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Do combined sustainable agricultural intensification practices improve smallholder farmers welfare? Evidence from eastern and western Kenya

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Abstract

Smallholder farmers often bundle different sustainable agricultural intensification (SAI) practices to boost crop yield and address soil fertility challenges. However, there is a dearth of empirical studies that investigate farmers' adoption of SAI bundles and their subsequent impacts. Using data from a three-wave panel survey of smallholder maize-legume producers in Kenya, we examine the adoption and payoffs from 10 SAI practices clustered into five dominant groups. We use a random effects multinomial logit model to determine the choice of SAI cluster at the plot level while controlling for unobserved individual heterogeneity. The results show that the number of extension contacts, farm labor availability, household wealth, and education of household heads positively and significantly affect the adoption of SAI clusters while renting plots and poor soil quality have negative effects. The multinomial endogenous treatment effects model results reveal significant variability in crop yield, total variable cost, revenue, and net income across the five SAI clusters. The benefits vary by crop system, region, and cropping year, indicating that a one-size-fits-all extension design is unsuitable for farmers. The study suggests the promotion of participatory extension policies that would allow locally adaptable and highly profitable bundles of SAI practices to be identified, refined, and disseminated.

KEYWORDS
clusters, multinomial endogenous treatment effects, sustainable agricultural intensification, welfare

JEL CLASSIFICATION
D13, Q01, Q16, Q33

1 | INTRODUCTION

Rural farm households in Sub-Saharan Africa (SSA) are primarily small-scale and depend heavily on agriculture as a source of livelihood. They operate under volatile environmental conditions that contribute to low land productivity and perennial food insecurity. Climate change is a major source of agricultural production risk (Jayne et al., 2018), mainly due to severe and frequent droughts and flooding. Reduced soil fertility is caused by continuous tilling of arable land using poor agronomic practices (Odendo et al., 2010) and land fragmentation from the growing population (Pretty et al., 2011). Enhancing smallholder agricultural productivity is key to ensuring food and nutrition security (Kim et al., 2019).

The Green Revolution (GR) aimed to increase agricultural productivity in developing countries but failed to take off in SSA due to institutional and political challenges (Evenson & Gollin, 2003). Conservation agriculture (CA) was subsequently proposed as an environmentally friendly approach to restoring land productivity but has not alleviated food shortages (Giller et al., 2009), mainly because of the slow release of nutrients to plants from manure compared to chemical fertilizers, particularly in intensive cereal production systems (Montt & Luu, 2020). Sustainable agricultural intensification (SAI) is another approach that has been promoted by international agencies and other commissions concerned with the sustainability of agricultural production. The approach aims to achieve more agricultural output with limited inputs and land while enhancing the sustainability of agricultural production. Notwithstanding the multiple benefits that the adoption of SAI practices stands to offer to smallholder farmers, it is still unclear what determines the level of adoption of SAI practices, especially when considered as bundles, the underlying motivation for full, partial, or non-adoption of a bundle or bundles of SAI practices across varying cropping practices. Also unclear from the existing body of literature are the underlying determinants of SAI practices adoption behavior by smallholder farmers across cropping patterns.

It is against this backdrop that this study investigates the adoption and impact of 10 SAI practices that are widely used under maize-legume farming systems in Kenya, and were promoted by the International Maize and Wheat Improvement Center (CIMMYT) under the Adoption Pathways Project[1] (APP). The SAI practices are namely: (1) chemical fertilizer; (2) improved seed varieties (yield enhancing); (3) pesticide; (4) herbicide (crop protection); (5) organic manure; (6) maize legume intercropping; (7) legume rotations (traditional soil restoring); (8) minimum tillage; (9) short-term soil and water conservation practices; and (10) long-term soil and water conservation practices (modern soil restoring). This study provides insights into the adoption constraints of SAI clusters and identifies SAI clusters with the most significant payoffs. It achieves this by grouping different SAI practices into clusters that better reflect farmers' choices of production practices. Using the identified clusters, a random-effects multinomial logit model is applied to investigate and establish the determinants of SAI cluster adoption while controlling for unobserved individual heterogeneity. Finally, a multinomial endogenous treatment effects model is used in the study to estimate the impact of adopting different SAI clusters on outcomes, including crop yield, revenue, total variable cost, net income, and labor use.

Although the adoption of SAI practices has the potential to transform SSA agricultural systems and improve the resilience of smallholder farmers (Pretty et al., 2011), there is a dearth of knowledge on the role of agricultural technology adoption on the development of African agriculture (Vink, 2022). However, there is an emerging strand of studies that have examined the adoption of SAI practices, although most of them have focused on the adoption of singular SAI practices, such as chemical fertilizer (Marenya & Barrett, 2009) and improved seed varieties (Kathage et al., 2016; Michler et al., 2018). In practice, farmers often adopt bundles of different SAI practices. Other studies considered the adoption of discrete but multiple SAI practices and not as combinations (Arslan et al., 2017; Kassie et al., 2015; Teklewold et al., 2013; Wainaina et al., 2016). Several studies have acknowledged the lack of SAI practices that are universally suitable for smallholder farmers (Petersen & Snapp, 2015; Pretty et al., 2011; Wainaina et al., 2016). Smallholder farmers operate in heterogeneous agro-climatic and resource conditions, making it difficult to generalize the use and effect of SAI practices across regions. Thus, the choice of the combinations of SAI practices adopted tends to be region- and context-specific (Yigezu et al., 2018).

A few studies have considered the adoption of selected combinations of SAI practices (Kassie et al., 2013, 2015; Teklewold et al., 2013) but with the scope limited to estimating adoption rates, determinants of adoption, and correlations in adopting different practices. Other empirical studies have reported that SAI practices improve soil fertility, crop yield, and income (Khonje et al., 2018, 2022; Teklewold et al., 2013; Tilman et al., 2011). Considering the multiple benefits that SAIs offer, there is a lack of empirical evidence on (1) the combinations of different SAI practices that mirror farmers' production practices; (2) factors that determine the adoption of different combinations of SAI practices; and (3) the benefits of adopting a combination of different SAI practices among smallholder producers. To our knowledge, no study has investigated these issues by applying a K-mode clustering algorithm to group SAI practices into dominant bundles that mirror what farmers do.

Teklewold et al. (2013) attempted to tease out the impacts of the combined use of a few SAI practices on household income and labor demand, whereas Kassie et al. (2018) explored the impact of the combined use of

[1] The APP project investigates how smallholder decisions are influenced by socioeconomic factors, changes in farming systems, and external factors (such as climate variability, markets, and policies).

SAI on yield and production costs. The main challenge is that the potential list of SAI practice combinations is large, although not all such combinations are relevant. Therefore, cluster analysis can be used to overcome this challenge as it can be used to combine and vary SAI practices into useful bundles that mirror those that are known to have been adopted by farmers. While most studies on SAI practices have solely focused on maize, our analysis includes maize and bean crops, representing the main staple crops in Kenya for which SAI practices are primarily promoted. Given the diversity in land uses, this study also segregates data into maize-beans intercrop, maize monocrop, and beans monocrop plots to provide policy insight into interactions of crop types with SAI adoption. Takahashi et al. (2020) point out the lack of analysis of profitability as a shortcoming of SAI studies, which is an issue we address by evaluating the benefits to smallholder farmers of adopting different combinations of SAI practices.

