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Determinants of Investments in Sustainable Agricultural Intensification Practices in Ethiopian Central Highlands

Wudineh Getahun[1, 2], Jema Haji[2], Abule Mehare[2], and Lemma Zemedu[1]

[1, 2] Ethiopian Institute of Agricultural Research (EIAR), Department of Agricultural Economics, Addis Ababa, Ethiopia. E-mail address: wudineh96@gmail.com; [2] Haramaya University, Department of Agricultural Economics, Haramaya, Ethiopia; [1] Ethiopian Institute of Agricultural Research, Department of Agricultural Economics, Addis Ababa, Ethiopia.

Abstract

Improving agricultural productivity and food security while reducing land degradation and poverty using sustainable agricultural intensification practices (SAIPs) has been a key development policy agenda in Ethiopia. However, investment in sustainable agricultural intensification practices remains low. Using a multivariate probit (MVP) and an ordered probit model (OPM), this paper investigates the factors influencing farmers' choice decisions and the extent of investments in eight SAIPs including improved crop varieties, inorganic fertilizers, pesticides, organic fertilizers, cereal-legume rotation, vegetation, drainages and soil conservation structures based on 385 household and 1465 plot surveys in the Ethiopian central highlands. Results reveal that some practices in major crop production are complementary while others are substitutable, and the factors had heterogeneous impacts on the choice decisions of farmers to invest in multiple SAIPs. Overall, results reveal variables such as crop income, livestock holding, access to extension and credit services, income diversification, membership to agricultural cooperatives, and agricultural commercialization clusters are important in determining choice decisions and the extent of investments in multiple SAIPs. Complementarity between practices and factors that positively determine investments in sustainable practices should be taken into consideration in agricultural policies. Specifically, strengthening local institutions (extension, microfinance, and cooperatives) and training on SAIPs and income diversification need to be in place to enhance sustainable production.

Keywords: Determinants, investment, sustainable practices, multivariate probit model

Introduction

Agriculture is the most important economic sector in Ethiopia. It constitutes about 33% share of Gross Domestic Product (GDP), contributes 25% to average real GDP growth, generates 82% of export earnings, and absorbs more than 66% of the labor force (EEA, 2021). It also provides an incentive to reduce poverty and improve food security and livelihoods, yet yields are low (2.9 t/ha for cereals compared to a global average of 4 t/ha) and food insecurity affects more than 16.7% of the population (CSA, 2021; FAO *et al*., 2021; Mare *et al*., 2022). Land degradation, soil nutrient depletion, climate change and low investments in sustainable agricultural intensification practices (SAIPs) have limited agricultural production and productivity, leading to food insecurity and poverty (Etongo *et al*., 2018; Horner and Wollni, 2021; Nigussie *et al*., 2018; Smith *et al*., 2017; Teklewold *et al*., 2013). Land degradation is particularly severe in the Ethiopian highlands where 23% of the cultivated land is adversely affected (Gashaw *et al.*, 2014; Nyanga *et al*., 2016). This underlines the need to enhance investment in SAIPs for improving productivity, food security, and conserving resources.

Investments in SAIPs are the main concern in SSA highlands, where rain-fed farming on the hillside often causes soil erosion leading to low yields and food insecurity (Abera *et al.*, 2020; Nyanga *et al*., 2016). Subsequently, for several decades, a range of SAIPs have been promoted in SSA including Ethiopia (Kassie *et al*., 2015; Teklewold *et al.*, 2013). These practices include land management and agronomic practices such as crop rotation, compost, crop residues, soil conservation structures, drainage (farm water management), and vegetation to improve soil fertility and maintain soil organic matter, and modern purchased inputs such as improved seeds, inorganic fertilizers, and pesticides (herbicides, fungicides, and insecticides) to sustainably enhance productivity (Abera *et al.*, 2020; Kassie *et al*., 2015; The Montpellier Panel, 2013). Farmers have started to invest in SAIPS. Investments referred to all exertions in the form of labor and fiscal and financial capital for some benefits.

Several studies in developing countries testified that SAIPs increased productivity, reduced poverty, built resilience to shocks, and maintained the quality of resources (Hundie *et al.,* 2017; Liao and Brown, 2018; Pretty *et al*., 2011; Reddy *et al*., 2020; Vanlauwe *et al*., 2019). While recognizing that sustainability is a disputed term, we identify farm practices that are commonly viewed as sustainable as they maintain yields and minimize adverse impacts on the environment. These include soil conservation structures, drainages, manure/compost, vegetation, rotation, improved seeds, inorganic fertilizers, and prudent use of pesticides. SAIPs is a broad term used to describe genetic materials, inputs, equipment, structures and farming techniques, and evolving processes that can vary in time and space (Godfray, 2015; Pretty and Bharucha, 2014; Ruzzante *et al*., 2021). Despite extensive past efforts from research and development actors to promote SAIPs and benefits, SAIPs investments remain low in Ethiopia (Kassie *et al*., 2015; Teshome *et al*., 2016; Teklewold *et al.*, 2013; Zeweld *et al*., 2019). Evidence suggests that SAIP investments by smallholder farmers are constrained by several, often interrelated factors. These factors include household demographics, resource endowments, institutional factors, weather conditions, farm characteristics, and risk and uncertainties (Asfaw *et al*., 2016; Kassie *et al*., 2013; Feder *et al*., 1985; Manda *et al*., 2016).

Several studies in developing countries have reported that SAIP investment decisions at the household level vary according to households' human capital including age, education, and family size, and resource endowments such as livestock holding, farm size and income (Ahmed, 2015; Hundie *et al*., 2017; Jabbar *et al*., 2020; Kassie *et al*., 2013; Ndiritu *et al*., 2014; Sileshi *et al*., 2019; Teklewold *et al*., 2013; Wainaina *et al*., 2016) and sex of the household head (Bekele *et al*., 2017; Ndiritu *et al*., 2014), plot characteristics including size, slope, fertility and distance (Ahmed, 2015; Asfaw *et al*., 2016; Hundie *et al*., 2017; Kassie *et al*., 2015; Ndiritu *et al*., 2014; Wainaina *et al*., 2016), institutional factors including extension service, cooperative/group membership, market access and access to credit (Asfaw *et al*., 2016; Kassie *et al*., 2015; Kassie *et al*., 2013; Ndiritu *et al*., 2014; Wainaina *et al*., 2016), and weather conditions such as rainfall, and temperature (Asfaw *et al*., 2016; Jabbar *et al*., 2020; Kassie *et al*., 2015; Kassie *et al*., 2013; Wainaina *et al*., 2016).

Nonetheless, most of the above prior studies focused on the single commodity of project interest particularly maize despite the fact that farmers grow several crops which often compute for land, capital, and labor. With the exception of the studies by Yirga *et al*. (2015) who included improved varieties of barley, potato, wheat, and faba bean crops, and Horner and Wollni (2021) who considered improved varieties of maize, wheat, and *tef* crops, and inorganic and organic fertilizers in their technology adoption analysis, with little attempt in sustainable agronomic and land management practices. In addition, investment in soil and water conservation practices (long-term) is not crop-specific but rather in a blend of crops. Further, smallholder farmers often face choice decisions between multiple SAIPs that have to be made simultaneously to solve multiple constraints faced by farming. Hitherto, most previous studies have also focused on a single technology/practice (Amsalu and de Graaff, 2007; Asrat and Simane, 2017; Mekuriaw and Horni, 2015; Mihretu and Yimer, 2017; Tefera *et al*., 2020), which ignores the interdependent and endogeneity of practices and choice decisions (Yirga *et al*., 2015; Kassie *et al*., 2015). Failure to recognize the interdependencies of SAIPs' choice in examining resource allocation constraints results in biased and inefficient estimates.

Overall, land degradation and low agricultural productivity persist as a challenge, partly due to problems with investments and sustained use of SAIPs, particularly in the Ethiopian central highlands (Abera *et al*., 2020). To this end, these areas require SAIPs policies, programs, strategies, and development measures. There is a strong need to generate information on the determinants of choice decisions and the extent of investments in SAIPs. Previous studies on the investments of SAIPs are largely limited to a few practices; they ignored the use of pesticides as farm inputs which is important to sustain production and productivity in the face of climate change, and failed to address the influence of income diversification and agricultural commercialization cluster in their analysis. This paper looks into these identified gaps in the literature by investigating factors influencing choice decisions and the extent of investments in SAIPs at the plot level in the Ethiopian central highlands.

Materials and Methods

The study areas

The study was conducted in the west Shewa zone of Oromia and North Shewa zone of Amhara regional states. Four districts namely Ejere and Toke Kutaye from west Shewa, Basona Werana and Mojana Wedera from North Shewa zone were selected. Further, twelve *kebeles*[1]three from each woreda were included in the study (Figure 1). Ejere has 26 rural and 3 urban *kebeles*. Toke Kutaye has 23 rural and 4 urban *kebeles.* Basona Werana has 30 rural and 3 urban *kebeles, and* Mojana Wadera has 13 rural and 2 urban *kebeles*.

