Soil & Tillage Research 227 (2023) 105595

Contents lists available at ScienceDirect

Soil & Tillage Research

journal homepage: www.elsevier.com/locate/still

Impact of integrated soil fertility management practices on maize yield in Ethiopia

Mohammed Adem [a,*], Hossein Azadi [b,c,d,e], Velibor Spalevic [f,g], Marcin Pietrzykowski [h], Jürgen Scheffran [b]

[a] Bahir Dar University, College of Business and Economics, Department of Economics, Bahir Dar, Ethiopia
[b] Research Group Climate Change and Security, Institute of Geography, University of Hamburg, Hamburg, Germany
[c] Faculty of Environmental Sciences, Czech University of Life Sciences Prague, Prague, Czech Republic
[d] Faculty of Environmental Science and Engineering, Babeș-Bolyai University, Cluj-Napoca, Romania
[e] Department of Economics and Rural Development, Gembloux Agro-Bio Tech, University of Liège, Gembloux, Belgium
[f] Biotechnical faculty, University of Montenegro, Podgorica, Montenegro
[g] Department of Geography, University of Montenegro, Niksic, Montenegro
[h] Department of Ecological Engineering and Hydrology, Faculty of forestry, University of Agriculture in Krakow, Poland

A R T I C L E I N F O

Keywords:
Soil depletion
Soil fertility replenishment
Endogenous switching regression
Sustainability
Adoption of integrated soil fertility management
Production

A B S T R A C T

Today, declining soil fertility is the main biophysical constraint to improve crop yield and poses a potential threat to food security. This study aims to explore the elements that could influence the adoption of integrated soil fertility management (ISFM) practices as well as their impact on maize yield. This study is based on a pseudo-panel collected by Ethiopia's central statistical agency (CSA) in collaboration with the World Bank. A Multinomial Endogenous Switching Regression model (MESR) was employed to achieve the specified objectives. The findings revealed that 15% of plots received no soil fertility-enhancing treatments, while 35% received a combination of inorganic fertilizer and manure to boost soil fertility. The average maize yield in the study was 3.44 tons per hectare, which was nearly equal to the average national yield in the prior year. Finally, maize yield was significantly influenced by soil fertility management measures, whether used alone or in combination of two or more soil fertility enhancing technologies. The extent of the impact, however, varies significantly depending on the inputs employed. Thus, using manure or compost alone had a moderate but significant impact on maize yield, but using inorganic fertilizer in combination with manure had the biggest impact. Therefore, policies that support the expansion of ISFM practices should be promoted. Farm households also receive technical assistance and training to better understand the use of ISFM practices, and policies that promote them should be expanded.

1. Introduction

In crop production, the soil fertility plays a vital role which is directly related to the loss or gain of plant nutrients. In intensive and continuous crop production systems there are high soil degradation rates with a reduction in the natural fertility in areas under cultivation. Consistent use of the recommended huge quantities of inorganic fertilizers is biologically unnecessary, economically extravagant, and ecologically damaging (Jaja and Barber, 2017). Thus, the sole use of inorganic fertilizers is not enough for sustainable crop production and soil ecosystem services. Some of the concepts that have been devised in recent decades to help in boosting the quality and quantity of crops farmed in various regions of the globe include conservation agriculture, organic agriculture, and agroforestry. Among the numerous methods for sustainable farming and food production are integrated natural resource management and integrated nutrition management (Kassam et al., 2019; Shah and Wu, 2019). All these paradigms promote combined use of various agricultural technologies which can be neither completely overlapping nor mutually exclusive.

Ethiopia aims to expand food production to feed a growing population and does not want to use traditional agriculture since it is easy to understand and already employs existing technology that is ecologically beneficial. In other words, traditional farming practices remove nutrients from the soil and this leads to an unproductive agricultural system (Moswetsi et al., 2017). Thus, application of modest amounts of mineral fertilizer using improved crop varieties may increase yield by

* Corresponding author.
E-mail address: ademoha@gmail.com (M. Adem).

https://doi.org/10.1016/j.still.2022.105595
Received 13 May 2022; Received in revised form 1 November 2022; Accepted 24 November 2022
Available online 23 December 2022

influencing crop utilization efficiency of nutrients (Schütz et al., 2018). As a result, combining mineral fertilizers with organic inputs helps to preserve soil fertility, which enhances nutrient use efficiency. Mineral fertilizers play a vital role in integrated soil fertility management but cannot stand alone as the only way of soil nutrient management. Sommer et al. (2018) state that when soils are responsive, mineral fertilizer can serve as an entry point for integrated soil fertility management (ISFM) practice, while if the soil is poor, mineral fertilizer must be applied in conjunction with the organic resource. In addition, ISFM provides environmental services by improving soil biological diversity and by capturing extra carbon that exists in the soil.

Soil fertility depletion has emerged as the leading serious issue to agricultural output and food security in Sub-Saharan Africa in recent years (Aloo et al., 2021; Bationo et al., 2020; Holden, 2018; Kim and Bevis, 2019). To reverse soil fertility depletion and increase agricultural productivity, the government of Ethiopia has promoted various soil fertility enhancing technologies and practices that include organic and inorganic fertilizers, bio-fertilizers,[1] conservation agriculture, and soil and water conservation practices among others (ATA, 2013 and 2017). Smallholder farmers have used these practices either to restore the lost nutrients of the soil or to maintain the existing fertility level. Smallholder farmers have also used traditional indigenous soil conservation measures such as terracing, stone bonding, contour plowing, and field ridging to minimize soil fertility deterioration (Zerihun, 2018).

However, for the vast majority of small-scale farmers, a separate injection of inorganic or organic fertilizers is inadequate to keep maize output stable. The use of inorganic fertilizers like di-ammonium phosphate (DAP) and urea, for example, has been impeded by a constant rise in fertilizer prices (World Bank, 2018). Also, the application of chemical fertilizers like DAP and Urea generates negative externalities such as soil acidity, water contamination, and loss of nutrient balance (Aryal et al., 2021). Organic fertilizers such as crop waste, manure, and compost may have tremendous potential to boost topsoil's structural, chemical, and microbiological features as well as the nitrogen supply (Singh et al., 2020; Verma et al., 2020). Conventional organic fertilizers also improve and stabilize soil organic matter and mitigate soil acidity, thereby improving soil water retention, infiltration rate, and microbial activities (Chen et al., 2018; Gurmu, 2019; Mockeviciene et al., 2021). However, organic fertilizers have a low mineral nutrient content and slow nutrient release rate so that larger volumes and longer periods are required to provide enough nutrients for crop growth (Chew et al., 2019; Thomas et al., 2019; Zandvakili et al., 2019). This has brought about the development of ISFM practices which are seen as a sustainable and environmentally friendly way of improving soil fertility.

ISFM practices are critical to advancing agricultural productivity while also building environmentally sustainable systems. Studies have been undertaken on how to effectively manage soil fertility in order to avoid the danger of soil fertility depletion in Ethiopia and other Sub-Saharan African nations. Danso-Abbeam et al. (2017) looked at how soil fertility improving inputs complement each other. Farm-level interventions may have a spillover effect on some other integrated soil nutrient management techniques due to the complementarities of various soil fertility improving management approaches. Lambrecht et al. (2016) explored how ISFM practices have been implemented on farms, with a particular focus on the interrelationships between ISFM components. The extent of soil fertility is the push factor behind ISFM adoption, although households' socioeconomic characteristics are also important. Mponela et al. (2016) looked into the socio-economic and environmental factors that influence farmers' adoption of ISFM practices. Ansong Omari et al. (2018) also highlighted the key points of farmers' perceptions of organic residue management, soil health indicators, and crop production patterns. Merante et al. (2017) investigated the importance of soil organic content and how management strategies depending on multiple soil characteristics might assist farmers in selecting the most appropriate and successful practices to protect or improve soil stability and to increase soil organic content.

Farmer's practices, perceptions and knowledge are invaluable. For example, farmers in some regions of Ethiopia follow the rotation of a leguminous crop as organic fertilizer by using manure to produce better yields for grain crops. This is important in the case of crops such as corn. Therefore, the combination of different agricultural systems and agricultural practices can help to solve the problems of reducing soil fertility in corn fields (Mohamed, 2016). It is useful to integrate different methods to minimize the costs for poor farmers, such as agro-forestry, or the use of green manure, animal manure and compost in combination with mineral fertilizers to increase crop productivity (Kelkay and Yohannes, 2015). In addition, small-scale farmers have a wide range of household characteristics and land area that can limit their choice to use soil fertility management strategies. Previous research (e.g., Jegede et al., 2021; Yussif, 2019) has emphasized the adoption of soil fertility management options by addressing purely socio-economic variables, while traits at the design level are key drivers for adopting ISFM practices. Farm households frequently utilize a combination of several strategies of enhancing soil fertility that complement or replace one another, despite earlier research (for instance, Zeweld et al., 2018) emphasizing the need of adopting particular methods to refill soil fertility in isolation. Therefore, this study was conducted to fill the identified knowledge gap associated with the use of ISFM practices. This study examines both household and plot-level drivers of ISFM practice adoption in isolation or in combination, as well as their impact on maize yield.