In Kenya, Ndiritu et al. (2014) analyzed seven SAI practices and evaluated gender differences in SAI uptake, and found that gender differences matter in the adoption of manure and minimum tillage practices. Wainaina et al. (2016) modeled the trade-offs and complementarities across seven SAI practices and found that SAI adoption varies across different ecological conditions. These two studies did not consider the adoption of herbicides and pesticides; yet herbicides (e.g., glyphosate) are mostly used as complements to minimum tillage to control weeds, and pesticides are used to control maize stem borer moths. Moreover, neither of these studies considered a combination of SAI practices that farmers often use. Generally, most studies on the adoption of SAI practices ignored the effect of adoption on farm net income, especially in maize-based farming (Takahashi et al., 2020).

Therefore, to our knowledge, this is the first study that has used a combination of indicators including yield, total variable cost, revenue, and net income to analyze the profitability of SAI practice after adoption. Furthermore, it generates information on the drivers of the adoption of the bundles of SAI practices chosen by farmers and the subsequent welfare benefits. This information is critical for designing and promoting appropriate policies to encourage the uptake of SAI clusters that are consistent with local farmer needs.

The rest of this article is structured as follows. We start by describing sustainable agricultural intensification practices, followed by the empirical strategy in Section 3. A summary of the study area and data sources is presented in Section 4. The results are presented and discussed in Section 5. Section 6 concludes the paper by drawing several implications.

2 | SUSTAINABLE AGRICULTURAL INTENSIFICATION PRACTICES

This section provides an overview of SAI practices and the clustering process.

2.1 | Description of SAI practices

Smallholders typically adopt a combination of SAI practices to increase land productivity and reduce natural resource degradation (Khonje et al., 2018). For instance, minimum tillage reduces soil disturbance and increases soil water holding capacity, thus limiting soil health degradation effects of conventional tillage. When combined with soil and water conservation practices such as crop residue retention and mulching, this can stabilize soil moisture and temperature and therefore conserve the structure of the uppermost soil layer (Montt & Luu, 2020). Intercropping enables plant roots to grow at different soil depths absorbing nutrients from different soil layers, while crop rotation interrupts the infection chain. Montt and Luu (2020) show that when combined with crop residue retention and minimum tillage, intercropping could serve as an integrated pest management practice and improve soil nutrient content. Manure application has the potential benefits of long-term maintenance of soil fertility, organic matter content, and nutrient supply (Teklewold et al., 2013).

Under favorable environments, input-intensive practices such as improved seed varieties have the potential to increase crop yield compared to traditional landraces (Wainaina et al., 2018). When combined with chemical fertilizer, this can lead to increased crop yields, improved food security, and income for rural households. Although minimum tillage helps to preserve soil structure, it requires weed management and hence the use of herbicides. Pesticides are also used, mainly to control maize stem borer moths that are widespread in Kenya.

2.2 | Clustering SAI practices

The 10 SAI practices we consider could generate a large number of possible combinations of practices available for farmers. Not all of these combinations are attractive or relevant. Therefore, we focus on dominant clusters of practices that farmers tend to adopt. For our dataset, we define SAI practices as discrete choices and use the K-modes clustering algorithm to group them into dominant clusters.

The algorithm uses frequency-based methods and minimizes the distances between SAI practices and group modes to define clusters. Huang (1997) and He et al. (2006) show that the K-modes algorithm is efficient and effective in classifying categorical data. The K-modes approach uses the dissimilarity measure to define total mismatches of the corresponding attribute to cluster plots. The smaller the number of mismatches between plots, the more similar the plots are (Huang, 1997). The K-mode algorithm takes the most frequent value for each attribute to reach the minima (He et al., 2006; Roever et al., 2018).

Following Roever et al. (2018), we use the “klaR” package in R to classify 3608 plots into clusters according to the types of SAI practices used. We follow the five basic steps involved in cluster analysis (Mooi & Sarstedt, 2010): (1) choosing the observational elements to be clustered (plots); (2) choosing the variables in each observational unit to be analyzed (10 SAI practices); (3) selecting of clustering algorithm (K-mode algorithm); (4) determining the number of cluster sets (first we use qualitative judgment based on cluster size and employ multiple random starting seeds by varying clusters from 3 to 8 K-modes solutions); and (5) validating cluster solutions (chi-square test statistic for testing independence between SAI clusters). Finally, a cluster size of 5 was chosen for its easy interpretation and stability despite variations in the random starting seed.

2.3 | Clusters

The K-modes clustering generated the following distinct SAI clusters:

Cluster 1 is yield-enhancing and protecting (EP).
Cluster 2 is yield-enhancing, protecting, traditional, and modern soil restoring (EPTM).
Cluster 3 is yield-enhancing and traditional soil restoring (ET).
Cluster 4 is yield enhancing, protecting, and traditional soil restoring (EPT).
Cluster 5 is traditional soil restoring (T).

Table 1 describes the attributes of each cluster. Major attributes in each cluster are circled based on the adoption rate relative to the overall adoption rate of all the other practices. Differences between clusters were tested using chi-square and multivariate tests due to the imprecision of the clustering methods, variable selection, and the target number of clusters. Results showed significant differences across cluster groups, suggesting the generation of a distinct set of SAI clusters is appropriate (see Table A1 of the Online Appendix.)

3 | CONCEPTUAL AND ECONOMETRIC FRAMEWORK

3.1 | Conceptual framework

Smallholders often adopt different combinations of SAI practices. Thus, the adoption of SAI clusters may improve smallholder welfare in various ways such as by increasing yield/food production and income from the sale of agricultural produce (Adolwa et al., 2019; Hörner & Wollni, 2022; Tesfaye et al., 2021). In the context of this study, Figure 1 depicts ten SAI practices available to farmers grouped into the following five clusters using the K-modes clustering algorithm as mentioned above. The adoption of these clusters is directly influenced by farm and social-economic variables and institutional factors. The adoption of various SAI clusters could directly increase land productivity and hence crop yield. It could also increase labor demand. For example, practices such as intercropping, manure use, and short-term soil and water conservation strategies such as mulching, are labor intensive and increase production variable costs practices such as minimum tillage are labor-saving and may lower production variable costs. We presume that the adoption of clusters EP, EPTM, and EPT, with yieldenhancing practices, may increase household earnings by generating larger marketable surpluses. We also postulate that the adoption of SAI clusters with soil and water conservation practices would lead to increased crop yields and household income.

3.2 | Random effects multinomial logit model

A random-effects multinomial logit model is used to investigate the determinants of SAI cluster choice while controlling for unobserved individual heterogeneity. Consider a sample of farm households indexed by $i = 1, \dots, I$, owning p plots, and let $j = 0, \dots, J$ be the feasible SAI cluster choices available to the household. Households cultivated more than one plot and may vary the SAI cluster used on a plot between production seasons. Given the panel nature of the data, the observed covariates that explain the choice of SAI cluster may be correlated with time-invariant unobserved household-level heterogeneity. Following Hartzel et al. (2001), we estimate a multinomial logit with a random effects model and include a latent variable at the household level as a random intercept. Random utility V_{ijpt} generated by a cluster is:

$$V_{ijpt} = (\alpha_j + u_{ij}) + X_{ipt}\beta_j + \varepsilon_{ijpt} \tag{1}$$

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TABLE 1 Adoption rates of the SAI practices across each of the five clusters defined using K-mode clustering.

