

Sariyev, Orkhan; Asravor, Jacob; Zeller, Manfred

**Article — Published Version**

## Poverty and food security impacts of sustainable intensification: Evidence from Ethiopia

Food Security

**Provided in Cooperation with:**

Springer Nature

*Suggested Citation:* Sariyev, Orkhan; Asravor, Jacob; Zeller, Manfred (2025) : Poverty and food security impacts of sustainable intensification: Evidence from Ethiopia, Food Security, ISSN 1876-4525, Springer Netherlands, Dordrecht, Vol. 17, Iss. 2, pp. 405-420, <https://doi.org/10.1007/s12571-025-01517-9>

This Version is available at:

<https://hdl.handle.net/10419/323637>

**Standard-Nutzungsbedingungen:**

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

**Terms of use:**

*Documents in EconStor may be saved and copied for your personal and scholarly purposes.*

*You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.*

*If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.*



<http://creativecommons.org/licenses/by/4.0/>



# Poverty and food security impacts of sustainable intensification: Evidence from Ethiopia

Orkhan Sariyev<sup>1</sup> · Jacob Asravor<sup>1</sup> · Manfred Zeller<sup>1</sup>

Received: 13 May 2024 / Accepted: 10 January 2025 / Published online: 12 February 2025  
© The Author(s) 2025

## Abstract

As sustainable intensification is a major pathway for improving agricultural productivity and reducing the environmental impacts of land use, the Government of Ethiopia and international development organizations have been promoting several practices and technologies for sustainable intensification. Using panel data from 368 farming households in Ethiopia from 2014, 2016, and 2019, this study gauges the poverty and food security impacts of Integrated Soil Fertility Management technologies and their combined use with conservation agriculture practices, specifically minimum tillage and crop rotation. We find significant positive effects of ISFM adoption in terms of increasing dietary diversity and food expenditure and reducing food insecurity. In terms of poverty, ISFM adoption decreases the probability of being poor, the poverty gap, and the severity of poverty. When combined with CA practices, we find that the effects are consistently larger for farmers who integrate ISFM and CA for all food security and poverty measures. Our findings strongly suggest that the adoption of ISFM technologies has significant positive implications for poverty reduction and improved food security. These benefits are likely to gain a considerable boost if ISFM technologies are applied together with CA practices.

**Keywords** Technology adoption · Integrated soil fertility management · Conservation agriculture · Multinomial endogenous switching regression

## 1 Introduction

The number of people facing hunger has been growing since 2014, especially in Africa which has witnessed a recent sharp increase in all regions of the continent (FAO et al., 2023). In Africa, continued population growth has increased food demand and climate variability has further strained farming systems that have long been performing below their productive potential (The Montpellier Panel, 2013). Agriculture is the backbone of the economy in most African countries, particularly those in sub-Saharan Africa (SSA), and has a strong correlation with economic growth (Jayne & Sanchez, 2021). Thus, increasing agricultural productivity

is an overarching goal for reducing hunger and sustaining economic growth in SSA countries.

Since 2000, crop production in SSA has experienced significant growth. However, much of this growth originates from the expansion of the area under cultivation, which is not a sound strategy on environmental and ecological grounds (Jayne & Sanchez, 2021). In light of this, national governments, development organizations, and foundations have been promoting various sustainable intensification (SI) approaches as a “new paradigm for African agriculture” in many SSA countries (Petersen & Snapp, 2015; The Montpellier Panel, 2013). Although the term “sustainable intensification” lacks a precise definition (Petersen & Snapp, 2015), it is often linked to agricultural technologies and practices that achieve more produce from the existing area under cultivation, while reducing the environmental footprint of agricultural production (Godfray et al., 2010; Pretty et al., 2011). Besides SI, several other approaches seek to reduce environmental externalities and improve productivity, e.g., conservation agriculture (CA), agroecology, and ecological intensification. In terms of SI, Integrated Soil Fertility Management (ISFM) technologies, which align well with

✉ Orkhan Sariyev  
o.sariyev@uni-hohenheim.de

Jacob Asravor  
jacob.asravor@uni-hohenheim.de

Manfred Zeller  
manfred.zeller@uni-hohenheim.de

<sup>1</sup> Department of Rural Development Theory and Policy,  
University of Hohenheim, Stuttgart, Germany

the principles of SI, have been recognized as means to expand agricultural productivity and prevent soil degradation (Pretty et al., 2011; Vanlauwe et al., 2015). Likewise, CA has received significant attention due to its potential to improve soil quality. Rural households are likely to adopt a combination of various approaches and practices. This paper seeks to answer the question of how SI impacts poverty and food security among rural smallholders in Ethiopia by utilizing three rounds of panel data from Ethiopia and concentrating on ISFM technologies and their combination with CA.

Agricultural intensification via ISFM is considered the leading pathway to the African Green Revolution (Petersen & Snapp, 2015). ISFM aims to enhance the agronomic use efficiency of inputs. It is defined as a set of soil fertility management practices which include fertilizer, improved germplasm, and organic inputs, such as manure, compost, or crop residues adapted to the local context (Vanlauwe et al., 2010). CA is another SI approach, which is based on minimal soil disturbance, crop residue retention, and crop rotation or intercropping (Giller et al., 2009). The combination of CA practices is likely to improve soil quality and profitability, assuming the sufficient availability of necessary machinery (Johansen et al., 2012) and inputs, such as fertilizer and herbicides (Giller et al., 2009). ISFM requires upfront investment in purchased inputs, such as fertilizer and improved seeds. CA practices are labor-intensive; thus, their adoption may increase labor costs (Montt & Luu, 2020; Vanlauwe et al., 2010). While ISFM adopters are likely to experience higher yields in the short term, the benefits of CA usually occur in the long term (Giller et al., 2009).

Considering the increasing efforts to promote SI in SSA, studies have investigated the implications of different SI practices on various livelihood indicators in different country contexts. However, despite existing studies (Hörner & Wollni, 2021, 2022; Kassie et al., 2018; Khonje et al., 2018; Maggio et al., 2022; Teklewold et al., 2013a, 2013b) that examine various CA or ISFM practices and technologies or their combinations, rigorous studies on the poverty and food security implications of ISFM technologies are scant. Among these studies, in a study from Uganda, Maggio et al. (2022) find that both organic fertilizer and maize-legume intercropping increases the total value of crop production. Using two rounds of data from Ethiopia, Kassie et al. (2018) show that different combinations of fertilizer, improved maize varieties, and legume diversification increase maize yield and income. In another study from Ethiopia, Teklewold et al. (2013b) report that maize farmers achieve the highest income when improved maize varieties, maize-legume rotations, and minimum tillage are adopted in combinations compared to in isolation. Tesfaye et al. (2021) further find that cereal-legume intercropping, reduced tillage, and their combination reduce poverty headcount, the poverty gap, and the severity of poverty in Ethiopia. Khonje et al. (2018)

show that Zambian farmers achieve higher yield and income when improved maize variety and CA are jointly adopted. Motivated by the fact that most of the evidence on the impact of ISFM type practices is limited to crop yield and revenue, Hörner and Wollni (2021) study ISFM implications on household income, food security, and child education. They find positive effects of ISFM on these welfare indicators depending on the agro-ecological zone. Using the same dataset, Hörner and Wollni (2022) show that ISFM practices and their combinations improve land and labor productivity. Besides Hörner and Wollni (2021), we are not aware of any other study that investigates the effects of ISFM adoption on poverty or food security outcomes. Employing three waves of panel data from a technology adoption survey in Ethiopia, this study contributes to the literature by concentrating on ISFM practices and analyzing their adoption implications on poverty and food security outcomes and by examining the joint effects of ISFM and CA adoption on these outcomes.

The paper proceeds as follows: Sect. 2 presents the data, variables of interest, and the methodology employed for the analyses; results are presented in Sect. 3 and discussed in Sect. 4; Sect. 5 concludes the paper. We provide detailed description of the study context in the appendix.

