the adoption decision of SFET, and to derive Inverse Mill's Ratio (IMR). In the second stage, the intensity of adoption was assessed by utilizing the IMR as an explanatory variable to address selection bias.

The specifications of the models for the two stages are as follows:

Adoption equation from probit is specified in Eq. (1);

$$Y_i = \alpha_0 + \alpha_1 X_1 + \alpha_2 X_2 + \dots \alpha_n X_n + \varepsilon \quad \text{……………………}1$$

(Di= 1 if Y_i> 0 and Di = 0 otherwise) Di is the binary data representing adoption

Where Y_i is the latent dependent variable representing the decision to adopt or not to adopt SFET, $X_1, X_2 \dots X_n$ are explanatory variables that effect adoption decision measured on the i[th] farmers choosing to adopt SFET, $\alpha_1, \alpha_2 .. \alpha_n$.is coefficient of the explanatory variable and ε is the error term assumed to be independent and normally distributed with zero mean and constant variance. Lambda (λi), associated with the conditional probability of an individual household's choice to adopt, is defined by the formula in Eq. (2):

$$\lambda_i = \frac{f\ (x\ \beta)}{1-F\ (X\beta)} \text{………………………………………………} 2$$

Where λ_i is the IMR, f (x β) denotes the standard normal probability density function, and 1−F (Xβ) indicates the cumulative distribution function for a standard normal random variable. The value of Xi remains unknown; however, the parameters (β) can be estimated using a probit model that is informed by the observed binary outcome (Yi). Ordinary Least Squares (OLS) was used to model the outcome equation as expressed in Eq. (3);;

$$Yi = \alpha_0 + \alpha_1 X_1 + \alpha_2 X_2 + \dots + \alpha_n X_n + p\lambda\_i + u_i \text{............................} 3$$

Y_i is land area under SFET, α_0 is intercept term, $X_1, X_2, \dots X_n$ independent variables, $\alpha_1, \alpha_2 \dots \alpha_n$ are coefficients of independent variable, ρ is coefficient of IMR,λ_i is the IMR and μ_i is error term.

RESULTS AND DISCUSSION

***Descriptive statistics*:** Factors influencing adoption of farming technologies among farmers was substantial, evident through numerous studies that have been conducted (Ncube, 2018; Krah *et al*., 2019). In this study, the focus was to determine factors affecting adoption and adoption intensity of soil fertility enhancement technologies (SFET). The findings in Tables 2 and 3 provide an overview of farmers' traits in Makueni County, Kenya. In total, 414 respondents took part in the study, and only 10% (n=39) were non-adopters, whereas 90% (n=375) of them were SFET adopters.

Specifically, results in Table 2 show the distribution of selected factors influencing adoption among adopters and non-adopters in the study. The results show that gender was not statistically significant but higher percentage of males (50.7%) adopted SFET in comparison to females (49.3%). The educational profile indicates that education significantly influenced the adoption. This could mean that farmers who possess a high level of educational attainment can be efficient in integrating knowledge of adoption in their farming systems. The proportion of adopters who had attained secondary and higher levels of education were 62.1%, in contrast to the 33.4% of non-adopters who had achieved the same educational milestones. This suggests that education is linked to the development of cognitive skills necessary for the adoption of advanced agricultural technology and simultaneously provides the capability to execute SFET.

Access to knowledge and training is a critical factor that can influence adoption. Conversely, only 6.7% of adopters' reported difficulties in accessing information, whereas 64.1% of non-adopters experienced such issues. Participation in SFET programs and informal agricultural training indicates that over 50% of adopters were engaged, whereas the remaining 40% of adopters exhibited less involvement. On the other hand, the proportion of non-adopters engaged in programs of SFET was 5.1%, while the proportion of non-

Table 2. Summary of categorical variables affecting adoption of SFET technologies.