Clusters	Percentage adoption rate of SAI per cluster									
	C	R	T	M	SWT	SWL	S	F	H	P
EP	8	17	7	13	13	26	23	15	22	19
EPTM	25	32	67	25	12	27	22	18	29	20
ET	29	13	8	21	9	25	22	30	13	12
EPT	10	25	14	22	36	15	25	28	32	46
T	28	13	4	19	30	7	8	9	4	3
	100	100	100	100	100	100	100	100	100	100

Note: C = Intercropping, R = Rotation, M = Manure, T = Minimum tillage, F = Fertilizer, S = Improved seed, H = Herbicide, P = Pesticide, SWT = Soil and water conservation: short term, SWL = Soil and water conservation: long term. The circled values indicate adoption rates for each SAI practice greater than 17% across the five clusters.

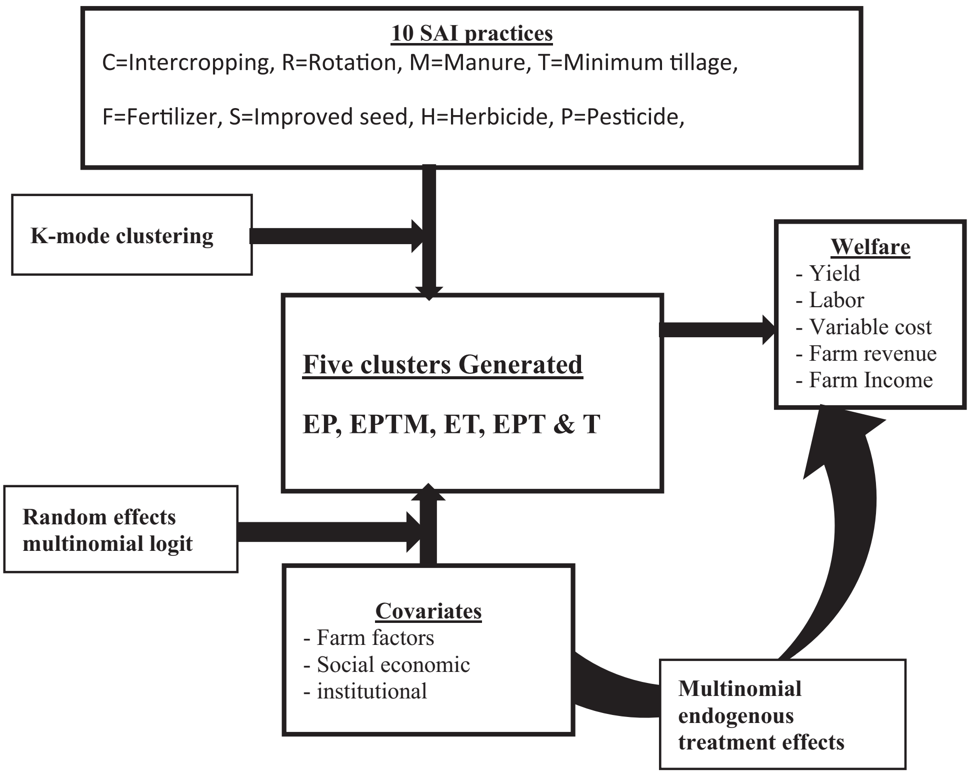

FIGURE 1 Conceptual framework.

Source: Authors' conceptualization.

where j represents the SAI cluster, i represents farm household, X_{it} is observed exogenous variables (household, physical, and institutional and farm characteristics) including year dummies, α_j is the constant term for cluster j, u_{ij} is the individual heterogeneity term representing the influence of idiosyncratic household characteristics, β_j denotes the vector of unknown model parameters to be estimated, and ε_{ijpt} is the error term independently distributed according to a type I extreme value distribution.

Although the independence of irrelevant alternatives (IIA) assumption always holds conditionally on all covariates and random errors for the multinomial logit model, the inclusion of random terms in the estimation model partially relaxes the IIA property (Grilli & Rampichini, 2007).

Hence, the IIA assumption does not marginally hold for the random error components.

For model identification, the estimated coefficients for one of the clusters are normalized to zero. We use the Generalized Structural Equation Model (GSEM) software package in STATA 14 to fit the model allowing for the inclusion of multinomial responses and random effects (Rabe-Hesketh et al., 2004; Stata, 2011).

3.3 | Multinomial endogenous treatment effects model (METE)

We also analyze the impact of adopting SAI clusters on yield,[2] labor input, total variable cost,[3] revenue, and net income. To understand the causal effect of cluster adoption on the outcome of interest, we simultaneously account for both cluster selection decisions and unobserved household-level heterogeneity. We adopt a treatment-effect approach to estimate the selection and outcome equations simultaneously. We first specify the model as:

$$L^*_{ipt} = X_{ipt}\beta_L + \delta_j Z_{ipt} + \lambda D_{ipt} + \mathcal{E}_{it} \tag{2}$$

where L^*_{ipt} is a latent variable representing the random utility associated with SAI cluster adoption and the outcome (labor cost, total variable cost, yield, and revenue net farm income). L_{ipt} denotes binary variables for SAI cluster adoption. Exogenous variables X_{ipt} are observable factors that determine SAI cluster adoption selection and exogenous variables Z_{ipt}[4] are control variables. D_{ipt} is a latent unobserved characteristic that underlies the correlation between selection and outcome. We assume that $\mathcal{E}_{it}$ has a bivariate normal distribution:

$$L_{ipt} = 1 \; if \; X_{ipt}\beta_L + \delta_j Z_{ipt} + \lambda D_{ipt} + \mathcal{E}_{it} \quad > 0 \text{ and } 1 \text{ otherwise} \tag{3}$$

In particular, we use the METE model proposed by Deb and Trivedi (2006) and Deb (2009), which relies on instrumental variables and accounts for endogeneity. To estimate the outcomes for the adoption of Clusters EP, EPTM, ET, and EPT relative to Cluster T, we use the following model:

$$E\left(Y_{ipt} | L_{iptj},\ X_{ipt},\ D_{iptj}\right) = X_{ipt}\beta + \sum_{j=1}^{J} \rho_{jt} L_{iptj} + \sum_{j=1}^{J} \lambda_{jt} D_{iptj} + \mathcal{E}_{it} \tag{4}$$

where: Y_{ipt} is the outcome from plot p for farmer i at time t, while X_{ipt} denotes observable household and farm characteristics. L_{iptj} denotes SAI cluster adoption binary variables. The average effects of the adoption of various clusters are captured by ρ_{jt}. D_{iptj} denotes the unobservable characteristics that simultaneously influence a given cluster adoption decision and outcome. Since the outcome variables are continuous, we assume a normal (Gaussian) distribution function. The model is estimated using a maximum simulated likelihood approach (MSL).[5] We set the number of random draws S at 400, as in Gregory and Deb (2015), since the number of quasi-random Halton sequence simulation draws should be higher than the square root of the number of observations.