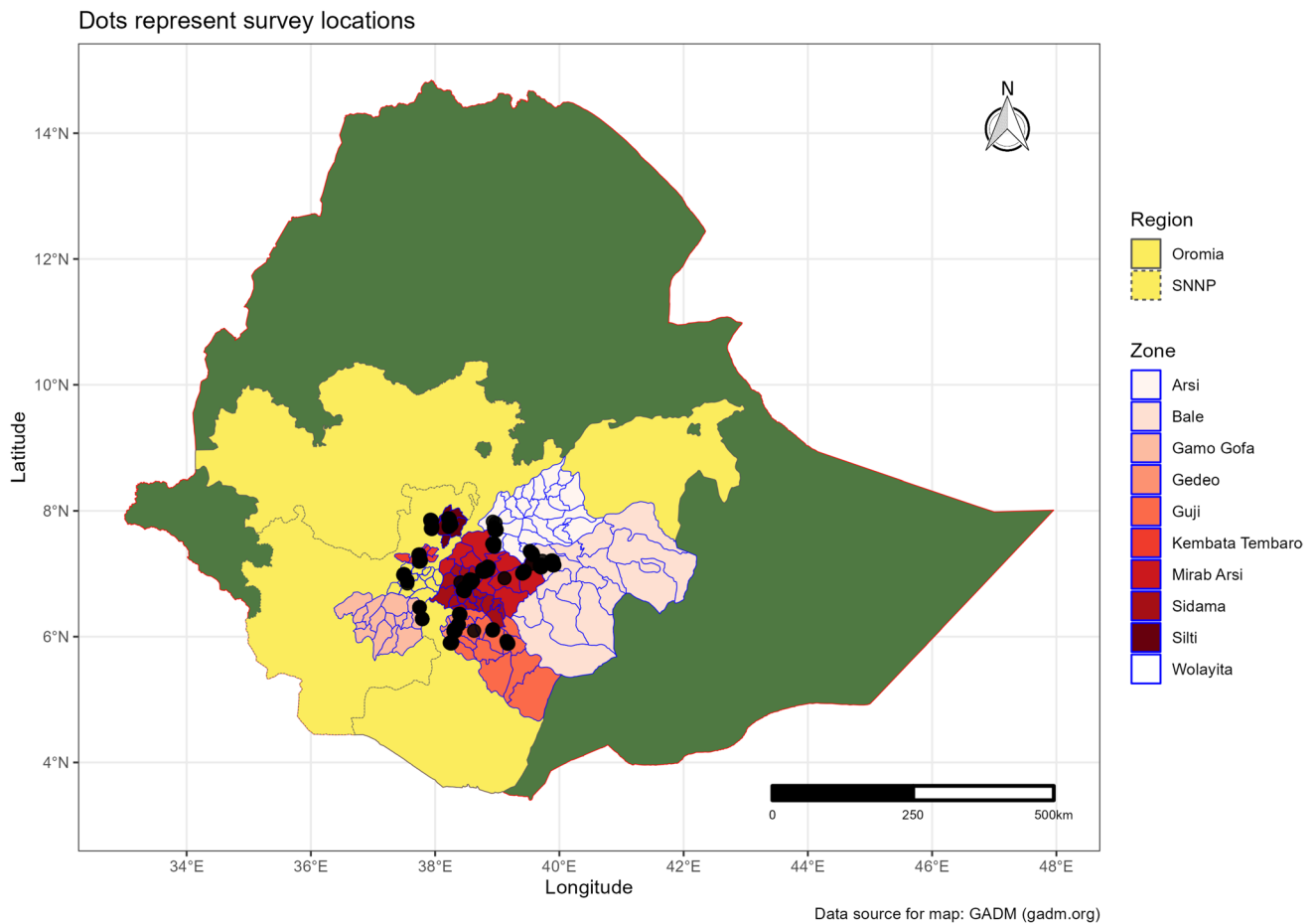
## 2 Data and methods

This section first presents the sampling strategy and data utilized for this study before describing in detail the poverty and food security measures and the strategy for empirical analyses.

### 2.1 Sampling and data

We employ household-level data collected from a random sample of farm households in 15 woredas (districts) across 10 zones in southwestern Ethiopia. Figure 1 shows the survey locations which have varying climatic and agro-ecological characteristics. The sample is derived from a sub-sample of a nationally representative baseline survey conducted in 2012 by the International Food Policy Research Institute (IFPRI) and the Agricultural Transformation Agency (ATA) of Ethiopia.<sup>1</sup> Due to administrative and logistical constraints, the surveyed households were randomly selected from the list of surveyed farmers situated within a radius of approximately 200 km around the town of Hawassa. The survey was different from the nationally representative baseline conducted in 2012 and was specifically designed for collecting data on smallholder farmers' risk management and

<sup>1</sup> For more details on this sample, see (Minot & Sawyer, 2013).



**Fig. 1** Location of sampled households

innovation strategies and their impacts on poverty and resilience. The areas cover parts of Southern Nations, Nationalities, and Peoples' (SNNP) and Oromia regions. Three follow-up surveys were conducted in 2014, 2016, and 2019. This study does not use the 2012 baseline by IFPRI and ATA because some important data collected in the follow-up surveys were not present in the baseline data. The sample consists of a balanced panel of 376 farm households; however, the data employed in this study covers 368 households due to missing consumption data for eight households in 2016. Using the geographical coordinates of the sampled households, we supplement the survey data with historical rainfall data extracted from the Climate Hazards Group InfraRed Precipitation with Station data. This is a quasi-global rainfall dataset that incorporates 0.05° resolution satellite imagery with in-situ station data to create gridded precipitation data (Funk et al., 2015). We extract annual rainfall data between 1981 and 2018 and calculate standard deviations and historical averages for the mentioned period.

## 2.2 Poverty and food security measures

Adoption of SI technologies and practices is expected to promote productivity and resilience among rural farmers. Higher productivity and improved resilience are expected to contribute to reduced poverty and improved food security among the adopters of SI technologies and practices. In this study, we employ different measures of poverty and food security which reflect short- and long-term outcomes. We assume that poverty outcomes accrue to long-term sustained productivity gains from SI. Food security outcomes like food expenditure and dietary diversity are likely to derive from short-term productivity gains. Moreover, these outcomes can also reflect the long-term resilience of the households.

Following Tesfaye et al. (2021), we employ the Foster-Greer-Thorbeck method in calculating the various poverty indices (Foster et al., 1984):

$$P_{\alpha} = \frac{1}{N} \sum_{i=1}^N \left( \frac{z - y_i}{z} \right)^{\alpha} I(y_i < z), \quad (1)$$

where  $y_i$  denotes the per adult equivalent monthly consumption expenditure deflated by the consumer price index using 2016 prices as the base,  $N$  denotes the sample size,  $z$  denotes the national poverty line,<sup>2</sup> and  $I(y_i < z)$  takes the value of 1 when the  $i^{\text{th}}$  household has a per adult equivalent monthly consumption expenditure below the national poverty line. Because we are not interested in the fraction of the population or sample below the poverty line, we remove  $\frac{1}{N}$  from the formula. We calculate three poverty indices: when  $\alpha = 0$ ,  $P$  is the poverty headcount which indicates if the  $i^{\text{th}}$  household is poor; when  $\alpha = 1$ ,  $P$  denotes the poverty gap index which shows how far the  $i^{\text{th}}$  household is from the poverty line; and when  $\alpha = 2$ ,  $P$  indicates the squared poverty gap or poverty severity index which reflects inequality among the poor.

We adopt three distinct indicators to ascertain the food security status of the sampled households. The household dietary diversity score (HDDS) is a commonly employed measure of household level dietary quality and food security. HDDS describes the household's ability to access different food items. Ruel (2003) concludes that considering its association with energy availability and per capita income, capturing dietary diversity is a practical method of understanding the food security status of households. The survey employed a seven-day recall period to capture day-to-day variation in household diets. Using this data, we calculate HDDS based on 12 food groups: cereals; white tubers and roots; vegetables; fruits; meat; eggs; fish and other seafood; legumes, nuts, and seeds; milk and milk products; oils and fats; sweets; and spices, condiments, and beverages (Kennedy et al., 2011). Our second measure of food security is the probability of experiencing low food availability in at least one month over the past 12 months. Finally, we calculate the adult equivalent real food expenditure based on the reported monthly food expenditure<sup>3</sup> deflated by the consumer price index using 2016 prices as the base.

### 2.3 Empirical strategy

Our objective is to unpack the adoption implications of ISFM practices and their combination with CA on poverty and food security. The CA practices considered in this study are minimum tillage and crop rotation. A household is considered an adopter of CA practices if either minimum tillage or crop rotation or both are adopted. To understand the impacts of technologies and practices adopted by households, for each household we must compare the respective

outcomes from adoption to the outcomes from non-adoption. However, for each household, we can only observe one state at a time because each household either adopts a certain combination of ISFM practices (or their combination with CA) or does not adopt. Thus, we have a missing counterfactual which is the fundamental challenge for causal inference. In this case, we need to compare adopters with non-adopters, which leads to another challenge – selection bias or endogeneity (Imbens & Wooldridge, 2009). Agricultural technology adoption is a choice outcome which can be influenced by some unobservable factors, such as skills, motivation, care for family, bond between family members, and their dedication to a common goal, that can also influence food security and/or poverty outcomes. Availability of panel data solves the problem if the unobserved heterogeneity is time-invariant. However, the bias still arises if the unobserved heterogeneity is time-variant.

To overcome potential endogeneity, we apply the multinomial endogenous switching regression (MESR) model, which has been employed in several technology adoption studies (Biru et al., 2020; Hörner & Wollni, 2022; Kassie et al., 2015, 2018; Khonje et al., 2018; Montt & Luu, 2020; Teklewold et al., 2013b; Tesfaye et al., 2021). MESR estimates separate outcome regressions for adopters and non-adopters, which allows for an interaction between the adoption decision and observed and unobserved heterogeneity. This ensures that adoption has an impact on both the slope and intercept in the outcome equations. The estimated outcomes represent the returns to the characteristics of adopters and non-adopters (Biru et al., 2020; Di Falco et al., 2011; Kassie et al., 2018).

Given that we examine the impacts of ISFM adoption and the combination of ISFM and CA, we run two separate MESR.<sup>4</sup> Here, we take ISFM impact estimation as an example to describe the implementation of the method. MESR is implemented in two steps. In the first step, we model the determinants of ISFM adoption. We assume that at each period, farmers select an ISFM technology set that maximizes their utility. Among the sampled households, chemical fertilizer is the dominant ISFM technology that is adopted. Hence, we consider chemical fertilizer as a core component and hypothesize two possible ISFM sets. One set entails the partial adoption of two out of three core ISFM technologies, specifically, either chemical fertilizer with an

<sup>2</sup> The Central Statistical Agency (2017) reports that the national poverty line for 2015/2016 is 7,184 Ethiopian Birr per year, which is equal to 599 Ethiopian Birr per month per adult person.

<sup>3</sup> This measure consists of two parts: food consumed at home which can be purchased or produced (based on the reported market price), and food consumed away from home.

<sup>4</sup> CA practices only include conservation tillage and crop rotation. Crop residue (i.e. mulch or compost) is considered as an ISFM technology in this study. For mulch, crop rotation, and conservation tillage, households are considered as adopters if they apply the practice on at least 10% of their farmland. Please refer to the appendix for further detail on the technology combinations that constitute a combination of ISFM and CA practices.



improved variety or with an organic input.<sup>5</sup> The second set comprises complete ISFM adoption, meaning that all three ISFM components are adopted: chemical fertilizer, improved seeds, and organic inputs.