Variable	Category	Non-Adopters (n=39) (Frequency/Percent)	Adopters (n=375) (Frequency/Percent)	Pooled (n=414) (Frequency/Percent)
Gender	Male	16 (41.0%)	190 (50.7%)	206 (49.8%)
	Female	23 (59.0%)	185 (49.3%)	208 (50.2%)
Education	None	8 (20.5%)	28 (7.5%)	36 (8.7%)
	Primary	18 (46.2%)	77 (20.5%)	95 (23.0%)
	Secondary	9 (23.1%)	144 (38.4%)	153 (37.0%)
	College	3 (7.7%)	92 (24.5%)	95 (23.0%)
	University	1 (2.6%)	34 (9.1%)	35 (8.5%)
Challenge on information access	Yes	25 (64.1%)	25 (6.7%)	50 (12.1%)
	No	14 (35.9%)	350 (93.3%)	364 (87.9%)
Main occupation	Farming	32 (82.1%)	230 (61.3%)	262 (63.3%)
	Self-Employed	7 (17.9%)	145 (38.7%)	152 (36.7%)
	Civil servant	1 (2.6%)	103 (27.5%)	104 (25.1%)
	Retired	7 (17.9%)	36 (9.6%)	43 (10.4%)
Reason for off-farm	Supplement farming	3 (7.7%)	123 (32.8%)	126 (30.4%)
	Manage financial risk	1 (2.6%)	70 (18.7%)	71 (17.1%)
	Insufficient income	12 (30.8%)	93 (24.8%)	105 (25.4%)
	Support expenses	4 (10.3%)	164 (43.7%)	168 (40.6%)
	Expand investment	0 (0%)	44 (11.7%)	44 (10.6%)
Land use	Food crop	37 (94.9%)	365 (97.3%)	402 (97.1%)
	Cash crop	4 (10.3%)	103 (27.5%)	107 (25.8%)
	Grazing	5 (12.8%)	194 (51.7%)	199 (48.1%)
	Woodlots	0 (0%)	11 (2.9%)	11 (2.7%)
	Bushes	0 (0%)	25 (6.7%)	25 (6.0%)
Off-farm income	Yes	9 (23.1%)	268 (71.5%)	277 (66.9%)
	No	30 (76.9%)	107 (28.5%)	137 (33.1%)
Participation in SFET programs	Yes	2 (5.1%)	191 (50.9%)	193 (46.6%)
	No	37 (94.9%)	184 (49.1%)	221 (53.4%)
Informal training	Yes	3 (7.7%)	218 (58.1%)	221 (53.4%)
	No	36 (92.3%)	157 (41.9%)	193 (46.6%)

adopters involved in informal agricultural training was 7.7%. Structured training and programs that promote the use of technologies are essential for equipping farmers with the necessary information and skills for the adoption and maintenance of SFET practices.

Off-farm income served as a significant factor in adoption of SFET. About 71.5% of adopters reported earnings from off-farm sources, whereas only 23.1% of non-adopters reported similar earnings. This suggests that adopters are likely equipped with the tools necessary to invest in new technologies and effectively manage the associated risks through financial diversification. Similarly, adopters demonstrated a higher prevalence of off-farm activities, utilizing these engagements to supplement household expenses and enhance their farming operations. The primary reason non-adopters engage in these activities is insufficient income which in most cases they use to supplement income.

Study results also show that adopters exhibited a more varied land use pattern, allocating a considerably larger percentage of their land to cash crops (27.5%) and grazing (51.7%). In comparison, non-adopters primarily allocate a substantial portion of their land to food crops (94.9%). The adopters are implementing a strategy that is more resource-intensive and commercialized, as evidenced by the increased diversity of land uses they are supporting. Individuals who have not adopted the practice exhibited limited diversification and do not allocate any land for activities such as woodlots or bushes. This may be attributed to insufficient comprehension of the advantages associated with the use of SFET or due to constraints in available resources. Therefore, land usage patterns represented a critical factor that warrants careful consideration. Adopters exhibited an increased willingness to invest in agricultural practices that prioritize diversification and sustainability. Further, adopters revealed diverse occupations, with self-employment representing 38.7% and government service accounting for 27.5%. This contrasts with the non-adopters, who are exclusively involved in farming at a rate of 82.1%. This diversification may provide adopters with an enhanced financial framework for investing in emerging productive agricultural technologies.

The results in Table 3 indicate notable disparities in several key variables when comparing adopters and non-adopters of SFET. The average age for adopters was 47.6 years, while for non-adopters it was 54.2 years, indicating a statistically significant difference with a t-value of 2.5743***. This means that young farmers might demonstrate a greater openness to embracing new technologies, potentially due to their inclination to an idealistic view of innovation in agriculture. Households of adopters had a smaller average size, consisting of 6 members, in contrast to the households of non-adopters, which had an average of 7 members. This difference is statistically significant, with a t-value of 1.750**. Smaller households may experience reduced labor limitations, allowing adopters to distribute resources more efficiently for the implementation of SFET.