3.3.1 | Controlling for endogeneity

In Equation (3), the cluster adoption variable L_{ipt} is most likely to be endogenous as a farmer makes adoption decisions with future outcomes in mind. Hence, there is a possibility that unobservable factors that influence SAI cluster adoption decisions are likely to influence the outcome variables. We use the instrumental variable (IV) strategy to address this problem. Deb and Trivedi (2006) show that the model's parameters estimated using control variables included in the selection equation are the same as those used in the outcome equation. The use of the exclusion restriction and instruments provides more robust estimates. We use one instrumental variable (the number of grain traders known to the farmer within the village), which influences the endogenous treatment effect but is uncorrelated with the outcomes or the error component. Finally, we determine the impact of the four SAI cluster adoption decisions on the outcome relative to T.

3.3.2 | Empirical validation of IV

We establish the suitability of the instrument variable (IV) regarding number of grain traders known to the farmer

[2] Quantity of maize equivalent is computed following (Liu & Myers, 2009). Where, maize quantity equivalent (Q_m) is computed as $Q_m = \frac{\sum Y_{ib} P_b}{P_m}$ where Y_{ib} is the output of bean b in kgs in household i; P_b is the price of bean and P_m is the price of maize.

[3] Costs and prices are deflated with 2015 as the base year (exchange rate; 1 KES = 89 USD in 2011, 1 KES = 91 USD in 2013 and 1 KES = 102 USD in 2015).

[4] The vector Z_{ipt} includes control variables used in the first stage of the estimation. The difference between the vectors of control variables Z_{ipt} and X_{ipt} is that Z_{ipt} includes instrumental variable (number of grain traders known to the farmer within the village).

[5] The STATA command used is *mtreatreg*, implemented by Deb (2009).

within the village, by performing a falsification test. A valid IV will influence the SAI cluster adoption decision but not affect the output equations (quantity of maize equivalent produced, labor costs, variable cost, revenue, and net income). We found the IV to be a statistically significant determinant of adoption decision for clusters (Model 1, $\chi 2 = 1978.02$; with significant p values) but not the outcome estimates (Model 2, F–stat. = 15.40, $P = .099$ for yield; F–stat. = 67.55, $P = .849$ for labor cost; F–stat. = 38.42, $P = .100$ for variable cost; F–stat. = 15.25, $P = .101$ for revenue; F–stat. = 16.45, $P = .596$ for net income). Hence, we argue that our IV is relevant and satisfies the exclusion restriction[6] thus valid in our model specifications.

3.3.3 | Controlling for unobserved heterogeneity

The error term $\mathcal{E}_{it}$ in Equation (2) has two components, u_i and v_{it}. The component v_{it} is the time-varying unobserved shocks that affect a household's SAI cluster adoption decision and the outcomes. The component u_i represents time-invariant unobserved heterogeneity, the individual characteristics affecting household SAI cluster adoption decisions and outcomes. These may include the farmer's managerial ability, preferences, and degree of risk aversion, which are unobservable. In a nonlinear panel data model, a correlation between time-invariant, unobserved household-level variables, and observed covariates could occur. A correlation between covariates and unobserved heterogeneity may lead to biased estimated coefficients. Following Mundlak (1978) and Chamberlain (1984), we use the correlated random effects (CREs) model estimator to relax the assumption of independence between covariates and unobserved heterogeneity. Unlike the standard random effects model, the CRE model controls for time-invariant unobserved heterogeneity as with the fixed effects model without encountering the incidental parameters problem in nonlinear panel models. The CRE estimator permits the correlation between unobserved heterogeneity (u_i) and vector of covariates across all time periods by assuming that the correlation takes the form: $u_i = \omega + \bar{X}_i \xi + e_i$, where ω and ξ are constants, $\bar{X}_i$[7] is a time average for all time-varying covariates in Equation (4), and e_i is a normally distributed error term with zero mean and constant variance. To implement the CRE, we model the distribution of unobserved heterogeneity in Equation (4) as a linear function of the time average of time-varying explanatory variables, $\bar{X}_{ipt}$ and $\bar{Z}_{ipt}$. The constant ω is absorbed into the intercept term.

4 | STUDY AREA AND DATA

We use a data set of farm households from Kenya. The data were collected as part of the CIMMYT-led Adoption Pathways Project. The sampling strategy involved two stages. First, three counties in the eastern region (i.e., Embu, Meru, and Tharaka-Nithi) and two in the western region (i.e., Siaya and Bungoma) were purposively selected based on their maize–legume production potential. Both regions have a bimodal rainfall pattern and two cropping seasons. Second, a multistage sampling design was used to randomly select households to interview in the lower levels (district, division, location, and villages). The sampled households were distributed proportionately to the total number of farming households in the two regions. A sample of 670, 535, and 495 farmers were interviewed in three waves between October and November of 2011, 2013, and 2015, respectively. The representatives of the sampled households were interviewed using a structured interview schedule. Information was collected on the adoption of ten SAI practices, in addition to socioeconomic profiles of households, resource constraints and access to input and output markets, social capital and information access, and plot characteristics. After excluding plots that did not grow maize and/or legumes, we ended up with an unbalanced panel of 3608 observations with about 1200 plots cultivated each year. The data constitute a panel at the household level but not at the plot level[8].

5 | RESULTS AND DISCUSSION

5.1 | Descriptive statistics

Descriptive statistics by cluster type showed that maize mono-cropping produced the highest yield in Clusters EPTM, ET, and EPT, while bean mono-cropping produced the highest yield in Clusters EP, EPTM, and EPT. For intercropping plots, Clusters EPTM and EPT had the highest yield. When all plots are considered, EPTM had the highest yield, ET had the highest labor cost, ET and EPT had the highest total variable cost, and ET and T had the highest revenues and net farm income, respectively (see Table A2 of the Online Appendix).

[6] Due to the challenge of identifying an extra IV we could not carry out an over-identification test.

[7] The $\bar{X}_i$ variables have the same value for each household in each year but vary across households.

[8] We assume that the implication of the non-panel nature of the plot-level data for panel data model result is negligible if any.

5.2 | Factors explaining the adoption of SAI package

To better elucidate the determinants of SAI cluster adoption, we estimated the coefficients and marginal effects for the random-effects multinomial logit model. For brevity, the coefficients are reported in Table A3 of the Online Appendix, and we only discuss the marginal effects of explanatory variables calculated at the sample means as presented in Table 2. The results indicate significant differences between the marginal effects for each SAI Cluster.

For the variables that characterize the household head (gender, age, and formal education), we find male-headed households to have negative effects on the probability of adopting EPT consisting of yield-enhancing, protecting, and traditional soil restoration practices. A study by Mishra et al. (2020) found that female-headed households face fewer learning opportunities, which exacerbates the gap in technology adoption across male and female-headed households. The probability of adopting EP reduces with age. Since Cluster EP consists of yield-enhancing and protecting practices that are labor intensive, we associate this with a loss of manpower and short-planning horizons. Nonetheless, age could also be a proxy for human capital accumulation and more exposure to production technologies. Thus, the impact of age on SAI cluster adoption is indeterminate. The results further reveal that having a household head with a higher level of education is positively associated with the adoption of Cluster EPT which is more knowledge-intensive and with traditional soil restoration practices, but not with adopting Cluster EP. These results are consistent with the findings by Kabunga et al. (2012), who showed that more experienced and better-educated farmers adopt knowledge-intensive technologies and are concerned about their adaptive capacity.