Since the ISFM principle requires the simultaneous use of these technologies, even if a household adopts one ISFM technology, we code that household as a non-adopter. Thus, assuming a technology set  $k = 0, 1, 2$ , where  $k = 0$  indicates that no ISFM set was adopted, we can show farmers' random utility at a certain time  $t$  as  $U_{kt}$ . A rational farmer will adopt a particular technology set given that the expected utility is higher than the alternatives, i.e.,  $U_{kt} > U_{mt}$ ,  $m \neq k$ . Following Kassie et al. (2018) under the assumption of independence of irrelevant alternatives (IIA),<sup>6</sup> we estimate the first stage with the multinomial logit model. The probability that a household  $i$  with characteristics  $X$  will adopt ISFM set  $k$  is given as:

$$Prob(k|X_{it}, H_i) = \frac{\exp(\alpha_k + X_{it}\beta_k + H_i)}{\sum_{m=1}^k \exp(\alpha_m + X_{it}\beta_m + H_i)}, k = 0, 1, 2 \quad (2)$$

where  $i$  denotes the household,  $k$  is the technology set,  $t$  indicates year,  $\alpha_k$  is a constant term of the technology set  $j$ ,  $\beta_k$  indicates represents parameters to be estimated, and  $X_{it}$  indicates various household socio-economic characteristics, survey year, and rainfall variables. To benefit from the panel structure of the dataset, we estimate the pooled selection and outcome (i.e., second step) models using the Mundlak approach and include the means of all time-varying variables into both equations. The Mundlak device helps to control time-invariant unobserved heterogeneity as with fixed-effects.  $H_i$  in Eq. 2 indicates the means of the time-varying explanatory variables. In the second stage, outcome models are estimated for adopters of each technology sets and non-adopters separately:

$$\begin{cases} \text{Regime0 : } O_{it0} = Z_{it0}\beta_0 + \hat{\lambda}_{it0}\sigma_0 + H_{i0} + \varepsilon_{it0} \text{ if non-adopter} \\ \text{Regime1 : } O_{it1} = Z_{it1}\beta_1 + \hat{\lambda}_{it1}\sigma_1 + H_{i1} + \varepsilon_{it1} \text{ if partial ISFM adopter} \\ \text{Regime2 : } O_{it2} = Z_{it2}\beta_2 + \hat{\lambda}_{it2}\sigma_2 + H_{i2} + \varepsilon_{it2} \text{ if complete ISFM adopter,} \end{cases} \quad (3)$$

where  $O_{it}$  indicates the outcome (i.e., food security or poverty indicators) observed for household  $i$  at time  $t$ ,  $Z_{it}$  indicates various household socio-economic characteristics and

survey years,  $\beta$  denotes parameters to be estimated,  $H_i$  indicates means of time-varying explanatory variables, and  $\sigma$  represents the covariance between outcome and selection equation errors. An important term in Eq. 3 is  $\hat{\lambda}$ , which represents the inverse Mills ratios derived from the selection equation to capture time-variant individual effects. Inverse Mills ratios generated from the first stage help improve identification; however, it is important that the first stage includes a selection instrument.

We include two instrumental variables in the first stage: the standard deviation of rainfall between 1981 and 2018 and the historical average for the same period. We assume that historical rainfall patterns can play a role in technology choices and adoption decisions of farmers, but that they are not directly related to the outcomes of interest. However, there is a possibility that rainfall variation could affect outcome variables of interest through non-farm income. Drought (i.e., within the last growing season) leads to increased employment in off-farm self-employment but not in off-farm wage-employment in Ethiopia (Musungu et al., 2024). Although the evidence provided is for the last growing season, we can assume that historical variation can affect farmers' expectations from agricultural production. Controlling for non-farm income, we block the effect of the instruments on outcome variables possible operating through non-farm income and achieve conditional independence of the instruments.

Teklewold et al. (2013a) show that the probability of manure application is high in areas where rainfall is reliable in terms of distribution, time, and amount. Dercon and Christiaensen (2011) find that fertilizer application is profitable for cereals in Ethiopia, given that rainfall does not largely deviate from its usual patterns. Farmers do not benefit from fertilizer if rainfall is not sufficient. Kassie et al. (2013) find that farmers in Tanzania choose to cultivate traditional varieties over improved varieties if the expected rainfall is insufficient. This implies that in the absence of a reliable rainfall amount, farmers do not invest in expensive inputs. Considering these results, we can assume that rainfall deviation and the historical average of rainfall are negatively and positively associated with the adoption of ISFM practices, respectively. In terms of CA practices, Teklewold et al. (2013a) report that similar to manure application, the probability of adopting crop rotation is high in areas where rainfall is reliable. Arslan et al. (2014) find a positive association between district-level historical rainfall variation and the adoption and intensity of minimum tillage. Given these findings, we again assume that rainfall variation and the historical average of rainfall are determinants of the adoption of the CA practices considered in this study.

Equation 3 is used to predict observed and counterfactual outcomes for adopters of the different technology sets. The

<sup>5</sup> We consider manure, mulch, and compost as organic inputs under ISFM. Unfortunately, the data does not allow us to differentiate organic mulch materials from other mulch materials, such as plastics.

<sup>6</sup> Bourguignon et al. (2007) show that selection bias correction based on the multinomial logit model provides sufficient correction for the second stage outcome equation even if IIA is violated. In this study, we employed Dubin and Mc Fadden's Model variant 1 using the "selmlog" Stata command developed by Bourguignon et al. (2007) with 200 bootstrapped replications.

observed outcomes are computed given the information in the data as:

$$E(O_{itK}|k=K) = Z_{itk}\beta_k + \hat{\lambda}_{itk}\sigma_k + \bar{Z}_{ik}\theta_k, k = 1, 2 \quad (4)$$

where  $\bar{Z}_i$  denotes observed means of time-varying explanatory variables;  $\beta, \sigma$ , and  $\theta$  are the coefficients estimated for adopters. To be able to estimate average treatment effects on the treated, it is important to also calculate the counterfactual outcomes for adopters of technology sets. The counterfactuals for adopters are calculated as follows:

$$E(O_{it0}|k=K) = Z_{itk}\beta_0 + \hat{\lambda}_{itk}\sigma_0 + \bar{Z}_{ik}\theta_0, k = 1, 2 \quad (5)$$

Parameters in Eq. 5 are coefficients obtained from the outcome regressions for non-adopters. With this equation, we calculate the outcomes that adopters would have obtained if the returns to their characteristics had been the same as the returns observed by non-adopters. The standard errors are obtained by 200 bootstrapped replications to account for the first stage. The difference between Eqs. 4 and 5 provides us with the average treatment effects on the treated:

$$ATT_i = E(O_{itK}|k=K) - E(O_{it0}|k=K) = (\beta_k - \beta_0)Z_{itk} + (\sigma_k - \sigma_0)\hat{\lambda}_{itk} + (\theta_k - \theta_0)\bar{Z}_{ik}. \quad (6)$$

The term  $(\beta_k - \beta_0)Z_{itk}$  represents the change observed in the outcome due to differences in observed characteristics. The second and third terms, namely  $(\sigma_k - \sigma_0)\hat{\lambda}_{itk}$  and  $(\theta_k - \theta_0)\bar{Z}_{ik}$ , denote the differences observed due to time-variant and time-invariant unobserved characteristics, respectively. Considering that we test multiple hypotheses, there is a probability of rejecting a true null hypothesis. Hence, we control for the false discovery rate and calculate and report the sharpened q-values as suggested by Anderson (2008).

### 3 Results

This section provides an overview of the surveyed households before presenting the results of the impacts of SI on food security and poverty outcomes.

#### 3.1 Sample characteristics

This subsection reports data on important sample characteristics. Table 1 lists relevant descriptive statistics, and Fig. 2 depicts adoption trends for ISFM and CA practices and technologies. Among the outcome variables, HDDS was close to six food groups in 2014, while in the later rounds, it increased to seven food groups, indicating an improvement in food security. Although real per capita food expenditure has declined over the years, the probability of experiencing

food insecurity has also declined significantly from the first survey round to the later rounds. In terms of poverty indicators, all show that poverty and its severity are growing among the sampled households. Regarding household characteristics, the sampled households have, on average, six members and 17% are headed by women. It appears that households have extended their social networks by taking active roles in social organizations. Approximately, 16% of households received loans and around 34% had non-farm income in all survey rounds.

Between 2014 and 2016, the average farm size increased, but did not change in 2019. The primary crops are barley and maize, with the share of farmers cultivating maize increasing to 40% in 2019, from approximately 33% in the previous survey rounds. Additionally, approximately 42% of the sampled households cultivate barley. Tropical livestock units (TLU) owned increased between 2014 and 2016, but declined in 2019. We observe growth in the number of farmers who perceive their soil quality to be either poor or good. Over the years, there have been improvements in infrastructure, as indicated by less time needed to reach the nearest periodic market and extension office. The share of farmers attending extension training has increased over the years. However, we observe a decline in the share of farmers receiving extension visits in 2019. On the other hand, the share of households referring to their fellow farmers for information regarding agricultural practices and technologies increased significantly, especially in 2019. In terms of rainfall, the year 2015 was, on average, drier than 2013 and 2018.

We observe that the number of ISFM adopters<sup>7</sup> increased from one survey round to the next. In terms of ISFM and CA combination, the number of farmers implementing both practices increased from 2014 to 2016, and in 2019 it remained close to the 2016 values. Overall, the number of farmers who do not practice any combination of ISFM or CA practices declined significantly from 2014 to 2016. The number of ISFM adopters who do not practice CA also increased from one survey round to the next. Moreover, the number of farmers who practice only CA increased from 2014 to 2016, but returned to 2014 levels in 2019.

Among the ISFM technologies, fertilizer application was the dominant component, with an increased share of households using fertilizer over the years. In 2019, almost 80% of the sampled households indicated applying some fertilizer. The share was 72% in 2014 and 77% in 2016. Regarding manure, 23%, 44%, and 49% of the sampled households reported its use in 2014, 2016, and 2019, respectively. Households have also increased their use of improved varieties over the years. Mulch was utilized by 9%, 6%, and 8% of

<sup>7</sup> Those who use chemical fertilizer with either manure or improved variety (partial ISFM) or both (complete ISFM).