These areas were chosen for this study because they are an area where knowledge about severe land degradation and SAIPs measures is widely available (Gashaw *et al*., 2014). The Ethiopian central highlands are characterized by a densely populated which resulted in frequent splits and shrinking of farmlands and expansion to hillsides farming, and 50% of arable land for agricultural production is affected by soil degradation in terms of erosion and nutrient depletion, which in turn results in low crop productivity, persistent poverty and food insecurity (EEA, 2021; Tesfa and Mekuriaw, 2014). Smallholder agriculture accounts for more than 90% of economic activity. Most farmers undertake mixed crop-livestock production mainly under rainfed conditions. The areas are dominated by the cultivation of cereals including *tef*, wheat, barley, and maize, legumes mainly faba bean, field peas, and chickpeas, and other crops such as potatoes and oilseeds (CSA, 2021.) The dominant livestock types include dairy cattle (both zebu and cross-bred), sheep, goats, equines, and chickens.

[1] The smallest administrative unit in Ethiopia

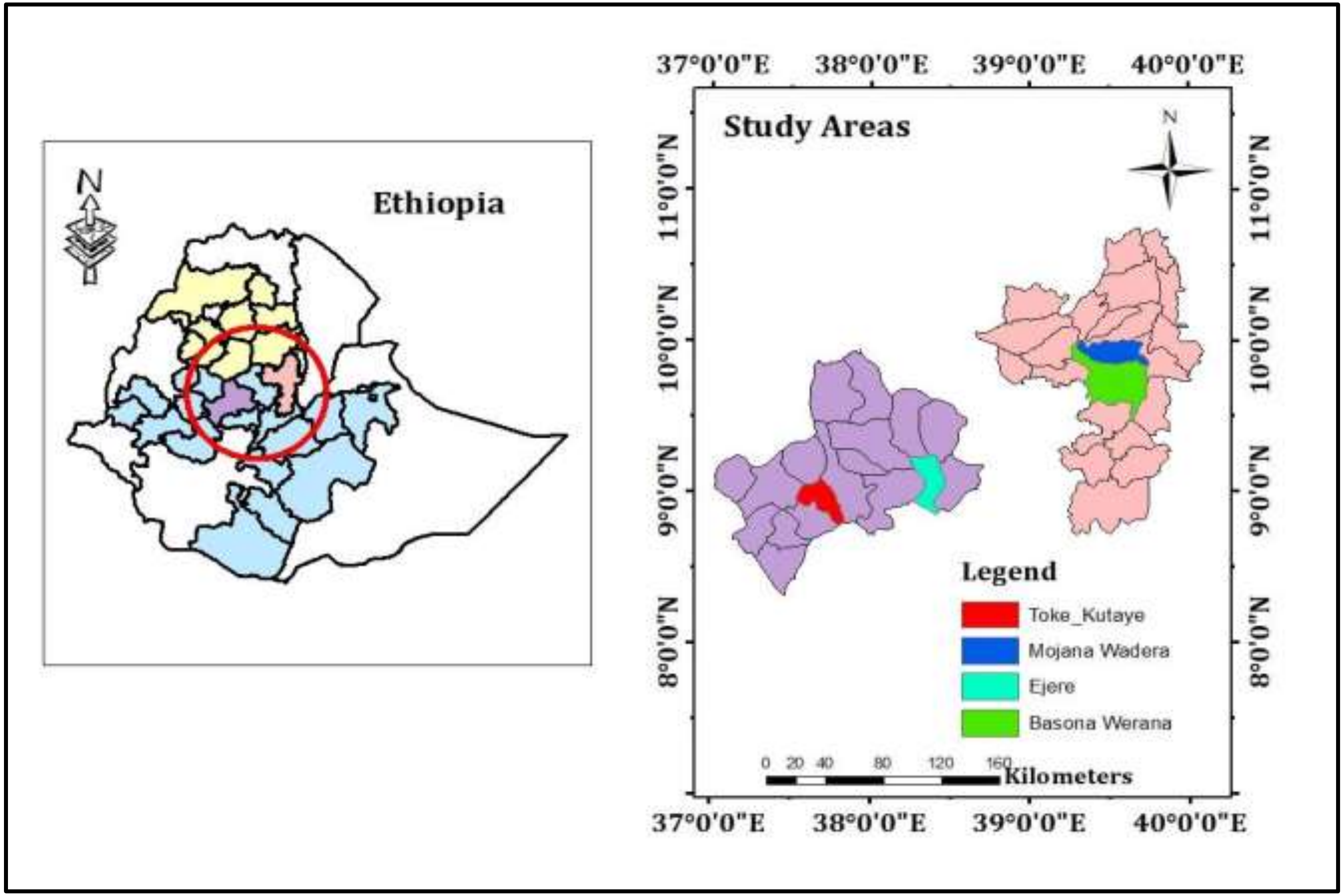

Figure 1. Map of study areas

Data collection and sample selection techniques

The required dataset was collected using combinations of standard data collection methods. These methods included desk review and qualitative and quantitative surveys. The desk review was made from print (both published and unpublished material sources) and electronic source. Information obtained from desk review has helped to design survey instruments of structured and semi-structured questionnaires. Supplementary information was collected through focus group discussions (FGDs) employing a qualitative approach. Qualitative information was collected from selected farm households (five to ten members per FGD per *kebele*), and experts representing different disciplines both at the district and *kebele* level Office of Agriculture. This has helped to understand and details of SAIPs and socioeconomic variables and describe and narrate quantitative results. Finally, the quantitative data were collected through a quantitative survey method.

Three-stage sampling techniques were used to select the regions, zones, districts, *kebeles*, and farm households. Based on the widely available knowledge on SAIP measures, first, two zones from two regions were purposively selected. Second, two districts and three *kebeles* were randomly selected from a list of districts and *kebele*s recorded by zonal and district levels of the Office of Agriculture based on SAIPs implementation. Finally, 23-39 sample households in each *kebeles* were selected based on a proportionate systematic random sampling technique.

The population of interest for this study was farming households as the objective of this study was to investigate the determinants of investments in SAIPs because investment in sustainable agricultural practices is not mainly crop-specific as opposed to previous studies. To obtain a representative sample size for this study, the sample size determination formula by Cochran (1977) was employed:

$$\mathrm{N_s} = \frac{\mathrm{Z^2 * pq}}{\mathrm{e^2}} = 385 \qquad (1)$$

Where N_s is the required sample size, Z is the inverse of the standard cumulative distribution that corresponds to the level of confidence, p is the estimated proportion of an attribute present in the population, q= 1-p, and e is the desired level of precision. The value of Z is found from the statistical table which contains the area under the normal curve of 95% confidence level, 5% precision level, and assumed the occurrence rate of p = 50% (the ratio of farm households who at least invested in one of the SAIPs on their plots), and hence q = 50%, and finally the Cochran formula gives a total of 385 samples to sufficiently represent the target population in the study areas.

Primary data were collected using a structured and pre-tested questionnaire designed with CSPro 7.5 software and a computer-assisted personal interview (CAPI). The data collected included information about households' demographics, asset ownerships, plot characteristics, land management practices, inputs used, access to institutional services, and their perceptions of land degradation. The survey questionnaire was administered by trained and experienced enumerators who have knowledge of local farming systems and languages. The survey was conducted between January and March of 2021, referring to the 2019/20 cropping season. In addition, we collected secondary data about *kebele* level rainfall and temperature (point data) from a national meteorological agency (NMA) through an official letter. Collected data were processed and analyzed using a complete and integrated statistical software Stata 15 package.

Modeling framework

Farm households' choice decisions to invest in available individuals or several technologies at a time was theoretically framed on random utility theory (McFadden, 1974) with a bounded rationality framework (Simon, 2000). The standard classical random utility theory assumes that smallholder farmers as rational economic agents with perfect information make choice decisions to invest in available technologies and maximize utility. However, this is highly criticized for human beings who have limited cognitive ability to make choice decisions to maximize utility because of limited information and knowledge (Simon, 2000). Henceforth, there is a shift from standard rationality to real bounded rational theory for economic agents to make optimal decisions which is sufficient to compare alternative utilities (Simon, 2000). While the utility is not directly observed the actions of farm households are often observed through the choice decision they make. Thus, the observed outcome of farmers' choice decisions to invest in multiple practices can be modeled following random utility formulation. Consider the h^{th} households (h = 1, ..., H) which is challenging a decision on whether or not to invest in the available sustainable agricultural practices on the same or another plot p (p = 1, …, P) over a specified time horizon.