We included the region variable and year dummies in the model to account for spatial and temporal factors. The results indicate that farmers in the western region have a higher probability of adopting ET and EPT. And the preference for EPTM and EPT increased between 2011 and 2013. This confirms the temporal effect of SAI adoption on clusters with soil-restoring practices and external input use, demonstrating a shift away from conventional agriculture.

With respect to plot level characteristics, the observation that the adoption of EPT is positively associated with soils that are perceived to be of medium quality is consistent with results from previous studies. For example, a study by Marenya and Barrett (2009) affirms that the adoption of SAI, particularly chemical fertilizers, is determined by farmers' knowledge and perception of their plot soil fertility. We find ownership of plots with a medium

TABLE 2 Marginal effect of adoption of SAI Clusters: Results from the random effects multinomial logit model.

Variables	EP	EPTM	ET	EPT
Base outcome T				
Gender	.009	.025	.046	−.050*
	(.026)	(.013)	(.032)	(.025)
Age	−.003**	.001	.001	.001
	(.001)	(.000)	(.001)	(.001)
Formal education	−.007*	.001	.003	.007**
	(.003)	(.001)	(.003)	(.003)
Household size	−.003	−.001	.003	.001
	(.004)	(.001)	(.005)	(.000)
Main occupation	.0292	−.0132	−.0161	.0203
	(.022)	(.011)	(.027)	(.022)
Region	−.0452	.0182	.122***	−.200***
	(.026)	(.012)	(.031)	(.027)
Year 2013	−.011	.113***	−.145***	−.041
	(.026)	(.116)	(.032)	(.026)
Year 2015	−.206***	.172***	−.0346	.0633*
	(.028)	(.017)	(.032)	(.026)
Season 0 = Short rain 1 = Long rain)	.006	−.010	−.007	.020
	(.015)	(.007)	(.018)	(.013)
Farm size (ha)	.013	−.007	−.003	−.005
	(.008)	(.005)	(.010)	(.009)
Distance to plot	.000	.001	.000	−.000
	(.000)	(.001)	(.001)	(.000)
Rented tenure	−.0135	.001	.052	−.018
	(.024)	(.012)	(.029)	(.022)
Borrowed tenure	−.113	.003	.064	−.009
	(.076)	(.029)	(.082)	(.067)
Medium fertility	−.005	−.018*	−.034	.041*
	(.018)	(.009)	(.023)	(.018)
Poor fertility	.018	.009	−.026	−.029
	(.030)	(.013)	(.035)	(.030)
Medium slope	.041*	.004	−.044*	.015
	(.018)	(.008)	(.023)	(.017)
Steep slope	.039	−.006	.007	−.038
	(.037)	(.019)	(.046)	(.037)
Years lived village	.001	−.001	−.001	.001
	(.001)	(.000)	(.001)	(.001)
Confidence in extension worker skills	.0222	.00523	−.108***	.0552**
	(.019)	(.009)	(.022)	(.018)
Extension contacts	−.001	−.002	.004	.000
	(.002)	(.001)	(.022)	(.002)
Labor cost	−.0001	−.000	.001*	.000
	(.141)	(4.531)	(1.301)	(1.013.)
Savings	−.001	.002	−.003	.006*
	(.002)	(.001)	(.002)	(.002)

(Continues)

TABLE 2 (Continued)

Variables	EP	EPTM	ET	EPT
Livestock unit	−.004	−.001	−.007	.006
	(.005)	(.002)	(.005)	(.004)
Asset value	−.001	−.002	.022**	−.018
	(.007)	(.003)	(.008)	(.007)
Household income	.007**	−.003	.00310	−.007***
	(.002)	(.001)	(.003)	(.002)
Maize monocrop	.288***	−.061***	−.360***	.138***
	(.022)	(.011)	(.026)	(.020)
Bean monocrop	.325***	−.0478***	−.399***	.130***
	(.025)	(.011)	(.031)	(.022)

Significance levels: ***$P < .01$, **$P < .05$, *$P < .1$; Standard errors are in parentheses.

slope to have a positive effect on the probability of adoption of EP. This cluster contains soil and water conservation strategies, such as mulching and terracing, which are more likely to be adopted in locations with medium slopes than flat slopes. This is consistent with the findings by Amsalu and De Graaff (2007), who found plot slope to be a key determinant of the adoption of soil and water conservation practices.

The results further indicate that the probability of adopting ET is reduced for farmers who have confidence in extension officers. The opposite is true for EPT adoption. Farmers who have confidence in extension officers are more likely to adopt clusters with modern soil restoration and crop protection strategies. For the successful diffusion of new SAI practices, effective extension systems are vital (Takahashi et al., 2020). This is consistent with the findings by Pan et al. (2018) that highlight the role of information and training in boosting agricultural productivity among farmers.

On wealth indicators, adoption of EPT is positively related to more savings and increased household income. As anticipated, households with resources can assume the possible risks associated with adopting SAI practices and may be less constrained to invest in long-term SAI practices such as constructing terraces. Furthermore, more saving ensures readily available cash for day-to-day farm management operations.

The estimated random-effects multinomial logit model results showed the within-cluster variation of idiosyncratic individual effects and correlations between clusters. The estimated relative-risk ratios for EPTM, ET, EPT, and EP are greater than one, indicating that a one-standard-deviation change in random effects within each cluster would increase the probability of its adoption relative to T. This implies that farmers would still adopt clusters EPTM, ET, EPT, and EP relative to T. The results also indicate that all six covariance terms are statistically significant, implying an underlying correlation between the random effect terms across clusters (see Table A4 of the Online Appendix).

5.3 | Effect of SAI cluster adoption on yield distribution

We illustrate the effects of SAI cluster adoption on maize and bean yields under mono-cropping[9] (Figure 2) using kernel densities. Under maize mono-cropping, Cluster T has the most plots producing the lowest yields and the fewest plots with higher yield levels. EP has few plots producing lower yields and more plots with higher yields than T. EPT has the fewest plots with low yields and the most plots with yields higher than EP and T. A similar pattern is shown for yield distributions under bean mono-cropping. T yields are exceptionally low relative to EP and EPT.

Figure 3 shows yield distributions under maize–bean intercropping[10]. The traditional soil restoring cluster has the most plots producing the lowest yields and the fewest plots with higher yields for maize and beans grown under intercropping. Likewise, for intercropped maize and bean, EPTM has fewer plots with lower yields and more plots with higher yields than ET. The low yields in T suggest that traditional soil-restoring practices alone might not be ideal for meeting food demands. However, clusters that offer higher yields (EPTM and EPT) are less adopted probably due to the excessive input cost.

5.4 | Effect of SAI cluster adoption on yield, labor use, variable cost, revenue, and net income

The results in Table 3 are based on the outcome equations from the multinomial endogenous treatment effect (METE) regression and show how cluster adoption is associated with yield, labor use, variable cost, revenue, and net income. Since it is difficult to account for all possible sources of endogeneity, particularly with recall data which is prone to measurement errors (Abay et al., 2021), we interpret our empirical results as associations rather than causal inferences. For brevity, we exclude results from the METE selection equation that confirms the robustness of random effects multinomial logit.

The results indicate that adopting EP, EPTM, ET, and EPT is associated with increased net farm income compared to T. Moreover, the adoption of ET and EPT is

[9] Mono-cropping systems are mainly common to Clusters EP and EPT.
[10] Intercropping systems are mainly common to Clusters EPTM and ET.