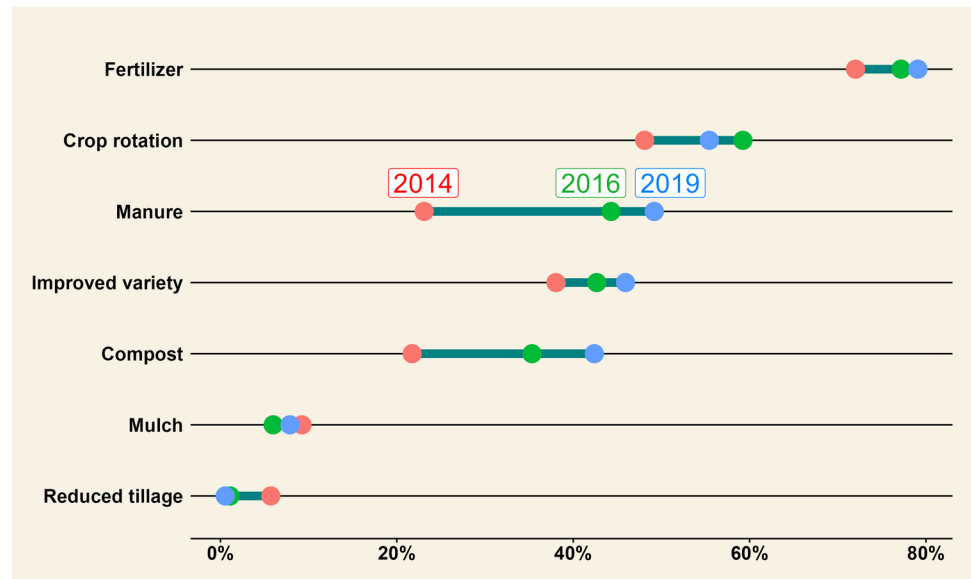
**Table 1** Sample characteristics

	2014	2016	2019
<i>Household characteristics</i>			
HDDS	6.36 (1.68)	6.71 (1.51)	6.67 (1.63)
Adult equivalent real food expenditure (ln)	6.25 (0.73)	6.18 (0.66)	6.09 (0.77)
Food insecurity experience (= 1 if yes)	0.67 (0.47)	0.39 (0.49)	0.39 (0.49)
Poverty headcount (= 1 if poor)	0.60 (0.49)	0.62 (0.49)	0.65 (0.48)
Poverty gap	0.22 (0.25)	0.22 (0.22)	0.26 (0.26)
Poverty severity	0.11 (0.16)	0.10 (0.14)	0.13 (0.18)
Female head	0.17 (0.37)	0.16 (0.37)	0.17 (0.38)
Head age	44.90 (13.85)	48.15 (13.41)	49.71 (14.53)
Years of formal schooling of head	3.17 (3.61)	3.12 (3.58)	3.13 (3.35)
Number of household members	6.37 (2.24)	6.45 (2.33)	6.33 (2.30)
Dependency ratio	1.20 (0.88)	1.16 (0.84)	1.09 (0.86)
<i>Farm-specific characteristics</i>			
Distance to periodic market (minutes)	52.63 (45.18)	47.84 (40.24)	40.90 (34.37)
Distance to ext. office (minutes)	46.46 (46.04)	37.53 (39.04)	31.25 (31.90)
Distance to parcel (minutes) <sup>a</sup>	14.90 (22.31)	20.48 (34.65)	18.78 (32.62)
Land certificate (= 1 if yes) <sup>a</sup>	0.83 (0.37)	0.67 (0.47)	0.78 (0.42)
Poor soil quality (= 1 if yes) <sup>a</sup>	0.04 (0.20)	0.03 (0.17)	0.08 (0.27)
Good soil quality (= 1 if yes) <sup>a</sup>	0.52 (0.50)	0.52 (0.50)	0.64 (0.48)
Farm size in hectares	1.47 (1.20)	1.67 (1.56)	1.67 (2.52)
TLU owned	3.88 (4.32)	4.59 (4.64)	3.96 (4.10)
Pesticides (= 1 if applied)	0.34 (0.47)	0.30 (0.46)	0.42 (0.49)
Maize (= 1 if produced in prev. season)	0.34 (0.48)	0.32 (0.47)	0.40 (0.49)
Barley (= 1 if produced in prev. season)	0.42 (0.49)	0.43 (0.50)	0.41 (0.49)
Number of shocks	0.36 (0.58)	0.25 (0.51)	0.42 (0.61)
No. of social organizations HH is active in	1.41 (1.06)	1.84 (1.45)	2.13 (1.52)
Loan (= 1 if acquired in past 12 months)	0.15 (0.35)	0.16 (0.37)	0.17 (0.37)
Non-farm income (= 1 if yes)	0.34 (0.47)	0.33 (0.47)	0.36 (0.48)
Extension visits (= 1 if yes in past 24 months)	0.39 (0.49)	0.39 (0.49)	0.17 (0.37)
Ext. training (= 1 if yes in past 24 months)	0.44 (0.50)	0.43 (0.50)	0.54 (0.50)
Fellow farmer as information source (= 1 if yes)	0.21 (0.41)	0.30 (0.46)	0.63 (0.48)
Annual rainfall previous season (mm)	1286.47 (301.01)	1095.16 (269.27)	1328.32 (263.97)
<i>ISFM <sup>b</sup> (% in parentheses)</i>			
No ISFM combination	207 (56.3%)	162 (44.0%)	142 (38.6%)
Partial adoption of ISFM technologies	115 (31.3%)	122 (33.2%)	143 (38.9%)
Complete adoption of ISFM technologies	46 (12.5%)	84 (22.8%)	83 (22.6%)
<i>ISFM and CA combination <sup>c</sup></i>			
No ISFM combination or CA	136 (37.0%)	77 (20.9%)	75 (20.4%)
ISFM+CA	111 (30.2%)	135 (36.7%)	138 (37.5%)
CA	71 (19.3%)	85 (23.1%)	67 (18.2%)
ISFM	50 (13.6%)	71 (19.3%)	88 (23.9%)
Observations	368	368	368

Notes: ISFM is Integrated Soil Fertility Management; CA is conservation agriculture; HDDS is the household dietary diversity score; HH is household; and TLU is tropical livestock units. <sup>a</sup> distance, soil quality, and land certificate are for the biggest parcel; soil quality is based on farmers' perceptions; <sup>b</sup> partial adoption of ISFM: either chemical fertilizer with improved variety or with organic input and complete adoption of ISFM: all technologies, chemical fertilizer, improved seeds, and organic input; <sup>c</sup> Partial or complete ISFM with crop rotation and/or minimum tillage as CA;



**Fig. 2** Adoption of ISFM and CA practices, by year



the sampled households in the years 2014, 2016, and 2019, respectively. Crop rotation was practiced by 48%, 59%, and 55% of the sampled households in 2014, 2016, and 2019, respectively. There was a significant growth in the share of farmers practicing composting over the years, i.e., 22% in 2014, 35% in 2016, and 42% in 2019. Very few households reported reduced tillage uptake.

### 3.2 Impacts of SI

The objective of this study is to evaluate the impacts of widely promoted SI practices on poverty and food security among rural smallholder farmers in Ethiopia. In this subsection, we concentrate on ISFM adoption and its combined use with CA before presenting their effects on outcome measures.

Table 2 presents the multinomial logistic regression results on ISFM adoption and the adoption of the combination of ISFM and CA. We perform the Hausman test of IIA and do not find any evidence of violating the IIA assumption. This implies that the multinomial logistic regression model can be applied to our data. We observe a significant positive effect of pesticide application on the adoption of ISFM technologies and CA practices, and their combined use. Maize and barley producers are likely to adopt ISFM technologies and their combination with CA practices. We find that farmers who are located in high altitude areas are less likely to adopt these practices. The results further show that participating in extension training programs and referring to a fellow farmer for agricultural-related information are positively associated with the uptake of the combination of ISFM and CA, as well as the adoption of CA alone.

Regarding the instruments, as hypothesized, the results suggest that historical average rainfall has a positive link

with ISFM adoption in both specifications. The standard deviation of historical rainfall is positively correlated with the adoption of CA practices and the combined use of ISFM and CA. To determine whether the instruments are admissible, we follow Di Falco et al. (2011) and perform a simple falsification test where the instruments are assumed to affect adoption decisions, but not the outcome for non-adopters. Tables A1 and A2 in the appendix report the results from this simple falsification test. The results do not provide any consistent evidence of a significant relationship between the instruments and the outcomes for non-adopters at 5% error probability. This suggests that the instruments are valid: they are jointly significant determinants of adoption decision but not the outcomes of households who do not adopt technology sets under consideration. Moreover, we run random effects, fixed effects, and Inverse Probability Weighted Regression Adjustment (separated for each round) impact estimation techniques to assess the robustness of the results. Tables A5 -A9 depict the results from these alternative techniques. Most of the results are in line with the MESR results.