Suppose, U_i represent the perceived expected benefits to the farmer from the conventional production system, and U_m represent the benefits of investing in the m^{th} SAIPs, and X_i and X_m are vectors of explanatory variables that influence the perceived benefits from technology choices i and m. Following Greene (2012), the utility of a farm household is specified as:

$$U_m = \beta'_m X_m + \varepsilon_m \text{ and } U_i = \beta'_i X_i + \varepsilon_i \qquad (2)$$

Where β_m and β_i are parameters to be estimated, and ε_m and ε_i are the stochastic noise terms, presumed to be independently and identically distributed. It follows that the perceived benefit or utility for the h^{th} household from choice m is greater than the utility derived from option i is presented as:

$$U_{hm}(\beta'_m X_m + \varepsilon_m) > U_{hi}(\beta'_i X_i + \varepsilon_i),\ m \neq i \qquad (3)$$

Assume that Y is the choice decision to invest in m so that Y takes the value of 1 if m is chosen and 0 otherwise, the probability that a farm household invests in SAIPs conditional on X can be specified as:

$$P(Y) = 1|X = P(U_{hm} > U_{hi}) \tag{4}$$
$$= \mathrm{P}(\beta'_m X_h + \varepsilon_m - \beta'_i X_h - \varepsilon_i > 0|X)$$
$$= \mathrm{P}(\beta'_m X_h - \beta'_i X_h + \varepsilon_m - \varepsilon_i > 0|X)$$
$$= \mathrm{P}(\beta^* X_h + \varepsilon^* > 0|X) = \mathrm{F}(\beta^* X_h)$$

Where P is a probability function, $\varepsilon^* = \varepsilon_m - \varepsilon_i$ is a random error term, $\beta^* = \beta'_m - \beta'_i$ is a vector of unknown parameters to be estimated and can be interpreted as the net influence of the vector of explanatory variables influencing choice decisions of SAIPs and $\mathrm{F}(\beta^* X_i)$ is the cumulative distribution function of ε^* evaluated at $\beta^* X_i$. The distribution of F depends on the distribution of ε^*, and utilities and explanatory variables are defined above.

Empirical estimation strategies

Both descriptive and econometric models were used for the analysis. The descriptive analysis involves summarization of dependent and independent variables used in the econometric models. A MVP model was used for estimating the determinants of farmers' choice of interrelated SAIPs, whereas an ordered probit model was used for estimating the determinants of the extent of investments in SAIPs.

A multivariate probit model

Farm households choose a mix of farm practices and inputs to deal with multiple farming constraints, implying that the choice decisions to invest in these technologies is integrally multivariate. Attempting single equation modeling such as probit, logit, Tobit, or multinomial model would exclude useful economic information contained in interdependent and simultaneous choice decisions to invest in technologies (Dorfman, 1996). We employ MVP model, which simultaneously models the influence of the set of explanatory variables on each of the different technologies while allowing for potential correlation between unobserved disturbances, as well as the relationship between the decision to invest in different SAIPs (Asfaw *et al*., 2016; Kassie *et al*. 2015; Teklewold *et al*., 2013). The possible sources of correlation in MVP model may be complementarity/synergy (positive correlation) or substitutability/trade-off (negative correlation between different practices (Kassie *et al*., 2015). Correlations (positive or negative) may also occur if there are unobservable household-specific features that influence several choice decisions but cannot be easily captured by measurable proxies (Ahmed, 2015). Attempting univariate probit or logit models while such correlation exists would result in biased and inefficient estimates (Greene, 2012; Kassie *et al*., 2015).

The MVP model consists of eight binary choice equations which include investments in improved crop varieties (V), crop rotation (R), inorganic fertilizers

(F), organic fertilizer (O), chemicals (C), drainage (D), vegetation (P) and soil conservation structures (S) which can be simultaneously analyzed. Following the above utility equations (2-4), the net benefit (Y^{*}_{hpm}) that the farmer derives from investing in the m^{th}SAIPs is a latent variable determined by observed explanatory variables and error terms. The equations for both latent and observed binary variables are:

$$Y^{*}_{hpm} = X_{hpm}\beta_{mp} + \bar{X}_i\gamma_k + \varepsilon_{hp}, \text{ (m= V, R, F, O, C, D, P, S)} \quad (5)$$

$$Y_{hpm} = \begin{cases} 1 \text{ if } Y^{*}_{hpm} > 0 \\ 0 \ \text{ otherwise} \end{cases} \quad (6)$$

Where Y^{*}_{hpm} is a latent variable that holds the degree to which a farm household views SAIPs m as useful and its estimation is based on observable Y_{hpm} which indicates whether or not a farm household invested in a particular SAIPs on his/her on p^{th} plot in the reference year, X_{hp} represents a vector of observed household and plot-level characteristics, and other factors, β_{mp} is a vector of parameters to be estimated, $\bar{X}$ is a vector of the mean value of Mundlak fixed effects (plot-varying variables including slope and fertility conditions of plots) added additionally to control for unobserved heterogeneity (Mundlak, 1978; Wooldridge, 2002) and ε_{hp} (for m=1, 2, …8) represent the unobserved random error terms, which are jointly follow a multivariate normal distribution with zero conditional mean and variance-covariance matrix (ω), is normalized to unity on the leading diagonal, and correlation $\rho_{mj} = \rho_{jm}$ as off-diagonal elements, and (ƐV, ƐR, ƐF, ƐO, ƐC, ƐD, ƐP, ƐS,)' ~MVN (0, ω), is shown in (eqn.7).

$$\omega = \begin{pmatrix} 1 & \rho VR & \rho VF & \rho VO & \rho VC & \rho VD & \rho VP & \rho VS \\ \rho RV & 1 & \rho RF & \rho RO & \rho RC & \rho RD & \rho RP & \rho RS \\ \rho FV & \rho FR & 1 & \rho FO & \rho FC & \rho FD & \rho FP & \rho FS \\ \rho OV & \rho OR & \rho OF & 1 & \rho OC & \rho OD & \rho OP & \rho OS \\ \rho CV & \rho CR & \rho CF & \rho CO & 1 & \rho CD & \rho CP & \rho CS \\ \rho DV & \rho DR & \rho DF & \rho DO & \rho DC & 1 & \rho DP & \rho DS \\ \rho PV & \rho PR & \rho PF & \rho PO & \rho PC & \rho PD & 1 & \rho PS \\ \rho SV & \rho SR & \rho SF & \rho SO & \rho SC & \rho SD & \rho SP & 1 \end{pmatrix} + (-) \quad (7)$$

Where ρ (rho) stands for the pairwise correlation coefficient of the error terms corresponding to any two investments in SAIPs. The fundamental of this assumption is that equation (5) produces an MVP model that jointly represents decisions to invest in particular SAIPs. The off-diagonal elements in the covariance matrix represent unobserved correlation between the error terms of several latent SAIPs equations, which can affect the choice of technologies. If each of the off-diagonal elements becomes non-zero, then equation 7 carries important information on correlation.

Ordered probit model

An ordered probit model (OPM) was used for examining the extent of investments in SAIPs. Several options exist for measuring the extent of adoption including Tobit (Dadi *et al*, 2001; Mwaura *et al*., 2021), Cragg's double hurdle (Danso-Abbeam *et al*., 2019), Heckman two-stage (Legesse *et al*, 2001), ordered probit (Aryal *et al*., 2017; Kiconco *et al*., 2022; Mengsitu and Assefa, 2019; Teklewold *et al*., 2013), and count data models (Kolady *et al*., 2021). These approaches have their own limitations, for example, in using Tobit, Heckman two -stages, and double hurdle models, the proportion of land under given technologies is used as the dependent variable implying less attention is paid to the number of package technologies adopted. In using count data models like Poisson, the assumption that all technologies have the same probability of adoption has a serious problem while they have a different probability of being adopted (Teklewold *et al*., 2013).

Several studies have used an OPM model for estimating the extent/intensity of adoption of several technologies as the MVP models only consider probability choices (Aryal *et al*., 2017; Kiconco *et al*., 2022; Mengsitu and Assefa, 2019; Teklewold *et al*., 2013). The study conducted by Gonzaga *et al*. (2019) also used an ordered logit to estimate the intensity of the adoption of multiple technologies. These studies, however, are with limitations in considering the number of technologies (count data) as ordinal data and could have been estimated with a Poisson regression model. More specifically, ordered probit/logit models are often used to account for the ordinality nature of outcome variables. We, therefore, use an OPM to investigate the determinants of the extent of investment in a bundle of SAIPs by scaling down the number of eight SAIPs (unrestricted) to five (restrict) extent levels (ordinal). Following Wooldridge (2002), the OP model, which allows the response variable to have more than two ordinal categorical is specified as:

$$Y'_{hp} = \begin{cases} 1 \;\; \text{none of SAIPs} \\ 2 \;\; \text{low lovel } (1-3 \text{ SAIPs}) \\ 3 \;\; \text{moderate level } (4 \text{ SAIPs}) \\ 4 \;\; \text{high leve } (5-7 \text{ SAIPs}) \\ \;\;\; \text{very high } (8\text{SAIPs}) \end{cases} = \; \mathrm{X}'_{\mathrm{hp}}\beta + \; u_i \qquad (8)$$

Where $\mathrm{Y}'_{\mathrm{hp}}$ is a latent variable representing the extent of investments in SAIPs at a plot level, and u_i is the error term which is assumed to be normally distributed with a standard normal cumulative function. For m = 1-4 categories, following a standard ordered probability model, the probability of observing outcome i corresponds to:

$$\Pr\left(\mathrm{outcome_j = i}\right) = \Pr(\mathrm{m_{i-1}} < \mathrm{X'_i}\beta + \mathrm{u_i} < \alpha_{\mathrm{i}}) \qquad (9)$$

Where β is a vector of coefficients to be jointly estimated with the cut points α_1, α_2, …, $\alpha_{\mathrm{m}-1}$ and m is the number of possible outcomes. For investment levels in SAIPs, both the likelihood ratio test (Greene and Hensher, 2010) and Akaike and

Bayesian information criterion (AIC and BIC) are used for comparison of unrestricted (L) and restricted (L^{*}) OP models. That is, λ=L*/L; 0≤λ≤1, and LR=2(ln L - ln L^{*}) ~ χ_m^2 (m restriction), higher pseudo R^2 widely dispersed cut-points, and a smaller of AIC and/ or BIC indicates better goodness of fit.