The farming experience varied considerably between the two groups, with a t-value of 1.8159**. Non-adopters reported an average of 17.7 years of experience, while adopters reported 14.7 years. This finding suggests that increased experience may correlate with a dependence on conventional practices, potentially leading to a reduced likelihood of adopting new technologies among farmers. Interestingly, while adopters possessed a greater average of 9 livestock compared to the 4 livestock held by non-adopters, the variance is notable and inversely related when it comes to land under cultivation. Non-adopters managed a larger area of land, averaging 5.6 acres, in contrast to adopters, who averaged 4.2 acres. However, this difference is only marginally significant, with a t-value of 1.4531*, suggesting potential variations in resource allocation priorities.

The utilization of labor demonstrated significant differences, with adopters depending on hired labor at a rate of 34.9%, in contrast to non-adopters at 6.9%, and displayed a greater reliance on family labour at 90.5% compared to 64.0% for adopters. However, there was a notable difference for family labor (t = 5.515***), which was highly significant. This suggests that adopters are accessing a wider range of labor sources, potentially placing them in a more advantageous position to implement scale- and labor-intensive SFET, which non-adopters may struggle to adopt due to their reliance on family labor.

Table 3. Summary of continuous characteristics affecting adoption of SFET technologies.

Variable	Unit	Adopters Mean (Std. Dev.)	Non-adopters Mean (Std. Dev.)	Pooled Mean (Std. Dev.)	T
Age	Years	47.6 (14.1)	54.2 (15.3)	48.2 (14.3)	2.574***
Household size	Number	6.0 (2.9)	7.0 (3.0)	6.0 (2.8)	1.750**
Years spent farming	Years	14.7 (9.9)	17.7 (9.9)	15.0 (9.9)	1.816**
Farm size	Acres	5.5 (6.0)	6.5 (6.5)	5.6 (4.9)	0.954
Livestock size	Number	9.0 (14.2)	4.0 (8.3)	8.0 (13.8)	-3.349
Land under cultivation	Acres	4.2 (3.5)	5.6 (6.0)	4.3 (3.9)	1.453*
Family labor	Percentage	64.0 (40.3)	90.5 (27.2)	66.5 (40.0)	5.515***
Hired labor	Percentage	34.9 (39.7)	6.9 (2.8)	32.3 (39.2)	-6.671

Table 4 illustrates the variability in the uptake rates of soil fertility enhancement technologies among adopters. Results show that compost manure was implemented by 14% of users, while 86% did not utilize the technique. Conversely, farmyard manure demonstrated the highest adoption rate at 90%, with 10% of adopters failing to implement it. Inorganic fertilizer was utilized by 51% of the respondents, while 49% did not apply it. Approximately 4% of individuals use micronutrient supplements, while 96% do not. Crop rotation was applied by only 37% of individuals, while 63% did not. The majority of adopters (79%) did not plant cover crops, while only 21% did. Approximately 20% of the farms utilized mulch, while the remaining 80% did not. Only 13% of adopters practiced irrigation, while 87% did not. The technique of zero tillage was implemented by only 1% of the population, while 99% did not employ the technology. Soil testing and mapping were conducted by only 3% of adopters, while 97% found it to be unhelpful.

Table 4. Distribution of soil fertility enhancement technologies (SFET) among adopters (n=375).

Variable	Category	Adopters (n=375) Frequency	Percent
Compost manure	Yes	54	14
	No	321	86
Farmyard manure	Yes	338	90
	No	37	10
Inorganic fertilizer	Yes	192	51
	No	183	49
Micro-nutrient supplementation	Yes	15	4
	No	360	96
Crop rotation	Yes	137	37
	No	238	63
Use of Cover crops	Yes	80	21
	No	295	79
Mulching	Yes	75	20
	No	300	80
Irrigation	Yes	46	13
	No	329	87
Zero tillage	Yes	4	1
	No	371	99
Soil testing and mapping	Yes	12	3
	No	363	97
Legume intercropping	Yes	27	7
	No	348	93
Crop residue	Yes	23	6
	No	352	94
Zaipit	Yes	22	6
	No	353	94
Terracing	Yes	117	31
	No	258	69

Only 7% of individuals employed legume intercropping, while 93% did not engage in this practice. Crop residue incorporation and Zai pit technology were implemented by only 6% of adopters, while 94% did not. Terracing was implemented by 31% of the adopters, while 69% did not use this practice. Even though they are adopters, it is clear that different methods are used in various ways to improve soil fertility. For example, a substantial number of individuals applied farmyard manure, while a few implemented practices such as the incorporation of micro-nutrients and zero tillage.