To visualize and compare the magnitude of the impacts, we depict the impacts of partial and complete ISFM adoption vs. no ISFM adoption in Fig. 3 and Fig. 4, respectively. These results are also available in table format in the supplementary appendix (in Tables A3 and A4). The figures illustrate the observed and counterfactual outcomes and the difference between them. There are positive average treatment effects for partial and complete adopters of ISFM technologies in terms of HDDS and adult equivalent per capita food expenditure. Also, both partial and complete adoption of ISFM technologies reduces the probability of experiencing food insecurity over the past 12 months by 8% and 6%, respectively. Both partial and complete adopters of ISFM technologies would have around 13%

**Table 2** Multinomial logistic regression results of ISFM adoption and the combination of ISFM and CA

	ISFM adoption				ISFM and CA combination			
	Partial ISFM adoption		Complete ISFM adoption		ISFM and CA		CA	
	Coeff	Std. Err	Coeff	Std. Err	Coeff	Std. Err	Coeff	Std. Err
Female head	-0.39	(0.433)	-0.63	(0.478)	-0.28	(0.512)	-0.17	(0.539)
Head age	0.00	(0.014)	0.01	(0.016)	-0.01	(0.015)	-0.02	(0.018)
Years of formal schooling of head	-0.02	(0.055)	-0.01	(0.070)	-0.10	(0.069)	-0.16*	(0.084)
Number of household members	0.00	(0.069)	0.16*	(0.082)	0.12	(0.089)	0.11	(0.105)
Dependency ratio	0.14	(0.148)	-0.01	(0.186)	0.09	(0.191)	-0.03	(0.204)
Distance to the nearest periodic market (minutes)	0.00	(0.004)	0.00	(0.004)	0.01	(0.005)	0.00	(0.005)
Distance to the nearest extension office (minutes)	-0.01**	(0.003)	-0.00	(0.004)	-0.01**	(0.003)	-0.00	(0.003)
Distance to the biggest parcel (minutes)	-0.00	(0.005)	-0.01	(0.005)	0.00	(0.005)	0.01	(0.005)
Land certificate (= 1 if yes)	0.02	(0.230)	0.10	(0.290)	0.19	(0.268)	0.23	(0.316)
Poor soil quality (= 1 if yes)	0.57	(0.516)	0.23	(0.681)	0.83	(0.594)	0.84	(0.521)
Good soil quality (= 1 if yes)	0.26	(0.193)	0.09	(0.236)	0.31	(0.222)	0.19	(0.261)
Farm size in hectares	-0.12*	(0.072)	0.22**	(0.088)	0.18	(0.151)	0.20	(0.129)
TLU owned	0.02	(0.036)	0.00	(0.043)	-0.01	(0.054)	-0.02	(0.075)
Pesticides (= 1 if applied)	0.69***	(0.262)	0.72**	(0.309)	1.16***	(0.322)	0.85***	(0.324)
Maize (= 1 if produced in prev. season)	0.83***	(0.243)	1.54***	(0.271)	0.92***	(0.287)	0.25	(0.333)
Barley (= 1 if produced in prev. season)	0.54*	(0.295)	0.68**	(0.307)	0.77**	(0.361)	0.04	(0.386)
Altitude (in meters)	-0.00***	(0.000)	-0.00**	(0.000)	-0.00**	(0.000)	-0.00	(0.000)
Number of shocks	0.11	(0.193)	0.26	(0.199)	0.25	(0.215)	0.22	(0.284)
Cost of coping strategies	-0.00	(0.000)	-0.00	(0.000)	-0.00	(0.000)	-0.00	(0.000)
Shallow slope (= 1 if yes)	-0.20	(0.196)	-0.14	(0.241)	-0.26	(0.241)	-0.32	(0.245)
Steep slope (= 1 if yes)	-0.34	(0.458)	0.81	(0.532)	-0.17	(0.525)	-0.42	(0.763)
Number of social organizations HH is active	0.05	(0.084)	0.16	(0.106)	0.15	(0.094)	0.06	(0.108)
Loan (= 1 if acquired in past 12 m.)	0.10	(0.286)	0.47	(0.308)	0.06	(0.330)	-0.53	(0.371)
Non-farm income (= 1 if yes)	-0.17	(0.223)	0.20	(0.277)	0.00	(0.254)	-0.28	(0.283)
Extension visits (= 1 if yes in past 24 m.)	0.04	(0.208)	0.41	(0.255)	0.27	(0.245)	0.02	(0.288)
Extension training (= 1 if yes in past 24 m.)	0.31	(0.216)	0.51**	(0.230)	1.03***	(0.253)	0.77***	(0.282)
Fellow farmer as information source (= 1 if yes)	0.13	(0.223)	-0.07	(0.254)	0.80***	(0.242)	1.02***	(0.252)
Annual rainfall previous season (mm)	-0.00	(0.001)	-0.00	(0.001)	0.00	(0.001)	0.00	(0.001)
Standard deviation of rainfall between 1981 and 2018	0.01	(0.008)	-0.01	(0.011)	0.03***	(0.011)	0.03**	(0.011)
Historical average of rainfall	0.01***	(0.002)	0.01***	(0.002)	0.01***	(0.002)	-0.00	(0.002)
Joint significance of Mundlak variables	$\chi^2(25) = 38.66^{**}$		$\chi^2(25) = 24.96$		$\chi^2(25) = 51.92^{***}$		$\chi^2(25) = 27.80$	
Hausman IIA test $\chi^2$ results	-3.25		-2.04		41.89		4.63	
							$\chi^2(25) = 25.79$	15.86

Table 2 (continued)

ISFM adoption		ISFM and CA combination			
Partial ISFM adoption	Complete ISFM adoption	ISFM and CA	CA	ISFM	
Coeff	Std. Err	Coeff	Std. Err	Coeff	Std. Err
$\chi^2(116) = 402.20^{***}$		$\chi^2(174) = 837.82^{***}$			

Note: ISFM is Integrated Soil Fertility Management; CA is conservation agriculture; IIA is the independence of irrelevant alternatives; No ISFM and no ISFM or CA are the base categories; standard errors are clustered at the household level; year and region fixed effects are included; number of observations: 1104; and \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , and \*  $p < 0.10$

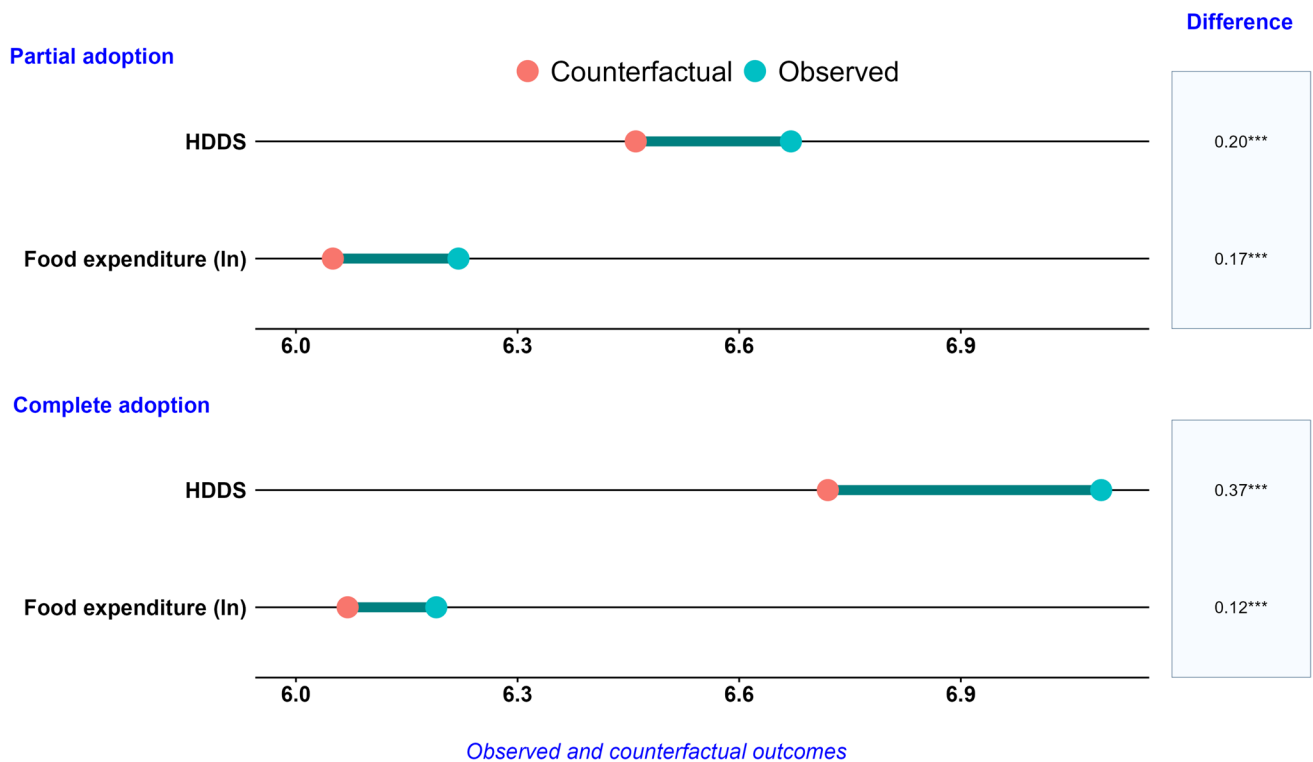
more probability of being poor had they not adopted these technology packages. Furthermore, we find the adoption of ISFM technologies to have reduced both the poverty gap and severity of poverty, and the magnitudes of these impacts appear to be larger for partial adopters. Overall, farmers who partially or completely adopted ISFM technologies would have been worse off had they not adopted these technology packages.

Considering that households often adopt different technologies and practices that fall under various SI approaches, in the second objective, we assume a possible ISFM and CA combination and study the joint effects of ISFM and CA adoption on the specified outcomes.