2. Methods

2.1. Description of the study area

Ethiopia is located between latitudes 3º and 33º north of the equator and longitudes 33º and 48º east of the Greenwich meridian. The country is bounded by Eritrea to the north and northeast, Djibouti and Somalia to the east, Sudan and South Sudan to the west, and Kenya to the south (Fig. 1). It is Africa's second-most populous nation, having cities constituting for one-fifth of the population (World Bank, 2019). The study area encompasses the four major regions that account for 91.6% of the country's population and agricultural production (CSA and WFP, 2017).

Ethiopia's climate is characterized by a monomodal and bimodal rainfall pattern ranging from 100 mm to 2400 mm per year. The Afar Delta has the greatest of maximum mean temperatures in the nation from April to September, while the highest mean temperatures are found in the highland regions between November and February (National Meteorological Services Agency, 2016). Maize is Ethiopia's second most extensively cultivated crop, produced under a variety of agro-ecological and socioeconomic settings, generally under rain-fed production. Ethiopia is also Africa's second biggest maize producer (Neelakantam et al., 2016).

2.2. Sources of data

This study relied on household plot level data of the 2018–2019 farming season. This data was taken from the World Bank's Living Standards Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA), which was collected in collaboration with Ethiopia's Central Statistics Agency. The dataset contains farmers who grew maize which is the staple food for the majority of the population. A pseudo panel of 4236 observations was formed by using three plots from each of the 1412 farm households in Ethiopia's four main maize producing regions, including Oromia, Amhara, SNNP, and Tigray.

[1] It is a substance which contains living microorganisms that promote plant growth by increasing the supply or availability of primary soil nutrients (Chen et al., 2018).

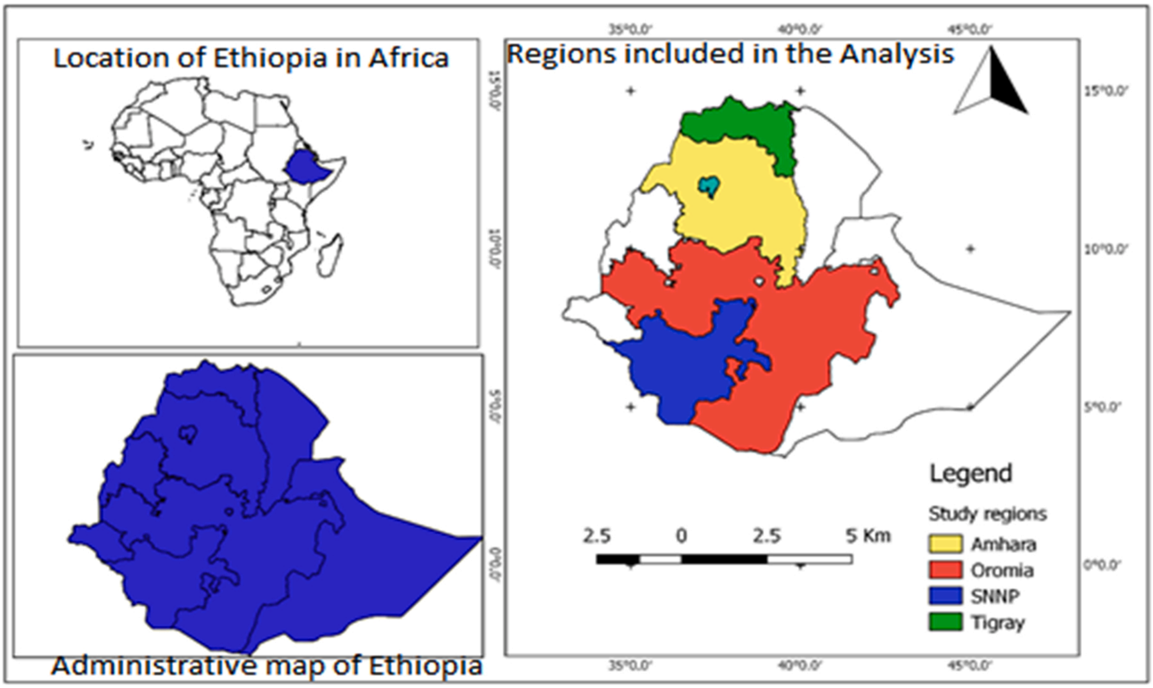

Fig. 1. Description of the study area.

2.3. Conceptual framework

It is critical to understand how technologies are adopted in reality if the promise of new technologies is to be realized. Understanding technology adoption can help in understanding how much socially valued technologies are unable to reach their full potential due to information constraints or externalities. A considerable body of knowledge exists in the field of agricultural technology adoption modeling. Modeling farm households' behavior is key to understanding the technology adoption patterns of smallholder farmers. Farm households chose the best mix of various soil increase soil fertility practices depending on the resources available to themselves (Nisa et al., 2019). Therefore, when a farmer faces multiple technical options (agricultural technologies), observed outcomes can be modeled within the framework of discrete choice analysis. Households' adoption decisions regarding a single technology or combination of technologies as a package can be modeled as follows:

Let U_{ipj} represent the benefit obtained by household i from plot p as a result of adopting technology package j, and U_{ipm} represents the benefit derived from household i from plot p as a result of adopting technology package m. Then, household i will decide to adopt a technology (or a package) j on plot p if the benefit from the adoption of package j is greater than the benefit from adopting package m. Mathematically, it is stated in Eq. 1 as follows:

$$D_{ip}^{*} = U_{ipj} - U_{ipm} > 0 \tag{1}$$

Where D_{ip}^{*} is the latent variable of the net benefit of adopting a practice (a combination of technologies) j. Rational farm households will choose a technology package that could result in better expectations benefits or utilities (Habineza et al., 2020).

In an observational study, the assignment of ISFM technology practices to control and treatment groups are non-random. Thus, the acceptance ISFM package could be voluntary or targeted, resulting in self-selection bias in both instances (Martey et al., 2019). Table 1 compares the actual yield of acceptors corn with the false result if ISFM packages are not accepted, and Table 2 compares the actual yield obtained by non-acceptors of ISFM packages with the false result if ISFM packages are accepted. This led to a biased and inconsistent estimate of the adoption impact on yield. Hence, self-selection to participate in a program or to adopt technologies can be a cause of endogeneity, and failure to consider such a problem would exaggerate the real impact of technologies. Similarly, a targeted program intervention is a source of endogeneity, and a failure to account for such a problem might minimize the real impact of interventions (White and Raitzer, 2017).

The straightforward method to estimate the impact of technology packages on yield outcome would be to incorporate a dummy variable in the yield equation for adoption and non-adoption to apply for ordinary least square estimation (Atinga, 2019). However, this method may produce skewed results due to the assumption that the adoption choice is exogenously influenced. Adoption, however, may be endogenous if a voluntary adoption choice may lead individuals to self-select (Sekyi et al., 2019). It might be problematic to use a pooled sample of adaptors of various packages and non-adopters as it assumes a set of covariates has the same impact on different package adopters (Bernedo Del Carpio, 2016). This suggests that package adoption has only a little effect on intercept shift which stays constant, regardless of the values of the other explanatory variables that influence yield outcomes. If it is assumed that technology packages have differential impacts on yield outcomes of farm households, separate yield equations that account for endogeneity problems must be specified for adopters and non-adopters of each package. To account for selection biases and endogeneity problems, this study used a multinomial endogenous switching regression (MESR) model. The MESR model was developed with the intent of eliminating endogeneity and sample selection bias (Khonje et al., 2018).

2.4. Econometric model

To analyse the factors affecting the decision to adopt ISFM packages and their impact on maize yield, this study employed a MESR model. This model has two stages: 1) In the first stage, the model assumes that farm households face a choice of j technology packages (i.e., the three-soil fertility enhancing technologies and their combination) and 2) In the second stage, the impacts of these technology packages on Maize yield are estimated.

At the first stage, let be the latent variable that denotes the expected benefit from adopting technology combination j (j = 0, 1, 2.…J where j

Table 1
Description of variables, measurement units, and expected signs.