***Diagnostic test*:** One of the known problems in high-dimensional data sets, when many predictors strongly correlate, is multicollinearity. It might result in unstable estimates in traditional regression models, such as ordinary least squares (OLS) hence reducing predictive power (Magklaras *et al*., 2024). Therefore, multicollinearity was examined to ascertain whether explanatory variables in the study were correlated. Results of variance inflation factor (VIF) in Table 5 show that there was no multicollinearity evident from the mean that was less than 10.

Table 5. Variance inflation factor.

	VIF	1/VIF
Sources off farm income	5.035	0.199
Age	2.628	0.381
Reason for off farm income	2.534	0.395
Farm size	2.060	0.485
Livestock size	1.796	0.557
Household size	1.521	0.657
Farming experience	1.519	0.658
Family labor	1.503	0.665
Participation in SFET	1.453	0.688
Main occupation	1.418	0.705
Limited access to agricultural information	1.341	0.745
Informal agricultural training	1.234	0.811
Education	1.154	0.867
Land use	1.136	0.880
Gender	1.100	0.909
Mean VIF	2.112	

***Empirical Findings*:** Table 6 presents first stage results of Heckman-two-stage model done using probit regression. The model was fit as indicated by R-Square of 0.543, meaning that the independent variables can explain up to 54.3% of the dependent variable. Specifically, the findings reveal that the reason for venturing in off-farm sources ($p = 0.041$) positively and significantly affects the adoption of SFET at the 5%. This implies that for every one-unit increase in the off-farm sources, there would be an approximate increase of 0.069 on the adoption of the technologies, indicating that adoption levels are higher for those who have clear reasons for engaging in off-farm sources. Education also showed a positive relationship with the adoption of SFET, with a coefficient of 0.268 at a p-value of 0.055 even though it was significant at a 10%, indicating that higher levels of education somewhat enhance adoption. However, the broad confidence

Table 6. Selected factors affecting adoption of SFET technologies.

SFET Adoption	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig.
Reason for off farm	0.069	0.034	2.04	0.041	0.003	0.136	**
Age	-0.020	0.012	-1.57	0.117	-0.044	0.005	
Education	0.268	0.139	1.92	0.055	-0.006	0.541	*
Sources off farm	0.969	0.344	2.82	0.005	0.295	1.643	***
Livestock size	0.020	0.015	1.34	0.179	-0.009	0.050	
Land use	0.183	0.089	2.05	0.040	0.008	0.358	**
Participation in SFET	1.439	0.492	2.93	0.003	0.476	2.403	***
Informal training	0.744	0.368	2.02	0.043	0.022	1.465	**
Main occupation	-0.051	0.053	-0.97	0.334	-0.155	0.053	
Farming experience	-0.010	0.016	-0.64	0.519	-0.041	0.021	
Limited access to agric info.	-1.426	0.315	-4.52	0.000	-2.044	-0.808	***
Family labor	-0.007	0.005	-1.36	0.175	-0.018	0.003	
Farm size	-0.104	0.034	-3.09	0.002	-0.170	-0.038	***
Household size	0.072	0.057	1.26	0.206	-0.039	0.182	
Gender	-0.112	0.279	-0.40	0.687	-0.659	0.434	
Constant	0.478	1.153	0.42	0.678	-1.781	2.738	
Mean dependent var	0.906		SD dependent var		0.292		
R-squared	0.543		Number of obs		414		
F-test	140.42		Prob > chi2		0.000		
Akaike crit. (AIC)	150.05		Bayesian crit. (BIC)		214.46		

**** p<.01, ** p<.05, * p<.1*

interval of -0.006 to 0.541 suggests that the effect may vary. This study aligns with the findings of Tadesse and Ahmed (2023) who found that education was positively significant in determining decision to adopt climate smart agriculture technologies. Studies of Branca and Perelli (2020) and Neway and Zegeye (2022) associated education with efficiency of inculcating technology into the farming system.