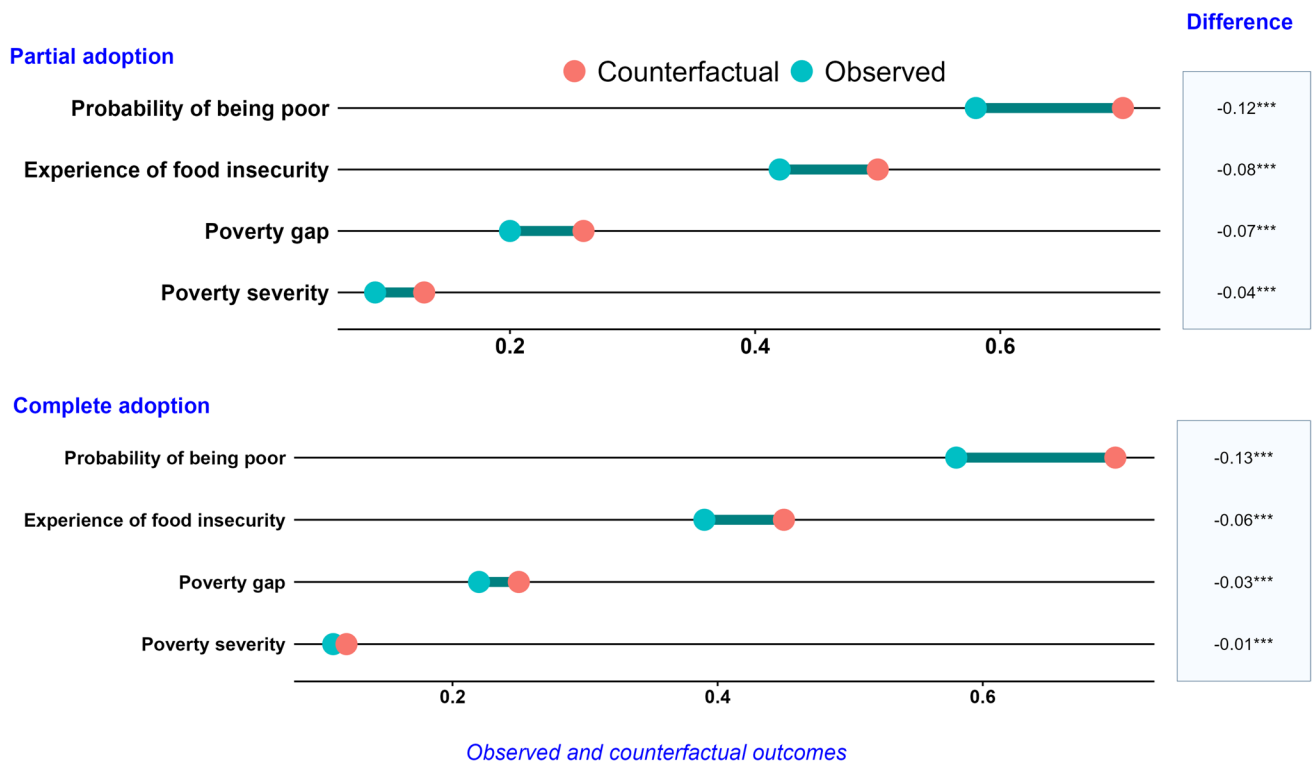
Figure 5 and Fig. 6 depict the impacts of the combination of ISFM and CA on poverty and food security outcomes. We find that the incorporation of ISFM technologies with CA practices leads to an almost 0.7-fold increase in the consumption of food groups among adopters. This is significantly larger than the benefits observed for the adopters of ISFM or CA only. We did not find any impact of ISFM or the combination of ISFM and CA on the adult equivalent real per capita food consumption, but did observe a negative impact for adopters of only CA practices. Further, the combined use of ISFM and CA reduces the probability of being poor for adopters by 17%, which is again much higher than the benefits observed by adopters of ISFM only. In terms of the likelihood of being poor, we did not find any evidence that the outcomes for the adopters of CA practices would have been statistically different if they had not adopted these practices. We found that the simultaneous use of ISFM and CA lessened the prospect of experiencing food insecurity in the past 12 months by 16%. The size of this effect is again larger than what is observed for the adopters of CA (11%) or ISFM (12%) only. Regarding both the poverty gap and severity of poverty, farmers who combine ISFM and CA would have been worse off had they not opted to adopt and combine these technology packages. Similar to farmers who combine ISFM and CA, those who adopt only ISFM practices would have been worse off had they not adopted these technologies. We find that the severity of poverty for CA adopters would have been better off had they not adopted these practices.

## 4 Discussion

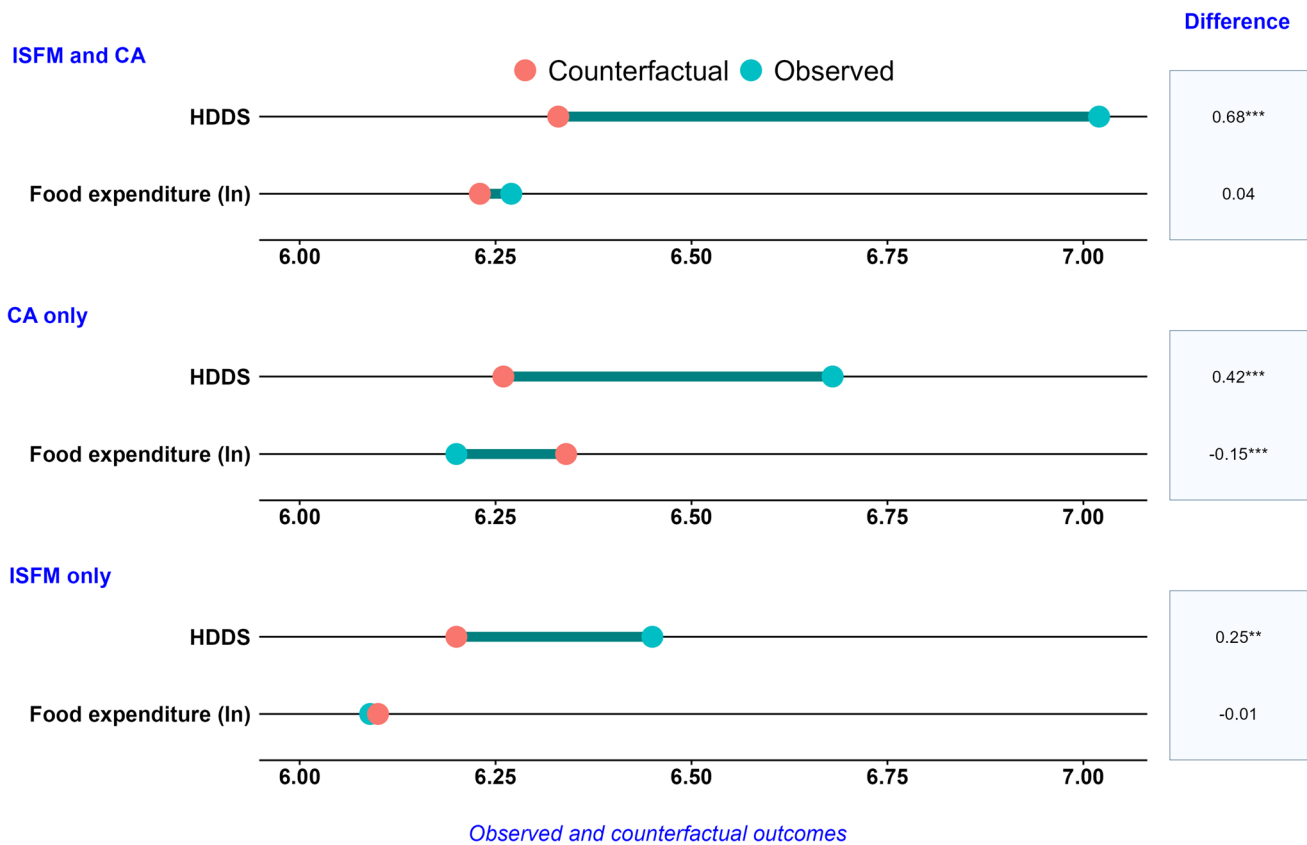
We find evidence of improved welfare for adopters of ISFM technologies. Both partial and complete adoption of ISFM technologies result in better dietary diversity, increased food expenditure, and a reduced probability of experiencing food insecurity. In terms of poverty, the results indicate that both partial and complete adoption of ISFM technologies reduce the probability of being poor by 13% for adopters. This is



**Fig. 3** Impacts of partial and complete ISFM adoption on food security. Notes: HDDS is the household dietary diversity score



**Fig. 4** Impacts of partial and complete ISFM adoption on poverty and experience of food insecurity



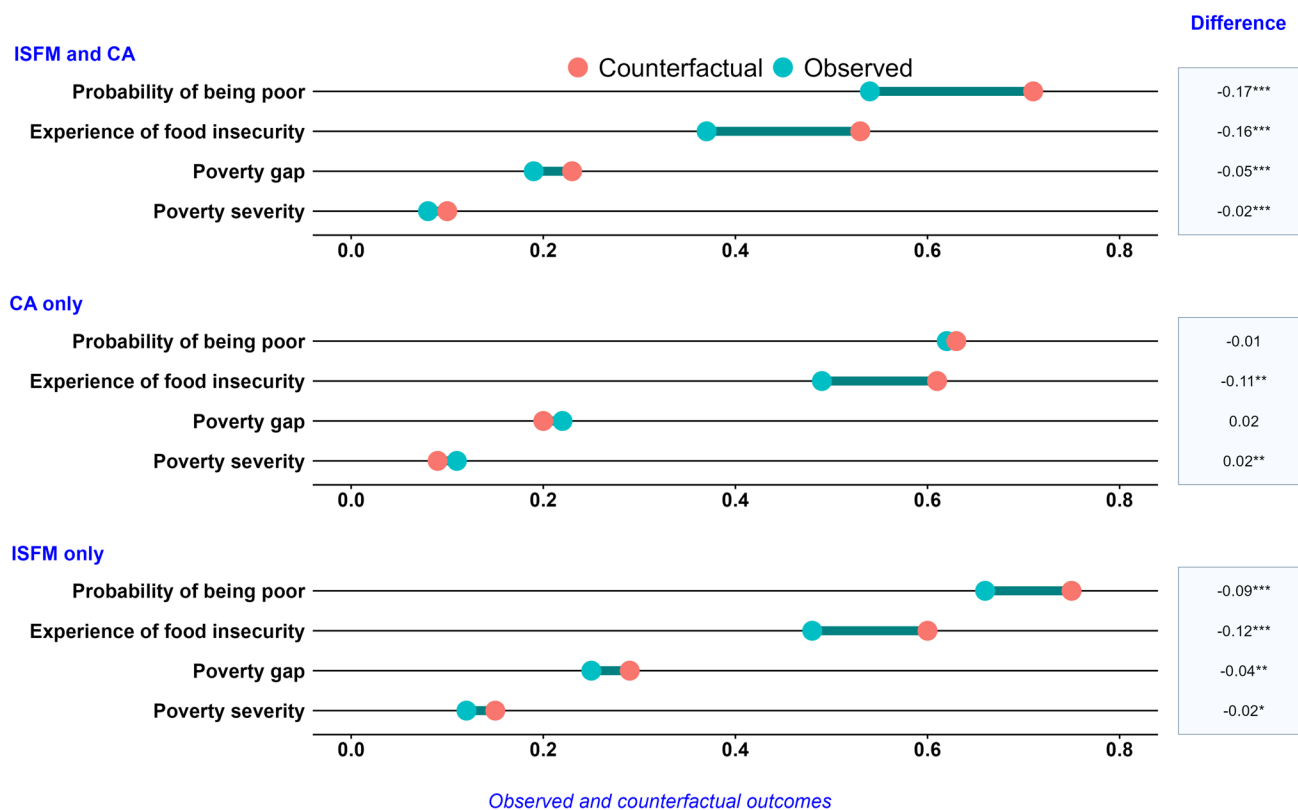
**Fig. 5** Impacts of ISFM and CA combination on food security