Description and measurement of variables

The dependent variables in the MVP model include eight dummy variables corresponding to investments in improved crop varieties, inorganic fertilizers, pesticides, cereal-legume rotation, organic fertilizers, drainages, vegetation, and soil conservation structures. Brief description, measurement and summary statistics are given in Table 1.

Table 1. Description and summary statistics of dependent variables (N=1465)

Variables	Description	measures	Rates (%)
Improved variety	Used improved varieties of wheat, *tef*, barley, faba bean and others, but recycled at most four seasons for self-pollinated and ones for cross-pollinated (maize) crops	1=yes, 0=no	47
Cereal-legume rotation	Used legumes (mainly faba bean, field peas and chickpea) as a precursor crop for rotation	1=yes, 0=no	32
Inorganic fertilizer	Used at least one blended fertilizer (NPS/NPSB) or urea	1=yes, 0=no	84
Organic fertilizer	Used manure or compost	1=yes, 0=no	19
Pesticides	Used at least one pesticide (herbicide, fungicide, insecticide)	1=yes, 0=no	69
Drainage	Used either ditches or waterways	1=yes, 0=no	56
Vegetation	Used at least one of the forage trees, broadleaved trees or grasses	1=yes, 0=no	11
Soil conservation structures	Used at least one practice (terrace, soil bund, stone bund, soil-stone bund or fanya juu)	1=yes, 0=no	45

Source: Own survey, 2021

Based on economic theories, empirical evidence, and field observation, relevant explanatory variables were included in the econometric models (Aryal *et al*., 2017; Dorfman, 1996; D'Souza *et al*., 1993; Kassie *et al*., 2013; Kassie *et al*., 2015; Kolady *et al*., 2021; Teklewold *et al*., 2013). The explanatory variables included in this study can be reported as: (1) household characteristics, (2) asset endowments, (3) plot characteristics, (4) institutional factors, and (5) weather conditions. Brief descriptions, measures, summary statistics and expected sign of the variables are presented in Table 2.

Table 2. Description and summary statistics of explanatory variables

Variables	Description	Mean	Std. Dev.	Expected sign
Continuous				
Age	Age of the household head in years	46	11.4	+/-
Education	Years of schooling of the household members	5	2	+
Family size	Family size in number of working-age groups	4	2	+
Livestock	Livestock holding in tropical livestock unit (TLU)	6.3	3.8	+
Plot size	Size of the plot under consideration in ha	0.48	0.37	+-
Temperature	Point (kebele level) historical (1981-2018) maximum temperature in coefficient of variation (456 observation)	8.7	0.8	+-
Rainfall	Point (kebele level) historical (1981-2018) rainfall in coefficient of variation (456 observation)	122.6	19.3	+-
Plot distance	Distance of the plot from a residence in waking minutes	23	22	-
Diversification	Intensity of income diversification (index) (%)	30	25	-
Income	Cash income earned from crops sale (1000 ETB)	23.51	21.7	+
Salary	Monthly salary of the head of development agents (1000 ETB)	8.386	1.87	+
Peer farms	Number of adjacent peer farmers reported	2	2	+
Dummy				
Sex	Sex of the household head (male=1, female=0)	0.92	0.28	+/-
Certificate	If a household had a land certificate for his/her plot (Yes=1, No=0)	0.86	0.34	+
Credit	If a household received credit to buy inputs (Yes=1, No=0)	0.23	0.42	+
ACC	If a household had at least one plot in agricultural commercialization cluster (Yes=1)	0.18	0.38	+
Membership	Household's membership to agricultural cooperative (Yes=1, No=0)	0.31	0.46	+/-
Soil fertility status	Good (Yes=1, No=0)	0.26	0.44	+-
	Poor (Yes=1, No=0)	0.09	0.29	+/-
Slope of the plot	Gentle (Yes=1, No=0)	0.35	0.48	+/-
	Steep (Yes=1, No=0)	0.17	0.38	+/-
Location	The study area (West Shewa zone=1, North Shewa=0)	0.50	0.5	+/-
Perception	A household perceived that a plot was degraded (Yes=1)	0.29	0.45	+/-
Training	If a household received training on crop production (Yes=1, No=0)	0.54	0.5	+

Source: Own survey, 2021

Results and Discussion

Descriptive results

In the study area, smallholder farmers were found to produce a blend of crops (Figure 2). From a total of 1465 plots, most (36%) of the plots were covered by wheat followed by *tef* (24%), faba bean (13%), barley (12%) and other crops including maize, sorghum and potato (15% in sum). On average, 65%, 49%, 18%, 42%, and 30% of wheat, *tef*, faba bean, barley, and other crop plots were sown with improved crop varieties, respectively (Table 3). Legume-cereal-crop rotation was used on 47%, 26%, 56%, and 9% of wheat, *tef*, barley, and other crops plots, respectively. Inorganic fertilizers were applied on 92%, 88%, 69%, 77%, and 77% of wheat, *tef*, faba bean, barley, and other crop plots, respectively. Organic fertilizer was used on 19%, 9%, 25%, 32%, and 16% of wheat, *tef*, faba bean, barley, and other crop plots, respectively. About 76%, 75%, 59%, 58%, and 60% of wheat, *tef*, faba bean, barley, and other crop plots were treated with pesticides, respectively. Drainage practices were used in 58%, 62%, 53%, 51%, and 50% of wheat, *tef*, faba bean, barley, and other crop plots, respectively. Live plants (vegetation) were used as a component of SAIPs on 11%, 10%, 13%, 15%, and 12% of wheat, *tef*, faba bean, barley, and other crop plots, respectively. On average, 44%, 39%, 56%, 57%, and 38% of the plots covered by wheat, *tef*, faba bean, barley, and other crop had soil conservation practices, respectively.

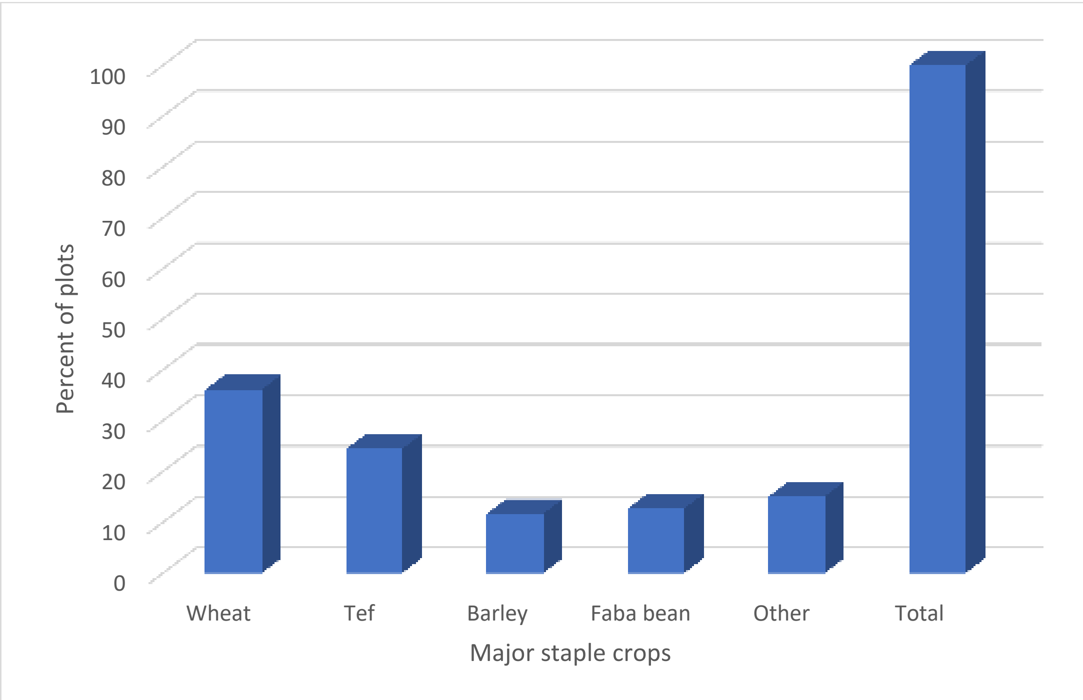

Figure 2. Distribution of plots by crops

Table 3. Summary statistics of SAIPs by plots of major crops

SAIPS	Major crops (% of plots with SAIPs)				
	Wheat (N=529)	*Tef* *(N=358)*	Faba bean (N=186)	Barley (N=171)	Other crops (N=221)
Improved variety	65	49	18	42	30
Cereal-legume rotation	47	26	X	56	9
Inorganic fertilizer)	92	88	69	77	77
Organic fertilizer	19	9	25	32	16
Pesticides	76	75	59	58	60
Drainage	58	62	53	51	50
Vegetation (agroforestry)	11	10	13	15	12
Soil conservation practices	44	39	56	57	38

Source: Own survey data, 2021. Note: X= cereals

The distribution of plots by the number of SAIPs farmers invested in combinations is presented in Table 4. The majority (79%) of the plots were treated with more than two SAIPs, about 25% of the plots were treated with more than half (4) of the SAIPs. The likelihood of investing from two to three SAIPs increased by 30% and from three to four SAIPs increased by 12%, implying that the likelihood of investing in a combination of SAIPs is higher than single/no SAIPs. Compared to a possible combination of practices, the descriptive results showed full (100%) combinations for two and all (eight) SAIPs, and 88%, 68%, 66%, 50%, and 43% of combinations for seven, six, three, five, and four SAIPs, respectively. These results imply that farmers only invest in a subset of practices; though applying the whole practice would be more profitable for different reasons (Mponenla *et al*., 2016). Moreover, descriptive results showed that most (77%) of plots were treated with both at least one external/purchased inputs such as improved seeds, inorganic fertilizers and pesticides, and sustainable practices such as land management practices (soil conservation structures, vegetation, and drainages,) and agronomic practices (cereal-legume rotation and organic fertilizers). The rest of the plots (14%) were treated with only external inputs while 8% of plots were treated only with sustainable practices, implying that the sole use of external inputs is much higher than the sole use of sustainable practices.