Variables	Description	Measurement	Expected sign
Socioeconomic characteristics			
Hh_size	Total family size	Numbers	+ /-
Head_sex	Gender of household head	1 =Male 0 =Female	+
Head_age	Age of household head	Years	+ /-
Head_edu	Education level of household head	1 =literate 0 =illiterate	+
Storage	The storage options available to a household for keeping harvested crops secure	1 =improved storage 0 =traditional storage	+
Shocks	If a household experienced a health shock	1 =Yes 0 =No	–
Land_size	Land used for Maize production	Ha	+
Farm_type	Types of farming a household engaged	1 =crop farming 0 =Both (crop and livestock farming)	-
Institutional variables			
Credit	If a household needed credit and was able to get it	1 =Yes 0 =No	+
Extn_visit	The frequency of extension visits by extension officers	Number	+
Own_radio	Cwnership of TV and Radio	1 =Yes 0 =No	+
Irrigation	If a household irrigated at least one of land allocated to Maize	1 =Yes 0 =No	+
Geographical Variables			
Market_dist	Households distance from nearest market	KMs	+ /-
Mainroad_dist	Households' distance from nearest main road	KMs	+ /-
Soil Quality			
Sq_poor	If the soil color is black (1 =yes, 0 =no)	Dummy	+ /-
Sq_fair	If the soil color is red (1 =yes, 0 =no)	Dummy	+ /-
Sq_good	If the soil color is sandy (grey color) (1 =yes, 0 =no)	Dummy	+ /-
Yield	Dependent Variable	Quintals/ha	

Source: ESS survey (2018).

Table 2
Descriptive statistics of variables.

Variables	Mean	Std. Dev.
Socioeconomic characteristics		
Hh_size	5.03	2.23
Head_sex	0.78	0.42
Head_age	47.2	15.5
Head_edu	0.37	0.48
Storage	0.85	0.36
Land_size	1.23	0.95
Farm_type	0.16	0.37
Off_farm	0.067	0.25
Institutional variables		
Credit	0.28	0.45
Own_radio	0.26	0.44
Ext_visit	1.96	3.24
Geographical Variables		
Market_dist	47.8	20.3
Mainroad_dist	14.3	15.0
Soil Quality		
Sq_poor	0.32	0.47
Sq_fair	0.33	0.47
Sq_good	0.33	0.47
Yield	34.4	8.5

Source: ESS survey (2018)

denotes the number of technology combinations available to households) on plot p.

Let D^*_{ip}.denote the expected benefit from using j technology package (j = 0, 1, 2., j) on plot p, where j is the available technology package and p is the plot number where the technology is being used. This study considers three-soil fertility replenishment technologies (inorganic fertilizer, manure, and compost) that provide eight possible combinations. Households can choose combination j over any other combination (m) based on the expected benefits. Thus, the latent variable is specified in Eq. (2) below:

$$D^*_{ipj} = Z_{ipj}\delta_j + \sigma_i + \varepsilon_{ipj}D = \left\{ \begin{array}{ll} 0 \text{ if } U^*_{ip0} > \max\left(U^*_{ipm}\right) \text{or } \eta_{it0} < 0 & \\ . & \\ . & \text{for all} \\ . & \\ J \text{ if } U^*_{ipj} > \max\left(U^*_{ipm}\right) \text{or } \eta_{ipj} < 0 & \end{array} \right\} m \neq j \tag{2}$$

Where $\eta_{ipj} = \max_{m \neq j}\left(U^*_{ipm} - U^*_{ipj}\right) \langle 0$. This implies that household i will adopt technology combination j if, and only if, the expected benefit from adopting technology combination j at time t is greater than the expected benefit of any other technology combination in the same period t ($m \neq j$). ε_{ip} denotes the error terms, σ_i captures unobserved individual-specific impacts such as skills or motivation of farm households, δ_j represents parameters to be estimated, and Z_{ipj} denotes covariates in the model. It is assumed that the observed stochastic component "Z" is uncorrelated with the idiosyncratic individual component "ε_{ipj}" under the assumption of being independently and identically Gumbel distributed. A multinomial logic model may be used to estimate how a household I, having a plot p and attributes of Z, would choose a technology combination j and the model specified in Eq. (3), as follows:

$$P_{ipj} = P\left(\varepsilon_{ipj} < 0 | Z_{ip}\right) = \frac{\exp\left(\delta_j Z_{ip}\right)}{\sum_{m=0}^{J} \exp\left(\delta_m Z_{ip}\right)}. \tag{3}$$

It is assumed that the observed stochastic component "Z" is uncorrelated with the idiosyncratic individual component "ε_{ipj}" under the assumption of being independently and identically Gumbel distributed (Oumer, 2019).

In the first stage of choosing ISFM technology packages, non-adoption of all the three technologies (fertilizer, manure, and compost) denoted as j = 0 was taken as a base category, and the rest of the packages were represented as j = 1, 2….7. Hence, the outcome equation of each possible regime was specified in Eq. (4), as follows:

$$(4a)\text{Regime}0.Y_{ip0} = X_{ip0}\beta_0 + \eta_i + \mu_{ip0}\text{if } J = 0 \tag{4}$$

$$(4j)\text{Regime } j.Y_{ipj} = X_{ipj}\beta_j + \eta_i + \mu_{ipj}\text{if } i = j$$

Where Y_{ipj} represents maize yield of household i from plot p in regime j (j = 0, 1…., 7), with X_{ipj} denoting the vector of explanatory variables (socioeconomic and institutional variables), β_j parameters to be estimated, and μ_{ip} representing the error term that is assumed as $E(\mu_{ip}/X,\beta) = 0$ and $V(\mu_{ip}/X,\beta) = \sigma^2_j$. The value Y_{ipj} is shown if, and only if, package j is adopted by household i at time t, i.e., $U^*_{ipj} > \max\left(U^*_{ipm}\right)$ for all$m \neq j$.

If the error terms in the selection model (2) ε_{ipj} are linked with the error terms μ_{ipj} in the outcome Eqs. (4a) to (4j), the estimations in Eq. (4) will be biased. To obtain a consistent estimate of β_j, Bourguignon et al. (2007) suggested that correlation between the error term ε_{ipj} from the first-stage selection model and the error term μ_{itj} from the sample selection equations be considered.

Then, the MESR model in Eq. (4) is restated by including selection correction terms in Eq. (5), as follows:

$$Y_{ip0} = X_{ip0}\beta_0 + \sigma_0\lambda_{ip0} + \eta_i + \epsilon_{ipj} \text{if } J = 0 \tag{5}$$

$$Y_{ipj} = X_{ipj}\beta_j + \sigma_1\lambda_{ipj} + \eta_i + \epsilon_{ipj} \text{if } J = j$$

Where σ_i denotes the covariance between ε_{ipj} and μ_{ipj}, and λ_j represents the inverse Mills ratio. Since generated regressors can be heteroscedastic, it is important to control the problem by bootstrapping the standard errors in the result equation. Selection instruments were added into the identification model based on a falsification test, as suggested by Di Falco et al. (2011). This testing enables the selection of variables that are predicted to have a major influence on the first stage selection equation but not on the outcome equation. Selection bias correction based on the multinomial logic model may provide a good correction for the outcome equation, even if the IIA assumption is violated (Kawatkar et al., 2018). The parameter estimates of the yield equations are used to create a selectively corrected prediction of the counterfactual of adopters (if they had not adopted) and non-adopters (if they had adopted the ISFM practices). Then, unpaired t-test was done to examine if a statistical difference existed among the actual and counterfactual values of both adopters and non-adopters.

2.4.1. Impact of ISFM practices on maize yield

In this section, this study evaluated the effects of accepting the ISFM j package on corn yield for those who accepted the j package. If there was no selection bias, it would have been easier to assign a counterfactual value to households which did not adopt the technology package. Unobserved heterogeneity in the yield equation, however, might generate a selection bias since it has the potential to influence farmers' adoption choice of integrated soil fertility management.

In impact assessment, there are three main metrics that may be used to quantify the impact of an intervention or technology on the intended outcome. The mean effects of treatment on the population (ATE), the mean effects of treatment on treated people (ATT) and the average effects of treatment on untreated people (ATE) are three categories (ATU). ATE measures the difference between the average outcomes of ISFM package adopters and non-adopters. Haneuse et al. (2019) and Kassie et al. (2015), however, had no influence over the technology package assignment in the observational study. The choice to adopt technology packages was more likely to be influenced by yield outcome, potentially leading to a biased estimator of ATE.