a considerable effect size which is compelling enough to warrant the promotion of chemical fertilizer application in combination with improved varieties or some organic inputs or both on smallholder farms. Moreover, the extent to which adopters fall below the poverty line and their severity of poverty would have been larger had they not adopted ISFM technology packages. Hörner and Wollni (2022) also report that ISFM adoption is associated with increased income and lower vulnerability to food insecurity among farmers in Amhara and Oromia regions. In general, both partial and full adoption of ISFM practices yield positive outcomes, with the magnitude of benefits varying—sometimes favoring partial adoption and other times complete adoption. Hörner and Wollni (2021) similarly find that, in terms of net crop value, the combination of organic fertilizer and improved seeds offer higher returns than the complete adoption of ISFM, though complete adoption leads to greater land and labor productivities. Hörner and Wollni (2021) also provide evidence of agro-ecological heterogeneity in the effects of ISFM. This is an aspect that this study did not investigate, and thus offers an opportunity for future research.

In terms of the combined use of ISFM technologies with CA practices, we find that farmers who exclusively adopt ISFM technologies as well as those who integrate ISFM

and CA, achieve better dietary diversity and food security. The magnitudes of these gains from adoption are consistently greater for farmers who combine ISFM and CA. The same holds true for the poverty indicators. Overall, our results strongly suggest that the adoption of ISFM technologies has positive implications for smallholder households in terms of poverty and food security, and these benefits are likely to gain a noteworthy boost if ISFM technologies are combined with CA practices. On the other hand, farmers that adopt only CA practices achieve better dietary diversity and a reduced probability of experiencing food insecurity. Nevertheless, we did not find any evidence of positive returns in other indicators — food expenditure, probability of being poor, poverty gap, or the severity of poverty — for farmers who adopt only CA practices. In terms of the effects of CA practices, there is a lack of consensus in the literature, with studies yielding divergent and sometimes contradictory results. Our findings are partly in line with Tambo and Mockshell (2018) who study welfare impacts of individual and combined CA practices in nine SSA countries. They also did not find any evidence of impact on income from minimum tillage, crop rotation, or their combination in Ethiopia. On the contrary, Tesfaye et al. (2021) find that adoption of minimum tillage reduces





**Fig. 6** Impacts of ISFM and CA combination on poverty and experience of food insecurity

the probability of being poor, poverty gap and the severity of poverty in Ethiopia. Similarly, Teklewold and Mekonnen (2017) demonstrate that minimum tillage increases farm income in low-rainfall areas of the Nile Basin, underscoring the heterogeneous impacts of the practice. Our results underscore the importance of encouraging users of CA practices to complement these with at least two inputs, such as improved germplasm, and organic or inorganic fertilizer.

## 5 Conclusion

We examined the impacts of adopting ISFM technologies, both independently and in combination with CA practices, on poverty and food security. Our analysis leveraged three rounds of panel data from Ethiopian households, along with location-specific historical rainfall data extracted from the Climate Hazards Group InfraRed Precipitation with Station data.

We considered three poverty indices (i.e., poverty headcount, poverty gap, and poverty severity) and three food security indicators (HDDS, adult equivalent real per capita food expenditure, and experience of food insecurity) as outcomes of interest. The analysis consisted of two parts:

the first concentrated on estimating the impact of ISFM adoption, and the second expanded the analysis to test for the impact of combining ISFM technologies with CA practices. The adoption of ISFM technologies or CA practices are decisions that can be affected by some unobserved factors that may also affect the outcome indicators. Availability of panel data deals with the problem if unobserved heterogeneity is time invariant. To deal with potential time variant heterogeneity, we utilized the MESR model and selection instruments, namely the standard deviation of rainfall between 1981 and 2018 and the historical average for the same period. In doing so, our assumption was that historical rainfall patterns can play a role in technology choices and adoption decisions of farmers, but are not directly related to the observed outcomes.

The results indicated that the adoption of ISFM technologies significantly improves welfare by reducing poverty, enhancing dietary diversity, and lowering food insecurity. Both partial and full adoption of ISFM provide positive outcomes, with varying magnitudes of benefits. Combining ISFM with CA yields even greater gains in food security and poverty reduction. However, adopting only CA practices shows limited benefits, mainly improving dietary diversity. We did not find any evidence of positive returns from only CA adoption in terms of poverty alleviation.

This study has few limitations. There is a caveat that, in MESR, if there is an alternative open path from weather variability to the outcome variables, the results may be biased. Additionally, the measurement of key variables relies on respondents' precise recall, which introduces the potential for recall bias. While the study area includes some diversity in agro-ecological zones, production systems, and infrastructure, we advise caution in generalizing these findings to the entire country, as previous research highlights agro-ecological heterogeneity in the effects of ISFM. We believe that the results of this study are robust and likely to hold in similar agro-ecological, production, and infrastructural contexts.

This paper contributes to the technology adoption literature, particularly on SI practices, with highlights on ISFM technologies and CA practices. The findings highlight the substantial benefits that ISFM technologies provide farm households in terms of poverty alleviation and improved food security. The combined use of ISFM and CA practices provides a further boost to these welfare gains. Based on these findings, we recommend that development programs aiming to alleviate poverty and boost food security in rural Ethiopia should enhance farm household's access to ISFM technologies and further encourage these households to adopt ISFM packages. We find strong evidence of greater welfare gains for farmers who combine ISFM technologies with CA practices. Therefore, programs that only promote CA practices would benefit more by incorporating ISFM technologies into their dissemination activities, since the combined use with ISFM technologies appears to be more promising than the sole use of CA only. This is also a call for future research and projects to study the impacts of ISFM, CA, and their integration in an experimental setting to provide more rigorous evidence for policymakers and donors.

**Supplementary Information** The online version contains supplementary material available at <https://doi.org/10.1007/s12571-025-01517-9>.

**Acknowledgements** This work was supported by the Deutsche Forschungsgemeinschaft (DFG) [ZE 502/1-1, AOBJ 602066], whose support is gratefully acknowledged. The authors extend their gratitude to the Editor-in-Chief, Deputy Editor-in-Chief, Associate Editor, and the four anonymous reviewers for their insightful feedback and constructive suggestions, which have significantly enhanced the quality of this paper.

**Funding** Open Access funding enabled and organized by Projekt DEAL. This work was supported by the Deutsche Forschungsgemeinschaft (DFG) [ZE 502/1-1, AOBJ 602066]. The data comes from the DFG funded project "Smallholder farmers' risk management and innovation strategies and their impacts on poverty and resilience " in Ethiopia. Replication files are provided as an online supplement to the article and are also accessible for viewing and download from the corresponding [GitHub repository](#).

**Data availability** The final datasets analyzed, and replication file are available in the GitHub repository: <https://github.com/orkhan-sari/isfmca-replication>.

## Declarations

**Conflict of Interests** The authors declared that they have no conflict of interest.

**Open Access** This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit <http://creativecommons.org/licenses/by/4.0/>.

## References

- Anderson, M. L. (2008). Multiple inference and gender differences in the effects of early intervention: A reevaluation of the abecedarian, perry preschool, and early training projects. *Journal of the American Statistical Association*, 103(484), 1481–1495. <https://doi.org/10.1198/016214508000000841>
- Arslan, A., McCarthy, N., Lipper, L., Asfaw, S., & Cattaneo, A. (2014). Adoption and intensity of adoption of conservation farming practices in Zambia. *Agriculture, Ecosystems & Environment*, 187, 72–86. <https://doi.org/10.1016/j.agee.2013.08.017>
- Biru, W. D., Zeller, M., & Loos, T. K. (2020). The impact of agricultural technologies on poverty and vulnerability of smallholders in Ethiopia: A panel data analysis. *Social Indicators Research*, 147, 517–544. <https://doi.org/10.1007/s11205-019-02166-0>
- Bourguignon, F., Fournier, M., & Gurgand, M. (2007). Selection bias corrections based on the multinomial logit model: Monte carlo comparisons. *Journal of Economic Surveys*, 21(1), 174–205. <https://doi.org/10.1111/j.1467-6419.2007.00503.x>
- Central Statistical Agency. (2017). *Ethiopia's progress towards eradicating poverty: an interim report on 2015/16 poverty analysis study*. 32.
- Dercon, S., & Christiaensen, L. (2011). Consumption risk, technology adoption and poverty traps: Evidence from Ethiopia. *Journal of Development Economics*, 96(2), 159–173. <https://doi.org/10.1016/j.jdeveco.2010.08.003>
- Di Falco, S., Veronesi, M., & Yesuf, M. (2011). Does adaptation to climate change provide food security? A micro-Perspective from Ethiopia. *American Journal of Agricultural Economics*, 93(3), 829–846. <https://doi.org/10.1093/ajae/aar006>
- FAO, IFAD, UNICEF, WFP, & WHO. (2023). The state of food security and nutrition in the world 2023: Urbanization, agrifood systems transformation and healthy diets across the rural–urban continuum. FAO, IFAD, UNICEF, WFP, WHO. <https://doi.org/10.4060/cc3017en>
- Foster, J., Greer, J., & Thorbecke, E. (1984). A class of decomposable poverty measures. *Econometrica*, 52(3), 761. <https://doi.org/10.2307/1913475>
- Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., Husak, G., Rowland, J., Harrison, L., Hoell, A., & Michaelsen, J. (2015). The climate hazards infrared precipitation with stations—A new environmental record for monitoring extremes.