Table 4. Distribution of plots by SAIPs combinations

Number of SAIPs	Freq.	Percent	Cum.	Combinations		
				Possible (A)	Observed (B)	Proportion (B/A) *100
Zero (local)	16	1	1	1	1	100
One	62	4	5	8	1	13
Two	236	16	21	28	28	100
Three	421	29	50	58	38	66
Four	384	26	76	70	30	43
Five	200	14	90	56	28	50
Six	98	7	97	28	19	68
Seven	38	3	99	8	7	88
All (8) SAIPs	10	1	100	1	1	100
Only external inputs	207	14				
Only LWMPs	122	8				
Both practices	1121	76.5				
Total (N)	1465	100				

Source: Own survey, 2021

Regarding the extent of investments in a combination of SAIPs, descriptive results showed that plots were treated with different number of SAIPs (Figure 3). The majority (49%) of the plots received low level of SAIPs (1-3) followed by moderate (26%) and high (23%).

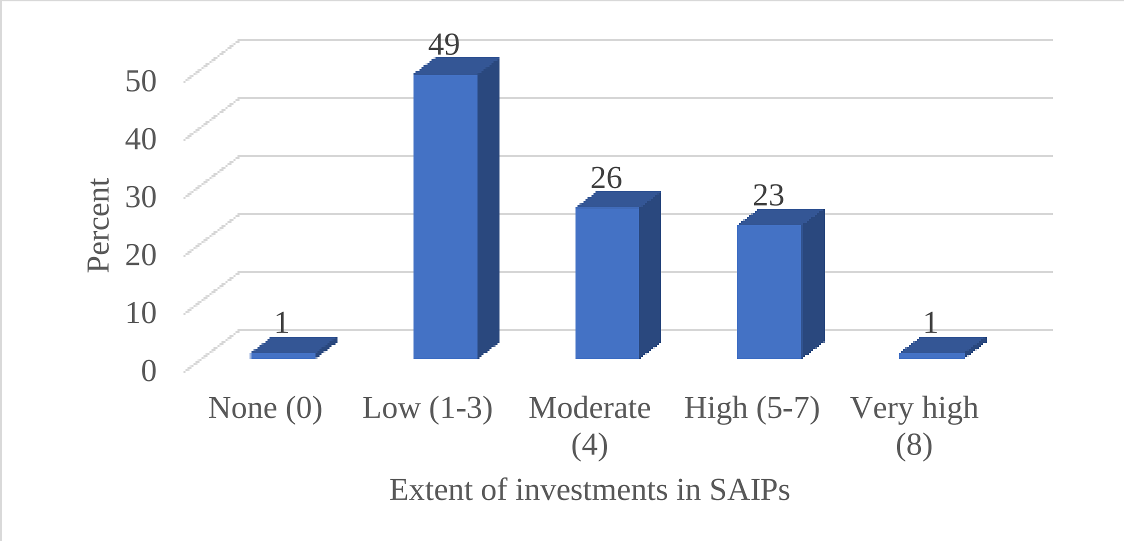

Figure 3. Extent of SAIPs

Econometric results

Factors influencing the choice decisions of investments in SAIPs

The MVP model is estimated with the maximum likelihood approach on plot level observation with Mundlak's average plot varying variables. The goodness of the MVP model is evaluated using the Wald test [Wald chi2 (208) =1937.6, p=0.000], implying that the null hypothesis that all regression coefficients of explanatory variables in each equation are jointly equal to zero is rejected. More specifically, the explanatory variables in each equation contribute significantly to explain the decision to invest in SAIPs. The correlation between the covariance of the error terms is evaluated using the likelihood ratio test [Wald chi2 (28) =270.29, p=0.000] result implies the null hypothesis of no correlation between covariance of the error terms between the decision to invest in SAIP across eight equations is also rejected. More specifically, the correlation coefficient among the eight equations is significantly different from zero at a 1% level, implying that the MVP model best fits the dataset, which accounts for the unobserved correlations across decisions to invest in multiple SAIPs.

Table 5 presents the simultaneous estimates of explanatory variables across eight equations and the correlations between error terms from MVP model results. It provides the direction and coefficient of the driving forces behind farmers' choice decisions to invest in SAIPs. Results showed that the choice decision to invest in SAIPs is different and the factors driving the decision of each of them are also different but interrelated implying the heterogeneity in the decision to invest in SAIPs. Apart from the main variables of interest, the estimates of the MVP model revealed that a number of hypothesized household and plot characteristics, asset endowments, institutional and environmental factors had a significant and differential impact on the choice decision to invest in SAIPs.

Male headed households are more likely to invest in improved seeds and inorganic fertilizers than their counterparts. This is consistent with the findings by Therioult *et al*. (2016). Nigussie *et al.* (2018) also reported that gender of the household increases inorganic fertilizers adoption. However, it is in contrast with the findings by Ndiritu *et al*. (2014), who found gender had no effect on the adoption of improved seed and chemical fertilizers, and Yirga *et al*. (2015), who found that household type in terms of gender negatively affects adoption of improved barley seeds. The results indicate that female-headed managed plots have less chance of receiving improved crop varieties and inorganic fertilizers implying that technology adoption is not gender-neutral. The possible explanation for this is that female-headed households own fewer resources, information, and credit on these inputs which may limit them to use. We also found that the gender of the household declines the decision to invest in drainages, implying that male-headed households are less likely to use drainages on their plots. In other words, plots managed by female-headed households are more treated with drainage. The possible explanation for this is that female-headed households mainly operate their own plots, in which drainage activities can be easily implemented with oxen plows.

Age of the household head was found to positively influence farmers' decisions to invest in both cereal-legume rotation and soil conservation practices. This indicates that plots managed by older farmers were more treated with legumes as a precursor crop and soil conservation practices. This is consistent with the findings by Theriault *et al*. (2016) and Nigussie *et al*. (2018) who found that age of the household head impacts the adoption of soil conservation practices. The possible explanation for this is that older farmers have more experience with these practices than their counterparts. The results showed that the average years of schooling of the household members positively impacted farmers' decisions to invest in improved seeds and declined farmers' decisions to invest in soil conservation and vegetation (agroforestry) practices. This is in line with findings by Asfaw *et al*. (2016) who found that education of the household positively impacted the adoption of modern inputs including improved seeds and Nigussie *et al*. (2018) who found that education declines the adoption of soil and water conservation practices. The possible explanation for this is that farmers are at a level of education (5 years of schooling on average). The results highlight the important role of a household's education for the choice to invest in improved seeds because it helps to acquire more information about improved seeds and interpret the advantages.

The results revealed that family size in the working-age group negatively influenced farmers' decisions to invest in most of SAIPs including improved seeds, drainages, and soil conservation practices, unexpectedly. This indicates that plots managed by a greater number of household members are less likely to receive improved seeds, drainages, and soil conservation practices. This is in line with the findings by Jabbar *et al*. (2020) who found that family size negatively affected adoption of agricultural technologies. However, Ndiritu *et al*. (2014) and Kassie *et al*. (2015) found family size positively correlated with the adoption of soil and water conservation practices. The possible explanation for this is persons in the working-age group may engage in various non-farm activities (observed) which may limit them to invest their time in labor-intensive practices and have liquidity constraints to buy improved seeds.

Livestock ownership positively and significantly influenced farmers' decisions to invest in organic fertilizers (manure/ compost), but declined the use of inorganic fertilizers. This implies that farm households with greater numbers of livestock are more likely to invest in organic fertilizers but less likely to invest in inorganic fertilizers. This is in line with the findings by (Teklewold *et al*., 2013; Ndiritu *et al*., 2014; Kassie *et al*., 2015) who found that livestock holding positively affected adoption of manure. This might be for the obvious reason that the availability of manure depends on the size of livestock a household owns. The negative effect on the choice of inorganic fertilizers indicates that the use of manure/compost substitutes inorganic fertilizers use.

The results revealed that plot size positively and significantly influenced the choice decisions of investments in drainage, but reduced choice decisions to invest in improved seeds, legume-cereal rotation, inorganic fertilizers, manure/compost, pesticides, vegetation, and soil conservation practices. This is similar to the findings by Kassie *et al*. (2015), Asfaw *et al*. (2016) and Nigussie *et al*. (2018) who found that increased farm size positively affected water conservation practices. It is contrary to the findings by Kassie *et al*. (2013) who found that plot size positively influenced the decision to invest in improved seeds, and Theriault *et al*. (2016) who found that plot size positively influenced the adoption of yield-enhancing inputs (improved seeds and mineral fertilizers) and yield-protecting inputs (herbicides, fungicides, and insecticides). This implies that large-sized plots are more likely to be treated with drainage practices compared to other SAIPs.