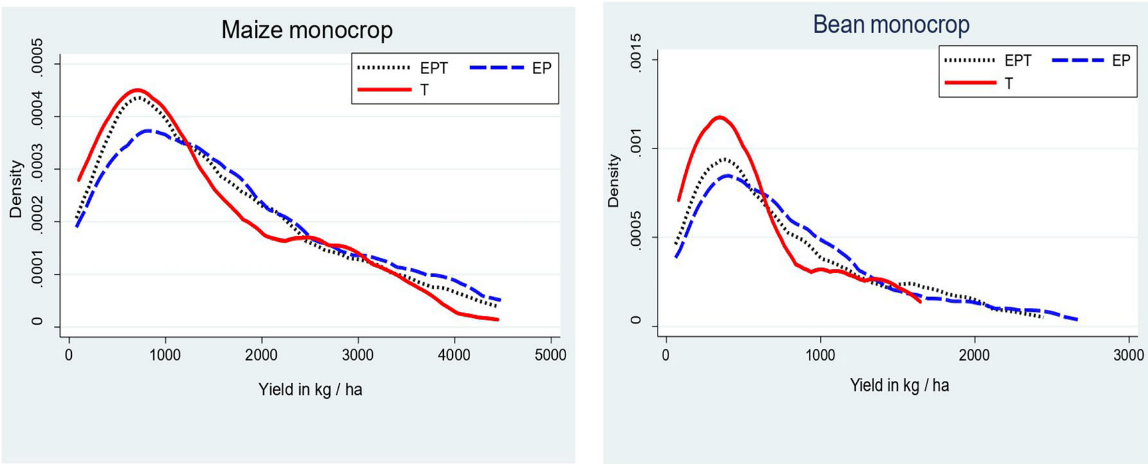

FIGURE 2 Kernel density distribution for maize and bean mono-cropping.

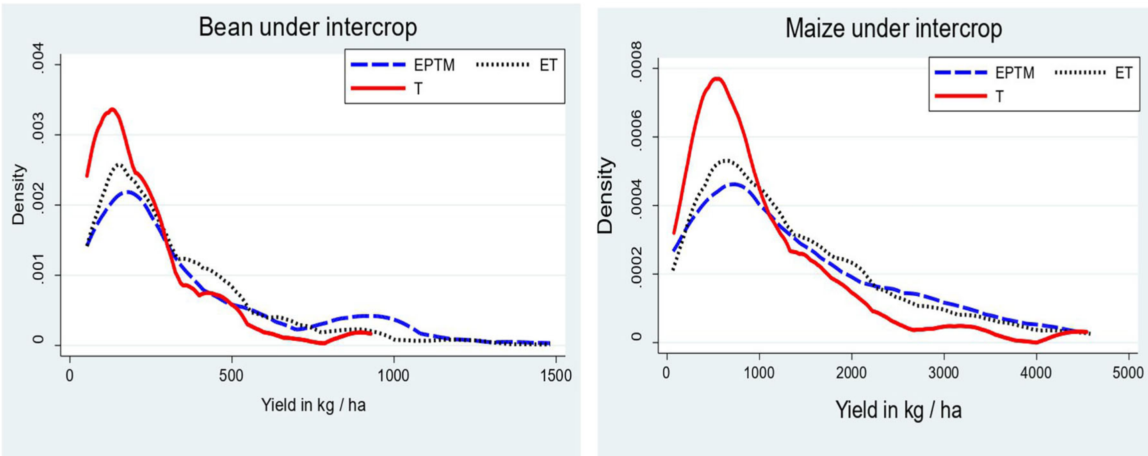

FIGURE 3 Kernel density distribution for maize-bean intercropping on same plot.

associated with higher profits. The adoption of EP is associated with higher crop yield when considering all plots. The clusters enhance yield and promote soil and water conservation. Similarly, several existing studies (Adolwa et al., 2019; Hörner & Wollni, 2022; Khonje et al., 2018; Manda et al., 2019; Tesfaye et al., 2021) found that the adoption of sustainable integrated soil fertility management practices increased crop yields and household income among smallholders. Adopting EP was significantly associated with an increase in total variable costs relative to T while ET is associated with increased revenue, resulting in higher net farm incomes. The higher returns in EP could be because most households with plots in this cluster do not adopt practices such as manure use, intercropping, or short-term soil and water conservation strategies such as mulching, which can increase labor costs.

Adopting EPTM is significantly associated with increased yield under maize mono-cropping, bean mono-cropping, and maize-beans intercrop; it is also associated with increased farm revenue, and thus net farm income relative to T. EPTM is associated with the use of lower labor costs and variable costs than ET and EPT, probably due to the high adoption of minimum tillage. However, these costs are not low enough to fetch the highest returns. Our results are consistent with the findings by Teklewold et al. (2013), who conclude that the adoption of different SAI practices may increase labor demand.

We found that ET, which had the highest adoption rate (37%), is significantly associated with increased yield under bean mono-cropping. The average returns could be high but remain variable. This corroborates the findings by Suri (2011) of a study in Kenya showing that a high rate of technology adoption does not necessarily increase average yields. A study by Michler et al. (2018) reported a similar trend in Ethiopia, where many households adopted improved chickpeas in the absence of yield gains. Despite

TABLE 3 Effect of SAI adoption on yield and other outcomes; Results from outcome equation of multinomial endogenous treatment effect regression.

	Yield							
	Maize monocrop plots	Bean monocrop plots	Maize & Bean intercrop plots	Yield all plots	Labor	V.cost	Revenue	Net farm income
EP	−6.389	146.402	−556.233***	931.417***	1137.168	6001.668***	9266.026***	6097.896*
	(200.625)	(366.202)	(140.027)	(92.541)	(2430.202)	(1620.808)	(3269.679)	(3289.724)
EPTM	506.544**	199.342*	760.660***	−4.431	5549.640	2497.384	7700.832*	8014.773*
	(210.105)	(116.544)	(151.200)	(108.872)	(3507.185)	(1934.198)	(4176.258)	(4391.125)
ET	−243.710	424.320*	178.216	86.166	7738.772***	8199.828***	20,153.600***	12,424.516***
	(182.300)	(229.321)	(122.101)	(141.763)	(2581.347)	(1572.078)	(3036.435)	(3373.876)
EPT	287.018	361.504**	−11.614	238.328**	5950.624**	7907.878***	17,165.130***	8755.514**
	(197.491)	(156.701)	(168.509)	(120.451)	(2703.902)	(1550.498)	(3357.207)	(3550.573)
Constant	484.290	−563.087**	544.881	266.338	25,206.180***	16,298.12***	5073.012	−12,101.404
	(446.174)	(264.304)	(373.082)	(273.679)	(8327.172)	(5252.201)	(9253.292)	(9802.343)
Lnsigma	6.616***	5.917***	6.677***	6.584***	25,101.878***	10.084***	10.659***	10.700***
	(.200)	(.409)	(.103)	(.107)	(8334.569)	(.062)	(.026)	(.025)
Observations	1073	798	1737	3608	3608	3608	3608	3608

Note: T is the base category; number of quasi-random Halton sequence-based simulation draws, S, was set to 400; Outcome density is normal and standard deviation of factor density is 1; Number of traders farmer knows is used as an instrumental variable; Robust standard errors in parentheses; Significance levels ***$P < .01$, ** $P < .05$, * $P < .1$.

not gaining higher yields relative to local varieties, farmers find adoption to be highly profitable because improved chickpea is more marketable and fetches more revenue.