- Scientific Data*, 2(1), 150066. <https://doi.org/10.1038/sdata.2015.66>
- Giller, K. E., Witter, E., Corbeels, M., & Tittonell, P. (2009). Conservation agriculture and smallholder farming in Africa: The heretics' view. *Field Crops Research*, 114(1), 23–34. <https://doi.org/10.1016/j.fcr.2009.06.017>
- Godfray, H. C. J., Beddington, J. R., Crute, I. R., Haddad, L., Lawrence, D., Muir, J. F., Pretty, J., Robinson, S., Thomas, S. M., & Toulmin, C. (2010). Food security: The challenge of feeding 9 billion people. *Science*, 327(5967), 812–818. <https://doi.org/10.1126/science.1185383>
- Hörner, D., & Wollni, M. (2021). Integrated soil fertility management and household welfare in Ethiopia. *Food Policy*, 100, 102022. <https://doi.org/10.1016/j.foodpol.2020.102022>
- Hörner, D., & Wollni, M. (2022). Does integrated soil fertility management increase returns to land and labor? *Agricultural Economics*, 53(3), 337–355. <https://doi.org/10.1111/agec.12699>
- Imbens, G. W., & Wooldridge, J. M. (2009). Recent developments in the econometrics of program evaluation. *Journal of Economic Literature*, 47(1), 5–86. <https://doi.org/10.1257/jel.47.1.5>
- Jayne, T. S., & Sanchez, P. A. (2021). Agricultural productivity must improve in Sub-Saharan Africa. *Science*, 372(6546), 1045–1047. <https://doi.org/10.1126/science.abf5413>
- Johansen, C., Haque, M. E., Bell, R. W., Thierfelder, C., & Esdaile, R. J. (2012). Conservation agriculture for small holder rainfed farming: Opportunities and constraints of new mechanized seeding systems. *Field Crops Research*, 132, 18–32. <https://doi.org/10.1016/j.fcr.2011.11.026>
- Kassie, M., Jaleta, M., Shiferaw, B., Mmbando, F., & Mekuria, M. (2013). Adoption of interrelated sustainable agricultural practices in smallholder systems: Evidence from rural Tanzania. *Technological Forecasting and Social Change*, 80(3), 525–540. <https://doi.org/10.1016/j.techfore.2012.08.007>
- Kassie, M., Teklewold, H., Jaleta, M., Marenja, 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. <https://doi.org/10.1016/j.landusepol.2014.08.016>
- Kassie, M., Marenja, P., Tessema, Y., Jaleta, M., Zeng, D., Erenstein, O., & Rahut, D. (2018). Measuring farm and market level economic impacts of improved maize production technologies in Ethiopia: Evidence from panel data. *Journal of Agricultural Economics*, 69(1), 76–95. <https://doi.org/10.1111/1477-9552.12221>
- Kennedy, G., Ballard, T., & Dop, M. C. (2011). *Guidelines for measuring household and individual dietary diversity*. Food and Agriculture Organization of the United Nations.
- 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. *Agricultural Economics*, 49(5), 599–609. <https://doi.org/10.1111/agec.12445>
- Maggio, G., Mastrorillo, M., & Sitko, N. J. (2022). Adapting to high temperatures: Effect of farm practices and their adoption duration on total value of crop production in Uganda. *American Journal of Agricultural Economics*, 104(1), 385–403. <https://doi.org/10.1111/ajae.12229>
- Minot, N., & Sawyer, B. (2013). *Agricultural production in Ethiopia: Results of the 2012 ATA baseline survey*. [https://reap.ifpri.info/files/2013/12/ag\\_production\\_in\\_ethiopia.pdf](https://reap.ifpri.info/files/2013/12/ag_production_in_ethiopia.pdf)
- Montt, G., & Luu, T. (2020). Does conservation agriculture change labour requirements? Evidence of sustainable intensification in Sub-Saharan Africa. *Journal of Agricultural Economics*, 71(2), 556–580. <https://doi.org/10.1111/1477-9552.12353>
- Musungu, A. L., Kubik, Z., & Qaim, M. (2024). Drought shocks and labour reallocation in rural Africa: Evidence from Ethiopia. *European Review of Agricultural Economics*, jbae020. <https://doi.org/10.1093/erae/jbae020>
- Petersen, B., & Snapp, S. (2015). What is sustainable intensification? Views from experts. *Land Use Policy*, 46, 1–10. <https://doi.org/10.1016/j.landusepol.2015.02.002>
- Pretty, J., Toulmin, C., & Williams, S. (2011). Sustainable intensification in African agriculture. *International Journal of Agricultural Sustainability*, 9(1), 5–24. <https://doi.org/10.3763/ijas.2010.0583>
- Ruel, M. T. (2003). Operationalizing dietary diversity: A review of measurement issues and research priorities. *The Journal of Nutrition*, 133(11 Suppl 2), 3911S–3926S. <https://doi.org/10.1093/jn/133.11.3911S>
- Tambo, J. A., & Mockshell, J. (2018). Differential impacts of conservation agriculture technology options on household income in Sub-Saharan Africa. *Ecological Economics*, 151, 95–105. <https://doi.org/10.1016/j.ecolecon.2018.05.005>
- Teklewold, H., & Mekonnen, A. (2017). The tilling of land in a changing climate: Empirical evidence from the Nile Basin of Ethiopia. *Land Use Policy*, 67, 449–459. <https://doi.org/10.1016/j.landusepol.2017.06.010>
- Teklewold, H., Kassie, M., & Shiferaw, B. (2013a). Adoption of multiple sustainable agricultural practices in rural Ethiopia. *Journal of Agricultural Economics*, 64(3), 597–623. <https://doi.org/10.1111/1477-9552.12011>
- Teklewold, H., Kassie, M., Shiferaw, B., & Köhlin, G. (2013b). Cropping system diversification, conservation tillage and modern seed adoption in Ethiopia: Impacts on household income, agrochemical use and demand for labor. *Ecological Economics*, 93, 85–93. <https://doi.org/10.1016/j.ecolecon.2013.05.002>
- Tesfaye, W., Blalock, G., & Tirivayi, N. (2021). Climate-Smart innovations and rural poverty in Ethiopia: Exploring impacts and pathways. *American Journal of Agricultural Economics*, 103(3), 878–899. <https://doi.org/10.1111/ajae.12161>
- The Montpellier Panel. (2013). *Sustainable intensification: A new paradigm for African agriculture*.
- Vanlauwe, B., Bationo, A., Chianu, J., Giller, K. E., Merckx, R., Mkwunye, U., Ohiokpehai, O., Pypers, P., Tabo, R., Shepherd, K. D., Smaling, E. M. A., Woomer, P. L., & Sanginga, N. (2010). Integrated soil fertility management. *Outlook on Agriculture*, 39(1), 17–24. <https://doi.org/10.5367/000000010791169998>
- Vanlauwe, B., Descheemaeker, K., Giller, K. E., Huising, J., Merckx, R., Nziguheba, G., Wendt, J., & Zingore, S. (2015). Integrated soil fertility management in Sub-Saharan Africa: Unravelling local adaptation. *The Soil*, 1(1), 491–508. <https://doi.org/10.5194/soil-1-491-2015>

**Publisher's Note** Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.



**Orkhan Sariyev** is a postdoctoral researcher at the Institute of Agricultural Sciences in the Tropics (Hans-Ruthenberg-Institute), University of Hohenheim, Germany. His primary interests revolve around agricultural and development economics, with a particular focus on food security, sustainable development, and women's empowerment. He is especially intrigued by rural development related policy and program evaluations, seeking to evaluate their effectiveness and identify areas for improvement.



**Jacob Asravor** is a doctoral candidate at the Institute of Agricultural Sciences in the Tropics (Hans-Ruthenberg-Institute), University of Hohenheim, Germany. His research interest encompasses issues of agricultural productivity and efficiency analysis, food security, technology and innovation adoption, and poverty reduction. He has keen interest in issues relating to how the adoption of agricultural technologies and innovations translate into greater food security and reduced poverty for rural farm families.



**Manfred Zeller** is a Professor and Chair of Rural Development Theory and Policy at the Hans-Ruthenberg-Institute, University of Hohenheim, Germany. He served as the Director of the Food Security Centre (2009–2014), worked as a Senior Research Fellow and Program Leader for the International Food Policy Research Institute (IFPRI) from 1993 to 1999 and again from 2014 to 2016, and held a professorship at the University of Goettingen (1999–2005). His academic work emphasizes

applied research on the impact of food, agriculture, and rural development policies on income, poverty status, and food security. His academic journey includes studies in Agricultural Sciences at the University of Bonn, where he earned a doctoral title in Agricultural Economics in 1990.