Temperature and rainfall are the most important weather variables which condition the use of modern inputs and soil-restoring practices. The results revealed that greater variability in maximum temperature positively and significantly influenced farmers' choice decisions to invest in drainage and soil conservation practices. Jabbar *et al*. (2020) also reported that high variability in temperature positively impacts the adoption of improved seeds, rotation, and organic fertilizers. We also found that greater variability in rainfall positively and significantly influenced farmers' choice decision to invest in improved seeds, inorganic fertilizers, drainage, and declined farmers' choice decision to invest in soil conservation practices. This is in line with findings by Theriault *et al*. (2016) who reported that an increase in the coefficient of variation of rainfall positively impacts the adoption of yield-enhancing practices. This indicates that rainfall with less variability means high rainfall which may cause waterlogging (common in highland areas) which suppresses crop growth and production. However, it is contrary to findings by Asfaw *et al.* (2016) who found that greater variability in rainfall is inversely related to the adoption of modern inputs (improved seeds and mineral fertilizers) which is common in water stress areas. Findings suggest that smallholder farmers are responding to climate variables diversely depending on the availability of SAIPs and the weather conditions taken into account.

Secure land tenure is believed to encourage farmers to invest in sustainable practices on their farms. The results revealed that land security in terms of having a land certificate positively and significantly influenced farmers' choice decisions to invest in drainage practices on their plots, holding other things constant. However, getting a land certificate was found to decline the likelihood of investments in inorganic fertilizers. The results indicate that plots with a land certificate are more likely to be drained, and plots without a land certificate are mainly rented/shared in-plots, which may limit the adoption of other sustainable practices. This is contrary to the findings by Theriault *et al*. (2016) who found that tenure security positively affects the adoption of yield-enhancing inputs including inorganic fertilizers.

Plot distance from a residence is an important variable to limit investment in agricultural practices, mainly soil-restoring activities. The results revealed that plots away from a residence are more likely to receive improved seeds but less likely to be treated with vegetation and soil conservation practices. This is similar to the findings by Teklewold *et al.* (2013), Ndiritu *et al.* (2014) and Asfaw *et al.* (2016) who found that plot distance positively affected adoption of improved seeds but negatively affected soil conservation practices. This implies that plots far away plot managers' residences are less likely to receive most sustainable practices implying distance bears more transaction costs via transportation, mainly for investments in labor-intensive practices.

Rural income diversification could be an important variable that limits investments in agricultural technologies through resources (labor, land, and finance) allocations. The results revealed that a relatively high level of income diversification positively and significantly influenced farmers' choice decisions to invest in cereal-legume rotation, organic fertilizers, pesticides, and vegetation. The results indicate that plots managed by households with more income-diversification are more likely to receive more than half of the SAIPs, implying a linkage exists between income diversification and investments in SAIPs. The possible explanation is earnings from diversification leverage to invest in the components of SAIPs. This is contrary to the findings by Nigussie *et al*. (2018) who reported income diversification (off-farm) negatively affects the adoption of soil and water conservation practices and inorganic fertilizers.

Farm income is an important element for rural livelihoods which may limit investments in agricultural technologies (Benitez-Altuna *et al*., 2021). As expected, we found that cash income from the sale of staple crops positively and significantly influenced farmers' decisions to invest in almost all SAIPs including improved seeds, legume-cereal rotation, inorganic fertilizers, manure/compost, pesticides, vegetation, and soil conservation practices. The results indicate that plots managed by households with higher cash crop income are more likely to receive almost all sustainable intensification practices. This implies that there exists a positive relationship between income and investments in agricultural technologies. This finding is in line with findings by Teklewold *et al*. (2017) who found that net farm income positively impacted drainage (farm water management), improved seeds, and inorganic fertilizers.

The agricultural commercialization cluster (ACC) is believed to enable smallholder farmers to engage in higher productivity and market-oriented production through information and input provision (FAO, 2010). The results revealed that ACC positively and significantly influenced farmers' decisions to invest in improved crop varieties and farm water management (drainages). This is in line with the findings by Ochieng *et al*. (2016) who found that ACC enhanced adoption of improved seeds and fertilizers. The results indicate that plots consolidated in ACC are more likely to receive improved seeds and drainages. This is because ACC mostly targets yield-enhancing improved crop varieties and farm water management often done in consensus with neighboring farm owners in the cluster.

The results revealed that access to credit positively and significantly influenced farmers' decisions to invest in vegetation and soil conservation practices. The results indicate that plots managed by households who received credit are more likely to receive vegetation and soil conservation practices. This is contrary to the findings by Ndiritu *et al*. (2014) who reported that access to credit less likely impacted the decision to invest in improved seeds, soil and water conservation practices, and minimum tillage. Other findings by Nigussie *et al*. (2018) reported that credit positively impacted manure application and Teklewold *et al*. (2013) also reported that credit influences the adoption of improved seeds and inorganic fertilizers.

Membership in any type of agricultural cooperative is believed to influence the adoption of agricultural technologies (Wossen *et al*., 2013). The results revealed that membership to agricultural cooperatives positively and significantly influenced farmers' decisions to invest in improved crop varieties, inorganic fertilizers and vegetation. This is in line with the findings by Kolade and Harpham (2014), and Hasen (2015) and Manda *et al*. (2020 who found that cooperative membership influenced adoption of improved seeds and fertilizers. The results indicate that plots managed by members of a cooperative are more likely to receive improved seeds, inorganic fertilizers, and vegetation. The results suggest the need for policies that promote agricultural cooperative and improve their effectiveness for scaling-out/ up of improved technologies.

Regarding plot characteristics, the results showed that plots with moderate to poor soil fertility conditions are more likely to receive farm water management and soil conservation practices, but they are less likely to receive cereal-legume rotation. Farmers' choice decision to invest in soil conservation practices is more likely on plots with steep topography. Plots with gentle to medium topography are less likely to receive soil conservation practices, and plots with steep topography are less likely to receive water management practices. The results suggest that investments in sustainable practices are heterogeneous based on plot-specific attributes. This is consistent with the findings by Teklewold *et al*. (2013), Kassie *et al*. (2015), Asfaw *et al*. (2016), and Theriault *et al*. (2016) who found that plots with steep slope received soil and conservation practices.

The results revealed that, on average, the amount of salary paid to extension (development) agents at the *kebele* level positively and significantly influenced farmers' decision to invest in improved seeds, inorganic fertilizers, and drainages, and declined the use of soil conservation practices. This is similar to the findings by Ndiritu *et al.* (2014), Asfaw *et al*. (2016), Theriault *et al*. (2016) and Jabbar *et al*. (2020) who found that extension contact enhanced adoption of external inputs. The results indicate extension agents with a better salary stay in their mandate *kebeles* to make frequent contact with farmers and share information, and hence plots in this area are more likely to receive these practices. Nigussie *et al*. (2018) also found that extension service negatively affects soil conservation, vegetation, and farm water management practices. The results revealed that training positively and significantly affects farmers' choice to invest in improved seeds and inorganic fertilizers. The results suggest the need for policies that strengthen extension systems to include soil-restoring practices in their daily routines.

Farmers usually learn new farming practices from their neighboring farms either through copying the same practices or teaching each other. Peer farmers and farms are alternative information sources on technology uptake (Adegbola and

Gardebreok, 2007). The results revealed that having a greater number of peer farms near the plots positively and significantly influenced the decision to invest in water management practices, but reduced the uptake of manure/compost. In other words, plots surrounded by a greater number of peer farms are more likely to receive drainages but less likely to receive manure/compost. The results also showed that plots perceived degraded are more likely to receive water management and vegetation practices.

With respect to study location which reflects unobservable spatial differences, the results revealed the differential effect of location on the decision to invest in SAIPs. *Ceteris paribus*, farmers' decision to invest in improved seeds, inorganic fertilizers, and manuring practices in the west Shewa zone are higher. Differently, investment in legume rotation, farm water management, and soil conservation by farmers were lower in the West Shewa zone. The results suggest that efforts to increase short term investments in improved crop varieties and inorganic fertilizers (yield-enhancing inputs) would likely be effective if directed towards north Shewa in the Amhara region, and long-term investments in soil-restoring practices of legume rotation, farm water management, and soil conservation would be effective if directed towards in west Shewa zone in Oromia region. This is consistent with the findings of Yirga *et al*. (2015) who found study sites affected adoption of agricultural technologies.

Study results also revealed that some of the sustainable agricultural intensification practices show complementarity/synergy while some others show substitutability/trade-offs. More specifically, improved variety and inorganic fertilizer, pesticides and inorganic fertilizer, vegetation, and organic fertilizer, and soil conservation practices and vegetation are positively correlated at a 1% significant level implying high complementarity between them. A negative correlation is observed between inorganic and organic fertilizers, pesticides and organic fertilizers, vegetation and cereal-legume rotation, soil conservation practices and variety, rotation and fertilizer use, implying investment in soil conservation practices can significantly reduce investments in other external inputs.