We further found that ET was significantly associated with higher variable costs, including labor costs, but also associated with generating more revenue and net income. Despite this cluster being associated with the highest variable costs (due to the application of fertilizer, manure, intercropping, and long-term soil and water conservation strategies), plots in this cluster generated the highest net farm incomes. This is consistent with other studies (Byerlee & Deininger, 2013) that found yield-enhancing and protecting inputs to be relatively expensive in Sub-Saharan Africa. The EPT cluster is significantly associated with higher yields, as well as higher variable costs, than T. The revenues and net farm income earned in EPT and ET are significantly higher than in EP and EPTM. Adopting T was associated with the lowest variable costs (e.g., less labor costs) as well as the lowest returns probably because it does not use yield-enhancing external inputs. Thus, to increase farm returns, households adopting T would need to complement it with other agronomic techniques, such as the use of improved seed varieties and targeted fertilizer application (Wainaina et al., 2018).

In addition to the robustness check of the METE results presented in Table 3, we estimated the standard Mundlak-Chamberlain (MC) regression and household fixed effects (FE) panel regressions. The findings of the MC and FE are reported in Table A5 of the Online Appendix. Overall, these results still uphold the conclusion that adopting cluster T was associated with the lowest returns possibly because it does not use yield-enhancing and protecting external inputs.

5.5 | Determinants of yield, labor use, variable cost, revenue, and net income

The results of the outcome equations of the multinomial endogenous treatment effect regression are reported in Table 4. The results show that having a male-headed household was associated with a significant reduction in labor costs, which could be the result of several factors. Doss and Quisumbing (2020) confirm that households often do not attain the maximum yield potential from their farms due to social norms that affect individual roles and responsibilities at the expense of overall household production. Those households whose main occupation was farming were associated with higher yields, revenue, and net income, and a significant reduction in total variable cost. This could be because they directly manage their farms, as opposed to hired laborers, and focus on cost minimization.

Plots in the western region were associated with fewer costs and higher farm revenue and income than plots in the eastern region. We found that the 2013 season was

TABLE 4 Determinants of yield and other outcomes; Results from selection equation of multinomial endogenous treatment effect regression.

	Yield							
	Maize monocrop plots	Bean monocrop plots	Maize & Bean intercrop plots	Yield all plots	Labor	V.cost	Revenue	Netfarm income
Variables[a]								
Gender	86.510	−41.647	25.009	−75.058	−7477.923**	−1908.707	4856.003	6479.500
	(219.518)	(122.855)	(189.019)	(121.646)	(3765.994)	(1884.723)	(4176.187)	(4124.630)
Age	12.850	8.869	−17.448**	6.429	93.583	−24.963	−229.012	−183.624
	(9.596)	(6.400)	(8.835)	(5.540)	(149.584)	(88.385)	(204.785)	(204.947)
Education	−12.668	−19.405	−28.997	−22.251	−475.066	125.774	−771.912	−894.932*
	(22.374)	(13.503)	(21.911)	(13.979)	(408.112)	(221.003)	(471.987)	(470.158)
Household size	−10.797	5.908	−8.602	−12.240	−821.375***	−86.193	−408.970	−326.456
	(16.358)	(12.390)	(11.016)	(9.042)	(292.773)	(149.843)	(314.751)	(315.935)
Occupation	33.701	127.929*	317.320***	212.311***	−3920.273**	−3585.555***	9027.880***	12,579.282***
	(86.787)	(69.793)	(71.832)	(52.212)	(1753.405)	(1138.587)	(1843.711)	(1960.696)
Region	−44.151	−292.918***	−85.371	−66.138	−1748.663	−6408.147***	5823.083***	12,225.049***
	(112.923)	(102.473)	(91.083)	(66.684)	(2519.411)	(1461.946)	(2232.708)	(2408.498)
Year 2013	−68.994	22.662	−267.227***	−254.561***	−5569.192**	−6827.797***	938.091	7647.349***
	(122.530)	(80.805)	(94.057)	(70.229)	(2198.500)	(1242.698)	(2589.493)	(2593.084)
Year 2015	−11.702	137.950	375.058***	348.513***	−9651.341***	3283.288**	−1774.46	−5094.632*
	(124.399)	(84.545)	(114.113)	(76.780)	(2544.398)	(1630.820)	(2718.881)	(2792.154)
Season	−9.578	5.596	198.499***	107.155**	−351.920	832.734	6307.297***	5495.896***
	(67.326)	(44.150)	(59.532)	(42.670)	(1377.415)	(799.553)	(1463.968)	(1515.803)
Agricultural farm size (ha)	−100.625***	−84.656***	−138.048*	−124.799**	514.760	−3230.611***	−4320.507***	−1070.223
	(38.564)	(26.200)	(71.181)	(53.020)	(1734.915)	(996.413)	(1625.020)	(1179.906)
Plot distance	.668	.049	−2.124*	−.250	−22.602	5.658	−14.856	−21.174
	(.656)	(.973)	(1.219)	(.581)	(14.886)	(7.982)	(15.579)	(14.700)
Rented tenure	44.076	−40.096	156.193*	113.152*	−3701.413***	2447.053***	−12.187	−2404.735
	(100.881)	(65.999)	(91.278)	(61.823)	(1351.975)	(899.307)	(2057.609)	(2025.620)
Borrowed tenure	−38.480	267.647	−404.504	37.271	268.964	2756.268	−613.684	−3116.425
	(188.493)	(206.150)	(296.854)	(203.860)	(4003.693)	(2718.528)	(7853.054)	(7043.855)
Medium fertility	28.574	.596	−23.153	15.174	4205.886**	1254.680	−473.299	−1605.218
	(74.765)	(47.271)	(75.472)	(50.588)	(1664.722)	(1068.082)	(1766.210)	(1840.857)
Poor fertility	−223.848*	−186.769**	−193.117**	−239.612***	1141.421	−2183.829*	−8222.145***	−5999.308**
	(118.857)	(74.774)	(91.955)	(72.293)	(1820.343)	(1155.777)	(2,469.896)	(2,389.213)

(Continues)

TABLE 4 (Continued)