The ATT responds to queries regarding how the average outcome would alter if someone used a technology package that had not previously been used. This study compared the projected maize yields of adopters and non-adopters to their respective counterfactuals using ATT and ATU. The expected real maize yield under the actual and counterfactual hypothetical scenarios was computed using Eq. (5), as explained by Di Falco et al. (2011), Teklewold et al. (2013), and Kassie et al. (2015). Then: Actual maize yield of adopters computed using Eq. (6):

$$E(Y_{ipj}|J_i = j) = X_{ipj}\beta_j + \sigma_j\lambda_{ipj} \tag{6}$$

Actual maize yield of non-adopters computed also using Eq. (7):

$$E(Y_{ip0}|J_i = 0) = X_{ipj}\beta_0 + \sigma_0\lambda_{ip0} \tag{7}$$

Adopters' counterfactual (if adopters had not to adopt) derived using Eq. (8):

$$E(Y_{ip0}|J_i = j) = X_{ipj}\beta_0 + \sigma_0\lambda_{ipj} \tag{8}$$

Non-adopters' counterfactual (if non-adopters had adopted) derived also using Eq. (9):

$$E(Y_{ipj}|J_i = 0) = X_{ipj}\beta_j + \sigma_j\lambda_{ip0} \tag{9}$$

The expected outcomes of adopters and non-adopters seen in the actual sample were expressed by Eqs. (6) and (7), respectively. However, Eqs. (8) and (9) denote the counterfactual of adopters and non-adopters of ISFM technology packages, respectively. Hence, the average impact of ISFM technology package adoption on adopters ATT was computed by taking the difference between Eqs. (6) and (8), as stated in Eq. (10) below:

$$ATT = E[Y_{ipj}|J_i = j] - E[Y_{ip0}|J_i = j] = X_{ipj}(\beta_j - \beta_0) + \lambda_{ipj}(\sigma_j - \sigma_0) \tag{10}$$

However, the average impacts of the adoption of the ISFM technology packages on non-adopters' ATU were computed using the differences of Eqs. (7) and (9) (effects of accepting ISFM technology package on non-acceptors if they have accepted any of the packages), as stated in Eq. (11) below:

$$ATU = E[Y_{ipj}|J_i = 0] - E[Y_{ip0}|J_i = j] = X_{ipj}(\beta_j - \beta_0) + \lambda_{ip0}(\sigma_j - \sigma_0) \tag{11}$$

ATT and ATU are expected outcome impact of adoption, controlling for selection bias on a randomly chosen farm household from a group of adopters and non-adopters of ISFM technology packages, respectively. The expected change in maize yield, if the characteristics and resources of adopters and non-adopters are the same, is indicated by the first term on the right-hand side of Eqs. (10) and (11). The second term is the selection term which may include all of the likely effects of the unobserved variables (Wekesa et al., 2018). The explanatory variables for the models described below were selected using an economic theory and earlier empirical adoption studies as a reference (Mutuku et al., 2017; Nalivata et al., 2017; Yadav et al., 2017; Zhang et al., 2018). The detailed description of the variables, measurement units, and their hypothesized direction of influence are presented in Table 1.

3. Results and discussion

3.1. Descriptive statistics of explanatory variables

The summary statistics of explanatory variables employed in ISFM practice adoption regression models are shown in Table 2. The average household size in the sample is five which is comparable to the national average. Based in the findings, 78% of the household heads were men, with an average age of 47 years ranging from 18 to 84 years. Furthermore, the majority of household heads (about 62%) had no formal education and were married (78%). The average dependencey ratio is 1.23, implying that one economically independent household member supports 1.23 dependent household members on average. In addition, 85% of the households used improved crop storage equipment (metal silos and bags) to store their harvested crops, while 15% used unprotected crop storing equipment, and 48% of the household heads have experienced a health shock. Furthermore, the households owned 1.25 ha of land on average. Only 16% of the households relied only on the crop production farm type, while the rest engaged in a mixed farming type that includes both crop production and animal husbandry. Similarly, only 6% of the households earned money from non-farm sources. Credit was available to 28% of the families. Radio sets were owned by 29% of households, allowing farmers access to critical agricultural information. Finally, extension agents made an average of 1.96 visits to farmers. The average distance between farm inhabitants' homes, the nearest market and main road was 47.8 km and 14.3 km, respectively.

3.2. Choices of integrated soil fertility management practices

Table 3 presents the descriptive statistics of the three-soil fertility-enhancing technologies and outcome variables of yield. Regardless of the fact that inorganic fertilizer prices have risen dramatically since the 1990 s, 70% of farmers have applied it on their farms (World Bank, 2018). This is because of the government's fertilizer subsidy programs and credit provision schemes; smallholder farmers were more inclined to apply inorganic fertilizer on their plots (Riesgo et al., 2016).

Table 3
Plots distribution by adoption of eight ISFM packages (%).

Choice (j = 1,0.7)	ISFM Packages	Inorganic Fertilizer		Manure (M)		Compost (C)		Mean
		F_0	F_1	M_0	M_1	C_0	C_1	
1	$F_0M_0C_0$	✓		✓		✓		0.15
2	$F_1M_0C_0$		✓	✓		✓		0.16
3	$F_0M_1C_0$	✓			✓	✓		0.07
4	$F_0M_0C_1$	✓		✓			✓	0.03
5	$F_0M_1C_1$	✓		✓	✓		✓	0.04
6	$F_1M_0C_1$		✓	✓			✓	0.04
7	$F_1M_1C_0$		✓			✓		0.35
8	$F_1M_1C_1$		✓		✓		✓	0.16
	Total							1.00

Source: own computation ESS survey (2018)

Similarly, the proportion of manure and compost adopters were 61% and 27%, respectively. The average maize yield was recorded as 34.4 quintals per hectare, which was a little bit lower than the average national Maize yield (Cochrane and Bekele, 2018). The three soil fertility replenishment technologies, which were selected based on the availability of information in the main data set for all plots, provide eight possible combinations from which households may choose based on the highest expected benefit or utility.

Among the eight possible combinations of soil fertility management practices in Table 4, most farm households adopted the combination of fertilizer and manure ($F_1M_1C_0$) package. Combination of inorganic fertilizer and compost ($F_1M_0C_1$) and the combination of manure and compost ($F_0M_1C_1$) were the least applied packages, with 4% of plots received these packages. About 15% of plots did not receive any of the three-soil fertility replenishment technologies ($F_0M_0C_0$).

The interdependence of the three soil fertility replenishment alternatives is shown in Table 4, which yields an unexpected result about the likelihood of conditional and unconditional adoption. Table 4 shows the interdependence of the three soil fertility replenishment options, giving an unexpected finding about the probability of conditional and unconditional adoption. Farm households' unconditional probabilities of adopting inorganic fertilizer were 70%, but this probability climbed to 83% when manure was added. In contrast, combining manure and compost increased the chance of using inorganic fertilizer by 80%. When inorganic fertilizer, compost, or a combination of the two were used, the conditional probability of farm households adopting manure rose by 72%, 73%, and 81%, respectively. Similarly, the conditional probability of farm households using compost increased to 32% and 31%, depending on whether they used livestock manure or a combination of mineral fertilizers and manure. In sum, the findings demonstrate that adopting one of the soil fertility replenishment technologies increases the likelihood of adopting other technologies, implying that soil fertility-enhancing inputs are complementary to each other. Zeweld et al. (2017) also found that there are significant complementarities between sustainable soil fertility enhancing technologies, demonstrating the interdependence of adoption of soil replenishment practices. The cross-technology correlation of soil fertility management practices has the potential to have substantial policy repercussions. Policy changes that influence one practice may have ramifications for other practices.

Table 4
Conditional and unconditional adoption probabilities of ISFM packages (%).

	Fertilizer (F)	Manure (M)	Compost (C)
$P(Y_I = 1)$	0.70	0.61	0.27
$P(Y_I = 1 \mid Y_F = 1)$	1.00	0. 72***	0.28
$P(Y_I = 1 \mid Y_M = 1)$	0.83***	1.00	0.32***
$P(Y_I = 1 \mid Y_C = 1)$	0.72 *	0.73***	1.00
$P(Y_I = 1 \mid Y_F = 1 \& Y_M = 1)$	1.00	100	0.31***
$P(Y_I = 1 \mid Y_F = 1 \& Y_C = 1)$	1.00	0.81***	1.00
$P(Y_I = 1 \mid Y_M = 1 \& Y_C = 1)$	0.8 ***	1.00	1.00

** show a statistically significant difference at 1% and 10%, respectively. Comparison is the unconditional probability of any technology package.
*** show $P \leq 0.0001$.
Source: own computation ESS survey (2018/2019)

3.3. Econometric model estimation

3.3.1. Multinomial choices of soil fertility management packages

Table 5 presents the sign and magnitude of parameter estimates of the factors that influence the choice of technology packages. Non-adopters ($F_0M_0C_0$) were used as the benchmark against which other packages were compared in the estimation. Before estimating the model, Hausman and McFadden (1984) and Small and Hsiao (1985) tests were used to check whether the assumption of independence of irrelevant alternatives (IIA) was violated or not (see Appendix B) (see Appendix B). The test results failed to reject the assumption of IIA. Furthermore, the Wald test [2 (133) = 668.47; p 0.0001] result validates the rejection of the null hypothesis that all regression coefficients are equal to zero. This signifies that the model and the data are a good fit. In MNLM, it appears that calculating the magnitude of the coefficients is problematic. Therefore, only the indicators of variables were used to understand the factors of selecting the soil fertility management package. The majority of the model's basic attributes had considerable positive or negative influence on each of the seven package possibilities. The model incorporates the means of time-variant explanatory variables to govern the link between unobserved individual-specific effects and the time-variant explanatory variable. This is because such a correlation would lead to biased and inconsistent parameter estimates (Mundlak, 1978).