Table 5. Estimates of the multivariate probit model with Mundlak's approach

Variables	Variety	Rotation	Fertilizer	Manure/com.	Pesticides	Drainage	Vegetation	Soil cons
	Coefficient (SE)	Coefficient (SE)	Coefficient (SE)	Coefficient (SE)	Coefficient (SE)	Coefficient (SE)	Coefficient (SE)	Coefficient (SE)
Sex	0.363** (0.142)	-0.086 (0.149)	0.356** (0.168)	-0.090 (0.175)	0.136 (0.136)	-0.313** (0.136)	-0.246 (0.206)	0.048 (0.157)
Age	-0.002 (0.004)	0.008* (0.004)	-0.004 (0.004)	-0.001 (0.004)	-0.005 (0.004)	-0.005 (0.003)	0.004 (0.005)	0.008** (0.004)
Education	0.057*** (0.020)	-0.027 (0.022)	-0.002 (0.027)	-0.009 (0.026)	-0.012 (0.020)	0.002 (0.020)	-0.089*** (0.034)	-0.042* (0.024)
Family size	-0.072** (0.029)	-0.011 (0.031)	0.053 (0.038)	-0.013 (0.036)	-0.028 (0.029)	-0.102*** (0.028)	0.080* (0.045)	0.002 (0.034)
Livestock	-0.039 (0.080)	-0.136 (0.086)	-0.330*** (0.115)	0.395*** (0.104)	-0.015 (0.078)	0.032 (0.079)	0.010 (0.122)	-0.002 (0.093)
Plot size	-1.451*** (0.156)	-1.062*** (0.156)	-1.135*** (0.198)	-1.192** (0.170)	-0.285* (0.155)	0.271* (0.139)	-1.007*** (0.211)	-1.341*** (0.162)
Temperature	-0.575 (0.385)	-0.695 (0.433)	-0.390 (0.573)	0.575 (0.518)	-0.649 (0.401)	0.983** (0.374)	0.471 (0.666)	0.886* (0.455)
Rainfall	1.016** (0.398)	0.783* (0.457)	3.587*** (0.956)	0.519 (0.576)	-0.628 (0.394)	2.439*** (0.411)	0.292 (0.777)	-1.509*** (0.540)
Land certificate	0.055 (0.121)	0.125 (0.133)	-0.374* (0.186)	0.072 (0.159)	-0.039 (0.121)	0.446*** (0.119)	0.019 (0.208)	0.160 (0.140)
Plot distance	0.121*** (0.033)	-0.007 (0.035)	-0.219*** (0.042)	-0.015 (0.038)	-0.067** (0.032)	-0.017 (0.032)	-0.106** (0.046)	-0.062* (0.037)
Extent of income diversification	-0.074 (0.167)	0.384** (0.181)	0.112 (0.213)	0.491** (0.201)	0.303* (0.165)	0.067 (0.162)	0.650*** (0.250)	0.126 (0.188)
Crop income	1.757*** (0.151)	1.284*** (0.149)	1.411*** (0.188)	1.206*** (0.162)	0.482*** (0.145)	-0.104 (0.131)	0.988*** (0.199)	1.470*** (0.153)
Plot clustering (ACC)	0.231** (0.103)	0.106 (0.106)	0.161 (0.126)	-0.072 (0.114)	0.145 (0.100)	0.238*** (0.102)	-0.134 (0.136)	-0.385 (0.120)
Credit	0.039 (0.091)	-0.172* (0.097)	0.149 (0.123)	-0.015 (0.109)	-0.088 (0.089)	0.035 (0.090)	0.466*** (0.120)	0.400*** (0.105)
Membership to coop	0.215*** (0.080)	0.047 (0.085)	0.431*** (0.112)	0.105 (0.094)	-0.010 (0.080)	0.060 (0.079)	0.314*** (0.116)	0.010 (0.093)

Table 5. (continued)

Variables	Variety	Rotation	Fertilizer	Manure	Pesticides	Drainage	Vegetation	Soil cons
	Coefficient (SE)	Coefficient (SE)	Coefficient (SE)	Coefficient (SE)	Coefficient (SE)	Coefficient (SE)	Coefficient (SE)	Coefficient (SE)
Soil fertility (moderate)	0.105 (0.121)	-0.065 (0.131)	0.203 (0.159)	0.111 (0.149)	0.049 (0.122)	0.211* (0.117)	-0.031 (0.194)	0.359** (0.139)
Soil fertility (poor)	-0.154 (0.210)	-0.493** (0.225)	-0.068 (0.250)	0.082 (0.244)	-0.038 (0.202)	0.462** (0.202)	-0.209 (0.306)	0.433* (0.231)
Slope (gentle to medium)	0.058 (0.128)	-0.008 (0.134)	-0.019 (0.161)	0.101 (0.154)	-0.099 (0.127)	-0.055 (0.124)	0.087 (0.202)	-0.497*** (0.147)
Slope (steep)	-0.111 (0.119)	-0.121 (0.126)	-0.230 (0.148)	0.072 (0.142)	-0.106 (0.118)	-0.360*** (0.116)	-0.117 (0.185)	0.250* (0.135)
Salary of DAs	2.237*** (0.340)	0.341 (0.404)	1.936*** (0.548)	-0.752 (0.506)	-0.027 (0.355)	0.744** (0.325)	0.561 (0.670)	-1.865*** (0.402)
Training on crop production	0.224*** (0.079)	-0.088 (0.084)	0.372*** (0.100)	-0.080 (0.095)	0.080 (0.078)	-0.027 (0.077)	0.152 (0.124)	-0.043 (0.092)
Peer farms	-0.007 (0.015)	-0.013 (0.016)	-0.019 (0.018)	-0.067*** (0.018)	-0.024 (0.015)	0.037** (0.015)	0.001 (0.021)	-0.013 (0.017)
Perception to plot degradation	0.061 (0.090)	0.129 (0.094)	-0.104 (0.113)	0.277 (0.102)	-0.039 (0.088)	0.425*** (0.089)	0.633*** (0.118)	0.907 (0.102)
Location	1.663*** (0.208)	-0.737*** (0.235)	3.035*** (0.452)	1.096*** (0.294)	-0.428 (0.206)	-1.515*** (0.208)	0.490 (0.390)	-2.567*** (0.265)
Constant	-40.691*** (3.928)	-20.249*** (4.423)	-42.273*** (6.948)	-13.202*** (5.211)	-1.448 (3.854)	17.072*** (3.691)	-21.700*** (7.320)	2.509 (4.492)
Number of observations (plots)	1465							
Number of observations (HHs)	385							
Wald chi2 test (208)	1937.6							
Prob >chi2	0.000							
Log likelihood	-5249.49							

Table 5. (continued)

SAIPs	Variety	Rotation	Fertilizer	Manure	Pesticides	Drainage	Vegetation	Soil conservation
Rotation	0.258*** (0.045)							
Fertilizers	0.259*** (0.054)	0.134** (0.055)						
Manure/com	-0.015 (0.051)	-0.040 (0.052)	-0.408*** (0.050)					
Pesticides	0.012 (0.044)	-0.023 (0.046)	0.482*** (0.044)	-0.312*** (0.047)				
Drainage	-0.076* (0.043)	-0.025 (0.045)	-0.012 (0.050)	-0.024 (0.048)	0.054 (0.042)			
Vegetation	-0.087 (0.062)	-0.150** (0.064)	-0.089 (0.068)	0.174** (0.068)	-0.183*** (0.064)	-0.018 (0.064)		
Soil conservation	-0.148*** (0.049)	-0.106** (0.052)	-0.180*** (0.058)	-0.011 (0.053)	-0.016 (0.049)	0.028 (0.049)	0.138** (0.063)	

Notes: LR test of rho21 = rho31 = rho41 = rho51 = rho61 = rho71 = rho81 = rho32 = rho42 = rho52 = rho62 = rho72 = rho82 = rho43 = rho53 = rho63 = rho73 = rho83 = rho54 = rho64 = rho74 = rho84 = rho65 = rho75 = rho85 = rho76 = rho86 = rho87 = 0: chi2(28) = 270.291 Prob > chi2 = 0.000; Significance level: *=10%; **=5% and ***=1%

The ordered probit model results

In the previous section, we investigated factors that influence farmers' choice decisions to simultaneously invest in particular SAIPs, taking into account the fact that the decision may be potentially correlated. Therefore, an ordered probit model examines factors that influence the extent of investments in various combinations of SAIPs (scaling the total number of SAIPs applied). Moreover, the variables that influence farmers' choice decisions to invest may differently influence the extent of investments in SAIPs.

The estimates of the restricted and unrestricted ordered probit model and results of marginal effects of explanatory variables are presented in Table 6. Although the magnitude of coefficients is different, the same variables were significant in both restricted and unrestricted models. We rejected the null hypothesis that the restricted and unrestricted ordered probit models are the same (χ^2_3 =12.838: Prob >chi2 = 0.000) with three degrees of freedom. Higher values of Pseudo R^2 (0.198), widely dispersed cut-points and a decrease in AIC and BIC magnitude implies a better improvement in the model's goodness-of-fits. Most of the explanatory variables such as coefficient of variation in maximum temperature and rainfall, income diversification, crop income, agricultural commercialization cluster, access to credit, membership to cooperative, perceived soil fertility and plot's slope condition, and extension services measured in monthly salary of extension agents had a strong positive relationship with the extent of investments in SAIPs. However, family size, plot size, steep topography, study sites, and a number of peer farms showed a strong negative relationship with the extent of investments in a combination of SAIPs.