	Yield							
	Maize monocrop plots	Bean monocrop plots	Maize & Bean intercrop plots	Yield all plots	Labor	V.cost	Revenue	Netfarm income
Medium slope	3.745	11.730	1.019	−45.692	−4531.956***	−1689.577**	1386.692	2943.556*
	(69.937)	(45.069)	(67.042)	(46.292)	(1521.683)	(819.351)	(1635.659)	(1676.526)
Steep slope	−305.672**	−138.434	−16.141	−261.314**	−4518.150*	−5137.925***	−6459.048*	−1448.756
	(141.800)	(114.560)	(159.667)	(102.572)	(2533.265)	(1566.901)	(3515.220)	(3568.883)
Years lived in village	5.271	−1.787	3.953	3.151	79.345	128.906***	29.929	−98.092
	(3.600)	(2.250)	(2.652)	(1.993)	(61.595)	(49.122)	(70.913)	(78.755)
Confidence in skills	−81.254	2.252	88.104	23.651	−2834.317*	722.840	449.968	−202.012
	(70.885)	(47.327)	(75.728)	(50.817)	(1639.044)	(873.879)	(1639.147)	(1693.414)
Extension contacts	3.158	8.530	.646	3.527	−128.319	−27.645	30.791	63.808
	(5.435)	(9.605)	(7.795)	(5.712)	(80.444)	(55.072)	(162.949)	(160.105)
Labor cost	.007***	.002***	.005***	.006***		.575***	.203***	−.370***
	(.001)	(.001)	(.001)	(.001)		(.103)	(.033)	(.085)
Savings	−7.256	2.834	22.496**	4.389	254.895	202.463	−114.934	−308.296
	(12.279)	(8.065)	(11.343)	(7.713)	(260.942)	(160.383)	(280.101)	(295.351)
Livestock units	−26.970	−12.249	−11.113	−10.242	−50.341	126.987	123.276	−4.630
	(37.669)	(18.968)	(19.730)	(16.304)	(394.254)	(302.039)	(580.662)	(593.575)
Asset value	13.573	6.116	−26.833	−2.705	3014.910***	750.279	−205.454	−987.517
	(39.820)	(24.672)	(33.769)	(24.440)	(710.492)	(475.499)	(824.492)	(866.524)
Household income	−1.943	8.604	−5.329	−14.739*	−629.516**	−243.770	−257.378	−15.877
	3.158	(7.831)	(12.952)	(8.410)	(316.532)	(158.330)	(287.233)	(299.120)
Maize monocrop				−600.204***	−356.582	−694.856	−16,783.760***	−16,390.652***
				(78.641)	(2255.747)	(1297.104)	(1990.236)	(2079.997)
Bean monocrop				−471.179***	3137.251	−12,244.88***	−11,677.167***	50.928
				(89.491)	(2738.837)	(1395.722)	(2411.928)	(2441.671)
Constant	484.290	−563.087**	544.881	266.338	25,206.180***	16,298.12***	5073.012	−12,101.404
	(446.174)	(264.304)	(373.082)	(273.679)	(8327.172)	(5252.201)	(9253.292)	(9802.343)
Lnsigma	6.616***	5.917***	6.677***	6.584***	25,101.878***	10.084***	10.659***	10.700***
	(.200)	(.409)	(.103)	(.107)	(8334.569)	(.062)	(.026)	(.025)
Observations	1073	798	1737	3608	3608	3608	3608	3608

Notes: T is the base category; number of quasi-random Halton sequence-based simulation draws, S, was set to 400; Outcome density is normal and standard deviation of factor density is 1; Number of traders farmer knows is used as an instrumental variable; Robust standard errors in parentheses; Significance levels *** $P < .01$,** $P < .05$, * $P < .1$.

[a]For brevity time averaged effects (CRE) –mean values and the coefficient of latent factors (*lambda*) that reflects the effects of unobservable characteristics are not included.

associated with lower yields, variable cost, and revenue, and significantly associated with higher net income, compared to the 2011 season. The low yield in 2013 could be a result of external shocks including changes in weather patterns, pests, and diseases. Although there was a significant increase in yield in 2015 relative to 2011, this was associated with an increase in total variable costs. Farming in the long-rain season was significantly associated with increased yield, revenue, and net income. This could be a result of more rainfall during the long season, which also varies yearly, thus SAI adoption patterns differ across seasons (Ochieng et al., 2022). For instance, Teklewold et al. (2017) found low adoption of minimum tillage and crop residue management in higher average rainfall zones, since these technologies help to better cope with the stress of water scarcity.

Though previous studies (Adolwa et al., 2019; Khonje et al., 2022) reported a positive relation between farm size and the adoption of agricultural technologies, crop yield, and farm income, we find a negative association between farm size and crop yield, variable costs, as well as revenue. We presume that having smaller agricultural land holdings will attract the adoption of land-saving SAI practices such as intercropping to enhance land productivity. Plots perceived to be of poor soil fertility had a significant association with reduced yields, production costs, revenue, and net income relative to plots perceived to be of good soil fertility quality. Equally, farms with steep and medium slopes were associated with significantly lower yields than farms with flat slopes. Prior research has linked the adoption of SAI practices in plots perceived to be of poor soil quality (Wainaina et al., 2016). Better-off households had higher yields and used more labor, which is consistent with the findings from the study by Khonje et al. (2022), which collaborate that such households can invest in relatively costly SAI practices.

6 | CONCLUSIONS AND IMPLICATIONS

In this study, we examine the adoption and payoffs from ten SAI practices clustered into five dominant groups. Studies on the adoption of SAI practices have mainly focused on single practices although smallholder households tend to adopt these practices in bundles. We used the K-modes clustering algorithm to group the ten SAI practices into five distinct clusters, and a random-effects multinomial logit model to analyze the determinants of adopting those clusters. We also applied a METE model to evaluate the impact of adopting the SAI clusters on crop yield, total variable cost, revenue, and net income.

Based on our results, we conclude that the adoption of SAI clusters varies by region and cropping system, confirming that the one-size-fits-all policy design for promoting the adoption of SAI practices may not be suitable for all farmers. The adoption rate of SAI clusters remains low and unstable, with smallholders dis-adopting those clusters with traditional soil restoring practices or those limited to yield enhancement and crop protection practices. The adoption of clusters that combine soil-restoring practices and external farm input use have increased over time, demonstrating a shift away from conventional agriculture. The important determinants of SAI clusters adoption include household wealth, gender of household head, number of extension contacts, plot soil fertility, and plot tenure status. The welfare effects of cluster adoption on yield, total variable cost, revenue, and net income differed across crop type, region, and production year.

The findings from this study have some relevant policy implications. First, effective agricultural extension systems are key for disseminating information about the SAI clusters, and promoting SAI practices that suit farmer needs. From a policy perspective, there is a need for the government and the private sector to identify and alleviate constraints to adopting context-specific and profitable SAI clusters. Specifically, participatory extension methods involving both extension agents and farmers could be used to identify, refine, and promote SAI clusters appropriate to local conditions. Another line of our policy recommendation relates to the finding that farmers with plots of poor soil quality are less likely to adopt SAI clusters with high net incomes. Policy interventions that enhance soil fertility could be developed and promoted to speed up the adoption process.

Much of the related literature (such as Kassie et al., 2015; Khonje et al., 2018, 2022; Kim et al., 2019; Ochieng et al., 2022; Teklewold et al., 2013) also provides empirical evidence to support the promotion of SAI practices. We note that prior empirical literature used at most two proxies to evaluate the effect of adoption of SAI combinations on smallholder welfare. For instance, a study by Teklewold et al. (2013) used household income and labor demand while Kassie et al. (2018) used plot yield and production costs. Due to lack of analyses of profitability of SAI studies, this study used yield, total variable cost, revenue, and net income as proxies of smallholder welfare. This is important because adopting various SAI clusters can lead to significant gains in both revenue and costs. It can also can lead to significant gains in revenue, with insignificant increases in costs. Hence, we conclude that it is the net effect that matters for adoption of SAI clusters.

This study has added to the literature by using the K-mode clustering algorithm to identify dominant SAI clusters that are often adopted by farmers in eastern and western Kenya. The study also analyzed the welfare effects of adopting different SAI clusters for different cropping systems. We acknowledge the limitation that our research only focused on maize-legume cropping systems. Future research can focus on other types of cropping systems such as rice.

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