Family size and gender showed significantly negative significant influences on the adoption of $F_1M_1C_0$ and $F_1M_1C_1$ technology packages, suggesting that bigger families were less likely to use a combination of inorganic fertilizer and manure ($F_1M_1C_0$). Similarly, male-headed households had a lower tendency to adopt a combination of inorganic fertilizers, manure, and compost ($F_1M_1C_1$). This is because a joint application of inorganic fertilizers, manure, and compost required more home-oriented work in which women were mostly involved. Manure and compost are prepared near the farm so that female-headed households can manage it well. This result differed from the findings of Assefa et al. (2019); Karna and Bauer (2020); Martey (2019) where female-headed households were less likely to adopt agricultural technologies.

Age and age squares of household heads were included in this model to show the marginal effect of decreasing or increasing age on family adoption decisions. The findings revealed that age had a significant and positive impact on $F_1M_0C_1$, $F_1M_1C_0$, and $F_0M_1C_1$ packages, whereas the sign of age square was negative for all packages but statistically significant for package $F_1M_0C_1$ alone. This means that as household heads grew older, they were more likely to adopt packages $F_1M_1C_0$ and $F_0M_1C_1$, while their likelihood of adopting package $F_0M_0C_1$ dropped. Getting older can be associated with loss of physical strength, which may lead to the decline in the rate of adoption of package $F_1M_0C_1$. This finding is congruent with that of Arslan et al. (2014) who examined the factors that influence the adoption of soil conservation farming practices. The head of household education variable was positive as expected and significant for packages $F_1M_0C_0$, $F_0M_1C_0$, $F_1M_1C_1$, $F_1M_1C_{0,}$ and $F_1M_0C_1$. The study found that educated family heads were more likely to adopt soil fertility replenishment technology packages than uneducated household heads ($F_1M_0C_0$, $F_0M_1C_0$, $F_1M_1C_1$, $F_1M_1C_{0,}$ and $F_1M_0C_1$). Bekele (2019) and Okuthe (2018) made similar observations that in places where educated heads of households have a strong tendency to adopt modern and intensive agricultural technologies. Farmers' capacity to acquire information and appraise the costs and benefits of new agricultural technology is expected to improve as education becomes more widely available. Shocks such as health variable is negatively associated with the likelihood of adopting soil fertility enhancing

Table 5
Multinomial logit estimates of the ISFM packages adoption.

VARIABLES	F1M0C0	F0M1C0	F0M0C1	F0M1C1	F1M0C1	F1M1C0	F1M1C1
hh_size	0.000	-0.029	-0.005	0.029	-0.005	-0.046 *	-0.030
	[0.990]	[0.475]	[0.925]	[0.581]	[0.933]	[0.091]	[0.349]
head_sex	-0.049	-0.059	0.016	-0.292	0.333	-0.116	-0.289 *
	[0.740]	[0.743]	[0.942]	[0.199]	[0.178]	[0.366]	[0.051]
head_age	0.004	0.015	0.001	0.093 * *	0.156 * **	0.040 *	0.034
	[0.866]	[0.609]	[0.974]	[0.023]	[0.000]	[0.060]	[0.194]
age_square	-0.001	-0.000	-0.002	-0.003	-0.003 *	-0.001	-0.001
	[0.222]	[0.910]	[0.108]	[0.164]	[0.087]	[0.198]	[0.478]
head_edu	0.441 * **	0.397 * *	0.151	0.223	0.358 *	0.386 * **	0.303 * *
	[0.000]	[0.012]	[0.454]	[0.289]	[0.072]	[0.000]	[0.015]
shock	0.060	-0.187	-0.251	-0.603 * **	-0.321 *	-0.273 * **	-0.447 * **
	[0.611]	[0.212]	[0.174]	[0.001]	[0.078]	[0.005]	[0.000]
land_size	0.650 * **	0.303 * **	0.468 * **	0.413 * **	0.759 * **	0.428 * **	0.369 * **
	[0.000]	[0.005]	[0.000]	[0.001]	[0.000]	[0.000]	[0.000]
farm_type	-0.441 * **	-0.397 * *	0.361	-0.507 *	-0.099	-0.363 * *	-0.426 * **
	[0.006]	[0.042]	[0.108]	[0.063]	[0.672]	[0.011]	[0.010]
credit	0.330 * *	-0.058	-0.148	0.357 *	0.529 * *	0.302 * *	0.338 * *
	[0.015]	[0.748]	[0.553]	[0.077]	[0.011]	[0.012]	[0.014]
extn_visit	0.037 *	-0.024	-0.034	0.135 * **	0.093 * **	0.037 *	0.079 * **
	[0.097]	[0.447]	[0.411]	[0.000]	[0.001]	[0.062]	[0.000]
own_radio	0.379 * **	0.443 * *	0.407 *	0.219	0.290	0.505 * **	0.188
	[0.007]	[0.011]	[0.058]	[0.347]	[0.188]	[0.000]	[0.203]
sq_poor	0.904 * **	0.539	1.029 * *	1.055 * *	1.392 * **	0.700 * **	0.412 * *
	[0.000]	[0.125]	[0.010]	[0.012]	[0.002]	[0.000]	[0.049]
sq_fair	1.149 * **	0.915	2.187 * **	1.337 *	1.835 * *	1.153 * **	0.662 *
	[0.002]	[0.162]	[0.001]	[0.082]	[0.021]	[0.000]	[0.066]
Selection instruments							
market_dist	-0.010 * **	-0.004	-0.006	-0.001	-0.005	-0.003	-0.007 * *
	[0.000]	[0.334]	[0.191]	[0.829]	[0.329]	[0.240]	[0.035]
mainroad_dist	-0.015 * **	-0.013 * *	-0.003	-0.018 * **	-0.030 * **	-0.020 * **	-0.019 * **
	[0.001]	[0.016]	[0.695]	[0.004]	[0.000]	[0.000]	[0.000]
Joint significance of time varying covariates χ2 (3)	74.93 * **	8.69 * *	18.09 * **	18.8 * **	0.57.64 * **	49.02 * **	27.55 * **
	[0.000]	.[0.034]	[0.000]	[0.000]	[0.000]	[0.000]	.[0.000]
Joint significance of selection instruments χ2 (2)	17.3 * **	5.9 *	2.3	9.38 * **	23.6 * **	25.4 * **	16.6 * **
	[0.000]	[0.052]	[0.316]	[0.009]	[0.000]	[0.000]	[0.000]
Observations 4236							
LR χ2 (126) 668.47							
Prob >chi2 0.000							
Pseudo R2 = 0.089							

*, **, and *** indicate statistically significant at 10%, 5%, and 1% level, respectively.
Source: own computation from ESS survey (2018)

technology packages and has a statistically significant impact on packages $F_1M_1C_1$, $F_1M_0C_1$, $F_1M_1C_0$, and $F_0M_1C_1$. This indicated that the presence of health shocks such as sickness or death of household heads significantly lessens the likelihood of adopting $F_1M_1C_1$, $F_1M_0C_1$, $F_1M_1C_0$, and $F_0M_1C_1$ technology packages. Tarfasa et al. (2018) found that unhealthy household heads were less likely to adopt natural resource management practices. A health shock affects the amount of labor available for farming and for planning horizons in response to illness or death of household heads which directly influences the decision to adopt soil fertility management technologies. Pradhan and Mukherjee (2018) also found that idiosyncratic health shocks impact farm management during both land preparation and harvesting periods, resulting in significant output losses.

Farm size has a significant influence on the choice to accept new agricultural technologies. Danso-Abbeam et al. (2017) found a strongly significant relationship between farm size and the decision to adopt new technologies. This study also found the positive and significant effect of farm size on the tendency to adopt various soil fertility management measures. Soil fertility-enhancing technology packages are more likely to be adopted by families with larger agricultural holdings. This could be owing to the fact that households with greater farm holdings may have less liquidity limitations and have more financial resources available, thus making agricultural inputs such as inorganic fertilizers more accessible. Miheretu and Yimer (2017) examined the factors of farmers' adoption of land management methods and discovered that farm size is crucial in adoption of farm technologies, but that farm size's influence on adoption is dependent on farm households' risk-taking behavior. Abay et al. (2016) who studied how farmers' technology adoption choices were impacted by input heterogeneity and complementarity, found that large families with larger landholdings were more inclined to adopt new agricultural inputs while maintaining their risk aversion. In contrast, Mponela et al. (2016) looked into the factors that influence whether or not farmers choose to use such a strategy, and they found no link between size and ISFM adoption. The two dominant farming systems in Ethiopia are crop and mixed farming systems. Mixed farming is an integration of crop and livestock production that is practiced in high-altitude areas between 1500 m and 2000 m above sea level (Amede and Lemenih, 2019). The farming system plays a key role in the adoption of integrated soil fertility replenishment practices because of manure from livestock. The type of farm variable has a significantly negative impact on all technology choices in the model except for the choice of compost only ($F_0M_0C_1$) and choice of a combination of inorganic fertilizer and manure ($F_1M_0C_1$) packages. Households who engaged only in the crop production farming system were less likely to adopt ISFM packages. This might be due to the fact that households that engaged in mixed farming could reuse their farm's crop and animal waste to make compost and manure. Hence, farmers who engaged in a mixed farming system had a higher propensity to adopt a combination of inorganic fertilizer, manure, and compost.