Sources of other income other than farming (p = 0.005), displayed a strong and positive relationship on adoption of SFET. This means that one-unit increase in the sources of off farm income augment adoption by 0.969 units. It implies that more diversified sources of income substantially improve adoption. This is inconsistent with the report that sources of off farm income decreased adoption of sustainable practices (Alemayehu *et al*., 2024). Land use (p = 0.04) revealed a positive impact on adoption of SFET. This means that good land use contributes to more adoption by 0.183 units. It can be deduced that farmers are more likely to embrace SFET if they make efficient use of their land, possibly by diversifying their crop production or maximizing its usage for sustainable activities. As a result, one of the most effective methods to encourage wider usage of these technologies could be to promote better land management practices. The study of Kolady *et al*. (2021) reported that allocated land to crop production affected adoption of precision agriculture technology.

Participation in specific programs that promote SFET was positive with a coefficient of 1.439 (p = 0.003). This implies that participation in programs related to SFET technologies is an important factor that enhances adoption. The study of Kolady *et al*. (2021), concluded that there is need to put up programs that promote the use of technologies such practices of precision agriculture. Informal agricultural training (p = 0.043) showed a positive influence on adoption of SFET. This suggests that access to informal agricultural training greatly increases adoption by 0.744 units. It has been observed that technical training encourages farmers who have not received training to embrace technology, and it has also improved information exchange among farmers in the same community (Mutungi *et al*., 2025). Training was effective in influencing adoption of low carbon technologies among rice farmers (Liu *et al*., 2019). This buttress the need to orient programs of SFET to be farmer centered for better adoption.

Limited access to information showed that it can lower adoption as indicated by its negative significance at 1%. It means that the more the less access to agricultural information, adoption of the technologies can be lowered by 1.426 units. This further depicts that access to information plays a very important role in improving the outcomes. The study of Dalango and Tadesse (2019) found that access to input information was significant in adopting mineral fertilizer. Gemtou *et al*. (2024) also reported that access to reliable information affected decision to adopt climate smart agriculture practices.

Farm size also contributed negatively towards adoption of SFET despite showing strong correlation (p = 0.002). This indicates that increasing farm size by one unit decreases adoption by 0.104 units. This could depict that the greater the size of the farm, the less the adoption, probably as a result of higher demands on time or resources. This report relates well with the findings of Tadesse and Ahmed (2023) who found that the size of land negatively affected adoption of irrigation systems. However, farm size positively influenced adoption of soil and water conservation technologies (Kifle 2021; Maru *et al*., 2022; Mosissa *et al*., 2019).

The Ordinary Least Squares (OLS) regression was used in the second stage to determine factors affecting adoption intensity of SFET (Table 7). The model accounts for a significant amount of the variation in adoption intensity, as evidenced by an R-squared value of 0.709, which shows that 70.9% of the variation in the dependent variable is explained by the independent variables in the model. The overall model demonstrates high significance ($F = 54.552$, $p < 0.01$), affirming its validity. The inverse Mills was significant at 10% ($p<0.1$), suggesting that at least the model account for selection bias.

The findings show that farm size was significant ($p < 0.01$) in affecting adoption intensity. This suggests that as the size of the farm increases, the likelihood and degree of SFET adoption intensity can rise by 0.647. More extensive farms tend to possess greater resources, such as land and capital, which can facilitate the adoption of SFET. More extensive farms might be in a stronger position to take advantage of economies of scale, which can render investments in sustainable technologies more feasible and cost-effective. The study of Asravor *et al*. (2022) reported that the use intensity of mobile banking services was influenced by the size of land of a household.

A notable negative correlation (p-value < 0.01) between livestock size and the intensity of adoption indicating that as livestock size increases, farmers show a reduced tendency to enhance the adoption intensity of SFET. This might arise from the fact that more land can be allocated to livestock production when it is given priority than in integrating SFET. Additionally, livestock operations may already depend on conventional farming methods and may view SFET as not immediately advantageous to their livestock-focused endeavors. Hence, these farmers might allocate additional resources to livestock management, thereby restricting their capacity to embrace new technologies. This results conflict the findings that livestock size positively affected the extent of adopting organic related soil fertility management technology such as farmyard manure (Mwaura *et al*., 2021). Similarly, results do not correlate with the report that livestock size positively influence intensity of adopting agriculture conservation technologies (Ngaiwi *et al*., 2023).