Regarding the marginal effects, the results revealed that family size reduced the extent of investments in moderate to a high level of SAIPs by 1% and 1.6%, respectively. Plots operated by farm households with more livestock holding received a high level of investment in more than four SAIPs. Plot size was found to reduce the extent of investments in a bundle of SAIPs. More specifically, it drastically reduces moderate, high, and very high levels of investments by 27%, 45.6%, and 0.3%, respectively. Rainfall in coefficient of variation was found to increase the extent of investments in a greater number of SAIPs, this may be the same possible reason mentioned in above. Land tenure security in terms of having a land certificate was found to increase the extent of investments in moderate to a high level of SAIPs by 3.1% and 4.4%, respectively. Plots operated by farm households with greater income diversification received moderate to a high level of SAIPs and increased by 3.8% and 6.4%, respectively.

Cash income from staple crops sales was found to substantially increase the extent of investments in moderate to a high level of SAIPs at the plot level by 32.4%, 54.8%, and 0.4%, respectively. Agricultural commercialization clustering was found to increase the extent of investment in moderate to high levels of SAIPs by 2.7% and 5.5%, respectively. Access to credit to buy agricultural inputs was found to increase the extent of investments in moderate to high levels of SAIPs by 2% and 3.7%, respectively. Membership to agricultural cooperatives was found to increase the extent of investments in moderate to very high levels of SAIPs by 3.7%, 7.2% and 0.1%, respectively. Plot characteristics such as fertility and topography were found to influence the extent of investments in various combinations of SAIPs. Extension services were also found to substantially increase the extent of investments in moderate to very high levels of SAIPs by 12.2%, 20.6% and 0.2%, respectively. Plots perceived degraded were found to receive an increased number of SAIPs; more specifically, it increases the extent of investments in moderate to a very high level of SAIPs by 6.3%, 15.5%, and 0.2%s, respectively. The results also showed that study sites reduce the extent of investments in a multiple of SAIPs (from moderate to high level).

Table 6. Coefficient estimates of the ordered probit model

Variables	Restricted (fixed-effect) OP model							Unrestricted (random) OP model	
	Coefficient	RoSE	Marginal effects on each outcome					Coefficient	RoSE
			None (1)	Low (2)	Moderate (3)	High (4)	Very high (5)		
Sex	0.131	0.135	0.001	-0.052	0.021	0.031	0.000	0.118	0.111
Age	0.002	0.003	-0.000	-0.001	0.000	0.001	0.000	0.000	0.003
Education	-0.010	0.019	0.000	0.004	-0.001	-0.002	-0.000	-0.007	0.016
Family size	-0.065**	0.029	0.000	0.025**	-0.010**	-0.016**	-0.000	-0.058**	0.024
Livestock	0.005	0.068	-0.000	-0.002	0.001	0.001*	0.000	0.007	0.058
Plot size	-1.826***	0.203	0.008***	0.721***	-0.270***	-0.456***	-0.003**	-1.566***	0.177
Temperature	0.092	0.348	-0.000	-0.036	0.014	0.023	0.000	0.279	0.287
Rainfall	1.511***	0.319	-0.006**	-0.597***	0.223***	0.377***	0.003*	1.284***	0.271
Land certificate	0.189*	0.105	-0.001	-0.074*	0.031*	0.044*	0.000	0.175**	0.086
Plot distance	-0.046	0.030	0.000	0.018	-0.007	-0.012	-0.000	-0.081***	0.026
Income diversification	0.257*	0.143	-0.001	-0.101*	0.038*	0.064*	0.000	0.277**	0.127
Crop income	2.196***	0.201	-0.009***	-0.867***	0.324***	0.548***	0.004**	1.900***	0.173
ACC	0.209**	0.092	-0.001**	-0.082**	0.027**	0.055**	0.000	0.214**	0.084
Credit	0.143*	0.079	-0.001	-0.056*	0.020*	0.037*	0.000	0.187***	0.072
Membership to coop	0.276***	0.068	-0.001	-0.109***	0.037***	0.072***	0.001*	0.227***	0.061
Soil fertility (mod.)	-0.049	0.187	0.000	0.019	-0.007	0.012	-0.000	-0.047	0.160
Soil fertility (poor)	0.227*	0.134	-0.001	-0.089*	0.035	0.055*	0.000	0.222*	0.115
Slope (gentle)	-0.055	0.113	0.000	0.022	-0.008	-0.014	-0.000	-0.090	0.098
Slope (steep)	-0.178*	0.101	0.001	0.070*	-0.029	-0.042*	-0.000	-0.186**	0.087
Salary of DAs	0.826***	0.296	-0.003*	-0.326***	0.122***	0.206***	0.002*	0.787***	0.23
Training	0.044	0.068	-0.000	-0.018	0.007	0.011	0.000	0.101*	0.059
Peer farms	-0.023*	0.013	0.000	0.009*	-0.003*	-0.006*	-0.000	-0.019*	0.011
Perception to degradation	0.562***	0.078	0.002**	-0.218***	0.063***	0.155***	0.002***	0.532***	0.071
Location	-0.414**	0.171	0.002*	0.163**	-0.061**	-0.103**	-0.001	-0.468***	0.146

Notes: *** p<0.01, ** p<0.05, * p<0.1

Table 6. (Continued)

Variables	Coefficient	RoSE	Coefficient	RoSE
μ_1	34.916***	3.766	30.656***	3.115
μ_2	37.934***	3.800	31.485***	3.115
μ_3	38.902***	3.807	32.457***	3.123
μ_4	41.224***	3.830	33.442***	3.13
μ_5			34.384***	3.139
μ_6			35.139***	3.144
μ_7			35.88***	3.149
Chi-square	522.789		533.663	
Prob > chi2	0.000		0.000	
Pseudo r-squared	0.198		0.128	
Log-likelihood	-1318.176		-2258.	
LR	1880.492, χ^2_3 =12.838 (Prob >chi2 = 0.000)			
AIC	2696.353		4584.845	(1888.5)
BIC	2855.041		4764.692	(1909.6)
Observation (plots)	1465			
Observation (households)	385			

Notes: *** *p<0.01*, ** *p<0.05*, * *p<0.1*

Conclusions and Implications

Investment in SAIPs is vital for increasing crops productivity, reducing poverty and hunger, and ensuring food security in Ethiopia. This study attempts to examine the determinants of decisions and extent of investments in multiple SAIPs by farm households using 1465 plot level observations. We employed a MVP model to examine determinants of farmers' decisions to invest in multiple SAIPs, and an OPM to investigate factors influencing extent of investments in SAIPs. The SAIPs considered include improved seeds, inorganic fertilizers, pesticides, organic fertilizers, cereal-legume rotation, vegetation, drainages, and soil conservation structures. Results from the MVP model show that while there is heterogeneity with regard to the determinants of investments in any of the eight SAIPs, variables such as gender and age of the household head, average education level of family members, livestock holding, crop income, membership to cooperatives, access to extension and credit services, training, agricultural commercialization cluster, income diversification, rainfall and maximum temperature, and perceived poor soil fertility and steep slope conditions were found to influence the choice decisions of farmers to invest in multiple SAIPs. The results demonstrate that the same factors display different influences and relationships (positive or negative) on decisions to invest in SAIPs. For instance, gender has a positive influence on improved seeds and inorganic fertilizers use, but a negative influence on drainage.

Results also reveal that there are strong complementarities between improved seeds and inorganic fertilizers, improved seeds and rotation, inorganic fertilizers and rotation, soil conservation and vegetation, and substitutability between inorganic fertilizers and manure/compost, inorganic fertilizers and soil conservation, and pesticides and vegetation, and other SAIPs, implying the interdependence of investments in SAIPs. Studies that consider investments in SAIPs in isolation ignore important correlation effects and potentially generate biased model estimates, and overlook heterogeneity effects of the same variables. These significant economic relationships are good characteristics of MVP model outcomes that cannot be captured by univariate models. Results from an ordered probit model also show that the extent of investments in a number of SAIPs is influenced by most of the same variables suggesting that decisions to invest and the extent of investment in SAIPs are governed by the same factors.

Our results offer important policy implications in Ethiopia and other developing countries. First, it can be concluded that SAIPs are interdependent. This suggests that the interdependency nature of farming practices should be considered in designing effective plans for development and diffusion of SAIPs by development practitioners. The knowledge on cross-SAIPs correlation offer policy changes for the convenience of promoting SAIPs jointly to take benefits of their complementarities/synergies, and help to target resource saving production from substitutability of practices. Last, given that several factors influence investments in different blend of SAIPs, policymakers should take into consideration the heterogeneity effects of policy variables including gender, extension, credit, income and plot specific features. This will require provision of gender-based extension and credit services and instant information on weather conditions to make farmers to benefit from SAIPs. This study contributes to the existing SAIPs uptake literature by highlighting the important variables which influence decisions to invest and extent of investments in multiple SAIPs in Ethiopia. Further research that explores the output, peril and wellbeing and environmental implications will be helpful.

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