Credit given at the right time and in a sufficient amount encourages the adoption of new agricultural technologies. Except for manure (F0M1C0) and compost (F0M0C1), most soil fertility management technology packages were positively associated with credit, and its influence was significant for the majority of them. This revealed that households with access to loans were better able to implement soil fertility-improving technologies. Thus, access to credit is an effective strategy for promoting improved agricultural technologies among smallholder farmers because they are financially constrained. This finding is broadly in line with several references (Ali and Awade, 2019; Ojo and Baiyegunhi, 2020; Twumasi et al., 2019; Ullah et al., 2020) who concluded that credit had a higher impact on the adoption of improved seed technology adoption.

The frequency of extension visits variable was positive and statistically significant in explaining all technology choices except for manure ($F_0M_1C_0$) and compost ($F_0M_0C_1$) technology choices. This implies that households who received more extension visits had a greater tendency to adopt ISFM practices. This might be attributed to the fact that farmers' contact with extension agents enhances their skills for knowledge-intensive soil fertility management through raising awareness about eco-friendly and sustainable technology practices. The result is consistent with the findings of Maertens et al. (2021). Likewise, inorganic fertilizers (F1M0C0), manure (F0M1C0), compost (F0M0C1), and a mix of inorganic fertilizers and manure (F1M1C0) technical packages were also influenced by radio ownership. Adoption of soil fertility-enhancing technologies was more common in households who had radios. Because access to information is vital to increasing farmers 'households' understanding of the importance of improved technologies, which has a direct impact on the decision to adopt and the rate at which technological diffusion occurs,

Market distance variable has a negative and significant impact on the likelihood to adopt inorganic fertilizers ($F_1M_0C_0$) and on combination of all the three technologies ($F_1M_1C_1$). This might be attributed to the fact that a shorter distance to the market reduces transaction costs and helps farmers avoid the challenges related to the timing of input access and output sales, thereby influencing the decision to making (Chandio and Yuansheng, 2018; Ghimire and Huang, 2016). Also, the variable of distance to the nearest main road is negatively associated with ISFM practices and statistically significant for all practices except for compost ($F_0M_0C_1$) with the same justification as market distance. Soil quality variables were also positive and significant for all packages except compost (F0M0C1) adoption, indicating that the propensity to adopt soil fertility enhancement technologies was higher for poor and fair soil qualities compared to the baseline, which is good soil quality. Faissal et al. (2017) also observed that changes in soil chemical characteristics and fertility conditions have a major influence on the adoption of soil fertility management approaches.

3.3.2. *Impact of ISFM practices on maize yield*

This study compares the average maize yield under the actual case in which farm households adopted or did not adopt (either alone or in conjunction with other soil fertility replenishment practices) with their respective counterfactuals. Table 6 compares the actual yields of acceptors with the false result if ISFM packages are not accepted, and Table 7 compares the actual yields obtained by non-acceptors of ISFM packages with the false result if they accepted ISFM packages. This comparison was made by computing the ATT and ATU, which are the differences between the actual and counterfactual yields, using Eqs. (10) and (11), respectively.

Table 6
Impact of ISFM Packages on Treated Households' Maize Yield (ATT).

combination	Actual Outcome Adopting j = 1)	Counterfactual Outcome Non-Adopting (j = 1)	Adoption Impact	
$F_1M_0C_0$	34.1	30.6	3.5	(12.7)***
$F_0M_1C_0$	33.5	31.7	1.8	(4.9)***
$F_0M_0C_1$	32.6	31.0	1.6	(29.1)***
$F_0M_1C_1$	33.7	31.5	2.2	(28.8)***
$F_1M_0C_1$	34.8	30.6	**4.2**	(8.9)***
$F_1M_1C_0$	35.4	31.3	4.0	(23.5)***
$F_1M_1C_1$	35.5	31.4	4.1	(15.2)***

*** indicates statistically significant at 1% level (figures in parentheses are standard errors).
Source: own computation from ESS survey (2018)

Table 7
Impact of ISFM Packages on Untreated Households' Maize Yield (ATU).

combination	Counterfactual Outcome Adopting (j = 1,2......7)	Actual Outcome Non-Adopting (j = 1)	Adoption Impact	
$F_1M_0C_0$	35.6	31.6	4.0	(16.5)***
$F_0M_1C_0$	33.5	31.6	1.9	(9.1)***
$F_0M_0C_1$	33.2	31.6	1.6	(6.3)***
$F_0M_1C_1$	35.4	31.6	3.8	(16.5)***
$F_1M_0C_1$	37.3	31.6	5.7	(26.5)***
$F_1M_1C_0$	36.4	31.6	4.8	(19.34)***
$F_1M_1C_1$	36.3	31.6	4.8	(19.4)***

*** indicates statistically significant at 1% level (figures in parentheses are standard errors).
Source: own computation from ESS survey (2018)

The use of soil fertility management practices in isolation or in combination has a statistically significant influence on maize output, according to both tables. In other words, adopters would have produced fewer quantities per hectare if they had not adopted the soil fertility amendment practices. The highest yield impact was achieved from the joint adoption of inorganic fertilizer and manure ($F_1M_1C_0$), which was equal to 4.2 quintals per hectare. The second-highest impact came from the joint adoption of inorganic fertilizer, manure, and compost ($F_1M_1C_1$) packages that had a yield impact of 4.1 quintals per hectare, and the third-highest impact came from the joint adoption of inorganic fertilizer and compost ($F_1M_0C_1$) packages at 4.0 quintals per hectare. The highest yield impact was achieved from the joint adoption of inorganic fertilizer and manure ($F_1M_1C_0$), which was equal to 4.2 quintals per hectare. The second-highest impact came from the joint adoption of inorganic fertilizer, manure, and compost ($F_1M_1C_1$) packages that had a yield impact of 4.1 quintals per hectare, and the third-highest impact came from the joint adoption of inorganic fertilizer and compost ($F_1M_0C_1$) packages, which equaled 4.0 quintals per hectare.In the same way, the isolated adoption of the practices had a significant impact, even though the impact was not as huge as that of the joint adoption of two or three technologies. In general, using a mixture of inorganic fertilizers with either manure or compost increases maize yield more than any other strategy, irrespective of technology. Iqbal et al. (2019) discovered that organic manure combined with inorganic fertilizer has a substantial impact on soil physiochemical characteristics, growth, physiology, grain production, and grain quality features. The use of manure in a 30:70 mix proportion with chemical fertilizer greatly increases leaf gas exchange capacities through increased root morphological features (Iqbal et al., 2019). Similarly, Timsina (2018) revealed that integrated and site-specific precision nutrient management is essential for long-term soil fertility management and food security.

Table 7 also compares the actual outcome of non-acceptance with the unintended consequences if households adopted any of the technology combinations. The unrealistic returns of non-acceptors are significantly higher than the actual returns of non-acceptors for all packet combinations. These findings are comparable to the counterfactual scenario for typical ATU farm households, where the adoption impact would have been greater if households had used a mixture of inorganic fertilizer and other organic fertilizers like manure and compost. If non-adopters had adopted inorganic fertilizers and compost ($F_1M_0C_1$), they would have produced an extra 5.7 quintals per hectare, followed by an increased yield of 4.8 per hectare if they had considered a joint adoption of inorganic fertilizers of manure and compost ($F_1M_1C_1$). An isolated adoption of manure and compost would have also resulted in an extra yield of 1.9 and 1.6 quintals per hectare, respectively.