Land use was negatively significant ($p < 0.05$) in influencing adoption intensity of SFET. This implies that purpose to which land is set to serve could reduce adoption intensity by 0.097 units. This finding suggests that a farmer's choice to utilize their entire land exclusively for other practices such as grazing or woodlot development rather than crop production likely diminishes their motivation to adopt new SFET. It is possible that land uses may not align with the primary

Table 7. Selected factors affecting adoption intensity of SFET technologies

Adoption intensity	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig.
Reason for off farm	-0.078	0.048	-1.63	0.104	-0.173	0.016	
Age	0.015	0.012	1.31	0.190	-0.008	0.039	
Education	0.107	0.081	1.31	0.190	-0.053	0.267	
Sources of off farm inc.	-1.273	0.517	-2.46	0.014	-2.290	-0.257	**
Livestock size	-0.037	0.010	-3.66	0.000	-0.057	-0.017	***
Land use	-0.097	0.041	-2.39	0.018	-0.178	-0.017	**
Participation inSFET	-0.014	0.237	-0.06	0.955	-0.480	0.453	
Informal agric training	-0.231	0.221	-1.05	0.296	-0.665	0.203	
Main occupation	-0.023	0.037	-0.63	0.527	-0.096	0.049	
Farming experience	-0.009	0.013	-0.70	0.482	-0.034	0.016	
Limited access to agric info.	-0.408	0.433	-0.94	0.346	-1.259	0.442	
Family labor	-0.005	0.003	-1.63	0.103	-0.011	0.001	
Household size	0.067	0.042	1.58	0.114	-0.016	0.149	
Gender	-0.255	0.211	-1.21	0.226	-0.670	0.159	
Farm size	0.647	0.032	20.39	0.000	0.585	0.709	***
IMR	-2.512	1.520	-1.65	0.099	-5.502	0.477	*
Constant	3.252	1.019	3.19	0.002	1.249	5.256	
Mean dependent var	4.154		SD dependent var		3.538		
R-squared	0.709		Number of obs		375		
F-test	54.552		Prob > F		0.000		
Akaike crit. (AIC)	1581.74		Bayesian crit. (BIC)		1648.50		

**** p<.01, ** p<.05, * p<.1*

objective of this SFET advancement aimed at enhancing crop cultivation. Size of land allocated to crop cultivation had a positive effect on uptake of precision agriculture practices as reported (Kolady *et al*., 2021)

The relationship between non-farm sources of income and adoption intensity was negatively significant ($p < 0.05$). This means that increase in the sources of off farm income in a household potentially reduce adoption intensity by 1.273 units. This implies that farming would experience significantly reduced burden and pressure with income from various sources, as reliance solely on farm-derived livelihood would not be the primary incentive for adopting improved farming technologies. Therefore, it demonstrates that enhancing off-farm income would redirect focus and concentration in farming activities. Similar finding was reported by Ishara *et al*. (2023) who reported that income from sources other than farming decreased the adoption intensity of mineral fertilizer.

***Conclusion*:** The aim of this study was to determine socio-economic characteristics influencing adoption and the intensity of adopting SFET. Heckman two-stage was used to model the relationship between farmers` traits and adoption of SFET. The study concludes that socio-economic factors such as sources of off farm income, participation in programs promoting SFET, informal agricultural training, education, reasons for sourcing in off farm income, farm size, limited access to agricultural information and land use contributed the most in the adoption of SFET, which implies a need to disseminate information and knowledge about the skills of seedbed management. Adoption intensity was affected by farm size, land use, sources of off farm income and livestock size. Therefore, to achieve full-scale adoption, policies should ensure access to increased training programs, improvement in the dissemination of information, better land management promotion, and integration of SFET into diversified farming systems. Besides, targeted interventions that address income diversification and optimization of farm size will further increase the level of adoption to ensure sustained agriculture and livelihoods.

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***SDGs addressed*:** No Poverty, Zero Hunger, Climate Action

***Policy referred*:** National Agricultural Policy (NAP); Climate-Smart Agriculture (CSA) Framework, National Climate Change Response Strategy (NCCRS) / Policy.

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