4. Conclusion and policy implications

This study has investigated how socio-economic and institutional factors determine households' decision to adopt soil fertility renewal technologies to improve crop yield using ISFM practices. ISFM was introduced between the late 1990 s and early 2000 s; therefore, there are not many empirical studies on how ISFM practices have contributed to maize yield growth. Improving maize production is achieved through the application of soil fertility management practices. Specifically, out of the eight combinations of ISFM, inorganic fertilizer and manure ($F_1M_1C_0$) were the most adopted by farm households. Institutional factors like access to credit, irrigation, and extension visits, as well as socioeconomic factors like household size, gender, age, education, radio ownership, and farm type and size, and geographic factors like market proximity, main road proximity, and soil characteristics variables all influenced plot level adoption decisions of ISFM practices. When organic and inorganic fertilizers are applied simultaneously, maize yields are much higher than when they have been treated separately. Farm households' decision on the various combinations of inorganic fertilizers, manure, and compost were influenced by household and institutional level factors which include the household heads' level of education, health shocks, frequency of extension visits, and media access. Therefore, these parameters could be used to target policies aiming at increasing the uptake of the rates of ISFM practices. The significant role of education, extension service, and media access suggests the expansion of basic education and extension systems into rural areas where most of the farm households reside. In addition, incentives that encourage promoters to have more contacts should be provided by the government to extension agents. Improve the capabilities of extension officers by hiring new professionals to increase the ratio of extension agent to farmer. Financial constraints of smallholder farmers hinder their adoption of agricultural technologies. Hence, provision of credit in the required amounts can help farmers to use inorganic fertilizers with organic materials. Therefore, a favorable environment for both formal and informal credit institutions must be created by the government to provide loans for farm households. In addition, health shocks reduce the likelihood of adopting of ISFM practices; thus, attention should be given to speed up the formation of a comprehensive and affordable health insurance scheme for smallholder farmers.

Policies that promote the ISFM practices are more likely to be successful because these practices provide tangible benefits to farm households by improving crop productivity and food security. Technical help and training must also be offered to farm households to increase their understanding of the advantages of ISFM practices. It is also necessary to evaluate complementarities among the three technologies to increase soil fertility.

The study did not consider the intensity of application (e.g., the amount of applied organic and inorganic fertilizers), owing to the unavailability of such information in the main data set. In the assessment of the impact of ISFM on maize production, this study analyzed only the total quantity of the applied fertilizer. Therefore, further research on the impact of ISFM practices based on the intensity of application of soil fertility replenishment practices is essential to apply to the recommended levels of each practice. Besides, ISFM is an approach that promotes the combined use of inorganic fertilizers, organic fertilizers (crop residue, manure, and compost), locally available soil amendments (lime and phosphate rock), and use of germplasms (improved seeds). The upcoming research should consider improved seeds as a component of ISFM practices, and if possible, it would be nice if it is done using experimental data.

CRediT authorship contribution statement

Mohammed Adem: Performed the study and developed the main text. **Hossein Azadi**: Contributed to the first draft manuscript and enriched it up to the final version. **Velibor Spalevic, Marcin Pietrzykowski** and **Jürgen Scheffran**: Worked on the preparation of the research concept and on the final version, addressed the responses to comments and enriched the revised version of the manuscript.

Declaration of Competing Interest

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

Data availability

Data will be made available on request.

Acknowledgment

Not applicable.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.still.2022.105595.

References

Abay, K.A. Berhane, G. Taffesse, A.S. Koru, B., Abay, K. 2016, Understanding farmers' technology adoption decisions: Input complementarity and heterogeneity.
Ali, E., Awade, N.E., 2019. Credit constraints and soybean farmers' welfare in subsistence agriculture in Togo. Heliyon 5 (4), e01550.
Aloo, B., Mbega, E., Tumuhairwe, J., Makumba, B., 2021. Advancement and practical applications of rhizobacterial biofertilizers for sustainable crop production in sub-Saharan Africa. Agric. Food Secur. 10 (1), 1–12.
Amede, T., Lemenih, M., 2019. The highland mixed farming system of Africa: Diversifying livelihoods in fragile ecosystems. Farming Systems and Food Security in Africa. Routledge,, pp. 248–281.
Ansong Omari, R., Bellingrath-Kimura, S.D., Sarkodee Addo, E., Oikawa, Y., Fujii, Y., 2018. Exploring farmers' indigenous knowledge of soil quality and fertility management practices in selected farming communities of the guinea savannah agro-ecological zone of Ghana. Sustainability 10 (4), 1034.
Aryal, J.P., Sapkota, T.B., Krupnik, T.J., Jat, M.L., Stirling, C.M., 2021. Factors affecting farmers' use of organic and inorganic fertilizers in South Asia. Environ. Sci. Pollut. Res. 1–17.
Assefa, E., Minato, K., Tsubura, M., Aida, T., Fukunish, T., Otchia, C.S., 2019. Towards the sustainability of the agricultural landscape The case of the watershed management and implication in the Rift Valley of Ethiopia. Dev. Econ. 57 (4).
ATA, 2013, 5-year Strategy for the Transformation of Soil Health and Fertility in Ethiopia: Vision, Systemic Bottlenecks, Interventions, and Implementation Framework. Retrieved from Addis Ababa: ⟨https://agriknowledge.org/downloads/7p88cg523⟩.
Atinga, D., 2019, Agricultural technology adoption and market participation among smallholder rice farmers in Northern Ghana.
Bationo, A., Singh, U., Dossa, E., Wendt, J., Agyiyin-Birikorang, S., Lompo, F., Bindraban, P., 2020. Improving Soil Fertility through Fertilizer Management in Sub-Saharan Africa. Soil and Fertilizers. CRC Press,, pp. 67–102.
Bernedo Del Carpio, M.N., 2016, Essays on behavioral economics in climate change adaptation.
Chandio, A.A., Yuansheng, J., 2018. Determinants of adoption of improved rice varieties in Northern Sindh, Pakistan. Sci. Direct 25 (2), 2.
Chen, J., Lü, S., Zhang, Z., Zhao, X., Li, X., Ning, P., Liu, M., 2018. Environmentally friendly fertilizers: A review of materials used and their effects on the environment. Sci. Total Environ. 613, 829–839.
Chew, K.W., Chia, S.R., Yen, H.-W., Nomanbhay, S., Ho, Y.-C., Show, P.L., 2019. Transformation of biomass waste into sustainable organic fertilizers. Sustainability 11 (8), 2266.
Cochrane, L., Bekele, Y.W., 2018. Average crop yield (2001–2017) in Ethiopia: Trends at national, regional and zonal levels. Data Brief. 16, 1025.
Danso-Abbeam, G., Bosiako, J.A., Ehiakpor, D.S., Mabe, F.N., 2017. Adoption of improved maize variety among farm households in the northern region of Ghana. Cogent Econ. Financ. 5 (1), 1416896.
Di Falco, S., Veronesi, M., Yesuf, M., 2011. Does adaptation to climate change provide food security? A micro-perspective from Ethiopia. Am. J. Agric. Econ. 93 (3), 829–846.
Faissal, A., Ouazzani, N., Parrado, J., Dary, M., Manyani, H., Morgado, B., Mandi, L., 2017. Impact of fertilization by natural manure on the microbial quality of soil: molecular approach. Saudi J. Biol. Sci. 24 (6), 1437–1443.
Ghimire, R., Huang, W.-C., 2016. Adoption pattern and welfare impact of agricultural technology: empirical evidence from rice farmers in Nepal. J. South Asian Dev. 11 (1), 113–137.

Gurmu, G., 2019. Soil organic matter and its role in soil health and crop productivity improvement. For. Ecol. Manag. 7 (7), 475–483.
Habineza, E., Nsengiyumva, J.N., Ruzigamanzi, E., Nsanzumukiza, M.V., 2020. Profitability Analysis of Small Scale Irrigation Technology Adoption to Farmers in Nasho Sector, Rwanda. J. Agric. Chem. Environ. 9 (2), 73–84.
Haneuse, S., VanderWeele, T.J., Arterburn, D., 2019. Using the E-value to assess the potential effect of unmeasured confounding in observational studies. Jama 321 (6), 602–603.
Hausman, J., McFadden, D., 1984. Specification tests for the multinomial logit model. Économ.: J. Econom. Soc. 1219–1240.
Holden, S.T., 2018. Fertilizer and sustainable intensification in Sub-Saharan Africa. Glob. Food Secur. 18, 20–26.
Iqbal, A., He, L., Khan, A., Wei, S., Akhtar, K., Ali, I., Jiang, L., 2019. Organic manure coupled with inorganic fertilizer: An approach for the sustainable production of rice by improving soil properties and nitrogen use efficiency. Agronomy 9 (10), 651.
Jaja, E.T., Barber, L.I., 2017. Organic and inorganic fertilizers in food production system in Nigeria. nature 7, e18.
Karna, R.D., Bauer, S., 2020. Analyzing soil nutrient balances on small-scale farms in the mid-hills of Nepal: Do socio-economic factors matter for sustainable land use? Land Degrad. Dev. 31 (18), 3014–3023.
Kassam, A., Friedrich, T., Derpsch, R., 2019. Global spread of conservation agriculture. Int. J. Environ. Stud. 76 (1), 29–51.
Kassie, M., Teklewold, H., Jaleta, M., Marenya, P., Erenstein, O., 2015. Understanding the adoption of a portfolio of sustainable intensification practices in eastern and southern Africa. Land Use Policy 42, 400–411.
Khonje, M.G., Manda, J., Mkandawire, P., Tufa, A.H., Alene, A.D., 2018. Adoption and welfare impacts of multiple agricultural technologies: evidence from eastern Zambia. Agric. Econ. 49 (5), 599–609.
Kim, K., Bevis, L., 2019. Soil fertility and poverty in developing countries. Choices 34 (2), 1–8.
Lambrecht, I., Vanlauwe, B., Maertens, M., 2016. Integrated soil fertility management: from concept to practice in Eastern DR Congo. Int. J. Agric. Sustain. 14 (1), 100–118.
Maertens, A., Michelson, H., Nourani, V., 2021. How do farmers learn from extension services? Evidence from Malawi. Am. J. Agric. Econ. 103 (2), 569–595.
Martey, E., 2019, Soil fertility management and economics of soybean in Ghana. University of Illinois at Urbana-Champaign,
Martey, E., Kuwornu, J.K., Adjebeng-Danquah, J., 2019. Estimating the effect of mineral fertilizer use on Land productivity and income: Evidence from Ghana. Land Use Policy 85, 463–475.
Merante, P., Dibari, C., Ferrise, R., Sánchez, B., Iglesias, A., Lesschen, J.P., Bindi, M., 2017. Adopting soil organic carbon management practices in soils of varying quality: Implications and perspectives in Europe. Soil Tillage Res. 165, 95–106.
Miheretu, B.A., Yimer, A.A., 2017. Determinants of farmers' adoption of land management practices in Gelana sub-watershed of Northern Highlands of Ethiopia. Ecol. Process. 6 (1), 19.
Mockeviciene, I., Repsiene, R., Amaleviciute-Volunge, K., Karcauskiene, D., Slepetiene, A., Lepane, V., 2021. Effect of long-term application of organic fertilizers on improving organic matter quality in acid soil. Arch. Agron. Soil Sci. 1–13.
Moswetsi, G., Fanadzo, M., Ncube, B., 2017. Cropping systems and agronomic management practices in smallholder farms in South Africa: Constraints, challenges and opportunities. J. Agron.
Mponela, P., Tamene, L., Ndengu, G., Magreta, R., Kihara, J., Mango, N., 2016. Determinants of integrated soil fertility management technologies adoption by smallholder farmers in the Chinyanja Triangle of Southern Africa. Land Use Policy 59, 38–48.
Mundlak, Y., 1978. On the pooling of time series and cross-section data. Économ.: J. Econom. Soc. 69–85.
Mutuku, M.M., Nguluu, S., Akuja, T., Lutta, M., Pelletier, B., 2017. Factors that influence adoption of integrated soil fertility and water management practices by smallholder farmers in the semi-arid areas of eastern Kenya. Trop. Subtrop. Agroecosyst. 20 (1).
Nalivata, P., Kibunja, C., Mutegi, J., Tetteh, F., Tarfa, B., Dicko, M.K., Bayu, W., 2017. Integrated soil fertility management in Sub-Saharan Africa. Fertil. Use Optim. sub-Sahar. Afr. 113–124.
Nisa, C.F., Bélanger, J.J., Schumpe, B.M., Faller, D.G., 2019. Meta-analysis of randomised controlled trials testing behavioural interventions to promote household action on climate change. Nat. Commun. 10 (1), 1–13.
Ojo, T., Baiyegunhi, L., 2020. Determinants of credit constraints and its impact on the adoption of climate change adaptation strategies among rice farmers in South-West Nigeria. J. Econ. Struct. 9 (1), 1–15.
Oumer, A.M., 2019, The Economics of Sustainable Agricultural Intensification in Ethiopia: Production Efficiency, Cost Efficiency and Technology Adoption.
Pradhan, K.C., Mukherjee, S., 2018. Covariate and idiosyncratic shocks and coping strategies for poor and Non-poor rural households in India. J. Quant. Econ. 16 (1), 101–127.
Riesgo, L., Louhichi, K., Paloma, S., 2016, Modelling farm-household level impacts of fertilizer subsidy programs on productivity and food security: The case of Ethiopia. Paper presented at the AAAE, Addis Ababa, Ethiopia. ⟨https://ageconsearch.umn.edu/bitstream/249265/2/315.%20Modelling%20farm-household%20level%20impacts%20of%20fertilizer%20subsidy%20programs%20in%20Ethiopia.pdf⟩.
Schütz, L., Gattinger, A., Meier, M., Müller, A., Boller, T., Mäder, P., Mathimaran, N., 2018. Improving crop yield and nutrient use efficiency via biofertilization—a global meta-analysis. Front. Plant Sci. 2204.
Sekyi, S., Domanban, P.B., Honya, G.K., 2019. The impact of informal credit on rural agricultural productivity in the savannah ecological zone of Ghana. Afr. J. Econ. Manag. Stud.
Shah, F., Wu, W., 2019. Soil and crop management strategies to ensure higher crop productivity within sustainable environments. Sustainability 11 (5), 1485.
Singh, T.B., Ali, A., Prasad, M., Yadav, A., Shrivastav, P., Goyal, D., Dantu, P.K., 2020, Role of organic fertilizers in improving soil fertility. Contaminants in Agriculture; Naeem, M., Ansari, AA, Gill, SS, Eds. 61–77.
Small, K.A., Hsiao, C., 1985. Multinomial logit specification tests. Int. Econ. Rev. 619–627.
Sommer, R., Paul, B.K., Mukalama, J., Kihara, J., 2018. Reducing losses but failing to sequester carbon in soils–the case of Conservation Agriculture and Integrated Soil Fertility Management in the humid tropical agro-ecosystem of Western Kenya. Agric., Ecosyst. Environ. 254, 82–91.
Tarfasa, S., Balana, B.B., Tefera, T., Woldeamanuel, T., Moges, A., Dinato, M., Black, H., 2018. Modeling smallholder farmers' preferences for soil management measures: a case study from South Ethiopia. Ecol. Econ. 145, 410–419.
Teklewold, H., Kassie, M., Shiferaw, B., Köhlin, G., 2013. Cropping system diversification, conservation tillage and modern seed adoption in Ethiopia: Impacts on household income, agrochemical use and demand for labour. Ecol. Econ. 93, 85–93.
Thomas, C.L., Acquah, G.E., Whitmore, A.P., McGrath, S.P., Haefele, S.M., 2019. The effect of different organic fertilizers on yield and soil and crop nutrient concentrations. Agronomy 9 (12), 776.
Timsina, J., 2018. Can organic sources of nutrients increase crop yields to meet global food demand? Agronomy 8 (10), 214.
Twumasi, M.A., Jiang, Y., Acheampong, M.O., 2019. Capital and credit constraints in the engagement of youth in Ghanaian agriculture. Agric. Financ. Rev.
Ullah, A., Mahmood, N., Zeb, A., Kächele, H., 2020. Factors determining farmers' access to and sources of credit: evidence from the rain-fed zone of Pakistan. Agriculture 10 (12), 586.
Verma, B., Pramanik, P., Bhaduri, D., 2020. Organic fertilizers for sustainable soil and environmental management. Nutrient dynamics for sustainable crop production. Springer,, pp. 289–313.
Wekesa, B.M., Ayuya, O.I., Lagat, J.K., 2018. Effect of climate-smart agricultural practices on household food security in smallholder production systems: micro-level evidence from Kenya. Agric. Food Secur. 7 (1), 1–14.
White, H., Raitzer, D.A., 2017, Impact evaluation of development interventions: A practical guide: Asian Development Bank.
World Bank., 2018, World Bank Commodity Price Data (Pink Sheet). Web Page. Retrieved from ⟨https://knoema.com/WBCPD2015Oct/world-bank-commodity-price-data-pink-sheet-monthly-update?tsId=1002420⟩.
Yadav, G.S., Datta, R., Imran Pathan, S., Lal, R., Meena, R.S., Babu, S., Saha, P., 2017. Effects of conservation tillage and nutrient management practices on soil fertility and productivity of rice (Oryza sativa L.)–rice system in north eastern region of India. Sustainability 9 (10), 1816.
Zandvakili, O.R., Barker, A.V., Hashemi, M., Etemadi, F., 2019. Biomass and nutrient concentration of lettuce grown with organic fertilizers. J. Plant Nutr. 42 (5), 444–457.
Zerihun, S., 2018, Soil Conservation Practices In Doba Woreda West Hararghe Zone, Oromia Regional State, Ethiopia. ASTU,
Zeweld, W., Huylenbroeck, Van, Tesfay, G., Speelman, S, G., 2017. Smallholder farmers' behavioural intentions towards sustainable agricultural practices. J. Environ. Manag. 187, 71–81.
Zhang, X., Zhu, A., Xin, X., Yang, W., Zhang, J., Ding, S., 2018. Tillage and residue management for long-term wheat-maize cropping in the North China Plain: I. Crop yield and integrated soil fertility index. Field Crops Res. 221, 157–165.